Journal of Renewable Energy and Environment

Journal Homepage: www.jree.ir

Materials and Energy Research Center
MERC

Research Article

Suitability of Solar PV Plant Sites Using A Combined GIS-AHP And Remote Sensing Approach; A Case Study of Khanewal District, Pakistan

Muhammad Roman[a], Muhammad Atiq Ur Rehman Tariq[a*], Abdullah Nadeem[a], Sadiq Ullah[a], Faris Ahmad[a], Muhammad Ali Haider[a]

[a]*Centre of Excellence in Water Resources Engineering, University of Engineering and Technology, Lahore 54890, Pakistan.*

PAPER INFO

Paper history:
Received: 14 March 2025
Revised: 25 May 2025
Accepted: 04 December 2025

Keywords:
Suitability,
Solar PV Plant,
AHP,
MCDA,
GIS,
RS,
WLC

ABSTRACT

Optimal siting of solar photovoltaic (PV) power plants is essential for maximizing efficiency. Given Pakistan's ongoing electricity shortages and rising energy costs over the past 30 years, identifying efficient and sustainable energy alternatives has become critical. This study integrates Geographical Information Systems (GIS) with a Multi-Criteria Decision Analysis (MCDA) approach to identify suitable locations. The combination of GIS and the Analytical Hierarchy Process (AHP) provides a structured, data-driven method for evaluating complex spatial factors. Seven thematic layers—slope, aspect, solar radiation, land use/land cover (LULC), smog, air temperature, and proximity to power lines—were analyzed. AHP was used to assign normalized weights to each criterion, and the weighted overlay method in GIS generated the final suitability map. Unsuitable areas were excluded using Boolean overlay and weighted linear combination (WLC). The results showed that 1.54% (42.94 km²) of the area was classified as very highly suitable, 36.52% (1024.4 km²) as highly suitable, and 30.88% (866.20 km²) as moderately suitable, while 30.97% (868.94 km²) was restricted from development. Uniquely, the study compares energy demand for horticultural crop production across grid, solar, and diesel sources, revealing the potential for solar energy integration. The novelty lies in combining spatial suitability with agricultural energy demand assessment, offering a replicable model for sustainable rural electrification.

https://doi.org/10.30501/jree.2025.507408.2278

1. INTRODUCTION

Nowadays, one of the fastest-growing renewable energy sources around the world is solar photovoltaic (PV) technology (Islam et al., 2024). In recent years, the cost of producing solar energy has dropped by 80%, and this downward trend is expected to continue, driven by stable factors such as decreasing production costs and expansion plans (Taghizadeh-hesary & Yoshino et al., 2020; Xu et al., 2019). According to the International Energy Agency (IEA), solar electricity generation could grow by up to 20–25% by 2050 (Charabi & Gastli et al., 2011a). One of the significant challenges societies face today is producing and utilizing energy in a sustainable manner (Guaita-Pradas et al., 2019; Nadeem et al., 2024). Currently, most energy comes from limited resources that could be depleted due to rapidly increasing demand (Gerbo et al., 2022). Solar, wind, geothermal, and hydroelectric power systems are increasingly being adopted for electricity generation in Pakistan. Researchers are exploring renewable energy sources in response to environmental pollution, climate change, and global warming (Günen et al., 2021).

Among the renewable energy sources, solar energy stands out as one of the most promising solutions to the global energy shortage. It includes a variety of technologies such as concentrated solar power, solar thermal energy, and photovoltaic panels (Chowdhury et al., 2020). Therefore, the site suitability of solar PV plants is crucial, as they are environmentally friendly and beneficial to both society and the environment (Gerbo et al., 2022).

Solar PV systems for horticultural irrigation have been in use since the early 21st century and are becoming increasingly important in global energy production (Dawson et al., 1979; Schnetzer & Pluscke et al., 2017). In 2021, solar PV generated 179 TWh of electricity—22% more than in 2020—contributing 3.6% of the world's electricity. The U.S. Energy Information Administration estimates that most of Pakistan (over 95% of its area) receives daily solar energy potential ranging from 5 to 7 kilowatt-hours per square meter (kWh/m²) (Sheikh et al., 2009; K. H. Solangi et al., 2011). This underscores the growing role of solar energy in supporting cleaner energy solutions.

The energy essential for biological, industrial, and physical processes on Earth comes from the sun (Dubayar & Rich et al., 1996; Fu & Rich et al., 1999; Ruiz-Arias et al., 2009; Šúri, M., & Hofierka et al., 2004). One of the many benefits of solar energy is that it is among the cleanest renewable energy sources, operating silently and emitting no carbon dioxide (CO_2) (Gerbo et al., 2022). According to life cycle assessments of PV technology, emissions from the solar industry are negligible compared to those from fossil fuels (DeCanio &

*Corresponding Author's Email: atiq.tariq@yahoo.com (M. A. Rehman Tariq)

URL: https://www.jree.ir/article_241525.html

Please cite this article as: Roman, M., Rehman Tariq, M. A., Nadeem, A., Ullah, S., Ahmad, F., Haider, M. A. (2026). Suitability of Solar PV Plant Sites Using A Combined GIS-AHP And Remote Sensing Approach; A Case Study of Khanewal District, Pakistan, *Journal of Renewable Energy and Environment (JREE)*, 13(2), 29-43. https://doi.org/10.30501/jree.2025.507408.2278.

2423-7469/© 2026 The Author(s). Published by MERC. This is an open access article under the CC BY license (https://creativecommons.org/licenses/by/4.0/legalcode).

Fremstad et al., 2011). PV technology is self-sufficient and adaptable to various situations (Hoffert et al., 1998; Wigley et al., 1996; Ackerman & Stanton et al., 2009) . While photovoltaic systems have become more accessible to rural communities lacking grid access, maintaining a consistent power supply can be challenging due to fluctuations in sunlight and environmental conditions (Koc et al., 2019). A detailed evaluation of solar sites is essential for achieving successful and cost-effective solar projects, as multiple factors influence the site selection process (Khan et al., 2023; Suprova et al., 2020). Land areas with high annual solar radiation levels offer significant potential for operating utility-scale solar PV systems (Fu & Rich et al., 1999; Ruiz-Arias et al., 2009). Therefore, solar energy holds vast potential as a sustainable power source capable of meeting diverse global energy needs.

Several studies emphasize the critical need for renewable energy solutions in Pakistan due to ongoing energy shortages and rising demand. GIS and MCDA approaches have been widely used to identify optimal sites for solar, wind, and hybrid energy systems. Research has assessed the suitability of both utility-scale and small-scale PV systems, including applications in off-grid rural areas and urban rooftops, revealing significant untapped solar potential. Innovative methods such as density-based clustering and spatial decision support system (SDSS) tools have enhanced site selection, particularly in regions like Baluchistan and Gwadar. Hybrid models combining solar and biomass have also shown promise, with over one-third of Pakistan identified as suitable for such projects.

Nowadays, the Geographical Information System (GIS) is widely used for suitability analysis, especially in energy projects (Delivand et al., 2015; Gastli et al., 2010; Janke et al., 2010; Kaijuka et al., 2007; Noorollahi et al., 2007; Sánchez-Lozano et al., 2014, 2016). Several studies and reports from the National Renewable Energy Laboratory (NREL) highlight that site selection for PV projects is a key part of the planning process (Al Garni & Awasthi et al., 2020; Delivand et al., 2015; Gastli et al., 2010; Janke et al., 2010; Kaijuka et al., 2007; Noorollahi et al., 2007; Pohekar & Ramachandran et al., 2004; Sánchez-Lozano et al., 2014, 2016; Wang et al., 2009). In various energy planning projects, Multi-Criteria Decision-Making (MCDM) techniques have been applied effectively (Al Garni & Awasthi et al., 2017). According to the literature, different MCDM methods have been integrated within the GIS environment using sub-criteria and main criteria across various regions (Kamdar et al., 2019). The combination of MCDM techniques and GIS has proven effective in resolving site suitability challenges for solar PV plant development (Lee et al., 2009, 2015; Sánchez-Lozano et al., 2013; Wilton et al., 2014). Several studies have also estimated the hosting capacity of green energy projects through the integration of GIS and MCDM approaches (Delivand et al., 2015; Kucuksari et al., 2014; Mussa & Suryabhagavan et al., 2021; Ren et al., 2012; Xiao et al., 2013). Furthermore, the authors (Aydin et al., 2010; Tegou et al., 2010) used GIS-MCDM integration to evaluate wind farm suitability. Weights were assigned to various criteria using the Analytic Hierarchy Process (AHP), considering environmental and technical factors (e.g., land use/land cover, proximity to water bodies), security considerations (e.g., distance from airports), and social impact factors (e.g., land transportation, protected areas) for solar park selection (Georgiou & Skarlatos et al., 2016). Hafeznia et al. (2017) used a Fuzzy AHP method along with Boolean MCDM for assessing solar PV site suitability. Their criteria included technical factors (roads, railways, mining activities), safety factors (airports, military zones), land use features (Sentinel-2A RGB bands), geographical features (slope, aspect, faults, elevation), socio-economic features (urban and rural areas), and climatic factors (GHI, temperature, precipitation). Their study identified Birjand as the most suitable location, verifying seven sites using Google Maps.

Sánchez-Lozano et al. (2014) applied the GIS-based ELECTRE method to identify ideal PV farm locations in Spain. In another study, Sánchez-Lozano et al. (2013) combined AHP to weigh the main criteria with TOPSIS for sub-criteria analysis, focusing on environmental features (agrologic capacity), location factors (proximity to roads, power lines, city centers, transformers), orographic characteristics (slope, aspect, plot area), and climatological features (solar irradiation, temperature). Hashemizadeh et al. (2019) included criteria such as climate factors (solar irradiation, average temperature, humidity), economic aspects (land and construction costs), location factors (urban areas, roads, power lines, waterways), and orographic features (slope, aspect, plot area). The current study integrates technical data (solar radiation, air temperature, and AQI/smog), economic data (slope, aspect, and LULC), and Boolean criteria (proximity to roads and power lines) to assess solar PV site suitability.

The integration of Geographic Information Systems (GIS), the Analytic Hierarchy Process (AHP), and Remote Sensing (RS) has emerged as a state-of-the-art approach for identifying suitable sites for solar photovoltaic (PV) plant installations. This combination enables a spatially informed, multi-criteria decision-making process that incorporates a wide range of environmental, technical, economic, and social variables. Across various global case studies, researchers have validated the effectiveness of GIS-AHP frameworks in optimizing solar site selection. For instance, in İzmir, Türkiye, a novel approach combined AHP with GIS and introduced Optimality-Based Site Growing (OBSG), which refined the outputs from GIS simulations by adjusting weights based on the PV plant's installed capacity, offering a more dynamic site selection model. Similarly, a study conducted in Ikorodu, Nigeria, utilized a GIS-based AHP model incorporating environmental and infrastructural criteria, classifying only 17.78% of the land as highly suitable for solar farms—highlighting the importance of accurate multi-criteria analysis in densely populated or spatially constrained environments (Onuoha et al., 2025).

In the Philippines, researchers applied AHP and GIS on Simara Island, categorizing 42.81% of the island as suitable and 39.73% as highly suitable for solar PV development, demonstrating the method's effectiveness in remote or island contexts (Garcia et al., 2024). Similarly, in Bangladesh, a GIS-AHP-based Multi-Criteria Decision Analysis (MCDA) framework identified 44.59% of the southern region as highly suitable for solar power development, highlighting the country's significant untapped solar potential (Islam et al., 2023). In Pakistan, researchers employed GIS-AHP to identify both large- and small-scale PV opportunities, reporting that over 25% of the land was suitable for utility-scale installations while also identifying potential for off-grid applications in underserved regions (Raza et al., 2023).

Beyond traditional AHP applications, recent studies have enhanced these models with additional techniques. In Algeria, the integration of fuzzy logic into AHP enabled more nuanced evaluations, identifying over 2.26 million hectares of land as suitable for solar PV in remote agricultural areas (Belaid et al., 2024). In China, the Ordinal Priority Approach (OPA) was introduced within an MCDM framework tailored to mountainous terrain, incorporating ecological policy constraints to assess PV potential in Yunnan Province (Feng et al., 2025). In Morocco, researchers conducted a GIS-AHP analysis for hybrid Concentrated Solar Power (CSP) and PV systems, incorporating a novel "Water Risk Index" to identify optimal locations that address both energy storage and resource limitations (Jbaihi et al., 2022).

In addition to technical factors like slope, solar irradiance, and proximity to infrastructure, some models have begun incorporating disaster risk. For example, a study in Hawke's Bay, New Zealand integrated solar potential with earthquake and flood risk analysis using a two-stage MCDM framework, reflecting a growing emphasis on resilience in solar site planning (Rahayani & Nair, 2023). Other innovations include the integration of hydrogen storage suitability and dust impact assessments in arid zones such as Iran, using a fuzzy SWARA method layered onto a GIS-based model (Dehshiri & Firoozabadi, 2023).

This study applied the AHP method to assess suitable sites for solar PV power plants in Khanewal District. Khanewal was selected due to its geographic location, intensive crop production, and high energy consumption in agriculture. As many rural areas lack reliable access to electricity, deploying decentralized solar PV systems is vital for energy security and promoting green agriculture in the district. AHP was employed for its effectiveness in assigning weights to various decision criteria in a structured and systematic way. Unlike traditional GIS-only approaches, this study integrates horticultural energy demand estimation with spatial analysis using GIS-AHP. It incorporates environmental and technical variables such as smog and uses Boolean constraints alongside weighted criteria to enhance both feasibility and reliability in decision-making. GIS played a central role in managing spatial data by integrating multiple datasets including land use, solar radiation, and infrastructure proximity. The integration of GIS and AHP in this study supports informed and strategic site selection, contributing to more sustainable horticultural practices. Selecting appropriate locations for solar PV plants ensures a stable and clean energy supply, which is particularly beneficial for agricultural operations. Although the AHP method has been widely used in solar PV site suitability studies (Hafeznia et al., 2017; Hashemizadeh et al., 2019; Lee et al., 2015; Sánchez-Lozano et al., 2013), this research differs in its combination of technical and agricultural energy criteria. Furthermore, while several studies have been conducted in Pakistan on solar PV suitability, many have relied primarily on limited Boolean criteria (Abbasi & Zeeshan et al., 2023; Iqbal et al., 2020; Raza et al., 2023; Y. A. Solangi et al., 2019). In contrast, this study employs an updated and more comprehensive methodology. The region receives consistent solar radiation year-round, with an average daily summer value of 6.33 kWh/m². However, challenges persist due to grid unreliability and lack of electrification in remote agricultural zones—issues that can be addressed effectively through solar PV deployment.

The novelty of this study lies in its integration of geospatial suitability analysis with horticultural energy demand—a topic that has received limited attention in prior research. By combining GIS-based AHP modeling with energy source comparisons for crop production, this study presents a unique framework for sustainable agricultural electrification. The primary objective was to identify suitable sites for solar PV power plants, aiming to maximize energy generation while minimizing investment costs. The findings are intended to support policymakers and urban developers in planning future solar PV projects. In addition, the study estimates the energy requirements for horticultural crop production and compares ranking methods, demonstrating the utility of the AHP-based MCDM framework in solar PV site selection.

2. METHOD

2.1. Study region

Khanewal, situated at 30°18'0" North and 71°55'0" East with an altitude of 128 meters (Figure 1), is an agricultural district known for its fertile grasslands. The region has a subtropical desert climate, with an average annual temperature of 31.79°C (89.22°F), which is higher than Pakistan's national average. Its abundant sunlight makes it a promising location for solar energy generation. Solar power production in Khanewal remains consistent throughout the year. During summer and spring, the average daily electricity generation per kilowatt (kW) of installed solar capacity reaches 6.33 kWh and 6.51 kWh, respectively. In autumn and winter, output declines to 4.82 kWh and 3.55 kWh due to shorter daylight hours, yet remains sufficient for effective solar energy use. This seasonal pattern underscores the potential for incorporating solar photovoltaic (PV) systems into the region's energy infrastructure.

Khanewal was selected for this study due to its high solar radiation potential, flat topography, and the availability of underutilized land suitable for PV installations. The district faces growing energy demands and an unreliable electricity supply, making it a strategic site for renewable energy development. Its semi-arid climate ensures consistent solar exposure, while the land use—largely agricultural and horticultural—requires careful site selection to avoid encroachment on fertile farmland. Additionally, the availability of detailed geospatial and climatic data supports robust GIS-AHP and remote sensing analysis. As part of Punjab Province, Khanewal is well-positioned within ongoing provincial renewable energy initiatives.

The district's agricultural sector, in particular, stands to benefit from solar-powered irrigation, which reduces dependence on conventional energy sources and supports sustainable farming practices. Moreover, integrating solar energy into the local grid can help alleviate electricity shortages in rural areas, providing a more reliable power supply for households and businesses. Embracing renewable energy also contributes to environmental conservation by reducing carbon emissions and improving energy self-sufficiency in the region.

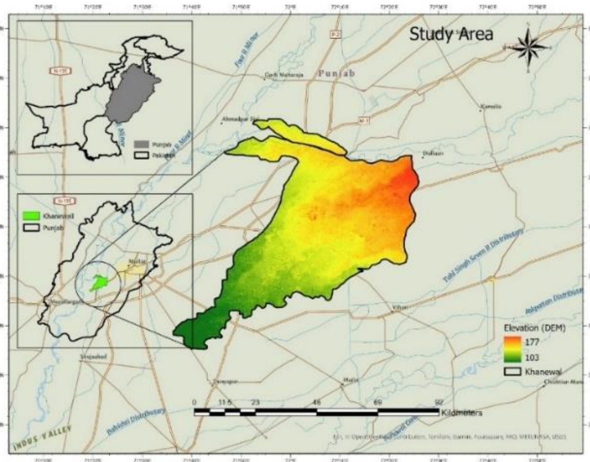

Figure 1. Khanewal district, Pakistan

2.2. Data collection

The following datasets were used in this study for site suitability analysis of solar PV plant installation:

- The Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) with a 90 m resolution was acquired from the National Aeronautics and Space Administration (NASA) website on June 10, 2024 (http://srtm.csi.cgiar.org).
- Global Horizontal Irradiation (GHI), which represents the total solar radiation received per unit area by a horizontal surface, was obtained at a 250 m resolution from the SolarGIS website on August 22, 2024 (http://www.solar-med-atlas.org).
- Roads vector shapefile data for the study region was downloaded from the OpenStreetMap website on July 23, 2024 (https://www.openstreetmap.org).
- Land use/land cover (LULC) data was derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) with a 500 m resolution, accessed on September 15, 2024 (https://modis.gsfc.nasa.gov/data/dataprod/mod12.php).
- Power transmission line vector shapefile data was obtained from the DIVA-GIS website and further processed within the GIS environment (https://diva-gis.org).
- Smog data was sourced from NASA's EarthData portal, accessed on November 10, 2024 (http://www.earthdata.nasa.gov).
- Observed 10-day energy consumption data (kWh) was collected from the Water and Power Development Authority (WAPDA), accessed via the official GRID website (https://www.grid.gov.pk).

2.3. Selection and preparation of thematic layer

The selection and preparation of thematic layers is a critical step in identifying suitable sites for solar PV plants using the MCDM methodology (. Thematic layers represent spatial factors that significantly influence solar site suitability and are typically derived from geospatial datasets (Uyan et al., 2013). The use of thematic layer analysis for solar PV site suitability has been well-documented by various researchers (Al Garni & Awasthi et al., 2017; Gerbo et al., 2022; Islam et al., 2024; Koc et al., 2019; Ruiz et al., 2020; Tunc et al., 2019; Uyan et al., 2013). In this study, solar radiation, land use/land cover (LULC), slope, proximity to transmission lines, air temperature (**Figure 3**), and aspect were selected as key criteria. These factors were further processed within the GIS environment to support site suitability analysis for solar PV plant installations. Several important factors must be considered in this process. The inclination and orientation of slopes significantly affect solar radiation reception (Charabi & Gastli et al., 2011a; Hermann et al., 2014; Watson & Hudson et al., 2015). Sites with solar radiation values ranging from 3.5 to 4.5 kWh/m²/day are considered suitable for solar energy generation (Adnan et al., 2012; Lee et al., 2015). In the Northern Hemisphere, the ideal aspect ranges from southeast to southwest to maximize solar exposure (Li et al., 2013; Watson & Hudson et al., 2015). Proximity to transmission lines is also a crucial economic factor, as it helps reduce both transmission losses and infrastructure costs during the construction and operational phases (Charabi & Gastli et al., 2011b; Hermann et al., 2014; Li et al., 2013). Barren or unused land is the most environmentally favorable for solar PV installations because it minimizes ecological disturbance and avoids conflicts with agricultural or residential zones (Al Garni & Awasthi et al., 2018; Uyan et al., 2013; Watson & Hudson et al., 2015). Smog is another important environmental factor, as it can directly reduce solar irradiance and thus affect the efficiency of PV systems. While solar PV systems offer clean energy, their deployment can also lead to negative environmental impacts such as visual intrusion and construction-related pollution. These impacts must be addressed through careful planning to avoid conflicts with nearby communities (Hermann et al., 2014; Li et al., 2013). Together, these factors ensure a comprehensive, efficient, and sustainable approach to site selection for solar energy development.

The CO, SO_2, and AOD values contributing to smog levels were obtained using NASA EarthData, incorporating both MODIS and MERRA-2 datasets. Data from 2020 through 2022 was used to calculate average pollution levels affecting solar irradiance in the model.

Data on horticultural units, including greenhouses and irrigation systems, was collected over a ten-day period during the peak growing season in Khanewal District. Electricity consumption in greenhouses was highest during early spring (March–April) and late autumn (October–November), primarily due to heating, cooling, and supplemental lighting. The estimated daily energy consumption per greenhouse was 8.7 kWh, with the maximum hourly demand recorded between 10 AM and 2 PM. During the summer months (June–August), when water demand for crops peaks, daily energy consumption for irrigation ranged from 5.2 to 6.5 kWh. This data was sourced locally and cross-validated with official records from the regional Water and Power Development Authority (WAPDA) office.

By incorporating seasonal load profiles into the site suitability model, this study ensures alignment between potential solar PV sites and the actual energy demands of agricultural operations. This enhances the overall efficiency and utility of solar-powered systems in the region.

Various factors were processed and prepared in the GIS environment for the solar PV site suitability analysis. Aspect and slope maps were generated using a 90 m resolution DEM. Proximity to transmission lines and roads was mapped using the Euclidean distance tool. Land use and land cover (LULC) maps were developed through unsupervised classification. Each criterion and its sub-factors were assigned appropriate weights for use in the suitability analysis (Table 1), and the overall methodology is illustrated in Figure 2.

To ensure consistency and account for temporal variability, data from each thematic layer was averaged annually (e.g., a three-year average for smog-related layers). This approach improves the temporal reliability of the study and enhances its applicability for long-term energy planning.

Table 1. Thematic layer weights and their classification

Criteria	Suitability Class	Sub class weights	% Weight	Main class weight
Solar Radiation			31.37	9
	Low	3		
	Moderate	4		
	High	5		
	Very high	6		
Air temperature			19.37	8
	Low	3		
	Moderate	4		
	High	5		
	Very high	7		
Slope			18.14	7
	Low	6		
	Moderate	4		
	High	3		

Criteria	Suitability Class	Sub class weights	% Weight	Main class weight
	Very high	2		
Aspect			11.22	6
	Low	3		
	Moderate	4		
	High	5		
	Very high	7		
LULC			9.84	5
	Built-up Area	0		
	Water bodies	0		
	Roads	0		
	Trees	0		
	Crops irrigated	0		
	Crops rainfed	0		
	Crops in flood plain	0		
	Shrubs dense	0		
	Shrubs in wet soil	3		
	Shrubs sparse	5		
	Bare soil	7		
	Wet soil	1		
	Wet lands	0		
Proximity to Roads			5.29	4
	Low	2		
	Moderate	3		
	High	5		
	Very high	6		
Smog			4.76	3
	low	1		
	Moderate	2		
	High	3		
	Very high	5		
			100%	

2.4. Boolean Criteria

Boolean criteria are categorical, representing conditions as either true or false (Ullah et al., 2024). In this study, Boolean criteria were applied to assess the influence of proximity to transmission lines and roads on site selection. Distances from these infrastructure elements were classified into binary suitability classes: (1) indicating suitable and (0) indicating not suitable. This approach ensured a clear and systematic exclusion of areas outside the defined distance ranges. Using Boolean criteria offers a straightforward yet effective way to incorporate infrastructure accessibility into the site suitability assessment, thereby enhancing both practical feasibility and economic viability for project implementation. In this context, Boolean criteria were applied to power transmission lines and roads within the selected region, as detailed in Table 2.

Table 2. Criteria for Boolean and their classification

Thematic Layers	**Feature class**	**Suitability class**	**Weightage**
Roads disatnce (m)	>12000 <12000	Unsuitable Suitable	0 1
Power lines distance (m)	>7000 <7000	Unsuitable Suitable	0 1

2.5. Multi criteria decision analysis using AHP

The final suitability map was prepared using a Multi-Criteria Decision-Making (MCDM) technique and categorized into five classes: low, moderate, high, very high, and restricted. The MCDM methodology is widely applied in various site suitability studies (Janke et al., 2010; Mussa & Suryabhagavan et al., 2021; Ullah et al., 2024; Uyan et al., 2013). The Analytic Hierarchy Process (AHP), a popular MCDM method, addresses complex decision problems by structuring them hierarchically. It systematically compares criteria and alternatives through pairwise comparisons, assigning weights to reflect their relative

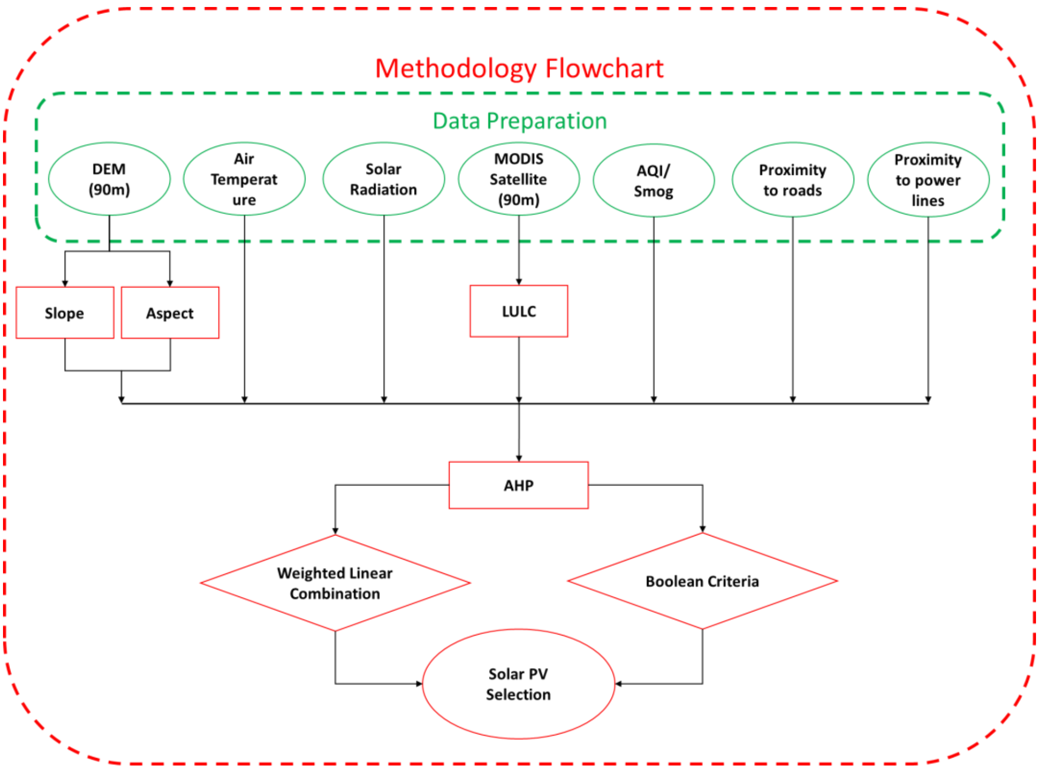

Figure 2. The proposed methodology flowchart for solar PV site suitability

importance. This process includes consistency checks to ensure the reliability of the weighting. Saaty's scale was used to construct the pairwise comparison matrix, converting qualitative judgments into quantitative values (Saaty et al., 1990). Weights were assigned to each thematic layer and normalized according to Saaty's AHP procedure. Additionally, the consistency ratio (CR) was calculated to assess the reliability of the assigned weights (Wind & Saaty et al., 1980). The following equation can be used for CR estimation:

$$CR = \frac{CI}{R_{CI}} \tag{1}$$

whereas CI is the consistency index and R_{CI} is the random consistency index. The value of CI can be estimated through the following equation:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{2}$$

whereas λ_{max} represents the maximum eigenvalue of the pairwise comparison matrix, and n is the total number of criteria (layers). The assigned weights for each factor are subject to change if the consistency ratio (CR) exceeds the threshold value of 0.1 (Wind & Saaty et al., 1980). The value of R_{CI} depends on the number of criteria; for this study, with the given number of layers, the RCI value is 1.36, as shown in Table 3. The weights presented in the pairwise comparison matrix (Table 3) were determined through consultation with both subject-matter experts and validated research articles. Three experts in renewable energy and geographic information systems contributed to assessing the relative importance of each criterion specifically for the Khanewal region. This approach follows Saaty's (2002) guidelines for effectively applying AHP in multi-criteria decision-making.

Solar radiation had the greatest influence on PV efficiency, accounting for 31.37%, as reported by Sánchez-Lozano et al. (2016) and Islam et al. (2023). Air temperature was also given high priority, since warmer conditions improve solar panel performance, as noted by Gerbo et al. (2022). The factors slope and aspect were assigned weights of 18.14% and 11.22%, respectively, reflecting their impact on installation costs and solar energy absorption, according to Charabi and Gastli (2011). Slightly over 10% weight was allocated to barren land to minimize conflicts with existing land uses (Uyan et al., 2013). Proximity to infrastructure (5.29%) and smog (4.76%) were considered less influential but still important, given the role of logistics and the negative effects of air pollution on solar energy performance demonstrated in recent studies (Neale et al., 2021; Dehshiri & Firoozabadi, 2023).

The Consistency Ratio (CR) of 0.08, being below the recommended threshold of 0.1 (Saaty, 1990), confirms the reliability and validity of the assigned weights.

2.6. Creation of solar PV plant suitability map

The suitability map for the solar PV plant was prepared by integrating eight thematic layers: land use/land cover (LULC), proximity to roads, slope, aspect, proximity to power lines, solar irradiance, air temperature, and smog levels. Each layer was carefully selected based on its relevance to solar PV site suitability. Slope (**Figure 7**) and aspect (**Figure 4**) were considered to optimize solar panel orientation, with a preference for south-facing slopes in the Northern Hemisphere to maximize solar exposure. Solar irradiance (**Figure 5**) and air temperature data provided critical insights into the region's energy generation potential. Proximity to power lines and roads (**Figure 6**) was factored in to ensure the economic viability of the project by reducing infrastructure costs and transmission losses. LULC identified barren and non-productive lands as the most suitable locations, helping to avoid conflicts with agricultural or urban areas (**Figure 8**). Additionally, smog levels were analyzed to assess the impact of atmospheric conditions on solar panel efficiency.

All thematic layers were processed within the GIS environment. The selected layers were combined through a multi-criteria decision analysis using the weighted overlay tool in ArcGIS to develop the final solar PV suitability map. This map serves as a vital tool for identifying optimal locations for solar PV plant installations, thereby supporting sustainable energy development. Calibration and validation procedures were conducted to ensure the reliability of the results. For AHP, the consistency of expert judgments was verified through the Consistency Ratio (CR), which was maintained below the acceptable threshold of 0.1. Sensitivity analysis assessed the impact of changes in criteria weights on site suitability outcomes. In GIS, calibration involved proper reclassification and buffering of spatial layers, while validation included comparing the final suitability map with known solar farm locations and land availability datasets. Remote sensing data were pre-processed with geometric and atmospheric corrections. The accuracy of the land use classification was validated using a confusion matrix and Kappa coefficient, supported by ground truth data and high-resolution satellite imagery.

3. RESULTS

Using the GIS-AHP method, this study identified the most suitable locations in Khanewal District for solar PV projects by analyzing factors such as solar radiation, air temperature, slope, land use/land cover (LULC), aspect, proximity to power lines and roads, and smog levels. ArcMap 10.8.1 software was used for spatial data processing, with variable weights determined through AHP and expert input. Solar radiation was the most influential factor, assigned a weight of 31.37%, and was highest in southern Khanewal. Air temperature followed at 19.36%, enhancing panel performance particularly in the warmer southwestern and eastern areas with strong sunlight. Recent studies also emphasized the importance of slope (18.14%) and aspect (11.22%); gently inclined, south-facing slopes were preferred due to easier installation and optimal sunlight exposure. Barren or sparsely vegetated lands were prioritized in the LULC analysis, while wetlands, forests, and urban areas were excluded. Proximity to infrastructure accounted for

Table 3. Random consistency index (RCI) based on number of criteria (R. W. Saaty, 1987)

Number of Factors	15	14	13	12	11	10	9	8	7	6	5	4	3
Random consistency index (R_{CI})	1.6	1.6	1.6	1.5	1.5	1.5	1.5	1	1.4	1.3	1.1	0.9	0.5

5.29%, reflecting the cost benefits of easier access to roads and transmission lines for grid connection and maintenance.

Although smog was given a lower weight (4.76%), assessing air quality was essential for evaluating site suitability. Levels of CO_2, CO, and AOD were generally within safe limits, but elevated SO_2 concentrations could potentially damage solar panels. Ozone levels (**Figure 9** , **Figure 10** , **Figure 11**) were average and had only a minor positive effect on suitability. This underscores the importance of including pollution data as a standard element in PV project planning. Overall, areas with solar radiation around 6 kWh per m² per day, moderate temperatures, flat terrain, and low pollution emerged as the most suitable. These conditions enhance technical efficiency while reducing both capital and operating costs. By integrating environmental, topographical, and infrastructure factors, this model offers a cost-effective and sustainable framework for solar energy planning in Khanewal and similar regions.

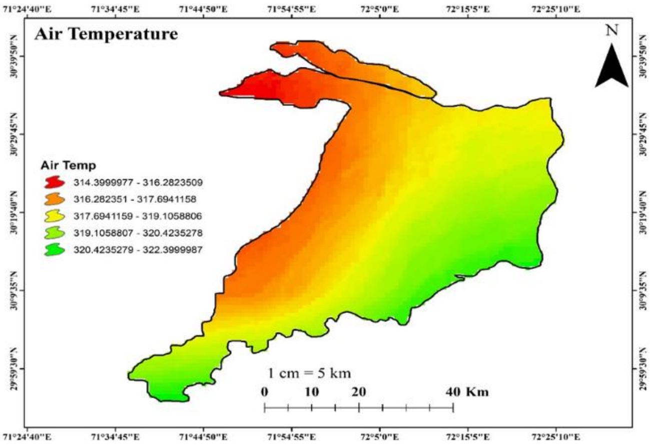

Figure 3. Air temperature map

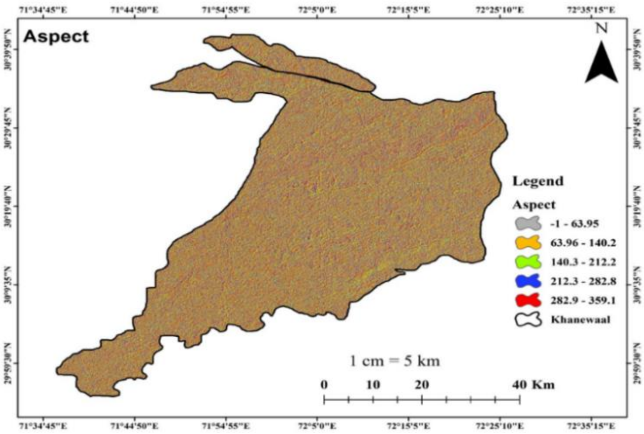

Figure 4. Aspect map of study region

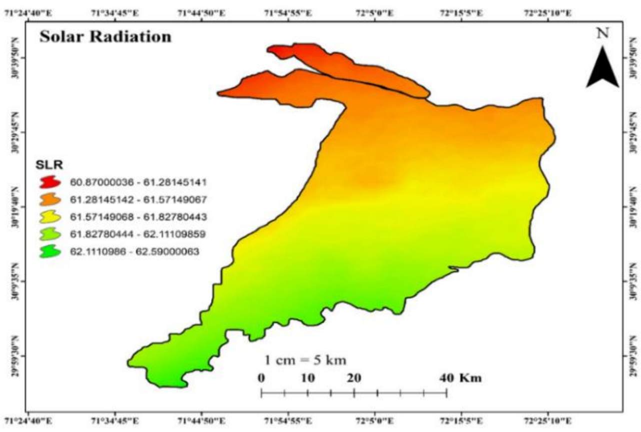

Figure 5. Solar radiation map

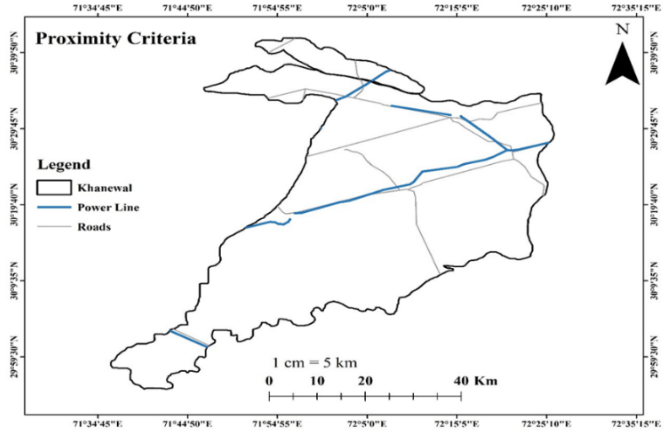

Figure 6. Proximity to power lines and roads

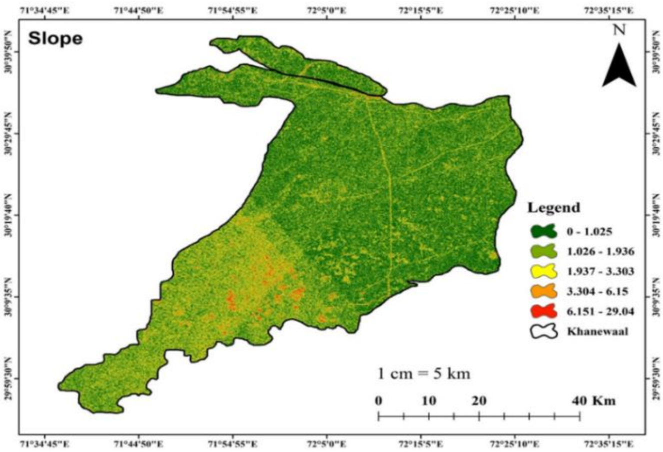

Figure 7. Slope map

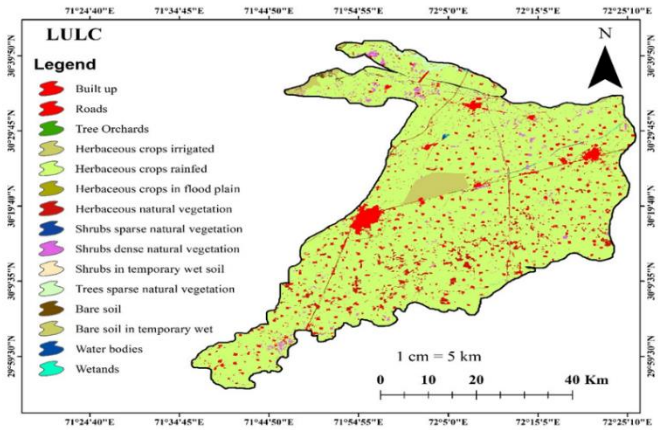

Figure 8. Land use and Land cover map

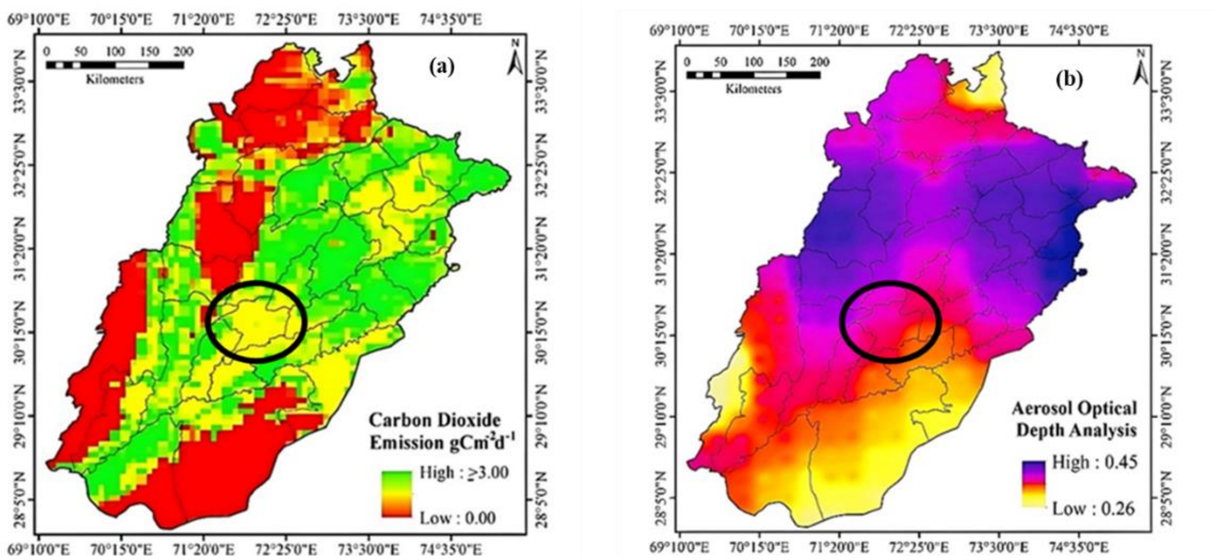

Figure 9. (a) Carbon dioxide emission, (b) Aerosol depth analysis

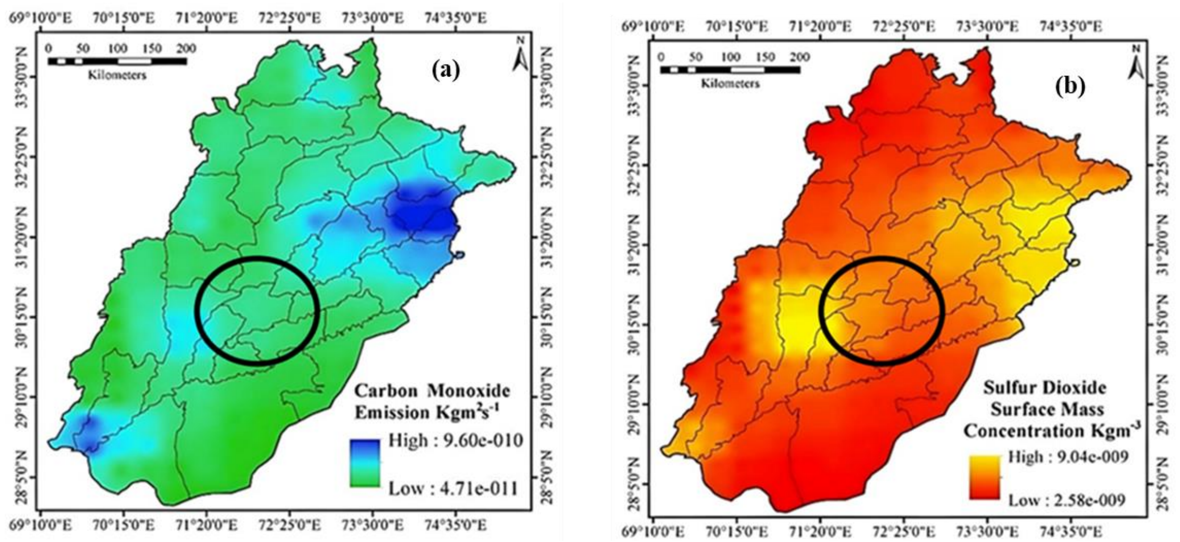

Figure 10. (a) Carbon monoxide emission, (b) sulfur dioxide surface mass concentration

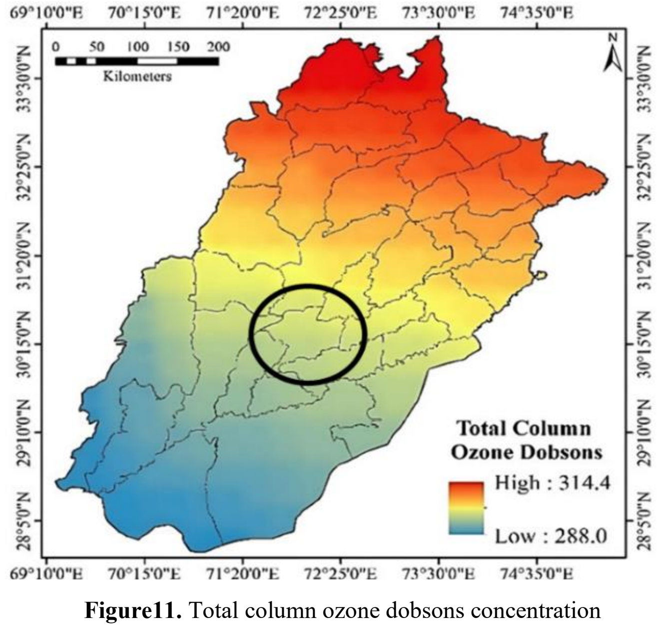

Figure11. Total column ozone dobsons concentration

The study employed Pearson correlation analysis to examine the relationship between solar irradiance measurements in Khanewal District and key air quality indicators: Aerosol Optical Depth (AOD), sulfur dioxide (SO_2), and carbon monoxide (CO). The analysis revealed a moderate to strong negative correlation between atmospheric pollution levels and surface solar energy, with both AOD and SO_2 similarly reducing solar radiation. These findings align with Neale et al. (2021) who reported that aerosols and gaseous pollutants decrease PV system efficiency by scattering and absorbing solar radiation.

In addition, regression analysis was conducted to quantify the effect of pollutants on solar irradiance. A linear regression model indicated that changes in atmospheric opacity (AOD) accounted for nearly 38% of the variation in solar energy output ($R^2 = 0.38$).

Beyond reducing sunlight availability, SO_2 and CO also degrade the lifespan and performance of solar panels by chemically damaging their surfaces. Incorporating pollution variables into our model thus improves the accuracy of future PV output estimates in areas with moderate to high smog levels, such as Khanewal.

Overall, this study clearly demonstrates how pollution decreases site suitability for solar energy and emphasizes the importance of integrating environmental factors into solar site selection. Sites with low pollution not only minimize ecological disruption but also support sustainable development. Although

Table 4. The matrix of pairwise comparisons for this analysis

Criteria	SLR	AT	SL	AS	LCLU	PTP	SM	NW
SLR	1	1.125	1.28	1.5	1.8	2.25	3	0.3137
AT	0.88	1	1.14	1.33	1.6	2	2.67	0.1937
SL	0.77	0.875	1	1.17	1.4	1.75	2.33	0.1814
AS	0.67	0.75	0.85	1	1.2	1.5	2	0.1122
LCLU	0.56	0.625	0.71	0.83	1	1.25	1.67	0.0984
PTPL	0.44	0.5	0.57	0.67	0.8	1	1.33	0.0529
SM	0.33	0.375	0.42	0.5	0.6	0.75	1	0.0476
								Sum = 1

proximity criteria were assigned lower weights, they remain important for reducing logistical and operational costs. Close proximity to power lines ensures efficient energy transmission, nearby road networks facilitate transportation logistics, and prioritizing areas with low smog helps maintain consistent solar panel performance.

3.1. Weights of thematic layers and MCDA

A scale of 1 to 9 was used to assign weights to each factor and its subclasses, as shown in Table 1. The AHP method was applied to determine normalized weights for these factors and their subclass features (T. L. Saaty, 2002). Table 4 presents the pairwise comparison matrix, which produced a consistency ratio (CR) of 0.08—well below the acceptable threshold of 0.1. This low CR value confirms the validity of the assigned weights, ensuring the accuracy and reliability of the evaluation process (T. L. Saaty, 1990). Consequently, the selected criteria are considered reliable and robust for this analysis.

Herein, SLR, LULC, SM, AT, SL, AS, and PPL are the solar radiation, land use land cover, air temperature, smog, slope, aspect, and proximity to power lines, respectively.

3.2. Suitability map of Solar PV plant and Boolean approach

The site suitability map for the solar PV plant was prepared using weighted overlay analysis within a GIS environment, as detailed in Table 1. The analysis classified the study region into four suitability classes: (1) low, (2) moderate, (3) high, and (4) very high. Results indicate that approximately 1.53% (42.94 km²) of the region is very highly suitable, 36.52% (1024.4 km²) is highly suitable, 30.88% (866.20 km²) is moderately suitable, and 2.65% (2.65 km²) is classified as low suitability. Spatially, moderately suitable areas are mainly found in the eastern and northern parts of the study region, while highly suitable zones occur in the western, eastern, southern, and central portions. Figure 12 shows the weighted linear combination (WLC) suitability map for solar PV plant installation. A Boolean approach was employed to eliminate certain locations, enhancing the accuracy of the suitability analysis. The Boolean map divided the study area into two classes: suitable (1) and unsuitable (0), as shown in Figure 13. This method incorporated critical constraints such as environmental protection zones, urban land use, and other restricted areas to ensure compliance with regulatory and environmental standards. Additional factors—including steep slopes, proximity to essential infrastructure, and potential land-use conflicts—were also considered to refine the analysis. Consequently, 16% (701 km²) of the total study area was identified as unsuitable, effectively narrowing down the available locations for solar PV installation.

This systematic exclusion of restricted areas improves resource allocation efficiency and strengthens the reliability of site selection. The final suitability map, presented in Figure 14, was produced by integrating the Boolean exclusion map with the weighted overlay suitability map. Figure 15 displays a bar graph summarizing the distribution of solar PV suitability classes. This integrated approach combines suitability rankings with exclusion criteria to generate a refined spatial representation of viable solar PV installation sites.

The Boolean analysis ensured that areas such as protected regions, water bodies, and steep terrains were excluded, while the weighted overlay method assessed multiple factors—including solar radiation, proximity to infrastructure, land use/land cover, and topography—assigning them relative importance. This multi-criteria decision-making process resulted in a comprehensive and practical site suitability assessment that balances environmental constraints with technical and economic considerations. By following this structured framework, the study successfully identified optimal locations aligned with both energy development needs and sustainability goals.

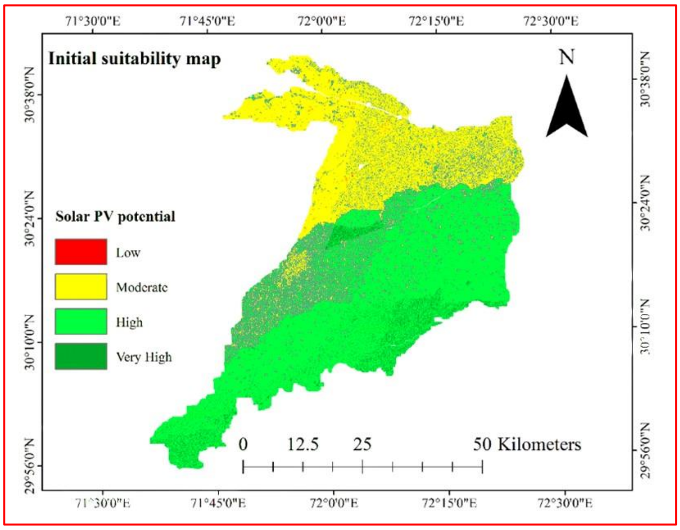

Figure 12. WLC map

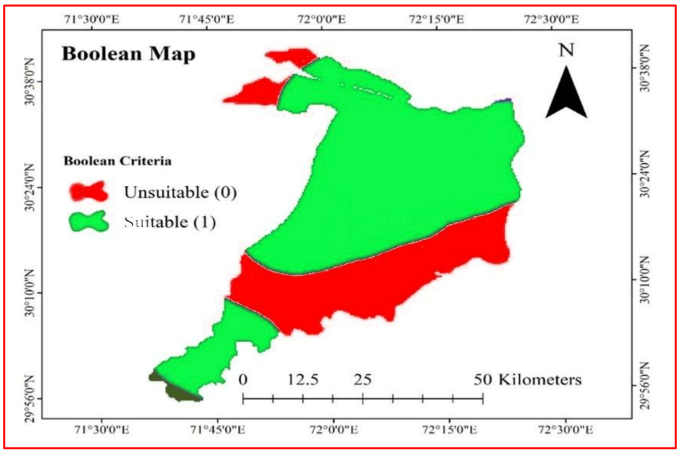

Figure 13. Boolean approach

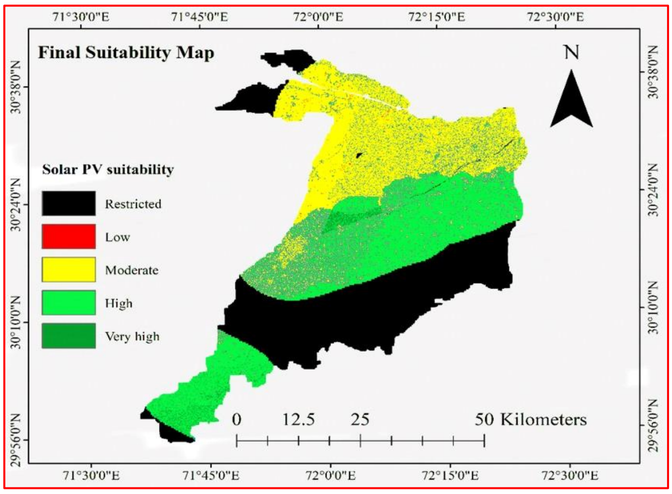

Figure 14. Final suitability map

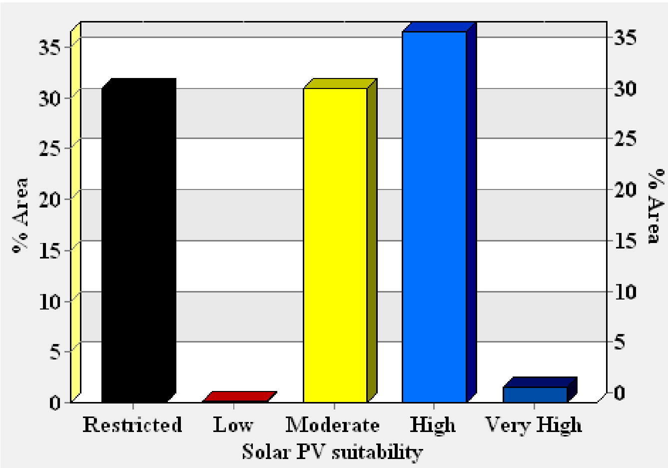

Figure 15. Solar PV suitability

The refined map not only identifies areas with high solar energy potential but also reduces the risk of project failure by addressing potential conflicts with local regulations and environmental policies. Additionally, this approach offers a replicable framework for similar studies in other regions, ensuring consistency and reliability in solar PV site selection. It highlights the value of integrating both quantitative and qualitative data to support evidence-based planning. By enabling well-informed decision-making, this comprehensive framework facilitates the implementation of renewable energy projects, playing a crucial role in advancing global sustainability initiatives and the transition to clean energy.

3.3. Diesel, Solar, and GRID energy contribution analysis

The hourly energy contributions from the grid between 7 AM and 5 PM over ten consecutive days show noticeable fluctuations in supply patterns, as illustrated in Figure 16. The data reveal variations in energy generation, with certain hours on some days recording no supply—possibly due to operational constraints, maintenance activities, or demand management strategies. For example, on Day 2, no energy was supplied during the early hours, whereas Day 1 exhibited a steady supply throughout the day. The highest energy supply occurred in the late morning and early afternoon, particularly at Hour 10, when Day 6 peaked at 270.85 kWh. In contrast, minimal or no energy was observed during early morning hours, such as Hour 3, across multiple days, indicating reduced activity or prioritized load distribution. These variations highlight the challenges of maintaining a stable supply and underscore the need for improved scheduling, resource allocation, and infrastructure upgrades to ensure consistent power availability. The findings provide valuable insights for enhancing energy management strategies, improving grid reliability, and better understanding supply-demand dynamics in the region.

Table 5. Comparison table with previous model used

Study	Study Area	Methodology	Most Suitable Area Identified (%)	Key Factors Considered	Remarks
This Study (2025)	Khanewal, Pakistan	GIS-AHP + Boolean + RS	1.54% (Very High), 36.52% (High)	Solar radiation, temperature, slope, aspect, LULC, smog, proximity factors	Incorporates smog and horticultural energy demand; validated via GHI and pollution data
Raza et al. (2023)	Pakistan (National Scale)	GIS-AHP	~25% (National Average Suitability)	Solar radiation, LULC, slope, infrastructure	Larger area, lacks pollution/environmental quality metrics
Abbasi & Zeeshan (2023)	Punjab, Pakistan	GIS-AHP	18.9% (High Suitability)	GHI, LULC, slope, population density	Focuses more on hybrid (solar-biomass); less environmental consideration
Islam et al. (2023)	Southern Bangladesh	GIS-AHP + MCDA	44.59% (High Suitability)	GHI, temperature, LULC, water bodies, roads	Similar method; excludes pollution or smog factors
Hashemizadeh et al. (2019)	Iran	GIS + Best–Worst Method (BWM)	~30% (High Suitability)	Economic cost, solar irradiation, climate, land cost	Includes economic analysis; different weighting method
Sánchez-Lozano et al. (2016)	Murcia, Spain	GIS-AHP + ELECTRE	~20% (High Suitability)	Environmental, technical, orographic, infrastructural	Advanced multi-criteria approach with validation

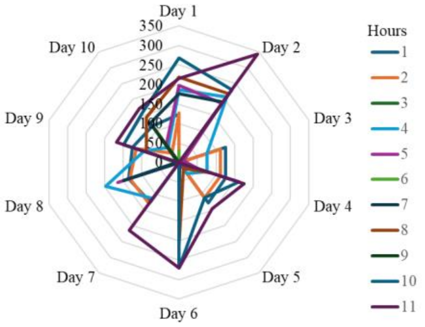

Figure 16. The GRID energy output (kWh) was recorded over a 10-day period from 7 AM to 5 PM

Figure 17 shows the output energy of the diesel generator from 7 AM to 5 PM over ten days. Most hours recorded zero contributions, especially during the early hours (Hours 1 and 2) and late afternoon (Hours 8 and 11), indicating idle periods, low demand, or operational downtime. Peak contributions occurred during Hour 9, with values exceeding 200 kWh on several days, including 242.03 kWh on Day 1 and 210.39 kWh on Day 2, reflecting periods of heightened energy demand or optimized generator performance. Hour 6 also consistently showed high contributions, peaking at 202.75 kWh on Day 3, highlighting its role as a significant operational period. Energy production during Hour 3 fluctuated widely, ranging from 61.49 kWh on Day 2 to 154.93 kWh on Days 1 and 6, further demonstrating irregular generator usage. Minimal contributions were sporadically observed during other hours, such as Hour 4, where values varied between 1.27 kWh and 79.76 kWh, indicating occasional partial use of the generator. These variations suggest the diesel generator functions primarily as a supplementary or backup energy source rather than the main provider. The intermittent nature of its output indicates opportunities for optimization to improve reliability, reduce downtime, and enhance fuel efficiency. Understanding these operational patterns is crucial for developing strategies to better integrate the generator into the energy system, ensuring cost-effectiveness and sustained performance.

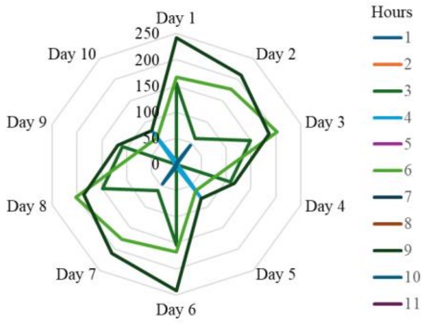

Figure 9. The diesel energy output (kWh) was recorded over a 10-day period from 7 AM to 5 PM

Figure 18 illustrates the solar panel energy output from 7 AM to 5 PM over ten days. Energy generation gradually rises from early morning, peaks around midday, and declines toward the evening, following the natural solar radiation cycle. The highest output was consistently recorded during Hour 7, peaking at 158.29 kWh on Day 1 and closely followed by 157.68 kWh on Day 5. This hour marked the period of maximum solar efficiency across all days. Hour 6 also showed significant contributions, reaching a peak of 156.41 kWh on Day 8, indicating another key energy generation period. Hour 5's production was substantial as well, ranging from 86.92 kWh on Day 10 to a maximum of 150.96 kWh on Day 8. In contrast, early morning output (Hour 1) was minimal, with values below 0.35 kWh, reflecting the limited energy generation potential at sunrise. Energy contributions during Hours 9 and 10 showed a noticeable decrease compared to peak hours, though still meaningful—for example, Day 4 recorded 102.41 kWh during Hour 9. Variability in energy output can be attributed to factors such as weather conditions, seasonal shifts, and system efficiency. These findings highlight the importance of optimizing panel orientation and incorporating storage solutions to maximize energy capture during peak periods and mitigate production shortfalls. Overall, the analysis confirms solar panels as a dependable renewable energy source during daylight hours, especially under favorable weather conditions.

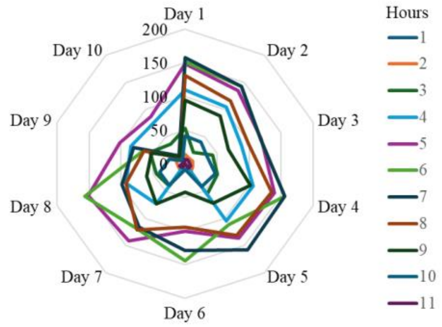

Figure 10. The solar panels' energy output (kWh) recorded over a 10-day period from 7 AM to 5 PM

3.4. Output Energy and economy Comparison: Solar Panels, GRID, and Diesel Generators

The output energy from solar panels, the GRID, and diesel generators was analyzed over a 10-day period from 7 AM to 5 PM to evaluate their performance. The GRID consistently provided the highest energy contribution across most days, reaching a maximum of 342.14 kWh on Day 2, thereby ensuring a reliable baseline supply. Solar panels demonstrated significant potential as a renewable energy source, with peak output reaching 150.01 kWh on Day 4, primarily during peak sunlight hours (Hours 6–8). However, solar energy generation exhibited substantial daily variability due to weather conditions, ranging from as low as 0.15 kWh on Day 10 to as high as 269.98 kWh on Day 4. In contrast, diesel generators functioned mainly as backup energy sources, with intermittent and limited contributions compared to the GRID and solar panels. Diesel generation peaked at 242.03 kWh on Days 1 and 6, typically compensating for deficits in GRID and solar supply. Notably, solar energy consistently outperformed diesel generation on most days; for example, solar output was 118.62 kWh on Day 3 and 102.23 kWh on Day 9.

The steady supply from the GRID was crucial for meeting the bulk of energy demand, while solar panels provided a clean, renewable supplement that reduced reliance on conventional sources. The diesel generator, though vital for flexibility and reliability, played a supplementary role. During midday hours (Hours 6–8), solar panels contributed significantly, alleviating the energy load on both the GRID and diesel generators. Conversely, solar efficiency declined during early morning (Hour 1) and late afternoon (Hour 11), with minimal contributions observed across all days. This analysis underscores the importance of integrating renewable energy sources like solar with conventional energy systems to optimize resource use and mitigate environmental impact. Despite its variability, solar energy effectively supports the energy mix and highlights the potential for hybrid systems to advance sustainable energy solutions.

A preliminary economic analysis using local cost inputs assessed the feasibility of solar PV systems for horticulture in Khanewal. The Levelized Cost of Electricity (LCOE) for solar PV was estimated at USD 0.055 per kWh, factoring in investment, maintenance, and typical daily generation. On average, this cost is significantly lower than diesel-generated power, which averages USD 0.19 per kWh due to high fuel expenses and operational inefficiencies. Solar PV offers a reliable long-term solution, especially given the grid's unreliability and frequent power outages in rural Pakistan. The payback period for a solar PV system used in horticulture is approximately 4.5 years, after which it provides virtually free electricity for 20 to 25 years. These findings align with IRENA (2020), which highlighted solar PV as a cost-effective and attractive option in off-grid and agricultural contexts. The economic advantages of solar PV make it a promising choice for small-scale farmers in Khanewal and support efforts to electrify rural areas.

Based on the 10-day data, replacing diesel generation with solar PV during equivalent hours could reduce diesel consumption by approximately 5,200 liters annually, assuming consistent year-round demand. This reduction would prevent the emission of roughly 13.6 metric tons of CO_2 per year, based on the standard combustion factor of 2.63 kg CO_2 per liter of diesel. Such savings not only decrease fuel costs but also significantly reduce greenhouse gas emissions, reinforcing both the environmental and economic benefits of adopting solar PV systems in Khanewal's horticultural sector.

4 .DISCUSSION

The findings of this study highlight the importance of applying a GIS-based Analytical Hierarchy Process (AHP) approach to identify optimal locations for solar photovoltaic (PV) installations in Khanewal District. The multi-criteria evaluation (MCE) method effectively integrates diverse environmental, topographical, and infrastructural parameters to produce a spatially explicit suitability analysis. The derived weights, validated by a low Consistency Ratio (CR = 0.08), ensure objectivity within the decision-making framework, consistent with Saaty's criteria for acceptable consistency in AHP models (Kabenla et al., 2024).

Results show that solar radiation (31.37%) is the most influential factor in site suitability, aligning with existing literature that identifies high Global Horizontal Irradiance (GHI) as essential for efficient solar energy production (Munkhbat & Choi, 2021). Areas with radiation values exceeding 6 kWh/m²/day, especially in the southern part of the district, provide optimal conditions for year-round energy generation and economic viability. This supports previous findings indicating that regions with high solar radiation offer greater return on investment for PV systems (Zaheb et al., 2023).

Air temperature (19.36%) was the second most critical criterion, showing a strong positive correlation with solar radiation. Moderate temperatures promote optimal panel efficiency, while extreme heat can diminish performance due to thermal losses. Spatial analysis identified the southern and eastern regions of Khanewal—characterized by both high radiation and favorable temperatures—as ideal locations for solar infrastructure development.

Topographical features, specifically slope (18.14%) and aspect (11.22%), also significantly affected site suitability. Gentle slopes (<5°) facilitate ease of construction, stability, and cost-effectiveness. South-facing aspects maximize sun exposure, enhancing energy yield. The land use/land cover (LULC) layer (9.84%) underscored the importance of selecting appropriate land, prioritizing barren and sparsely vegetated areas to minimize ecological disruption (Shah et al., 2021). Avoiding urban, forested, and agricultural zones prevents land-use conflicts and helps preserve biodiversity, consistent with UNDP recommendations for environmentally responsible energy planning.

Infrastructure factors, including proximity to power lines (5.29%) and roads, though weighted lower, remain operationally critical. Close access to the existing grid and road networks reduces construction and transmission costs, improves accessibility, and facilitates timely maintenance. A developed infrastructure network thus enhances the feasibility and scalability of solar projects.

Environmental quality, particularly smog and related pollutants (4.76%), adds complexity to site assessment. The inclusion of indicators such as CO_2, Aerosol Optical Depth (AOD), CO, and SO_2 was essential to ensure the long-term performance and durability of PV installations. Elevated SO_2 levels, known to degrade panel surfaces and reduce efficiency, highlight the detrimental effects of atmospheric pollutants on solar systems. While ozone levels carried less weight, their role in filtering UV radiation and maintaining atmospheric balance supports their inclusion in comprehensive site evaluations (Neale et al., 2021).

The site suitability classification revealed that only 1.53% of Khanewal is very highly suitable, with a substantial portion (36.52%) classified as highly suitable. The spatial clustering of highly suitable areas in the southern and central district further confirms the predominance of climatic and terrain factors in determining solar feasibility. The use of a Boolean exclusion approach refined the spatial analysis by removing 16% (701 km²) of the area deemed unsuitable due to environmental protection zones, urban constraints, steep terrain, and regulatory restrictions. This step improves the credibility of the final results by ensuring compliance with policy, legal, and environmental frameworks. By integrating weighted overlay analysis with Boolean constraints, the study produced a comprehensive final suitability map, offering a robust decision-support tool for policymakers and investors. This integrative approach ensures that energy planning is economically viable, environmentally sustainable, and legally compliant.

5. CONCLUSIONS

This study presents a novel theoretical framework that integrates GIS, multi-criteria decision analysis (MCDA), and additional thematic maps to enhance the accuracy and reliability of solar PV site suitability assessments. The key theoretical contribution lies in the comprehensive consideration of both biophysical factors (such as land use, solar radiation, and slope) and socioeconomic factors (including proximity to built-up areas and infrastructure access), validated through consistency analysis to ensure robust decision-making. This integrative approach advances traditional site selection methodologies by providing a scalable and replicable model adaptable to resource-scarce regions.

The results indicate that 1.54% (42.94 km²) of Khanewal District is very highly suitable for solar PV plants, 36.52% (1024.4 km²) highly suitable, 30.88% (866.20 km²) moderately suitable, and 0.095% (2.65 km²) poorly suitable, while approximately 31% of the area is restricted. Energy source analysis demonstrates the complementary roles of the GRID, diesel generators, and solar panels, with solar energy showing significant potential to reduce dependence on non-renewable sources during peak daylight hours.

The study's limitations include reliance on static input data, the absence of economic feasibility and social impact assessments, and assumptions regarding climatic and infrastructural stability. Future research should focus on integrating dynamic datasets, conducting detailed field validations, and employing advanced techniques such as fuzzy AHP and machine learning algorithms—including random forests, neural networks, and support vector machines—to further improve site suitability assessments.

Subsequent studies could explore incorporating economic cost-benefit analyses and social acceptance factors for a more holistic evaluation of solar PV deployment. Additionally, investigating the long-term environmental impacts and the potential for hybrid renewable energy systems would deepen the understanding of sustainable energy solutions. The inclusion of real-time monitoring data and climate change scenarios will also enhance the resilience and adaptability of solar energy planning frameworks.

While this study successfully applied a structured GIS-AHP methodology, future research can benefit from integrating machine learning (ML) and deep learning (DL) techniques for faster and more accurate spatial suitability assessments. Methods such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting can uncover complex relationships between environmental and infrastructural variables, as well as historical solar installation data, improving location predictions. Deep learning models, particularly Convolutional Neural Networks (CNNs), can analyze detailed remote sensing images to identify spatial features, accurately classify landforms, and regularly update suitability maps as conditions change. These models can also incorporate large datasets, including time-series satellite data, weather patterns, and socioeconomic indicators, often with automated processing. Unlike rule-based AHP, data-driven approaches can adapt to new information and improve with increasing real-world data. Thus, ML and DL methods have strong potential to scale, automate, and enhance decision support in national and regional solar energy planning.

This research contributes new knowledge by providing a cost-effective, adaptable, and integrative decision-support framework for renewable energy planning. It offers practical guidance for energy engineers, planners, and policymakers aiming to optimize solar energy deployment and promote sustainable development in Khanewal District and similar regions. These findings can directly inform energy policy by supporting solar incentive programs, off-grid electrification initiatives, and spatially targeted renewable energy investments in underserved rural areas.

6. Limitations

Several factors identified in this study may limit the accuracy and practical usefulness of the site suitability results. The varying resolutions of input data—such as the 90-meter DEM, 500-meter LULC, and intermediate resolutions for other layers—could introduce spatial inconsistencies or generalization errors when these datasets are overlaid. Another challenge arises from the differing time spans covered by datasets like smog and solar radiation, which may affect temporal consistency. Furthermore, reliance on static land use data means recent rapid developments or land conversions might have been overlooked, potentially impacting future suitability assessments. The absence of ground-truth smog measurements also limits the reliability of pollution data, which was based solely on satellite observations. In addition, while the AHP method provides a logical framework for comparisons, it depends on expert judgments that—despite being research-informed—cannot entirely eliminate subjective bias. Given these limitations, future studies should incorporate advanced, frequently updated models and leverage datasets capable of providing higher spatial and temporal resolution in near real-time.

ACKNOWLEDGEMENT

Conceptualization, M.R., M.A.U.R.T and A.N.; data curation and software, M.R.; formal analysis, S.U. and M.R.; supervision, M.A.U.R.T.; validation, S.U.; visualization, M.S, F.A and M.A.U.R.T.; writing—original draft, S.U.; writing—review and editing, F.A, S.D., M.S. All authors have read and agreed to the published version of the manuscript.

REFERENCES

1. Abbasi, H. N., & Zeeshan, M. (2023). An integrated Geographic Information System and Analytical Hierarchy process based approach for site suitability analysis of on-grid hybrid concentrated solar-biomass powerplant. *Renewable and Sustainable Energy Reviews*, *187*(September), 113786. https://doi.org/10.1016/j.rser.2023.113786

2. Ackerman, F., & Stanton, E. (2009). The economics of 350: the benefits and costs of climate stabilization. …, *October*, 51.

3. Adnan, S., Hayat Khan, A., Haider, S., & Mahmood, R. (2012). Solar energy potential in Pakistan. *Journal of Renewable and Sustainable Energy*, *4*(3). https://doi.org/10.1063/1.4712051

4. Al Garni, H. Z., & Awasthi, A. (2017). Solar PV power plant site selection using a GIS-AHP based approach with application in Saudi Arabia. *Applied Energy*, *206*. https://doi.org/10.1016/j.apenergy.2017.10.024

5. Al Garni, H. Z., & Awasthi, A. (2018). Chapter 2 - Solar PV Power Plants Site Selection: A Review. In I. Yahyaoui (Ed.), *Advances in Renewable Energies and Power Technologies* (pp. 57–75). Elsevier. https://doi.org/10.1016/B978-0-12-812959-3.00002-2

6. Al Garni, H. Z., & Awasthi, A. (2020). Chapter 20 - A Monte Carlo approach applied to sensitivity analysis of criteria impacts on solar PV site selection. In P. Samui, D. Tien Bui, S. Chakraborty, & R. C. Deo (Eds.), *Handbook of Probabilistic Models* (pp. 489–504). Butterworth-Heinemann. https://doi.org/10.1016/B978-0-12-816514-0.00020-5

7. Aydin, N. Y., Kentel, E., & Duzgun, S. (2010). GIS-based environmental assessment of wind energy systems for spatial planning: A case study from Western Turkey. *Renewable and Sustainable Energy Reviews*, *14*(1), 364–373. https://doi.org/10.1016/j.rser.2009.07.023

8. Belaid, A., Guermoui, M., Khelifi, R., Arrif, T., Chekifi, T., Rabehi, A., El-Kenawy, E.-S., & Alhussan, A. (2024). Assessing Suitable Areas for PV Power Installation in Remote Agricultural Regions. *Energies*. https://doi.org/10.3390/en17225792

9. Charabi, Y., & Gastli, A. (2011). PV site suitability analysis using GIS-based spatial fuzzy multi-criteria evaluation. *Renewable Energy*, *36*(9). https://doi.org/10.1016/j.renene.2010.10.037

10. Chowdhury, M. S., Rahman, K. S., Chowdhury, T., Nuthammachot, N., Techato, K., Akhtaruzzaman, M., Tiong, S. K., Sopian, K., & Amin, N. (2020). An overview of solar photovoltaic panels' end-of-life material recycling. *Energy Strategy Reviews*, *27*. https://doi.org/10.1016/j.esr.2019.100431

11. Dawson, F. G., Alexander, G., & Hofmann, P. L. (1979). Solar Powered Irrigation. In *Sunworld* (Vol. 3, Issue 5).

12. DeCanio, S. J., & Fremstad, A. (2011). Economic feasibility of the path to zero net carbon emissions. *Energy Policy*, *39*(3), 1144–1153. https://doi.org/10.1016/j.enpol.2010.11.038

13. Dehshiri, S. S. H., & Firoozabadi, B. (2023). A novel four-stage integrated GIS based fuzzy SWARA approach for solar site suitability with hydrogen storage system. *Energy*. https://doi.org/10.1016/j.energy.2023.127927

14. Delivand, M. K., Cammerino, A. R. B., Garofalo, P., & Monteleone, M. (2015). Optimal locations of bioenergy facilities, biomass spatial

availability, logistics costs and GHG (greenhouse gas) emissions: a case study on electricity productions in South Italy. *Journal of Cleaner Production*, *99*, 129–139. https://doi.org/10.1016/j.jclepro.2015.03.018

15. Dubayar, R., & Rich, P. M. (1996). GIS-based solar radiation modeling. *GIS and Environmental Modeling: Progress …*, *0*, 129–134.

16. Feng, X., Zhang, Z., Chen, Q., Guo, Z., Zhang, H., Wang, M., Gao, W., & Liu, X. (2025). Integrating Remote Sensing, GIS, and Multi-Criteria Decision Making for Assessing PV Potential in Mountainous Regions. *Renewable Energy*. https://doi.org/10.1016/j.renene.2025.122340

17. Fu, P., & Rich, P. M. (1999). Design and Implementation of the Solar Analyst: an ArcView Extension for Modeling Solar Radiation at Landscape Scales. *19th Annual ESRI User Conference*, *February*, 1–24.

18. Garcia, J., Gacu, J., & Lawrence, M. (2024). Suitability Analysis for Solar PV Farm Installation using GIS and Analytical Hierarchy Process (AHP) in Simara Island, Province of Romblon, Philippines. *E3S Web of Conferences*. https://doi.org/10.1051/e3sconf/202447301013

19. Gastli, A., Charabi, Y., & Zekri, S. (2010). GIS-based assessment of combined CSP electric power and seawater desalination plant for Duqum—Oman. *Renewable and Sustainable Energy Reviews*, *14*(2), 821–827. https://doi.org/10.1016/j.rser.2009.08.020

20. Georgiou, A., & Skarlatos, D. (2016). Optimal site selection for sitting a solar park using multi-criteria decision analysis and geographical information systems. *Geoscientific Instrumentation, Methods and Data Systems*, *5*(2), 321–332. https://doi.org/10.5194/gi-5-321-2016

21. Gerbo, A., Suryabhagavan, K. V., & Kumar Raghuvanshi, T. (2022). GIS-based approach for modeling grid-connected solar power potential sites: a case study of East Shewa Zone, Ethiopia. *Geology, Ecology, and Landscapes*, *6*(3), 159–173. https://doi.org/10.1080/24749508.2020.1809059

22. Guaita-Pradas, I., Marques-Perez, I., Gallego, A., & Segura, B. (2019). Analyzing territory for the sustainable development of solar photovoltaic power using GIS databases. *Environmental Monitoring and Assessment*, *191*(12). https://doi.org/10.1007/s10661-019-7871-8

23. Günen, M. A. (2021). Determination of the suitable sites for constructing solar photovoltaic (PV) power plants in Kayseri, Turkey using GIS-based ranking and AHP methods. *Environmental Science and Pollution Research*, *28*(40). https://doi.org/10.1007/s11356-021-14622-x

24. Hafeznia, H., Yousefi, H., & Razi Astaraei, F. (2017). A novel framework for the potential assessment of utility-scale photovoltaic solar energy, application to eastern Iran. *Energy Conversion and Management*, *151*, 240–258. https://doi.org/10.1016/J.ENCONMAN.2017.08.076

25. Hashemizadeh, A., Ju, Y., & Dong, P. (2019). A combined geographical information system and Best–Worst Method approach for site selection for photovoltaic power plant projects. *International Journal of Environmental Science and Technology*, *17*(4), 2027–2042. https://doi.org/10.1007/s13762-019-02598-8

26. Hermann, S., Miketa, A., & Fichaux, N. (2014). Estimating the Renewable Energy Potential in Africa: A GIS-based approach. *IRENA-KTH Working Paper*, 70.

27. Hoffert, M. I., Caldeira, K., Jain, A. K., Haites, E. F., Harvey, L. D. D., Potter, S. D., Schlesinger, M. E., Schneider, S. H., Watts, R. G., Wigley, T. M. L., & Wuebbles, D. J. (1998). Energy implications of future stabilization of atmospheric CO2 content. *Nature*, *395*(6705), 881–884. https://doi.org/10.1038/27638

28. Iqbal, S., Ali, S. M., Islam, A., Zaidi, S. N. F., & Ali, I. (2020). Alternate energy source selection in Gilgit Baltistan Pakistan using geographical information system and analytical hierarchy process. *International Journal of Energy and Water Resources*, *4*(3), 257–270. https://doi.org/10.1007/s42108-020-00076-3

29. Islam, M. R., Aziz, M. T., Alauddin, M., Kader, Z., & Islam, M. R. (2023). Sites suitability assessment for solar power plants in Bangladesh: A GIS-based analytical hierarchy process (AHP) and multi-criteria decision analysis (MCDA) approach. *Renewable Energy*. https://doi.org/10.1016/j.renene.2023.119595

30. Islam, M. R., Aziz, M. T., Alauddin, M., Kader, Z., & Islam, M. R. (2024). Site suitability assessment for solar power plants in Bangladesh: A GIS-based analytical hierarchy process (AHP) and multi-criteria decision analysis (MCDA) approach. *Renewable Energy*, *220*(October 2023), 119595. https://doi.org/10.1016/j.renene.2023.119595

31. Janke, J. R. (2010). Multicriteria GIS modeling of wind and solar farms in Colorado. *Renewable Energy*, *35*(10), 2228–2234. https://doi.org/10.1016/j.renene.2010.03.014

32. Jbaihi, O., Ouchani, F.-Z., Merrouni, A., Cherkaoui, M., Ghennioui, A., & Maaroufi, M. (2022). An AHP-GIS based site suitability analysis for integrating large-scale hybrid CSP+PV plants in Morocco: An approach to address the intermittency of solar energy. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2022.133250

33. Kabenla, R., Ampofo, S., Owusu, G., Atulley, J. A., & Boateng, A. (2024). *Application of Analytical Hierarchy Process (AHP) and Multi-Criteria Evaluation (MCE) for a Case Study and Scenario Assessment of Flood Risk in the White Volta Basin of the Upper East Region, Ghana*. https://doi.org/10.21203/rs.3.rs-4186633/v1

34. Kaijuka, E. (2007). GIS and rural electricity planning in Uganda. *Journal of Cleaner Production*, *15*(2), 203–217. https://doi.org/10.1016/j.jclepro.2005.11.057

35. Kamdar, I., Ali, S., Bennui, A., Techato, K., & Jutidamrongphan, W. (2019). Municipal solid waste landfill siting using an integrated GIS-AHP approach: A case study from Songkhla, Thailand. *Resources, Conservation and Recycling*, *149*, 220–235. https://doi.org/10.1016/j.resconrec.2019.05.027

36. Khan, A., Ali, Y., & Pamucar, D. (2023). Solar PV power plant site selection using a GIS-based non-linear multi-criteria optimization technique. *Environmental Science and Pollution Research*, *30*(20), 57378–57397. https://doi.org/10.1007/s11356-023-26540-1

37. Koc, A., Turk, S., & Şahin, G. (2019). Multi-criteria of wind-solar site selection problem using a GIS-AHP-based approach with an application in Igdir Province/Turkey. *Environmental Science and Pollution Research*, *26*(31), 32298–32310. https://doi.org/10.1007/s11356-019-06260-1

38. Kucuksari, S., Khaleghi, A. M., Hamidi, M., Zhang, Y., Szidarovszky, F., Bayraksan, G., & Son, Y.-J. (2014). An Integrated GIS, optimization and simulation framework for optimal PV size and location in campus area environments. *Applied Energy*, *113*, 1601–1613. https://doi.org/10.1016/j.apenergy.2013.09.002

39. Lee, A. H. I., Chen, H. H., & Kang, H.-Y. (2009). Multi-criteria decision making on strategic selection of wind farms. *Renewable Energy*, *34*(1), 120–126. https://doi.org/10.1016/j.renene.2008.04.013

40. Lee, A. H. I., Kang, H.-Y., Lin, C.-Y., & Shen, K.-C. (2015). An Integrated Decision-Making Model for the Location of a PV Solar Plant. *Sustainability*, *7*(10), 13522–13541. https://doi.org/10.3390/su71013522

41. Li, D. (2013). Using GIS and Remote Sensing Techniques for Solar Panel Installation Site Selection. *Master of Science Dissertation, Department of Geography, University of Waterloo*, 1–140.

42. Munkhbat, U., & Choi, Y. (2021). GIS-Based Site Suitability Analysis for Solar Power Systems in Mongolia. *Applied Sciences*, *11*, 3748. https://doi.org/10.3390/app11093748

43. Mussa, A., & Suryabhagavan, K. V. (2021). Solid waste dumping site selection using GIS-based multi-criteria spatial modeling: a case study in Logia town, Afar region, Ethiopia. *Geology, Ecology, and Landscapes*, *5*(3), 186–198. https://doi.org/10.1080/24749508.2019.1703311

44. Nadeem, A., Tariq, M. A. U. R., Sarwar, K., Iqbal, M., Ahmad, K., & Ahmed, K. (2024). Assessing the environmental impacts of reclaimed and conventional water in hydroponics based on a life cycle assessment approach. *Water Supply*, *24*(8), 2765–2780. https://doi.org/10.2166/ws.2024.160

45. Neale, R. E., Barnes, P. W., Robson, T. M., Neale, P. J., Williamson, C. E., Zepp, R. G., Wilson, S. R., Madronich, S., Andrady, A. L., Heikkilä, A. M., Bernhard, G. H., Bais, A. F., Aucamp, P. J., Banaszak, A. T., Bornman, J. F., Bruckman, L. S., Byrne, S. N., Foereid, B., Häder, D.-P., … Zhu, M. (2021). Environmental effects of stratospheric ozone depletion, UV radiation, and interactions with climate change: UNEP Environmental Effects Assessment Panel, Update 2020. *Photochemical & Photobiological Sciences*, *20*(1), 1–67. https://doi.org/10.1007/s43630-020-00001-x

46. Noorollahi, Y., Itoi, R., Fujii, H., & Tanaka, T. (2007). GIS model for geothermal resource exploration in Akita and Iwate prefectures, northern Japan. *Computers & Geosciences*, *33*(8), 1008–1021. https://doi.org/10.1016/j.cageo.2006.11.006

47. Onuoha, H., Denwigwe, I., Babatunde, O., Abdulsalam, K., Adebisi, J., Emezirinwune, M., Okharedia, T., Akindayomi, A., Adisa, K., & Hamam, Y. (2025). Integrating GIS and AHP for Photovoltaic Farm Site Selection: A Case Study of Ikorodu, Nigeria. *Processes*. https://doi.org/10.3390/pr13010164

48. Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. *Renewable and Sustainable Energy Reviews*, *8*(4), 365–381. https://doi.org/10.1016/j.rser.2003.12.007

49. Rahayani, R., & Nair, N. (2023). A Double MCDM-GIS Analysis for Solar Power Plant Site Selections in Disaster-Prone Area: A case study of Hawkes Bay. *2023 International Conference on Power and Renewable Energy Engineering (PREE)*, 64–69. https://doi.org/10.1109/PREE57903.2023.10370716

50. Raza, M. A., Yousif, M., Hassan, M., Numan, M., & Abbas Kazmi, S. A. (2023). Site suitability for solar and wind energy in developing countries using combination of GIS- AHP; a case study of Pakistan. *Renewable Energy*, *206*, 180–191. https://doi.org/10.1016/j.renene.2023.02.010

51. Ren, Y., Zhou, Y., & Shi, L. (2012). Decision-making approach in charging mode for electric vehicle based on cumulative prospect theory. *China International Conference on Electricity Distribution, CICED*, 1–4. https://doi.org/10.1109/CICED.2012.6508496

52. Ruiz-Arias, J. A., Tovar-Pescador, J., Pozo-Vázquez, D., & Alsamamra, H. (2009). A comparative analysis of DEM-based models to estimate the solar radiation in mountainous terrain. *International Journal of Geographical Information Science*, *23*(8), 1049–1076. https://doi.org/10.1080/13658810802022806

53. Ruiz, H. S., Sunarso, A., Ibrahim-Bathis, K., Murti, S. A., & Budiarto, I. (2020). GIS-AHP Multi Criteria Decision Analysis for the optimal location of solar energy plants at Indonesia. *Energy Reports*, *6*, 3249–3263. https://doi.org/10.1016/j.egyr.2020.11.198

54. Saaty, R. W. (1987). The analytic hierarchy process-what it is and how it is used. *Mathematical Modelling*, *9*(3–5), 161–176. https://doi.org/10.1016/0270-0255(87)90473-8

55. Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research*, *48*(1), 9–26. https://doi.org/10.1016/0377-2217(90)90057-I

56. Saaty, T. L. (2002). Decision making with the Analytic Hierarchy Process. *Scientia Iranica*, *9*(3), 215–229. https://doi.org/10.1504/ijssci.2008.017590

57. Sánchez-Lozano, J. M., García-Cascales, M. S., & Lamata, M. T. (2016). Comparative TOPSIS-ELECTRE TRI methods for optimal sites for photovoltaic solar farms. Case study in Spain. *Journal of Cleaner Production*, *127*, 387–398. https://doi.org/10.1016/j.jclepro.2016.04.005

58. Sánchez-Lozano, J. M., Henggeler Antunes, C., García-Cascales, M. S., & Dias, L. C. (2014). GIS-based photovoltaic solar farms site selection using ELECTRE-TRI: Evaluating the case for Torre Pacheco, Murcia, Southeast of Spain. *Renewable Energy*, *66*, 478–494. https://doi.org/10.1016/j.renene.2013.12.038

59. Sánchez-Lozano, J. M., Teruel-Solano, J., Soto-Elvira, P. L., & Socorro García-Cascales, M. (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

60. Schnetzer, J., & Pluscke, L. (2017). *Solar-Powered Irrigation Systems: A clean-energy, low-emission option for irrigation development and modernization*. 9.

61. Shah, F., Wei, L., Lashari, A., Islam, A., Khattak, H., & Rasool, U. (2021). Evaluation of land use and land cover Spatio-temporal change during rapid Urban sprawl from Lahore, Pakistan. *Urban Climate*, *39*, 100931. https://doi.org/10.1016/j.uclim.2021.100931

62. Sheikh, M. A. (2009). Renewable energy resource potential in Pakistan. *Renewable and Sustainable Energy Reviews*, *13*(9), 2696–2702. https://doi.org/10.1016/j.rser.2009.06.029

63. Solangi, K. H., Islam, M. R., Saidur, R., Rahim, N. A., & Fayaz, H. (2011). A review on global solar energy policy. *Renewable and Sustainable Energy Reviews*, *15*(4), 2149–2163. https://doi.org/10.1016/j.rser.2011.01.007

64. Solangi, Y. A., Shah, S. A. A., Zameer, H., Ikram, M., & Saracoglu, B. O. (2019). Assessing the solar PV power project site selection in Pakistan: based on AHP-fuzzy VIKOR approach. *Environmental Science and Pollution Research*, *26*(29), 30286–30302. https://doi.org/10.1007/s11356-019-06172-0

65. Suprova, N. T., Zidan, R., & Rashid, A. R. M. H. (2020). Optimal Site Selection for Solar Farms Using GIS and AHP: A Literature Review. *Proceedings of the International Conference on Industrial & Mechanical Engineering and Operations Management, Dhaka, Bangladesh*, 26–27.

66. Šúri, M., & Hofierka, J. (2004). (n.d.). *Šúri, M., & Hofierka, J. (2004). A new GIS-based solar radiation model and its application to photovoltaic assessments. Transactions in GIS, 8(2), 175-190.*

67. Taghizadeh-hesary, F., & Yoshino, N. (2020). Sustainable Solutions for Green Financing and. *Energy Economics and Policy in Developed Countries*, *13*(4).

68. Tegou, L.-I., Polatidis, H., & Haralambopoulos, D. A. (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

69. Tunc, A., Tuncay, G., Alacakanat, Z., & Sevimli, F. S. (2019). Gis based solar power plants site selection using analytic hierarchy process (ahp) in istanbul, Turkey. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *42*(2/W13), 1353–1360. https://doi.org/10.5194/isprs-archives-XLII-2-W13-1353-2019

70. Ullah, S., Iqbal, M., Waseem, M., Abbas, A., Masood, M., Nabi, G., Tariq, M. A. U. R., & Sadam, M. (2024). Potential Sites for Rainwater Harvesting Focusing on the Sustainable Development Goals Using Remote Sensing and Geographical Information System. *Sustainability (Switzerland)*, *16*(21). https://doi.org/10.3390/su16219266

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

72. Wang, J.-J., Jing, Y.-Y., Zhang, C.-F., & Zhao, J.-H. (2009). Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renewable and Sustainable Energy Reviews*, *13*(9), 2263–2278. https://doi.org/10.1016/j.rser.2009.06.021

73. Watson, J. J. W., & Hudson, M. D. (2015). Regional Scale wind farm and solar farm suitability assessment using GIS-assisted multi-criteria evaluation. *Landscape and Urban Planning*, *138*, 20–31. https://doi.org/10.1016/j.landurbplan.2015.02.001

74. Wigley, T. M. L., Richels, R., & Edmonds, J. A. (1996). Economic and environmental choices in the stabilization of atmospheric CO2 concentrations. *Nature*, *379*(6562), 240–243. https://doi.org/10.1038/379240a0

75. Wilton, E., Delarue, E., D'haeseleer, W., & van Sark, W. (2014). Reconsidering the capacity credit of wind power: Application of cumulative prospect theory. *Renewable Energy*, *68*, 752–760. https://doi.org/10.1016/j.renene.2014.02.051

76. Wind, Y., & Saaty, T. L. (1980). Marketing applications of the analytic hierarchy process. *Management Science*, *26*(7), 641–658.

77. Xiao, J., Yao, Z., Qu, J., & Sun, J. (2013). Research on an optimal site selection model for desert photovoltaic power plants based on analytic hierarchy process and geographic information system. *Journal of Renewable and Sustainable Energy*, *5*(2). https://doi.org/10.1063/1.4801451

78. Xu, X., Wei, Z., Ji, Q., Wang, C., & Gao, G. (2019). Global renewable energy development: Influencing factors, trend predictions and countermeasures. *Resources Policy*, *63*(August). https://doi.org/10.1016/j.resourpol.2019.101470

79. Zaheb, H., Amiry, H., Ahmadi, M., Fedayi, H., Amiry, S., & Yona, A. (2023). Maximizing Annual Energy Yield in a Grid-Connected PV Solar Power Plant: Analysis of Seasonal Tilt Angle and Solar Tracking Strategies. *Sustainability*, *15*(14). https://doi.org/10.3390/su151411053