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The Impact of Aggregation Method Choice in GIS-Based Multi-Criteria Decision-Making Techniques for Site Selection of Green Hydrogen Production: A Brazilian Case Study

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ABSTRACT

Renewable hydrogen is key to Brazil's transition to a carbon-neutral energy system, utilizing its abundant solar and wind resources for large-scale decarbonization. Despite its vast renewable potential, high costs and infrastructure gaps keep deployment limited to early-stage pilot projects. This study presents a grid-level, GIS-integrated multi-criteria decision-making framework that evaluates hydrogen suitability in Brazil. The model integrates renewable resources, topography, land-use constraints, infrastructure, and industrial demand. A comprehensive comparative assessment of aggregation techniques is conducted through mathematical validation and benchmarking against existing projects. Results show that understanding each method enables decision-makers to select the approach that best aligns with specific planning objectives, considering input characteristics and regional context. The Northeast and Central-West are consistently identified as the most suitable regions, aligning with existing initiatives and confirming the framework's practical relevance. The study offers a flexible methodology combining quantitative rigor with expert judgment to guide national hydrogen roadmaps and large-scale deployment.

Keywords: Renewable Hydrogen; Production Siting; Renewable Resources; Multi-Criteria Decision-Making; Objective Weighting; Aggregation Methods

1. Introduction

1.1. Motivation

The urgency of mitigating climate change and enhancing energy security has accelerated the global transition toward low-carbon energy systems. Following the Paris Agreement [1], countries worldwide have committed to limiting global temperature rise to 1.5 °C, prompting large-scale investments in clean technologies. Within this context, green hydrogen (H₂V), which is produced via water electrolysis powered by renewable energy, has emerged as a versatile, low-carbon energy carrier capable of decarbonizing sectors where direct electrification is difficult. These include heavy industry, long-distance transport, refineries, maritime applications, and high-temperature industrial processes. H₂V also enables large-scale energy storage and sector coupling through Power-to-X pathways, allowing surplus renewable electricity to be converted into chemical energy and later reconverted to electricity, heat, or synthetic fuels [2]. It is positioned as a cornerstone of future sustainable energy systems. Consequently, it has been placed at the center of clean energy strategies in several major economies, where governments are mobilizing support through targeted investments, regulatory mandates, financial incentives and infrastructure plans to accelerate its adoption [3].

Brazil is particularly well positioned to participate in this emerging H₂V economy. The country possesses abundant renewable resources, including high solar irradiation, strong and complementary wind regimes, and a predominantly low-carbon electricity mix in which renewables account for more than 88 % of generation [4]. In addition, hydrogen already plays an important role in Brazil's industrial sector, representing a significant share of Latin America's consumption, primarily for petroleum refining and fertilizer production [5]. However, current production relies largely on steam methane reforming from natural gas, resulting in considerable associated emissions. Institutional support for H₂V has evolved over more than two decades, beginning with early research and strategic roadmaps advancing toward comprehensive national planning. This process culminated in the National Hydrogen Program (PNH₂) [6], its implementation agenda, and the integration of H₂V into broader energy and industrial policies aimed at accelerating deployment in industry and transport.

Despite this favorable context, large-scale deployment remains limited. Current projects are concentrated on pilot plants or early development stages [7], reflecting barriers as high capital costs, technological dependence on imported equipment, infrastructure constraints for storage and transport, and uncertainties in certification schemes, and regulatory frameworks [8]. Moreover, H₂V production facilities require complex integration with renewable generation, water availability, transmission networks, industrial demand centers, and environmental restrictions. Poor location choices can significantly increase system costs, reduce operational efficiency, and compromise long-term viability. Therefore, identifying suitable sites for H₂V production is a multidimensional problem involving technical, economic, environmental, spatial, and social considerations. Brazil's continental scale further complicates this challenge since renewable resources, infrastructure availability, land-use constraints, and industrial activity are unevenly distributed across the country.

In this context, the combination of Geographic Information Systems (GIS) and Multi-Criteria Decision-Making (MCDM) methods emerge as a powerful framework for site selection. GIS enables the processing of spatially explicit data layers, while MCDM provides systematic tools to evaluate and rank alternatives based on multiple factors. Together, they allow the generation of suitability maps that identify locations where renewable potential, infrastructure access, environmental compatibility, and demand proximity converge. Such analyses can reduce planning uncertainty, support strategic infrastructure development, and guide the formation of regional H₂V hubs.

1.2. Literature review

Since H₂V has emerged as a key pillar of global decarbonization strategies, it has driven extensive research across multiple dimensions including production technologies [9–11], system design and integration [12–14], techno-economic performance [15–17], and large-scale deployment feasibility. For instance, technical-economic studies indicate that the cost and efficiency of H₂V production via electrolysis are highly sensitive to renewable resource quality, infrastructure availability, and system configuration. Therefore, H₂V plants siting is inherently complex: they must simultaneously consider H₂V specific factors, such as proximity to demand centers, transport, water supply, pipeline or port infrastructure, and renewable constraints, including resource availability, land suitability, and grid access. As a result, the identification of optimal production locations is being studied as it represents a significant challenge for energy planners and policymakers because of the many criteria involved.

The MCDM method is an invaluable tool for evaluating and ranking different options based on these criteria [18]. Several studies have employed MCDM techniques to address complex problems in renewable energy systems, energy efficiency and optimization, grid and power system management, and policy and planning [19,20]. More recently, these methods have been increasingly applied to renewable H₂V production site suitability analysis, frequently in combination with GIS to enable spatially explicit decision support. Table 1 compiles representative studies across diverse geographic contexts.

Table 1

Literature review on studies on the location of renewable H₂V facilities using MCDM.

Ref.	Location	Spatial Implementation	Weighting Technique	Aggregation Technique	Renewable Source	H ₂ V Demand Estimation
[21]	Germany	Regional/Point Locations	Entropy	TOPSIS	Solar	Population Density
[22]	Southern Thailand	Regional/Point Locations	Expert Judgement	AHP	Solar	Urban Centers
[23]	Iran	Regional/Point Locations	Expert Judgement	TOPSIS	Solar	-
[24]	Uzbekistan	Regional/Point Locations	Expert Judgement	SWARA, WASPAS, COPRAS	Solar	Number of Refineries
[25]	Afghanistan	Regional/Point Locations	Expert Judgement	EDAS	Wind	Number of Refineries
[26]	Yazd province	Regional/Point Locations	Expert Judgement	AHP	Wind	Industrial Centers
[27]	Iran	Regional/Point Locations	Expert Judgement	FVIKOR, FTOPSIS	Wind	Population Density
[28]	Fars Province	Regional/Point Locations	Expert Judgement	DEA	Wind	Population Density
[29]	Qatar	Regional/Point Locations	Expert Judgement	FTOPSIS	Wind and Solar	Population Density
[30]	Southern Morocco	Regional/Point Locations	Expert Judgement	AHP	Solar	Population, Per-capita vehicle ownership, Projections for daily H ₂ V use per vehicle, market penetration level
[31]	Turkey	Regional/Point Locations	Expert Judgement	WSM	Solar	-
[32]	Saudi Arabia	Regional/Point Locations	Expert Judgement	WASPAS	Wind	Number of Refineries and Industrial Development Ratio
[33]	Poland	Regional/Point Locations	Expert Judgement	WSM	Wind	Residential buildings
[34]	China	Regional/Point Locations	Hybrid BWM CRITIC	MABAC	Solar	Industrial Demand
[35]	China	Regional/Point Locations	Hybrid EWM CRITIC	TOPSIS, VIKOR	None	Petrol- H ₂ V fueling stations
[36]	China	Regional/Point Locations	Hybrid BWM EWM	TODIM	Wind and Solar	Demand at specific locations
[37]	Morocco	National Continuous	Expert Judgement	AHP	Solar	Phosphate Industry
[38]	Bangladesh	National Continuous	Expert Judgement	AHP	Solar	Fertilizer Industry
[39]	Cameroon	National Continuous	Expert Judgement	FAHP	Solar	Population Density
[40]	Algeria	National Continuous	Expert Judgement	AHP	Solar	Population, per-capita vehicle ownership, projections for daily H ₂ V use per vehicle, market penetration level
This Paper	Brazil	National Continuous	Entropy	WSM, WPM, WASPAS, MOORA, TOPSIS, VIKOR	Wind and Solar	Hard-to-abate Industries

Collectively, these studies demonstrate the versatility of MCDM frameworks in integrating heterogeneous and multi-domain datasets within a single decision structure. The evaluated criteria typically span renewable resource indicators (e.g., solar irradiation, wind speed, ambient temperature, renewable power density), techno-economic variables (e.g., leveled cost of energy, land acquisition cost, investment and operating expenditures, policy or government support), environmental and physical constraints (e.g., elevation, terrain slope, natural hazards, protected or conservation areas), infrastructure accessibility (e.g., proximity to roads, transmission networks, ports, water resources, and industrial facilities), and socio-economic considerations (e.g., social acceptance, employment generation potential, population distribution).

As observed in Table 1, most studies conduct assessments at regional or discrete point scales [21–36], limiting the analysis to a predefined and relatively small set of candidate locations such as provinces, cities, industrial zones, or specific sites and the primary objective is to rank these alternatives according to their overall suitability. In this approach, each candidate is treated as a single decision unit, and the outcome is a prioritized list of a few feasible options. In contrast, a smaller subset of studies [37–40] performs national-scale continuous suitability mapping, in which the entire territory is evaluated at high spatial resolution (e.g., raster grid cells), potentially generating suitability scores for thousands to millions of spatial units simultaneously. Rather than selecting among a limited number of predefined sites, this approach identifies spatial patterns of suitability across the landscape, revealing both highly favorable zones and exclusion areas.

In terms of weighting, most analyses rely on subjective, expert-driven approaches, in which the relative importance of each criterion is determined through human judgement, typically using structured methods such as the Analytic Hierarchy Process (AHP), Stepwise Weight Assessment Ratio Analysis (SWARA), or similar pairwise-comparison frameworks [22–33, 37–40]. These methods translate expert preferences into numerical weights, allowing decision makers to incorporate domain knowledge, policy priorities, or stakeholder perspectives; however, the resulting weights may vary depending on the selected experts, their experience, and potential biases. By contrast, objective or data-driven weighting techniques, such as Entropy Weight Method (EWM), Criteria Importance Through Intercriteria Correlation (CRITIC), or Best–Worst Method (BWM) appear only sporadically. These methods derive weights directly from the statistical properties of the data, assigning greater importance to criteria that exhibit higher variability, information content, or discriminating power across alternatives. This scheme reflects the informational structure of the dataset rather than subjective judgment, as further discussed in the work in progress by [41]. Despite offering improved reproducibility and reduced subjectivity, these quantitative methods appear less frequently in the literature [21, 34–36].

Aggregation in these studies is performed using a variety of MCDM algorithms that can be grouped by approach. Distance-to-ideal and compromise methods include TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) [21,23,27,29,35], VIKOR (VIšekriterijumsko Kompromisno Rangiranje) [35], and EDAS (Evaluation based on Distance from Average Solution) [25]. Additive and proportional methods include WASPAS (Weighted Aggregated Sum Product Assessment) [24,32], COPRAS (Complex Proportional Assessment) [24], and WSM (Weighted Sum Method) [31,33]. Efficiency and distance-based methods include DEA (Data Envelopment Analysis) [28] and MABAC (Multi-Attributive Border Approximation area Comparison) [34]. Finally, risk and preference based methods include TODIM (Interactive and Multi-criteria Decision Making) [36], which accounts for decision-makers' risk attitudes.

Furthermore, H₂V demand is often represented using simplified spatial proxies, as illustrated in column 7 of Table 1, including variables such as population density, refineries, urban areas, or major industrial centers. However, relatively few studies incorporate a broader representation of potential H₂V demand hubs, despite the growing number of industrial sectors considering H₂V as a key decarbonization pathway. As H₂V applications expand beyond traditional uses, sectors such as steel, chemicals, heavy transport, and power generation are increasingly expected to contribute to future demand. Consequently, hydrogen demand is underestimated as an important site location factor.

1.3. Research gaps

Within the Brazilian context, GIS-based MCDM methods have been extensively applied across diverse domains, showcasing their versatility for spatial planning and resource management. Typical applications include coastal and environmental management, pollution and sustainability assessments, water resources planning, hazard and risk mapping, and renewable energy site selection [42–48]. In contrast, studies explicitly targeting H₂V production site suitability remain very limited, generally confined to regional or sector-specific case studies, and rarely employ nationwide

continuous mapping or fully integrate MCDM frameworks [49–57]. This contrast highlights the potential for applying established GIS-MCDM methodologies to support comprehensive, high-resolution H₂V infrastructure planning nationwide in Brazil.

The literature shows that existing H₂V siting studies often rely on subjective expert-driven weighting, apply only a single aggregation method, and focus on discrete candidate locations rather than national analyses. This leaves open opportunities for data-driven weighting, cross-method aggregation comparisons, and national-scale continuous mapping that can capture large spatial regions, integrate diverse criteria, and support more robust and transparent decision-making in the context of Brazil's emerging green H₂V landscape.

Additionally, previous studies often rely on simplified proxies such as population density, urban areas, refineries, or transport demand, overlooking the representation of a broader set of industrial demand centers. This creates a gap in capturing sectors such as steelmaking, chemicals, and other energy-intensive industries, where hydrogen is expected to play a critical role in decarbonization. Consequently, such approaches may underestimate the spatial distribution and future scale of H₂V demand, limiting the accuracy of suitability assessments for hydrogen deployment.

1.4. Contributions

This paper develops high-resolution site suitability maps for H₂V production potential across Brazil, providing a spatially explicit assessment of where large-scale deployment is most favorable under the country's diverse climatic, geographic, and infrastructural conditions. The study integrates data-driven inputs with expert knowledge to support strategic decision-making.

The main contributions of this study are as follows:

1. High-resolution national suitability mapping: Development of a detailed, country-wide spatial assessment of H₂V production potential using GIS-integrated MCDM techniques.
2. Systematic comparison of aggregation techniques: Application and evaluation of multiple MCDM aggregation methods to analyze how methodological choices affect suitability rankings and spatial patterns.
3. Reproducible and transferable framework: Provision of a transparent methodology that can be adapted to different geographic contexts.
4. Integration of H₂V demand from hard-to-abate sectors: Incorporation of a broader range of H₂V -consuming industries aligned with decarbonization pathways, enabling a more realistic representation of future H₂V demand.

Together, these contributions position the study as a decision-support tool for identifying priority areas for H₂V deployment in Brazil while demonstrating the critical influence of aggregation choice in GIS-MCDM suitability analyses.

1.5. Paper organization

The structure of this study is organized as follows. Section 2 provides an overview of H₂V and MCDM techniques, Section 3 presents the proposed methodology. Section 4 presents the results, and Section 5 offers the main conclusions.

2. Multi-Criteria Decision-Making

This section presents the mathematical formulations of the techniques used in the proposed MCDM framework. First, normalization methods are introduced to ensure comparability among the selected criteria. Next, objective weighting techniques to reflect the relative importance of each criterion based on their statistical properties. Finally, aggregation and ranking methods to combine the criteria and evaluate the suitability of each alternative.

2.1. Normalization Techniques

2.1.1. Min–max normalization

Min–max normalization rescales each criterion to a standard range [0, 1], so that values from different units or scales become comparable.

For benefit-type criteria (higher values increase suitability):

$$x'_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (1)$$

For cost-type criteria (higher values reduce suitability):

$$x'_i = \frac{\max(x) - x_i}{\max(x) - \min(x)} \quad (2)$$

2.1.2. Vector normalization

Vector normalization scales the values of each criterion relative to the overall magnitude of its vector, ensuring that the sum of squared normalized values equals one. Since algorithms that use vector normalization incorporate a separate step to handle benefit and cost criteria, both types are normalized using the same formula:

$$x'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (3)$$

2.2. Weighting Techniques

2.2.1. Entropy Weighting Method

The EWM, based on Shannon's measure of information uncertainty, is employed to determine objective criterion weights by analyzing the dispersion of the underlying data. The fundamental premise of EWM is that criteria exhibiting greater variability across alternatives contain more discriminative information and therefore should receive higher weights, whereas criteria with uniform values contribute less to differentiation and receive lower weights. The EWM procedure is defined by Equations (4)–(6). First, the entropy value E_j or each criterion j is computed as:

$$E_j = -\frac{\sum_{i=1}^m p_{ij} \ln(p_{ij})}{\ln(m)} \quad (4)$$

where m is the number of alternatives and p_{ij} represents the probability distribution of the i -th alternative under criterion j , calculated as:

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^m x'_{ij}} \quad (5)$$

Here, x'_{ij} denotes normalized value of alternative i for criterion j . Finally, the objective weight w_j of each criterion is derived from its entropy value:

$$w_j = \frac{1 - E_j}{\sum_{i=1}^n (1 - E_i)} \quad (6)$$

where n is the total number of criteria.

2.3. Aggregation Techniques

2.3.1. Weighted Sum Method

WSM is an aggregation technique that works by combining multiple criteria into a single score, SI , for each alternative. First, the criteria are normalized using Equations (1) and (2). Then, each normalized criterion value is multiplied by its corresponding weight, and the weighted values are summed to produce the overall score. Mathematically, WSM is expressed as:

$$SI_i = \sum_{j=1}^n x'_{ij} w_j \quad (7)$$

where x'_{ij} denotes the normalized value of criterion j for alternative i , w_j is the weight assigned to criterion j , and n is the total number of criteria.

2.3.2. Weighted Product Model

WPM is a multiplicative approach for MCDM. It operates on ratios and preserves proportional differences by raising criterion values to the power of their assigned weights. Normalization of criteria is performed using Equations (1) and (2). The suitability score of an alternative is obtained by multiplying the normalized criterion values, each raised to the power of its corresponding weight. Mathematically:

$$SI_i = \prod_{j=1}^n (x'_{ij})^{w_j} \quad (8)$$

2.3.3. Weighted Aggregated Sum Product Assessment

The WASPAS method is a hybrid MCDM technique that combines the advantages of both the WSM and the WPM. By integrating additive and multiplicative aggregation approaches, WASPAS enhances ranking robustness, rather than using either method alone. The method starts by normalizing the criteria using Equations (1) and (2), and the suitability score is then calculated mathematically as:

$$SI_i = \lambda \sum_{j=1}^n x'_{ij} w_j + (1 - \lambda) \prod_{j=1}^n (x'_{ij})^{w_j} \quad (9)$$

where $\lambda \in [0,1]$ balances additive and multiplicative components. Commonly, $\lambda = 0.5$ is used giving equal weight to both, but it can be adjusted to reflect the decision-maker preferences.

2.3.4. Multi-Objective Optimization by Ratio Analysis

The Multi-Objective Optimization by Ratio Analysis (MOORA) [58] is a widely used MCDM technique that ranks alternatives with both beneficial and non-beneficial criteria. First, the decision matrix is normalized using vector normalization (Equation 3). The SI of each alternative is obtained by subtracting the aggregated normalized values of cost (non-beneficial) criteria from those of benefit (beneficial) criteria, mathematically expressed as:

$$SI_i = \sum_{j \in B} w_j x'_{ij} - \sum_{j \in C} w_j x'_{ij} \quad (10)$$

where B is the set of beneficial criteria, C is the set cost criteria.

2.3.5. Technique for Order Preference by Similarity to Ideal Solution

TOPSIS ranks alternatives based on their geometric proximity to an ideal solution. The main concept is that the best alternative should be closest to the Positive Ideal Solution (PIS), which maximizes benefit criteria and minimizes cost criteria, and farthest from the Negative Ideal Solution (NIS), which represents the worst possible performance.

The procedure begins by normalizing the decision matrix using Equation (3) and then applying the criterion weights to generate the weighted normalized matrix.

$$V_{ij} = x'_{ij} w_j \quad (11)$$

Then, the PIS, $V^{(+)}$, and NIS, $V^{(-)}$, identified:

$$V^{(+)} = (\text{Max}(V_{ij}) | j \in B), (\text{Min}(V_{ij}) | j \in C) \quad (12)$$

$$V^{(-)} = (\text{Min}(V_{ij}) | j \in B), (\text{Max}(V_{ij}) | j \in C) \quad (13)$$

and the Euclidean distances of each alternative from these two reference points are calculated.

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (14)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (15)$$

where D_i^+ is the Euclidean distance of alternative i from the PIS, D_i^- is the distance from the NIS. The relative closeness coefficient, or suitability score, of each alternative to the ideal solution is given by:

$$SI_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (16)$$

2.3.6. Multi-criteria Optimization and Compromise Solution (VIKOR)

The VIKOR method focuses on identifying a compromise solution that provides a maximum group utility (overall satisfaction) while minimizing the individual regret of the worst-performing criterion.

The procedure begins by determining the best ($F^{(+)}$) and worst ($F^{(-)}$) values for each criterion across all alternatives.

$$F^{(+)} = (\text{Max}(x_{ij}) | j \in B), (\text{Min}(x_{ij}) | j \in C) \quad (17)$$

$$F^{(-)} = (\text{Min}(x_{ij}) | j \in B), (\text{Max}(x_{ij}) | j \in C) \quad (18)$$

Then, each value is then transformed into a dimensionless measure representing its normalized distance from the ideal solution:

$$d_{ij} = \frac{f_j^+ - x_{ij}}{f_j^+ - f_j^-} \quad (19)$$

This term d_{ij} quantifies the relative loss or dissatisfaction. A $d_{ij} = 0$ corresponds to the best observed performance, while $d_{ij} = 1$ corresponds to the worst.

Using these normalized distances, two measures are computed for each alternative. The group utility S_i , representing the overall distance from the ideal solution, and the individual regret R_i , representing the maximum dissatisfaction across criteria:

$$S_i = \sum_{j=1}^n w_j d_{ij} \quad (20)$$

$$R_i = \max_j [w_j d_{ij}] \quad (21)$$

These measures are then aggregated into the VIKOR index Q_i , which represents the compromise ranking:

$$Q_i = v \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*} \quad (22)$$

where $S^* = \min S_i$, $S^- = \max S_i$, $R^* = \min R_i$, $R^- = \max R_i$, and $v \in [0,1]$ is the weight representing the decision strategy, typically $v = 0.5$, giving equal importance to group utility and individual regret.

The resulting score Q_i provides the basis for ranking alternatives; lower values indicate solutions closer to the ideal compromise and are more desirable, therefore the suitability index is:

$$SI_i = 1 - Q_i \quad (23)$$

Table 2 summarizes the mathematical logic underlying each aggregation method, highlighting how low- and high-performing criteria influence the resulting suitability scores.

Table 2

Conceptual comparison of aggregation methods.

Method	Mathematical rationale	Effect of low-performing criterion	Effect of high-performing criterion	Resulting Behavior
WSM	Additive aggregation (weighted sum)	Limited penalization; can be compensated by other criteria	Contributes linearly to increase the overall score	Since values are added, a low value only subtracts a small amount from the sum
WPM	Multiplicative aggregation (geometric mean)	Strong penalization; near-zero values significantly reduce the overall score	Enhance the score only if all criteria perform well	Values are multiplied meaning one low value reduces the entire product
WASPAS	Hybrid of additive and multiplicative aggregation	Moderate penalization; partially compensated	Balanced contribution to the final score	Combination of additive and multiplicative yields partial compensation
MOORA	Linear ratio-based formulation (benefit-cost normalization)	Reduces score proportionally	Increases score proportionally	Based on differences (addition/subtraction) creating moderate compensability
TOPSIS	Euclidean distance to ideal and anti-ideal points	Increases distance from ideal significantly	Decreasing distance to ideal	Uses Euclidean distance meaning that deviations accumulate across criteria
VIKOR	Compromise solution based on group utility and individual regret	Penalizes strongly if it is the worst criterion	Improves overall score but limited by worst criterion	Combines total distance (sum) and maximum deviation (worst case)

3. Proposed Methodology

The methodological framework consists of sequential and interrelated stages, as shown in Fig. 1, integrating geospatial analysis with MCDM techniques.

The first phase involves spatial data preparation and harmonization. Geospatial datasets are collected from official sources to represent renewable energy availability, infrastructure, environmental constraints, and H₂V-related technical factors. All criteria layers are processed to ensure spatial consistency through rasterization and transformation into a common Coordinate Reference System (CRS). This ensures full comparability across all criteria.

Following preprocessing, constraint analysis and spatial masking are conducted. Technical, environmental, and infrastructure-related thresholds are defined to identify unsuitable areas for H₂V production facilities. These constraints are implemented through Boolean logic to generate a binary suitability mask, excluding unfeasible locations from subsequent analysis.

The next stage comprises criteria analysis and weighting. Continuous criteria are normalized to ensure scale comparability and subjected to statistical analysis to assess distributional properties and variability. Objective weights are then determined using the EWM.

Subsequently, aggregation and ranking are performed using six different MCDM techniques. Each method integrates the weighted criteria to compute a composite suitability score for every spatial alternative. These scores are mapped to generate six independent suitability maps for H₂V production.

Finally, a comparative performance analysis is conducted to evaluate consistency and behavioral differences among the applied aggregation methods, enabling a comprehensive assessment of methodological sensitivity and decision stability.

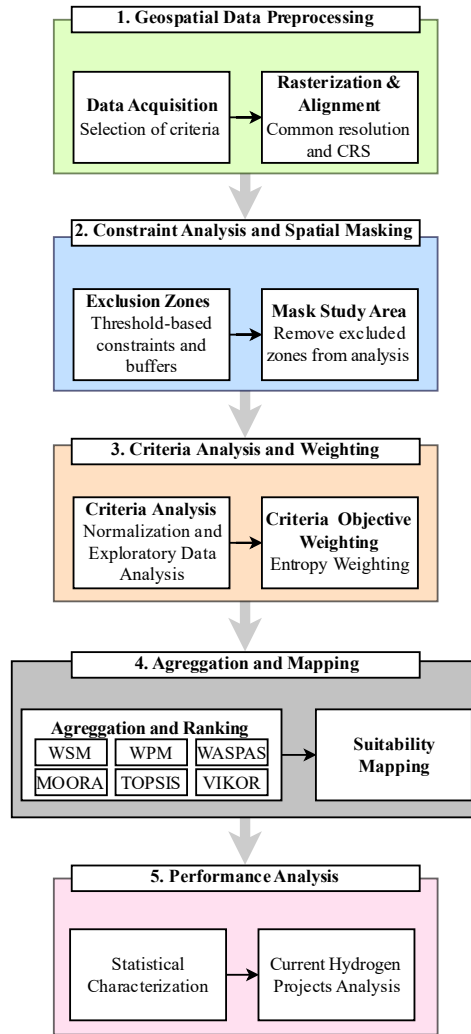


Fig. 1. Flowchart of the methodology.

3.1. Study area and Data Preprocessing

This study focuses specifically on Brazil, situated in South America covering 8,510,418 km² (latitudes 6°N and 34°S, and longitudes 28° and 74°W). All spatial datasets used in this study are from official national institutions and recognized global databases to ensure reliability, transparency, and reproducibility. The collected information represents renewable energy resources (wind and solar potential), infrastructure networks, environmental and territorial constraints, and H₂V-related demand. A complete description of the datasets is provided in Table 3.

Table 3

Collected Data.

Main	Sub	Unit	Source
Resource	Solar Resource	kWh/kWp	[59]
	Wind Resource	Capacity factor (%)	[60]
	Superficial Water Availability	distance to water (m)	[61]
Environmental and Technical	Elevation	m.a.s.l.	[62]
	Slope	degrees (°)	[62]
	Land Use	categorical	[63]
	Protected Areas	binary (0 = outside, 1 = inside)	[64,65]
Economic	Highways	distance (m)	[66]
	Powerlines	distance (m)	[67]
	Marine Ports	distance (m)	[68]
	Pipelines	distance (m)	[69]
	Hydrogen Demand	demand centers	[70–76]

Following acquisition, all datasets undergo a structured preprocessing workflow. Vector layers are rasterized and then every rasterized layer is resampled to a common spatial resolution. All layers are aligned to a unified grid extent and projected to a common CRS, ensuring pixel-to-pixel correspondence across criteria.

This harmonization step is critical in GIS-based MCDM, as inconsistencies in resolution, projection, or spatial alignment can introduce systematic errors.

3.2. Constraint Analysis

Areas considered unsuitable due to technical, environmental, and topographic constraints are systematically excluded prior to the MCDM stage. This preliminary screening ensures that subsequent suitability assessment is restricted to locations that are both technically feasible and environmentally compliant, thereby preventing unrealistic alternatives from influencing the ranking process.

The exclusion framework integrates environmental protection zones (e.g., conservation units and indigenous territories), infrastructure-related

buffers, hydrological constraints, and terrain limitations. The criteria considered include elevation, slope, proximity to highways, proximity to power transmission lines, proximity to surface water resources, and legally protected areas. The threshold values adopted in this study are based on analysis of the study area's geography, a comprehensive literature review [22,26,31,39,40], and expert recommendations as summarized in Table 4.

Table 4

Exclusion Thresholds.

Constraint	Unit	Threshold
Elevation	m.a.s.l.	>2000
Slope	°	>5
Distance from Highways	km	<0.5 and >10
Distance from Power Lines	km	<0.5 and >10
Distance from Water Resources	km	<0.5 and >10
Distance from protected Areas	km	<1

The constraint map is generated using a Boolean overlay procedure within a GIS environment. Each exclusion criterion is converted into a binary raster layer, where pixels satisfying feasibility conditions are assigned a value of 1 (suitable) and pixels violating at least one threshold are assigned a value of 0 (unsuitable). The final constraint layer is obtained through the intersection of all binary layers, producing a wider feasibility mask. This mask is then applied to the preprocessed criteria dataset, permanently removing unsuitable alternatives from further multi-criteria evaluation.

3.3. Criteria Analysis

This stage examines the statistical properties, spatial behavior, and interrelationships of the selected criteria prior to weighting and aggregation. The objective is to ensure scale comparability across heterogeneous variables and detect potential redundancy or multicollinearity. The selected criteria for the MCDM analysis include renewable resource availability (solar and wind potential), infrastructure accessibility (distance to highways, power lines, ports, and pipelines), hydrological availability (distance to surface water resources), land-use compatibility (Table 5), and H₂V demand potential.

Land-use compatibility indicates how suitable each land category is for hydrogen infrastructure deployment. The index ranges from 1 (least compatible) to 5 (most compatible), where forests, urban areas, and water bodies have the lowest compatibility, while pastures and non-irrigated arable land are considered the most suitable due to fewer land-use constraints.

Table 5

Land use index.

Compatibility	Land use type
5	Non-irrigated arable land
4	Pastures
3	Permanently irrigated land occupied by agriculture
2	Mixed forest and grassland
1	Forest, urban land & water bodies

The Demand Potential criterion combines demand level and distance to industry. Demand level is an intrinsic importance score assigned to each industrial sector, ranging from 1 (low H₂V intensity) to 5 (high H₂V intensity), as detailed in Table 6. This score is assigned empirically based on references [77–79]. Distance to industry is the Euclidean distance between each spatial alternative and each industrial facility.

The objective is to spatially propagate the influence of H₂V-consuming industries, such that locations closer to high-demand sectors exhibit greater potential. The Demand Potential at alternative (x, y) is defined as:

$$DP(x, y) = \sum_{i=1}^N \frac{D_i}{(d_i(x, y) + \epsilon)^\alpha} \quad (24)$$

Where N is the total number of industries, D_i is the demand level of industry i , $d_{i,xy}$ is the Euclidean distance from alternative (x, y) to industry i , α is the distance decay exponent controlling spatial attenuation and ϵ is a small constant prevention of division by zero.

This gravity-based structure [80] ensures that high-demand industries exert stronger spatial influence, while their effect decreases progressively with distance.

Table 6

Classification of demand level.

Level	Industries
5	Fertilizers / Ammonia, Refinery
4	Chemicals, Steelmaking
3	Cement, Ceramics
2	Glass, Aluminum
1	Paper, Margarine

Each criterion is classified as either:

1. Benefit-type: higher values increase suitability (e.g., solar resource, wind resource, H₂V demand potential, land-use compatibility).
2. Cost-type: higher values reduce suitability (e.g., distance-based variables).

The complete set of criteria and their classification as benefit or cost is presented in Table 7. This procedure ensures directional consistency, where higher values represent higher suitability.

To evaluate interdependence among criteria, Pearson correlation coefficients are computed. This analysis identifies potential multicollinearity and spatial redundancy that could distort weighting and aggregation outcomes. Highly correlated criteria are carefully examined to prevent implicit overweighting of structurally similar information within the final suitability index.

Table 7

Set of criteria.

Criterion	Description	Type
Solar Resource	Photovoltaic energy generation potential. Higher values indicate greater electricity production capability and increased suitability.	Benefit
Wind Resource	Expected wind turbine performance measured through capacity factor (%), representing the ratio of actual to maximum possible output. Higher capacity factors enhance project viability.	Benefit
Land Use Compatibility	Reclassified index representing territorial and environmental suitability for industrial deployment. Higher values indicate greater compatibility.	Benefit
Demand Potential	Index capturing the influence of hydrogen-consuming industries, combining demand intensity and proximity. Higher values reflect stronger attractiveness.	Benefit
Distance to Highways	Euclidean distance to major road infrastructure, reflecting transportation accessibility and logistics costs for construction and operation. Greater distances increase costs.	Cost
Distance to Power Lines	Distance to electricity transmission infrastructure, indicating grid connection feasibility and associated capital expenditures. Larger distances reduce suitability.	Cost
Distance to Pipelines	Distance to existing gas pipeline infrastructure, representing potential integration and transport feasibility. Greater distances imply higher connection costs.	Cost
Distance to Ports	Distance to maritime terminals, reflecting export potential and access to international hydrogen markets. Increased distance reduces economic attractiveness.	Cost
Distance to Water Resources	Distance to surface water bodies, representing availability of water required for electrolysis processes. Longer distances imply higher abstraction and transport costs.	Cost

3.4. Criteria Objective Weighting

The determination of criteria weights directly influences the contribution of each criterion to the final suitability index. Weighing approaches are typically classified as subjective or objective methods. Subjective techniques may introduce cognitive bias and can be sensitive to the number of criteria considered, while objective techniques capture the informational contribution of each criterion based on its statistical dispersion across the study area.

To minimize subjectivity and enhance reproducibility, this study adopts EWM as the objective weighting approach. EWM derives weights from the statistical properties of the data, reflecting the inherent informational content of each criterion. After testing alternative objective weighting methods and comparing results guided by expert judgment, EWM was found to best represent the relative importance of the criteria and was therefore selected for the subsequent MCDM analysis.

3.5. Aggregation and Ranking

Once the objective weights are determined, criteria are aggregated to compute composite suitability indices and generate spatial rankings. Since this work adopts a fully objective MCDM framework to enhance reproducibility and minimize subjectivity, methods such as AHP, which rely on expert judgment, are not considered. Instead, the selected methods include WSM, WPM, WASPAS, MOORA, TOPSIS, and VIKOR, which are widely applied in hydrogen infrastructure planning [81], enabling consistency and comparability with existing studies.

These techniques are deliberately chosen to represent distinct aggregation logics, including additive (WSM), multiplicative (WPM), hybrid (WASPAS), ratio-based (MOORA), distance-based (TOPSIS), and compromise-based approaches (VIKOR). This selection allows for a systematic evaluation of how different mathematical formulations influence suitability outcomes in hydrogen deployment analysis.

The WSM is an additive model and represents the most widely used aggregation approach. The WPM extends this logic using a multiplicative structure, reducing full compensability among criteria. The WASPAS method integrates both additive and multiplicative formulations, combining the strengths of WSM and WPM to enhance ranking stability. In contrast, MOORA is based on ratio analysis, separating benefit and cost criteria and computing a net performance score through differences. Finally, TOPSIS and VIKOR belong to the family of distance-based compromise methods. Both identify ideal and non-ideal solutions and rank alternatives according to their relative closeness to these benchmarks.

Each aggregation technique is independently implemented to compute a suitability index for every spatial alternative within the feasible area. The resulting suitability scores are structured as raster outputs, preserving the spatial resolution and grid alignment defined in the preprocessing phase.

These rasterized suitability layers are subsequently exported to the GIS environment, where they are symbolized using continuous heat-color gradients to generate spatially explicit suitability maps. This procedure enables direct visual comparison among methods.

By producing six independent suitability rasters, the framework facilitates a comparative assessment of ranking consistency and convergence patterns.

3.6. Performance Analysis

The performance analysis systematically evaluates and compares the outputs of the six MCDM methods in terms of statistical properties, spatial consistency, and alignment with real-world H₂V production projects. This assessment ensures that the generated suitability scores are robust, interpretable, and actionable for planning and decision-making purposes.

3.6.1. Statistical Characterization

For each method, a comprehensive set of statistical measures is computed, including mean, median, standard deviation, variance, interquartile range, skewness and kurtosis. These metrics quantify the distribution, variability, and differentiation of suitability scores, providing insight into the concentration and spread of high-potential alternatives.

To visualize these characteristics, boxplots and histograms are generated for each method, highlighting central tendency, dispersion, skewness, and outliers. These visualizations allow for a clear comparison of how each method ranks alternatives and identifies top-performing locations.

3.6.2. Alignment with Existing H₂V Production Sites

To assess practical reliability, the high-suitability zones identified by each method are compared with the locations of operational H₂V production plants. This empirical alignment complements statistical assessment by grounding methodological consistency in real-world evidence and helps discriminate which methods better reflect actual deployment patterns.

Project location data are obtained from official sources, filtered to retain only operational plants for industrial H₂V production [82]. Suitability scores across all spatial units are then compared with these locations, providing an external benchmark to assess accuracy and practical relevance of the methods.

4. Results

This section evaluates the spatial suitability for locating H₂V production facilities across Brazil, considering the two primary renewable electricity pathways: solar photovoltaic and wind power, together with additional H₂V-related infrastructure and environmental criteria. MCDM techniques are implemented using the Python programming language, while geospatial processing and mapping are conducted in QGIS.

4.1. Study Area and Preprocessing

The study area encompasses the entire Brazilian territory, represented using a spatial resolution of 500 × 500 m. All spatial analyses are performed using the SIRGAS 2000 / Brazil Polyconic projection (CRS EPSG:5880), expressed in meters to ensure spatial consistency in distance-based calculations. At this resolution, the Brazilian territory is discretized into ≈34.5M potential spatial alternatives.

4.2. Constraint Analysis

After applying the exclusion thresholds, approximately 60% of the territory is classified as unsuitable, leaving ≈14.3M potential alternatives for subsequent suitability analysis. The spatial distribution of the excluded territories is illustrated in Fig. 2, where unsuitable areas are highlighted in black.

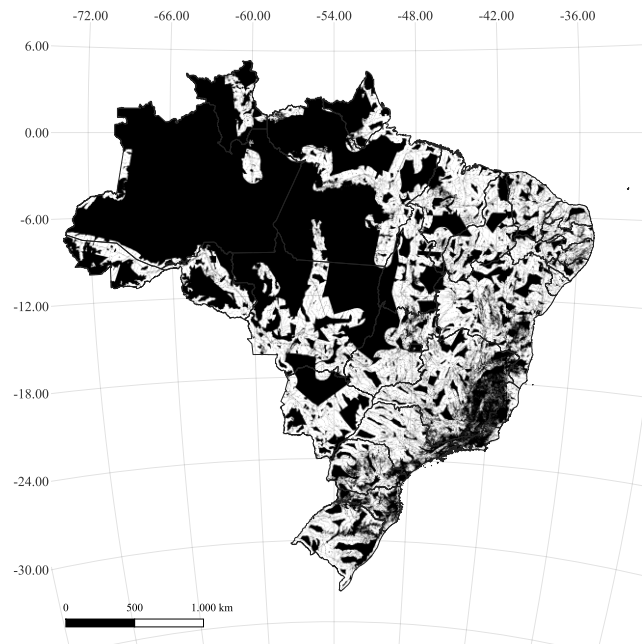


Fig. 2. Excluded areas of the analysis.

A significant portion of the excluded area corresponds to the Amazon region in northern Brazil. Large areas of the Amazon are designated as conservation units or protected territories, and the region generally presents low accessibility due to the limited presence of highways, transmission infrastructure, and industrial development. Additionally, indigenous territories represent an important component of the excluded areas. These lands are protected under the Brazilian Constitution of 1988 [83], playing a fundamental role in the preservation of indigenous cultures and ecosystems. Indigenous territories account for approximately 13% of Brazil's national territory, with the majority located within the Amazon basin.

Topographic constraints also contribute to the exclusion process. Several mountainous and highland regions, including the *Serra do Mar*, *Serra da Mantiqueira*, *Chapada Diamantina*, and other southeastern plateau formations, present steep slopes and terrain conditions that complicate large-scale industrial deployment and infrastructure installation.

4.3. Criteria Analysis

Following the exclusion of unsuitable areas, all criteria are normalized according to the procedure described in Section 3.3, applying the corresponding normalization formula for benefit and cost criteria. Fig. 3 presents the histograms of the normalized criteria, where the red dashed vertical line represents the mean value of each distribution.

Infrastructure accessibility criteria generally exhibit negatively skewed distributions, indicating that a large portion of the territory is located relatively close to major infrastructure networks. This is expected, as areas located more than 10 km from such networks were previously excluded. For instance, the distance to highways shows that most areas have moderate accessibility to road infrastructure, with fewer locations located at greater distances. A similar pattern is observed for distance to power lines, suggesting relatively good electrical grid coverage across much of the territory, although some isolated regions remain farther from transmission infrastructure.

The distribution of distance to pipelines also indicates that many locations are situated relatively close to existing pipeline networks, with a limited number of areas located at greater distances. Likewise, distance to ports shows that most alternatives maintain reasonable proximity to maritime infrastructure, although accessibility is somewhat less uniform compared to highway networks.

In contrast, the distance to water resources presents a flatter distribution, indicating a balanced distribution of water availability across the study area.

The land-use compatibility criterion suggests that most spatial alternatives fall within compatible land-use categories suitable for potential infrastructure development.

Regarding renewable energy resources, the solar resource exhibits a slight tendency toward higher suitability values. This reflects the widespread availability of favorable solar irradiance conditions across much of the Brazilian territory. Conversely, the wind resource distribution is positively skewed, indicating that while most locations present moderate wind potential, a smaller number of sites exhibit significantly higher wind capacity

factors.

Finally, the H₂V demand potential displays a highly positively skewed distribution, indicating that demand is strongly concentrated in a limited number of locations, while most areas exhibit relatively low demand potential. This pattern reflects the spatial concentration of population and industrial activity in Southeastern Brazil, particularly in the states of *São Paulo*, *Rio de Janeiro*, and *Minas Gerais*. These states historically constitute the main drivers of economic activity in the country, hosting major industrial sectors such as manufacturing, mining, agriculture, and energy production. In particular, *São Paulo* is Brazil's primary financial and industrial hub, and plays a central role in national and international economic activity.

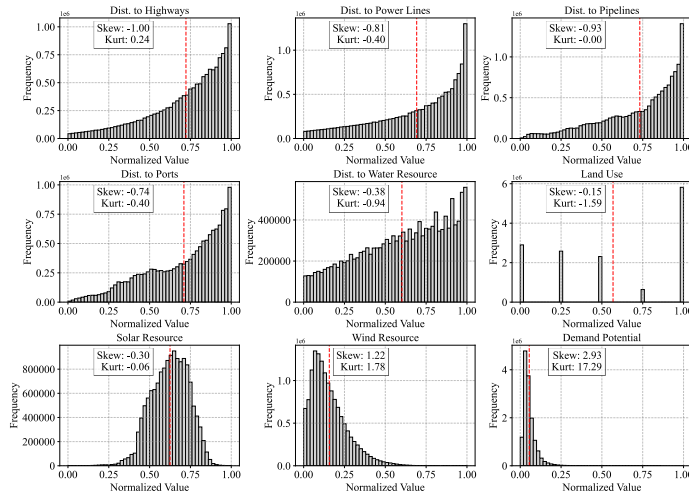


Fig. 3. Histograms of normalized criteria.

To further examine the relationships among criteria, Fig. 4 presents the Pearson correlation matrix. The highest observed correlation corresponds to distance to ports and distance to pipelines, with a coefficient of 0.81, indicating strong collinearity between these variables. To address this issue, Principal Component Analysis (PCA) is applied to combine these two highly correlated variables into a single criterion named Distance to Ports & Pipelines. The first principal component explains 90.63% of the total variance, the resulting component loadings are 0.676 for distance to pipelines and 0.737 for distance to ports. The new composite variable effectively captures the shared information contained in both original criteria while reducing redundancy.

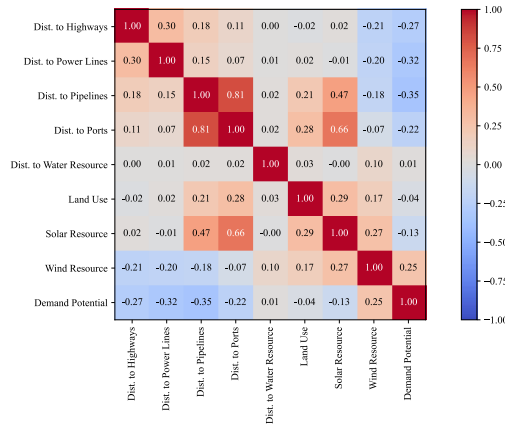


Fig. 4. Pearson Correlation Matrix between Criteria.

4.4. Objective Weighting

The next stage of the proposed methodology is the assignment of criterion weights using the EWM, which determines weights based on the variability and informational content of each criterion. Fig. 5 presents the resulting weights obtained from this method.

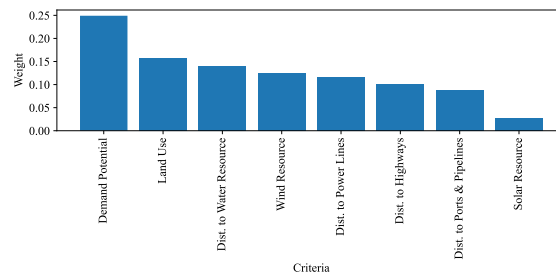


Fig. 5. Criteria weights from objective approaches.

The EWM assigns the highest weight to the H₂V demand potential criterion, reflecting the strong variability and spatial concentration of industrial demand across the study area. H₂V demand potential is highly concentrated geographically, particularly in the southeastern region of Brazil, where

industrial activity and population density are significantly higher, explaining why the entropy method identifies it as the most influential criterion.

Land use is also considered highly relevant, receiving the second-highest weight, which confirms its importance in determining feasible locations for H₂V production facilities.

The EWM assigns similar weights to most infrastructure-related criteria (distance to highways, power lines, pipelines, and ports), reflecting their comparable statistical distributions and information content. Slightly higher weights are assigned to water availability and wind resources, indicating that these criteria present greater spatial variability and therefore contribute more information to the decision-making process. Infrastructure criteria display similar distribution patterns, which explains why both objective weighting methods assign them relatively balanced weights.

The lowest weight is assigned to the solar resource. This result can be explained by the relatively uniform distribution of solar irradiance across the Brazilian territory, where most regions present favorable conditions for photovoltaic generation. Because EWM weighting prioritizes criteria with higher variability, the limited differentiation of solar potential across the study area reduces its relative influence. In contrast, wind resources exhibit greater spatial variability, which justifies their higher weight under the EWM.

4.5. Aggregation and Suitability Mapping

The suitability maps for H₂V production sitting generated by each aggregation method are presented in Figs. 6–11. To ensure a consistent visual comparison across methods, the same color gradient is applied to all maps. In this scale, light yellow represents the highest suitability indices, while dark blue indicates lower suitability values. Areas displayed in black correspond to locations previously excluded and therefore have a suitability value of zero. A comparison of the resulting maps reveals noticeable differences in the spatial distribution.

As illustrated in Fig. 6, the WSM produces the highest suitability scores among all methods. Since it operates through a linear additive formulation, where the weighted contributions of each criterion are summed, high values in some criteria can compensate for lower values in others, often leading to higher overall suitability scores across the study area. As a result, WSM produces more permissive SI.

In contrast, WPM exhibits more restrictive behavior, as shown in Fig. 7. Unlike WSM, WPM aggregates criteria through a multiplicative function, where each criterion value is raised to the power of its corresponding weight and multiplied across all criteria. This formulation has important implications. If any criterion assumes a low value, its multiplicative effect can significantly reduce the final suitability score. As a result, WPM strongly penalizes alternatives that perform poorly in even a single criterion, producing generally lower suitability values.

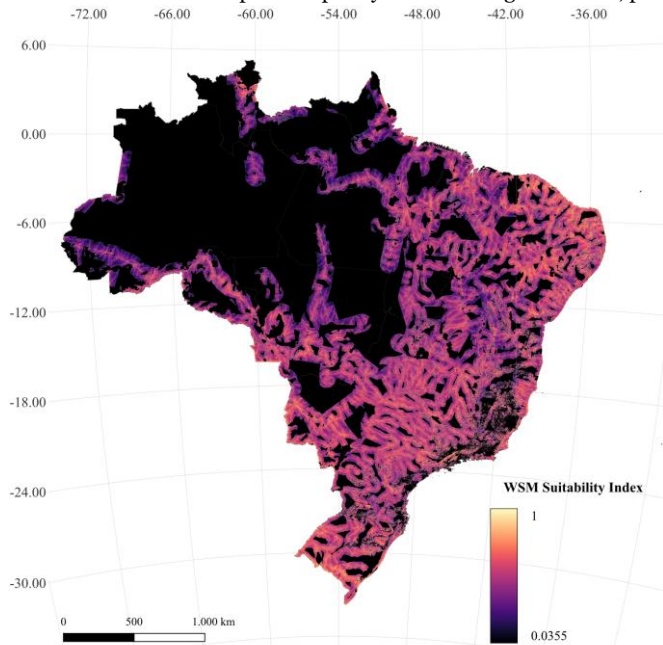


Fig. 6. WSM Suitability Mapping.

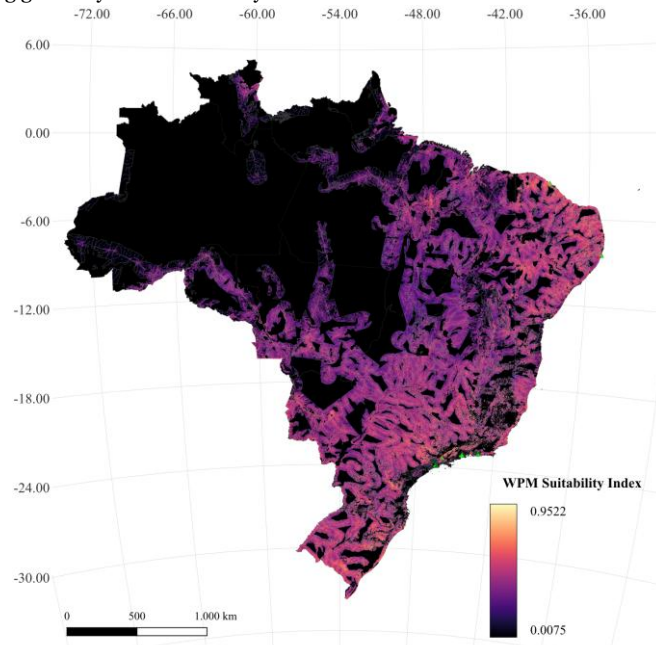


Fig. 7. WPM Suitability Mapping.

The WASPAS method, shown in Fig. 8, and which combines the WSM and WPM formulations, inherits part of this additive behavior when implemented in its standard version having equal influence from both components. Consequently, the relatively high scores produced by WSM partially propagate into the final WASPAS suitability results, explaining why its scores remain comparatively elevated.

In Fig. 9, the suitability map produced using the MOORA technique exhibits generally lower suitability scores compared with the WSM, WASPAS, and even WPM approaches. MOORA evaluates alternatives in a different form. Specifically, after normalization, the weighted values of benefit criteria are summed, while the weighted values of cost criteria are subtracted from this sum. The final score therefore represents a balance between positive and negative contributions rather than a cumulative aggregation of all criteria. This subtractive structure impacts the overall index. When an alternative performs poorly in a high weight cost-related criteria, the subtraction of this weighted term can significantly reduce the final score. Overall, multiple negative contributions directly offset the benefits obtained.

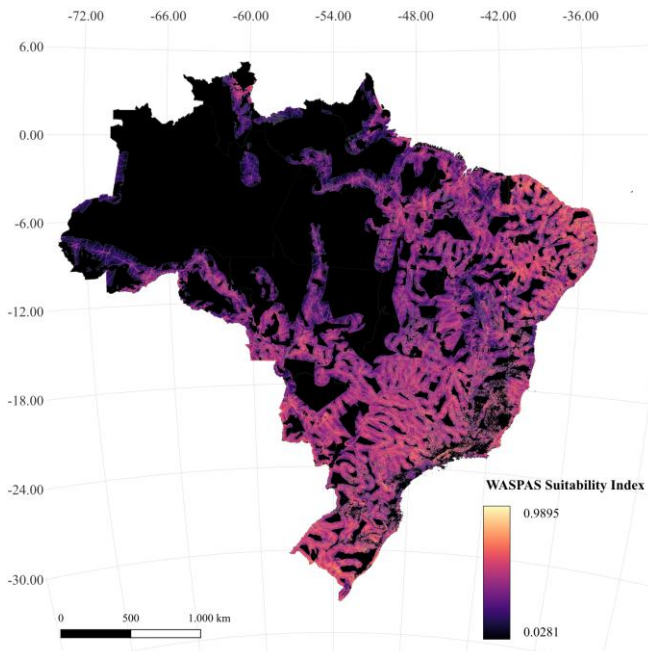


Fig. 8. WASPAS Suitability Mapping,

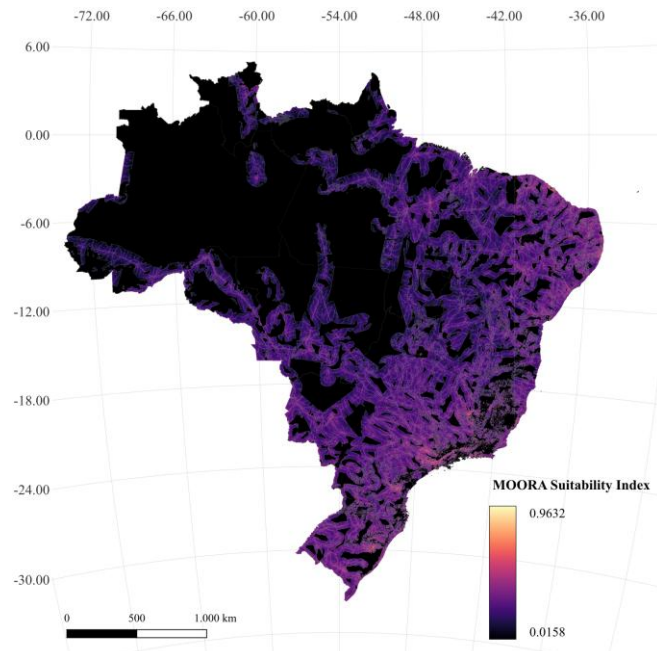


Fig. 9. MOORA Suitability Mapping.

TOPSIS, on Fig. 10, produces the lowest suitability indices across the study area. TOPSIS ranks alternatives according to their relative distance to two reference solutions: the positive ideal solution and the negative ideal solution. One represents an alternative that simultaneously achieves the best value for every benefit criterion and the lowest value for every cost criterion, while the other represents the opposite case.

In large-scale spatial problems such as the present study, where millions of alternatives are evaluated, the ideal solution is constructed from the extreme values observed across the entire dataset. The resulting ideal solution often corresponds to a theoretical combination of best values that might not actually exist. Consequently, most alternatives remain relatively far from this ideal reference point. The method implicitly benchmarks every alternative against a theoretical optimal location defined by the best observed values of all criteria, which are difficult to match especially in large datasets.

Finally, the VIKOR method produces suitability scores with intermediate behavior, which can be explained by its compromise-based mathematical formulation. Like TOPSIS, VIKOR evaluates alternatives based on their distance from an ideal solution, but the aggregation mechanism differs. Instead of relying on a Euclidean distance, VIKOR combines two measures: the weighted sum of normalized distances across all criteria (group utility) and the maximum distance for the worst-performing criterion (individual regret). These components are integrated into the VIKOR index to balance overall performance and worst-case performance. Consequently, VIKOR is less sensitive to extreme deviations than TOPSIS, which prevents suitability scores from dropping excessively.

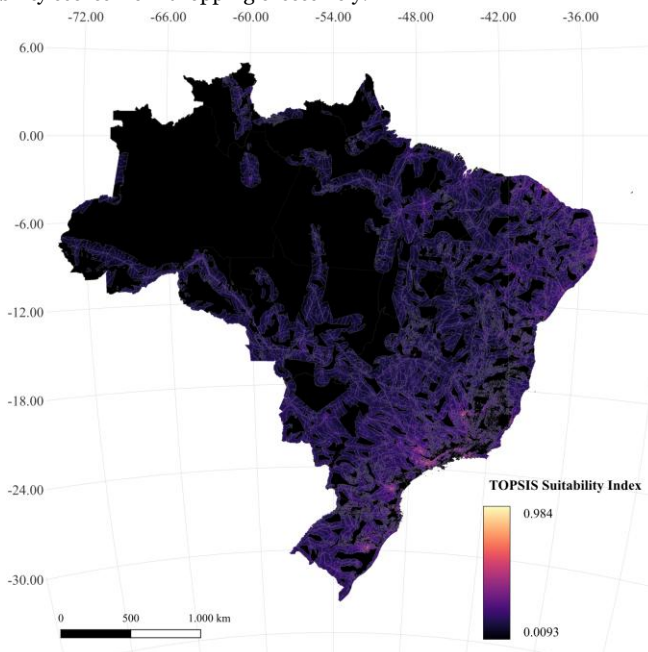


Fig. 10. TOPSIS Suitability Mapping.

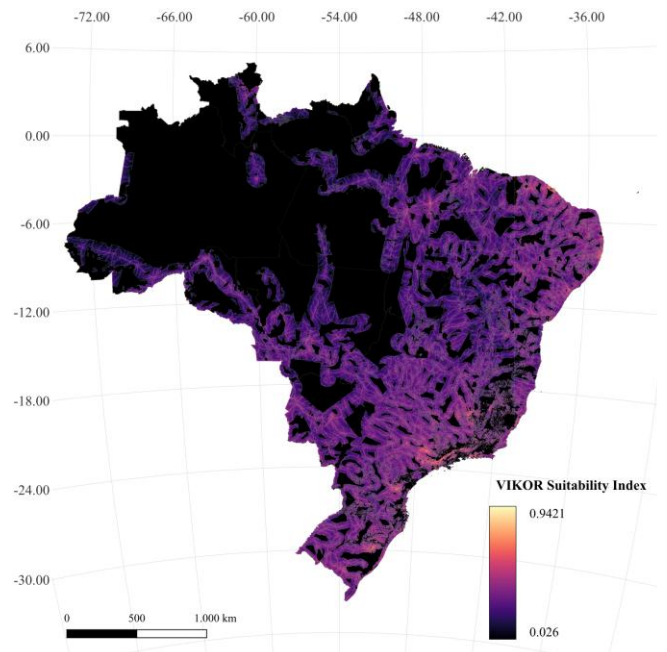


Fig. 11. VIKOR Suitability Mapping.

4.5.1. Statistical Characterization

Fig. 12 and Table 8 reveal several other key differences in how the six MCDM techniques evaluate suitability for H₂V production deployment. First, WSM and WASPAS show the highest mean and median suitability scores, indicating that additive aggregation methods tend to produce higher and more permissive suitability values across the territory. This is also reflected in the boxplots, where these methods display higher central tendencies and wider interquartile ranges.

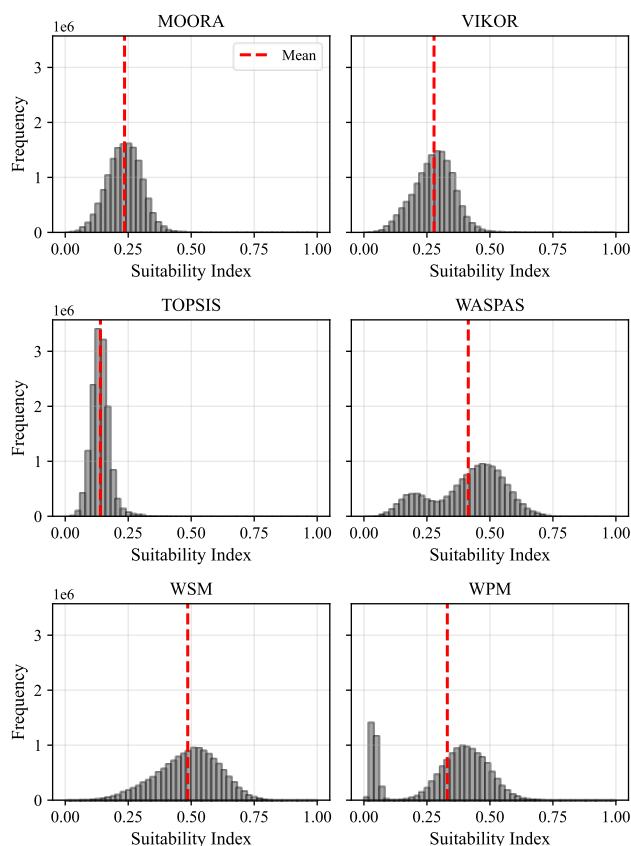


Fig. 12. Histograms of Suitability Scores.

In contrast, TOPSIS produces the lowest suitability scores, with the smallest mean (0.14) and the narrowest distribution. The strong positive skewness and very high kurtosis reported in Table 8 indicate that most locations receive low suitability values, while only a few alternatives approach high scores.

MOORA and VIKOR present intermediate mean values (around 0.25–0.30) and relatively moderate dispersion, suggesting a more balanced and conservative evaluation of potential sites.

The dispersion measures (standard deviation, variance, and IQR) further highlight differences among the methods. WPM exhibits the highest variability (Std = 0.17), indicating that the multiplicative formulation produces a wider spread of suitability scores and stronger differentiation between high- and low-performing alternatives. Conversely, TOPSIS, VIKOR and MOORA show lower variability, suggesting a more compressed distribution of suitability values across the study area.

All methods display numerous outliers, particularly toward the upper range of the distribution. These points correspond to localized areas with exceptionally favorable combinations of criteria, which consistently appear as highly suitable alternatives regardless of the aggregation method.

Table 8

Statistical characteristics of suitability scores.

Method	Mean	Median	Std	Variance	Iqr	Skewness	Kurtosis
WSM	0.49	0.50	0.12	0.02	0.17	-0.35	-0.14
WASPAS	0.41	0.44	0.14	0.02	0.19	-0.46	-0.55
WPM	0.33	0.37	0.17	0.03	0.18	-0.68	-0.62
VIKOR	0.28	0.28	0.08	0.01	0.11	0.03	0.53
MOORA	0.24	0.24	0.07	0.00	0.09	0.12	0.46
TOPSIS	0.14	0.14	0.04	0.00	0.04	1.76	12.41

Overall, the figures and statistical metrics indicate that additive methods identify broader suitable areas, multiplicative aggregation emphasizes differentiation among sites, and distance-based approaches such as TOPSIS generate the most restrictive suitability patterns for H₂V deployment.

For a H₂V deployment, these differences directly affect how candidate locations are identified and prioritized. Additive methods tend to highlight large regions with acceptable renewable resources and infrastructure access, making them suitable for early-stage screening of hydrogen hubs. In contrast, multiplicative and distance-based approaches favor locations where all critical requirements (e.g., high renewable potential, infrastructure proximity, water availability, and demand access) are simultaneously satisfied, which is more aligned with final site selection for industrial-scale projects installation.

4.5.2. Analysis Against Existing H₂V Production Sites

The results presented in Fig. 13 and Fig. 14 provide insight into how the different MCDM methods evaluate locations where H₂V production projects are currently deployed in Brazil, being 9 in operation. As shown in Fig. 13, most existing project locations receive relatively high suitability scores across the evaluated methods. Additive aggregation methods such as WSM and WASPAS tend to assign higher suitability values to project locations, while TOPSIS generally produces lower scores, reflecting the more restrictive behavior previously observed for distance-based approaches.

A complementary perspective is provided in Fig. 14, which shows the highest suitability percentile in which the existing H₂V projects appear for each method. The results indicate that project locations consistently fall within the top-ranked alternatives, although the ranking position differs among methods. VIKOR, MOORA, and TOPSIS place the projects within the top 0.11%, 0.12%, and 0.26% of alternatives, respectively, indicating that these methods rank the existing project locations among the highest suitability classes. Meanwhile, WSM, WASPAS, and WPM place the projects within the top 1.14%, 4.00%, and 4.61% of the ranking, respectively. Considering the very large number of alternatives evaluated in the study, these results indicate that the locations of existing H₂V projects correspond to areas that the model identifies as highly suitable.

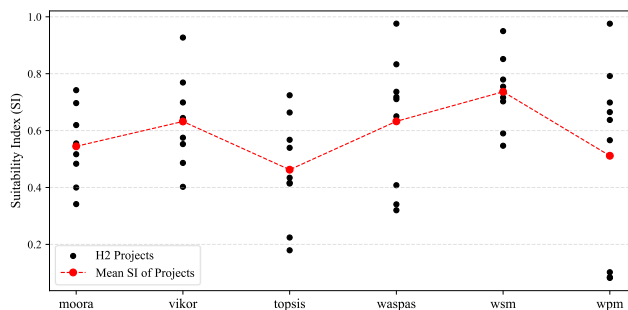


Fig. 13. Suitability indices of alternatives with actual H₂V projects.

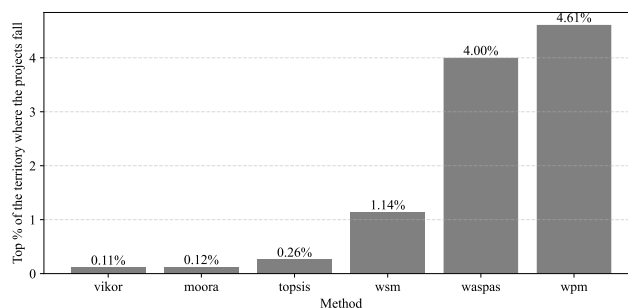


Fig. 14. Top percentile of alternatives with current hydrogen production projects.

In Fig. 14 two low performance projects can be observed, most clearly highlighted under the WPM approach. This low performance can be explained by poor results in key criteria, particularly water accessibility and land use, which are among the highest-weighted factors. In addition, both projects exhibit the lowest solar resource potential; although this criterion has the smallest weight, it still contributes to the cumulative reduction of the overall score.

Although demand potential carries the highest weight, both projects exhibit only moderate values, which are insufficient to offset these critical deficiencies. Additionally, the projects present moderate conditions in infrastructure-related criteria (e.g., distance to highways, power lines, and ports & pipelines). Due to the multiplicative structure of WPM, low values in these high-priority criteria (water and land use) cannot be compensated by performance in other dimensions.

Overall, the combination of moderate demand potential, poor performance in key criteria such as land use and water accessibility, and the lowest performance in solar resource results in a substantial reduction in the overall suitability score under the WPM framework.

5. Conclusions

This study compared six MCDM techniques to analyze how different mathematical aggregation mechanisms influence spatial suitability results for H₂V production deployment. Although all methods identify broadly similar favorable regions, significant differences emerge in dispersion and ranking of suitability scores.

Additive methods such as WSM and WASPAS tend to generate higher and smoother suitability values, highlighting broader areas as suitable for H₂V deployment. In contrast, the multiplicative formulation of WPM increases differentiation among alternatives by strongly penalizing low-performing criteria. Distance-based approaches, particularly TOPSIS, produce the most restrictive distributions, assigning lower suitability values due to their sensitivity to deviations from the ideal solution. MOORA and VIKOR show more balanced behavior, with moderate score distributions and stable rankings.

The comparison with the locations of existing H₂V projects in Brazil shows that these projects consistently appear within the highest-ranked alternatives, although this comparison should not be interpreted as a direct validation due to the limited number of projects and the influence of external factors such as policy decisions and industrial strategies. Among the evaluated methods, VIKOR places the projects in the highest-ranked alternatives, suggesting that its compromise-based formulation captures spatial trade-offs effectively.

Results confirm that the choice of aggregation method should match the objectives of the analysis and the physical requirements of the hydrogen system. A key question is whether all critical conditions must be met in the same location. When renewable resources, water availability, and infrastructure must coexist, more restrictive methods that strongly penalize low-performing criteria are more appropriate. In contrast, if the system allows for more flexibility, such as projects with local storage or grid support, then less restrictive and more compensatory methods can be used. For example, smaller, localized projects may rely less on infrastructure, while large-scale or export-oriented projects require strong infrastructure and

therefore benefit from stricter aggregation methods.

The choice of aggregation method also depends on the preprocessing stage, especially the definition of exclusion criteria. If unsuitable areas are already removed, then less restrictive methods can be applied safely. However, if these constraints are only partially addressed, more penalizing methods are needed. The maturity of the hydrogen deployment in the study area is also important. In regions with little or no hydrogen-oriented infrastructure, stricter methods help identify locations where all necessary conditions are present. In more developed regions, where transport and infrastructure networks already exist, more flexible methods can be used.

From an application perspective, different methods serve different roles in the decision process. Additive methods such as WSM tend to produce optimistic results and are useful for early-stage screening, where the goal is to identify broad areas of potential. Methods like WASPAS, MOORA, and VIKOR offer more balanced behavior and are suitable for intermediate prioritization, helping refine candidate locations. In contrast, WPM and TOPSIS strongly penalize poor-performing criteria and ensure that all conditions are met, making them well-suited for final site selection and investment decisions.

Overall, the selection of the MCDM method should consider the need for co-location, the type of criteria used, the level of prior exclusions, and the maturity of hydrogen deployment in the region. There is no “one-size-fits-all” method. The choice of aggregation approach should be seen as a context-dependent decision, guided by the characteristics of the hydrogen system and the goals of the analysis and therefore, expert judgment remains essential when selecting the most appropriate method.

Future research could extend the proposed framework by incorporating indicators that capture the complementarity between solar and wind resources at each site. Such indicators would allow H₂V producers to identify locations where renewable generation profiles offset each other, reducing variability and improving the reliability of electricity supply for hydrogen production.

CRediT authorship contribution statement

Edna S. Solano: Writing – original draft, Visualization, Software, Resources, Data curation, Methodology, Investigation. **Rafael Cossent:** Writing – review & editing, Supervision, Validation, Formal analysis. **Carolina M. Affonso:** Writing – review & editing, Supervision, Resources, Validation, Project administration, Formal analysis, Funding acquisition.

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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