

A Comparative Objective Weighting MCDM-GIS Approach to Renewable Hydrogen Production Site Selection: A Spanish Case Study

Santiago Serna Zuluaga¹, Edna S. Solano², Timo Gerres¹, Rafael Cossent¹

¹Institute for Research in Technology, Comillas Pontifical University, Santa Cruz de Marcenado 26, Madrid, Spain

²Faculty of Electrical and Biomedical Engineering, Federal University of Para, Belem, Brazil

Correspondence: sserna@comillas.edu

Abstract

Deciding on the optimal location for a hydrogen production plant is a complex task that involves multiple factors, including proximity to demand centers, availability of renewable energy resources or existing infrastructure. Identifying suitable sites, therefore, requires integrating diverse geospatial criteria, typically addressed through Geographic Information Systems (GIS) and multi-criteria decision-making (MCDM) frameworks. Existing analyses rely on subjective weighting, which introduces biases and hampers replicability. Objective weighting methods offer a data-driven alternative but have generally been applied to selecting among only a few regional alternatives.

This study fills this gap by developing a high-resolution spatial MCDM framework to evaluate thousands of candidate locations across Spain. Increasing spatial resolution from aggregated units (e.g., provinces) to site-level alternatives reveals greater variability in the input indicators, including a wider dispersion of values that is typically masked by spatial averaging. These differences may influence the resulting weights and rankings. To examine this issue, we compare five objective weighting methods using mathematical validation and an empirical comparison with the spatial distribution of existing hydrogen projects.

Our results show that all methods are robust and consistently identify the most suitable areas, aligning well with existing project locations. The main differences between methods emerge in intermediate rankings and in their stability to changes in input data, with some methods being more sensitive to constraint definitions, such as the maximum allowable distance to demand centers. These findings highlight that, although objective methods substantially reduce the reliance on expert judgment, they do not eliminate it. Methodological choices materially influence prioritization outcomes, and informed expert judgment remains essential to ensure that methodological choices reflect the objectives and constraints of the analysis.

Acronyms

<i>ADR</i>	Agreement concerning the International Carriage of Dangerous Goods by Road
<i>AHP</i>	Analytical Hierarchy Process
<i>CRITIC</i>	CRiteria Importance Through Intercriteria Correlation
<i>DEA</i>	Data Envelopment Analysis
<i>DEMATEL</i>	Decision Making Trial and Evaluation Laboratory
<i>DRI</i>	Direct Reduced Iron
<i>EHB</i>	European Hydrogen Bank
<i>EU</i>	European Union
<i>GIS</i>	Geographic Information System
<i>MCDM</i>	Multi-criteria Decision-Making
<i>PV</i>	Photovoltaic
<i>RES</i>	Renewable Energy Sources
<i>RHPP</i>	Renewable Hydrogen Production Project
<i>RIMP</i>	Dangerous Goods Transport Network
<i>SI</i>	Suitability Index
<i>STD</i>	Standard Deviation
<i>TODIM</i>	Interactive Multi-Criteria Decision Making
<i>TOPSIS</i>	Technique for Order Preference by Similarity to Ideal Solution
<i>TYNDP</i>	Ten-Year Network Development Plan
<i>VIKOR</i>	Multi-Criteria Optimization and Compromise Solution
<i>WLC</i>	Weighted Linear Combination

1. Introduction

Limiting the global temperature increase to 1.5°C above pre-industrial levels requires decarbonizing all economic sectors by 2050. H₂ plays a key role in achieving this target, enabling the decarbonization of sectors where direct electrification is challenging. However, most of the H₂ produced today comes from carbon-intensive sources, resulting in significant CO₂ emissions [1]. This makes the development of sustainable alternatives essential, with the most promising pathway being renewable H₂ generated via electrolysis powered by Renewable Energy Sources. (RES).

As part of the global energy transition and the decarbonization of hard-to-abate sectors, in line with the European Union’s decarbonization objectives for 2030 and climate neutrality by 2050, H₂ is increasingly recognized by EU member states as a key energy vector and is explicitly incorporated into European energy system planning frameworks, such as the Ten-Year Network Development Plan (TYNDP) [2].

Spain offers a particularly promising context for renewable H₂ and is considered essential to achieving the European Union’s decarbonization targets, owing to its advantageous geographic location, high solar irradiation, and substantial wind potential. In 2025, renewables accounted for nearly 56% of Spain’s total electricity generation, with this share expected to continue increasing in the coming years [3]. Spain has established itself as a top-performing participant in the European Hydrogen Bank (EHB) [4], positioning the country as a potential producer, consumer, and exporter of renewable hydrogen [5].

Hydrogen production plants can be classified according to their electricity supply configuration into isolated plants, which are exclusively connected to a dedicated renewable energy source and operate without grid access; fully grid-connected plants, which rely solely on grid electricity; and hybrid plants, which combine both options. According to the Spanish Hydrogen Association [6], around 41 % of announced projects follow a hybrid configuration, 17 % are isolated, and the remainder depend exclusively on grid electricity. The prevalence of co-located hydrogen and renewable generation facilities makes plant siting inherently complex, as location decisions must simultaneously account for hydrogen-specific criteria—such as proximity to

demand centers and pipeline infrastructure—and renewable generation constraints, including resource availability and land suitability. Consequently, identifying optimal locations for hydrogen production facilities becomes a critical determinant of overall system costs and efficiency.

Addressing this challenge requires a decision framework capable of simultaneously evaluating multiple technical, economic, environmental, and spatial criteria. While different approaches, such as machine learning or mathematical optimization, can be applied to site-selection problems, they are typically tailored to single-objective optimization or rely on extensive historical datasets. In contrast, Multi-Criteria Decision-Making (MCDM) methods, often combined with Geographical Information Systems (GIS), are particularly well suited to H₂ site selection, as they explicitly allow for the integration of diverse criteria with spatial data and focus on ranking alternative locations. MCDM–GIS enables high-resolution suitability mapping of potential H₂ production sites, supporting policymakers, investors, and system operators in identifying locations that balance renewable resource availability, infrastructure constraints, and economic feasibility [7].

According to a recent literature review [8], the application of MCDM–GIS for siting renewable H₂ production projects is still emerging. Despite differences in spatial scale and methodology, these studies generally follow a similar workflow: (i) selection and acquisition of data; (ii) normalization of the selected criteria; (iii) weighting of criteria; and (iv) aggregation into a final ranking or suitability index. As summarized in Table 1, the literature differs primarily along four dimensions: spatial resolution, criteria considered, weighting approaches, and aggregation or ranking methods.

Table 1: Comparison of studies on the location of H₂ renewable facilities using MCDM

Ref.	Spatial Resolution	Environ. Criteria	Economic Criteria	H ₂ -Specific Criteria	Socio-economic	Norm. Method	Weighting Strategy	Ranking Method
[9]	30 m grid	✓	—	—	—	Reclassification	Subjective	SI
[10]	100 m grid	✓	✓	water	—	Buffer-based	Subjective	WLC
[11]	30 m grid	✓	✓	water, demand	—	Standardization	Subjective	WLC
[12]	30 m grid	✓	✓	water, demand	—	Reclassification	Subjective	WLC
[13]	1 km grid	✓	✓	water	—	Threshold classification	Subjective	WLC
[14]	Regional	—	✓	—	✓	Triangular fuzzy	Subjective	TODIM
[15]	Regional	—	✓	—	—	Efficiency-based	Subjective	DEA
[16]	Regional	✓	✓	—	—	Min–max	Subjective	AHP
[17]	Regional	✓	✓	—	—	Reclassification	Objective	TODIM
[18]	Regional	✓	✓	demand	✓	Triangular fuzzy	Subjective	VIKOR
[19]	Regional	—	✓	—	—	Triangular fuzzy	Subjective	TOPSIS
This Paper	500 m grid	✓	✓	✓	—	Min–max normalization	Objective	WLC

Regarding spatial resolution, studies generally follow one of two paths: regional-scale analyses [14]–[19], covering hundreds of square kilometers across administrative provinces, and high-resolution assessments [9]–[13], which produce cell-level suitability maps with square-meter precision. While regional-scale approaches are useful for broad strategic screening, they pose significant limitations for siting hydrogen projects. In particular, they mask intra-regional heterogeneity in both demand and resource availability. Regions with similar aggregate hydrogen demand may differ substantially in their spatial concentration, with more dispersed demand implying higher transport costs and greater logistical complexity. Likewise, key supply-side variables, such as wind speed, cannot be meaningfully represented by regional averages. As a result, high-spatial-resolution approaches are more appropriate to assess the location of a Renewable Hydrogen Production Project (RHPP).

Across the reviewed studies, the criteria considered span technical, economic and environmental dimensions. Technical factors typically include resource availability and terrain-related constraints such as slope. Economic dimensions often encompass proximity to infrastructure, investment costs, market accessibility, and grid-related indicators, as highlighted by [14]. Broader regional assessments, such as [18] and [20], further expand the scope by incorporating socio-economic indicators.

In terms of weighting, some contributions rely on subjective methods [9]-[16]. These methods determine weights based on expert judgment and qualitative assessments; while they capture practical experience, they may introduce biases or inconsistencies and lack replicability. In contrast, objective methods calculate weights solely through mathematical and statistical analysis of the dataset, identifying patterns and variability within the data itself making them less prone to personal bias, robust and reproducible. Studies employing objective methods to locate renewable hydrogen plants are typically regional in scale [17]. Although it is important to note that objective methods have been applied to MCDM-GIS high-resolution problems in other areas, such as flood hazard assessment [21] or landslides susceptibility [22].

In terms of ranking methods, the literature highlights Weighted Linear Combination (WLC) as the most compatible approach for high-resolution studies [10]-[13]. This preference is due to its transparency, computational efficiency, and ability to generate continuous suitability maps. By contrast, outranking and compromise-based methods, typically employed to better account for uncertainty and subjectivity, are more frequently applied in regional-scale assessments where spatial resolution is less granular [14]-[19].

As reviewed in Table 1, the existing literature on renewable H₂ production project siting reveals two significant methodological gaps. First, there is a heavy reliance on subjective weighting strategies, which are often applied without transparent documentation of the expert panel’s composition or expertise. In contrast, objective, data-driven weighting methods, which determine criteria weights based on the inherent variation or information content of the data rather than expert judgment, are scarce and have so far been applied primarily to regional-scale studies with a limited number of alternatives [9, 17]. Their efficacy in high-resolution analyses with thousands of potential sites remains largely unexplored and statistically challenging. Moreover, few studies examine the sensitivity of their results to the weighting method chosen, leaving it unclear how alternative weighting schemes could affect the ranking of candidate sites.

Second, most studies overlook essential H₂-specific factors, such as H₂ demand, existing infrastructure, and future developments. Some studies introduce partial hydrogen-related criteria, such as distance to water sources, yet only a small subset explicitly considers H₂ demand. Rezaei et al. [18] approximates H₂ demand using population as a proxy, assuming that more populous areas correspond to higher potential consumption. Messaoudi et al. [12] estimates transport-related H₂ demand based on population, per-capita vehicle ownership, and projected daily H₂ use per vehicle. These approaches generally assume that light-duty transport will drive future H₂ demand, overlooking hydrogen’s current largest use: industry. Among the reviewed studies, only Taoufik and Fekri [11] explicitly includes industrial demand, approximated as distance to industrial hubs; however, they do not differentiate between industrial sub-sectors or their heterogeneous H₂ requirements. Some sectors rely on H₂ as feedstock, whereas others use it as a fuel. Within the latter category, only high-temperature processes are likely candidates for H₂ substitution, as low-temperature heat can typically be electrified. In addition, existing analyses tend to capture only the spatial distribution of demand, neglecting its magnitude. This omission is non-trivial, as demand volume strongly influences economies of scale in H₂ production and infrastructure deployment [23].

Taken together, these gaps highlight the need for methods that can integrate objective, data-driven weighting with H₂-specific spatial constraints while remaining computationally tractable at high resolution. This study addresses the identified research gaps by implementing and comparing multiple objective weighting methods for high-resolution renewable H₂ facility siting. The analysis evaluates their influence on MCDM outcomes and their effectiveness for site selection, while also integrating a critical, often-overlooked factor

such as industrial H₂ volume and demand. The key contributions of this study are as follows:

- **Implementation of Objective Weighting:** Application of several distinct objective weighting methods, providing a transparent, data-driven alternative to relying solely on subjective expert judgment.
- **High-Resolution Suitability Mapping:** Demonstration of the scalability of these methods by evaluating thousands of potential sites, moving beyond the regional-scale analyses that currently dominate the literature.
- **Comprehensive H₂-Specific Criteria:** The proposed MCDM framework integrates critical, often-overlooked factors, including industrial H₂ demand and alternative water sources.
- **Easily Replicable Methodology:** Development of a generalisable approach that can be directly applied to different H₂ project typologies and regions, without requiring repeated rounds of expert elicitation (e.g., surveys) that subjective methods typically demand.

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

2. Materials and Methods

Multi-Criteria Decision-Making is a family of analytical methods designed to evaluate and prioritize complex alternatives based on multiple, often conflicting criteria. The core of MCDM methods comprises four different stages: data collection and treatment, weighting of criteria, ranking of criteria, and statistical validation of results.

The methodological workflow followed in this study is illustrated in Figure 1. In the first stage, preprocessing, the evaluation criteria are defined, encompassing technical, environmental, and economic aspects. These criteria are categorized into exclusion and classification types: exclusion criteria to remove unsuitable areas, while classification criteria are retained for further assessment. The classification criteria are normalized using the Min–Max method and analyzed to avoid redundant information by identifying highly correlated criteria. In the second stage, criterion weights are derived using five objective weighting methods, which are then applied to aggregate and rank the alternatives. In the third stage, suitability mapping is performed to identify favorable locations for RHPP deployment. Finally, a set of evaluation indicators is used to assess the performance and consistency of the different weighting approaches.

Figure 1: Flowchart of the methodology

2.1. Criteria definition and data collection

The foundation of this GIS-based suitability analysis is a comprehensive, multi-source dataset encompassing relevant factors to renewable H₂ production in Spain. All data were sourced from official national sources, European repositories, and global databases to ensure reliability and were processed to a uniform spatial resolution and coordinate system for consistent analysis. The complete collected data and their sources is detailed in Table 2.

Table 2: Summary of data and criteria collected for the analysis.

Category	Criterion / Indicator	Data Source
Environmental and Technical	Natura 2000 protected areas	Ministry for Ecological Transition and the Demographic Challenge [24]
	Land use and land cover compatibility	Regulation on the Protection of Land Use [25] and Corine Land Cover [26]
Resource	Solar resource availability (capacity factor)	Global Solar Atlas [27]
	Wind resource availability (capacity factor)	Global Wind Atlas [28]
	Wastewater treatment plants	National Geographic Institute [29]
Economic	Industrial facilities	EU Emission Trading System [30]
	Water bodies and waterways	National Geographic Institute [31]
	Roads, Motorways and Highways	Ministry of Transport and Sustainable Mobility [32]
	Transmission power lines	Open Street Infrastructure Map [33]
	H ₂ Demand	Authors’ own estimation (Appendix C)

2.2. Categorization into Classification and Exclusion Criteria

Once the relevant datasets are collected, the criteria are categorized into exclusion and classification criteria. Exclusion criteria identify areas unsuitable for RHPP, while classification criteria evaluate the suitability of remaining areas based on resource, environmental, and economic conditions.

2.2.1. Exclusion Criteria

Exclusion criteria are applied to systematically eliminate areas that are legally prohibited, environmentally sensitive, or technically unfeasible for RHPP development, which ensures that all potential sites adhere to regulatory frameworks and present viable conditions for construction and operation, with the specific criteria and their corresponding thresholds detailed in Table 3. The exclusion logic is governed by two foundational principles. First, all areas included in the Natura 2000 network—comprising EU-designated protected sites for biodiversity conservation—are excluded. Second, mandatory buffer zones are established around water bodies, roads, and power lines to prevent environmental damage, ensure operational safety, and respect infrastructure rights-of-way. The minimum exclusion distance is set to one raster cell (500 m), preventing siting directly on linear infrastructure due to discretization effects. For water bodies, the buffer is extended to two cells (1,000 m) to incorporate additional environmental and safety considerations while remaining consistent with the model’s resolution.

Table 3: Exclusion criteria and applied thresholds.

Criteria	Threshold
Protected areas	Exclude areas under Red Natura 2000
Distance to roads, motorways and highways	< 500 m
Distance to transmission lines	< 500 m
Distance to protected areas	< 1000 m
Distance to water bodies and waterways	< 1000 m

2.2.2. Classification Criteria

Classification criteria evaluate the relative suitability of potential sites for RHPPs across continuous spectrums. Each criterion is classified as either a *Benefit* (higher values increase suitability) or a *Cost* (lower values increase suitability). The complete set of criteria and their classifications are summarized in Table 5, with spatial distributions detailed in Appendix A. The rationale for each classification is as follows:

Benefit Criteria

- **Solar and Wind Resource Availability:** Higher capacity factors indicate greater energy generation efficiency, which directly increases H_2 output and reduces leveled costs.
- **Land Use Compatibility:** Higher scores (defined in Table 4) reflect lower environmental impacts and fewer legal barriers, facilitating project development.
- **Hydrogen demand:** This criterion is constructed by combining H_2 demand magnitude and distance to demand centres. Prior to aggregation, both components are normalized to ensure comparability: H_2 demand is treated as a benefit criterion (higher demand is preferred), while distance is treated as a cost criterion (shorter distances are preferred). The criterion is then computed as the product of the normalized demand and distance terms, resulting in a demand–distance “moment” . Conceptually, this formulation penalizes locations that are either close to small demand centres or far from large ones, favouring sites that balance demand scale and logistical proximity.

Cost Criteria

- **Distance ¹ to Water Sources:** Shorter distances to water sources (e.g., wastewater treatment plants) reduce capital and operational costs for water supply infrastructure.
- **Distance to roads:** H_2 transport is subject to the Agreement concerning the International Carriage of Dangerous Goods by Road (ADR) under Spanish legislation. Consequently, H_2 must be transported along specific Dangerous Goods Transport Network (RIMP, from the Spanish Red de Itinerarios para Mercancías Peligrosas), which establishes preferential routes aimed at maximising road safety. These itineraries primarily consist of highways and motorways, which are designated corridors for ADR transport. As the RIMP is not available in a GIS-compatible format, highways are used as a proxy to represent authorised ADR transport routes in Spain.
- **Distance to power lines:** H_2 production plants require proximity to electricity transmission infrastructure. First, when co-located with renewable electricity generation, production facilities are often oversized, resulting in surplus electricity that can be injected into the grid and monetized. Second, H_2 plants may rely on grid electricity to supply balance-of-plant (BoP) components or to supplement H_2 production [34]. In this paper, only transmission lines are considered, as large-scale H_2 production facilities typically involve high power capacities that exceed the technical limits of distribution networks. Transmission grids are therefore more suitable to accommodate the power flows associated with electrolyzer operation and surplus electricity injection.

Table 4: Land use compatibility with H_2 production

Compatibility score	Land use type
5	Non-irrigated arable land
4	Pastures
3	Land principally occupied by agriculture with significant areas of natural vegetation
2	Permanently irrigated land
1	Rice fields, vineyards, fruit trees, olive groves, complex cultivation patterns
0	Forest, urban land, and other incompatible land uses

¹All distances in this paper are measured as Euclidean distances between the centers of two cells.

Table 5: Indicator Categories and Classification Criteria

Category	Criteria	Unit	Type	Values
Resource	Solar Capacity Factor	%	Benefit	0-100
	Wind Capacity Factor	%	Benefit	0-100
	Distance to Wastewater Treatment Plants	km	Cost	0-10
Environmental	Land Use Compatible with H ₂ production	Score	Benefit	0-5
Economic	Distance to Roads, Motorways and Highways	km	Cost	0-10
	Distance to transmission power lines	km	Cost	0-10
	Distance to H ₂ Demand (Industrial Facilities)	km	Cost	0-40
	Volume and distance of H ₂ Demand	kton-km	Benefit	0-10

2.3. Normalization of Classification Criteria

Once the classification criteria for RHPP siting are defined, they must be normalized to ensure comparability among indicators that differ in units, direction, and scale. In this study, the min-max normalization method was applied, as it is widely used in MCDM applications [7]. This technique rescales each criterion to a common range of [0, 1], where higher normalized values represent greater suitability.

2.4. Evaluation of input data distributions

Prior to applying weighting methods, it is essential to examine the statistical properties of the input criteria to identify highly correlated criteria, which may introduce redundancy that could lead to an over-representation of certain dimensions in the final suitability index. Beyond pairwise correlations, analyzing data distributions can provide a more nuanced interpretation of the results and the differences between the various weighting methods.

2.5. Weighting of Classification Criteria

Following normalization, the next step is to assign relative weights to each criterion, quantifying its importance in the overall assessment of site suitable locations for RHPPs. This study considers a range of complementary objective methods with different approaches.

The standard deviation method (STD) uses the variance of a criterion, which is a measure of how far values deviate from the mean. Consequently, criteria with many similar values tend to present low variance. In contrast, the entropy method focuses on how evenly values are distributed across alternatives. Consequently, a small number of high values can lead to high entropy if they cause significant disorder in the overall distribution. The CRITIC method extends STD by explicitly accounting for inter-criteria correlations, penalizing redundant information avoiding overlapping indicators. In addition, CILOS is selected to represent optimization-based objective methods, in which criterion importance is inferred from its influence on the relative ranking of alternatives rather than solely from statistical properties of the data. Finally, IDOCRIW is included as a hybrid approach that combines entropy and CILOS to balance data dispersion with structural ranking effects. Further descriptions of each of the aforementioned methods can be found in [35].

2.6. Ranking of Weighted Criteria

After the weights are calculated, they are aggregated using the WLC ranking method. The WLC is a well-established spatial MCDM technique particularly suited for renewable energy site location. This process ultimately produced the final different suitability maps for RHPP site location.

2.7. Validation of Weighting Methods

To ensure the reliability and practical relevance of the derived criterion weights, a series of validation methods are proposed which can be grouped into two categories: statistical and empirical validation.

2.7.1. Statistical Comparison of Weighting Methods

Concordance. Concordance assesses the extent to which a given weighting method produces results consistent with those obtained using alternative methods. It is quantified by comparing the Spearman correlation across suitability computed for each spatial cell under different methods. In addition, standard deviation, distance to consensus, and Kendall’s coefficient of agreement are reported as complementary indicators. Consensus is defined as the average suitability score across all methods, while Kendall’s agreement is calculated as the arithmetic mean of pairwise concordance among methods.

Resilience. Resilience evaluates the stability of weighting methods to perturbations. For each method, criteria were sequentially removed, and new weights were calculated. The resulting rankings were then compared with the baseline ranking obtained using the full set of criteria, again using Spearman’s rank correlation coefficient as an indicator. High correlation values indicate that the method preserves the relative importance of criteria despite the exclusion of individual elements, reflecting strong resilience.

Discrimination. Discrimination assesses how a weighting method distributes importance across criteria, that is, whether all criteria are treated similarly or whether a subset is clearly prioritized, and to capture this, two complementary indicators are used. First, the standard deviation of the weights indicates how different the weights are from one another, where low values indicate that most criteria receive similar weights, implying limited discrimination, whereas high values reflect a more heterogeneous distribution in which some criteria are assigned substantially higher importance than others. Second, an entropy-based indicator captures the degree of concentration of the weights across criteria, with high entropy values corresponding to a relatively uniform allocation of importance, while low entropy values indicate that a small number of criteria concentrate a large share of the total weight.

2.7.2. Empirical Alignment with Existing H_2 Projects

The final stage of validation determines how well the suitability maps produced by each weighting method align with the spatial distribution of existing RHPPs. Empirical validation complements statistical evaluation by grounding methodological consistency in real-world evidence. When statistical validation reveals low concordance across methods, empirical validation helps discriminate among them by identifying those that better match observed deployment patterns. Conversely, when statistical validation indicates high concordance, empirical validation serves to verify that this agreement is correct and that the resulting suitability patterns are consistent with reality, rather than reflecting a shared but misleading result.

To this end, the suitability scores across all spatial units are compared with the observed locations of announced RHPPs. Project location data are obtained from a proprietary database developed by the authors and made publicly available [36], which compiles announced H_2 projects in Spain. From this database, projects explicitly intended for industrial H_2 production are retained

The exact coordinates of a project are rarely disclosed, and typically, only the municipality is announced. To account for this spatial uncertainty, a 2.5 km buffer was created around each project’s announced location. This radius corresponds to five cells in the 500×500 m suitability grid, ensuring robustness against localization errors while maintaining the local nature of the assessment.

2.8. Robustness and Sensitivity analysis

In this study, sensitivity analysis focuses on the definition of hydrogen demand, operationalized through the maximum admissible distance between production sites and demand locations. This parameter plays a critical role in hydrogen supply chain design and is subject to substantial uncertainty at early planning stages, particularly regarding the spatial concentration of demand and the timing of infrastructure deployment.

Three distance thresholds are considered: A short-distance threshold of 10 km represents a localized supply paradigm, in which hydrogen production is directly linked to nearby demand centers. An intermediate

threshold of 40 km captures the emergence of regional hydrogen clusters, or “hydrogen valleys,” where shared infrastructure enables coordination among multiple producers and consumers at a functional regional scale. Finally, a long-distance threshold of 100 km reflects a more integrated system in which hydrogen production can rely on national-scale transport infrastructure, such as a hydrogen backbone, enabling demand to be served beyond immediate regional boundaries

3. Results

Using the proposed multi-criteria evaluation framework, a high-resolution spatial analysis (500×500 m) was conducted for the Spanish case study, discretizing the territory into approximately 2.4×10^6 candidate spatial units for renewable H_2 production. This discretization serves as a proxy for total spatial potential for suitability screening, recognizing that individual projects may span multiple adjacent cells or occupy only a fraction of a single cell. After applying the exclusion criteria, around 45% of the total area was deemed unsuitable for H_2 production. The majority of excluded areas corresponded to regions with high environmental sensitivity and proximity to protected areas, water bodies, and other critical infrastructure.

3.1. Analysis of Criteria

This section analyzes the distribution, correlation, and other statistical indicators for each criterion after the exclusion thresholds. This step is essential to understand following results and to identify correlation and trends among included criteria.

The statistical distributions of the seven normalized criteria are shown in Figure 2. The solar resource exhibits a strongly left-skewed distribution, reflecting consistently high potential across most of the study area. In contrast, the wind resource shows a more dispersed pattern. The slightly left-skewed distribution of distance to water indicates a relative predominance of locations at moderately suitable distances, with a slight tendency to be nearer to water. For distance to roads, the strong positive skew indicates that the values are concentrated at the lower end of the scale. This means that most of the territory is relatively far from the suitable road network considered in this analysis. Conversely, the negative skew in distance to the power grid indicates a concentration at the high end of the suitability scale, suggesting that a large share of sites are favorably located near existing electrical infrastructure. The land-use criterion has peaks near the suitability extremes, partitioning the territory into highly suitable and highly unsuitable areas. Finally, the distribution of H_2 demand is heavily concentrated at the lower end, indicating that most regions have very low projected consumption. The long right tail, however, highlights the critical few industrial clusters or regions intended to be the primary drivers of the H_2 market.

Variance analysis reveals distinct patterns; land use has the highest dispersion, while criteria dominated by zero values show negligible variance. Wind speed approximates a normal distribution confined to 0.2–0.5, with low variability; whereas The solar resource shows a negatively skewed distribution, where the majority of data points lie toward the right side, reflecting high and favorable radiation values. The correlation matrix among the criteria is shown in fig. 3. The results indicate that none of the selected criteria exhibit strong correlations.

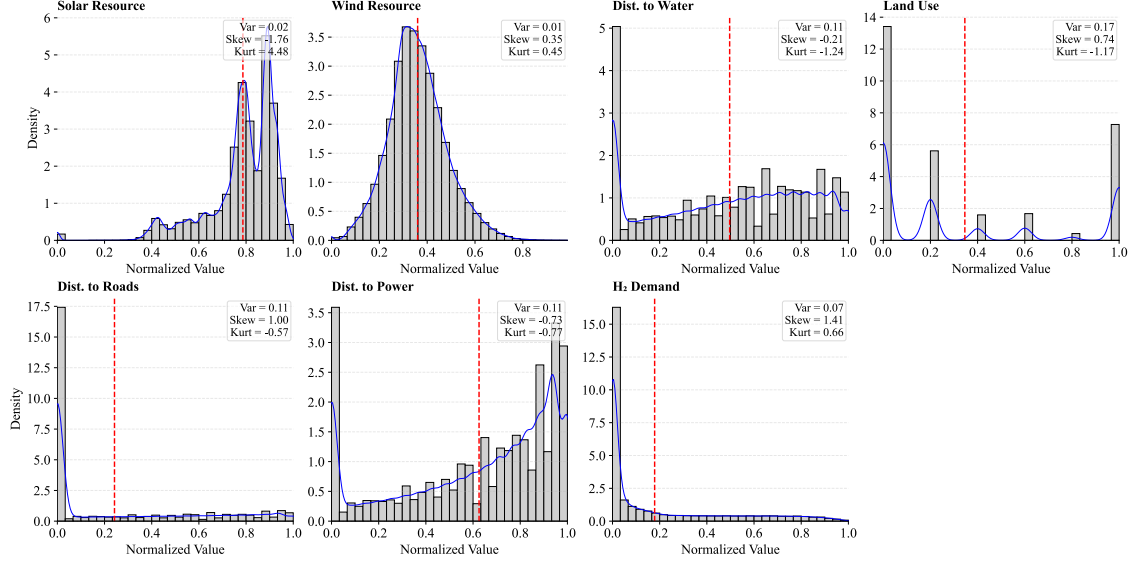


Figure 2: Distribution of criteria. The red line indicates the mean, and summary statistics (variance, skewness, and kurtosis) are reported in the inset text box.

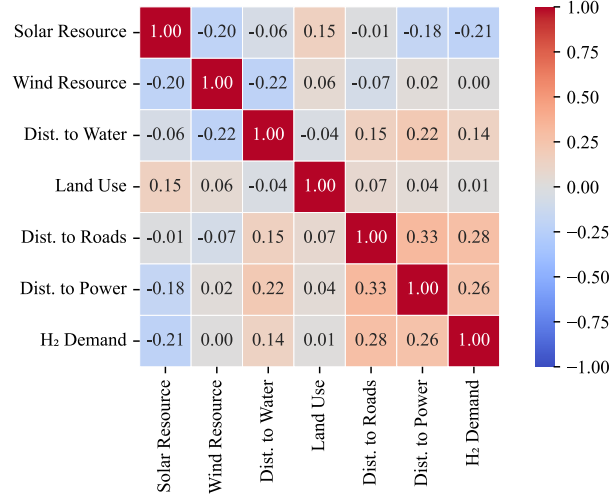


Figure 3: Correlation Matrix of Criteria

3.2. Weighting Attribution

The resulting criterion weights using different methods are presented in fig. 4, revealing significant divergence in how these methods prioritize the siting criteria for RHPPs.

Entropy assigns a high weight to H₂ Demand while reducing the importance of most remaining criteria, reflecting its strong sensitivity to skewness and dispersion in the underlying data. In contrast, CRITIC, CI-LOS, and STD produce more homogeneous weighting profiles, with moderate and nearly identical values for resource-related variables (solar and wind), land use, and distances to power and water. IDOCRIW exhibits an intermediate pattern, although generally aligned with the entropy behaviour it assigns comparatively higher weight to Land Use. Notably, H₂ demand emerges as the dominant criterion under Entropy and, to

a lesser extent, IDOCRIW, whereas CRITIC, STD, and CILOS attribute it only moderate relevance. Conversely, renewable resources and distance to water and power network receive higher weights from CRITIC, STD, and CILOS but are consistently downweighted by Entropy and IDOCRIW.

Overall, the weighting methods form two distinct clusters. The *standard deviation-based methods* (CRITIC, STD, and CILOS) constitute the first group and generate relatively balanced suitability distributions that avoid extreme concentration. In contrast, the *entropy-based methods* (Entropy and IDOCRIW) form the second cluster and assign greater importance to criteria characterized by strong informational contrast. In the present case, this results in a pronounced emphasis on H₂ demand, which is spatially concentrated in a limited number of industrial hubs while remaining negligible across extensive areas.

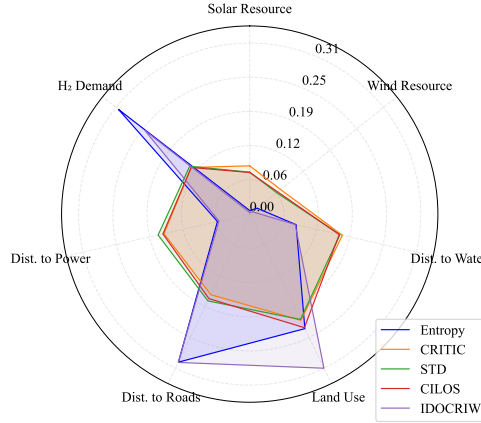


Figure 4: Weights assigned to criteria by weighting method

3.3. Suitability Mapping

Figure 5 presents the suitability maps generated by each weighting method. White markers indicate the locations of Spain’s renewable hydrogen production projects, which are predominantly oriented toward industrial applications. A grey dashed line represents the planned H₂ pipeline network². The color gradient ranges from black (least suitable areas) through purple to light yellow (most suitable locations).

For clarity and consistency, throughout the remainder of the paper, suitability levels are classified as follows: **very high** (0.8–1.0), **high** (0.6–0.8), **moderate** (0.4–0.6), **low** (0.2–0.4), and **very low** (0–0.2). Any subsequent reference to these qualitative categories corresponds strictly to these numerical intervals.

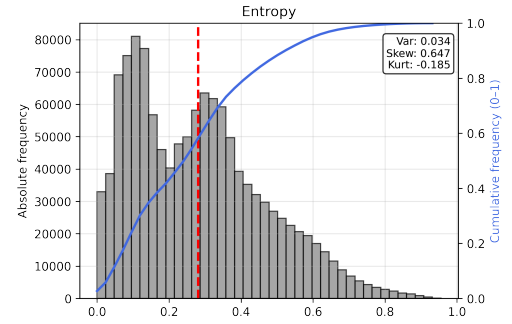
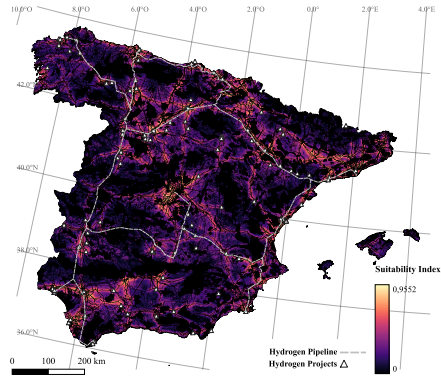
Our results show that standard deviation-based methods have similar spatial patterns with strong agreement among them. Compared with entropy-based approaches, these methods produce larger areas of medium- to high-suitability, characterized by smoother gradients and less pronounced contrasts. Consequently, large yellow-to-orange regions extend across the country.

Consequently, the two methodological families differ in their statistical properties. Entropy-based methods produced lower average suitability values (mean 0.29) and more skewed distributions (skewness 0.64), with most cells concentrated at low suitability levels. In contrast, standard deviation-based methods pro-

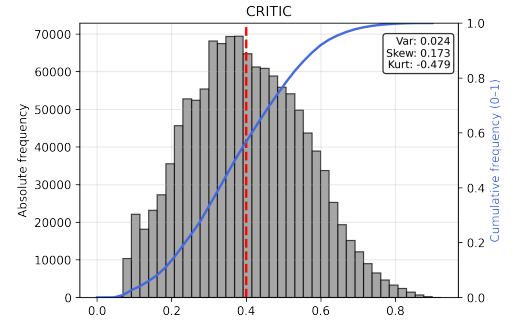
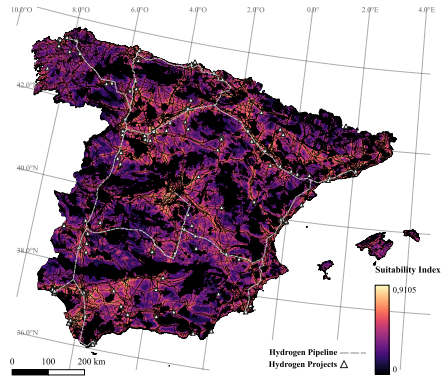
²The future development of H₂ infrastructure in Spain aligns with the European Hydrogen Backbone (EHB) initiative, which outlines a strategic infrastructure pathway to be developed by 2040 [37].

duced higher average values (mean 0.40) and more symmetric distributions (skewness 0.20).

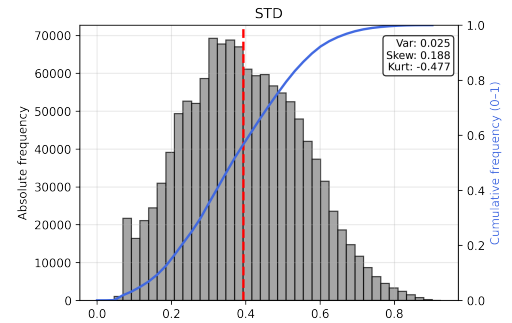
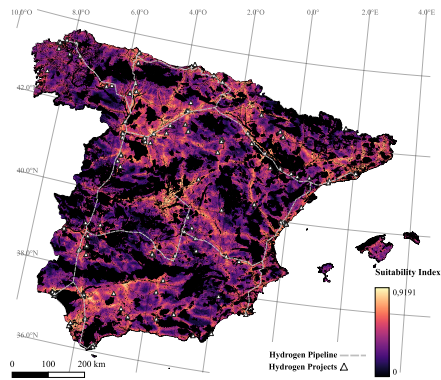
Despite these differences, all methods appear to be well aligned with existing projects and the forecasted location of the hydrogen pipeline. In section 3.4.2, more details regarding the empirical validation of the results are provided.



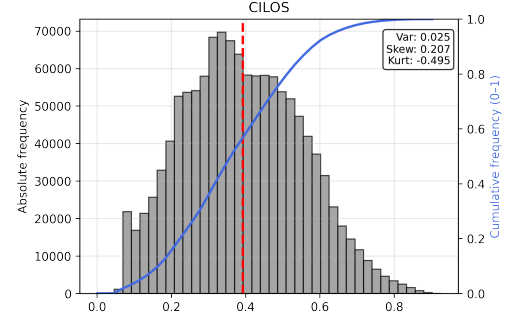
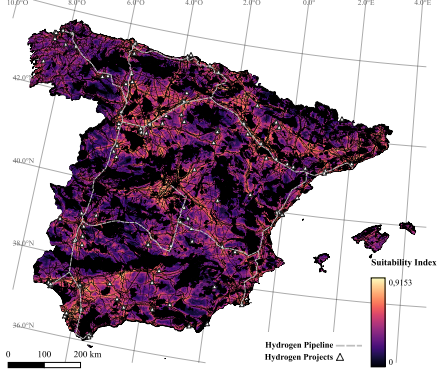
(a) Entropy



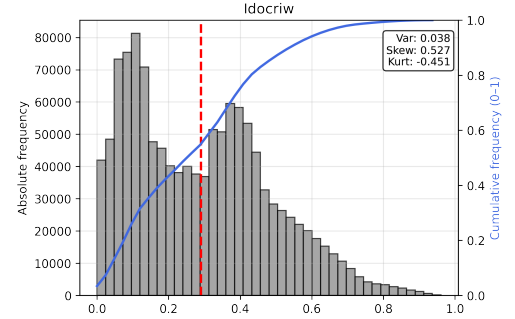
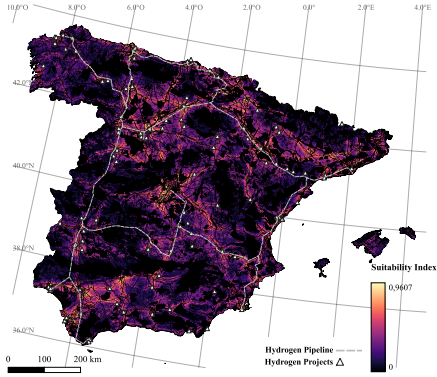
(b) CRITIC



(c) STD



(d) CILOS



(e) IDOCRIW

Figure 5: Suitability maps and corresponding cell score distributions for each weighting method. White markers denote Spain’s renewable hydrogen production projects, and the grey dashed line represents the planned H₂ pipeline network. The accompanying histograms display the distribution of cell scores; the red line indicates the mean, and summary statistics (variance, skewness, and kurtosis) are reported in the inset text box.

3.4. Statistical and Empirical Validation

The validation of the proposed framework is conducted in two distinct stages. Initially, the robustness of the five objective weighting approaches is evaluated by measuring their concordance, resilience, and discrimination capabilities. Subsequently, the resulting suitability mapping is empirically validated by benchmarking the identified high-potential areas against the geographical locations of existing H₂ projects.

3.4.1. Statistical Comparison of Weighting Methods

Concordance. The Spearman correlation matrix (fig. 6) confirms the two distinct clusters with CRITIC, STD, and CILOS highly cohesive with intercorrelations of $\rho = 0.89 - 0.96$. The second cluster, comprising entropy and IDOCRIW, is less internally coherent ($\rho = 0.86$). Entropy shows the lowest overall concordance with other methods ($\rho = 0.5$), reflecting its unique information-theoretic foundation. IDOCRIW occupies an intermediate position, displaying partial alignment with the first cluster ($\rho = 0.79 - 0.86$).

The concordance metrics (table 6) show that CILOS is the most aligned method, with the highest average Spearman correlation ($\rho = 0.743$), the smallest distance to consensus (0.126), and the strongest Kendall agreement ($\tau = 0.643$). CRITIC and STD display similar, high concordance ($\rho = 0.70 - 0.71$) and low dispersion. IDOCRIW has higher variability, while Entropy is the least aligned ($\rho = 0.457$), confirming its

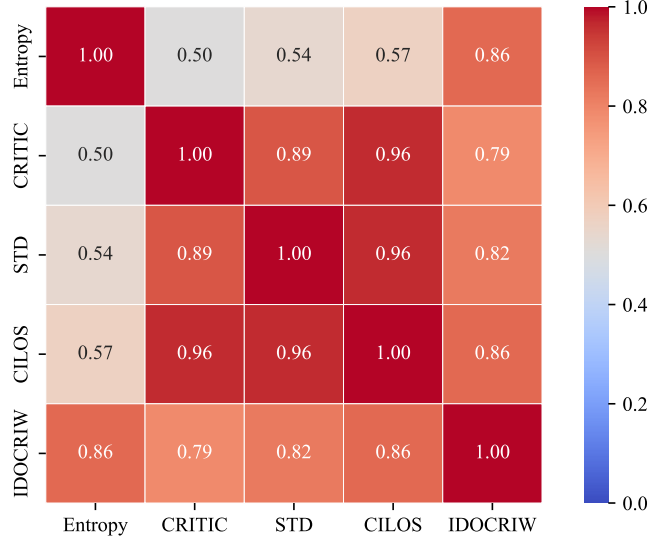


Figure 6: Spearman Correlation matrix of the weighting methods.

divergent behavior.

Table 6: Agreement Metrics of the Weighting Methods

Weighting Method	Avg. Spearman Corr.	Distance to consensus	Standard Deviation	Kendall Agreement
Entropy	0.692	0.165	0.130	0.452
CRITIC	0.828	0.110	0.005	0.666
STD	0.864	0.155	0.014	0.666
CILOS	0.871	0.096	0.057	0.738
IDOCRIW	0.842	0.099	0.054	0.666

Resilience. The resilience assessment shows that weighting methods are generally stable when individual criteria are excluded. Entropy and STD show perfect resilience (average $\rho = 1.00$), maintaining identical rankings across all perturbations. This behaviour reflects their strong dependence on global dispersion patterns, which remain largely unchanged even when a single criterion is removed. CRITIC also demonstrates very high resilience ($\rho \approx 0.99$), with only minor reordering among criteria under perturbation. IDOCRIW and CILOS show lower but still high resilience ($\rho \approx 0.98$). The top-ranked criteria tend to be the most resilient across all methods, whereas the lowest-weighted criteria exhibit slightly more positional shifts when excluded. Overall, the results confirm that all five techniques produce rankings that are highly resistant to criterion omission.

Discrimination. The dispersion metrics indicate clear differences in discriminatory power across methods. By standard deviation, Entropy ($\sigma = 0.142$) and IDOCRIW ($\sigma = 0.137$) show the greatest discrimination. This means they produce the most contrasted weights and therefore separate criteria most sharply. CILOS, STD, and CRITIC show much lower standard deviations, indicating weaker discrimination and more evenly distributed weights. The entropy statistic corroborates this pattern from the opposite perspective. Entropy and IDOCRIW have the lowest entropy values ($S = 0.744$ and 0.749 respectively), consistent with peaked, less-uniform weight distributions, while CRITIC, STD and CILOS have higher entropy, indicating flatter, more uniform weight profiles. Taken together, both indicators agree that Entropy and IDOCRIW are the most discriminating methods.

Table 7: Discrimination metrics of the Weighting Methods

Weighting Method	Standard Deviation	Entropy
Entropy	0.125	0.764
CRITIC	0.004	0.971
STD	0.051	0.964
CILOS	0.052	0.962
IDOCRIW	0.120	0.764

3.4.2. Empirical Alignment with Existing H_2 Projects

Figure 7 shows the distribution of suitability scores from the five weighting methods using violin plots. The quartiles are marked by dashed lines, and the locations of existing hydrogen projects are shown as black points.

CRITIC, STD, and CILOS display very similar violin shapes, with smooth and relatively symmetrical distributions and a strong concentration of candidate locations around moderate suitability values (approximately 0.4–0.6). By contrast, Entropy and IDOCRIW display wider distributions with more pronounced upper tails. This leads to a larger share of candidate locations attaining very high suitability values.

Overall, we see that almost all projects (95%) are located within the upper quartile in all methods. Entropy-based methods yield a wider range within the top 25% (approximately 0.40–0.96) than standard deviation-based approaches (approximately 0.55–0.95). Projects falling within the lower quartiles should not be interpreted as model misclassifications. Rather, they likely reflect the prioritization of factors not included in the present analysis. As illustrated in the suitability maps (Figure 5), several lower-scoring projects are situated near the planned hydrogen pipeline network. This suggests that developers may be prioritizing anticipated access to dedicated transport infrastructure connecting production sites with industrial off-takers, even when other suitability criteria are less favorable.

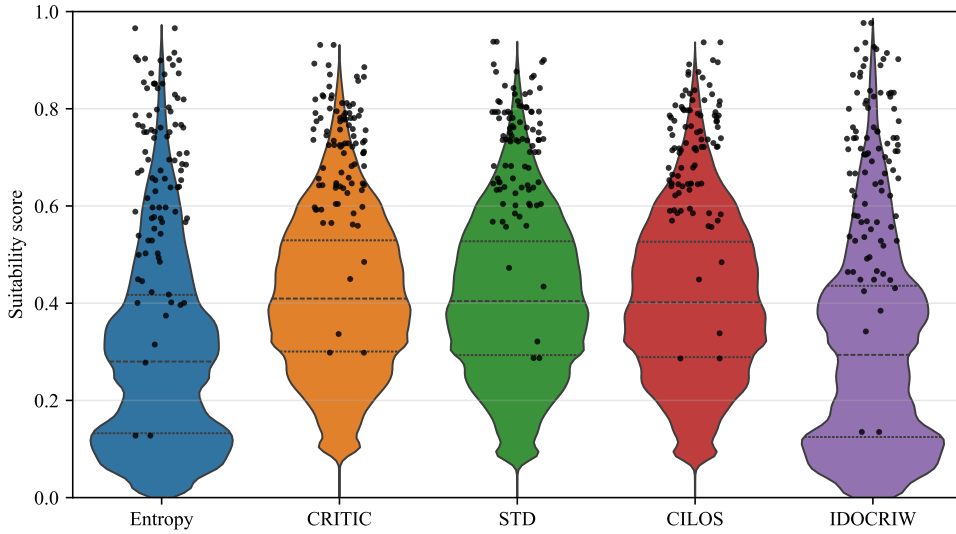


Figure 7: Distribution of suitability scores produced by the five weighting methods using violin plots. Dashed lines indicate quartiles, and black points represent the locations of 96 existing H_2 projects included in the validation.

3.5. Sensitivity analysis to variations in distance to Industrial Demand

Finally, to evaluate the robustness of the proposed methodology, a sensitivity analysis is performed using the most uncertain criterion for hydrogen projects: maximum distance from hydrogen demand.

H₂ demand under three maximum distances: 10, 40 and 100 km is evaluated. Figure 8 illustrates how the distribution of the demand criterion shifts under different maximum-distance thresholds. With a 10 km radius, only a very small number of cells lie close enough to existing demand centres. Consequently, more than 95% of all cells take the value zero, resulting in a highly sparse distribution. As the maximum distance increases to 40 km, the distribution becomes less concentrated. Over 50% of the cells have non-zero values, though fewer than 10% exceed 0.6. Finally, with a 100 km cutoff, the distribution changes substantially: most cells score above zero, and roughly half exceed 0.6, reflecting a much more spatially diffuse representation of accessible demand.

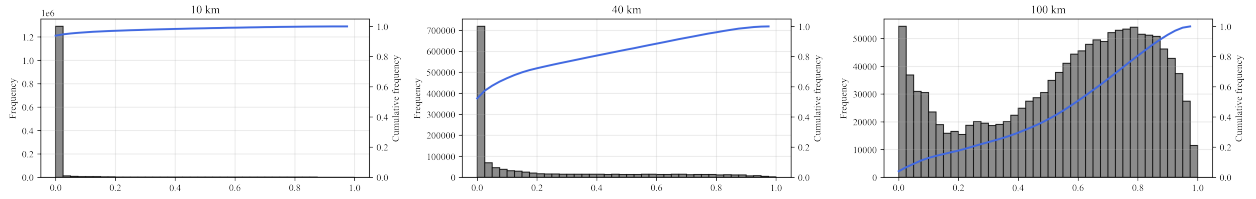


Figure 8: Distribution of normalized demand criteria using different upper-bound limits in distance to demand

These differences in the input distribution directly affect the weights of criteria (see Annex B for a detailed presentation of weights variation) and the distribution of the resulting suitability scores. As shown in fig. B.10, the impact is particularly pronounced for entropy-based weighting. For a 10 km threshold, almost all cells have a suitability below 0.4. This is caused by the extremely high weight assigned to demand (0.57). Conversely, when the distance is set to a maximum of 100 km, the entropy method only assigns a weight of 0.06 to this criterion and becomes significantly less discriminatory with a more uniform distribution. Methods based on standard deviation remain the most stable, with demand weights consistently between 0.05 and 0.14.

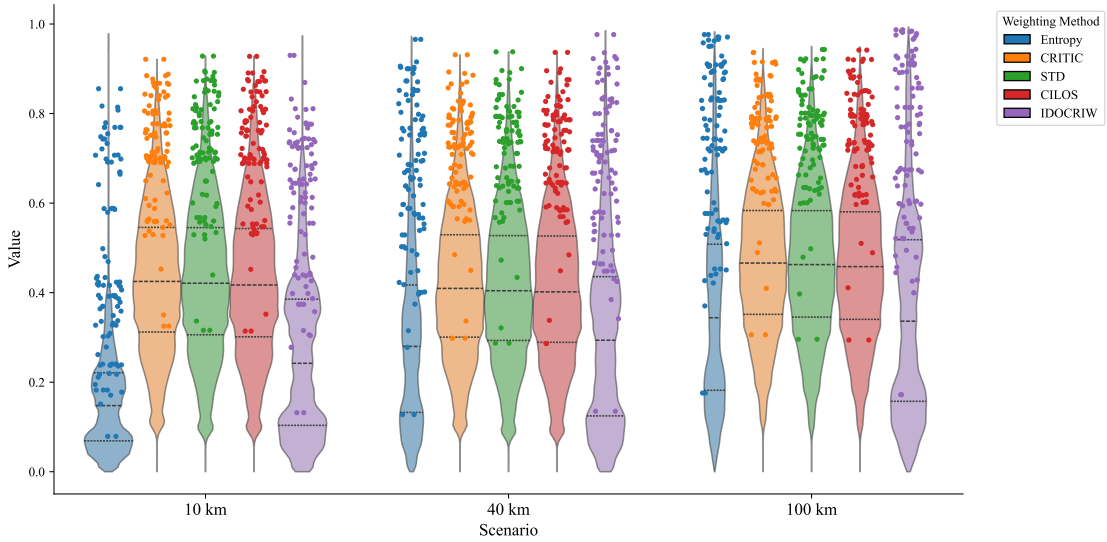


Figure 9: Distribution of suitability scores based on different distance thresholds relative to demand. Dashed lines indicate quartiles, and points represent the locations of 96 existing H₂ projects included in the validation.

4. Discussion

This study shows that objective GIS-based MCDM methods are useful tools for identifying suitable locations for hydrogen projects. By deriving weights from data rather than expert opinion, they reduce bias and improve transparency and replicability. However, they do not fully remove subjectivity. Expert judgment is still required at key stages of the process: defining criteria, setting normalization thresholds, and selecting the weighting framework.

The sensitivity analysis on distance to demand shows that the normalization threshold strongly shapes the resulting weights and suitability distribution, especially under entropy-based weighting. The choice between a decentralized supply logic (distance to demand ≤ 10 km), a regional hydrogen valley approach (≤ 40 km), or a broader national-scale configuration (≤ 100 km) directly affects the resulting suitability patterns.

Regarding weighting approaches, the weighting methods analyzed presented distinct analytical logics. Standard deviation-based methods generate more balanced weights and maps, while entropy-based methods tend to amplify localized variation and produce more discriminatory maps. These different "storylines" can support expert judgment in complementary ways: standard deviation methods are well-suited for broad territorial screening exercises (e.g., national assessments of hydrogen mobility infrastructure), whereas entropy-based approaches may be more informative in project-level assessments where fine spatial differentiation is required.

Despite these structural differences, both families perform well in empirical validation. On average, more than 95% of existing projects fall within the upper quartile of each suitability distribution. Entropy-based methods assign a wider range of values within this top quartile, thereby achieving greater discrimination among high-ranking cells. At the same time, all methods identify largely overlapping sets of locations in the highest suitability class (0.8–1). The most favorable areas score consistently high across criteria, making them relatively robust to the weighting approach.

This convergence should not be generalized. In regions with greater spatial heterogeneity or under expanded or more restrictive criterion sets, methodological choice may exert a stronger influence on outcomes. Applying at least one method from each family, contrasting their results, can provide a more comprehensive assessment in those contexts.

All mathematical validation metrics confirm internal consistency under the selected criteria. However, objective weights remain data-dependent. Changes in dispersion, correlation structures, or the inclusion of additional variables can modify derived weights. If certain criteria are measured with uncertainty or incomplete coverage, entropy-based methods may assign excessive influence to unreliable inputs, whereas variance-based approaches tend to be more stable under such conditions.

Overall, a key advantage of the proposed framework is its replicability across regions. Because weights are derived from observed spatial distributions, the method adapts endogenously to regional conditions without requiring detailed local expert calibration. For example, water availability is not a limiting factor in Spain, so it does not receive high weight. In contrast, in water-scarce regions such as Algeria, the same methodology would likely assign higher weight to water-related criteria due to greater dispersion and constraint intensity.

This adaptive behavior contrasts with subjective methods, where weights may reflect perceived importance rather than actual spatial variation. For instance, solar resource availability may receive high weights as it is essential for renewable hydrogen production. However, in contexts where solar potential is broadly homogeneous, such subjective emphasis may artificially distort rankings. Objective methods mitigate this risk by linking the magnitude of weight to empirical variability.

Although our proposed method of criteria weighting for hydrogen site selection has proven to be robust, further examination of the impact of different ranking methods would be beneficial. This study relies on a

weighted linear combination (WLC) framework. Future research could compare alternative aggregation and ranking methods to assess the effect of more complex decision rules on spatial prioritization and ranking stability.

In addition, the analysis centers on industrial hydrogen use. Expanding the framework to other applications—such as e-fuel production combining H_2 and CO_2 —would require incorporating additional spatial criteria, including proximity to CO_2 sources and fuel distribution infrastructure.

5. Conclusion

This study developed and applied a high-resolution spatial multi-criteria evaluation framework to identify suitable locations for renewable H_2 production in Spain while systematically comparing five objective weighting methods. By analyzing thousands of candidate sites at a 500×500 m resolution, the framework revealed substantial spatial heterogeneity in technical, environmental, and infrastructural conditions relevant to RHPP deployment. Nearly half of the national territory was excluded during the initial screening stage, underscoring the importance of rigorous land-use, environmental, and topographical constraints in determining the feasibility of large-scale H_2 development.

Results demonstrate that the choice of methodology plays a decisive role in suitability analysis based on objective MCDM techniques. Far from being a purely technical exercise, methodological decisions, such as data preprocessing, the definition of criteria limits, and the selection of the weighting method, substantially shape the resulting suitability maps, leading to markedly different spatial patterns even when relying exclusively on so-called objective approaches.

This sensitivity arises from the strong dependence of objective MCDM methods on the statistical properties of the input criteria. Because weights are derived from distributional measures such as variance, entropy, or correlation, the shape and dispersion of the underlying data directly influence the relative importance assigned to each criterion.

While the different objective weighting methods analyzed exhibit reasonable stability and acceptable inter-method concordance at the highest-suitability locations, significant divergences occur in the medium-suitability range. This finding indicates that the apparent objectivity of weighting methods should be interpreted with caution. Although objective approaches are formally data-driven, they inevitably embed implicit subjective choices related to data treatment and methodological design. Accordingly, the use of objective methods does not eliminate the need for expert judgment; rather, domain expertise remains essential to ensure robust and interpretable MCDM outcomes.

Overall, objective MCDM approaches can provide a robust, transparent, and reproducible framework for RHPP siting. However, rather than seeking a universally “best” method, methodological choices should be explicitly aligned with the specific decision-making objectives and accompanied by a clear articulation of the underlying assumptions. Consequently, suitability maps cannot be universally generalized across project typologies; instead, they should be interpreted as context-dependent decision-support tools, whose relevance depends on the selected criteria, their statistical distributions, and the underlying energy system context. Future research could build on this work by exploring hybrid combinations of objective and subjective weighting schemes, assessing robustness under alternative data-generating processes, and examining how methodological uncertainty propagates into downstream planning and investment decisions.

Declarations

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

AI usage statement

During the preparation of this work, the authors used GPT 4.0 and Grammarly to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Acknowledgments

This research was supported by the Centre for Low Carbon Hydrogen Studies of the Pontifical University of Comillas (Spain) and by Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES, Brazil).

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

- [1] IEA. Global hydrogen review 2024. Technical report, International Energy Agency, 2024.
- [2] Repowereu: A plan to rapidly reduce dependence on russian fossil fuels and fast forward the green transition, 05 2022. URL https://enlargement.ec.europa.eu/news/repowereu-plan-rapidly-reduce-dependence-russian-fossil-fuels-and-fast-forward-green-transition-2022-05-18_en.
- [3] Redeia. Electricity demand in spain consolidates its growth trajectory in 2025, 2025. URL <https://www.ree.es/es/sala-de-prensa/actualidad/nota-de-prensa/2025/12/la-demanda-de-electricidad-en-espana-consolida-la-senda-de-crecimiento-en-2025>.
- [4] European Commission. Communication from the commission to the european parliament, the council, the european economic and social committee and the committee of the regions on the european hydrogen bank. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52023DC0156>, 03 2023. 52023DC0156.
- [5] Ministerio para la Transición Ecológica y el Reto Demográfico . Hydrogen roadmap: a commitment to renewable hydrogen, 2020. URL <https://www.miteco.gob.es/es/ministerio/planes-estrategias/hidrogeno.html>.
- [6] AeH2. 2025 census of projects analysis. URL <https://aeh2.org/en/hydrogen-project-census/>.
- [7] Meng Shao, Zhixin Han, Jinwei Sun, Chengsi Xiao, Shulei Zhang, and Yuanxu Zhao. A review of multi-criteria decision making applications for renewable energy site selection. 157:377–403. ISSN 0960-1481. doi: 10.1016/j.renene.2020.04.137. URL <https://www.sciencedirect.com/science/article/pii/S0960148120306753>.
- [8] S. Serna, T. Gerres, and R. Cossent. Multi-criteria decision-making for renewable hydrogen production site selection: a systematic literature review. 10(3):119–129. ISSN 2196-3010. doi: 10.1007/s40518-023-00219-0. URL <https://doi.org/10.1007/s40518-023-00219-0>.
- [9] Fatih Karipoğlu, Mustafa Serdar Genç, and Beyhan Akarsu. Gis-based optimal site selection for the solar-powered hydrogen fuel charge stations. *Fuel*, 324:124626, 2022. ISSN 0016-2361. doi: <https://doi.org/10.1016/j.fuel.2022.124626>. URL <https://www.sciencedirect.com/science/article/pii/S0016236122014752>.
- [10] Fida Ali, Adul Bennui, Shahariar Chowdhury, and Kuaanan Techato. Suitable site selection for solar-based green hydrogen in southern thailand using gis-mcdm approach. *Sustainability*, 14(11), 2022. ISSN 2071-1050. doi: 10.3390/su14116597. URL <https://www.mdpi.com/2071-1050/14/11/6597>.
- [11] Meryem Taoufik and Ahmed Fekri. A gis-based multi-criteria decision-making approach for site suitability analysis of solar-powered hydrogen production in the souss-massa region, morocco. *Renewable Energy Focus*, 46:385–401, 2023. ISSN 1755-0084. doi: <https://doi.org/10.1016/j.ref.2023.08.004>. URL <https://www.sciencedirect.com/science/article/pii/S1755008423000753>.
- [12] Djilali Messaoudi, Nouredine Settou, Belkhir Negrou, and Belkhir Settou. Gis based multi-criteria decision making for solar hydrogen production sites selection in algeria. *International Journal of Hydrogen Energy*, 44(60):31808–31831, 2019. ISSN 0360-3199. doi: <https://doi.org/10.1016/j.ijhydene.2019.10.099>. URL <https://www.sciencedirect.com/science/article/pii/S036031991933887X>.
- [13] Salah eddine Amrani, Ahmed Alami Merrouni, samir Touili, Hanane Ait Lahoussine Ouali, and Hassane Dekhissi. An ahp-gis combination for site suitability analysis of hydrogen production units from csp pv solar power plants in morocco. *International Journal of Hydrogen Energy*, 56:369–382, 2024. ISSN 0360-3199. doi: <https://doi.org/10.1016/j.ijhydene.2023.12.165>. URL <https://www.sciencedirect.com/science/article/pii/S0360319923064650>.

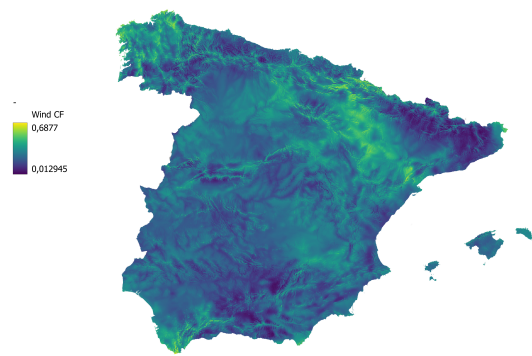
- [14] Yunna Wu, Chenghao Wu, Jianli Zhou, Feiyang He, Chuanbo Xu, Buyuan Zhang, and Ting Zhang. An investment decision framework for photovoltaic power coupling hydrogen storage project based on a mixed evaluation method under intuitionistic fuzzy environment. *Journal of Energy Storage*, 30: 101601, 2020. ISSN 2352-152X. doi: <https://doi.org/10.1016/j.est.2020.101601>. URL <https://www.sciencedirect.com/science/article/pii/S2352152X20314389>.
- [15] Mostafa Rezaei-Shouroki, Ali Mostafaeipour, and Mojtaba Qolipour. Prioritizing of wind farm locations for hydrogen production: A case study. *International Journal of Hydrogen Energy*, 42(15):9500–9510, 2017. ISSN 0360-3199. doi: <https://doi.org/10.1016/j.ijhydene.2017.02.072>. URL <https://www.sciencedirect.com/science/article/pii/S0360319917305475>.
- [16] Seyyed Shahabaddin Hosseini Dehshiri and Seyyed Jalaladdin Hosseini Dehshiri. Locating wind farm for power and hydrogen production based on geographic information system and multi-criteria decision making method: An application. *International Journal of Hydrogen Energy*, 47(58):24569–24583, 2022. ISSN 0360-3199. doi: <https://doi.org/10.1016/j.ijhydene.2022.03.083>. URL <https://www.sciencedirect.com/science/article/pii/S036031992201120X>. Hydrogen Sourced from Renewables and Clean Energy: Feasibility of Large-scale Demonstration Projects.
- [17] Yunna Wu, Feiyang He, Jianli Zhou, Chenghao Wu, Fangtong Liu, Yao Tao, and Chuanbo Xu. Optimal site selection for distributed wind power coupled hydrogen storage project using a geographical information system based multi-criteria decision-making approach: A case in china. *Journal of Cleaner Production*, 299:126905, 2021. ISSN 0959-6526. doi: <https://doi.org/10.1016/j.jclepro.2021.126905>. URL <https://www.sciencedirect.com/science/article/pii/S0959652621011240>.
- [18] Mostafa Rezaei, Kaveh R. Khalilpour, and Mehdi Jahangiri. Multi-criteria location identification for wind/solar based hydrogen generation: The case of capital cities of a developing country. *International Journal of Hydrogen Energy*, 45(58):33151–33168, 2020. ISSN 0360-3199. doi: <https://doi.org/10.1016/j.ijhydene.2020.09.138>. URL <https://www.sciencedirect.com/science/article/pii/S0360319920335783>.
- [19] Chia-Nan Wang, Ming-Hsien Hsueh, and Da-Fu Lin. Hydrogen power plant site selection under fuzzy multicriteria decision-making (FMCDM) environment conditions. 11(4):596, . ISSN 2073-8994. doi: 10.3390/sym11040596. URL <https://www.mdpi.com/2073-8994/11/4/596>. Number: 4 Publisher: Multidisciplinary Digital Publishing Institute.
- [20] Djilali Messaoudi, Noureddine Settou, Belkhir Negrou, Soumia Rahmouni, Belkhir Settou, and Ishak Mayou. Site selection methodology for the wind-powered hydrogen refueling station based on ahp-gis in adrar, algeria. *Energy Procedia*, 162:67–76, 2019. ISSN 1876-6102. doi: <https://doi.org/10.1016/j.egypro.2019.04.008>. URL <https://www.sciencedirect.com/science/article/pii/S1876610219313670>. Emerging and Renewable Energy: Generation and Automation.
- [21] Narjes Mahmoodi Vanolya and Mohammadreza Jelokhani-Niaraki. The use of subjective-objective weights in GIS-based multi-criteria decision analysis for flood hazard assessment: a case study in mazandaran, iran. 86(1):379–398. ISSN 1572-9893. doi: 10.1007/s10708-019-10075-5. URL <https://doi.org/10.1007/s10708-019-10075-5>.
- [22] Wei-Dong Wang, Jing Guo, Li-Gang Fang, and Xin-Sheng Chang. A subjective and objective integrated weighting method for landslides susceptibility mapping based on GIS. 65(6):1705–1714, . ISSN 1866-6299. doi: 10.1007/s12665-011-1148-z. URL <https://doi.org/10.1007/s12665-011-1148-z>.
- [23] IRENA. Green hydrogen cost reduction. URL <https://www.irena.org/publications/2020/Dec/Green-hydrogen-cost-reduction>.
- [24] Ministry for Ecological Transition and Demographic Challenge (MITECO). Red natura 2000, .

- [25] Ministerio Agricultura Pesca y Alimentación. Propuesta de regulación relativa a la protección de los usos del suelo de las zonas regables declaradas de interés general. URL https://www.mapa.gob.es/es/desarrollo-rural/temas/gestion-sostenible-regadios/20230208_propuestadisposicionenleydesperdicio_proteccion_zrig_tcm30-644011.pdf.
- [26] CORINE land cover — copernicus land monitoring service. URL <https://land.copernicus.eu/en/products/corine-land-cover>.
- [27] Global solar atlas. URL <https://globalsolaratlas.info/map>.
- [28] Global wind atlas. URL <https://globalwindatlas.info>.
- [29] Ministry for Ecological Transition and Demographic Challenge (MITECO). Urban wastewater treatment infrastructure and discharge points (directive 91/271/eec), . URL <https://www.miteco.gob.es/es/cartografia-y-sig/ide/descargas/agua/situacion-q2021.html>.
- [30] EU emissions trading system (ETS) data viewer. URL <https://www.eea.europa.eu/en/analysis/maps-and-charts/emissions-trading-viewer-1-dashboards>.
- [31] National Geographic Institute. Ign. URL <http://www.ign.es>.
- [32] Autonomous Agency National Information Center Geographical. Spanish transport road infrastructure. URL <http://centrodedescargas.cnig.es>.
- [33] Open infrastructure map. URL <https://openinframap.org>.
- [34] Santiago Serna Zuluaga, Timo Gerres, and Rafael Cossent. Beyond green hydrogen: the role of low-carbon hydrogen in the optimal operation of electrolytic plants. URL <https://papers.ssrn.com/abstract=5810424>.
- [35] Bartosz Paradowski, Andrii Shekhovtsov, Aleksandra Bączkiewicz, Bartłomiej Kizielewicz, and Wojciech Sałabun. Similarity analysis of methods for objective determination of weights in multi-criteria decision support systems. *Symmetry*, 13:1874, 10 2021. doi: 10.3390/sym13101874. URL <https://www.mdpi.com/1300044>.
- [36] Universidad Pontifica Comillas. Observatory of hydrogen projects in spain. URL <https://www.comillas.edu/catedras-de-investigacion/catedra-de-estudios-sobre-el-hidrogeno/mapa-de-proyectos-en-espana/>.
- [37] EHB. European hydrogen backbone, implementation roadmap — cross border projects and costs update. URL <https://ehb.eu/files/downloads/EHB-2023-Implementation-Roadmap-Part-1.pdf>.

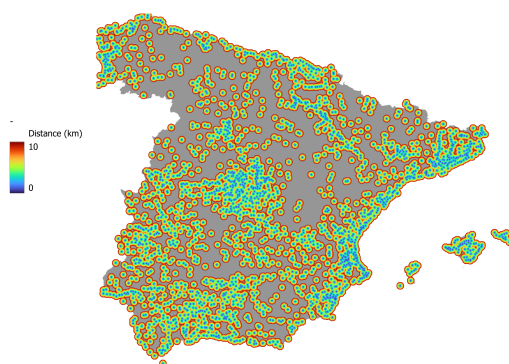
Appendix A. Spatial Distribution of Criteria



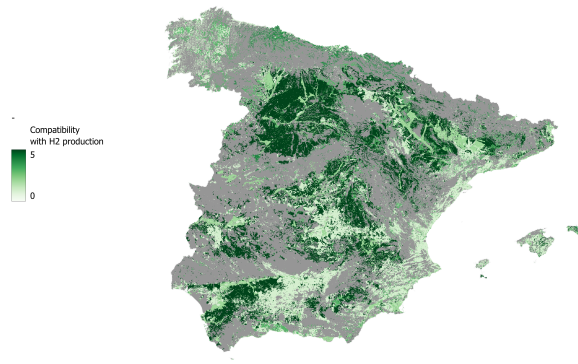
Solar Capacity Factor



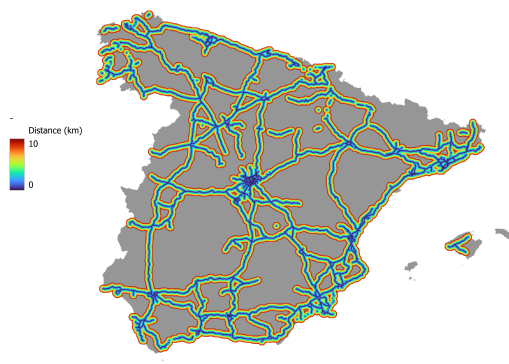
Wind Capacity Factor



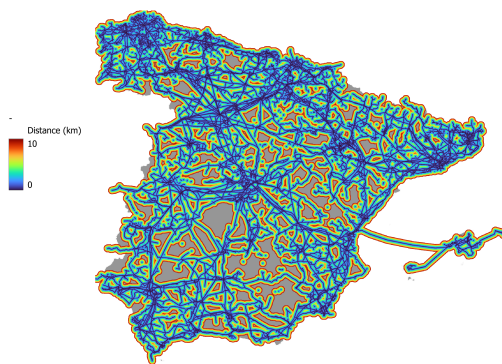
Distance from Water Sources



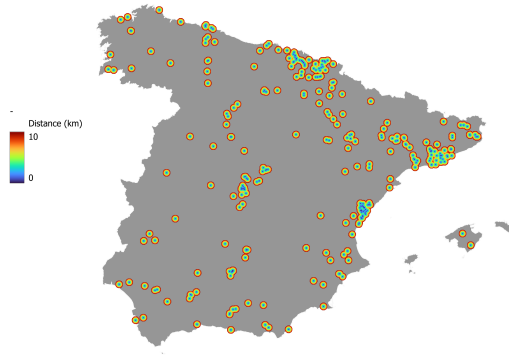
Land Use



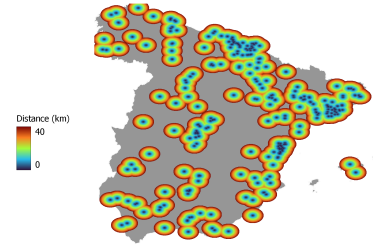
Distance from Highways



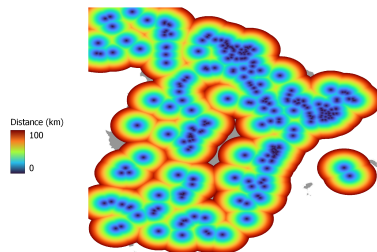
Distance from Powerlines



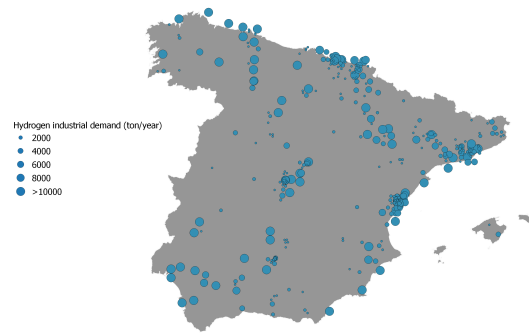
10 km buffer distance from Hydrogen Demand



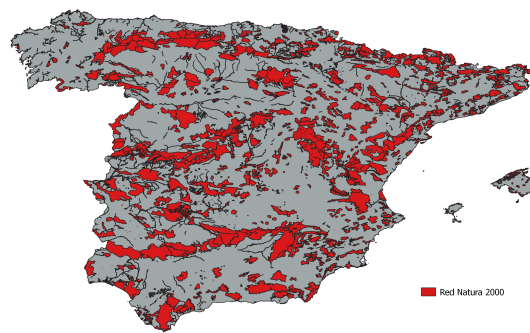
40 km buffer distance from Hydrogen Demand



100 km buffer distance from Hydrogen Demand



Industrial hydrogen demand



Red Natura 2000 areas

Appendix B. Criterion weights under the sensitivity analysis

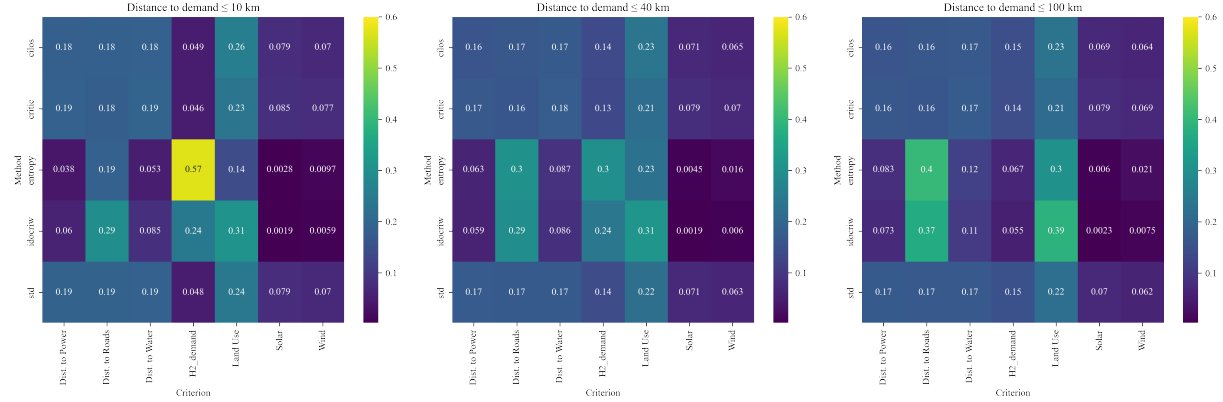


Figure B.10: Weighting of criteria based on different distance thresholds relative to demand.

Appendix C. Industrial H₂ Demand

H₂ is a versatile energy carrier with demand currently concentrated in industrial applications. The primary uses are as a chemical feedstock in refining (44%), ammonia (37%), and methanol (14%) production [1]. A key emerging application is its role in decarbonizing heavy industry, particularly as a clean reducing agent in Direct Reduced Iron steel production and a source of high-temperature heat for sectors like cement and glass manufacturing. This analysis quantifies potential H₂ demand using a sector-specific approach. For established feedstock uses and DRI steelmaking, demand is calculated directly from facility-level data, applying a standard consumption factor where necessary. For high-temperature heat applications, where direct energy data is scarce, CO₂ emissions reported under the EU Emissions Trading System serve as a proxy to estimate the energy input that could be replaced by H₂. The conversion ratios and detailed methodology for each industrial sector are provided in Appendix B.

Table Appendix C.1: Industrial Processes and Their CO2 Emissions and Energy Consumption

NACE Code	Description	tCO2/t	GJ/t
17.11	Manufacture of pulp	0.308	10.296
17.12	Manufacture of paper and cardboard	0.37	4.896
17.21	Manufacture of corrugated paper and cardboard; manufacture of containers and packaging of paper and cardboard	0.37	4.896
17.22	Manufacture of household, sanitary and hygienic paper and cardboard articles	0.37	6.912
17.29	Manufacture of other paper and cardboard articles	0.37	4.896
23.13	Manufacture of hollow glass	0.36	5.688
23.11	Manufacture of flat glass	0.54	7.668
23.14	Manufacture of glass fiber	0.52	12.348
23.19	Manufacture and processing of other glass, including technical glass	0.52	12.348
23.51	Manufacture of cement	0.815	2.9
23.31	Manufacture of ceramic tiles and flags	0.3	5.6
23.41	Manufacture of ceramic household and ornamental articles	0.3	45
23.42	Manufacture of ceramic sanitary ware	0.3	21.87
23.49	Manufacture of other ceramic products	0.3	5.6
23.32	Manufacture of bricks and tiles	0.115	2.31
23.52	Manufacture of lime and plaster	0.725	4.25
24.51	Iron casting	1.28	0.82
24.52	Steel casting	1.28	0.82
24.53	Light metal casting	1.28	0.82
24.54	Casting of other non-ferrous metals	1.28	0.82
24.31	Cold drawing	0.31	0.8
24.32	Cold rolling	0.31	0.8
24.33	Production of profiles in cold by folding	0.31	0.8
24.34	Cold drawing	0.31	0.8
24.42	Aluminum production	1.5	19