sustainability

MDPI

Article

A Hybrid IVN-Fuzzy TOPSIS and GIS Spatial Suitability Approach for Sustainable Solar Power Plant Site Selection in Türkiye

Mustafa Güler

Engineering Sciences Department, Engineering Faculty, Istanbul University-Cerrahpaşa, 34320 Istanbul, Türkiye; m.guler@iuc.edu.tr

Abstract

The move to sustainable energy systems has increased the requirement for comprehensive decision support frameworks that are uncertainty-aware to guide the selection of solar power plant sites. The rapid growth of investments in solar energy has increased the demand for systematic and accurate decision-support tools to choose the best sites for photovoltaic (PV) power facilities. The selection of solar power plant sites is a complicated multi-criteria decision-making (MCDM) problem that involves technical, economic, environmental, social, and technological aspects. The process is typically associated with ambiguity and incomplete knowledge of experts. To overcome these problems, this paper offers an interval-valued neutrosophic fuzzy TOPSIS (IVN-TOPSIS) method, which extends the standard TOPSIS methodology by including truth, indeterminacy, and falsity membership degrees as interval values. The methodology is utilized in a real case study in the Mediterranean region of Türkiye, comprising three provinces with great potential: Antalya, Mersin, and Adana. An assessment of a complete set of environmental, economic, social, and technological criteria is performed using expert judgments stated in interval-valued neutrosophic language assessments. They were incorporated into a Geographic Information System (GIS) to produce a suitability map indicating the most suitable sites for the facility. The suggested approach is different from the traditional crisp or fuzzy MCDM techniques since it clearly models the degrees of truth, indeterminacy, and falsehood, thus providing a more detailed representation of the expert evaluations. According to the data, Mersin is the most ideal site for the construction of a solar power plant, followed by Antalya, and the least suitable site is Adana. The results suggest that sustainable solar energy planning must go beyond technical resource potential and include integrated and uncertainty-aware assessments. The suggested IVN-TOPSIS framework can serve as a powerful decision-support tool to policymakers, planners, and investors that wish to encourage regionally balanced and sustainable renewable energy development.

Keywords: solar power plant site selection; MCDM; IVN-TOPSIS; renewable energy planning; GIS

Check for updates

Academic Editor: Firoz Alam

Received: 16 May 2026
Revised: 9 June 2026
Accepted: 17 June 2026
Published: 23 June 2026

Copyright: © 2026 by the author. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

The global shift to sustainable energy systems has raised the strategic relevance of solar photovoltaic (PV) technology, as a critical component of low-carbon development paths. Many countries are ramping up investments in solar energy, in accordance with international climate agreements and sustainable development goals, to cut greenhouse

gas emissions, improve energy security and bolster regional economic development. Solar power in particular has become a key aspect of sustainable energy initiatives with rapidly falling costs, improved efficiency and abundant availability. With ongoing technology developments that have made solar energy more reliable and affordable than ever, photovoltaic solar systems are now ready to lead the transition to a low-carbon energy supply [1]. Recent improvements in the efficiency of PV cells and the benefits of economies of scale have hastened solar deployment, making solar energy a key technology in the transition to sustainable power systems. Recent studies emphasize that, to ensure long-term energy security and grid reliability, future energy systems will require integrated energy portfolios that combine renewable energy sources with more stable baseload generation technologies, including nuclear energy [2]. Especially, this global rise in solar penetration is also paralleled by national efforts. Türkiye, for example, has more than doubled its PV capacity in the last few years, reaching around 20 GW of installed solar power by the end of 2024 and accounting for almost 6% of the electricity in the country [3]. Türkiye is a country with a high solar potential located between 36° and 42° N latitudes and has an annual average of 2700 sunlight hours and solar irradiation of 1300–1500 kWh/m^2 per year [4]. "Given the latitude and climate, Türkiye's Mediterranean coast enjoys particularly good solar irradiance." Provinces like Antalya, Mersin, and Adana have some of the highest sunlight durations in the country (sometimes more than 8 h per day) and daily insolation values of about 4.5–5 kWh/m^2. This exceptional solar resource in the Mediterranean region makes it a focal area for new PV projects and underpins its strategic role in Türkiye's renewable expansion. At the same time, however, identifying optimal sites in these provinces is a complex task. Solar farm siting must navigate a web of technical, environmental, and socio-economic constraints, from land availability, terrain, and grid proximity to land use, climate, and cost considerations. Balancing such multifaceted criteria calls for systematic decision-support tools in order to maximize energy yield and sustainability while minimizing costs and conflicts [5].

The application of MCDM methods has been very beneficial in the complexity of renewable energy site selection. MCDM allows planners to consider a number of (often contradicting) factors in a structured analysis and ranking of alternatives, as opposed to single factor evaluations. The problem of selecting a location for a solar power plant is multidimensional and complex. This involves thorough study of environmental, economic and technical elements to ensure that sites picked optimize energy yields while minimizing costs and harmful impacts. Critical factors consist of solar irradiance levels, availability and properties of land (e.g., slope, orientation, land cover type), proximity to the grid, infrastructure and access roads and socio-environmental constraints such as avoiding protected areas or minimizing resettlements [6]. There are sometimes challenges with technical issues such as the potential of grid connection and maintenance logistics, as well as economic considerations such as land pricing, project finance conditions and availability of incentives. Wrong choice of site may lead to poor performance, increased transmission losses, environmental problems or inflated project cost [7]. Hence, a systematic multi-criteria decision-making technique is needed for solar site selection. This complexity can be addressed in a structured manner using Multi-Criteria Decision-Making (MCDM) methodologies that allow planners to account for numerous criteria simultaneously and to explicitly examine the trade-offs among them. As Ghasempour et al. [8] have pointed out in a thorough study, the relative importance of site criteria (such as resource quality, grid proximity, land value, etc.) can vary considerably depending on the regional context, economic conditions, and grid infrastructure. This uncertainty presents the need for strong decision models that are suited to the context in which renewable energy projects are being selected.

In recent years, a considerable amount of worldwide literature has used MCDM techniques for renewable energy site difficulties, especially for the solar power plant's location selection. More and more researchers have integrated decision analysis with geospatial techniques and expert opinion to determine the best sites under various conflicting criteria. This methodological progression has yielded the Interval-Valued Neutrosophic Fuzzy TOPSIS (IVN-TOPSIS) technique, a potent instrument for decision-making in the presence of uncertainty. IVN-TOPSIS is an extension of the standard TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) that incorporates neutrosophic fuzzy set theory. Each evaluation is described in three degrees of membership, truth, indeterminacy, and falsehood, expressed as intervals [9]. This enables decision makers to expressly consider uncertain or reluctant judgments besides the typical positive and negative evaluations. Unlike the traditional crisp MCDM or even the fundamental fuzzy logic (which usually deals only with membership and non-membership degrees), the neutrosophic approach can reflect an additional degree of uncertainty due to missing, inconsistent, or imprecise information [10]. IVN-TOPSIS uses interval values for the truthiness (T), indeterminacy (I), and falsity (F) of each criterion evaluation to express expert views in a more flexible and robust way in complex decision settings [11]. This has important benefits in terms of dependability and transparency: the method can better handle linguistic and subjective inputs with greater nuance, and the resulting rankings are less sensitive to the ambiguities that typically hamper strategic planning judgments. Different applications of IVN-based MCDM in many areas have confirmed its effectiveness in providing balanced judgments under uncertain conditions (e.g., site selection challenges in event planning and waste management), and this stimulates its adoption in renewable energy planning as well [12].

Given the ambitious renewable energy targets of Türkiye and the importance of the correct site selection for solar investments, the IVN fuzzy TOPSIS methodology is applied to a real-world decision problem: the best city for a photovoltaic power plant in the Mediterranean region of Türkiye. We concentrate on three high-potential provinces, Antalya, Mersin, and Adana, which not only have outstanding sun irradiation but also represent different local situations in terms of geography, infrastructure, and land use. A full set of evaluation criteria is defined, covering technical, economic, and environmental/social aspects. Technical aspects include the level of solar resource and the distance to the grid. Economic aspects include land price and expected energy yield and revenue. Environmental/social aspects include the type of land cover and the distance to protected areas and settlements, for example [13]. These criteria will be examined by energy experts and regional planners. The judgments of these experts will be encoded as interval-valued neutrosophic fuzzy evaluations to reflect the uncertainty and/or indeterminacy of their assessments. Then, integrating MCDM-based provincial prioritization with GIS-supported spatial suitability analysis can provide a more comprehensive and operational decision-support framework. In previous studies, geographic information system (GIS)-based methodologies, which are typically used to mitigate environmental impacts and reduce costs, are frequently employed in site selection studies. We systematically aggregate these evaluations using the IVN-TOPSIS approach to evaluate the three potential cities based on the overall suitability to host a large-scale solar PV installation. This use of interval-valued neutrosophic sets in the decision process allows us to deal with the inherent uncertainty in multi-criteria weighting and scoring. This leads to a more robust prioritization than typical crisp or single-valued fuzzy techniques.

In response to the growing need for sustainability oriented and uncertainty aware energy planning frameworks, this study introduces the interval-valued neutrosophic TOPSIS (IVN-TOPSIS) method to the solar power plant site selection problem, with a case application in Türkiye's Mediterranean Region. The originality of this work is beyond the

direct execution of the IVN-TOPSIS methodology. The aim of the paper is to evaluate and rank three candidate provinces Antalya, Mersin, and Adana for a new solar PV installation, by integrating a comprehensive set of criteria under the IVN-TOPSIS and GIS framework. To our knowledge, this work represents one of the first applications of IVN fuzzy logic to renewable energy siting in Türkiye, thereby addressing a notable gap in the literature. While previous studies conducted in Türkiye have predominantly relied on conventional GIS-based MCDM approaches or fuzzy AHP models, such methods often provide limited capacity to represent the uncertainty and hesitation inherent in expert-driven sustainability assessments. However, the literature on solar site-selection research based on sophisticated neutrosophic decision-making methodologies is limited in spite of the strategic relevance of this issue. I posit that the IVN-TOPSIS approach provides a novel contribution by capturing the indeterminacy in expert assessments more effectively than standard fuzzy or crisp methods. We are working to minimize uncertainty by combining this contribution with an innovative GIS-based method. In our methodology, decision-makers can express their evaluations of each province (on each criterion) with interval-valued neutrosophic ratings, reflecting not just favorable or unfavorable judgments but also the degree of hesitancy or uncertainty about those judgments. By processing these through the TOPSIS ranking technique, we obtain a prioritization of the candidate sites that is robust against the ambiguous or incomplete information inherent in real world decision settings. The results yield a recommended site for the solar power plant, along with an analysis of the critical criteria influencing the choice. In the end, the proposed approach provides real-world planning and policy contributions by identifying the region-specific sustainability dynamics that influence the deployment of solar power plants. The results are anticipated to help planners and policy makers in Türkiye and elsewhere to make well-informed, uncertainty aware decisions regarding where to site solar energy investments, ultimately enhancing the sustainability and success of such projects.

2. Related Works

There are numerous studies in the literature on multi-criteria decision-making. A wide variety of methods have been used, and the application areas show diversity. The site selection of solar photovoltaic (PV) power plants is inherently a multi-criteria decision-making (MCDM) problem, requiring the simultaneous consideration of technical feasibility, economic viability, environmental constraints, and social/policy conditions. Because most criteria are spatially dependent, the literature has largely converged on GIS–MCDM hybrid frameworks to operationalize PV siting decisions and produce suitability maps that support planning and investment processes [14–16]. A dominant stream employs GIS-based AHP to weight criteria and aggregate multiple thematic layers (e.g., solar radiation, slope/elevation/aspect, land-use/land-cover, and distances to roads and power infrastructure) into suitability classes. This approach is widely applied in Türkiye-oriented case studies such as Niğde [17], Gaziantep [18], and Çanakkale [19] and in regional contexts like Kirkuk (Iraq) [20]. These studies commonly report that GIS–AHP outputs (suitable/highly suitable zones) are decision-relevant and often show alignment with existing PV deployments (when such validation is performed) [17,18]. Comparable GIS–AHP logic is also used at broader scales (e.g., Bangladesh), where multi-layer overlays and AHP-based weighting generate nationwide suitability zonation and are validated through the distribution of existing solar plants [15]. In parallel, the literature recognizes that classical AHP may be insufficient to capture vagueness and uncertainty in expert judgments. As a response, fuzzy extensions are increasingly adopted to model linguistic evaluations more realistically. A notable advanced extension is Z-fuzzy AHP, which explicitly accounts for both the fuzzy

assessment and its reliability, aiming to improve the representation of human judgment under uncertainty in PV plant location selection [18].

Beyond AHP-centered workflows, researchers increasingly diversify both weighting and ranking stages. For example, in a Saudi Arabia suitability study, fuzzy AHP is used for weighting and PROMETHEE II for evaluating suitability, demonstrating the value of combining fuzzy weighting with an outranking method in GIS-supported PV siting [14]. Separately, a criteria-focused contribution proposes fuzzy LAAW to derive the importance of PV site-selection criteria through expert elicitation, highlighting the salience of solar radiation and economic performance indicators alongside policy and environmental considerations [5]. Recent studies further emphasize robustness, sensitivity analysis, and cross-method validation. A hybrid fuzzy pipeline that integrates fuzzy LMAW (weighting) and fuzzy ARTASI (ranking) systematically examines stability across aggregation parameters and validates rankings through comparisons with multiple fuzzy MCDM methods (e.g., F-TOPSIS, F-WASPAS), reinforcing methodological reliability [21].

Another important direction expands PV siting from project-level mapping to strategic, multi-stage decision-support and road mapping. In Portugal, a two-stage framework first prioritizes municipalities using GIS and TOPSIS and then performs site-level assessment by integrating GIS with additional weighting/ranking approaches (e.g., ENTROPY and AHP alongside TOPSIS), explicitly linking PV siting with national-scale planning objectives [22]. In Türkiye, a scenario-based province selection model integrates fuzzy AHP and GIS with additional decision axioms and employs sensitivity analysis to support higher-level prioritization across alternative provinces [13]. Finally, the scope of PV-related spatial decision support is increasingly broadened to include risk and resilience considerations under climate change. A risk-oriented GIS framework for South Korea evaluates existing PV stations under landslide hazard conditions (via susceptibility modeling and risk classification) and proposes proactive mitigation measures, complementing traditional "suitability mapping" by focusing on the long-term security of operational assets [16].

Overall, the reviewed works indicate that (i) GIS–MCDM hybrids remain foundational for PV siting decisions [14,17,19]; (ii) uncertainty-aware extensions (fuzzy and Z-fuzzy) and hybrid evaluation methods improve realism and decision defensibility [13,16,18]; and (iii) contemporary studies increasingly integrate robustness checks, planning-scale prioritization, and climate-risk considerations into PV decision-support frameworks [16,22–25].

Despite the fact that the GIS-based MCDM techniques have proved their effectiveness in the site selection of solar power plants in prior studies, there are numerous significant research gaps. First, most of the available research are based on deterministic evaluation frameworks or traditional fuzzy-based approaches, which generally have limited capacity to clearly model the uncertainty, hesitation and imperfect expert knowledge in the decision-making process. Second, most studies focus on technical and economic criteria, and the inclusion of environmental, social and technological sustainability components is still somewhat restricted. Third, there is a growing interest in Türkiye in the field of renewable energy planning research, but uncertainty-aware decision-support frameworks based on interval-valued neutrosophic techniques are still absent, particularly for strategically important locations like the Mediterranean corridor.

The suggested approach contributes to the literature in numerous ways compared to the existing studies. The IVN-TOPSIS technique, in contrast to the traditional GIS–AHP, fuzzy AHP or classical TOPSIS applications, represents truth, indeterminacy and falsity memberships simultaneously, giving a more complete depiction of the uncertainty of experts. Moreover, the combination of IVN-TOPSIS with GIS-based spatial suitability analysis allows for both regional priority and spatially explicit decision assistance. Finally, the suggested framework gives practical insights for renewable energy planning in Türkiye

with the determination of the most appropriate provinces for solar power plant construction according to environmental, economic, social and technological sustainability criteria under uncertain choice conditions.

3. Materials and Methods

This study was developed to evaluate the suitability of Antalya, Mersin, and Adana provinces in Turkey's Mediterranean Region for solar power plant investments. To manage uncertainties, the Interval-Valued Neutrosophic TOPSIS (IVN-TOPSIS) method was used, and the results were supported by Geographic Information Systems (GIS) based spatial suitability analyses. The research process consists of six main stages: (i) identification of the study area, (ii) Neutrosophic Sets and Preliminaries, (iii) determination of criteria, (iv) GIS-based weight analysis and (vi) creation of GIS-based suitability maps.

3.1. Study Area

Within the scope of this research, the provinces of Antalya, Mersin, and Adana, located in Türkiye's Mediterranean region, were designated as the study area. The region represents one of the most favorable solar belts of the country, with high irradiation levels, extensive daylight duration, and suitable climatic characteristics. Geographically, the study area lies between approximately 36° and 38° north latitudes and 30° and 35° east longitudes, extending along the southern coastal corridor of Türkiye. These three provinces collectively offer diverse socio-economic structures, flat topographic formations, and access to major energy transmission networks, making them notable alternatives for utility-scale solar energy installations.

Antalya, located in the western part of the region, has a surface area of approximately 20,177 km^2 and is positioned at around 36.88° N and 30.70° E. The province is characterized by long hot summers and mild winters, supporting high solar exposure throughout the year. Antalya is one of Türkiye's major tourism centers, resulting in seasonal fluctuations in electricity consumption. In addition, the presence of several high-capacity substations and electricity transmission lines increases the feasibility of integrating large solar-based electricity generation units into the existing grid infrastructure. Its wide flat hinterlands, particularly in inland districts, also provide suitable land availability for PV-based power generation facilities.

Mersin, located centrally at approximately 36.81° N and 34.64° E, covers an area of nearly 15,620 km^2. It is an important coastal settlement and home to the Port of Mersin, one of Türkiye's largest international trade ports. Due to the combination of port activities, agricultural-industrial production, and logistics networks, Mersin has a rapidly growing energy demand. The province also has vast plains suitable for PV farms, especially along its central districts. The existence of industrial clusters and processing facilities creates favorable conditions for solar-supported manufacturing operations and grid-connected renewable electricity utilization.

Adana, positioned further east at approximately 37.00° N and 35.32° E, has an area of nearly 13,844 km^2 and is among Türkiye's leading industrial regions. The province hosts several organized industrial zones and is characterized by high electricity consumption intensity. Located within the Çukurova basin, Adana benefits from extensive fertile plains and flat terrain, which historically supported agricultural productivity. However, rising industrialization and urban expansion create a strategic need for sustainable energy investments. From an infrastructural standpoint, Adana has multiple transmission corridors and substation infrastructures facilitating electricity injection from large photovoltaic facilities.

Turkey's Mediterranean region is one of the places with the highest solar energy potential in the country. The average daily solar radiation values in the region are between

4.5 and 5.5 kWh/m^2. High sunshine duration, low cloud cover, and suitable meteorological conditions improve the efficiency of energy generation of solar systems. Antalya and Mersin have high sunshine durations, especially in the coastal regions, while Adana is greatly advantageous for large-scale solar power plants with its wide flat terrain. The first map depicts the basic map of Türkiye and the second map indicates the locations of three provinces in the Mediterranean region (Figure 1).

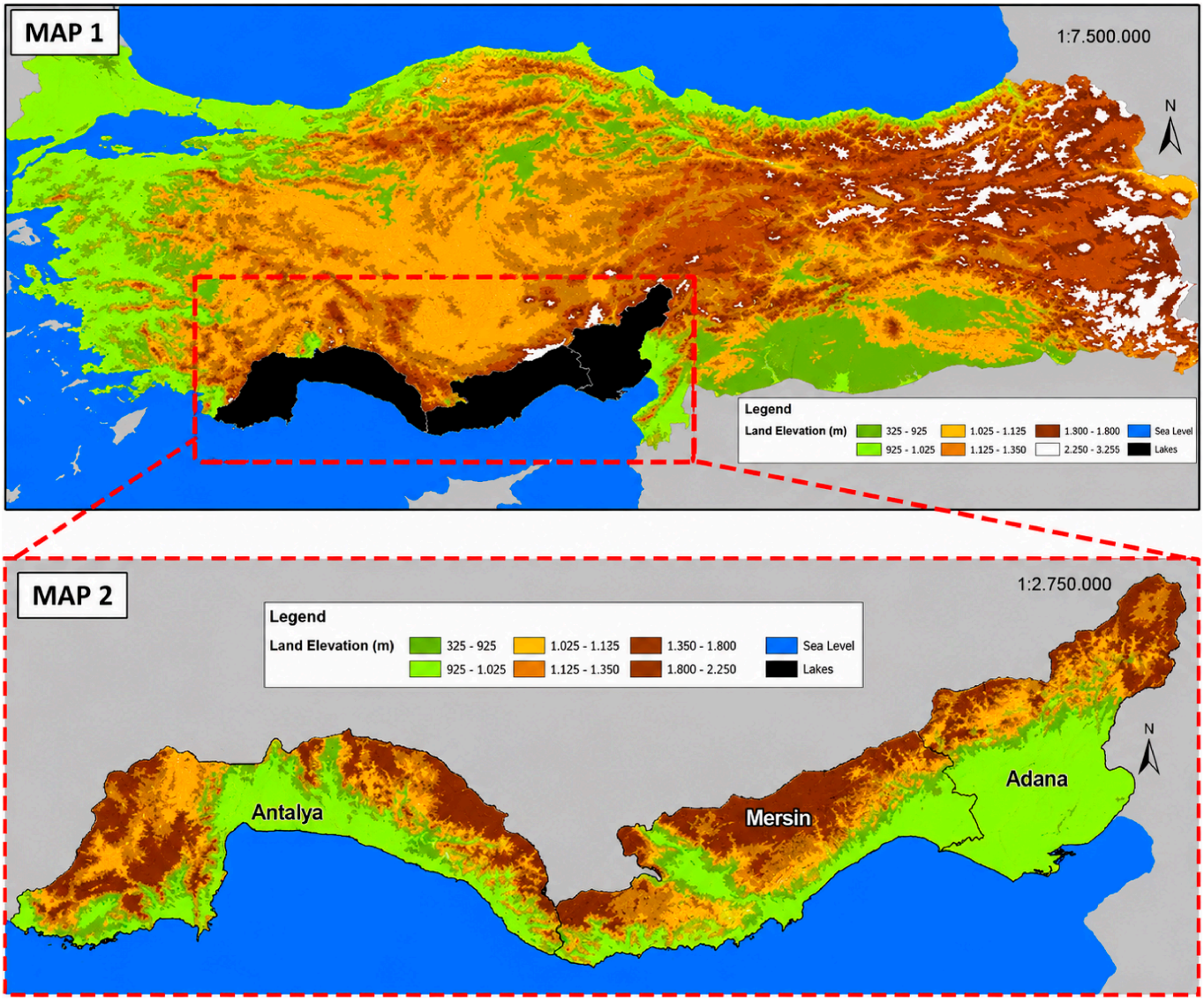


Figure 1. Geographic location of the study area.

In general, the Mediterranean Region exhibits advantageous solar energy conditions, including long sunshine hours, moderate annual temperatures and low cloud coverage. The selected provinces collectively represent strategic development zones within national renewable energy planning due to their growing population, industrial activities and increasing electricity demand. Considering these environmental, geographical and economic characteristics, an analytical evaluation of Antalya, Mersin and Adana using a structured multi-criteria approach allows a clearer understanding of regional suitability.

3.2. Neutrosophic Sets and Preliminaries

Since the introduction of fuzzy set theory by Zadeh [26], various methods have been developed to address uncertainty. Building on this, Atanassov [27], introduced

intuitionistic fuzzy sets by incorporating degrees of membership and non-membership. Later, Smarandache [28], extended this concept with neutrosophic sets, adding a third component: indeterminacy (I), alongside truth (T) and falsity (F). Unlike traditional fuzzy sets, the sum of these values in neutrosophic sets does not have to equal 1, offering greater flexibility in managing ambiguity. The fundamental operations of IVNS, such as aggregation, comparison, and ranking, rely on specific mathematical definitions. For instance, the IVN Weighted Arithmetic Average (INWAA) operator combines individual expert opinions based on assigned weights. Ranking and decision-making within IVNS are achieved through specialized formulas that calculate aggregate scores by integrating the lower and upper bounds of T, I, and F values. These operations make IVNS a powerful tool for handling ambiguity in multi-criteria problems [29]. The fundamental definitions and operations of neutrosophic sets are outlined as follows [30].

Definition 1. *Consider* $x_j = \langle [T_j^L, T_j^U], [I_j^L, I_j^U], [F_j^L, F_j^U] \rangle$ *where j refers to the decision makers deciders (j = 1.2. . . . .n). The Interval-Valued Neutrosophic Weighted Arithmetic Average (INWAA) operator aggregates these values according to Equation (1). This operator computes the weighted average of IVN numbers based on the assigned weights of the decision makers:*

$$(x1,\ x2.\ \ldots\ .\ xn)\ =\ \sum_{k=1}^{n} y_k x_j \tag{1}$$

where y_k *represents the importance (weight) of each decision maker, and the aggregated neutrosophic set is calculated as:*

$$\left\langle \left[1-\prod_{k=1}^{n}\left(1-T_j^L\right)^{y_k}, 1-\prod_{k=1}^{n}\left(1-T_j^U\right)^{y_k}\right], \left[\prod_{k=1}^{n}\left(I_j^L\right)^{y_k}, \prod_{k=1}^{n}\left(I_j^U\right)^{y_k}\right], \left[\prod_{k=1}^{n}\left(F_j^L\right)^{y_k}, \prod_{k=1}^{n}\left(F_j^U\right)^{y_k}\right] \right\rangle$$

Definition 2. *The ranking of alternatives within the IVN framework is carried out using Equation (2). This ranking function calculates a comprehensive value by considering both lower and upper bounds of the membership degrees:*

$$K(x) = \frac{\left(T_x^L * \left(2 - I_x^L - I_x^U\right)\right) + \left(T_x^U * \left(2 - I_x^L - I_x^U\right)\right) + \left(1 - F_x^L\right) * \left(2 - I_x^L - I_x^U\right) + \left(1 - F_x^U\right) * \left(2 - I_x^L - I_x^U\right)}{8} \tag{2}$$

where $x = \left\langle \left[T_x^L, T_x^U\right], \left[I_x^L, I_x^U\right], \left[F_x^L, F_x^U\right] \right\rangle$.

Definition 3. *To identify the maximum value among IVN numbers, Equation (3) is applied. If the ranking value* $K(x_j)$ *is greater than zero, the element is considered; otherwise, it is set to zero:*

$$Z(x_j) = \begin{cases} x_j,\ if\ K(x_j) > 0 \\ 0,\ if\ K(x_j)\ \leq 0 \end{cases} \tag{3}$$

where $x = \left\langle \left[T_j^L, T_j^U\right], \left[I_j^L, I_j^U\right], \left[F_j^L, F_j^U\right] \right\rangle$ *and* $0 = \langle [0,0], [1,1], [1,1] \rangle$.

Definition 4. *Let X denote the universal set. An interval-valued neutrosophic (IVN) set N on X is described through three membership functions: truth* $T_N(x)$*, indeterminacy* $I_N(x)$*, and falsity* $F_N(x)$*, each defined for* $x \in X$*:*

$$T_N = \left[T_{N(x)}^{L}, T_{N(x)}^{U} \subseteq [0,1]\right], \mathrm{I_N(x)} = \left[\mathrm{I_{N(x)}^{L}, I_{N(x)}^{U}} \subseteq [0.1]\right] \text{and} F_N(x) = \left[F_{N(x)}^{L}, F_{N(x)}^{U} \subseteq [0,1]\right]$$

IVN set $0 \leq T_{N(x)}^{L} + I_{N(X)}^{L} + F_{N(x)}^{L} \leq 3$.
The IVN set is expressed as:

$$N = \left\{ \left\langle x. \left[T^{L}_{N(x)}, T^{U}_{N(x)} \right], \left[I^{L}_{N(x)}, I^{U}_{N(x)} \right], \left[F^{L}_{N(x)}, F^{U}_{N(x)} \right] \right\rangle \middle| x \in X \right\} \quad (4)$$

Alternatively, IVN sets can be represented more compactly as $\left[T^{L}_{N}, T^{U}_{N}\right], \left[I^{L}_{N}, I^{U}_{N}\right], \left[F^{L}_{N}, F^{U}_{N}\right]$.

Considering two neutrosophic numbers $a = \left[T^{L}_{a}, T^{U}_{a}\right], \left[I^{L}_{a}, I^{U}_{a}\right], \left[F^{L}_{a}, F^{U}_{a}\right]$.

$b = \left[T^{L}_{b}, T^{U}_{b}\right], \left[I^{L}_{b}, I^{U}_{b}\right], \left[F^{L}_{b}, F^{U}_{b}\right]$ *basic operations follow specific neutrosophic arithmetic rules, such as:*

- *Complement:*

$$a^{c} = \left\langle \left[T^{L}_{a}, T^{U}_{a}\right], \left[1 - I^{L}_{a}, 1 - I^{U}_{a}\right], \left[F^{L}_{a}, F^{U}_{a}\right] \right\rangle$$

- *Inclusion:*

$a \subseteq b$ *if and only if* $a \subseteq b$ *and* $T^{L}_{a} \leq T^{L}_{b}, T^{U}_{a} \leq T^{U}_{b}; I^{L}_{a} \geq I^{L}_{b}, I^{U}_{a} \geq I^{U}_{b}; F^{L}_{a} \geq F^{L}_{b}, F^{U}_{a} \geq F^{U}_{b}$ *provided that* $a = b$*; if and only if* $a \subseteq b$ *and* $b \subseteq a$.

- *Addition*

$$a \bigoplus b = \left\langle \left[T^{L}_{a} + T^{L}_{b} - T^{L}_{a}T^{L}_{b}, T^{U}_{a} + T^{U}_{b} - T^{U}_{a}T^{U}_{b}\right], \left[I^{L}_{a}I^{L}_{b}, I^{U}_{a}I^{U}_{b}\right], \left[F^{L}_{a}F^{L}_{b}, F^{U}_{a}F^{U}_{b}\right] \right\rangle$$

- *Multiplication:*

$$a \otimes b = \left\langle \left[T^{L}_{a}T^{L}_{b}, T^{U}_{a}T^{U}_{b}\right], \left[I^{L}_{a} + I^{L}_{b} - I^{L}_{a}I^{L}_{b}, I^{U}_{a} + I^{U}_{b} - I^{U}_{a}I^{U}_{b}\right], \left[F^{L}_{a} + F^{L}_{b} - F^{L}_{a}F^{L}_{b}, F^{U}_{a} + F^{U}_{b} - F^{U}_{a}F^{U}_{b}\right] \right\rangle$$

Definition 5. *The subtraction of two neutrosophic numbers is calculated using Equation (5):*

$$x \ominus y = \left\langle \left[T^{L}_{x} - T^{U}_{y}, T^{U}_{x} - T^{L}_{y}\right], \left[Max\left(I^{L}_{x}.I^{L}_{y}\right), Max\left(I^{U}_{x}.I^{U}_{y}\right)\right], \left[F^{L}_{x}.F^{U}_{y}, F^{U}_{x} - F^{L}_{y}\right] \right\rangle \quad (5)$$

where $x = \left\langle \left[T^{L}_{x}, T^{U}_{x}\right], \left[I^{L}_{x}, I^{U}_{x}\right], \left[F^{L}_{x}, F^{U}_{x}\right] \right\rangle ve\ y = \left\langle \left[T^{L}_{y}, T^{U}_{y}\right], \left[I^{L}_{y}, I^{U}_{y}\right], \left[F^{L}_{y}, F^{U}_{y}\right] \right\rangle$.

Definition 6. *The deneutrosophication of an IVN number*

$A = \langle [T^{L}.T^{U}].[I^{L}.I^{U}].[F^{L}.F^{U}] \rangle$ *is determined by Equation (6):*

$$K(A) = \frac{T^{L} + T^{U} + 2 - F^{L} - F^{U} + T^{L} * T^{U} + \sqrt{(1 - F^{L}) * (1 - F^{U})}}{6} * \left[\left(1 - \frac{I^{L} + I^{U}}{2} \right) - \left(\sqrt{I^{L} * I^{U}} \right] \right. \quad (6)$$

3.3. Interval-Valued Neutrosophic (IVN) Fuzzy TOPSIS Method

The TOPSIS method, introduced by Hwang and Yoon [30], identifies the best alternative as the one closest to the positive ideal solution (PIS) and farthest from the negative ideal solution (NIS) [31]. To better handle uncertainty, the classical TOPSIS approach can be integrated with fuzzy methods. The Interval-Valued Neutrosophic (IVN) Fuzzy TOPSIS method extends this by using IVN numbers to represent truth (T), indeterminacy (I), and falsity (F), offering a more flexible framework for uncertain decision-making problems.

The IVN Fuzzy TOPSIS method is particularly effective in situations involving high ambiguity and incomplete information. The general procedure involves creating a decision

matrix, normalizing it with neutrosophic weights, determining the ideal solutions, calculating distances, ranking alternatives, and conducting sensitivity analysis. The steps for implementing the IVN Fuzzy TOPSIS method are illustrated in Figure 2.

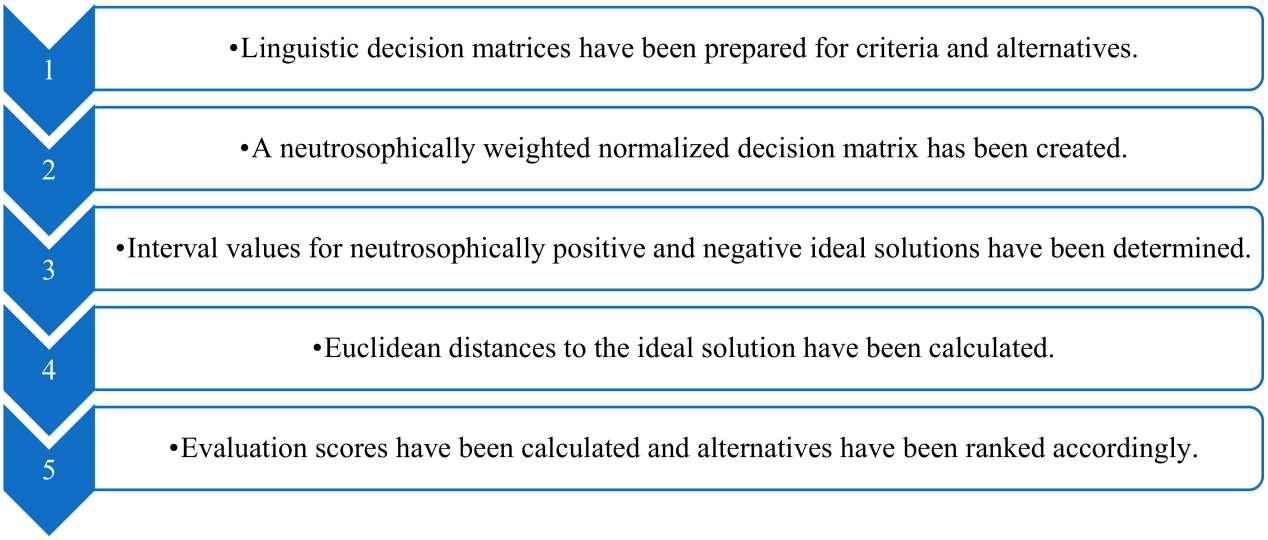


Figure 2. Stages of the IVN Fuzzy TOPSIS method.

In addition, steps of the IVN Fuzzy TOPSIS Method are as follows [32];

Step 1: Construct the IVN decision matrix ($\tilde{\ddot{X}}$) where each: $\tilde{x}_{ij}$ represents the IVN values for the j-th criterion of the ith alternative:

$$\tilde{x}_{ij} = \left\langle \left[T_{ij}^{L}.T_{ij}^{U}\right].\left[I_{ij}^{L}.I_{ij}^{U}\right].\left[F_{ij}^{L}.F_{ij}^{U}\right] \right\rangle$$

The decision matrices (Dj) are created by j experts, based on benefit and cost criteria. Linguistic terms are used to assign IVN values, as shown in Table 1.

Table 1. IVN Linguistic terms and scales.

Linguistic Terms		⟨*T*, *I*, *F*⟩
CL	Certainly Low	⟨[0.15, 0.25], [0.15, 0.25], [0.85, 0.95]⟩
VL	Very Low	⟨[0.25, 0.35], [0.35, 0.45], [0.75, 0.85]⟩
L	Low	⟨[0.35, 0.45], [0.45, 0.55], [0.65, 0.75]⟩
BA	Below Average	⟨[0.45, 0.55], [0.55, 0.65], [0.55, 0.65]⟩
A	Average	⟨[0.55, 0.60], [0.65, 0.75], [0.45, 0.55]⟩
AA	Above Average	⟨[0.55, 0.65], [0.55, 0.65], [0.45, 0.55]⟩
H	High	⟨[0.65, 0.75], [0.45, 0.55], [0.35, 0.45]⟩
VH	Very High	⟨[0.75, 0.85], [0.25, 0.35], [0.25, 0.35]⟩
CH	Certainly High	⟨[0.85, 0.95], [0.15, 0.25], [0.15, 0.25]⟩

Step 2: Convert linguistic values into IVN numbers and apply the neutrosophic weights $\tilde{w}_j$ to create the weighted normalized decision matrix $\tilde{\ddot{R}}$.

Step 3: Determine the positive ideal solution $\tilde{\ddot{S}}+$ and the negative ideal solution $\tilde{\ddot{S}}-$ using:

$$\tilde{\ddot{S}}+ = \left[max_j\left(T_j^L\right), max_j\left(T_j^U\right)\right], \left[min_j\left(I_j^L\right), min_j\left(I_j^U\right)\right], \left[min_j\left(F_j^L\right), min_j\left(F_j^U\right)\right] \quad (7)$$

$$\tilde{\ddot{S}}- = \left[min_j\left(T_j^L\right), min_j\left(T_j^U\right)\right], \left[max_j\left(I_j^L\right), max_j\left(I_j^U\right)\right], \left[max_j\left(F_j^L\right), max_j\left(F_j^U\right)\right] \quad (8)$$

Step 4: Calculate the Euclidean distances between each alternative and the ideal solutions as follows:

$$d\left(\tilde{\tilde{N}}_1, \tilde{\tilde{N}}_2\right) = \sqrt{\frac{\left(T^L_{N1} - T^L_{N2}\right)^2 + \left(T^U_{N1} - T^U_{N2}\right)^2 + \left(I^L_{N1} - I^L_{N2}\right)^2 + \left(I^U_{N1} - I^U_{N2}\right)^2 + \left(F^L_{N1} - F^L_{N2}\right)^2 + \left(F^U_{N1} - F^U_{N2}\right)^2}{6}} \quad (9)$$

Step 5: Compute the relative closeness εi of each alternative:

$$\varepsilon i = \frac{D_i^{NIS}}{\left(D_i^{NIS} + D_i^{PIS}\right)} \quad (10)$$

Step 6: Rank the alternatives based on their εi values in descending order.

3.4. Case Study, Criteria and Alternatives

In our study, an application was carried out in the Mediterranean region of Türkiye for the purpose of selecting a location for a solar power plant using the Interval-Valued Neutrosophic Fuzzy TOPSIS Method. After conducting a literature review, the 'Environmental, Economic, Social & Cultural, and Technological Criteria' were determined as the main criteria, as shown in Figure 3. Additionally, 24 sub-criteria were determined under these four main criteria by gathering opinions from three different experts. In addition, Table 2 shows in which similar studies the criteria used in this study have been used previously. Some of these criteria are being used for the first time in this study.

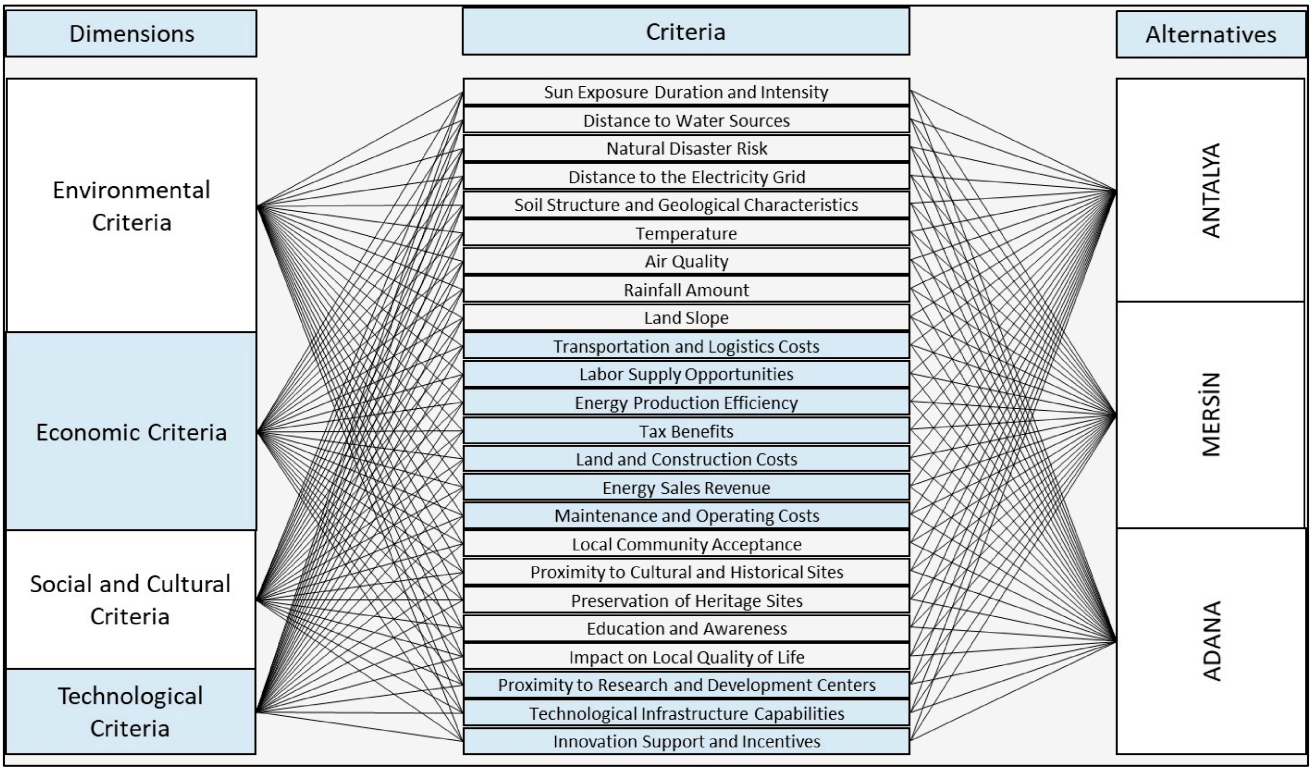


Figure 3. Dimensions, criteria, and alternatives for the site selection decision problem.

Table 2. Explanations of criteria.

ID	Criteria	Explanation of the Criteria	Covered by
C1.1	Sun Exposure Duration and Intensity	Higher solar irradiation and longer sunshine duration directly increase expected electricity generation and improve the feasibility of the solar power plant.	[24]
C1.2	Distance to Water Sources	Adequate distance to water bodies helps reduce potential ecological impacts while also considering water needs for panel cleaning and site operations where applicable.	[33]
C1.3	Natural Disaster Risk	Locating the plant in areas with lower disaster risk (e.g., flood, wildfire, extreme storms) improves operational continuity and reduces potential damages and insurance costs.	[16]
C1.4	Distance to the Electricity Grid	Proximity to transmission/distribution lines lowers connection costs, reduces line losses, and accelerates grid-integration processes.	[14]
C1.5	Soil Structure and Geological Characteristics	Suitable soil and geology increase construction safety and reduce foundation/earthwork costs; they also mitigate long-term settlement and stability issues.	[20]
C1.6	Temperature	Extreme temperatures may decrease PV efficiency and accelerate equipment degradation; moderate thermal conditions support stable energy output and longer component life.	[24]
C1.7	Air Quality	High dust/particulate levels can reduce panel performance and increase cleaning frequency; better air quality supports higher effective generation.	[34]
C1.8	Rainfall Amount	Rainfall affects cleaning cycles and soil erosion/runoff risks; balanced rainfall can support natural cleaning but excessive rainfall may increase maintenance and site risks.	[35]
C1.9	Land Slope	Lower slope areas reduce grading and construction costs, ease installation, and decrease erosion risk; steep slopes can increase both CAPEX and OPEX.	[27]
C2.1	Transportation and Logistics Cost	Easier access and lower logistics costs reduce construction, maintenance, and replacement expenses across the project lifecycle.	[18]
C2.2	Labor Supply Opportunities	Availability of skilled and unskilled labor supports timely construction and efficient operations, reducing labor-related delays and costs.	This study
C2.3	Energy Production Efficiency	Sites that enable higher conversion efficiency (due to irradiation, temperature, shading, and terrain suitability) improve profitability and project viability.	[23]
C2.4	Tax Benefits	Regional incentives and tax advantages improve project economics by lowering effective costs and shortening payback periods.	[36]
C2.5	Land and Construction Costs	Lower land acquisition and construction costs reduce initial investment and improve the overall financial feasibility of the plant.	[1]
C2.6	Energy Sales Revenue	Higher expected revenue (market access, tariff structure, demand conditions) strengthens economic sustainability and investment attractiveness.	This study

Table 2. *Cont.*

ID	Criteria	Explanation of the Criteria	Covered by
C2.7	Maintenance and Operating Costs	Lower O&M costs improve long-term performance; site conditions (dust, access, weather) strongly influence maintenance frequency and expenses.	[21]
C3.1	Local Community Acceptance	Social acceptance reduces the risk of delays, objections, and reputational impacts, facilitating smoother permitting and long-term operations.	[24]
C3.2	Proximity to Cultural and Historical Sites	Keeping appropriate distance from cultural assets helps avoid visual/noise impacts, legal restrictions, and potential conflicts with conservation policies.	[22]
C3.3	Preservation of Heritage Sites	Protecting heritage areas supports sustainability principles and regulatory compliance, minimizing the risk of project suspension or redesign.	[18]
C3.4	Education and Awareness	Higher awareness can increase acceptance and cooperation (e.g., local workforce, community engagement), reducing social resistance during implementation.	This study
C3.5	Impact on Local Quality of Life	Minimizing negative effects (land use conflicts, aesthetics, traffic during construction) supports social sustainability and reduces stakeholder opposition.	This study
C4.1	Proximity to Research and Development Centers	Nearness to R&D centers supports innovation, technical support, monitoring solutions, and collaboration for performance improvement.	This study
C4.2	Technological Infrastructure Capabilities	Adequate infrastructure (telecom, SCADA readiness, equipment availability) improves monitoring, maintenance response, and operational reliability.	This study
C4.3	Innovation Support and Incentives	Regional innovation ecosystems and incentives encourage adoption of advanced technologies and can enhance competitiveness and efficiency.	This study

The set of criteria defined in this study has been systematically classified under environmental, economic, social, and technological dimensions in order to address the solar power plant site selection problem within a multidimensional decision-making framework. Environmental criteria include parameters such as solar radiation and sunshine duration, temperature, precipitation, air quality, terrain slope, and soil and geological characteristics, which have a direct determining effect on the energy conversion efficiency, structural safety, and long-term operational continuity of photovoltaic systems. Furthermore, natural disaster risk has been considered a critical environmental risk indicator to assess the resilience of facilities against climate and geophysical uncertainties. Criteria evaluated under the economic dimension include factors such as land acquisition and construction costs, maintenance and operating expenses, transportation and logistics costs, tax incentives, and energy sales revenues. These are directly related to the net present value of the investment, the payback period, and overall financial sustainability. Social criteria aim to ensure regulatory compliance and social license for the project within the framework of local community acceptance, impacts on quality of life, and sensitivity to cultural and historical areas. Finally, technological criteria such as proximity to R&D centers, technological infrastructure adequacy, and innovation support mechanisms have been included in the model as complementary factors that enhance the plant's traceability, operational flexibility, and long-term competitive advantage.

The opinions of three specialists who participate in international decision-making processes were collected through personal interviews. In these meetings, the experts offered linguistic evaluations of the criteria and the alternatives with respect to suitable places for solar power plant implementation in the Mediterranean region. In order to reflect the variations in professional background and foreign exposure, the experts were given unequal relevance weights. Expert 1 has a PhD in Energy Systems Engineering and more than 12 years' expertise in renewable energy planning and energy infrastructure projects. Expert 2 has a PhD in Sustainable Energy Planning and roughly 11 years of professional and academic expertise in renewable energy policy and sustainability evaluation. Expert 3 is a senior professor with over 18 years of experience in renewable energy systems, multicriteria decision-making approaches, and international energy initiatives. Expert 3 was assigned a somewhat higher weight (0.40) on account of her wider professional experience and extensive engagement in international research and planning activities. Experts 1 and 2 were assigned weights of 0.30 each. In the first step of the research, experts individually evaluated the criteria and alternatives, without any effect on each other. Subsequently, a collaborative meeting was organized where the experts presented, compared and debated their separate evaluations. This participatory procedure allowed perspectives to be shared, helped to reconcile differences and created coherence in the judgments. The assessments were iteratively refined, to improve the reliability of the linguistic scale and its application in the proposed model, and thus to provide a more robust and well-grounded representation of uncertainty.

3.5. GIS-Based Overlay Weighted Sum Analysis for Intra-Provincial Site Selection

In this study, map data from alternative provinces were used after the criteria were determined and the IVN–TOPSIS method was applied. At this stage, the method we present aims to determine the appropriate area by performing overlay analysis in two stages with the help of GIS. During this process, data for all criteria of three provinces were obtained. In cases where the data was insufficient, expert opinions were consulted to compile the data. The collected data were used to create raster maps for each province, and after completing the same processes for all criteria, these maps were overlaid to create a density map. To spatially interpret the IVN–TOPSIS results, a GIS-based suitability analysis was performed. Subsequently, the Weighted Overlay method was applied. The suitability index was calculated as follows:

$$\text{Suitability Index} = \Sigma\ (\text{Criterion Weight} \times \text{Raster Score})$$

The results obtained were divided into five classes:

* Very Low Suitability;
* Low Suitability;
* Moderate Suitability;
* High Suitability;
* Very High Suitability.

The final maps, which were developed based on criteria established in the maps created for the three alternative cities, were combined using the IVN-TOPSIS method to make the most precise site selection decisions. Finally, Figure 4 shows the steps of the method.

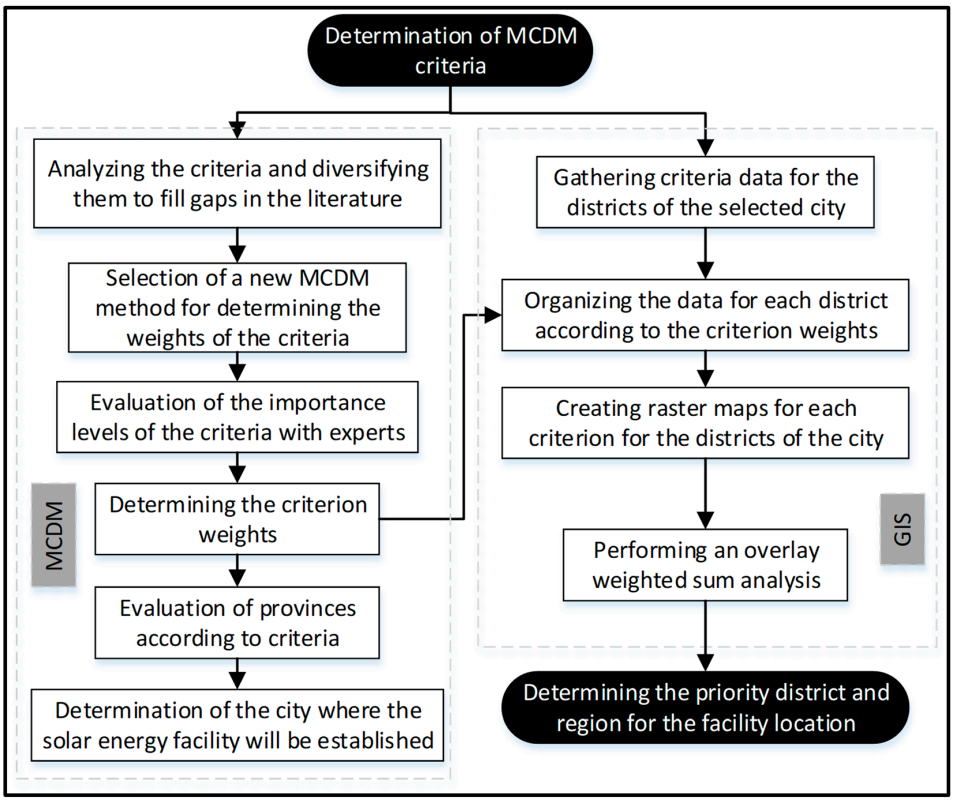


Figure 4. The application steps of MCDM and GIS methods.

4. Analysis and Results

The linguistic weighted evaluations of three decision-makers (DM1, DM2, and DM3) for each of the 24 evaluation criteria (C1–C24) used in the study are given in Table 3. The decision-makers indicated the relative relevance of each criterion using a preset nine-level language scale (CL: Certainly Low, VL: Very Low, L: Low, BA: Below Average, A: Average, AA: Above Average, H: High, VH: Very High, CH: Certainly High). This approach permits determination of the criterion weights in the form of qualitative expressions based on the perception of experts and not on the numerical values. The columns are the criteria, and the rows are the individual assessment of the criteria made by each decision-maker. For example, criteria C14 has been rated as "Very High" (VH) by DM1, which means that this criterion is of extremely high importance to the decision problem. Also, the evaluations of DM2 and DM3 for the same criterion reflect the perceptual discrepancies and uncertainty among experts.

Table 3. Linguistic values of criterion weights.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
DM1	A	L	VL	CL	CL	CL	VL	CL	VL	A	L	A	AA	VH	H	VH	CH	A	BA	H	A	BA	A	H
DM2	A	L	VL	CL	CL	VL	L	CL	VL	A	L	AA	AA	VH	VH	H	CH	AA	BA	H	AA	A	AA	VH
DM3	BA	L	VL	VL	CL	VL	L	VL	L	A	BA	H	H	CH	H	VH	CH	A	A	H	H	BA	AA	VH

Table 4 presents the decision matrix reflecting the relative significance of the alternatives with respect to the criteria, as evaluated by the first, second, and third experts. For example, the second expert assigned the linguistic assessment "AA" to the second alternative under the second criterion, which corresponds to a high level of importance. The linguistic entries reported in Table 4 are derived directly from the experts' judgments and constitute the primary input data of the analysis. In total, nine distinct linguistic terms are employed in the evaluation process. Each criterion's level of importance for a given

alternative is determined by selecting one of these nine predefined linguistic scales based on expert assessments.

Table 4. Decision matrices for DM-1, DM-2 and DM-3.

	A1			**A2**			**A3**		
	DM-1	**DM-2**	**DM-3**	**DM-1**	**DM-2**	**DM-3**	**DM-1**	**DM-2**	**DM-3**
C1	VH	AA	L	H	BA	L	VH	BA	BA
C2	VH	BA	VL	CH	AA	L	VH	BA	L
C3	L	H	H	L	H	VH	VL	AA	H
C4	CH	AA	L	VH	A	L	CH	H	VL
C5	BA	CH	VH	A	VH	VH	BA	VH	H
C6	VH	A	BA	VH	AA	AA	VH	A	A
C7	VH	A	BA	VH	AA	A	H	AA	BA
C8	A	A	A	A	AA	A	AA	A	A
C9	VL	VH	AA	L	VH	H	VL	VH	A
C10	H	A	BA	H	AA	BA	H	BA	L
C11	BA	VH	AA	BA	VH	A	A	VH	AA
C12	AA	VH	BA	A	VH	BA	A	VH	A
C13	AA	BA	BA	AA	A	BA	A	BA	BA
C14	H	A	BA	VH	A	BA	H	AA	A
C15	H	BA	BA	H	BA	A	H	A	BA
C16	A	A	A	BA	BA	A	A	BA	BA
C17	L	BA	AA	VL	BA	AA	L	AA	AA
C18	L	L	H	VL	L	H	VK	L	AA
C19	AA	AA	AA	A	AA	AA	AA	AA	A
C20	H	AA	AA	VH	AA	AA	H	A	A
C21	VH	A	AA	VH	AA	A	VH	AA	A
C22	VH	A	AA	VH	A	AA	H	A	A
C23	H	AA	BA	VH	AA	A	H	A	BA
C24	VH	A	AA	H	A	AA	VH	AA	AA

Aggregated decision matrices were produced for each decision maker by aggregating their linguistic evaluations for all criteria and options. Table 5 presents the integrated interval-valued neutrosophic (IVN) decision matrix constructed for DM-1, which includes 24 evaluation criteria. In this step, the language evaluations were converted to numerical representations by the use of the INWAA operator formally given in Definition 1. The computational steps in the INWAA formulation were performed using basic arithmetic operations according to Definitions 4 and 5. Furthermore, we performed neutrosophic multiplication and subtraction according to the algebraic laws of neutrosophic number.

Hence in this transformation all the criteria were characterized by six parameters, which made it possible to carry out the full numerical characterization of the expert opinions. The main goal of this step was to convert the qualitative information into a quantifiable format and to provide the first decision matrix that constitute the basis of the suggested technique. Thus, the aggregated decision matrix is constructed by combining the linguistic scale in Table 1 with the INWAA operator formulation, as shown in Table 5. The lower and upper bounds of all the membership functions were explicitly computed using the "if" operator, and so the uncertainty structure of the expert evaluations was maintained. For example, the estimate of boundary values for the first criterion enabled accurate mathematical representation of choice uncertainty. In conclusion, this aggregation paradigm provides a systematic and consistent approach to synthesizing expert inputs, which will ultimately improve the robustness and credibility of the subsequent decision-making process through extensive quantitative modelling.

Table 5. Aggregated decision matrix for criteria.

	<[T, I, F]>		<[T, I, F]>
C1	<[0.52, 0.58], [0.13, 0.24], [0.46, 0.52]>	**C13**	<[0.52, 0.63], [0.35, 0.46], [0.46, 0.58]>
C2	<[0.35, 0.46], [0.46, 0.58], [0.63, 0.74]>	**C14**	<[0.74, 0.85], [0.58, 0.69], [0.24, 0.35]>
C3	<[0.24, 0.35], [0.58, 0.69], [0.40, 0.85]>	**C15**	<[0.63, 0.74], [0.46, 0.58], [0.35, 0.46]>
C4	<[0.08, 0.24], [0.69, 0.80], [0.85, 1.00]>	**C16**	<[0.74, 0.85], [0.58, 0.69], [0.24, 0.35]>
C5	<[0.08, 0.24], [0.69, 0.80], [0.85, 1.00]>	**C17**	<[0.85, 1.00], [0.69, 0.80], [0.08, 0.24]>
C6	<[0.08, 0.24], [0.69, 0.80], [0.85, 1.00]>	**C18**	<[0.52, 0.58], [0.13, 0.24], [0.46, 0.52]>
C7	<[0.24, 0.35], [0.58, 0.69], [0.40, 0.85]>	**C19**	<[0.46, 0.58], [0.35, 0.46], [0.52, 0.63]>
C8	<[0.08, 0.24], [0.69, 0.80], [0.85, 1.00]>	**C20**	<[0.63, 0.74], [0.46, 0.58], [0.35, 0.46]>
C9	<[0.24, 0.35], [0.58, 0.69], [0.40, 0.85]>	**C21**	<[0.52, 0.58], [0.13, 0.24], [0.46, 0.52]>
C10	<[0.52, 0.58], [0.13, 0.24], [0.46, 0.52]>	**C22**	<[0.46, 0.58], [0.35, 0.46], [0.52, 0.63]>
C11	<[0.35, 0.46], [0.46, 0.58], [0.63, 0.74]>	**C23**	<[0.52, 0.58], [0.13, 0.24], [0.46, 0.52]>
C12	<[0.52, 0.58], [0.13, 0.24], [0.46, 0.52]>	**C24**	<[0.63, 0.74], [0.46, 0.58], [0.35, 0.46]>

Table 6 presents the interval-valued neutrosophic (IVN) decision matrices of the alternatives with respect to each criterion, constituting the initial phase of the IVN Fuzzy TOPSIS procedure. In this table, illustrative results corresponding to Criteria 1 and 24 are reported. At this stage, experts' linguistic assessments were systematically transformed into numerical representations, resulting in six quantitative values for each matrix element. Furthermore, the table explicitly reports the lower and upper bounds associated with each of the three neutrosophic parameters employed in the analysis. The construction of Tables 6 and 7 was carried out in accordance with the formulations introduced in Step 1 and the mathematical principles defined in Definitions 1, 3, 4, and 5, which collectively governed the conversion and structuring of the IVN decision matrices.

Table 6. Aggregated IVN decision matrix of alternatives by criteria.

AL	**C1**	...	**C24**
A1	<[0.56, 0.67], [0.43, 0.53], [0.50, 0.60]>	...	<[0.62, 0.72], [0.51, 0.62], [0.40, 0.50]>
A2	<[0.49, 0.59], [0.48, 0.58], [0.55, 0.65]>	...	<[0.58, 0.67], [0.56, 0.66], [0.42, 0.52]>
A3	<[0.57, 0.68], [0.48, 0.58], [0.48, 0.58]>	...	<[0.62, 0.73], [0.48, 0.58], [0.40, 0.50]>

Table 7. Aggregated weighted IVN decision matrix of alternatives by criteria.

AL	**C1**	...	**C24**
A1	<[0.28, 0.39], [0.56, 0.69], [0.74, 0.83]>	...	<[0.44, 0.59], [0.78, 0.87], [0.56, 0.69]>
A2	<[0.24, 0.34], [0.60, 0.72], [0.77, 0.85]>	...	<[0.41, 0.55], [0.80, 0.88], [0.58, 0.71]>
A3	<[0.28, 0.39], [0.59, 0.72], [0.73, 0.82]>	...	<[0.44, 0.60], [0.76, 0.86], [0.56, 0.69]>

Table 7 reports the aggregated weighted interval-valued neutrosophic (IVN) decision matrix. At this stage, the original decision matrix obtained in the initial step is combined with the corresponding criterion weights through a multiplication process, thereby generating a new weighted decision matrix in accordance with the IVN Fuzzy TOPSIS framework. This operation represents a critical phase of the methodology, as it integrates the relative importance of the criteria into the evaluation structure.

Subsequently, Table 8 summarizes the neutrosophic positive ideal solutions derived in the third step of the IVN Fuzzy TOPSIS method by applying Equation (7). For each criterion, the table provides the lower and upper bounds of the truth, indeterminacy, and falsity membership functions, denoted as TL, TU, IL, IU, FL, and FU, respectively. In parallel, the neutrosophic negative ideal solution matrix is presented in Table 9. This

matrix is constructed by employing Equation (8) within the same methodological step and represents the worst performance levels for each criterion under the IVN environment.

Table 8. IVN-positive ideal solution table.

C1	**TL**	**0.281141**	**C2**	**TL**	**0.218773**	**C3**	**TL**	**0.151594**	**C4**	**TL**	**0.093311**
	TU	0.392283		TU	0.352399		TU	0.259636		TU	0.221402
	IL	0.559948		IL	0.671874		IL	0.738488		IL	0.76546
	IU	0.691095		IU	0.787925		IU	0.838395		IU	0.864547
	FL	0.729791		FL	0.806463		FL	0.657019		FL	0.863392
	FU	0.817717		FU	0.892197		FU	0.930378		FU	1
C5	TL	0.058263	**C6**	TL	0.12154	**C7**	TL	0.198524	**C8**	TL	0.081229
	TU	0.204		TU	0.232255		TU	0.306244		TU	0.176137
	IL	0.792902		IL	0.798882		IL	0.756402		IL	0.867892
	IU	0.887297		IU	0.885453		IU	0.853928		IU	0.934092
	FL	0.897495		FL	0.761051		FL	0.741798		FL	0.856359
	FU	1		FU	1		FU	0.889228		FU	1
C9	TL	0.17709	**C10**	TL	0.284857	**C11**	TL	0.246895	**C12**	TL	0.353385
	TU	0.288737		TU	0.377084		TU	0.367087		TU	0.467681
	IL	0.719664		IL	0.549456		IL	0.694952		IL	0.654495
	IU	0.824111		IU	0.682837		IU	0.804283		IU	0.771974
	FL	0.721339		FL	0.711821		FL	0.75215		FL	0.648946
	FU	0.914681		FU	0.792537		FU	0.849552		FU	0.7571
C13	TL	0.290761	**C14**	TL	0.46786	**C15**	TL	0.371466	**C16**	TL	0.391034
	TU	0.405298		TU	0.687586		TU	0.498998		TU	0.493853
	IL	0.728407		IL	0.819067		IL	0.760664		IL	0.811
	IU	0.829076		IU	0.900891		IU	0.855291		IU	0.892562
	FL	0.704808		FL	0.525615		FL	0.629092		FL	0.601153
	FU	0.811		FU	0.669302		FU	0.746975		FU	0.723325
C17	TL	0.422888	**C18**	TL	0.332073	**C19**	TL	0.266668	**C20**	TL	0.392332
	TU	0.599173		TU	0.462493		TU	0.377		TU	0.539134
	IL	0.84423		IL	0.538941		IL	0.671324		IL	0.716756
	IU	0.919835		IU	0.672173		IU	0.783315		IU	0.823001
	FL	0.558163		FL	0.704481		FL	0.723264		FL	0.607639
	FU	0.713289		FU	0.797218		FU	0.815231		FU	0.728658
C21	TL	0.353385	**C22**	TL	0.298139	**C23**	TL	0.323829	**C24**	TL	0.442756
	TU	0.478009		TU	0.41613		TU	0.439376		TU	0.599669
	IL	0.679586		IL	0.654921		IL	0.660959		IL	0.762447
	IU	0.793868		IU	0.772069		IU	0.774196		IU	0.856897
	FL	0.648946		FL	0.699836		FL	0.674039		FL	0.56226
	FU	0.7571		FU	0.798981		FU	0.780331		FU	0.691056

Table 9. IVN-negative ideal solution table.

C1	**TL**	**0.241742**	**C2**	**TL**	**0.177978**	**C3**	**TL**	**0.126153**	**C4**	**TL**	**0.083144**
	TU	0.342907		TU	0.28753		TU	0.221075		TU	0.189231
	IL	0.599046		IL	0.693083		IL	0.771318		IL	0.815498
	IU	0.72336		IU	0.804283		IU	0.862603		IU	0.899607
	FL	0.765902		FL	0.846588		FL	0.721511		FL	0.874457
	FU	0.848459		FU	0.921926		FU	0.947395		FU	1
C5	TL	0.051013	**C6**	TL	0.115386	**C7**	TL	0.174632	**C8**	TL	0.081229
	TU	0.178599		TU	0.219193		TU	0.278986		TU	0.171644
	IL	0.823807		IL	0.831326		IL	0.762447		IL	0.877486
	IU	0.906801		IU	0.90949		IU	0.858761		IU	0.94042
	FL	0.908854		FL	0.779481		FL	0.771727		FL	0.856359
	FU	1		FU	1		FU	0.904719		FU	1
C9	TL	0.160279	**C10**	TL	0.253008	**C11**	TL	0.237615	**C12**	TL	0.335494
	TU	0.259774		TU	0.342907		TU	0.353671		TU	0.458102
	IL	0.754005		IL	0.614403		IL	0.724126		IL	0.71023
	IU	0.852336		IU	0.74071		IU	0.828929		IU	0.819825
	FL	0.764377		FL	0.754609		FL	0.76663		FL	0.676023
	FU	0.932449		FU	0.831831		FU	0.860478		FU	0.780331
C13	TL	0.273592	**C14**	TL	0.433502	**C15**	TL	0.346752	**C16**	TL	0.342783
	TU	0.383889		TU	0.635846		TU	0.485464		TU	0.465558
	IL	0.748131		IL	0.839234		IL	0.783554		IL	0.841489
	IU	0.845487		IU	0.91418		IU	0.873514		IU	0.915108
	FL	0.722055		FL	0.562205		FL	0.657701		FL	0.653422
	FU	0.824726		FU	0.70093		FU	0.771174		FU	0.767957
C17	TL	0.376488	**C18**	TL	0.244563	**C19**	TL	0.266668	**C20**	TL	0.367088
	TU	0.545572		TU	0.344387		TU	0.365862		TU	0.482927
	IL	0.851844		IL	0.56157		IL	0.702758		IL	0.783554
	IU	0.924518		IU	0.691326		IU	0.810601		IU	0.874752
	FL	0.623921		FL	0.781142		FL	0.723264		FL	0.624127
	FU	0.771889		FU	0.864419		FU	0.815231		FU	0.741922
C21	TL	0.353385	**C22**	TL	0.278957	**C23**	TL	0.284857	**C24**	TL	0.414268
	TU	0.475479		TU	0.378511		TU	0.391465		TU	0.552023
	IL	0.687538		IL	0.715651		IL	0.685581		IL	0.799273
	IU	0.800689		IU	0.821581		IU	0.795877		IU	0.884149
	FL	0.648946		FL	0.712449		FL	0.711821		FL	0.580655
	FU	0.7571		FU	0.808807		FU	0.81105		FU	0.706157

In the fourth phase of the IVN Fuzzy TOPSIS procedure, Euclidean distance measures were computed by applying Equation (9), and the resulting values are reported in Table 10. During this step, the six interval-valued linguistic parameters contained in each element of the decision matrix were systematically consolidated into a single representative linguistic

value through the use of neutrosophic aggregation operations. This transformation enabled the quantification of the separation between each alternative and the corresponding ideal solutions within a unified neutrosophic distance framework.

Table 10. Distance table of alternatives from positive ideal solution (Euclidean distances).

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.002509	0.015244	0.008141	0.005701	0.000383	0.004951	0.004519	0.002057	0.009198	0.014564	0.003505	0.006656
A2	0.015643	0.002041	0	0.011663	0.004926	0	0.00129	0	0	0.007688	0.007553	0.008809
A3	0.0075	0.011841	0.015135	0.001844	0.00775	0.006876	0.008282	0	0.012094	0.012424	0.004842	0.012243
	C13	**C14**	**C15**	**C16**	**C17**	**C18**	**C19**	**C20**	**C21**	**C22**	**C23**	**C24**
A1	0.004937	0.013501	0.007814	0.00632	0.008925	0.02511	0	0.009379	0	0	0.01227	0.003978
A2	0.004276	0.003967	0.004876	0.012735	0.018845	0.029814	0.005455	0	0.001796	0	0.000996	0.012635
A3	0.00726	0.005488	0.004203	0.014769	0.00149	0.000407	0.007182	0.017783	0.001796	0.015072	0.014203	0

Table 11 reports the computed negative Euclidean distances together with the mean values of the alternatives, obtained by adopting the same computational framework applied in the preceding table. These values were derived by employing Equation (9) within Step 4 of the IVN Fuzzy TOPSIS methodology. Subsequently, Table 12 presents the concluding phase of the IVN Fuzzy TOPSIS process, in which the alternatives are ordered according to their relative performance. The ranking is determined by calculating the revised closeness coefficients using Equation (10) in Step 5. Based on the outcomes summarized in this table, the second alternative emerges as the most preferable option, whereas the third alternative is ranked as the least favorable.

Table 11. Distance table of alternatives from negative ideal solution (Euclidean distances).

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.014354	0.004464	0.008687	0.00713	0.007666	0.003683	0.004196	0	0.005725	0.011855	0.006511	0.012319
A2	0	0.015436	0.015135	0.001005	0.003428	0.007779	0.008249	0.002057	0.012094	0.014169	0	0.006693
A3	0.013201	0.005317	0	0.011633	1.85×10^{-17}	0.003327	0.00065	0.002057	0	0.014498	0.004342	0.006841
	C13	**C14**	**C15**	**C16**	**C17**	**C18**	**C19**	**C20**	**C21**	**C22**	**C23**	**C24**
A1	0.004692	0.000839	0.004876	0.014769	0.010424	0.006077	0.007182	0.009669	0.001796	0.015072	0.005661	0.009757
A2	0.005867	0.011839	0.007814	0.005729	0.00149	0.004929	0.001726	0.017783	0	0.015072	0.013883	0
A3	0	0.010574	0.005953	0.00632	0.018845	0.030181	0	0	0	0	0	0.012635

Table 12. Revised proximities and ranking of alternatives.

Proximity Coefficients		**Ranking**	
AL1	0.511153	2	ANTALYA
AL2	0.526237	1	MERSIN
AL3	0.434523	3	ADANA

In particular, following the identification of Mersin as a priority province at the macro level using the IVN-Fuzzy TOPSIS method, the use of GIS-based Overlay Weighted Sum analysis to reveal the spatial distribution of suitability within the province provides a methodologically robust and consistent framework. The color intensities visible on the map reflect the combined effect of criterion weights and raster layers. Green tones represent low to moderate suitability, while yellow, orange, and red areas indicate high suitability levels. The analysis reveals that high suitability concentrations are particularly evident in the northern parts of Mersin, specifically in regions near the Çamlıyayla–Toroslar line. This finding can be explained by the combined effect of the environmental, economic, technological, and infrastructural criteria used in the study. Maps of the Mersin region are shown in Figure 5.

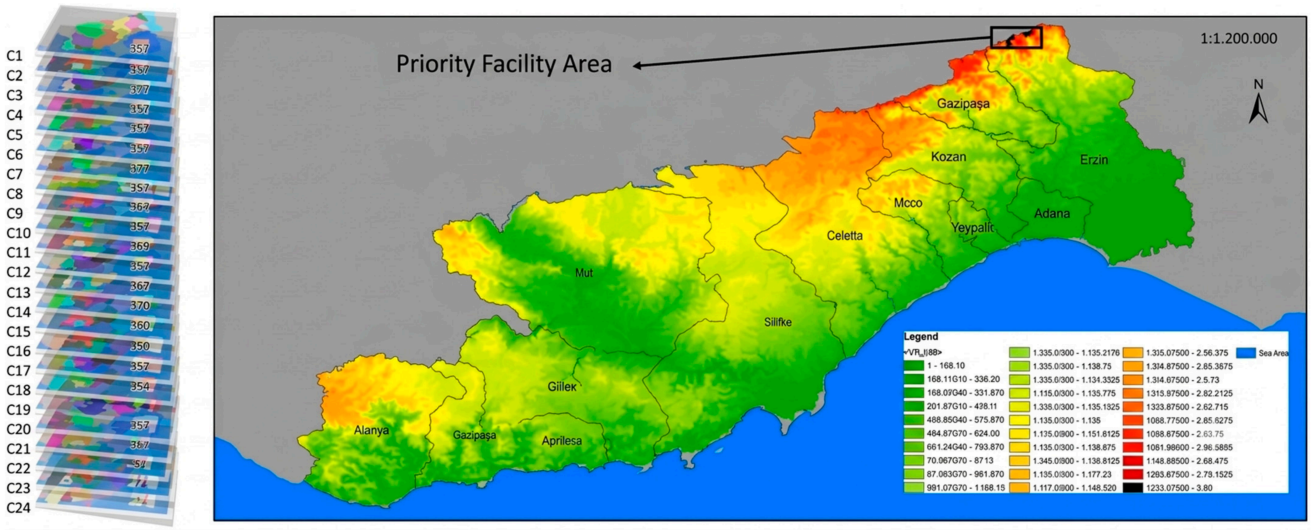


Figure 5. Maps created as a result of sensitivity analysis of the criteria.

To further examine the robustness and sustainability of the obtained ranking results, a one at-a-time sensitivity analysis was performed following the baseline prioritization presented in Table 12. Given the reliance on expert judgments in sustainability-oriented multi-criteria decision-making problems, such an analysis is essential to evaluate the stability of the results against potential subjectivity and uncertainty in criterion weighting. In this framework, each criterion weight was independently perturbed by ±20%, while all remaining criteria were held constant in order to isolate the individual impact of each sustainability dimension on the final ranking. Within the IVN fuzzy TOPSIS methodology, criterion weights directly influence the separation measures by scaling the contribution of each criterion to the distances from the positive and negative ideal solutions. Accordingly, the criterion-specific distance components were proportionally adjusted for each perturbation scenario, and the revised separation measures and closeness coefficients were recalculated. The resulting rankings of the alternative locations were then systematically compared with the baseline solution derived under the original weight structure.

The findings of the sensitivity analysis show that the ranking of the baseline, in which Mersin is the most sustainable option, followed by Antalya and Adana, does not vary much despite mild changes in the relevance of the criteria. This result demonstrates the great resilience of the suggested IVN fuzzy TOPSIS-based prioritizing and shows that the sustainability-oriented site selection outcomes are not highly susceptible to reasonable changes in the weights supplied by the experts. In terms of sustainable energy planning, this robustness increases the credibility and policy significance of the results, since it means that the suggested site selection is resilient to uncertainty in the expert assessments and weighting assumptions.

In Figure 6, the sensitivity analysis was complemented by a stakeholder multi-scenario study. Renewable energy planning is often performed by various parties such as government agencies, commercial investors, local communities, and energy infrastructure operators who may have diverse evaluation criteria. Three choice scenarios have been constructed. The first scenario is an investor-oriented view, which is concerned with economic performance and financial possibility. The second case shows a policy focus on environmental protection and sustainable resource management in the context of sustainability. The third scenario embodies a community-based position with a focus on social acceptance and quality of life issues. Scenario analysis showed that Mersin was one of the top-ranked choices for all stakeholder perspectives. This proved the stability and robustness of the suggested decision framework. However, small differences were identified

between Antalya and Adana depending on the relative relevance of the environmental and social variables. These findings emphasize the necessity of considering diverse perspectives in renewable energy planning processes and suggest that stakeholder preferences may impact site selection choices. The results suggest that, from a policy perspective, future investment strategies for solar energy should take into account not only technical and economic feasibility but also stakeholder expectations and regional development goals.

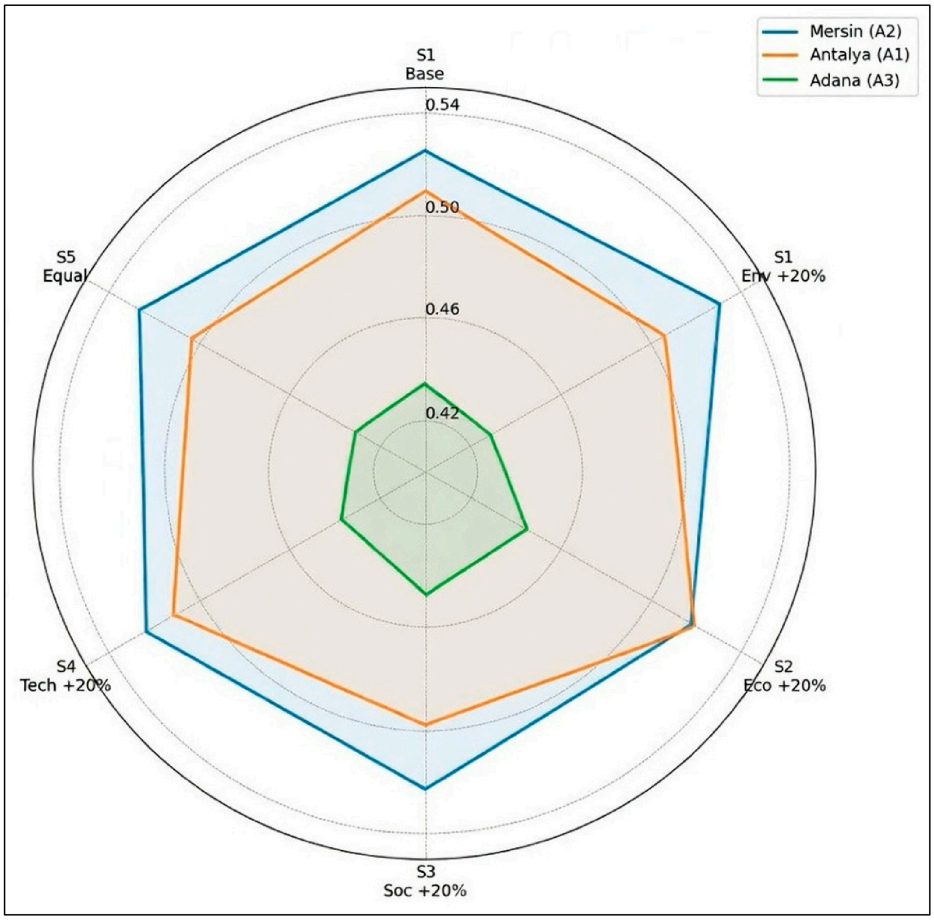


Figure 6. Sensitivity analysis IVN Fuzzy TOPSIS method.

5. Discussion

The results produced from the interval-valued neutrosophic fuzzy TOPSIS analysis give clear and consistent results on the relative suitability of the candidate provinces for the construction of solar power plants in the Mediterranean region of Türkiye. According to the updated closeness coefficients in Table 12, Mersin (A2) was the most appropriate alternative, followed by Antalya (A1), while Adana (A3) was the least appropriate alternative. This rating is the outcome of the combined effect of environmental, economic, social, and technological criteria inside uncertainty-aware decision modeling. Mersin's outperformance can be explained to a great extent by the fact that it enjoys balanced advantages across various dimensions such as favorable solar resource conditions, relatively lower logistics and infrastructure constraints, and stronger economic feasibility indicators such as expected energy sales revenue and accessibility to industrial and transmission networks.

Antalya, with strong solar irradiation and well-developed grid infrastructure, was ranked second mainly because of land availability limits and higher land-use competition and social environmental sensitivity emerging from extensive tourism activity. Similar results are reported in the earlier GIS-based MCDM research in Türkiye, where the places

of high solar potential are not always guaranteed to be suitable in general when the socio-economic and land use limitations are explicitly taken into account. The lower ranking of Adana can be explained by the relatively higher values of the operational and environmental risk indicators such as climate-related variables and industrial land-use pressures that negatively affected its aggregated neutrosophic distance from the positive ideal solution.

Methodologically, the use of interval-valued neutrosophic fuzzy TOPSIS combined with GIS-based overlay analysis offered a more complete and operational decision-support framework than standard ranking methods at the province level. The interval-valued neutrosophic sets provided a more detailed representation of the expert judgments by means of directly modeling the degrees of truth, indeterminacy and falsehood through the lower and upper interval bounds. This approach was particularly helpful in conveying the hesitance and ambiguity that is sometimes unavoidable in large-scale renewable energy planning challenges in regard to expert judgments. Moreover, the GIS-aided spatial analysis improved the practical usability of the framework by changing the macro-level prioritization to the site-specific determination of suitability at district and regional scales.

Finally, in the discussion section, IVN-TOPSIS and three similar Multi-Criteria Decision Making methods were recalculated and compared using membership functions, decision-makers' evaluations, and finally, GIS data. As shown in Table 13, the IVN-TOPSIS method allowed experts to capture their hesitations more effectively than classical and fuzzy logic approaches. The IVN-TOPSIS technique had a better discrimination among the options with a bigger difference between the top and worst performing provinces. This result is because of the interval valued neutrosophic representation which takes into account the truth, indeterminacy and falsity membership degrees together. IVN-TOPSIS differs from standard TOPSIS and Fuzzy TOPSIS as it clearly considers uncertainty and hesitation of the expert, providing a fuller depiction of the subjective assessments.

Table 13. Comparative results of alternative methods.

Method	Mersin	Antalya	Adana	Ranking
TOPSIS	0.712	0.681	0.625	Mersin > Antalya > Adana
Fuzzy TOPSIS	0.741	0.702	0.648	Mersin > Antalya > Adana
VIKOR	0.231	0.352	0.487	Mersin > Antalya > Adana
IVN-TOPSIS	0.784	0.733	0.661	Mersin > Antalya > Adana

From the point of view of practical planning, the comparison analysis shows that IVN-TOPSIS is particularly useful for decision makers who have to deal with unclear or conflicting judgments. The selection of sites for solar power plants is naturally subjective with respect to environmental sustainability, societal acceptance, economic viability and technological preparedness. The interval-valued neutrosophic structure allows to explicitly take into account these uncertainties in the evaluation process without limiting them to exact numerical values. Therefore, the proposed methodology not only finds the most suitable province but also gives a more realistic depiction of the uncertainty underlying expert assessments and hence supports better informed and dependable investment decisions.

6. Conclusions

The main aim of this study is to solve the solar power plant site selection problem in the Mediterranean Region of Türkiye, namely for the provinces of Antalya, Mersin and Adana, by using an interval-valued neutrosophic fuzzy TOPSIS (IVN-TOPSIS) framework. By considering environmental, economic, social and technological criteria, in an uncertainty-aware decision-making framework, the proposed model achieved a systematic

and comprehensive assessment of different location options under vagueness and lack of experts' knowledge. The results suggested that Mersin is the most suited location for large-scale photovoltaic investment, with Antalya and Adana being the least suitable option.

The results highlight the need, from a policy standpoint, of not relying only on technical indicators such as solar irradiation levels for optimal renewable energy planning. Instead, authorities need to develop integrated evaluation frameworks that consider infrastructure preparedness, economic viability, social acceptability and long-term operational resilience simultaneously. The outperformance of Mersin points to the need to match the solar resource potential with grid accessibility, logistics capacity and market conditions, pointing to the need to design regional incentive schemes and investment priority strategies. Moreover, the results highlight the importance of differentiated regional policies, especially in regions where conflicting land uses or environmental sensitivity may hinder the deployment of renewable energies.

From the scientific point of view, this work is one of the first studies that have used the interval-valued neutrosophic fuzzy TOPSIS for solar power plant site selection in Türkiye. In contrast to classic crisp or single-valued fuzzy MCDM methods, the IVN method clearly takes into account the degrees of truth, indeterminacy, and falsity as intervals, which more accurately captures the hesitation and ambiguity in experts' opinions. Methodological enhancement improves the robustness, transparency, and trustworthiness of the decision-support findings and contributes to the burgeoning literature on neutrosophic-based decision analysis in renewable energy planning.

Despite such achievements, many limitations should be addressed. The research was confined to a limited number of possibilities in one geographical region and expert assessments were acquired from a small group of decision-makers. The IVN-TOPSIS method removes the subjectivity by uncertainty modelling, but the results are still sensitive to the choice of the criteria set and expert weighting scheme.

The suggested framework can be extended in future study by increasing the options and decision-makers or combining IVN-TOPSIS with other neutrosophic or hybrid MCDM methods for comparative validation. In addition, dynamic criteria could be incorporated to reflect climate change impacts, legislative changes and technical developments for long-term strategic planning of renewable energy. Such extensions would significantly enhance the usefulness of neutrosophic decision-support models in sustainable energy investment and policy making.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Al-Ali, S.; Olabi, A.G.; Mahmoud, M. Multi-Criteria Decision Making for Selecting the Location of a Solar Photovoltaic Park: A Case Study in UAE. *Energies* **2024**, *17*, 4235. [CrossRef]
2. Poulek, V.; Aleš, Z.; Finsterle, T.; Libra, M.; Beránek, V.; Severová, L.; Belza, R.; Mrázek, J.; Kozelka, M.; Svoboda, R. Reliability characteristics of first-tier photovoltaic panels for agrivoltaic systems: Practical consequences. *Int. Agrophysics* **2024**, *38*, 383–391. [CrossRef] [PubMed]
3. URL-1. Available online: https://www.pv-magazine.com/2025/01/29/Türkiyes-cumulative-solar-capacity-doubles-in-2-5-years-to-19-6-gw/ (accessed on 4 March 2026).

4. Kulcu, R.; Suslu, A.; Cihanalp, C.; Yilmaz, D. Modelling of global solar radiation on horizontal surfaces for Mersin city. *J. Clean Energy Technol.* **2017**, *5*, 77–80. [CrossRef]
5. Mordor Intelligence. Türkiye Solar Energy Market Size & Share Analysis—Growth Trends and Forecast (2025–2030). 2024. Available online: https://www.mordorintelligence.com/industry-reports/Türkiye-solar-energy-market (accessed on 7 December 2025).
6. Heo, J.; Moon, H.; Chang, S.; Han, S.; Lee, D.-E. Case Study of Solar Photovoltaic Power-Plant Site Selection for Infrastructure Planning Using a BIM-GIS-Based Approach. *Appl. Sci.* **2021**, *11*, 8785. [CrossRef]
7. Demir, A.; Dincer, A.E.; Yılmaz, K. A novel method for the site selection of large-scale PV farms by using AHP and GIS: A case study in İzmir, Türkiye. *Sol. Energy* **2023**, *259*, 235–245. [CrossRef]
8. Ghasempour, R.; Nazari, M.A.; Ebrahimi, M.; Ahmadi, M.H.; Hadiyanto, H. Multi-Criteria Decision Making (MCDM) Approach for Selecting Solar Plants Site and Technology: A Review. *Int. J. Renew. Energy Dev.* **2019**, *8*, 15–25. [CrossRef]
9. Türkan, Y.S.; Alioğulları, E.; Tüylü, D. Optimizing Location Selection for International Education Fairs: An Interval-Valued Neutrosophic Fuzzy Technique for Order of Preference by Similarity to Ideal Solution Approach. *Sustainability* **2024**, *16*, 10227. [CrossRef]
10. Şahin, G.; Koç, A.; van Sark, W. Multi-criteria decision making for solar power-Wind power plant site selection using a GIS-intuitionistic fuzzy-based approach with an application in The Netherlands. *Energy Strategy Rev.* **2024**, *51*, 101307. [CrossRef]
11. Çelikbilek, Y. A new interval-valued neutrosophic AHP-MOORA approach: Application to project manager selection. *Qual. Quant.* **2025**, *60*, 3873–3894. [CrossRef]
12. Karaşan, A.; Kahraman, C.; Boltürk, E. Interval-valued neutrosophic EDAS method: An application to prioritization of social responsibility projects. In *Fuzzy Multi-Criteria Decision-Making Using Neutrosophic Sets*; Springer International Publishing: Cham, Switzerland, 2018; pp. 455–485.
13. Samastı, M.; Türkan, Y.S.; Güler, M.; Ciner, M.N.; Namlı, E. Site Selection of Medical Waste Disposal Facilities Using the Interval-Valued Neutrosophic Fuzzy EDAS Method: The Case Study of Istanbul. *Sustainability* **2024**, *16*, 2881. [CrossRef]
14. Almasad, A.; Pavlak, G.; Alquthami, T.; Kumara, S. Site suitability analysis for implementing solar PV power plants using GIS and fuzzy MCDM based approach. *Sol. Energy* **2023**, *249*, 642–650. [CrossRef]
15. Rana, M.S.P.; Moniruzzaman, M. Demarcation of suitable site for solar photovoltaic power plant installation in Bangladesh using geospatial techniques. *Next Energy* **2024**, *3*, 100109. [CrossRef]
16. Adhikari, M.D.; Yum, S.G.; Yune, C.Y. Geospatial-based risk analysis of solar plants located in the mountainous region of Gangwon Province, South Korea. *Renew. Energy* **2025**, *251*, 123408. [CrossRef]
17. Kurnaz, T.F.; Erdi, A. GIS-based AHP approach for solar power plant site selection: A case study of Niğde Province. *SN Appl. Sci.* **2020**, *2*, 4112. [CrossRef]
18. Akay, S.S. Investigating Land Suitability for PV Farm and Existing Sites Using a Multi-Criteria Decision Approach in Gaziantep, Türkiye. *Appl. Sci.* **2025**, *15*, 2441. [CrossRef]
19. Kocabaldır, C.; Yücel, M.A. GIS-based multi-criteria decision analysis of site selection for photovoltaic power plants in Çanakkale Province. *Int. J. Environ. Geoinformatics* **2020**, *7*, 347–355. [CrossRef]
20. Hassan, G.M.; Kamran, K.V.; Ghanbari, A.; Ajaj, Q. GIS-Based Multi-Criteria Analysis for Solar Energy Cells Site Selection over Kirkuk City. *Turk. J. Eng.* **2025**, *10*, 267–282. [CrossRef]
21. Demir, G. Sustainable energy solutions: Evaluation of solar panel installation using fuzzy multi-criteria decision-making methods. *J. Intell. Decis. Mak. Inf. Sci.* **2024**, *1*, 65–94. [CrossRef]
22. Spyridonidou, S.; Loukogeorgaki, E.; Vagiona, D.G.; Bertrand, T. Towards a sustainable spatial planning approach for PV site selection in Portugal. *Energies* **2022**, *15*, 8515. [CrossRef]
23. Kahraman, C.; Otay, I. Solar PV power plant location selection using a Z-fuzzy number based AHP. *Int. J. Anal. Hierarchy Process* **2018**, *10*, 409–430. [CrossRef]
24. Deveci, M.; Cali, U.; Pamucar, D. Evaluation of criteria for site selection of solar photovoltaic (PV) projects using fuzzy logarithmic additive estimation of weight coefficients. *Energy Rep.* **2021**, *7*, 8805–8824. [CrossRef]
25. Sazvar, Z.; Shorabeh, S.N.; Mahmoodi, H.; Firozjaei, M.K. A scenario-based framework for spatial assessment of multi-source renewable energy parks: A case study of Makran region in Iran. *Sci. Rep.* **2026**, *16*, 6406. [PubMed]
26. Zadeh, L.A. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
27. TAtanassov, K. On a second new generalization of the Fibonacci sequence. *Fibonacci Q.* **1986**, *24*, 362–365. [CrossRef]
28. Smarandache, F. *Neutrosophy: Neutrosophic Probability, Set, and Logic: Analytic Synthesis & Synthetic Analysis*; Rehoboth American Research Press: Rehoboth, NM, USA, 1998. Available online: https://philpapers.org/rec/SMANNP (accessed on 15 October 2025).
29. Karaşan, A.; Kahraman, C. A novel interval-valued neutrosophic EDAS method: Prioritization of the United Nations national sustainable development goals. *Soft Comput.* **2018**, *22*, 4891–4906. [CrossRef]

30. Hwang, C.L.; Yoon, K. Methods for multiple attribute decision making. In *Multiple Attribute Decision Making: Methods and Applications a State-of-the-Art Survey*; Springer: Berlin/Heidelberg, Germany, 1981; pp. 58–191.
31. Uzun, B.; Taiwo, M.; Syidanova, A.; Uzun Ozsahin, D. The technique for order of preference by similarity to ideal solution (TOPSIS). In *Application of Multi-Criteria Decision Analysis in Environmental and Civil Engineering*; Springer International Publishing: Cham, Switzerland, 2021; pp. 25–30.
32. Karasan, A.; Erdogan, M.; Ilbahar, E. Prioritization of production strategies of a manufacturing plant by using an integrated intuitionistic fuzzy AHP & TOPSIS approach. *J. Enterp. Inf. Manag.* **2018**, *31*, 510–528. [CrossRef]
33. Soydan, O. Solar power plants site selection for sustainable ecological development in Nigde, Türkiye. *SN Appl. Sci.* **2021**, *3*, 41.
34. Nasehi, S.; Nohegar, A. Photovoltaic Farm Site Selection using Fuzzy Multi Criteria Evolution with Emphasis on Air Quality and Environmental Conditions. *Environ. Energy Econ. Res.* **2025**, *9*, S102.
35. Yildiz, O.A.; Cebi, S.; Yildiz, O. Multicriteria decision support for sustainable energy planning: An evaluation of alternative scenarios for the solar power plant site selection. *Environ. Dev. Sustain.* **2025**, 1–35. [CrossRef]
36. Ramana, S.V.; Devakumar, M.L.S.; Hemalatha, S. Ranking of Sites of Solar Power Plants in Fuzzy Environment. *Int. J. Sustain. Dev. Plan.* **2023**, *18*, 3845–3854. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.