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Integrating GIS and Fuzzy BWM for Solar PV Power Plant Site Selection: A Case Study of Konya, Turkey

Ömer Öztaş[1], Bilal Ervural[2]*

1 Department of Industrial Engineering, OSTIM Technical University, 06374 Ankara, Türkiye
2 Department of Industrial Engineering, Necmettin Erbakan University, 42090 Konya, Türkiye
* bervural@erbakan.edu.tr
* Orcid No: 0000-0002-5206-7632

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Abstract

The global demand for energy continues to rise, driving the need for sustainable and efficient energy solutions. This study presents a comprehensive framework that combines the fuzzy best-worst method (BWM) with geographic information systems (GIS) to optimize solar power plant site selection. Eight criteria, including solar irradiation, slope, aspect, and proximity to infrastructure and water resources, were evaluated using the fuzzy BWM approach. These weighted criteria were integrated into GIS to create a suitability map, categorized into five levels of potential. The proposed framework was applied to Konya, Türkiye, a region with abundant solar energy resources, and highly suitable sites for solar photovoltaic (PV) power plant development were successfully identified. Furthermore, a sensitivity analysis was conducted to validate the robustness of the results. The findings demonstrate the framework's potential as a reliable decision-support tool for energy planners and policymakers, offering a replicable model for regions with similar characteristics.

Keywords: Best-Worst Method, Fuzzy Logic, GIS, MCDM, Renewable Energy, Solar.

1. Introduction

The energy demand is growing globally due to an increasing population and intensive industrial activities. This has emphasized the need for sustainable and efficient energy solutions [1]. As a result, there has been a noticeable shift towards exploring alternative energy sources, with a particular focus on renewable energy. This shift is motivated by the environmental consequences and limitations of conventional fossil fuels. Solar energy is considered a leading candidate among renewable options because of its renewable nature and consistent availability [2].

Today, the utilization of solar energy has experienced a surge in global popularity. In alignment with this global trend, Türkiye is directing its attention toward optimizing the use of renewable resources, with a particular emphasis on solar energy, as a strategic approach to efficiently address its expanding energy requirements. According to Türkiye's National Energy Plan [3], Türkiye aims to achieve net zero emissions by 2053. The plan outlines strategic actions until 2035 and anticipates that Türkiye's primary energy consumption,

which was 147.2 million tons of oil equivalent in 2020, is expected to increase to 205.3 million tons of oil equivalent by 2035. Electricity consumption of Türkiye, displaying an average annual increase of 4.4 percent during the period spanning 2000 to 2020, is projected to sustain an average annual growth rate of 3.5 percent through 2035, culminating in a total of 510.5 TWh (terawatt-hours). The proportion of electricity in final energy consumption, constituting 21.8 percent in 2020, is expected to rise to 24.9 percent by 2035. The installed electricity capacity in Türkiye, standing at 95.9 GW (gigawatt) after 2020, is forecasted to attain 189.7 GW by 2035, with renewable energy sources increasing their share, rising from 52 percent in 2020 to 64.7 percent in 2035 (see Fig. 1). Notably, renewable energy sources are planned to contribute 74.3 percent to the anticipated 96.9 gigawatts of new electricity capacity to be commissioned by 2035. The most significant increase in investment in renewable resources is allocated to solar energy. The installed solar power capacity in Türkiye, which is quantified at 6.7 GW at the end of 2020, is projected to rise to 52.9 GW by 2035. This significant increase represents almost five times the 9.32 GW recorded in 2022. Once the capacity is realized in 2035, solar energy will have the highest share of Türkiye's total installed capacity, displacing other sources.

The initial step in establishing solar power plants involves identifying regions with high solar energy potential by considering environmental, economic, and social factors. Proper site selection is critical for maximizing energy generation, minimizing costs, and ensuring the long-term sustainability of renewable energy projects. The integration of multi-criteria decision-making (MCDM) methodologies with geographic information system (GIS) techniques has proven highly effective for renewable energy planning [4–9]. Through this integration, decision-makers can employ GIS as a dominant tool for handling spatial solar energy data, while MCDM methods aid in assessing alternative solar power plant locations [10]. The techniques of MCDM enable the weighting and identification of the most suitable areas by considering many criteria. Various approaches, including their fuzzy versions, are employed in selecting locations for photovoltaic energy plants.

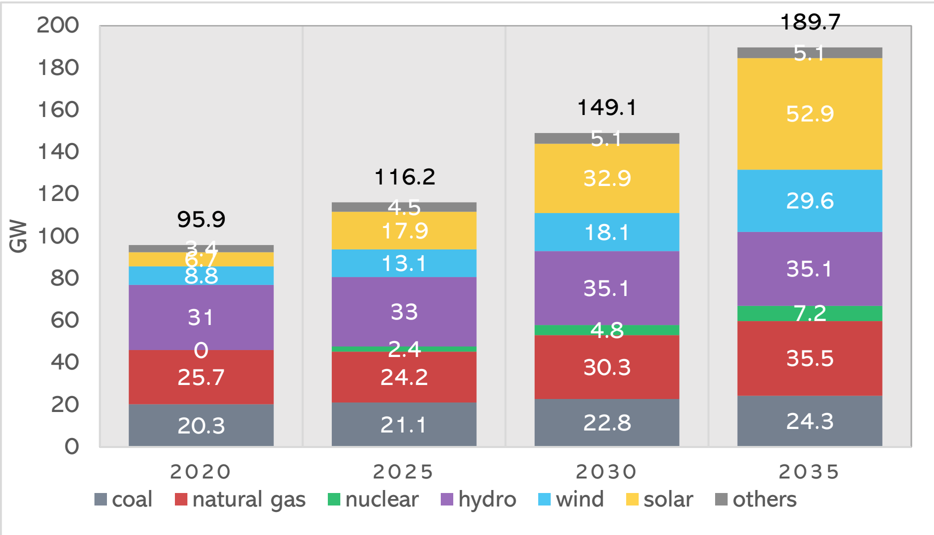

Figure 1. Installed capacity by source in Türkiye [2]

The literature underscores the importance of integrating GIS with MCDM methods for solar PV power plant site selection. The analytic hierarchy process (AHP) is widely applied among these methods. Akkas et al. [11] utilized AHP alongside methods such as ELECTRE, TOPSIS, and VIKOR for site selection in Central Anatolia, Türkiye, while Aktas and Kabak [12] integrated AHP with TOPSIS to evaluate solar plant sites across Türkiye. Aragonés-Beltrán et al. [13] used AHP for PV solar power plant investment decisions in Spain, and Colak et al. [14] employed GIS-AHP for optimal site selection in Malatya province of Türkiye. Similarly, Al Garni and Awasthi [15] adopted a GIS-AHP approach for site selection in Saudi Arabia, further demonstrating the adaptability of AHP-based models across regions.

GIS integration in solar PV power plant site selection extends beyond AHP to various other MCDM methods. Lee et al. [16] employed a hybrid MCDM approach, using the fuzzy analytic network process (ANP) and VIKOR for PV solar plant site selection in Taiwan. Shorabeh et al. [10] utilized a GIS-based method for solar power plant site selection in Iran, emphasizing the pivotal role of geographical information in decision-making. Hybrid models that combine multiple decision-making methods are emerging as an intriguing aspect. Badi et al. [17] introduced a hybrid SWARA-DEMATEL model for solar park site selection in Libya, demonstrating the versatility of hybrid models in considering financial, social, and environmental dimensions in decision-making processes. Beyond MCDM methods, fuzzy logic has found application in certain studies. Zoghi et al. [18], in their case study in Isfahan, Iran, employed a fuzzy logic model and weighted linear combination method for solar site selection, demonstrating the adaptability of fuzzy logic in decision support systems. Noorollahi et al. [1] designed a decision support tool for suitable sites for a solar photovoltaic power plant in Iran, using Fuzzy and Boolean logic, AHP, and GIS. The literature emphasizes the integration of GIS with various fuzzy techniques for effective solar energy plant site selection. These studies highlight the critical role of fuzzy techniques in enhancing the robustness of renewable energy planning by managing uncertainties inherent in the decision-making process [19–22].

While AHP has been a dominant tool for prioritizing criteria in renewable energy site selection, the best-worst method (BWM) has recently emerged as a robust alternative. Its crisp version has been successfully

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applied in various renewable energy contexts, including assessing renewable energy sources [23], wind and solar power plant sites [20,24], solar panel technology [25], sites for wind-powered hydrogen production [26], and onshore wind plants [27]. However, the integration of fuzzy BWM with GIS remains underexplored. Fard et al. [28] demonstrated the use of fuzzy BWM with GIS for solar site selection, applying the version proposed by Guo and Zhao [29]. However, our study adopts the improved fuzzy BWM methodology developed by Dong et al. [30], which addresses the key limitations of the earlier method and provides more accurate and reliable results.

This study focuses on the need for site selection in Konya, Türkiye, to utilize its vast solar energy potential for PV projects. Despite having enormous potential, there has been a lack of comprehensive studies focusing on site selection for such regional projects. This research aims to fill this gap by thoroughly analyzing potential sites using a methodological framework outlined in Fig. 2. The study provides valuable insights for renewable energy planning and development in Konya. This study uses the improved fuzzy BWM method to weight the evaluation criteria. This method allows for the representation of vague or imprecise information, enhancing the robustness and comprehensiveness of the decision-making process. The study identifies highly suitable areas within Konya through a systematic investigation, including criterion weighting, GIS analysis, suitability mapping, and sensitivity analysis. This demonstrates the model's efficacy in addressing the complexities of site selection for solar PV projects. The research provides information to aid decision-makers in selecting the most suitable sites for solar energy infrastructure development in Konya.

Based on the characteristics mentioned above, the proposed methodology offers the following contributions:

- Firstly, the study uses tailored criteria reflecting Konya's geographical and environmental characteristics. These criteria are weighted with the fuzzy BWM method to yield more accurate results in uncertain conditions.
- Secondly, a comprehensive sensitivity analysis is conducted within the GIS environment to evaluate the robustness of the results and to understand the impact of individual criteria on the overall suitability map.
- Finally, the study proposes a sustainable and adaptable approach by developing a framework that can be applied to other regions with similar characteristics, even though it is specifically tailored for Konya.

The remainder of this study is organized as follows: Section 2 delineates the study area and identifies the criteria and restriction factors. The fuzzy BWM is then introduced as a methodology. Sections 3 and 4 present the results and discuss findings from the study. This includes calculating the criteria weights using fuzzy BWM and conducting suitability and sensitivity analysis. Finally, Section 5 concludes the study, highlighting its limitations and providing suggestions for further research.

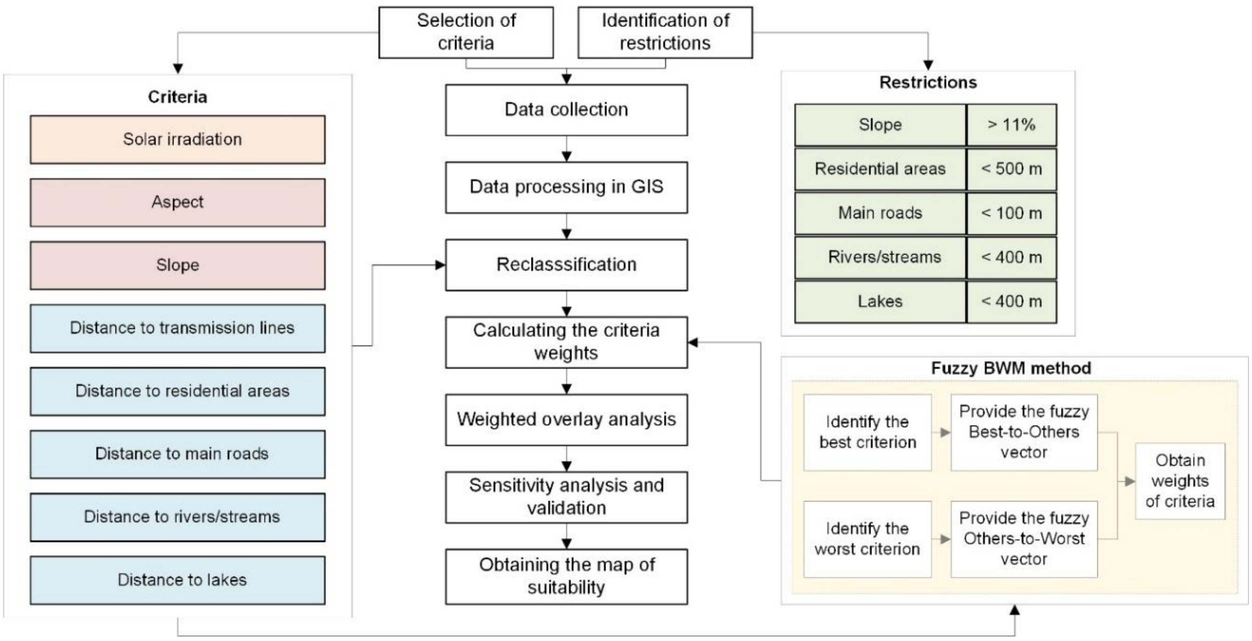

Figure 2. Schematic representation for the solar PV site selection.

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2. Materials and Methods

The primary aim of this study is to evaluate site alternatives to determine optimal locations for solar PV projects in Konya, Turkey, which is renowned for its significant solar energy potential. Data for this investigation were gathered from various sources, including governmental institutions, open-access databases, and existing literature. This section provides information regarding the study area, the criteria, and the methodological framework used. The methodological framework employed in this study is depicted in Fig. 2.

2.1 Study Area

The study area is Konya province, with an area of 40,838 km^2 in southwest Central Anatolia, Turkey. It is located between the latitudes of 36°41' and 39°16' N and the longitudes of 31°14' and 34°26' E and is recognized as the largest province in the country. Konya boasts a robust solar resource, surpassing many other regions. With high global horizontal irradiance (GHI) levels, Konya has the potential for efficient and cost-effective solar power generation. The region's favorable weather further enhances the feasibility of solar PV systems. As of 2020, Konya's annual electricity consumption was 8.4 TWh (Terawatt-hour) [31]. The province of Konya in Turkey is identified as possessing significant solar energy potential, as indicated by the Solar Energy Potential Atlas (GEPA) [32], as shown in Fig. 3.

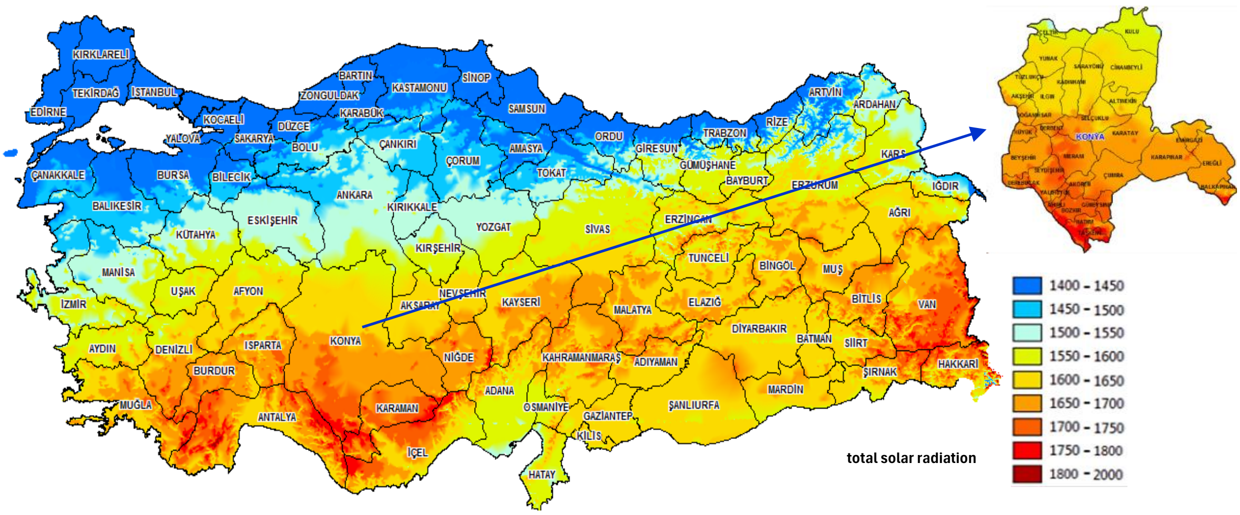

Figure 3. Solar energy potential map of Turkey [32].

Global radiation values and sunshine hours for the Konya Province are shown in Fig. 4. Konya, Turkey, boasts a substantial solar resource, outperforming many other regions in Turkey regarding sunlight availability. In comparison to other areas with lower solar irradiance, Konya has the potential to generate solar power efficiently and cost-effectively. The region's solar potential suggests it could achieve a significant power output, potentially requiring fewer PV modules and less installation space than locations with lower solar irradiance levels. In addition, Konya benefits from favorable weather conditions conducive to PV development, including low cloudiness and a limited number of days with precipitation [33]. These weather characteristics enhance the feasibility and effectiveness of solar PV systems in the region.

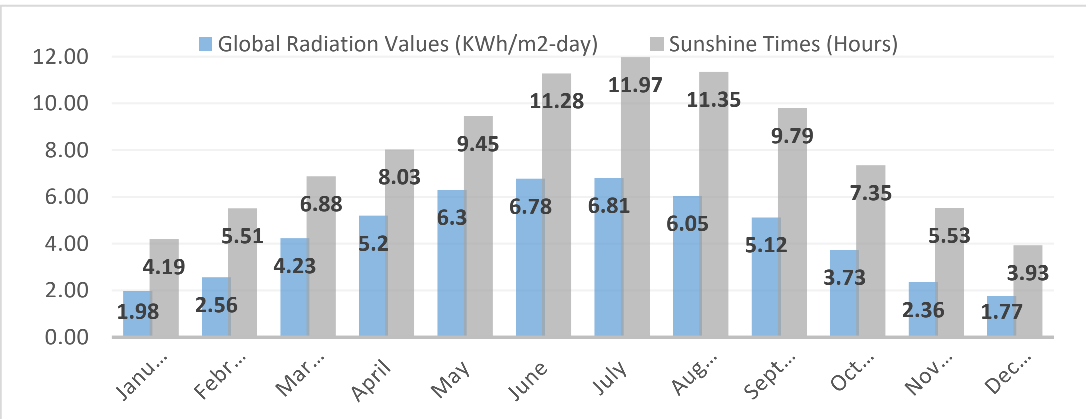

Figure 4. Global radiation values and sunshine times in Konya province.

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2.2 Identification of criteria and restriction factors

Careful consideration of specific conditions is essential to establish a solar power plant and ensure its optimal functionality. The criteria for selecting suitable areas vary depending on the solar power plant's intended purpose and geographic location. To identify regions unsuitable for such installations, a comprehensive literature review was conducted, enabling the recognition of critical conditions that require attention. Based on these conditions, eight distinct criteria have been established: solar radiation levels, distance to power transmission infrastructure, aspect orientation, slope, distance to residential areas, distance to main roads, distance to rivers/streams, and distance to lakes. These factors collectively contribute significantly to a comprehensive framework for placing solar PV projects. The study encompasses various constraints, including ensuring that the slope gradient remains below 11%, maintaining a minimum distance of 400 m from rivers and lakes, maintaining a distance of at least 100 m from highways and railways, and locating the farms at a distance greater than 500 m from residential areas. The regions characterized by spatial suitability scores of 0, denoting restricted areas for each criterion, are delineated in Table 1. This tabular presentation also provides the threshold limits alongside their corresponding spatial suitability scores, including categories very high suitability (5), high suitability (4), moderate suitability (3), low suitability (2), and very low suitability (1). The determination of these limitation values for all pertinent factors influencing solar photovoltaic (PV) site selection is derived from expert consensus and literature. The following subsections elaborate on each criterion, demonstrating their relative importance.

2.2.1 Solar Irradiation

Solar irradiance refers to the amount of solar radiation absorbed within a given area influenced by factors such as latitude, longitude, time of day, humidity, evaporation, air temperature, sun angle, and other variables. It is usually measured per unit area by a specific surface area (expressed in watts per square meter, W/m^2). It is the most significant parameter in assessing the potential for energy generation within a solar PV power plant [5,34]. Selecting a location with low solar energy potential can lead to inefficiencies in establishing and operating a power plant. The reclassified solar irradiation map of Konya is shown in Fig.5 (a).

2.2.2 Aspect

The aspect of the land plays a crucial role in the site selection process for solar PV power plants, particularly concerning the land slope. Evaluating slope orientations necessitates the creation of an aspect map, which is derived from elevation maps and provides insights into the topography of the terrain. Understanding the terrain ensures optimal use of sunlight, contributing to the efficiency of solar power generation systems [8,35,36]. The aspect map of Konya is presented in Fig.5 (b).

2.2.3 Slope

Highly sloping and rough terrain is critical when installing a solar PV power plant. Generally, areas with slopes above 11% are considered unsuitable, whereas slopes of 4% and below are deemed appropriate [37,38]. An excessive slope can lead to shading between solar panels, potentially affecting efficiency. In addition, failure to meet the specified slope requirements may necessitate excavation or filling operations in the area, leading to potential setbacks in terms of time and cost [1,17,35]. Fig.5 (c) shows the reclassified slope map of Konya.

2.2.4 Distance to the transmission lines

Ensuring efficient transmission and distribution of electricity with minimal loss is vital. While traditional power structures are typically reliable, areas with solar PV power plants can present installation cost challenges for power infrastructure [39]. Therefore, situating solar PV power plants near existing power lines aids in reducing transmission losses and enhancing overall reliability [8,35,40]. It's important to maximize the utilization of current power lines to avoid additional associated with introducing new ones. Moreover, locating solar PV power generation near a transformer center proves advantageous, as it reduces expenses by negating the need to construct new transformers. The transmission line map is depicted in Fig.5 (d).

2.2.5 Distance to residential areas

The construction of a solar PV power plant within a prospective residential zone can be avoided by considering the anticipated development trajectory of these areas. Simultaneously, positioning solar power plants close to settlements becomes essential to meet the region’s energy demands while addressing cost considerations [14,15,36,41]. Fig.5 (e) shows the map of the reclassified distance to residential areas.

2.2.6 Distance to the main roads

Transportation is crucial in regional investments, especially in the installation of solar PV power plants. This significance arises from the substantial transportation needs linked to solar energy infrastructure [6,17,18]. To establish these plants, it is essential to carefully assess the existing road network. Introducing new roads increases expenses, particularly in areas without established transportation systems. Therefore, the feasibility of solar energy plant installation hinges on the condition and accessibility of the road network. Fig.5 (f) shows the reclassified distance to the main road map.

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Table 1. Evaluation criteria and suitability scores

Criteria	References	Unit	Classes	Scores
C1 - Solar Irradiation	[10,17,38,42,43]	kWh/m^2	< 1200	1
			1200 – 1300	2
			1300 – 1400	3
			1400 – 1500	4
			> 1500	5
C2 - Aspect	[6,9,39,42,44]	direction	North	1
			Northeast, Northwest	2
			East, West	3
			Southeast, Southwest	4
			South	5
C3 - Slope	[1,5,7,44]	%	< 1	5
			1 – 4	4
			4 – 7	3
			7 – 9	2
			9 – 11	1
			> 11	0
C4 - Distance to transmission lines	[38,41,45]	km	0 – 2	5
			2 – 4	4
			4 – 6	3
			6 – 10	2
			> 10	1
C5 - Distance to residential areas	[14,15,40]	km	0 – 0.5	0
			0.5 – 0.75	1
			0.75 – 1	2
			1 – 2	3
			2 – 5	4
			> 5	5
C6 - Distance to main roads	[6,15,17,18]	km	0 – 0.1	0
			0.1 – 1	5
			1 – 2	4
			2 – 5	3
			5 – 10	2
			> 10	1
C7 - Distance to rivers/streams	[42,44,45]	km	< 0.4	0
			0.4 – 2	5
			2 – 5	4
			5 – 7.5	3
			7.5 – 10	2
			> 10	1
C8 - Distance to lakes	[14,35,46]	km	< 0.4	0
			0.4 – 2	5
			2 – 5	4
			5 – 7.5	3
			7.5 – 10	2
			> 10	1

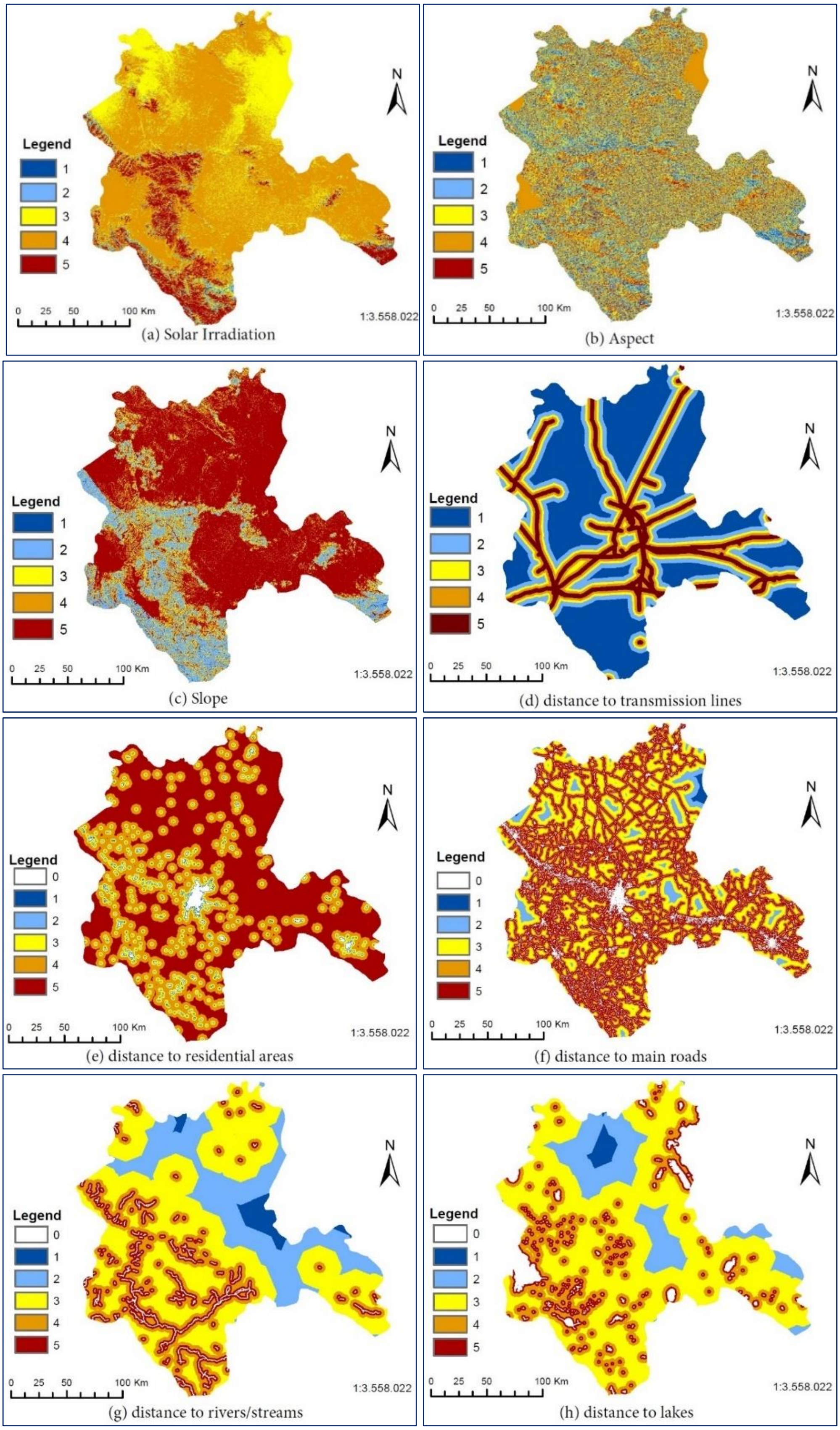

Figure 5. Reclassified layers of evaluation criteria: (a) solar irradiation; (b) aspect; (c) slope; (d) distance to transmission lines; (e) distance to residential areas; (f) distance to main roads; (g) distance to rivers/streams; (h) distance to lakes.

2.2.7 Distance to rivers/streams

The location of land near rivers or streams carries a notable risk of substantial material losses, particularly during winter floods. Hence, the criteria for considering proximity to rivers and streams are of utmost importance, as natural disasters in such areas can severely damage the facility [44,45]. This scenario can elevate operational costs and impede electricity generation. Furthermore, establishing a power plant in a river or stream region has been found to negatively impact efficiency due to factors such as fog, evaporation, and humidity risks, which are believed to influence the overall effectiveness of the plants. The reclassified distance to the river map is presented in Fig. 5 (g).

2.2.8 Distance to the lakes

To ensure safety and prevent environmental pollution caused by the potential adverse effects of floods due to variations in the volumes of lakes at different times of the year, it is recommended that solar power plants be located at a minimum distance of 400 m from lakes. This precautionary measure mitigates the impact of potential flooding and protects the surrounding environment [14,35,46]. The reclassified space in the lake map of Konya is presented in Fig. 5 (h).

2.3 Fuzzy BWM

In this study, fuzzy Best Worst Method (BWM) is adopted to ascertain the weights of the criteria within a fuzzy framework. Initially introduced by Rezaei in [47], classical BWM is a relatively recent technique that has successfully addressed various MCDM problems, such as firms' R&D performance evaluation [48], comparing communication technologies [49], and measuring the importance of logistics performance indicators [50]. Compared to other subjective weighting methods, such as AHP, BWM is notable for its ease of implementation. The methodology presents various advantages, particularly concerning the number of pairwise comparisons required, consistency, and reliability. Notably, BWM necessitates only (2n − 3) pairwise comparisons, which is a notably lower number compared to AHP, which demands n(n − 1) pairwise comparisons. The abundance of pairwise comparisons and extensive data involvement in AHP often leads to inconsistent results. Rezaei [47,51] demonstrated that BWM is more consistent than AHP, emphasizing its reliability as a preferred method for MCDM applications.

In decision-making under uncertainty, expressing preferences using crisp numbers can be challenging, especially when decision-makers compare alternatives with inherent vagueness or ambiguity. To address these challenges, Dong et al. [30] proposed an enhanced fuzzy BWM approach based on triangular fuzzy numbers, which incorporates fuzzy logic into the BWM framework. This method overcomes the limitations of traditional methods by offering greater flexibility and improved reliability in capturing decision-makers' preferences.

For this study, criteria weights were calculated using the neutral decision-maker model, one of the three approaches outlined by Dong et al. [30]. This model is specifically designed to strike a balance between optimistic and pessimistic decision-making tendencies, making it well-suited for neutral contexts (mixed approach). The neutral model ensures a robust and balanced evaluation by integrating the adaptability of fuzzy BWM with improved consistency in weight estimation. The mathematical formulation and detailed application of this approach are thoroughly presented by Dong et al. [30].

The fuzzy comparison scale delineated in Table 2 serves as a tool for converting the linguistic assessments provided by experts into fuzzy ratings (represented by TFNs). The procedural framework of the fuzzy-BWM approach proposed by Dong et al. [30] encompasses the following steps:

Table 2. Linguistic scale for criteria weighting

Linguistic Terms	TFN scale
Equally important (EI)	(1,1,1)
Weakly important (WI)	(2/3,1,3/2)
Fairly important (FI)	(3/2,2,5/2)
Very important (VI)	(5/2,3,7/2)
Absolutely important (AI)	(7/2,4,9/2)

Step 1. Define a set of decision criteria denoted as $C = \{C_1, C_2, \ldots, C_n\}$.

Step 2. Identify the best criterion (C_B) which is considered the most important, and the worst criterion (C_W), regarded as the least important.

Step 3. Provide preference for the best criterion over all other criteria. Let $\tilde{a}_{Bj} = \left(a_{Bj}^l, a_{Bj}^m, a_{Bj}^u\right)$ be the triangular fuzzy preference of the best criterion C_B over criterion C_j, satisfying $\tilde{a}_{BB} = (1,1,1)$. Formulate the best-to-others vector as follows:

$$\tilde{A}_B = [\tilde{a}_{B1}, \tilde{a}_{B2}, \ldots, \tilde{a}_{Bn}]$$

Step 4. Provide preference for all criteria over the worst criterion. Let $\tilde{a}_{jW} = \left(a_{jW}^l, a_{jW}^m, a_{jW}^u\right)$ be the triangular fuzzy preference of a criterion C_j over the worst criterion C_W, satisfying $\tilde{a}_{WW} = (1,1,1)$. Formulate the Others-to-Worst vector as follows:

$$\tilde{A}_W = [\tilde{a}_{1W}, \tilde{a}_{2W}, \ldots, \tilde{a}_{nW}]$$

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Step 5. Determine appropriate values for the tolerance parameters (d_j^t and q_j^t) within the interval [1, 9] according to expert preferences and the specific characteristics of the problem. This study calculates the global optimum solution by using tolerance parameter 1.

Step 6. Derive the optimal weight vector $\widetilde{w}^* = [\widetilde{w}_1^*, \widetilde{w}_2^*, \ldots, \widetilde{w}_n^*]$ and the optimal satisfaction degree β. In this study, the Mixed Approach-I for obtaining the weights of the criteria from the perspective of a neutral decision-maker is employed. Eq. (1) presents the linear programming model used to compute the criteria weights under the neutral decision-making assumption, ensuring a balanced and robust evaluation framework.

$$max\ \beta$$

$$\text{s.t.}\begin{cases} 1-\frac{w_B^t-w_j^t a_{Bj}^t}{d_j^t} \geq \beta,\ \ 0 \leq w_B^t - w_j^t a_{Bj}^t \leq d_j^t\ (j=1,2,\ldots,n; t=l,m,u) \\ 1+\frac{w_j^t-a_{jw}^t w_w^t}{q_j^t} \geq \beta,\ \ -q_j^t \leq w_j^t - a_{jw}^t w_w^t \leq 0\ \ (j=1,2,\ldots,n; t=l,m,u) \\ 0 \leq \beta \leq 1 \\ \sum_{i=1}^n w_i^m = 1,\ \ w_j^u + \sum_{i=1, i\neq j}^n w_i^l \leq 1,\ \ w_j^l + \sum_{i=1,i\neq j}^n w_i^u \geq 1\ (j=1,2,\ldots,n) \end{cases} \tag{1}$$

Then, the optimal weight vector ($\widetilde{w}^*$) based on the TFNs is converted to crisp weights using Eq. (2).

$$R(\tilde{a}) = \frac{1}{6}(a^l + 4a^m + a^u) \tag{2}$$

Step 7. Compute the fuzzy deviation of the comparisons $\tilde{\xi}^* = (\xi^{*l}, \xi^{*m}, \xi^{*u})$.

$$\begin{aligned} \xi'^l &= \frac{1}{2n}\sum_{j=1}^n\left(|w_B^{*l} - w_j^{*l}a_{Bj}^l| + |w_j^{*l} - a_{jw}^l w_w^{*l}|\right) \\ \xi'^m &= \frac{1}{2n}\sum_{j=1}^n\left(|w_B^{*m} - w_j^{*m}a_{Bj}^m| + |w_j^{*m} - a_{jw}^m w_w^{*m}|\right) \\ \xi'^u &= \frac{1}{2n}\sum_{j=1}^n\left(|w_B^{*u} - w_j^{*u}a_{Bj}^u| + |w_j^{*u} - a_{jw}^u w_w^{*u}|\right) \end{aligned} \tag{3}$$

where ξ'^l, ξ'^m and ξ'^u denote the possible lower bound, possible mode and possible upper bound of the fuzzy deviation $(\tilde{\xi}^*)$, respectively.

Step 8: Calculate the fuzzy consistency ratio (FCR) using Eq. (4).

$$FCR = \frac{\tilde{\xi}^*}{\tilde{\zeta}} = \frac{(\xi^{*l}, \xi^{*m}, \xi^{*u})}{(\zeta^l, \zeta^m, \zeta^u)} = \left(\frac{\xi^{*l}}{\zeta^u}, \frac{\xi^{*m}}{\zeta^m}, \frac{\xi^{*u}}{\zeta^l}\right) \tag{4}$$

where fuzzy consistency index, $\tilde{\zeta} = (\zeta^l, \zeta^m, \zeta^u)$, is obtained using Table 3.

Table 3. Fuzzy Consistency Index (FCI) for Fuzzy BWM

Linguistic Terms	Equally important (EI)	Weakly important (WI)	Fairly important (FI)	Very important (VI)	Absolutely important (AI)
$\tilde{a}_{BW}$	(1,1,1)	(2/3,1,3/2)	(3/2,2,5/2)	(5/2,3,7/2)	(7/2,4,9/2)
FCI ($\tilde{\zeta}$)	(0, 0, 0)	(0, 0, 1.36)	(0.34, 0.44, 2.16)	(0.71, 1, 4.29)	(1.31, 1.63, 5.69)

Step 9. Compute the graded mean integration representation (GMIR) of FCR, i.e., R(FCR), to check consistency using Eq. (5).

$$R(FCR) = \frac{1}{6}\left(\frac{\xi^{*l}}{\zeta^u} + \frac{4\xi^{*m}}{\zeta^m} + \frac{\xi^{*u}}{\zeta^l}\right) \tag{5}$$

If $R(FCR) \leq 0.1$, the fuzzy pairwise comparisons are considered acceptable consistent; however, if $R(FCR) > 0.1$, the comparisons are not consistent.

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3. Results

3.1 Calculating the weights of the criteria using fuzzy BWM

After selecting relevant criteria, a team of experts evaluates the importance of these criteria using fuzzy BWM. Section 2.3 provides an overview of the implementation of the fuzzy BWM method suggested by Dong et al. [30].The optimal overall weights of the criteria are determined through pairwise comparisons from the standpoint of an impartial decision-maker, taking into account mixed approach-I and all tolerance parameters (d_j^t) 1.

In the initial stage of the fuzzy BWM process, experts begin by choosing the most favorable (best) and least favorable (worst) criteria from a preset list. After identifying these, experts are assigned the task of providing assessments involving comparisons among the criteria using fuzzy numbers. The comparisons of the best criterion with the other criteria ($\tilde{a}_{Bj}$) and all the criteria with the worst criterion ($\tilde{a}_{jW}$) are systematically displayed in Table 4.

Upon identifying the best-to-others ($\tilde{A}_B$) and others-to-worst vectors ($\tilde{A}_W$), we utilized the Lingo 19.0 optimization software to solve the linear programming (LP) model in Eq. (1) in order to calculate the optimal weight vector. The resulting fuzzy weights, which were obtained from the LP model, are detailed in Table 5. Furthermore, Eq. (2) was employed to determine the crisp weights for TFNs.

Table 4. Collective preferences of experts

Best Criterion	Worst Criterion	TFN preferences	C1	C2	C3	C4	C5	C6	C7	C8
C1	C8	$\tilde{a}_{Bj}$	EI (1,1,1)	FI (3/2,2,5/2)	FI (3/2,2,5/2)	VI (5/2,3,7/2)	AI (7/2,4,9/2)	VI (5/2,3,7/2)	AI (7/2,4,9/2)	AI (7/2,4,9/2)
		$\tilde{a}_{jW}$	AI (7/2,4,9/2)	VI (5/2,3,7/2)	VI (5/2,3,7/2)	FI (3/2,2,5/2)	FI (3/2,2,5/2)	FI (3/2,2,5/2)	WI (2/3,1,3/2)	EI (1,1,1)

Table 5. Weights of the criteria

	Solar Irradiation (C1)	Aspect (C2)	Slope (C3)	Distance to the transmission lines (C4)	Distance to residential areas (C5)	Distance to the main roads (C6)	Distance to rivers/streams (C7)	Distance to lakes (C8)
Fuzzy weights	(0.13, 0.304, 0.34)	(0, 0.137, 0.137)	(0, 0.137, 0.137)	(0, 0.098, 0.098)	(0, 0.076, 0.076)	(0, 0.098, 0.098)	(0.025, 0.08, 0.08)	(0.037, 0.08, 0.08)
Crisp Weights	0.32	0.13	0.13	0.09	0.07	0.09	0.08	0.08

Table 6 provides essential metrics, including the minimal acceptance degree (β), fuzzy deviations ($\tilde{\xi}^*$), fuzzy consistency index ($\tilde{\zeta}$) and *R(FCR)* value. As observed in Table 6, the R(FCR) value is less than 0.1, indicating that the comparisons are reasonably consistent.

Table 6. Consistency values

β^*	0.8709
$\tilde{\xi}^*$	(0.0281, 0.0348, 0.0656)
$\tilde{\zeta}$	(1.31, 1.63, 5.69)
FCR	(0.0049, 0.0213, 0.05)
$R(FCR)$	0.0234

3.2 Suitability Analysis

In the context of suitability analysis, the input criterion layers used in overlay analysis necessitate reclassification into raster layers. Hence, the initial preparation and reclassification of the input criterion layers were executed, as illustrated in Fig. 5 (a-h), to delineate the eight resultant maps. Comprehensive class intervals alongside corresponding suitability values are elaborated in Table 1.

Following the reclassification of input criterion layers and the determination of weights through fuzzy BWM, a weighted overlay analysis technique was applied. This method integrated the derived weights with raster layers corresponding to the eight identified criteria. In line with previous studies, the suitability map in this study was

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divided into six categories, including restricted areas, to ensure consistency with the literature and enhance interpretability. This classification approach provided a well-structured differentiation among varying suitability levels while effectively capturing the spatial characteristics of the study area. The outcome of this process generated a suitability map that classifies areas into six discrete categories: 'unsuitable,' 'very low suitability,' 'low suitability,' 'moderate suitability,' 'high suitability,' and 'very high suitability.' Sequential values spanning from 0 to 5 were assigned to these suitability classes to facilitate the overlay analysis.

The criterion layers underwent stacking via the weighted sum tool. Subsequent to this, the output layer, featuring values ranging from 0 to 5, underwent division utilizing the reclassify tool, thereby partitioning it into five equally spaced suitability classes. Following this step, restriction factors were considered, and unsuitable areas were removed from the map. The resulting suitability map, created using ArcGIS software, is shown in Fig. 6.

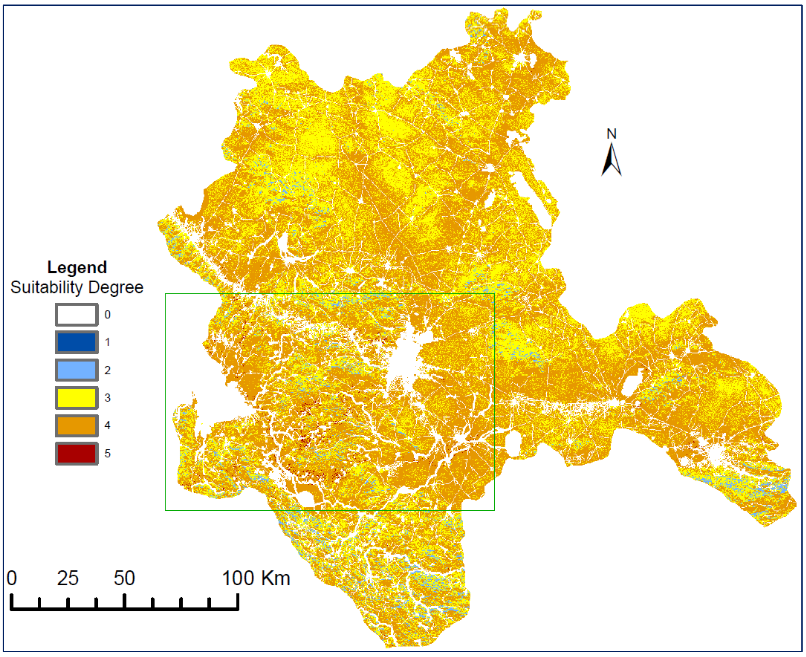

Figure 6. Suitability map results using fuzzy BWM weights.

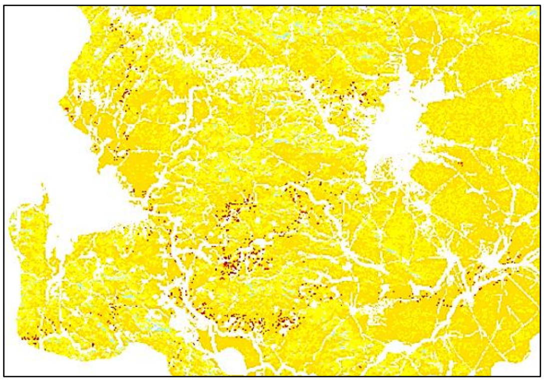

Figure 7. A close-up view of areas with the highest suitability.

Notably, approximately half of the entire area exhibits high potential for solar PV installations, with 137.03 km^2 (0.3%) classified as 'very high suitable'. The regions identified as exhibiting the highest suitability are predominantly situated within the city's central belt, notably in its central and western sectors (as delineated within the enclosed area in Fig. 6). This concentration is further elucidated in a distinct graphical representation showcased in Fig. 7, where enhanced contrast has been applied to facilitate more precise visualization.

Fig. 8 shows the spatial distribution of the three photovoltaic facilities with the highest installed capacity in Konya. As shown in Figure 8, the Karapınar solar power plant, with an installed capacity of 1,000 MW and occupying an area of 27.18 km^2, is located in an area with high suitability and above. Similarly, the Alibeyhoyugu (18-MW) and Apa (13-MW) facilities are also situated in high suitability areas. It reveals a robust correlation between potentially suitable areas and current installations. This correlation underscores the validity of the methodology employed in this study.

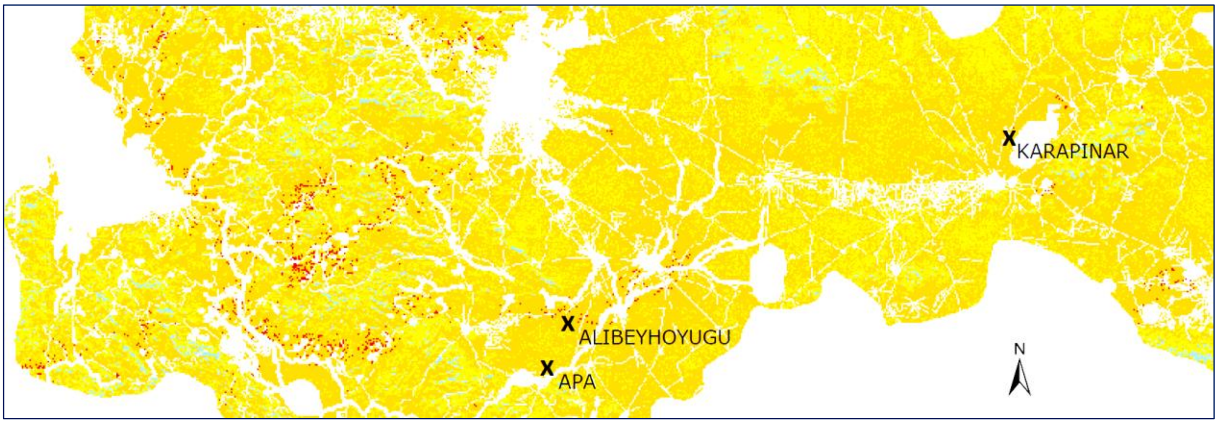

Figure 8. Current solar PV plants.

3.3 Sensitivity Analysis

In this section, a sensitivity analysis was conducted by changing the criterion weights and examining the changes in the suitability map to assess the robustness of the proposed fuzzy BWM-GIS approach. For this purpose, three scenarios were developed. Scenario 1 assumes equal importance of all criteria and assigns equal weights to them. Scenario 2 disregarded distance criteria (C4-C6), while Scenario 3 excluded the evaluation of distance criteria to rivers and lakes (C7, C8), ensuring the proportional distribution of weights to the remaining criteria. Table 7 presents all scenarios and their associated weights.

Table 7. Sensitivity analysis scenarios and criteria weights

Scenarios	Criteria Weights							
	Solar Irradiation (C1)	Aspect (C2)	Slope (C3)	Distance to the transmission lines (C4)	Distance to residential areas (C5)	Distance to the main roads (C6)	Distance to rivers/streams (C7)	Distance to the lakes (C8)
Current situation (Fuzzy BWM)	0.322	0.131	0.131	0.093	0.073	0.093	0.077	0.080
Scenario 1 - Equal weighting	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
Scenario 2- Ignore distance criteria (C4-C6)	0.435	0.177	0.177	-	-	-	0.104	0.108
Scenario 3- Ignore distance to rivers/lakes criteria (C7, C8)	0.382	0.155	0.155	0.110	0.087	0.110	-	-

The results of this analysis are presented in detail in Fig. 9. The most straightforward method, equal weighting (Scenario 1), which allows avoidance of risks and disregards the relative importance already known, yielded the lowest percentage of “very high suitable” areas (206.26 km^2, 0.3%). Because the weight of the solar radiation criterion is significantly reduced in Scenario 1, it helps us observe the impact of this criterion. In this scenario, while the percentage of “highly suitable” areas decreases by approximately 10% compared with the current situation, the area covered by “moderate suitable” areas increases by 10%. In Scenario 2, when distances to transmission lines, residential areas, and main roads are disregarded, the percentage of “very high suitable” areas increases to 1.3% (543.76 km^2). In Scenario 3, when distance to the lakes and rivers criteria are excluded, the percentage of "high suitable" areas rises to 1.8% (718.56 km^2).

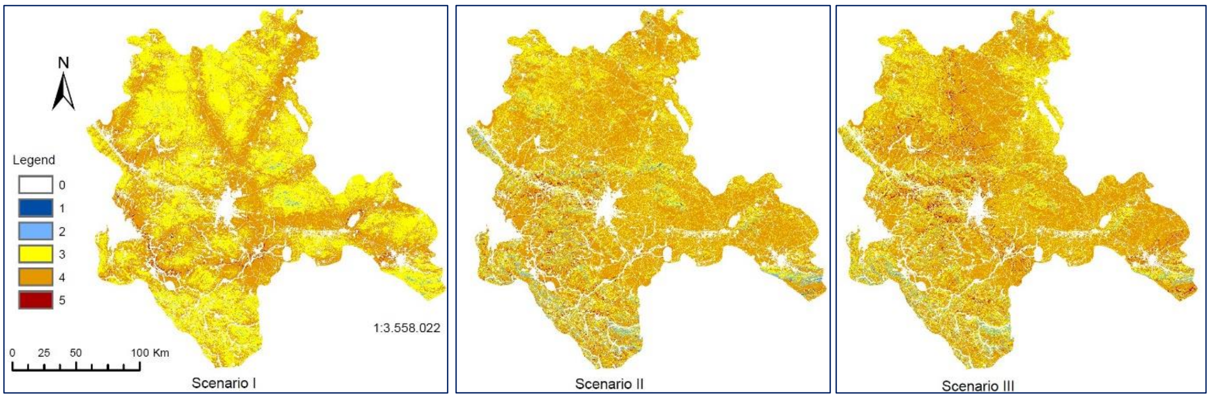

Figure 9. Sensitivity analysis results considering scenarios.

4. Discussion

The findings of this study highlight the significant potential of Konya for solar PV power plant deployment. By integrating fuzzy BWM with GIS-based suitability mapping, the research provides a systematic framework for selecting optimal solar energy sites. The analysis revealed that approximately 50.02% of the study area is classified as highly suitable, while 137.03 square kilometers (0.3%) of the region is considered very highly suitable, emphasizing the region's viability for large-scale solar investments. The methodology effectively addresses uncertainties in decision-making by incorporating expert judgments and spatial data, ensuring a comprehensive evaluation of site suitability.

From a policy and industry perspective, the findings offer valuable insights for decision-makers, urban planners, and investors in the renewable energy sector. Policymakers can leverage this study to design incentive programs for solar energy investments, streamline land-use regulations, and develop infrastructure in high-suitability zones. Energy stakeholders can use this framework to minimize project risks, optimize investment strategies, and accelerate the integration of solar energy into Türkiye's energy mix.

5. Conclusions

The increasing global demand for sustainable energy has accelerated the need for systematic site selection methodologies for solar power projects. This study introduced a fuzzy BWM-GIS framework to identify optimal locations for solar PV installations in Konya, Türkiye. By integrating MCDM techniques with geospatial analysis, this research ensures a comprehensive and adaptable approach for renewable energy site selection.

A key contribution of this study is the incorporation of neutral decision-making in the fuzzy BWM process, which balances optimistic and pessimistic biases in expert evaluations. Additionally, the study employs a customized set of eight criteria, tailored to Konya's geographical and environmental conditions. Furthermore, the use of sensitivity analysis enhances the robustness of the decision-making process, demonstrating the model's applicability across different regions and scenarios.

Despite its strengths, this study has some limitations that should be addressed in future research. The accuracy of the site suitability analysis is highly dependent on the quality and availability of geospatial data, which may impact the precision of the results. Incorporating real-time solar radiation data and economic feasibility analysis could enhance the decision-making process by providing more dynamic and financially viable site recommendations. Additionally, while this study offers a structured methodological foundation, further research should integrate financial cost-benefit analysis to assess the economic viability of solar PV deployment.

Overall, this research contributes to both academic literature and practical applications, offering a reliable decision-support tool for advancing renewable energy planning in Türkiye and beyond. By systematically addressing site selection complexities, this study aligns with Türkiye's National Energy Plan, reinforcing efforts to enhance sustainability and energy security in the transition toward a low-carbon future.

Author's Contributions

Ömer Öztaş: Drafted and wrote the manuscript, performed the experiment and result analysis.

Bilal Ervural: Assisted in analytical analysis of the structure, supervised the experiment's progress and result interpretation, and studied manuscript preparation.

Note

This study is based on the master's thesis titled 'A GIS Based Hybrid Approach for Solar PV Power Plant Site Selection' conducted by Ömer Öztaş at Necmettin Erbakan University, Institute of Science and Technology, Department of Industrial Engineering, under the supervision of Dr. Bilal Ervural.

Ethics

There are no ethical issues after the publication of this manuscript.

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