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Mapping solar energy potential in the mining sector: A hybrid Fuzzy-AHP approach in South Khorasan Province, Iran

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ABSTRACT

This study presents a comprehensive framework for Solar Energy Potential Mapping (SEPM) and optimal site selection for photovoltaic (PV) power plants in the mining regions of South Khorasan Province, Iran. A hybrid approach was developed by integrating Geographic Information System (GIS) analysis with Fuzzy Analytic Hierarchy Process (FAHP) and fuzzy overlay techniques. The assessment incorporates multiple spatial criteria, including climatic, topographic, environmental, and infrastructural factors. The results indicate that climatic variables, particularly PVOUT, are the primary drivers of solar suitability. Comparative analysis shows that while the fuzzy overlay model identifies broad potential zones, the FAHP model provides a more constrained suitability pattern. By synthesizing these methods through a Coupled-SEPM (C-SEPM) approach using the fuzzy GAMMA operator, a balanced and high-precision suitability map was produced. Validation against existing PV facilities confirms the high predictive accuracy of the C-SEPM framework. Numerical results from the final C-SEPM model reveal that 23.5% of the study area falls within the “very high” suitability class, while 33.3%, 30.5%, and 12.7% are classified as “high,” “moderate”, and “low” suitability, respectively. Considering the prevalence of small- to medium-scale operations in South Khorasan’s mining sector, the identified zones are highly suitable for distributed PV systems (50 kW to 2 MW). These systems can operate in hybrid modes or supplement diesel generation, significantly reducing operational costs and fossil fuel dependence. This framework serves as a robust decision-support tool for sustainable energy transition in arid mining environments.

KEYWORDS

Solar energy, C-SEPM, South Khorasan mines, renewable energy potential, climatic criteria

I. INTRODUCTION

The growing global demand for energy, coupled with increasing concerns about greenhouse gas emissions and the depletion of fossil fuel resources, has accelerated the transition toward renewable energy systems worldwide (Yilmaz et al., 2024). Among the available renewable resources, solar energy has emerged as one of the most promising options due to its abundance, environmental compatibility, and rapidly declining technological costs. Solar PV systems, in particular, provide a scalable and clean solution for electricity generation, especially in regions characterized by high solar irradiation and extensive open land. However, the effective deployment of solar energy infrastructure depends not only on the availability of solar resources but also on the careful identification of suitable locations that satisfy environmental, technical, and infrastructural constraints.

Site selection for solar power plants is inherently a complex spatial decision-making problem influenced by multiple factors, including solar radiation, topography, land use, environmental restrictions, and accessibility to infrastructure such as transportation networks and power transmission lines (Almasad et al., 2023). To address this complexity, GIS have become an essential tool for renewable energy planning, enabling the integration and spatial analysis of diverse datasets. Within GIS-based frameworks, Multi-Criteria Decision Analysis (MCDA) techniques are widely used to evaluate and prioritize different suitability criteria. Among these methods, fuzzy logic and the FAHP have proven particularly valuable because they allow the incorporation of expert knowledge while accounting for uncertainties inherent in spatial data and decision-making processes (Drozd & Kussul, 2024; Yilmaz et al., 2024). Compared with conventional overlay approaches,

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hybrid fuzzy–MCDA models provide more realistic representations of gradual suitability transitions and improve the reliability of spatial suitability assessments.

Iran possesses considerable solar energy potential due to its geographical location within the global sunbelt. The country experiences approximately 300 sunny days per year and has an estimated technical solar potential of about 14.7 TWe (Najafi et al., 2015). Consequently, solar energy has been recognized as a key component of Iran's long-term strategy for enhancing energy security and reducing environmental impacts associated with fossil fuel consumption (Mazandarani et al., 2010). Several studies have explored solar energy potential and site selection across different regions of Iran using GIS-based approaches. For instance, Alamdari et al. (2013) and Noorollahi et al. (2016) conducted spatial assessments of solar radiation and identified eastern Iran as one of the most promising regions for photovoltaic development. Similarly, Najafi et al. (2015) and Fathi and Lavasani (2017) highlighted the growing role of small-scale solar projects in improving regional electricity supply in the Khorasan region. Nadizadeh et al. (2019) also applied a risk-based spatial framework combining the Analytic Hierarchy Process (AHP) and Ordered Weighted Averaging (OWA) methods to identify suitable areas for solar power plants in eastern Iran, reporting that nearly 28% of the studied region falls within suitable or highly suitable classes.

South Khorasan Province, located in eastern Iran, represents one of the most favorable regions of the country for solar energy development. The province is characterized by an arid to semi-arid climate, low cloud cover, and more than 300 sunny days annually, with an average solar radiation of approximately 6.3 kWh/m^2/day (Mohamadi et al., 2021; Hosseini et al., 2024). In addition to its significant solar resource potential, South Khorasan hosts numerous mining activities that play a critical role in the regional economy. Mining operations often require reliable and continuous electricity supply for activities such as extraction, crushing, pumping, and material processing. However, many mines are located in remote areas where access to conventional electricity infrastructure is limited or associated with high operational costs. In such contexts, solar energy can provide a sustainable and cost-effective alternative for decentralized power generation.

Despite the favorable solar conditions and the economic importance of mining activities in South Khorasan, research specifically addressing the integration of solar energy within the mining sector remains limited. Most previous studies have focused on general land-use suitability or regional solar resource assessments without considering the unique spatial and infrastructural characteristics of mining areas. Mining sites differ from conventional land-use contexts because they often involve remote locations, specific operational energy demands, and logistical constraints related to transportation and infrastructure access. Therefore, dedicated spatial decision-support frameworks are required to evaluate solar energy potential in mining environments more effectively.

From a methodological perspective, combining fuzzy logic with multi-criteria decision-making methods such as FAHP offers significant advantages for addressing the uncertainties associated with spatial decision problems. Fuzzy approaches allow the representation of gradual transitions in environmental suitability, while FAHP improves the reliability of criterion weighting by incorporating expert judgment within a structured analytical framework. Integrating these techniques within a GIS environment enables the development of robust spatial models capable of supporting strategic energy planning in complex industrial landscapes.

Accordingly, the objective of this study is to develop a comprehensive spatial framework for mapping and evaluating solar energy potential in the mining areas of South Khorasan Province using a hybrid GIS–FAHP approach referred to as the C SEPM method. The novelty of this research lies in its specific focus on mining environments and in the integration of fuzzy spatial analysis with FAHP-based weighting to simultaneously evaluate solar resource availability and the practical feasibility of photovoltaic deployment in remote mining areas. By identifying high-potential locations for solar power generation, the proposed framework aims to support sustainable mining operations, improve regional energy security, and contribute to environmentally responsible resource development. Moreover, the methodology presented in this study can be adapted to other arid and semi-arid mining regions facing similar infrastructural and energy challenges.

II. MATERIALS AND METHODS

A. *Study Area*

South Khorasan Province is located in eastern Iran, bordering Afghanistan to the east and Yazd and Kerman provinces to the south and west. The province plays an important role in Iran's economy and mining industry due to its rich mineral reserves, including iron ore, copper, gold, lead, zinc, bentonite, and coal, as well as extensive mining activities (Hosseini et al., 2024; Saeedi et al., 2011). The mining sector in South Khorasan is also known for its high energy consumption. Most mining operations are heavily dependent on fossil fuels to power machinery, extract and process minerals, and transport. This dependence not only increases operating costs, but also increases greenhouse gas emissions and environmental degradation.

South Khorasan Province has an arid and semi-arid climate, and the annual solar radiation in this region ranges from 1547 to 2016 kWh/m2 (Fig. 1), indicating the high potential of solar energy to meet the energy needs of mines and develop photovoltaic power plants in this province.

South Khorasan Province stands as a pivotal mining hub in Iran, possessing a rich and diverse mineral portfolio. The region hosts over 870 mining sites (both active and inactive) and extracts 58 distinct mineral types, including copper, gold, decorative building stones, bentonite, and coal. This sector serves as a critical engine for both national industrial production and local socio-economic development. According to the 2024 national statistical data, there are 6,670 active mining operations across Iran, with South Khorasan ranking 7th nationwide, contributing 319 active mines to this total (Fig. 2).

The geographical distribution of these operations, depicted in Fig. 3, reveals a dispersed mining landscape primarily composed of small- to medium-scale enterprises. While these operations vary in production capacity, their collective energy requirement is significant. Fig. 4 delineates the current energy consumption profile, highlighting a heavy reliance on conventional on-site power plants powered by diesel generators, which account for 28,299 thousand kWh of electricity, compared to a negligible 9 thousand kWh contribution from solar power (Statistical Center of Iran, 2024). The remaining electricity demand for mining activities in South Khorasan province is supplied by the national power grid. This critical data underscores a substantial energy gap in the region. Given the dispersed nature of these small-to-medium-scale mines, the economic justification for solar deployment is rooted in the transition toward decentralized, modular photovoltaic systems. Such systems offer a viable, scalable alternative to costly grid connectivity and emission-intensive fossil-fuel generation, making solar energy both a technically feasible and economically attractive solution for the diverse mining landscape of South Khorasan.

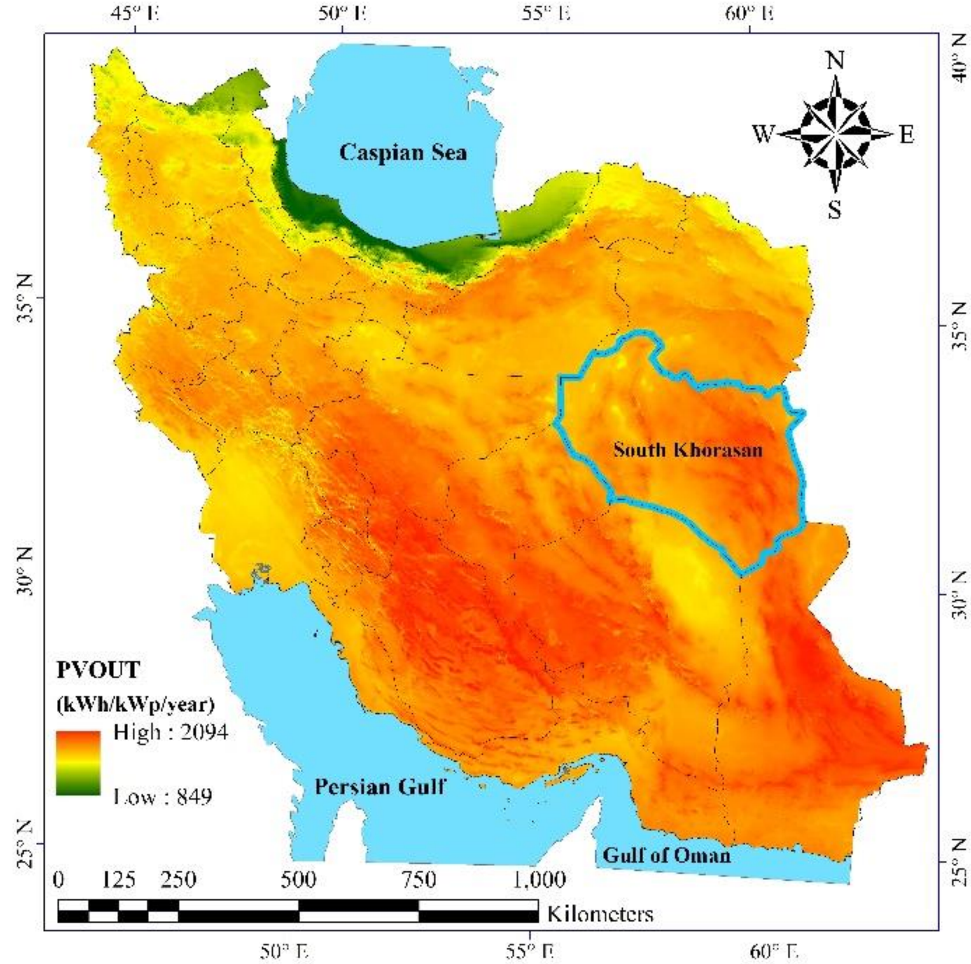


Fig. 1. Annual photovoltaic energy potential in South Khorasan Province based on long-term average data from the World Bank Solar Atlas (Source: ESMAP, 2026)

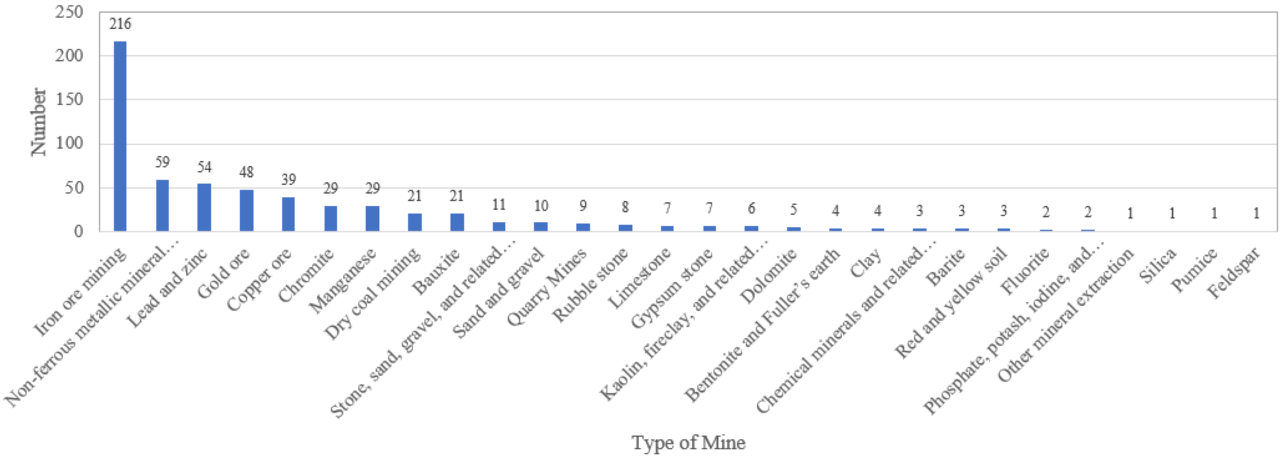


Fig. 2. Number of Operating Mines in South Khorasan Province (Statistical Center of Iran, 2024).

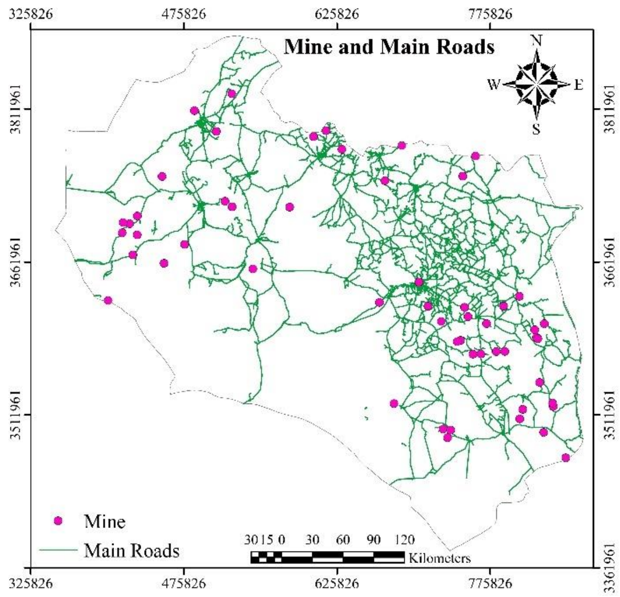


Fig. 3. Geographical distribution of mines and the main road network in South Khorasan Province

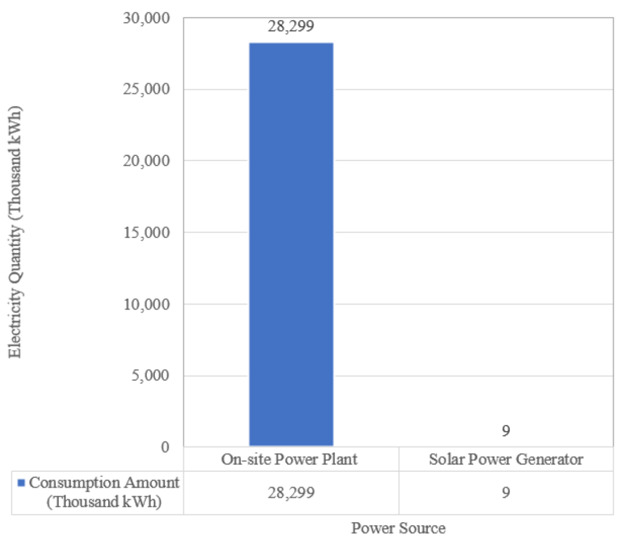


Fig. 4. Electricity Consumption: Purchased vs. On-site Generation in Operating Mines of South Khorasan Province (Statistical Center of Iran, 2024).

B. *Criteria Selection*

In this study, a comprehensive set of spatial and environmental data was integrated to analyze the solar energy potential for the mining sector of South Khorasan Province. The dataset comprises:

- Topographic layers: slope, aspect, and elevation.
- Location layers: distance to mines, existing roads, and power transmission lines.
- Environmental layers: distance to protected wildlife areas, land use/land cover (LULC), and drainage lines.
- Climatic layers: Annual photovoltaic energy output (PVOUT), average annual temperature, and precipitation.

The selection of these spatial criteria was informed by a synthesis of international literature on arid environments, technical standards from the Renewable Energy and Energy Efficiency Organization of Iran (SATBA), and the specific socio-economic requirements of South Khorasan's mining sector. While additional parameters such as Aerosol Optical Depth (AOD) or seismic risk could potentially influence site suitability, this framework prioritizes the most decisive climatic, topographic, and infrastructural factors governing the feasibility of distributed PV systems. The inclusion of further localized indicators remains a possibility for future high-resolution, site-specific investigations.

1) *Slope*

Slope is a key topographic parameter that strongly influences the technical and economic feasibility of solar energy installations. Steep terrains increase construction difficulty, mounting constraints, and grid-connection costs, whereas flat or gently sloping areas allow easier site preparation, stable foundation installation, and efficient panel deployment. Previous studies have consistently shown an inverse relationship between slope and suitability for solar energy development (Hernandez et al., 2024; Li et al., 2025).

2) *Slope Aspect*

Slope aspect is an important topographic factor in solar energy potential assessment because it controls the amount and duration of solar radiation received by the surface, directly affecting the performance of PV systems. Proper orientation relative to the sun's path is therefore essential for maximizing energy production and improving the economic feasibility of solar power plants (Hernandez et al., 2024; Li et al., 2025).

In the Northern Hemisphere, slopes facing south, southwest, and west generally receive higher solar irradiance, while flat surfaces provide uniform exposure and greater flexibility for solar infrastructure layout (IRENA, 2023; Zhang et al., 2024).

3) *Elevation*

Elevation is a key topographic factor affecting microclimatic conditions, air density, accessibility, construction difficulty, and the overall performance of solar energy systems. Recent studies show that lower elevations are generally more suitable for renewable energy development—especially in arid and resource-rich regions—because they offer easier access, simpler construction requirements, and lower installation and maintenance costs (IRENA, 2023; Li et al., 2024).

4) *Distance to Mine*

Proximity to mining sites is an important spatial and operational factor in solar energy potential assessment, as locating solar power plants near mines can reduce energy supply costs, support on-site power generation, and promote low-carbon and sustainable mining practices. Previous studies highlight that co-locating solar facilities with mining operations—especially in remote areas—improves energy security and reduces dependence on fossil fuels (Sovacool et al., 2023; World Bank, 2024).

In South Khorasan Province, mining activities are widely distributed, with higher concentrations in the eastern, southeastern, and central regions. Accessibility to supporting infrastructure, particularly main roads, plays a key role in operational feasibility by influencing transportation, construction, and maintenance costs. Mines located farther from the road network, mainly in the western and southwestern parts of the province, face greater development and energy supply challenges.

5) *Distance to Main Road*

Proximity to the main road network is a key spatial and accessibility factor influencing the suitability of sites for solar energy development. Efficient transportation infrastructure reduces equipment and material transport costs, simplifies logistics, and supports reliable long-term operations and maintenance (Charabi & Gastli, 2011; Al-Yahyai et al., 2012; Tegou et al., 2010).

In South Khorasan Province, major roads are concentrated in the central and eastern regions, coinciding with economic centers and transit corridors, while the western and southwestern areas have sparse networks that limit accessibility and increase project costs. Proximity to main roads improves logistics for transporting PV modules, construction materials, maintenance personnel, and even mined resources or generated electricity, making these areas more suitable for solar energy facilities (Mehrjerdi & Zandieh, 2020; Uyan, 2013).

6) *Distance to Transmission Lines*

Proximity to high-voltage transmission lines is a critical infrastructure factor in solar energy site selection because it directly influences grid-connection costs, transmission losses, and overall project feasibility. In large-scale renewable energy projects, constructing new substations and extending transmission networks can represent a substantial portion of total investment, particularly in remote regions. Therefore, sites located closer to existing transmission lines generally offer higher technical and economic viability (Uyan, 2013; Sánchez-Lozano et al., 2013; Noorollahi et al., 2016).

In South Khorasan Province, the transmission network is mainly concentrated in the central, eastern, and northeastern corridors, which correspond to major population and economic centers. This distribution creates advantages for mines located near transmission infrastructure, enabling efficient grid connection or direct electricity supply from solar power systems. Conversely, remote mining areas with limited grid access may require costly network expansion or decentralized renewable systems such as PV–diesel or PV–storage configurations.

7) *Distance to Wildlife Area*

Proximity to wildlife protected areas is an important environmental criterion in evaluating the suitability of locations for renewable energy development. Constructing solar or wind facilities near ecologically sensitive zones can cause habitat fragmentation, wildlife disturbance, and ecological imbalance. Therefore, maintaining adequate buffer distances from protected areas is essential to minimize environmental impacts and comply with conservation regulations (Tsoutsos et al., 2005; Hernandez et al., 2014).

In South Khorasan Province, wildlife protected areas are mainly located in the western and southwestern regions. These zones impose strict environmental and legal constraints on both mining and renewable energy projects, often functioning as exclusion areas where large-scale infrastructure such as solar farms, wind turbines, roads, and substations cannot be developed.

8) *Distance to Drainage Lines*

Distance from drainage networks and water flow lines is an important environmental and hydrological factor in assessing solar and wind energy potential. Locating renewable energy infrastructure too close to waterways may increase risks such as flooding, soil erosion, water contamination, and land instability, particularly in arid and semi-arid regions like South Khorasan Province. Therefore, establishing protective buffer zones around hydrographic features is necessary to reduce environmental impacts and ensure sustainable project development (Li et al., 2024; Zhang et al., 2023).

In South Khorasan, the hydrographic network is denser in the eastern and central highlands, where steep slopes and greater surface runoff increase the likelihood of erosion and flash flooding. These conditions make such areas less suitable for large-scale infrastructure development. In contrast, the western, southwestern, and parts of the central plains have more dispersed drainage patterns and gentler terrain, offering more stable conditions for renewable energy projects.

9) *Land use / Land cover*

Land use and land cover are key environmental and spatial factors in evaluating renewable energy potential, as they directly affect installation feasibility, environmental impact, and land-use compatibility. In general, barren land, deserts, and wastelands are the most suitable areas for solar and wind projects because they have low ecological sensitivity and minimal conflict with agricultural or residential uses. In contrast, agricultural land, water bodies, and protected areas often limit or restrict development (IRENA, 2023; Sovacool et al., 2024).

For South Khorasan Province, the LULC map was generated using satellite imagery and existing land cover datasets in ArcGIS. The region's predominantly arid to semi-arid conditions result in extensive natural and sparsely populated land cover types.

10) *Annual Precipitation Amount*

Annual precipitation is an important climatic factor in evaluating solar energy potential because it is inversely related to solar radiation availability and PV system performance. Higher precipitation reduces direct sunlight, increases humidity, and leads to dust or debris accumulation on panels, all of which lower energy output (IRENA, 2023; Li et al., 2025).

Arid and semi-arid regions with low rainfall generally provide more favorable conditions for solar energy generation due to higher insolation and fewer cloudy days. Incorporating precipitation into site-selection analyses therefore enhances both the efficiency and economic viability of solar installations (Hernandez et al., 2024; Sovacool et al., 2024).

In this study, the annual precipitation layer was created using data from meteorological stations and satellite-based products such as CHIRPS within ArcGIS. The results show that South Khorasan Province experiences predominantly arid to semi-arid conditions, with annual precipitation ranging from about 59.4 to 375.9 mm. Higher rainfall occurs mainly in the eastern and northeastern mountains due to elevation and orographic effects, while the central, western, and southwestern regions receive much less precipitation.

11) *Mean Annual Air Temperature*

Mean annual air temperature is an important climatic factor in evaluating solar energy potential because it influences the efficiency and performance of PV systems. Extremely high temperatures can reduce PV efficiency, while moderate temperature ranges generally support more stable solar power generation (IRENA, 2023; Li et al., 2025). Considering temperature conditions in site selection can therefore improve both energy yield and project feasibility (Hernandez et al., 2024; Sovacool et al., 2024).

In this study, a mean annual air temperature layer was generated using meteorological station records and satellite data within the ArcGIS environment. Across South Khorasan Province, temperatures range from about 9.65 °C to 28.85 °C, with spatial variations largely controlled by elevation and topography. Cooler conditions occur mainly in the eastern and northeastern mountainous areas, whereas the central, western, and southwestern plains experience higher average temperatures.

12) *PVOUT*

PVOUT is a key climatic indicator for evaluating solar energy potential because it directly quantifies the expected electricity generation of PV systems at a given location. PVOUT integrates the effects of solar radiation, geographic setting, and local climate, and is therefore considered the most important criterion for assessing the technical and economic performance of solar projects (IRENA, 2023; Li et al., 2025; Hernandez et al., 2024; Sovacool et al., 2024). In this study, PVOUT received the highest weight (0.275) in the FAHP analysis.

The PVOUT layer was derived from monthly and annual solar radiation data provided by the Global Solar Atlas (GSA) and simulations from the PVGIS model, and then processed in ArcGIS for spatial analysis. Across South Khorasan Province, PVOUT ranges from about 1546.83 to 2016.18 kWh/kWp/year, indicating generally high potential for solar power generation. The highest values are mainly located in the central, southern, and southeastern parts of the province, while lower values occur in the northern and northwestern areas.

C. Theoretical Background

In solar energy potential studies, selecting an optimal site requires the analysis of multiple spatial layers related to climate, topography, environmental constraints, and infrastructure. GIS plays a central role in collecting, managing, processing, and analyzing these spatial datasets, enabling researchers to integrate heterogeneous information and produce spatial suitability maps for renewable energy planning (Yilmaz, Kocer & Aksoy, 2024). By combining geospatial data with analytical models, GIS provides a robust platform for evaluating solar resource availability and identifying locations suitable for PV power plant development.

Various analytical methods have been developed to integrate spatial information layers within the GIS environment. One of the most basic approaches is the Simple Overlay method, in which different thematic layers are combined directly. In this approach, each layer is typically represented as a binary or categorical variable, and areas that satisfy predefined conditions are identified as suitable. Although this method is computationally efficient and easy to implement, it lacks the capability to account for uncertainty or gradual variations in suitability and therefore may oversimplify complex spatial relationships (Drozd & Kussul, 2024).

To overcome these limitations, the Weighted Overlay method has been widely used in GIS-based site selection studies. In this method, each spatial criterion is assigned a weight based on its relative importance, and all standardized layers are combined to produce a final suitability index. This approach allows researchers to quantify the influence of each factor and evaluate the relative contribution of climatic, environmental, and infrastructural parameters to solar energy development. Weighted overlay analysis is particularly useful when working with quantitative datasets such as solar radiation, slope, or distance to infrastructure (Almasad et al., 2023).

Another widely applied approach in spatial energy analysis is Fuzzy Logic and Fuzzy Overlay modeling. Fuzzy methods are designed to address uncertainty and ambiguity in environmental data by representing suitability as a continuous spectrum rather than a strict binary classification. In this framework, each criterion is transformed into a fuzzy membership function with values ranging from 0 to 1, where higher values indicate greater suitability. Different fuzzy operators are then used to combine the membership layers and generate a composite suitability surface. Compared with conventional overlay methods, fuzzy modeling better reflects the gradual transitions that occur in natural systems and produces more realistic spatial suitability patterns (Gökler, 2025; Noorollahi et al., 2022).

In addition to fuzzy modeling, MCDA techniques are frequently integrated with GIS to support complex spatial decision-making processes. MCDA methods allow multiple criteria to be evaluated simultaneously while incorporating expert judgment in the weighting process. Among these techniques, the AHP and its extension, the FAHP, are widely used in renewable energy planning. FAHP improves the conventional AHP approach by incorporating fuzzy numbers into pairwise comparisons, which allows uncertainty in expert evaluations to be represented more realistically. As a result, FAHP provides more reliable criterion weights and enhances the robustness of site-selection models (Yilmaz et al., 2024; Drozd & Kussul, 2024).

Recent studies on solar energy planning increasingly emphasize integrating GIS with fuzzy logic and FAHP-based MCDA frameworks. Such hybrid approaches enable researchers to simultaneously consider climatic variables (such as solar radiation, temperature, and precipitation), topographic characteristics (elevation, slope, and aspect), environmental constraints (land use, wildlife habitats, and water resources), and infrastructural accessibility (roads, transmission lines, and industrial facilities). By integrating these diverse datasets into a unified spatial model, GIS-based MCDA methods provide a powerful decision-support tool for identifying optimal locations for PV power plants (Hosseini et al., 2024; Chiarani et al., 2023).

In the context of mining regions, this type of integrated analysis is particularly valuable. Mining operations often occur in remote areas where energy infrastructure is limited and operational costs are high. Evaluating solar energy potential using spatial decision models can therefore support the development of alternative energy strategies that enhance energy security and reduce dependence on fossil fuels. By combining GIS, fuzzy overlay analysis, and the FAHP method within the C-SEPM framework, it becomes possible to manage complex spatial datasets, address uncertainty in environmental conditions, and generate reliable solar suitability maps for PV power plant deployment in the mining areas of South Khorasan Province.

1) *FAHP Method*

The synergy of Remote Sensing (RS) and GIS has become an indispensable tool in modern resource management, with significant applications in hydrological and hydrogeological studies for resource evaluation and exploration. Extending this capability to renewable energy, particularly solar energy potential mapping, involves integrating diverse thematic datasets to construct robust suitability assessments. A crucial precursor to this spatial integration is the rigorous determination of the relative significance of various influencing factors. The FAHP stands out as a powerful technique for this purpose, adeptly handling the inherent uncertainties and vagueness associated with decision-making. By allowing decision-makers to articulate preferences using fuzzy numbers rather than precise values, FAHP provides a more realistic and reliable evaluation framework (Yilmaz et al., 2024; Gökler, 2025).

This research adopts the FAHP methodology as proposed by Chang (1996), renowned for its straightforward implementation in calculating criterion weights via pairwise comparisons, often favored over more complex FAHP variants (Kahraman et al., 2006; Chaudhry et al., 2021). Within this framework, triangular fuzzy numbers are utilized for pairwise comparisons of the identified criteria, leading to the establishment of a fuzzy pairwise comparison matrix. Subsequently, the fuzzy synthetic extent, is calculated for each row of this matrix, as detailed in Eq. (1):

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} \tag{1}$$

where *i* represents the row number, and j denotes the column number. In this equation, M_{gi}^{j} are the triangular fuzzy numbers in the pairwise comparison matrix.

To calculate $\sum_{j=1}^{m} M_{gj}^{j}$, the fuzzy addition $M_{gi}^{j}\left(j=1,2,\ldots,m\right)$ is done using Eq. 2.

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j , \sum_{j=1}^{m} m_j , \sum_{j=1}^{m} u_j \right) \quad (2)$$

Then, the reverse of Eq. 2 was obtained using the following formula:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \quad (3)$$

$$V(M_2 \geq M_1) = \begin{cases} 1 & if\ m_2 \geq m_1 \\ 0 & if\ l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} & otherwise \end{cases} \quad (4)$$

Where l_i, m_i and u_i are the first to third components of fuzzy numbers, respectively.

The degree of possibility (V) of two fuzzy numbers $M_1 = (l_{1,}, m_1, u_1)$ and $M_2 = (l_{2,}, m_2, u_2)$ was calculated as follows:

The weights of the criteria were calculated using Eq. 5.

$$d'(A_i) = \min V(S_i \geq S_k) \qquad k = 1, 2, \cdots, n \quad , \quad k \neq i \quad (5)$$

Therefore, the weight vector can be given by Eq. 6:

$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_n))^T \quad (6)$$

Finally, via the normalization process, the normalized non-fuzzy W is computed as Eq. 7:

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \quad (7)$$

This FAHP framework allows for robust and reliable weighting of the criteria, facilitating the integration of GIS layers for producing solar energy potential maps in mining areas. The method effectively manages expert judgment uncertainty and provides a scientifically defensible basis for site selection, especially in remote and infrastructure-limited regions such as the mines of South Khorasan Province (Noorollahi et al., 2022; Chiarani et al., 2023).

2) *Fuzzy Overlay*

The Fuzzy Overlay method is a sophisticated technique within GIS for the integration and classification of diverse spatial datasets, representing a significant advancement in data layer combination. This approach facilitates the probabilistic assessment of a location's membership across various suitability categories, offering a robust mechanism for managing inherent spatial data uncertainty (Tirpáková et al., 2021; Safari et al., 2023).

This methodology involves assigning weights to disparate GIS layers, reflecting their comparative significance. These weights are typically derived from expert insights, thereby embedding specialized knowledge directly into the analytical process. It proves particularly effective for spatial potential evaluations, such as in assessing solar energy viability, where a simultaneous consideration of numerous environmental, topographical, climatic, and infrastructural variables is essential.

The operational core of fuzzy overlay relies on fuzzy logic operators to aggregate layers based on their calculated membership values. Key operators commonly employed include:

- Fuzzy AND (Intersection): Prioritizes areas where all contributing factors exhibit high membership simultaneously.
- Fuzzy OR (Union): Identifies locations demonstrating favorable conditions in at least one of the input criteria.
- Fuzzy Algebraic Product (PRODUCT): Achieves layer integration through multiplicative calculations.
- Fuzzy Algebraic Sum (SUM): Combines membership values using an additive approach.
- Fuzzy GAMMA Operator (GAMMA): A hybrid operator that reconciles the outcomes of AND and SUM operations, frequently enhancing the precision of suitability assessments (An et al., 1991; Bonham-Carter, 1994).

The selection of an optimal fuzzy operator is contingent upon the specific attributes of the data layers and the analyst's domain expertise. Notably, studies in environmental and resource evaluation have frequently indicated that the GAMMA operator yields a more balanced and accurate spatial suitability estimation(Malczewski, 1999).

When applied to mapping solar energy potential in mining regions, the fuzzy overlay technique consolidates layers pertaining to topography, environment, climate, and infrastructure into a unified suitability map. This process effectively encapsulates the cumulative impact of multiple criteria while mitigating the uncertainties linked to individual factors (Jasmin & Mallikarjuna, 2011). The method involves transforming vector GIS data into raster grids, assigning a membership value to each cell, which streamlines multicriteria spatial analysis and subsequent visualization.

D. Research Framework

Fig. 5 illustrates the overall research framework and methodology adopted in this study. The proposed approach integrates Fuzzy Overlay and Fuzzy AHP within a GIS environment. Initially, the required input data were collected and classified into four main categories: climatic, environmental, locational, and topographic factors. The corresponding criteria included precipitation, average temperature, PVOUT, land use/land cover, protected areas, drainage lines, distance to main roads, distance to power transmission lines, distance to mines, elevation, slope, and aspect, all of which were considered as analytical layers.

In the subsequent stage, all criteria were standardized using fuzzy membership functions to account for uncertainty and variability in the input data. These layers were then integrated using logical AND and OR operators through the Fuzzy Overlay method. In parallel, the Fuzzy AHP approach was employed to determine the relative importance of the criteria. Pairwise comparisons were conducted in a fuzzy environment, and the final weights of the criteria were calculated through fuzzification and normalization procedures.

Then, all thematic layers were converted into raster format and standardized through a reclassification process based on their suitability levels. A weighted overlay analysis was then performed using raster-based calculations to generate a spatial suitability index for solar energy development. Finally, the outputs derived from the Fuzzy Overlay and Fuzzy AHP models were integrated within the C-SEPM framework to produce the final solar energy potential map for the mining areas of South Khorasan Province.

Finally, the results of the proposed models were evaluated and validated to assess their accuracy and effectiveness. This integrated and step-by-step framework enables effective management of data uncertainty, incorporation of expert knowledge, and generation of reliable solar energy potential maps. The outcome of this methodology is the identification of suitable areas for solar power plant development and the provision of practical decision-support information for strategic planning in the mining sector of the study area.

III. RESULTS

In this section, the outputs of the spatial suitability modeling for solar energy development in South Khorasan province are presented. The analysis initiated with the standardization and reclassification of thematic layers, followed by the application of the FAHP to determine criteria significance. These weighted layers were then integrated within a Fuzzy Overlay framework to generate the comprehensive solar energy potential map.

The results demonstrate that the incorporation of diverse spatial variables—ranging from high-resolution climatic data to infrastructural proximity—enables a precise identification of optimal zones for PV infrastructure. By leveraging this fuzzy-based approach, the model effectively manages the inherent uncertainties in spatial data, providing robust and reliable sites for energy transition in the mining sector. The following sub-sections detail the outcomes of the standardization process and the final suitability distribution across the province.

1) *Reclassification and Standardization of layers*

To ensure spatial consistency across the study, all datasets were standardized in terms of scale, coordinate system, and format. Vector-based data were converted into raster grids with a uniform spatial resolution to facilitate seamless integration within the GIS environment. Subsequently, a Fuzzy Membership approach was employed to transform each thematic layer into a continuous suitability scale ranging from 0 to 1. In this framework, a value of 1 indicates optimal suitability for PV plant installation, while 0 represents unsuitable areas or physical constraints. Depending on the nature of each criterion (e.g., cost-based or benefit-based), appropriate linear or non-linear functions were applied to ensure accurate normalization.

The feature classes within each thematic layer were weighted and normalized according to their relative importance to solar energy potential and the specific requirements of the mining sector. This weighting process was synthesized from expert judgment, a review of international literature, and localized field surveys conducted across South Khorasan Province. By integrating these diverse data sources, the methodology accounts for both the theoretical energy potential and the practical, site-specific constraints inherent in mining regions. This multi-layered approach ensures that the final model identifies sites that are not only high in solar resources but also logistically and environmentally feasible for mining-related energy projects.

2) *Slope*

To evaluate this factor, a slope map was derived from the high-resolution Digital Elevation Model (DEM) of South Khorasan Province in the GIS environment. The map reveals substantial topographic variation, from flat plains to slopes exceeding 70°, although much of the study area falls within the 0°–15° range, which is highly favorable for solar infrastructure. Within the MCDA framework, the slope layer was reclassified into suitability classes and weighted according to its influence on site selection (Fig. 6 and Fig. 7). This weighting pattern clearly prioritizes flatter areas as the most suitable locations for solar energy projects.

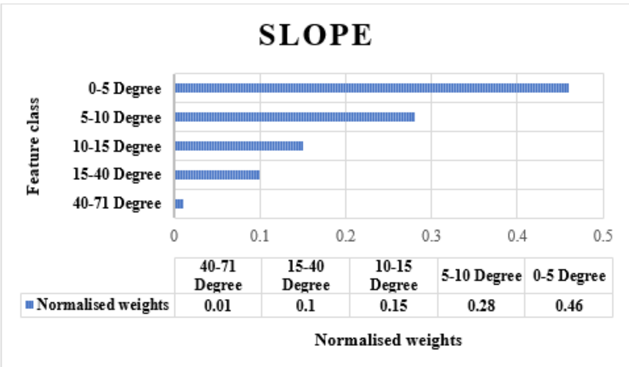


Fig. 6. Assigned normalized weights for feature class of slope

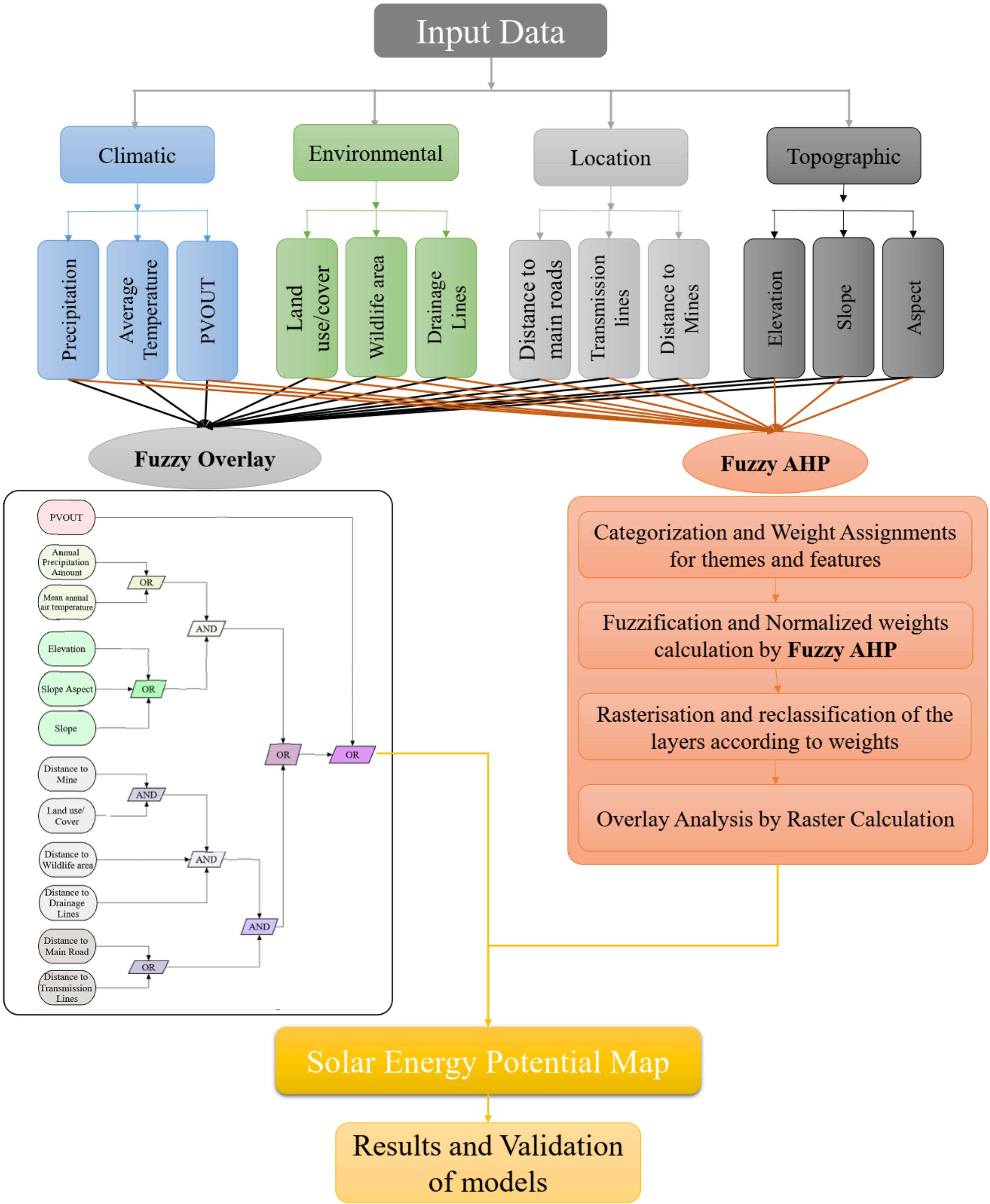


Fig. 5. Flowchart describing the applied research methodology

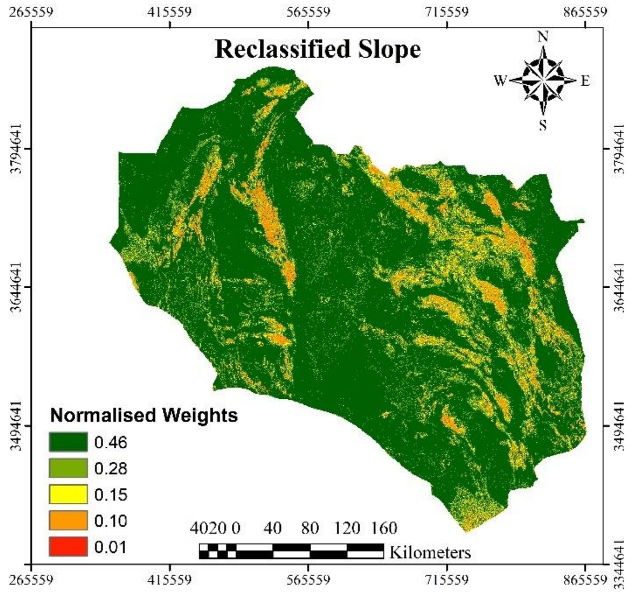


Fig 7. Reclassified and normalized of slope layer

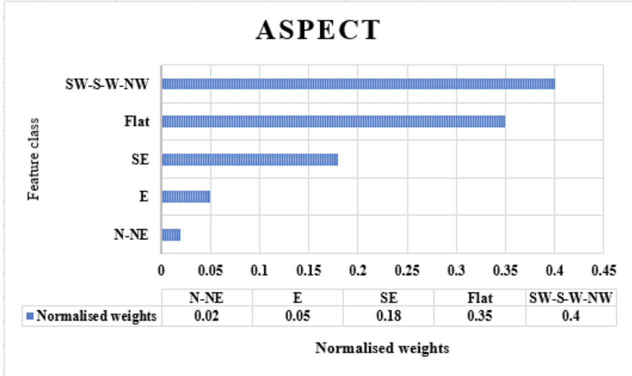


Fig. 8. Assigned normalized weights for feature class of slope aspect

3) *Slope Aspect*

Within the MCDA framework, the aspect layer was reclassified into five suitability classes and assigned normalized weights based on their solar radiation reception potential (Fig. 8 and Fig. 9). This weighting scheme prioritizes orientations that maximize solar radiation and enhances the accuracy of site selection for solar energy development.

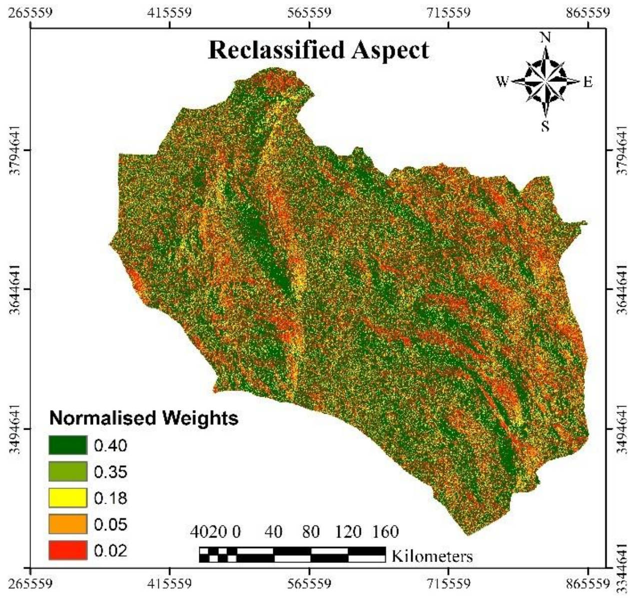


Fig. 9. Reclassified and normalized of aspect layer

4) *Elevation*

The elevation layer for South Khorasan Province was generated from the regional DEM, showing altitudes ranging from about 514 m to 2964 m. This wide elevation range reflects the province's complex terrain: medium to high elevations dominate the eastern and northeastern areas, while the western, southwestern, and central regions are mostly lower and flatter. These low-lying zones provide more favorable conditions for both mining and solar energy infrastructure due to better accessibility and reduced engineering challenges. Additionally, lower elevations often correspond to higher temperatures and potentially higher solar radiation levels, which can improve PV system performance.

Following the principle that site suitability decreases with increasing elevation due to operational and accessibility constraints, the elevation map was reclassified and normalized in ArcGIS (Fig. 10 and Fig. 11). As shown in Fig. 8, higher elevation categories were assigned lower weights, indicating their reduced suitability for solar energy development. This weighting approach aligns with established findings that low-elevation areas, when combined with favorable topographic and climatic conditions, enhance system efficiency and reduce the life-cycle costs of renewable energy projects (Zhang et al., 2023; Chen et al., 2025).

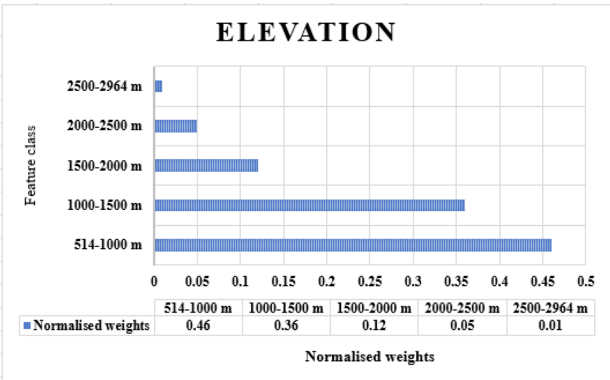


Fig. 10. Assigned normalized weights for feature class of elevation.

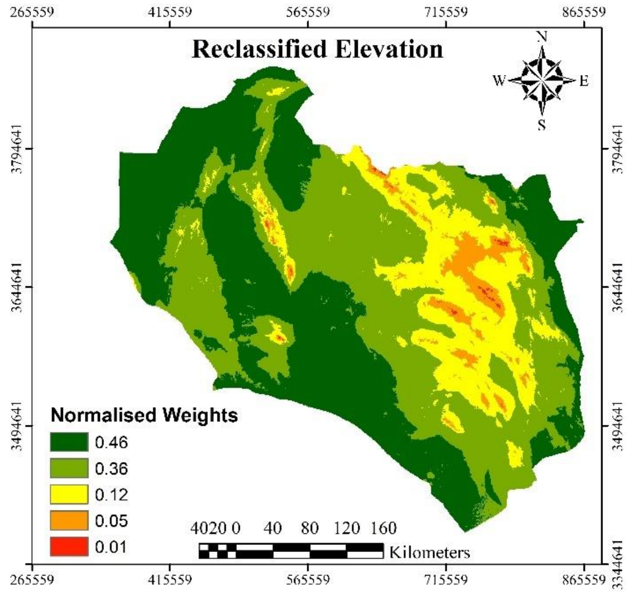


Fig. 11. Reclassified and normalized of elevation layer

5) *Distance to Mine*

The distance-to-mines layer was generated using the Buffer tool in ArcGIS and then reclassified and normalized. Suitability was assumed to decrease with increasing distance from mining sites due to higher transmission losses and infrastructure costs. Accordingly, areas closest to mines were assigned the highest suitability weight, with progressively lower weights for more distant zones (Fig. 12 and Fig. 13). This weighting scheme emphasizes the effectiveness of deploying solar energy systems near mining operations to enhance energy efficiency and reduce greenhouse gas emissions in the mining sector (Sovacool et al., 2023; Ali et al., 2024).

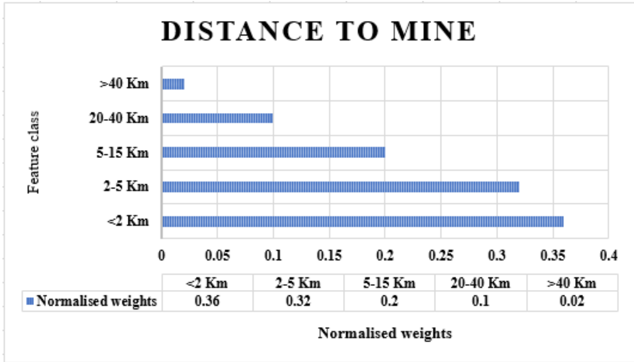
6) *Distance to Main Road*

To incorporate this criterion into spatial decision-making, the distance-to-main-roads layer was produced using the Buffer tool in ArcGIS, then reclassified and normalized based on Fig. 14 (Fig. 15). Suitability was assumed to decrease with greater distance from roads.

This weighting approach aligns with previous GIS-based MCDA studies, confirming that proximity to well-developed road networks significantly enhances the technical and economic viability of renewable energy installations (Charabi & Gastli, 2011; Al-Yahyai et al., 2012; Ramli et al., 2016; Tegou et al., 2010; Uyan, 2013).

7) *Distance to Transmission lines*

To incorporate this factor into the spatial evaluation, the distance-to-transmission-lines layer was generated using the Buffer tool in ArcGIS and then reclassified and normalized. Suitability was assumed to decrease with increasing distance from transmission lines due to higher interconnection costs and transmission losses (Fig. 16). As shown in Fig. 17, closer distances received higher weights, while more distant areas were assigned lower suitability scores. This approach is consistent with previous GIS-based MCDA studies that highlight proximity to transmission infrastructure as a key determinant of renewable energy project feasibility and grid integration.



	<2 Km	2-5 Km	5-15 Km	20-40 Km	>40 Km
Normalised weights	0.36	0.32	0.2	0.1	0.02

Fig. 12. Assigned normalized weights for feature class of distance to mine

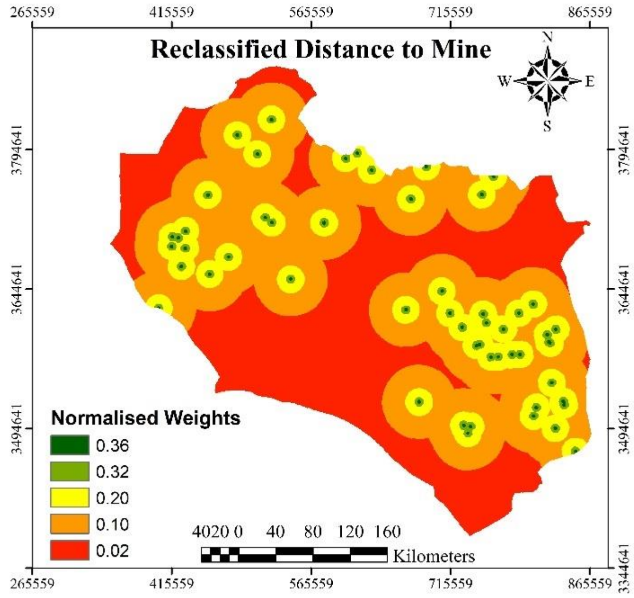
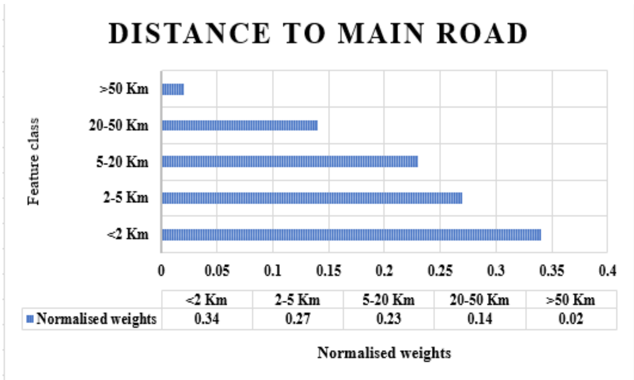


Fig. 13. Reclassified and normalized of distance to mine layer



	<2 Km	2-5 Km	5-20 Km	20-50 Km	>50 Km
Normalised weights	0.34	0.27	0.23	0.14	0.02

Fig. 14. Assigned normalized weights for feature class of distance to main road

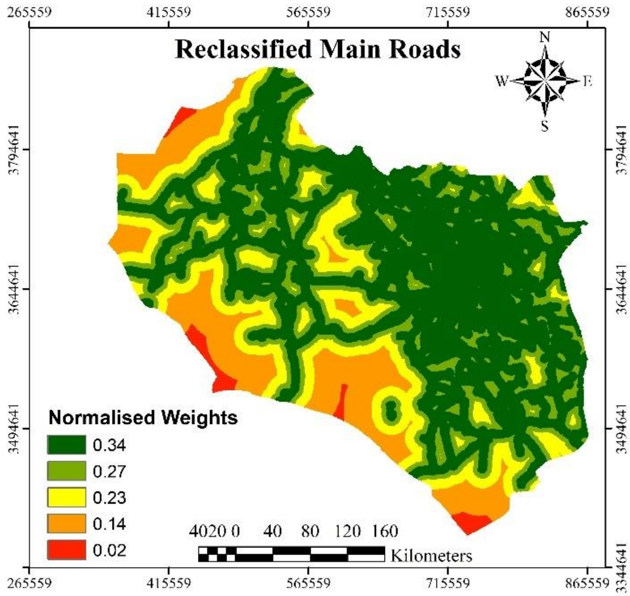


Fig. 15. Reclassified and normalized of distance to main road layer

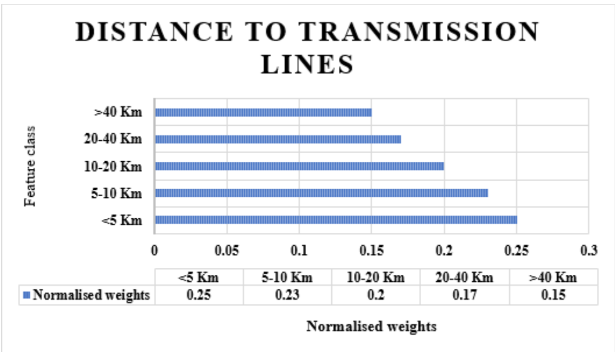


Fig. 16. Assigned normalized weights for feature class of distance to transmission lines

8) *Distance to Wildlife area*

To incorporate this environmental constraint into the spatial analysis, a "Distance from Wildlife Protected Areas" layer was generated in ArcGIS using a buffer approach, followed by reclassification and normalization. The suitability of locations was assumed to increase with greater distance from protected areas due to reduced ecological risk and regulatory limitations. Areas closest to protected zones received the lowest suitability scores, while locations farther away were assigned progressively higher weights (Fig. 18 and Fig. 19). This approach aligns with previous studies emphasizing the need to maintain sufficient ecological buffers to protect biodiversity while enabling sustainable renewable energy development (Hernandez et al., 2014; Tsoutsos et al., 2005; Al-Yahyai et al., 2012).

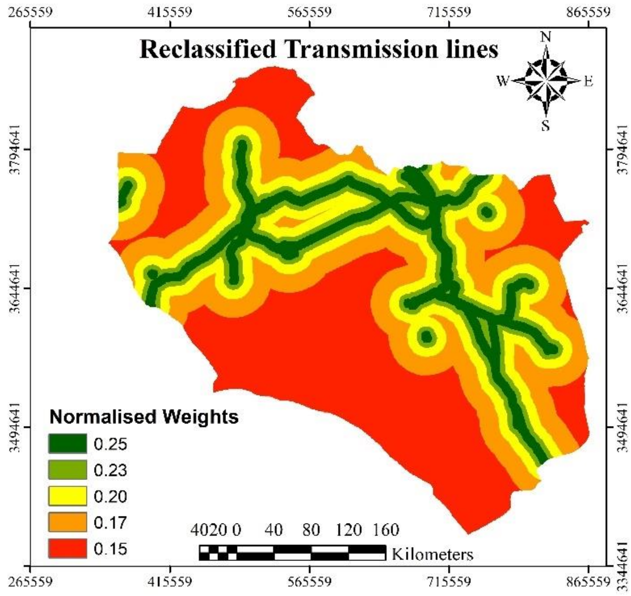


Fig. 17. Reclassified and normalized of distance to transmission lines layer

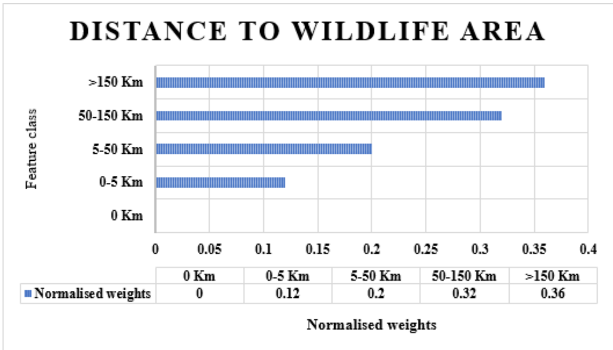


Fig. 18. Assigned normalized weights for feature class of distance to wildlife area

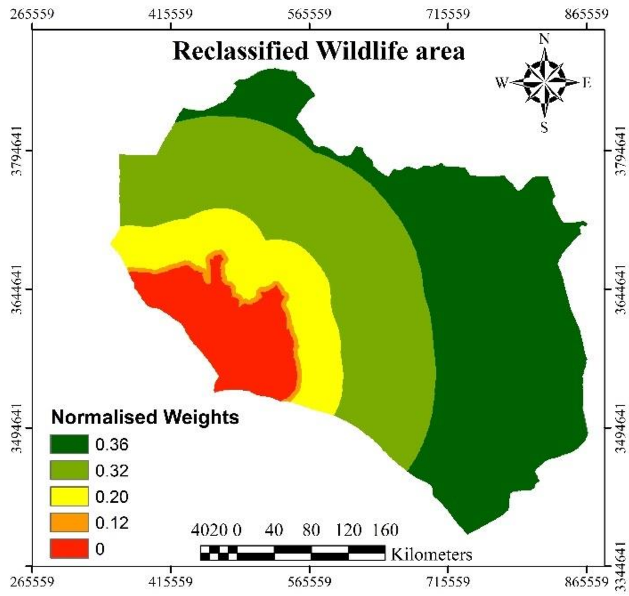


Fig. 19. Reclassified and normalized of distance to wildlife area layer

9) *Distance to Drainage Lines*

To incorporate this factor into the spatial analysis, a distance-to-drainage layer was generated from DEM data using the Buffer tool in ArcGIS, followed by reclassification and normalization (Fig. 20). Suitability was assumed to increase with greater distance from waterways, reflecting lower environmental risk. Areas closest to watercourses received the lowest suitability scores, while progressively higher weights were assigned to more distant zones (Fig. 21). This approach is consistent with previous studies emphasizing the need to maintain safe buffers from water resources to minimize ecological impacts and support sustainable renewable energy development (Chen et al., 2025; Zhang et al., 2023; Li et al., 2024).

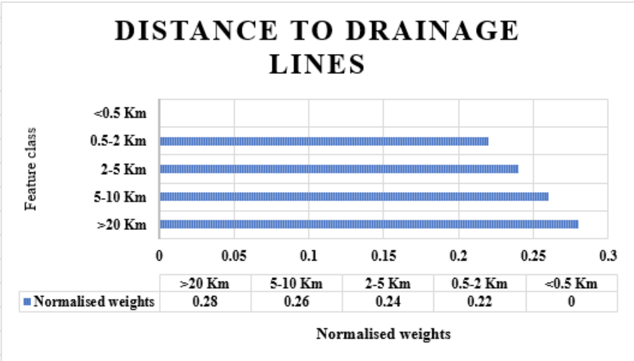


Fig. 20. Assigned normalized weights for feature class of distance to drainage lines

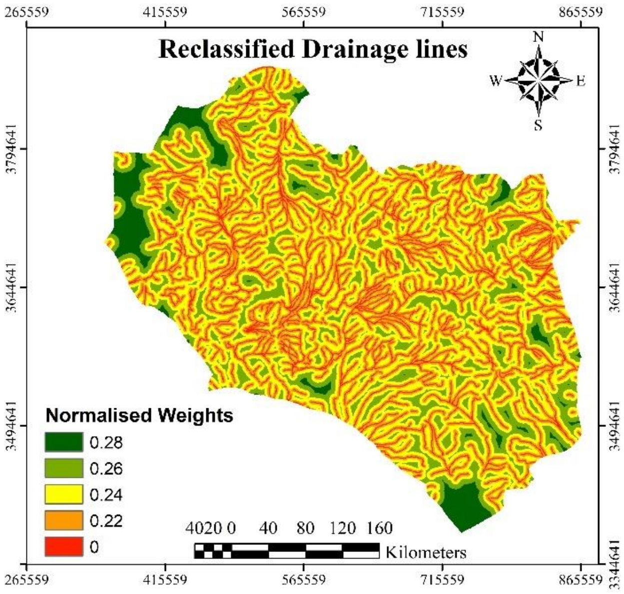


Fig. 21. Reclassified and normalized of distance to drainage lines
Layer

10) *Land use / Land cover*

The suitability analysis classified LULC types into five categories as shown in Fig. 22.

This classification aligns with recent studies emphasizing the use of wastelands and sparsely vegetated areas for renewable energy expansion to reduce environmental impacts and avoid land-use conflicts (Hernandez et al., 2024; Li et al., 2025). The reclassified LULC layer used in both solar and wind assessments is shown in Fig. 23.

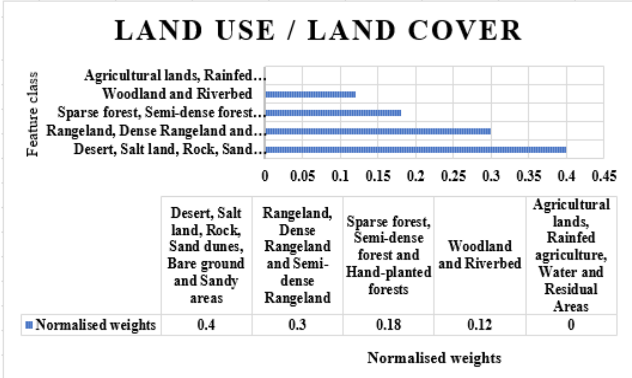


Fig. 22. Assigned normalized weights for feature class of Land use

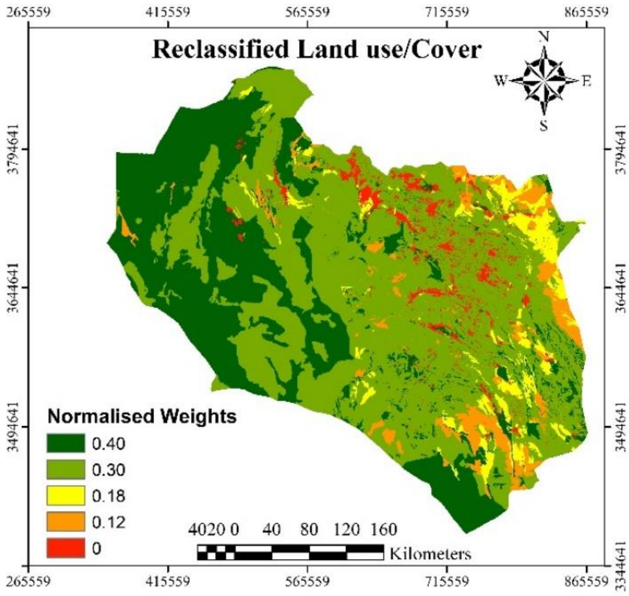


Fig. 23. Reclassified and normalized of Land use layer

11) *Annual Precipitation Amount*

Within the FAHP–GIS decision-making framework, the precipitation layer was reclassified and normalized so that areas with lower rainfall received higher suitability scores. This reflects the assumption that drier environments are generally more advantageous for solar project installation and performance. The classification and normalized weights are presented in Fig. 24 and Fig. 25.

12) *Mean Annual Air Temperature*

Within the FAHP–GIS framework, this layer was standardized and reclassified so that temperature ranges closer to 25–29 °C received the highest suitability scores, while lower temperature zones were assigned progressively lower scores. The resulting suitability map and corresponding normalized weights are presented in Fig. 26 and Fig. 27.

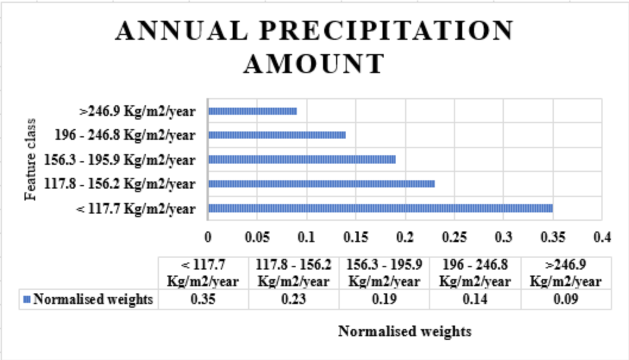


Fig. 24. Assigned normalized weights for feature class of annual precipitation amount

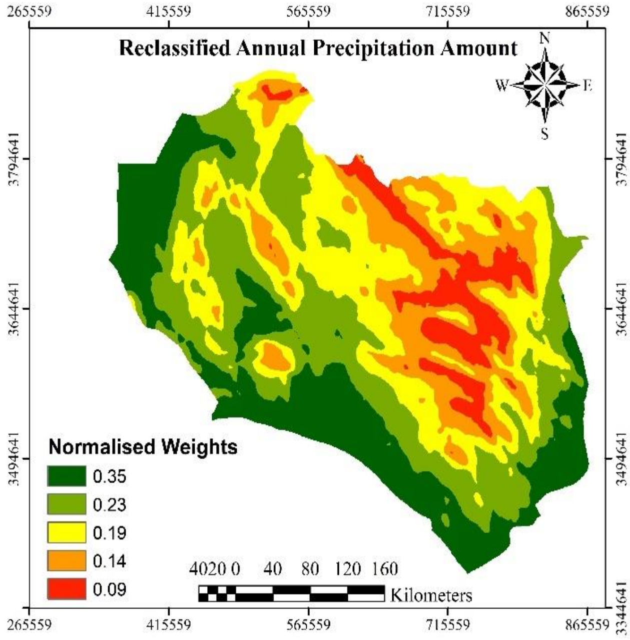


Fig. 25. Reclassified and normalized of annual precipitation amount layer

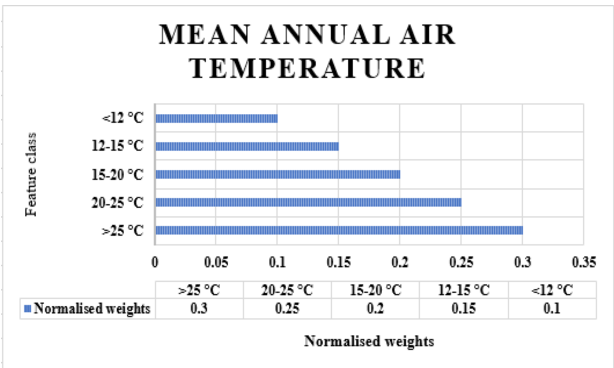


Fig. 26. Assigned normalized weights for feature class of annual air temperature

13) *PVOUT*

Within the decision-making framework, the PVOUT layer plays a central role in identifying priority zones for solar development. During standardization and normalization, higher PVOUT values were assigned higher suitability scores, reflecting their superior power generation potential. The reclassified and normalized PVOUT map, divided into five classes, is presented in Fig. 28 and Fig. 29.

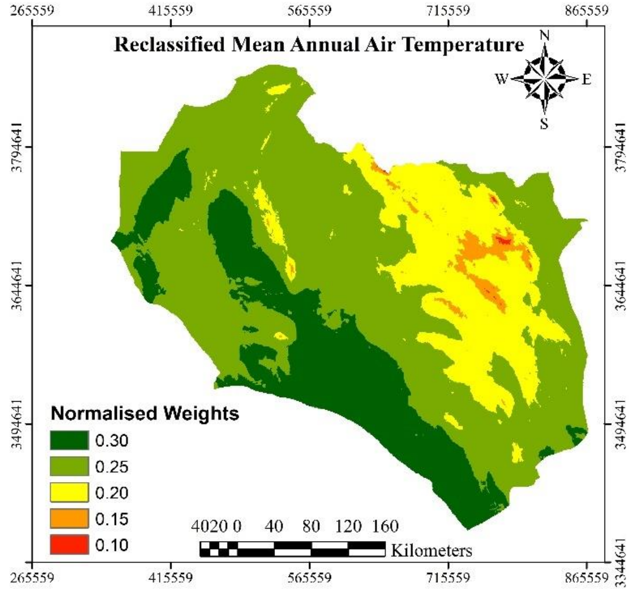


Fig. 27. Reclassified and normalized of annual air temperature layer

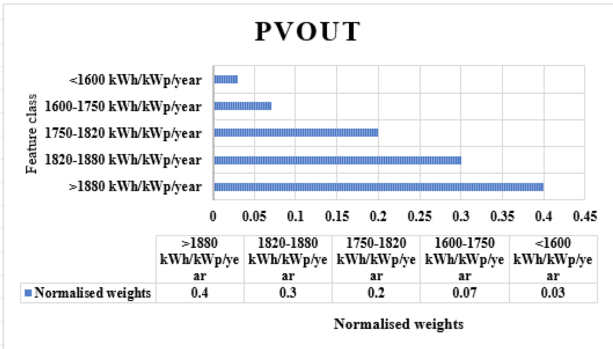


Fig. 28. Assigned normalized weights for feature class of PVOUT

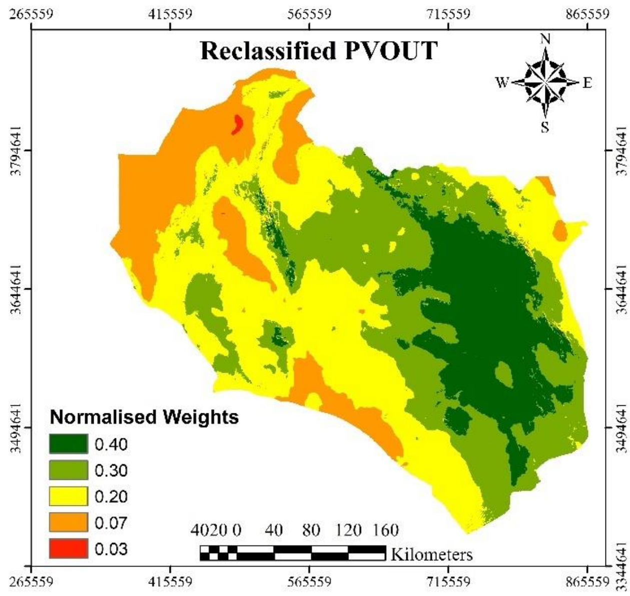


Fig. 29. Reclassified and normalized of PVOUT layer

B. SEPM by Fuzzy Overlay

The fuzzy overlay method is built upon five principal operators—OR, AND, SUM, PRODUCT, and GAMMA—used to integrate multiple spatial datasets. In this study, the most relevant operators were selected to generate the solar energy potential map. This procedure combines normalized and weighted input layers, producing a composite surface that reflects the cumulative influence of all criteria (Fig. 30). The resulting map represents the final solar energy potential distribution across the study area (Fig. 31).

As illustrated in Fig. 31, the solar energy potential map was classified using the Natural Breaks (Jenks) method into four distinct categories: very high potential (34%), high potential (47.5%), moderate potential (2.5%), and low potential (16%). Areas with the highest potential are displayed in dark green, whereas regions with the lowest potential appear in dark red. This classification provides a clear visual differentiation of solar energy availability, supporting informed decision-making for energy infrastructure planning.

C. SEPM by FAHP

In this study, spatial layers influencing solar energy potential in the mining areas of South Khorasan Province were prepared and processed within a GIS environment. Each thematic layer was categorized into suitability classes, as detailed in Section 3.1, and a normalized weight was assigned to each class (X_i) to represent its degree of suitability.

Since these information layers do not contribute equally to the final potential, the FAHP was employed to compute the relative importance (criteria weights, W_i). To ensure a comprehensive evaluation, a structured questionnaire was distributed to a panel of 20 academic and industry experts, including 5 Renewable Energy Specialists, 5 GIS and Remote Sensing Experts, 5 Environmental Engineers, and 5 Mining Engineers with specific knowledge of South Khorasan's infrastructure.

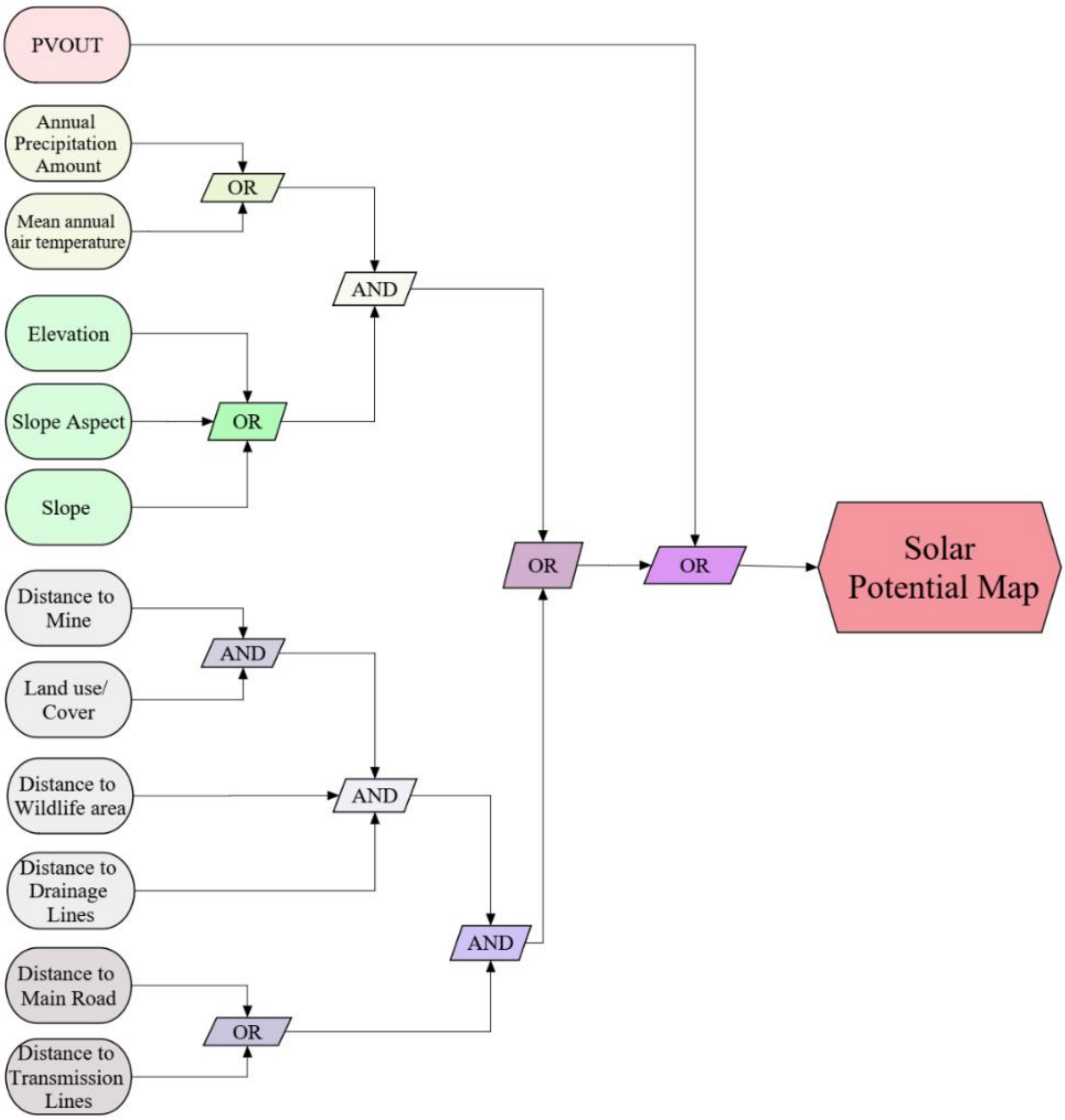


Fig. 30. Fuzzy overlay algorithm for SEPM

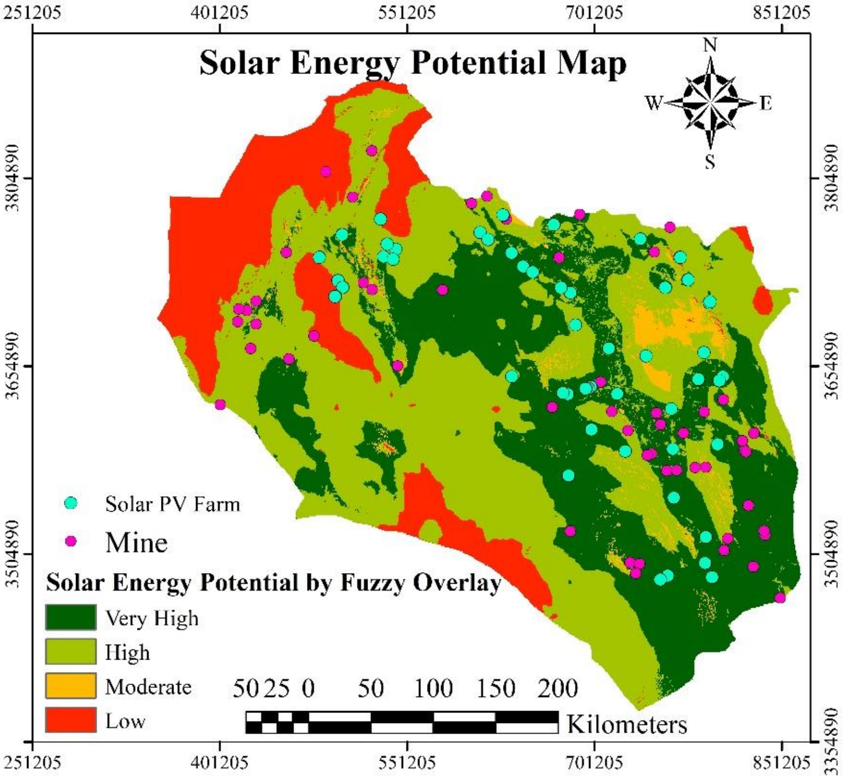


Fig. 31. Solar Energy potential map using Fuzzy overlay method

Pairwise comparison matrices were constructed using Triangular Fuzzy Numbers (TFNs) based on the scale provided in Table 2. Individual expert judgments were aggregated using the geometric mean method to form the final decision matrix. The final weights for all 12 criteria were calculated using Eq.s. 1–7, and the results are presented in Fig. 32. To maintain the conciseness of the manuscript, the complete 12 × 12aggregated fuzzy pairwise comparison matrix is provided as Supplementary Material (Table S1).

Finally, all weighted layers were integrated using the Weighted Linear Combination (WLC) method via the Raster Calculator tool (Eq. (8)):

$$SEPM = \sum_{i=1}^{9}(W_i \times X_i) \tag{8}$$

The resulting solar energy potential map (Fig. 33) was classified into four classes: very high potential (28.3%), high potential (43.8%), moderate potential (18.3%), and low potential (9.7%). Similar to the previous model, dark green areas represent the highest suitability zones.

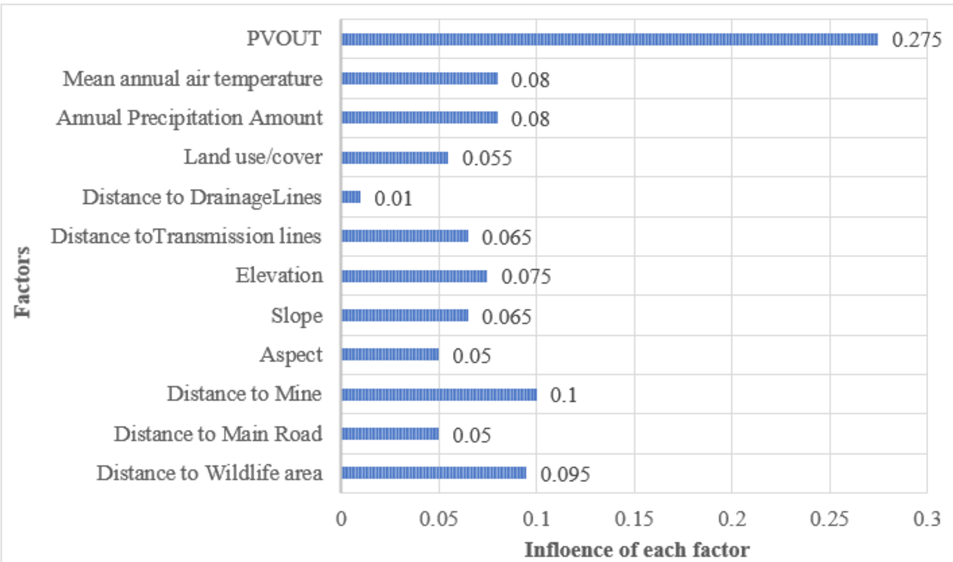


Fig. 32. Influence (Weight) of each parameter by FAHP in a Solar Energy potential map

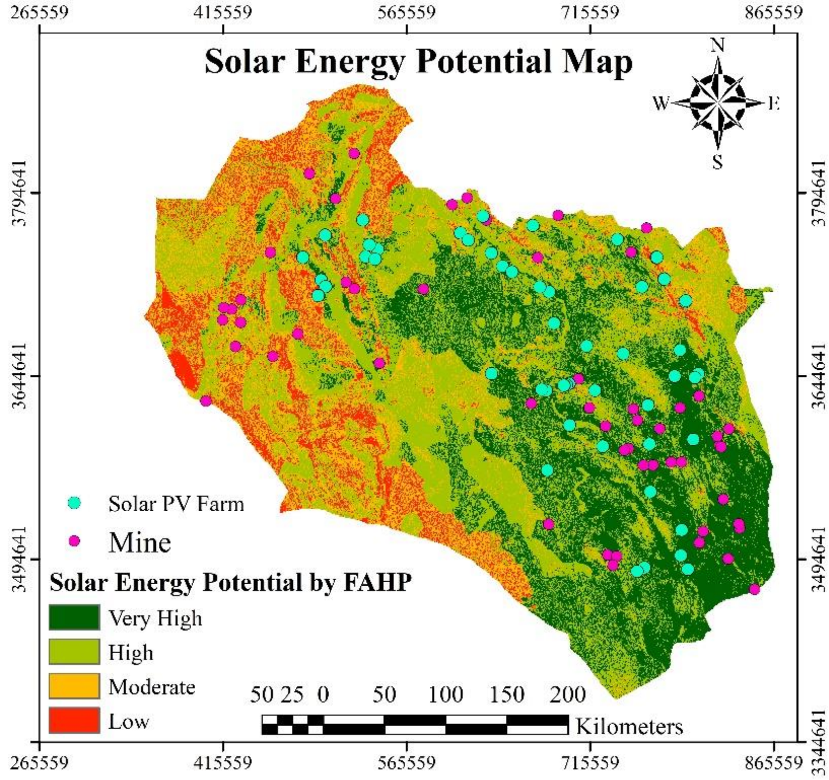


Fig. 33. Solar Energy potential map using FAHP method

D. SEPM by C-SEPM

To achieve more reliable and robust results, this study employed a C-SEPM framework. Integrating outputs from different methods reduces uncertainty and improves the overall accuracy of the final suitability map. The results of the Fuzzy Overlay and FAHP models were combined using the fuzzy GAMMA operator. This operator was selected due to its ability to balance the restrictive nature of the "AND" operator with the flexible behavior of the "OR" operator, providing a weighted compromise suitable for multi-criteria spatial assessments.

The final C-SEPM map was classified into four categories (Fig. 34): very high potential (23.5%), high potential (33.3%), moderate potential (30.5%), and low potential (12.7%). In this final output, areas with the highest potential are highlighted in dark green, providing a clear visual basis for selecting optimal zones for future solar energy development in the mining sector of South Khorasan.

Table 2. Fuzzified Saaty's scale (Al-Mulla, et al, 2025; Zhang et al, 2025; Mishra & Rani, 2024)

Importance	FAHP weights
Absolutely important	(9, 9, 9)
Strongly important	(6, 7, 8)
Fairly important	(4, 5, 6)
Weakly important	(2, 3, 4)
Equally important	(1, 1, 1)

IV. SENSITIVITY ANALYSIS

Sensitivity analysis was carried out to evaluate how changes in the weights of the criteria and the contribution of input layers affect the solar energy suitability maps produced using the FAHP and fuzzy overlay methods. The results indicate that PVOUT is the most influential factor in identifying highly suitable areas. Changes in its weight or membership values lead to the most noticeable variations in the spatial extent of the Very High suitability class. Climatic variables, particularly mean annual air temperature and annual precipitation, showed a moderate influence, mainly affecting the eastern and southeastern parts of the study area where favorable climatic conditions coincide with high solar radiation. In comparison, environmental and topographic factors such as land use/cover, slope, and elevation acted more as local constraints, reducing suitability in areas characterized by steep terrain or dense vegetation.

The analysis also showed that infrastructure-related criteria, including distance to roads, transmission lines, and drainage networks, have relatively low sensitivity in both modeling approaches. Even when their weights were varied by ±20%, the resulting changes in the distribution of highly suitable areas were minimal. On the other hand, distance to mines and distance to wildlife habitats had more noticeable local effects, particularly in the central and western parts of the study area, where higher weights led to a reduction in suitability. The fuzzy overlay model, which combines thematic layers through nested logical operators (AND/OR), further demonstrated that areas characterized by high solar radiation and favorable terrain conditions consistently remain within the highest suitability class, suggesting that the model is not highly sensitive to small parameter changes.

In general, the results suggest that both the FAHP and fuzzy overlay approaches show a high level of structural stability. Significant changes in the output maps occur mainly when major factors—especially PVOUT and, to some extent, distance to mines—are substantially modified. Variations in the weights or fuzzification of less influential criteria produce only minor differences in the final suitability pattern. This indicates that the developed models are robust and can provide a reliable basis for identifying suitable locations for solar energy development in the study area.

V. Validation and Discussion

The reliability of the three spatial modeling approaches-Fuzzy Overlay, FAHP, and the C-SEPM-was assessed by comparing the resulting suitability maps with the spatial distribution of existing solar PV farms and mining areas across the study region. The spatial correspondence between model outputs and operational solar plants provides an empirical basis for evaluation. The results indicate that areas identified as highly suitable largely coincide with current PV facilities, suggesting that the selected criteria effectively represent the environmental, climatic, and infrastructural conditions governing solar development in the region. However, distinct differences in predictive behavior were observed among the three models.

The Fuzzy Overlay approach generated the most spatially generalized pattern. Extensive, continuous areas were classified as “High” and “Very High” suitability, effectively identifying broad zones with strong solar potential. This is consistent with fuzzy logic’s ability to represent spatial uncertainty and gradual environmental transitions. However, this method tends to overestimate suitability in some locations, as it emphasizes regional potential while giving less weight to localized constraints, such as specific mining or environmental limitations.

In contrast, the FAHP model produced a more differentiated structure with clearer contrasts. High suitability zones appear more concentrated, particularly in the eastern and southeastern parts of the province. Because FAHP integrates expert-derived weights, the resulting map reflects the priority of factors like PVOUT and topography. However, FAHP exhibits a more fragmented pattern due to the strong influence of restrictive factors (slope, land cover), which, while improving local site identification, may lead to less continuous suitable zones.

To harness the complementary strengths of both methods, the C-SEPM framework was developed using the fuzzy GAMMA operator. This model presents a more balanced spatial structure. While the extent of the “Very High” class is more refined than in the Fuzzy Overlay, the continuity of suitable zones is superior to the FAHP results. A substantial proportion of existing PV installations fall within the top classes of the C-SEPM map, confirming its improved predictive consistency. By mitigating the overestimation of the fuzzy model and the fragmentation of the FAHP model, the C-SEPM framework provides the most realistic representation of solar potential.

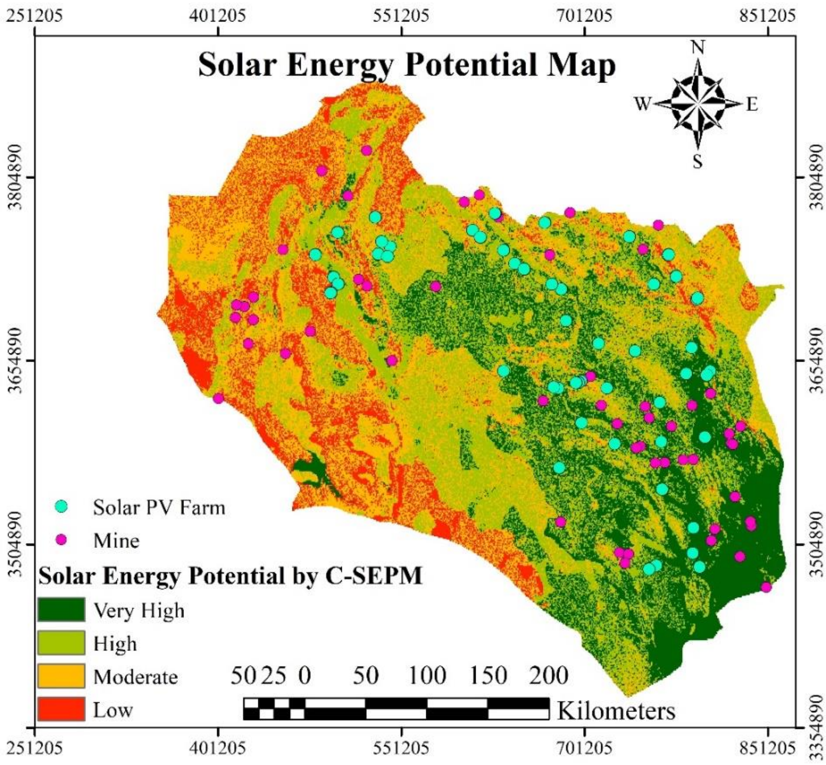


Fig. 34. Solar Energy potential map using C-SEPM

A. Practical Implications for the Mining Sector

The mining sector in South Khorasan Province consists predominantly of small- and medium-scale operations producing minerals such as coal, gold, chromite, and bentonite. According to statistics from the Ministry of Industry, Mine and Trade of Iran, many of these mines have annual production levels below 100,000 tons with moderate electricity demands for crushing, milling, and ventilation.

Consequently, the suitable zones identified in this study are highly appropriate for distributed PV systems (50 kW to 2 MW) rather than large utility-scale plants. Such decentralized systems can operate in hybrid modes with the national grid or supplement diesel generation in remote locations, significantly reducing operational costs and fossil fuel dependence. This framework thus serves as a robust decision-support tool for a sustainable energy transition in arid mining environments, aligning energy production with local industrial demand.

VI. Conclusion

This study developed an integrated framework for solar energy potential assessment in the mining regions of South Khorasan Province by combining FAHP, fuzzy overlay, and GIS-based spatial analysis within the C-SEPM approach. The results demonstrate that this methodology effectively identifies optimal locations for photovoltaic development by balancing regional solar resources, environmental constraints, and spatial decision-making uncertainties. By synthesizing expert knowledge with fuzzy logic, the C-SEPM model significantly improves the reliability and precision of solar suitability mapping.

The final suitability map reveals that 23.5% of the study area falls within the "very high" suitability class, while 33.3% and 30.5% are classified as "high" and "moderate" suitability, respectively. These findings confirm that a substantial portion of the province possesses favorable conditions for solar energy integration, particularly in arid regions with high PVOUT levels. Notably, given the predominance of small- to medium-scale mining operations in the region, the identified zones are highly suitable for distributed PV systems (50 kW to 2 MW). Such decentralized installations can function in hybrid modes or supplement diesel generation, providing a practical solution to reduce operational costs and fossil fuel dependence.

From a planning perspective, the C-SEPM framework offers a robust decision-support tool for sustainable energy transitions in mining environments. Its ability to integrate heterogeneous criteria makes it a transferable methodology for other regions facing similar land-use and environmental challenges. Beyond supporting renewable energy expansion, the application of this framework facilitates the alignment of energy production with local industrial demand, contributing to long-term operational sustainability and reducing carbon emissions in the mining sector.

References

Alamdari, P., Nematollahi, O., & Alemrajabi, A. A. (2013). Solar energy potentials in Iran: A review. Renewable and Sustainable Energy Reviews, 21, 778–788. https://doi.org/10.1016/j.rser.2012.12.052.

Alayi, S., Mohammadi, S., & Shafiee, M. (2023). Hybrid solar–wind potential assessment using GIS and MCDM techniques in semi-arid regions. Energy Conversion and Management, 274, 116523. https://doi.org/10.1016/j.enconman.2023.116523

Ali, S. H., Giurco, D., Arndt, N., et al. (2024). Minerals, renewable energy and the low-carbon transition. Nature Reviews Earth & Environment, 5, 45–58.

Almasad, A., Pavlak, G. S., Alquthami, T., & Kumara, S. (2023). Site suitability analysis for implementing solar PV power plants using GIS and fuzzy MCDM based approach. Solar Energy, 249, 642–650. https://doi.org/10.1016/j.solener.2022.11.046.

Al-Mulla, M., Al-Obaidi, Z. R., & Al-Obaidi, A. R. (2025). A two-stage model of the fuzzy analytic hierarchy process and the fuzzy synthetic evaluation technique to prioritize sustainable sanitation services under uncertainty. Scientific Reports, 15(1), 3820.

Al-Yahyai, S., Charabi, Y., & Gastli, A. (2012). GIS-based site selection for wind farms in Oman. Renewable Energy, 44, 80–90. https://doi.org/10.1016/j.renene.2012.01.006.

An, P., Bonham-Carter, G. F., & Wright, D. (1991). Application of fuzzy logic in spatial modeling. International Journal of Geographical Information Systems, 5(3), 327–340. https://doi.org/10.1080/02693799108927823.

Bonham-Carter, G. F. (1994). Geographical Information Systems for Geoscientists: Modelling with GIS. Pergamon Press.

Charabi, Y., & Gastli, A. (2011). GIS-based wind farm site selection using multi-criteria analysis: Case study of the Sultanate of Oman. Renewable and Sustainable Energy Reviews, 15(9), 4602–4609. https://doi.org/10.1016/j.rser.2011.07.082.

Chen, L., Sun, Y., & Zhang, D. (2025). GIS-based assessment of wind–solar hybrid potential considering topographic constraints. Renewable and Sustainable Energy Reviews, 186, 113812.

Chen, Y., Liu, X., & Zhang, H. (2025). Hydrological considerations in renewable energy siting: A GIS-based approach. Environmental Management, 65(2), 245–259. https://doi.org/10.1007/s00267-024-01655-3.

Chiarani, E., Antunes, A. F. B., Drago, D., & Oening, A. P. (2023). Optimal site selection using GIS-based multi-criteria decision analysis (MCDA): A case study to concentrated solar power plants (CSP) in Brazil. Anuário do Instituto de Geociências, 46. https://doi.org/10.11137/1982 3908_2023_46_48188

Dastorani, M., & Jafari Shalamzari, M. (2025). GIS-aided site selection for solar panel installation in rangeland areas of Mashhad County of Iran. Journal of Rangeland Science, 15(4), 1–10. https://doi.org/10.57647/j.jrs.2025.1504.31

Drozd, S., & Kussul, N. (2024). Solar energy potential mapping in Ukraine through integration of GIS, remote sensing, and fuzzy logic. European Journal of Remote Sensing, 57(1). https://doi.org/10.1080/22797254.2024.2362390

ESMAP. (2026). Global Solar Atlas: Photovoltaic Power Potential by Country. World Bank Group. Available at: https://globalsolaratlas.info

Fathi, S., & Lavasani, A. M. (2017). A review of renewable and sustainable energy potential and assessment of solar projects in Iran. Journal of Clean Energy Technologies, 5(2).

Global Solar Atlas. (2025). A global database of solar resource and photovoltaic potential. World Bank / ESMAP & Solargis. Retrieved from https://globalsolaratlas.info

Gökler, S. H. (2025). Enhanced site selection for solar power plants utilizing GIS with Pythagorean fuzzy AHP. Sustainable Energy, Grids and Networks, 44, 101929. https://doi.org/10.1016/j.segan.2025.101929.

Hernandez, R. R., Easter, S. B., Murphy-Mariscal, M. L., Maestre, F. T., Tavassoli, M., Allen, E. B., … & Allen, M. F. (2024). Environmental impacts of utility-scale solar energy. Renewable and Sustainable Energy Reviews, 29, 766–779.https://doi.org/10.1016/j.rser.2013.08.041.

Hernandez, R. R., Hoffacker, M. K., et al. (2024). PV output optimization for large-scale solar farms in drylands. Applied Energy, 352, 120985.

Hosseini, A., Ramezani, F., & Mirhosseini, M. (2024). Solar and wind energy potential assessment for Razavi Khorasan Province in Iran. Journal of Central South University, 31(6), 2027–2038. https://doi.org/10.1007/s11771-023-5535-x.

International Renewable Energy Agency (IRENA). (2023). World Energy Transitions Outlook 2023: 1.5°C Pathway. IRENA.

Jasmin, S., & Mallikarjuna, R. (2011). GIS-based fuzzy overlay analysis for groundwater potential mapping. Hydrogeology Journal, 19(5), 1047–1058. https://doi.org/10.1007/s10040-011-0731-2.

Li, H., Zhang, D., & Chen, Y. (2025). Spatial assessment of photovoltaic energy potential using GIS-based PV models. Renewable Energy, 209, 120456.

Li, Q., Zhao, M., & Wang, J. (2025). Geospatial analysis for environmentally sustainable renewable energy development. Renewable Energy, 202, 1142–1154. https://doi.org/10.1016/j.renene.2024.01.059.

Li, X., Gu, Q., Chang, Y., et al. (2024). Renewable energy in the mining industry: Status, opportunities and challenges. Energy Strategy Reviews, 56, 101597.

Malczewski, J. (1999). GIS and Multicriteria Decision Analysis. John Wiley & Sons.

Mazandarani, A., Mahlia, T. M. I., Chong, W. T., & Moghavvemi, M. (2010). A review on the pattern of electricity generation and emission in Iran from 1967 to 2008. Renewable and Sustainable Energy Reviews, 14(7), 1814–1829.

Mehrjerdi, M., & Zandieh, M. (2020). A GIS-based multi-criteria analysis for solar power plant site selection in Iran. Sustainable Energy Technologies and Assessments, 37, 100605. https://doi.org/10.1016/j.seta.2019.100605.

Mishra, A. R., & Rani, P. (2024). Fuzzy Multi-Criteria Decision-Making: Advanced Approaches and Applications. Springer, 2nd ed.

Mohamadi, H., Saeedi, A., Firoozi, Z., Sepasi Zangabadi, S., & Veisi, S. (2021). Assessment of wind energy potential and economic evaluation of four wind turbine models for the east of Iran. Heliyon. https://doi.org/10.1016/j.heliyon.2021.e07234.

Nadizadeh Shorabeh, S., Neisany Samany, N., & Abdali, Y. (2019). Mapping the potential of solar power plants based on the concept of risk: Case study: Razavi Khorasan Province. Geographical Data Quarterly, 28, 127–149.

Najafi, G., Ghobadian, B., Mamat, R., Yusaf, T., & Azmi, W. H. (2015). Solar energy in Iran: Current state and outlook. Renewable and Sustainable Energy Reviews, 49, 931–942.

Noorollahi, E., Fadai, D., Shirazi, M. A., & Ghodsipour, S. H. (2016). Land suitability analysis for solar farms exploitation using GIS and fuzzy analytic hierarchy process (FAHP): A case study of Iran. Energies, 9(4), 643.

Noorollahi, Y., Ghenaatpisheh Senani, A., Fadaei, A., & Simaee, M. (2022). A framework for GIS based site selection and technical potential evaluation of PV solar farm using fuzzy Boolean logic and AHP multi criteria decision making approach. Renewable Energy, 186, 89–104. https://doi.org/10.1016/j.renene.2021.12.124.

Noorollahi, Y., Yousefi, H., & Mohammadi, M. (2016). Multi-criteria decision support system for wind farm site selection using GIS. Sustainable Energy Technologies and Assessments, 13, 38–50. https://doi.org/10.1016/j.seta.2015.11.002.

Ramli, M. A. M., Twaha, S., & Ishaque, K. (2016). A review of optimal design and site selection for hybrid renewable energy systems. Renewable and Sustainable Energy Reviews, 59, 722–739. https://doi.org/10.1016/j.rser.2016.01.015.

Saeidi, D., Mirhosseini, M., Sedaghat, A., & Mostafaeipour, A. (2011). Feasibility study of wind energy potential in two provinces of Iran: North and South Khorasan. Renewable and Sustainable Energy Reviews, 15(9), 4528–4537. https://doi.org/10.1016/j.rser.2011.05.011.

Sánchez-Lozano, J. M., Teruel-Solano, J., Soto-Elvira, P. L., & García-Cascales, M. S. (2013). Geographical Information Systems (GIS) and multi-criteria decision making (MCDM) methods for the evaluation of solar farms locations: Case study in south-eastern Spain. Renewable and Sustainable Energy Reviews, 24, 544–556. https://doi.org/10.1016/j.rser.2013.03.019.

Sovacool, B. K., Ali, S. H., Bazilian, M., et al. (2023). Sustainable minerals and renewable energy integration. Renewable and Sustainable Energy Reviews, 176, 113170.

Sovacool, B. K., Kester, J., & Noel, L. (2024). The political economy of renewable energy transitions. Energy Research & Social Science, 107, 103345. https://doi.org/10.1016/j.erss.2023.103345.

Statistical Center of Iran. (2024). Detailed Results of the Census of Operating Mines in Iran - South Khorasan Province. Available at: https://amar.org.ir/statistical-information/statid/57127 (Accessed: June 24, 2026).

Tegou, L., Polatidis, H., & Haralambopoulos, D. (2010). Environmental management framework for wind farm siting: Methodology and case study. Journal of Environmental Management, 91(11), 2134–2147. https://doi.org/10.1016/j.jenvman.2010.05.010.

Tirpáková, V., Beňuš, R., & Konečný, M. (2021). Fuzzy overlay as a multicriteria approach in GIS for environmental suitability assessment. Environmental Modelling & Software, 136, 104926. https://doi.org/10.1016/j.envsoft.2020.104926.

Tsoutsos, T., Frantzeskaki, N., & Gekas, V. (2005). Environmental impacts from the solar energy technologies. Energy Policy, 33(3), 289–296. https://doi.org/10.1016/j.enpol.2003.11.014.

Uyan, M. (2013). GIS-based solar farms site selection using analytic hierarchy process (AHP) in Karapınar region, Konya/Turkey. Renewable and Sustainable Energy Reviews, 28, 11–17. https://doi.org/10.1016/j.rser.2013.07.042.

World Bank. (2024). Decarbonizing the Mining Sector: Opportunities for Renewable Energy Integration. World Bank Group.

Yilmaz, I., Kocer, A., & Aksoy, E. (2024). Site selection for solar power plants using GIS and fuzzy analytic hierarchy process: Case study of the Western Mediterranean Region of Turkiye. Renewable Energy, 237, 121799. https://doi.org/10.1016/j.renene.2024.121799.

Zhang, Q., Liu, Y., & Wang, S. (2024). GIS-based wind power density mapping for wind farm site selection. Renewable Energy, 214, 121045.

Zhang, Y., Wang, H., & Li, S. (2025). Optimizing healthcare supply chain capacity planning during disasters using Fuzzy AHP and Fuzzy TOPSIS. Scientific Reports, 15(1), 4321.

Zhang, Y., Wang, J., & Liu, X. (2023). Topographic effects on solar and wind power site suitability using GIS-based MCDM. Renewable Energy, 206, 1201–1214.