Iraqi Journal of Science, 2026, Vol. 67, No. 10, pp: 5540-5563
DOI: 10.24996/ijs.2026.67.10.32

ISSN: 0067-2904

Evaluation of Solar Farm Sites in Karbala Governorate Using GIS and Fuzzy Hierarchy Techniques

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Received: 8/5/2025 Accepted: 15/1/2026 Published: 30/10/2026

Abstract:
The rapid growth of renewable energy has become a cornerstone of the contemporary global energy landscape. Solar energy, with its vast potential, holds promise for meeting the escalating energy demands and expanding its prominence within the energy sector. This research aims to assess feasible locations for the establishment of utility-scale solar photovoltaic (PV) plants in Karbala Governorate, situated in central Iraq. In this research, Geographic Information Systems (GIS) tools and techniques were used within the framework of a Multi-Criteria Decision-Making (MCDM) methodology. Data were collected from several reliable sources, including the Iraqi Ministry of Agriculture, the Iraqi Meteorological Organization, the Ministry of Planning, and the United States Geological Survey (USGS). These sources helped to create a realistic picture of the environmental conditions and infrastructure in the study area. The research first identifies and assigns weights to various factors (such as slope, solar radiation, proximity to power grid, distance from urban areas, proximity to road networks, distance from water bodies, Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), precipitation, proximity to fault lines, and annual dust accumulation) that influence the suitability of potential solar PV plant sites. This is achieved through the Fuzzy Analytical Hierarchy Process (FAHP), which discerns distinct categories of suitability. Subsequently, all layers are transformed into fuzzy membership layers to delineate constraints across the study area, thereby accentuating unsuitable sites. The culmination of this effort involves multiplying the fuzzy-weighted set of relevant factors by the fuzzy-logic layer to produce the final suitability map. Upon scrutinizing the results, it becomes apparent that constraints envelop 83% of the study area, while a discernible 17% meets the requisite criteria, rendering them suitable for the establishment of utility-scale solar installations. Notably, a significant proportion of these potential areas is located near power transmission infrastructure and urban centers, highlighting their economic viability and potential impact.

Keywords: GIS, Fuzzy-AHP, Multi-Criteria Decision Analysis (MCDA), Solar Farm, Site Selection, Renewable Energy, Suitability Mapping, Karbala

1.1 INTRODUCTION

Energy is also important in economic activity because a competitive, sustainable energy supply is a key driver of economic growth and social development. One indicator of societal development is per capita energy consumption. The world economy is highly dependent on fossil fuels, which are coal, oil, and natural gas. Nevertheless, the fact that fossil fuel reserves

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are finite implies that they will ultimately run out sometime in the next century if current trends of consumption do not change [1]. In addition, the high usage of fossil fuels has resulted in serious environmental damage. Greenhouse gases and other pollutants emitted through the combustion of fossil fuels have a direct effect on the environment. Incomplete combustion specifically emits high amounts of carbon dioxide, sulfur dioxide, and nitrogen oxides, among other greenhouse gases, into the atmosphere [2].

On the other hand, demand for energy is growing rapidly worldwide due to population and economic growth, particularly in developing nations, and is exceeding the ability of existing energy sources to meet it. The energy demand will increase by two or three times by 2050. Thus, it is necessary to have clean, renewable energy sources that are environmentally friendly to ensure long-term sustainability. Renewable energy, which was traditionally considered a source of energy derived from naturally replenished resources and with a short time frame, has become more viable due to the speedy technological improvement. The growth of renewable energy use, along with the enhanced efficiency of energy conversion devices, has the potential to boost energy security, curb the impacts of climate change, and yield economic benefits [3]. The chosen renewable energy sources can supply energy to the remote communities at competitive prices. In addition, renewable energy sources have a lower environmental footprint compared to fossil fuels and nuclear power. Nowadays, replacing non-renewable energy sources with renewable ones is a crucial challenge and an energy goal for most states. This increasing trend in electricity and thermal energy demand poses a formidable challenge to the energy sector, and researchers have taken it upon themselves to develop safe and sustainable energy conversion systems [3].

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1.2 Fuzzy Method

Fuzzy logic is a modeling methodology that addresses logical reasoning with some uncertain or imprecise utterances, like Peter is young (rich, tall, hungry, etc.). It falls under multi-valued logic, in which the truth values are viewed as degrees of truth. In fuzzy logic, a compound statement, e.g., Carlisle is tall, and Chris is rich, has its truth value based on the truth values of the parts of the statement. Fuzzy logic follows the truth function principle.
A criticism of the traditional Analytical Hierarchy Process (AHP) is that the method has significant difficulty with the nature of uncertainty and the imprecision of transferring the perceptions of decision-makers into specific numerical values; therefore, the Fuzzy Analytical Hierarchy Process (FAHP) was created to overcome this problem. FAHP was created to manage ambiguous situations that characterize decision-making problems, given their common occurrence [4]. FAHP allows decision-makers to convey rough or flexible preferences as fuzzy numbers and introduces fuzziness into both inputs and the judgments. Fuzzy set theory [5] is a theory in mathematics that was created to represent the vagueness of human cognitive processes.

The concept of fuzzy logic originates in the theory of fuzzy sets, in which a fuzzy set assigns a membership degree (typically a real number between 0 and 1) to each element of a universe. Fuzzy logic extends this notion by assigning degrees of truth to propositions. The typical range of truth values in fuzzy logic is the fundamental unit interval [0, 1], where 0 represents "completely false" and 1 represents "completely true," with intermediate values reflecting varying degrees of truth**.** In the Fuzzy Analytical Hierarchy Process (FAHP), the truth values are expressed as fuzzy numbers, typically triangular fuzzy numbers, that represent different levels of importance or preference between elements. These criteria enable assigning subjective weights to express the relative importance of criteria in FAHP while capturing decision-making uncertainty. Table 1 lists the standard fuzzy numbers. "Fuzzy

logic" is often used broadly to encompass various formalisms and techniques for systematically managing degrees of imprecision. In engineering contexts (e.g., fuzzy control, fuzzy classification, soft computing), the focus lies on efficient computational methods that accommodate sub-optimality and imprecision [6].
The membership function of the fuzzy set was defined as a probability distribution function, and the set's probability, concerning A times X, is defined by $\boldsymbol{\mu A}$ as follows: [7]

Equation 1: μA:X×Ω→[0,1],(x,ω)↦μA(x,ω)
$$\boldsymbol{\mu A: X \times \Omega \ni (x, \omega) \rightarrow \mu A(x, \omega) \in \Omega C \text{ and } (\Omega C, BC) = [0, 1] \text{are Borel sets}}$$
Where:

- μA\ = membership function of fuzzy set A.
- X = universe of discourse, i.e., the set of all possible elements.
- Ω\ = set of possible outcomes or scenarios.
- μA(x,ω)= degree of membership of element x under scenario ω, where 0 = completely false, 1 = completely true, and intermediate values represent **partial membership**.

. The numerical fuzzy triangle (TFN) is a commonly used application due to its ease of arithmetic operations, particularly its efficiency. In practical applications, the fuzzy triangle can be defined as
Equation 2: $\boldsymbol{\tilde{A} = (l, m, u)}$**,**
Where:

- A~: A fuzzy trinomial representing a fuzzy parameter or criterion.
- l: The lower bound of the fuzzy number, i.e., the smallest possible value.
- m: The most probable value, or peak, of the fuzzy number, representing the expected value.
- u: The upper bound of the fuzzy number, i.e., the largest possible value.

Serving the purpose of determining the level of inaccuracy associated with parameters in decision-making processes.

Equation 3:μ_A(x) = { (x - l)/(m - l), l ≤ x ≤ m;
(u - x)/(u - m), m ≤ x ≤ u;
0, otherwise }
Parameters:
• l: the lower bound of the triangular fuzzy number.
• m: the modal (or peak) value of the triangular fuzzy number.
• u: the upper bound of the triangular fuzzy number.
• x: a crisp input value.
• \mu_A(x): the membership degree of x in fuzzy set A, where \mu_A(x) \in [0,1].
Where parameter m is the upper bound of the function $\boldsymbol{\mu\tilde{A}(x)}$ and the parameters l and u are the lower and upper bounds that define The domain of expected values, as an example, let us have the following numerical fuzzy triangle case $\boldsymbol{\tilde{A}1=(l1,m1,u1)}$and $\boldsymbol{\tilde{A}2=(l2,m2,u2)}$, the arithmetic operations are performed on it as shown in(equatin 4)
Equation 4:
$\boldsymbol{(l_1, m_1, u_1) + (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2)}$
$\boldsymbol{(l_1, m_1, u_1) - (l_2, m_2, u_2) = (l_1 - l_2, m_1 - m_2, u_1 - u_2)}$
$\boldsymbol{(l_1, m_1, u_1) \times (l_2, m_2, u_2) = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2)}$
$\boldsymbol{(l_1, m_1, u_1) \div (l_2, m_2, u_2) = (l_1/u_2, m_1/m_2, u_1/l_2)}$
$\boldsymbol{(l_1, m_1, u_1)^{-1} = (1/u_1, 1/m_1, 1/l_1)}$

where l_i, m_i, $u_i \geq 0$

• l_1, m_1, u_1: lower, modal, and upper bounds of the first triangular fuzzy number.
• l_2, m_2, u_2: lower, modal, and upper bounds of the second triangular fuzzy number.
• All parameters satisfy l, m, u \geq 0.

A fuzzy set is interpreted as a possibility-based probability distribution, where each element's membership degree reflects the likelihood of belonging to the set. **Triangular Fuzzy Numbers (TFNs)**, defined as $\tilde{A}$ = (l, m, u), are employed to quantify uncertainty and inaccuracy in expert judgments or parameter values. TFNs facilitate arithmetic operations and can be further transformed into probabilistic terms using **defuzzification** or **Monte Carlo simulation** if required.

Table 1: scale in the pair-wise comparison process

fuzzy scale of relative importance		
		F-number
1	Equal	1,1,1
3	Moderate	2,3,4
5	Strong	4,5,6
7	Very Strong	6,7,8
9	Extremely strong	9,9,9
(2,4,6,8)	**intermediate value**	
	2	1,2,3
	4	3,4,5
	6	5,6,7
	8	7,8,9
	A = (L , M , U) = (1/U , 1/M , 1/L)	

1.3 Literature Review

Many studies have proven that combining Geographic Information Systems (GIS) with multi-criteria decision-making techniques, e.g., Fuzzy-AHP and AHP, is very efficient in the selection of sites across different projects. A fuzzy logic model integrated with GIS was applied in Iran [8], in Markazi Province, to determine the most appropriate sites for a solar power plant, based on technical, economic, and environmental considerations. Their findings saw places around Mahallat and Zarandineh as the most favorable places to develop.

Likewise,[9] have carried out a national evaluation in Iran based on 11 variables of solar radiation, temperature, nearness to infrastructure, elevation, slope, and land use, weighted by Fuzzy-AHP. They categorized 1,057 regions into five levels of suitability, and provinces such as Kerman, Yazd, and Isfahan are the most promising.

A study [10] was conducted in Turkey to use Geographic Information Systems (GIS) and the AHP to identify locations for solar farms, considering topography, climatic conditions, transport routes, farmland, and environmental conservation. Sites were divided into four levels of suitability; the best part of the site was around 14-16% which was rated highly suitable.

AHP and GIS were used in Egypt [11] to select an ideal location of a wastewater pumping station in El Mahalla El Kubra. The integration helped address uncertainty in expert judgments and generate a suitability map. Furthermore,

In Yemen, [12] an experiment revealed that GIS, remote sensing, and fuzzy logic were superior to fuzzy logic in determining good locations to handle solid waste, thus indicating the strength of the techniques in spatial decision-making.

These works establish that GIS combined with AHP or fuzzy logic gives an effective methodology in choosing the best locations in different areas. The approach adopted in this research for Iraq is compliant with these findings: the high potential of solar energy areas could be successfully identified, considering local environmental factors and infrastructure into account.

2. Study Area

This paper is about the Karbala Province, located in central Iraq, about 110 km southwest of Baghdad, covering a total of about 5,034 km^2 with a latitude of 32N - 33N and a longitude of 43E - 44E. Karbala has Karbala, Hindiyah, and Ean Altamer districts. Unlike the other provinces, the province has grown at a rate of rapid urbanization over the last twenty years due to population growth and migration of people, and this has led to the creation of residential, commercial, industrial, and educational infrastructure. The region covers a huge agricultural area used to produce crops such as date palms, wheat, and barley. The study will determine the best locations for installing solar panels by focusing on the relationships between urban and agricultural areas, accounting for solar exposure, land availability, and shading risk. This will help in the sustainable energy planning and use in Karbala. (Figure 1).

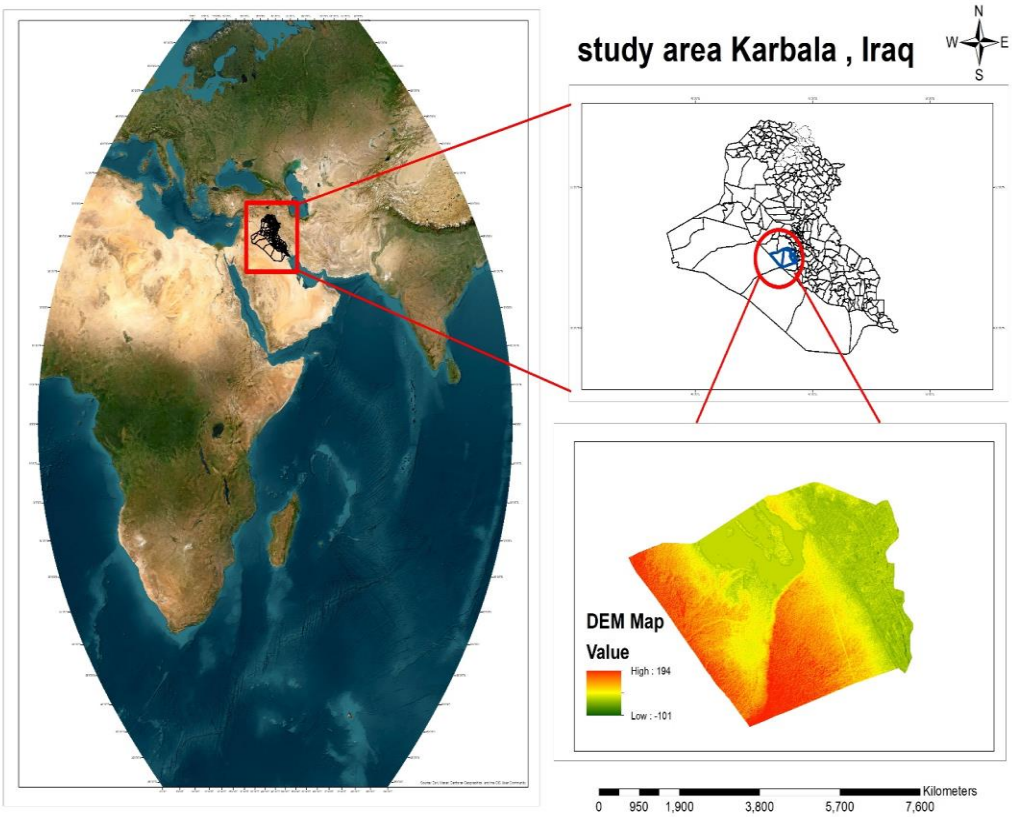

Figure 1: Study area

2.1 Materials and methodology

Step 1: Criteria Selection

Eleven key criteria, including topographical, climatic, environmental, and infrastructural factors, were identified based on a literature review and expert knowledge.

Step 2: Data Preparation
Point and polygon data were collected, and vector data were converted to raster format to facilitate spatial analysis and Euclidean distance calculations.
Step 3: Categorization & Fuzzification
Raster layers were classified into discrete categories, and each category was transformed into a fuzzy membership map with values ranging from 0 to 1.
Step 4: Weight Assignment
Weights for each criterion were determined using the Fuzzy Analytical Hierarchy Process (FAHP) and applied to each layer via map algebra.
Step 5: Weighted Overlay & Final Suitability Map
The weighted fuzzy layers were overlaid to produce the final suitability map for solar PV installation.
Step 6: Verification & Conceptual Framework
Results were validated in the GIS environment (Figure 2), which illustrates the methodology's conceptual framework.

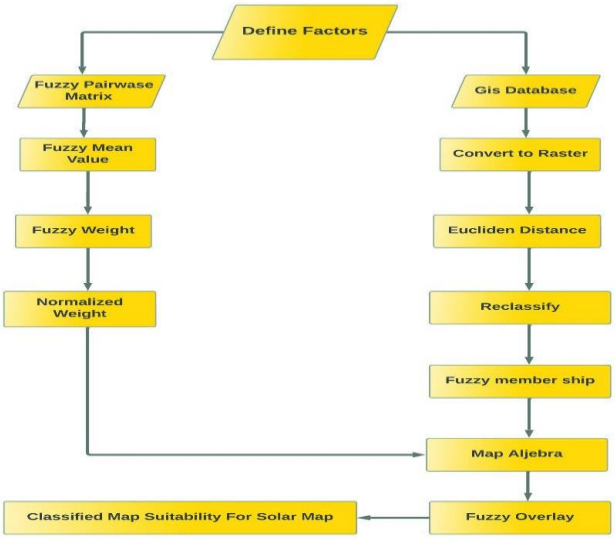

Figure 2: Flowchart of the work

Table 2: F-AHP comparison matrix of the criteria.

			FUZZY PAIRWISE								
	solar	LST	POWER	NDVI	SLOPE	ROAD	FAULT	URBAN	RAINFALL	DUST	WATER
solar	(1,1,1)	(1,2,3)	(2,3,4)	(3,4,5)	(3,4,5)	(4,5,6)	(6,7,8)	(6,7,8)	(4,5,6)	(5,6,7)	(7,8,9)
LST	(1/3,1/2,1/1)	(1,1,1)	(1/3,1/2,1/1)	(1,2,3)	(1,2,3)	5/3,5/2,5/1	(7/3,7/2,7/1)	(7/3,7/2,7/1)	(5/3,5/2,5/1)	(2,3,4)	(3,4,5)
POWER	(1/4,1/3,1/2)	(2/4,2/3,2/2)	(1,1,1)	(4/4,4/3,4/2)	(4/4,4/3,4/2)	5/4,5/3,5/2	(7/4,7/3,7/2)	(7/4,7/3,7/2)	(5/4,5/3,5/2)	(1,2,3)	(8/4,8/3,8/2)
NDVI	(1/5,1/4,1/3)	(2/5,2/4,2/3)	(3/5,3/4,3/3)	(1,1,1)	(1,1,1)	5/5,5/4,5/3	(7/5,7/4,7/3)	(7/5,7/4,7/3)	(5/5,5/4,5/3)	(6/5,6/4,6/3)	(1,2,3)
SLOPE	(1/5,1/4,1/3)	(3/5,3/4,2/3)	(3/5,3/4,3/3)	(1,1,1)	(1,1,1)	5/5,5/4,5/3	(7/5,7/4,7/3)	(7/5,7/4,7/3)	(5/5,5/4,5/3)	(6/5,6/4,6/3)	(1,2,3)
ROAD	(1/6,1/5,1/4)	(2/6,2/5,2/4)	(3/6,3/5,3/4)	(4/6,4/5,4/4)	(4/6,4/5,4/4)	(1,1,1)	(7/6,7/5,7/4)	(7/6,7/5,7/4)	(1,1,1)	(6/6,6/5,6/4)	(8/6,8/5,8/4)
FAULT	(1/8,1/7,1/6)	(2/8,2/7,2/6)	(3/8,3/7,3/6)	(4/8,4/7,4/6)	(4/8,4/7,4/6)	5/8,5/7,5/6	(1,1,1)	(1,1,1)	(5/8,5/7,5/6)	(6/8,6/7,6/6)	(8/8,8/7,8/6)
URBAN	(1/8,1/7,1/6)	(2/8,2/7,2/6)	(3/8,3/7,3/6)	(4/8,4/7,4/6)	(4/8,4/7,4/6)	5/8,5/7,5/6	(1,1,1)	(1,1,1)	(5/8,5/7,5/6)	(5/8,5/7,5/6)	(8/8,8/7,8/6)
RAINFALL	(1/6,1/5,1/4)	(2/6,2/5,2/4)	(3/6,3/5,3/4)	(4/6,4/5,4/4)	(4/6,4/5,4/4)	(1,1,1)	(7/6,7/5,7/4)	(7/6,7/5,7/4)	(1,1,1)	(6/6,6/5,6/4)	(8/6,8/5,8/4)
DUST	(1/7,1/6,1/5)	(2/7,2/6,2/5)	(3/7,3/6,3/5)	(4/7,4/6,4/5)	(4/7,4/6,4/5)	5/7,5/6,5/5	(7/7,7/6,7/5)	(7/7,7/6,7/5)	(5/7,5/6,5/5)	(1,1,1)	(8/7,8/6,8/5)
WATER	(1/9,1/8,1/7)	(2/9,2/8,2/7)	(3/9,3/8,3/7)	(4/9,4/8,4/7)	(4/9,4/8,4/7)	5/9,5/8,5/7	(7/9,7/8,7/7)	(7/9,7/8,7/7)	(5/9,5/8,5/7)	(6/9,6/8,6/7)	(1,1,1)

2.2 Fuzzy Analytic Hierarchy Process (FAHP) utilizing Triangular Fuzzy Numbers (TFN)

The methodological framework used in this work was the Fuzzy Analytic Hierarchy Process (FAHP), which includes relevant triangular Fuzzy Numbers (TFNs) that were added to deal with the imprecision and uncertainty that decision-making is associated with. Given the current situation in the Republic of Iraq, where there is no overall policy for planning and countrywide-approved standards for locating solar farms, this study attempted to develop appraisal parameters.

The criteria and alternatives were compared to help rank their relative importance. The uncertainty in the expert judgments was modeled using Triangular Fuzzy Numbers (TFNs), as they are typically used in similar studies due to their flexibility in handling human estimates, compared to crisp numbers.

The five specialists in solar energy and urban planning were consulted on the assessment. The differences in opinion have been deliberated and summarized to achieve agreement, and hence the derived weights as well as the final ranking of the sites include the professional judgment taken into account. The method will improve the validity of the findings and minimize the impact of personal bias or random estimates.
The comparison matrix and the weights of the criteria are illustrated in Tables 1 and 2, respectively, where the values of the scales applied in the pairwise comparisons are in Table 1.

Table 3: Criteria weights

Criteria	*weight*	*normalized weight*
solar	***0.474666***	***0.43***
LST	***0.182666***	***0.17***
POWER	***0.077666***	***0.07***
NDVI	***0.0712333***	***0.065***
SLOPE	***0.0712333***	***0.065***
ROAD	***0.049***	***0.05***
FAULT	***0.02233***	***0.025***
URBAN	***0.02233***	***0.025***
RAINFALL	***0.049***	***0.05***
DUST	***0.03666***	***0.03***
WATER	***0.024333***	***0.02***
Total	***1.0811***	***1***

The comparison matrix analysis shows that the value of solar radiation is quite important, with a weight of eighty times that of proximity to water bodies and three times greater than the proximity to the road network. The second step entails creating weights for the criteria (Table 3), which will depend on the outcomes of the previous pairwise comparisons. The weight of the weight is associated with the relative significance of the weight. Climatic factors, especially solar radiation and Land Surface Temperature (LST), are considered the most determining factors because of their direct effect on the electricity production of the solar PV systems. These are the environmental factors that influence the effectiveness and yield of potential solar locations. It is through the normalization of fuzzy weights within the

FAHP system that an equitable and comprehensive decision-making endeavor is undertaken so that the importance of each of the criteria is duly taken into account in the ultimate evaluation, even though they may vary in their original weighting. Any information used in this research study was acquired through credible sources and was tested to be correct. The fuzzy weights were re-calculated on the principal criteria so that the final analysis not only represents valid information but also shows how the individual factors actually matter.

2.3 Consistency Verification

To confirm the reliability of the fuzzy pairwise comparison matrix, I conducted a consistency check. First, the maximum eigenvalue (λ_max) of the comparison matrix was calculated, yielding 11.256. Using this result, the Consistency Index (CI) was obtained according to Equation (1):

Equation 5: $CI = (\lambda_{max} - n) / (n - 1)$

where n = 11. The calculated CI was 0.0256. Considering that the Random Index (RI) for n=11 is 1.51, I computed the Consistency Ratio (CR) as follows:

$CR = CI / RI = 0.017$

Since the CR value is well below the generally accepted threshold of 0.10, I concluded that the pairwise comparison matrix is consistent. This outcome indicates that the judgments are reliable and can be used confidently in the fuzzy AHP weighting process.

Table 4*: Set of rules from previous studies.*

Variable	*Criteria*	*Reference*
Slope	**< 7 %**	[13]
Power network	**> 1000 m buffer**	[14]
Water bodies	**> 500 m buffer**	[14]
Urban areas	**> (1-5)km buffer**	[13]
Roads	**> 500 m buffer**	[15]
Solar radiation	**Maximum**	[16]
LST	**Maximum**	[16]
NDVI	**Minimum**	[16]
Rainfall	**Minimum**	[16]
Dust	**Minimum**	[16]
Distance to fault		[9]

Table 5*: categorizes the highest suitability*

Suitability Class	Description	Meaning
1	Very High Suitability	Ideal for solar farm installation, **with** minimal constraints
2	High Suitability	Suitable with minor constraints
3	Moderate Suitability	Acceptable, but some limitations
4	Low Suitability	Limited suitability due to significant constraints
5	Very Low Suitability	Not recommended for solar farm development

These classes were applied to each criterion (rainfall, NDVI, dust, etc) to categorize them into five levels of suitability. Class 1 represents the highest suitability, while Class 5 represents the lowest. This classification provides a clear framework for comparing and evaluating potential sites before applying the GIS-Fuzzy AHP methodology.

3. DEM and Satellite images

Remote Sensing Methodology (DEM and Satellite Images Acquisition)

SRTM satellite data were used to create a digital elevation model (DEM) of the study area with a 30 by 30 m spatial resolution. The DEM is a product of the Umm al-Gharagher station of the Iraqi Ministry of Agriculture, and it contains valuable details on the features of the earth, such as slope and solar radiation, which are important data for determining the viability of the solar panel locations. DEM is needed in acquisition to conduct specialized studies of solar energy applications.

During the information-gathering stage, Landsat 8 was used to obtain high-resolution satellite images of the study site. The geometric resolution of the pictures is 10 m, and the images were shot in June 2022 in the WGS 84 ZONE 38 N frame of reference. These images were meant to provide a proper land classification analysis. No other high-resolution images could be used in this study due to certain limitations. After the satellite images were processed and subsequently classified in ArcGIS 10.8.2, the information required for the study was obtained.

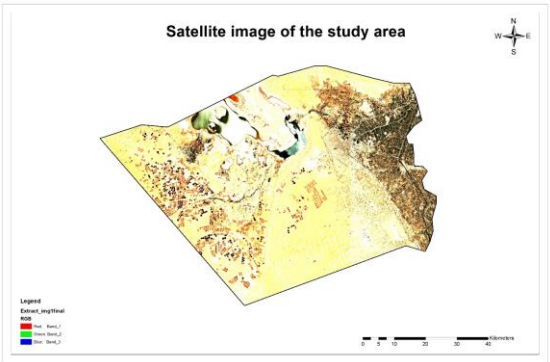

Figure 3: Satellite image of Karbala

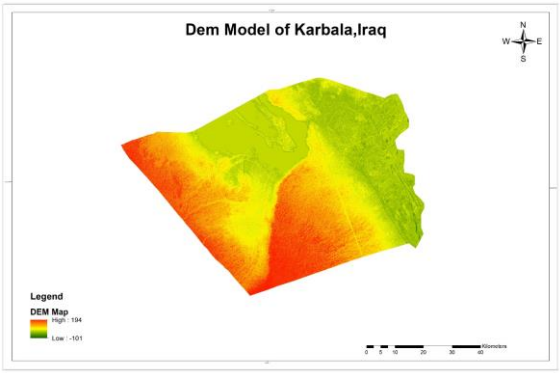

Figure 4: DEM model of Karbala

3.2 Data preparation

3.2.1 Preparation of a water bodies dataset

The effectiveness of solar panel installations may be affected by the presence of nearby bodies of water [17]. To determine the proximity of water bodies, rivers, lakes, and reservoirs to potential solar panel sites in Karbala, GIS techniques were used. This research helps identify locations where bodies of water may pose safety hazards [14]**.** Areas within 500 m of a water body were considered restricted due to potential safety hazards, including flooding, high humidity, and structural risks. Buffer zones were assigned ratings based on their distance from the feature of interest. Areas less than 500m received a score of 1; zones between 500 and 5,000 m were rated 5; zones from 5,000 to 10,000 m received a score of 4; zones between 10,000 and 20,000 m were assigned a rating of 3; and areas beyond 20,000 m were given a score of 2.

Table 6: Reclassification values for the water bodies dataset

Water Bodies	*Suitability*
500- 5000	5
5000-10000	4
10000 -20000	3
>20000	2
< 500	1

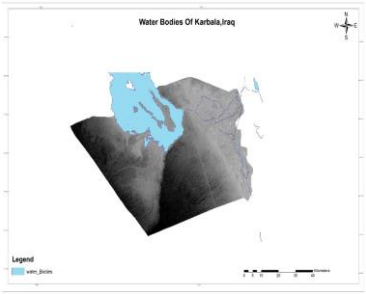

Figure 5:Waterbody map

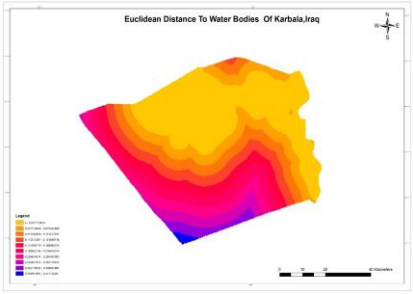

Figure 6:Euclidean distance

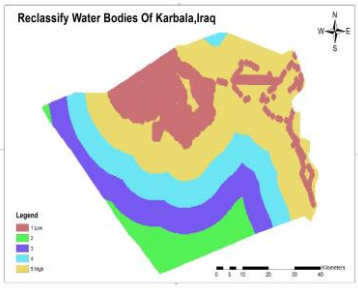

Figure 7: Re-classification of **waterbody**

3.2.2 Distance setting from urban dataset

The closeness to populated areas is one of the key economic factors in determining the suitability of the site. On the other hand, the introduction of solar farms may have a significant aesthetic effect [8] and negatively affect the growth of cities and people [10]. In this regard, it was considered fitting to have a buffer zone of 1-5km around residential areas. Notably, the buffer zones were categorized by distance from. Buffer zones were assigned ratings based on their distance from the feature of interest. Areas less than 1,000 m were given a score of 1; zones between 1,000 and 5,000 m received a rating of 5; zones from 5,000 to 10,000 m were rated 4; areas between 10,000 and 20,000 m received a score of 3; and zones beyond 20,000 m were assigned a rating of 2. [13]**.**

Table 7: Reclassification values for the Urban Area dataset

Urban Area	Suitability
1000- 5000	5
5000-10000	4
10000 - 20000	3
>20000	2
< 10000	1

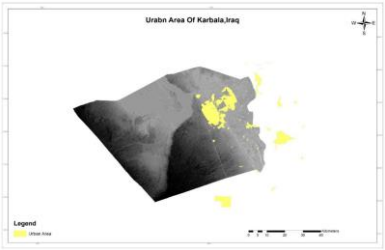

Figure 8: Urban area map

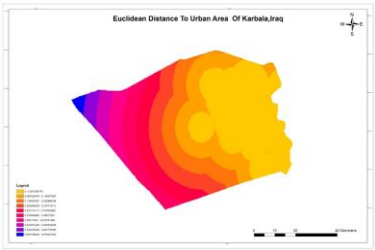

Figure 9 :Euclidean distance

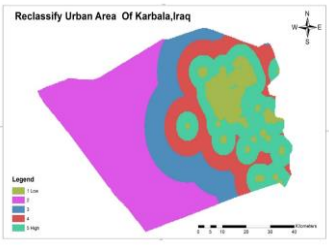

Figure 10: Re-classification **of** Urban area

3.2.3 Preparation of the Slope Data Set

The slopes were calculated from the DEM with an accuracy of 30 m. The slope was calculated using the following method.

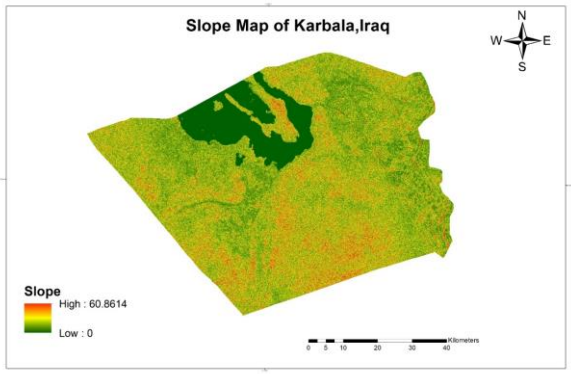

Figure 11: Slope map

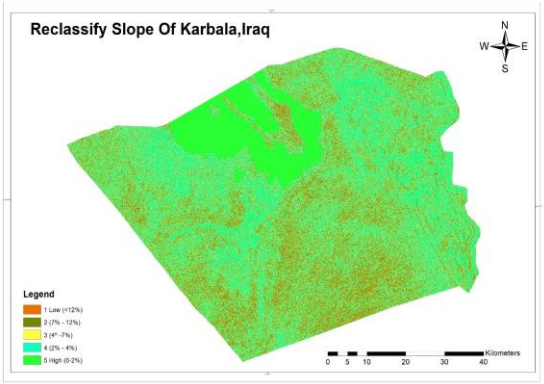

Figure 12 : Re-classification of slope

3.2.4 Preparation of the solar radiation data set

The solar radiation dataset was prepared using the Solar Radiation tool in ArcMap. In this process, (DEM) derived from a 30 m × 30 m Shuttle Radar Topography Mission (SRTM) dataset was employed as the foundational input layer for the specified study area. The calculations were conducted every month throughout the entire year of 2022

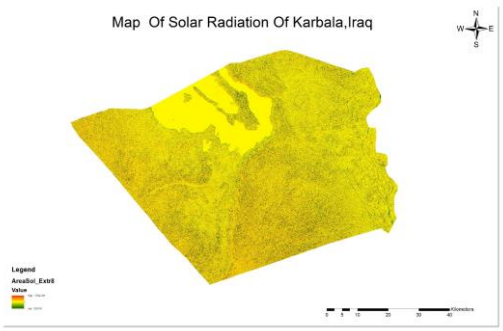

Figure 13: Solar map

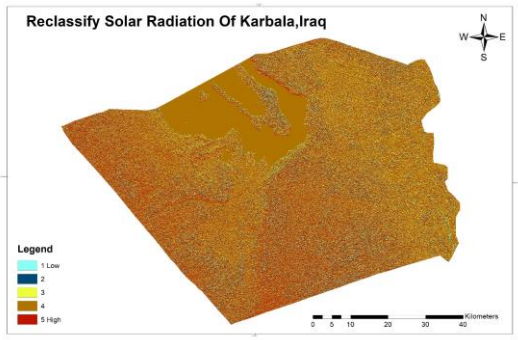

Figure 14: **Re-classification of solar**

3.2.5 Distance setting from road dataset

Calculations of proximity to roads and the availability of the most convenient sites have strong economic consequences, directly affecting the price of constructing solar installations [14] [10]. However, social risks, including possible thefts and vandalism around power plants connected to roads, should be considered [18].

A buffer distance of 500 m was used in this research as a compromise figure in the process of solar farm site selection, with areas beyond 10,000 m deemed inappropriate as far as the development of solar farms is concerned.

To operationalize distance measurement in the road network, straight-line distance was calculated, and five buffer zones were obtained, each serving as a factor variable. It used the Euclidean distance, a common metric, to produce distance maps for measuring distances to or from particular objects, which align with most GIS-based research studies in solar planning. It should be mentioned that there is a weakness in Euclidean distance. It presupposes a linear course of action, which may not necessarily be possible due to barriers.

The subsequent classification scheme was applied as follows:

- Buffer area < 500 - 3000m: Scored as 5
- Buffer area 3000 - 6000m: Scored as 4
- Buffer area 6000 - 10000m: Scored as 3
- Buffer area < 10000m: Scored as 2
- Buffer area > 500m: Scored as 1

This classification system enabled quantification of site suitability based on proximity to roads and accessibility, providing a comprehensive foundation for subsequent solar farm siting decisions.

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Table 8*: Reclassification values for the roads dataset*.

Roads network	*Suitability*
500- 3000	5
3000-6000	4
6000 - 10000	3
>10000	2
< 500	1

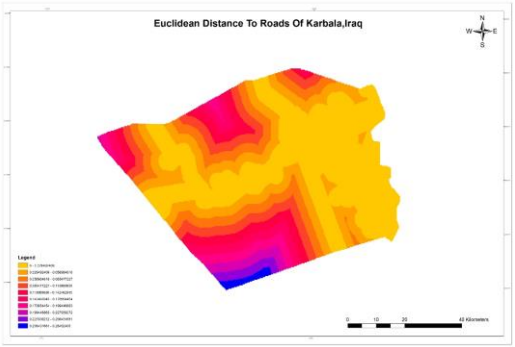

Figure 15: Euclidean distance of Roads

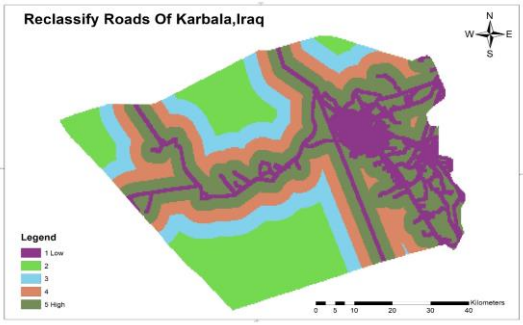

Figure 16: Re-classification of Roads

3.2.6 Distance setting from the Power Network dataset

The proximity of a solar power plant to power supply lines has significant economic implications, as it reduces the costs of constructing new infrastructure. To evaluate this factor, the Euclidean distance function was employed to
compute the distance between the solar power plant site and the power lines. Drawing on the findings of [14], a threshold distance of 1000 m from power lines was considered.
As a result, the buffer zone delineation was assigned the following scores:

- Buffer zone less than 1,000 m: Scored as 1
- Buffer zone 1,000–3,000 m: Scored as 5
- Buffer zone 3,000–6,000 m: Scored as 4
- Buffer zone 6,000–10,000 m: Scored as 3
- Buffer zone greater than 10,000 m: Scored as 2

By adopting this scoring system, the proximity of the solar power plant site to power lines is effectively evaluated, facilitating the identification of areas with favorable conditions for cost-efficient infrastructure installation.

Table 9: Reclassification values for the power network dataset.

Power network	*Suitability*
1000- 3000	5
3000-6000	4
6000 - 10000	3
>10000	2
< 1000	1

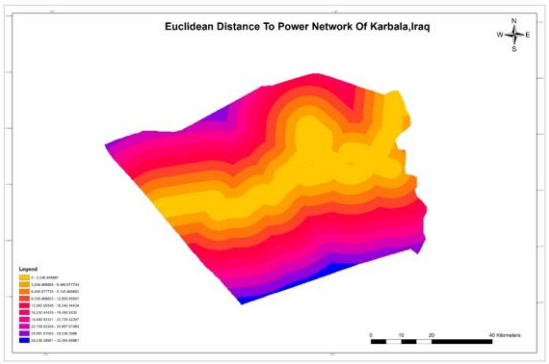

Figure 17: Euclidean distance of power lines

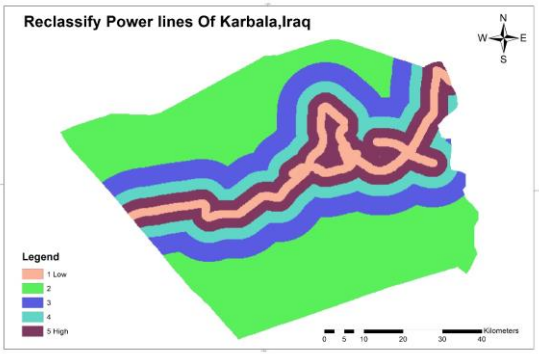

Figure 18: Re-classification of power lines

3.2.7 Preparation of the Rainfall Data Set

This parameter takes a central position because it directly influences the complicated hydrological cycle. Regions that receive high annual rainfall have a positive relationship with the humidity and particle content.

The rainfall thresholds were based on data from meteorological stations in Karbala Governorate and made sure that the areas used to obtain rainfall values are adequately precipitated so the solar system can operate steadily without impacting the infrastructure.

The joint impact of all these variables has a significant effect on the processes involved in absorption or reflection of the shortwave radiation. To define them, the precipitation distribution in the chosen region was taken from meteorological stations' data. It was represented using the distance-weighted inverse distance (IDW) method, which is effective for visualizing locations. A similar study [16] affirmed that the low precipitation areas are the most proper areas to exploit solar energy. Therefore, the analyzed area was grouped into 5 categories, with the one accounting for the lowest amount of precipitation receiving a numerical sign of five and the one with the highest amount of precipitation assigned a numerical sign of 1.

Table 10*: Reclassification values for Rainfall dataset.*

Rainfall	*Suitability*
107- 115	5
115-123	4
123 - 131	3
131-138	2
138 - 146	1

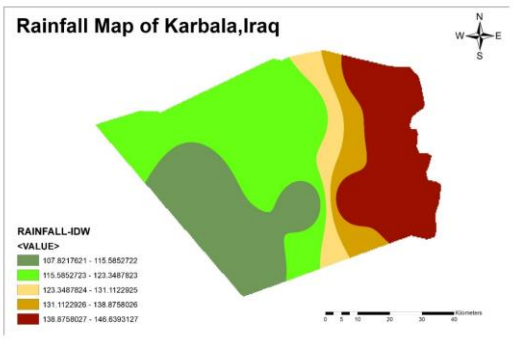

Figure 19: Rainfall map

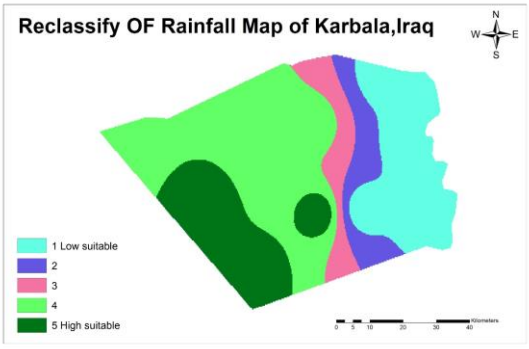

Figure 20: Re-classification of rainfall

3.2.8 Preparation of the LST Data Set

Another important process for ensuring optimal panel sizes is to determine the efficiency of solar panels. This is primarily determined by the surface temperature of the solar panel. This temperature not only accounts for local climatic conditions but also the intensity of the solar radiation. Solar power plants are therefore more practical in locations that experience high temperatures as compared to relatively low temperatures. Landsat 8 satellite imagery at 10 m spatial resolution, namely 4th, 5th, and 10th spectral bands, was used to measure the surface temperature of the selected locations on Earth (LST).

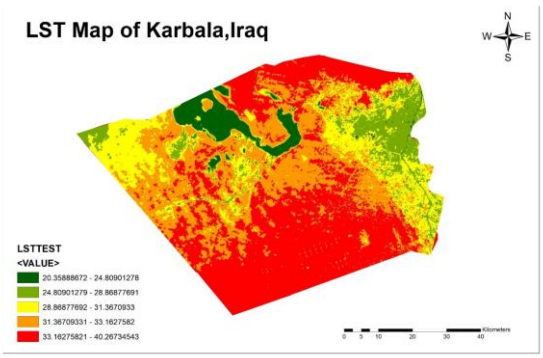

Figure 21: LST Map

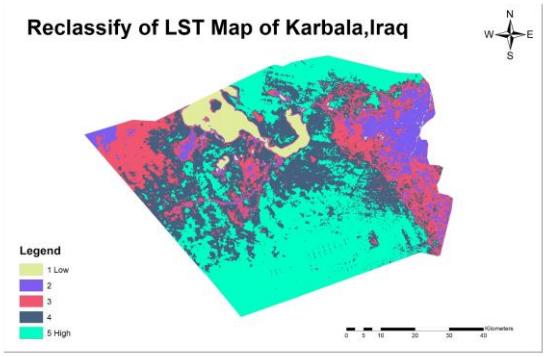

Figure 22: Re-classification of LST

3.2.9 Preparation of the NDVI Data Set

To provide a high efficiency of photovoltaic systems and lessen possible adverse impacts of vegetation, vegetation assessment criteria must be involved in the location selection process of solar power plants. This is especially with respect to the environmental effects that may be caused, such as habitat disturbance, interference with indigenous flora and fauna, and the general disruption of the entire ecosystem. Therefore, regions with varying NDVI values are very important for mapping the location of solar infrastructure deployment to assist in identifying the areas where solar panels can be erected with minimal influenced. In this study, NDVI values were extracted directly from satellite imagery by the researcher, and threshold values were established based on previous studies [16] and local vegetation data, allowing the study area to be classified reflecting varying levels of vegetation density."

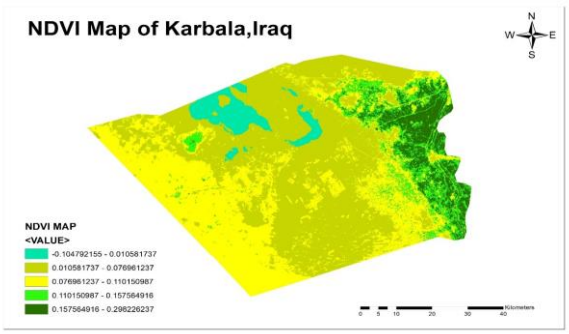

Figure 23: NDVI Map

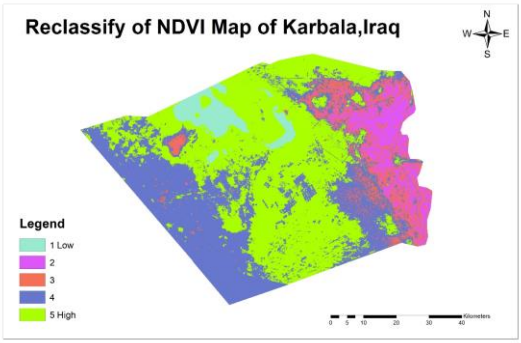

Figure 24: Re-classification of NDVI

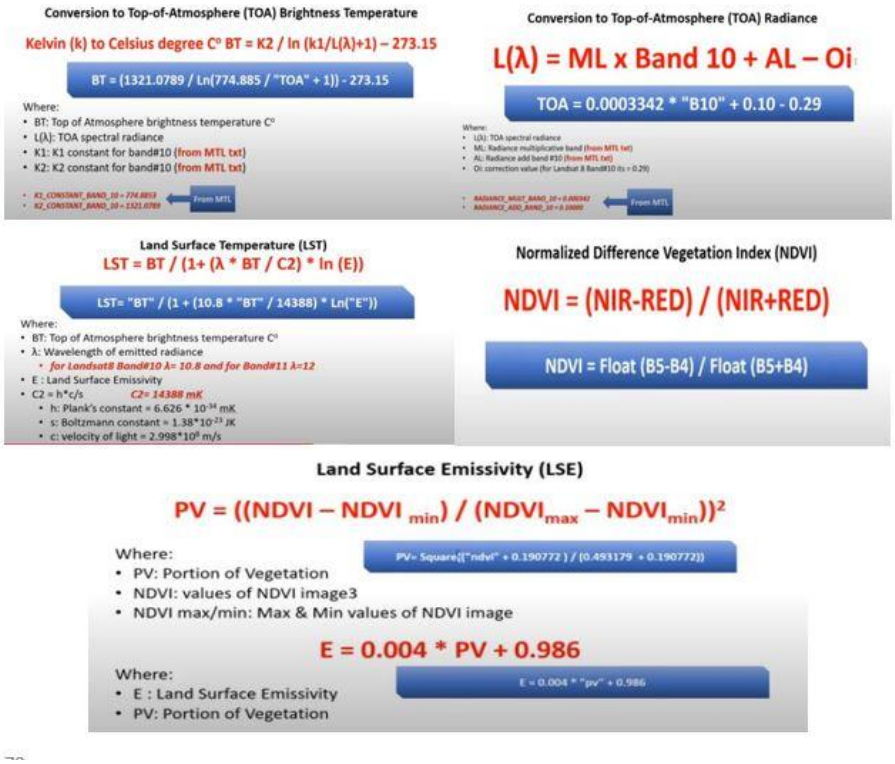

Figure 25: NDVI, LST Extraction process

3.2.10 Preparation of the Fault Lines dataset

When choosing appropriate locations for solar power plants (SPPs) in an academic setting, proximity to potential faults is an important consideration. There is a high risk of seismic activity close to geological fault lines. To confirm that a potential solar panel site is suitable, other requirements must be met, including a suitable slope, enough solar radiation, a safe distance from bodies of water, closeness to the power grid, road accessibility, and avoidance of densely populated areas. When considered together, these factors ensure the locations chosen are ideal and safe for utility-scale solar installations. These elements may manifest as latent risks or direct dangers to the project's successful execution. Iraq's tectonic map, obtained from the Agency, was used to create the fault proximity map. Obtained from the Agency for Meteorology and Seismic Monitoring. The Euclidean distance was then calculated after conversion to a raster format. Therefore, [19] underlined how crucial it is to establish precise distance thresholds for this criterion. They suggested a classification scheme wherein regions within 500 meters of the feature were categorized as Category 1. A Category 5 rating was given to areas between 500 m and 10 km. This classification system offers a systematic framework for assessing and managing the suitability of possible locations. Geological hazards are also considered when choosing a location for a solar power plant.

Table 11: Reclassification values for the Fault lines dataset.

Fault lines	*Suitability*
500- 10000	5
10000- 15000	4
15000 – 25000	3
25000 – 35000	2
0 – 500	1

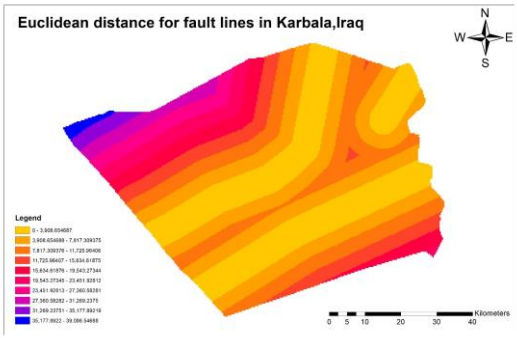

Figure 26: Euclidean distance of fault lines

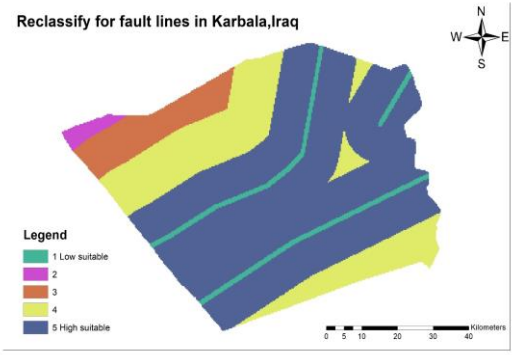

Figure 27: Re-classification of fault lines

3.2.11 Preparation of the Dust dataset

Dust, in the context of this study, is characterized as minute solid particles with a diameter less than 500 µm. The deposition of dust is influenced by various environmental and meteorological factors, which in turn affect the efficiency of photovoltaic (PV) energy systems. These particulate matter constituents can absorb approximately 15% of the sun's shortwave energy. Given recent shifts in environmental conditions, regions with the fewest annual average dry days are more favorable for deploying energy systems [20]. Annual dust data were obtained from the Meteorological Agency in an Excel file, which was mapped. "The data were processed using the IDW method and subsequently categorized into five levels, with areas of lowest dust concentration assigned a score of 5 and areas with the highest dust concentration assigned a score of 1."

Table 12: *Reclassification values for the DUST dataset.*

DUST	*Suitability*
500- 10000	5
10000- 15000	4
15000 – 25000	3
25000 – 35000	2
0 – 500	1

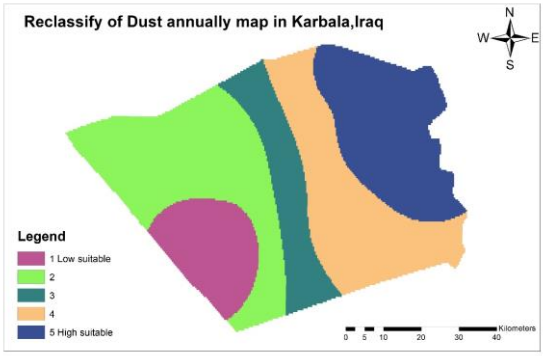

Figure 28: DUST MAP

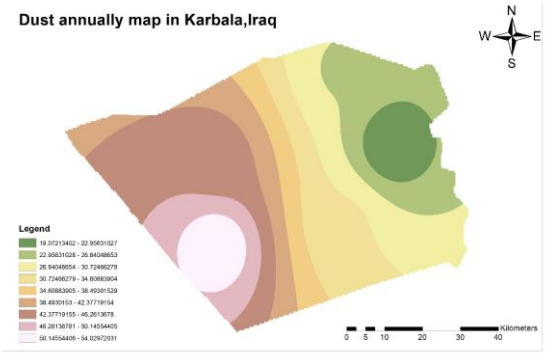

Figure 29: Re-classification of Dust

Fuzzy membership maps for all layers

All constraint layers were reclassified using a fuzzy binary scale, with linear membership type from the fuzzy membership window and weights for all layers. This process was implemented using fuzzy hierarchical analysis, where 0 indicates the presence of a constraint and the weight for each layer indicates the absence of a constraint. Restricted classes (slope,

solar radiation, distance from urban areas, distance from the road, distance from the road network, distance from water bodies, LST, NDVI, Rainfall Dust annually, Fault lines) Final constraint layer

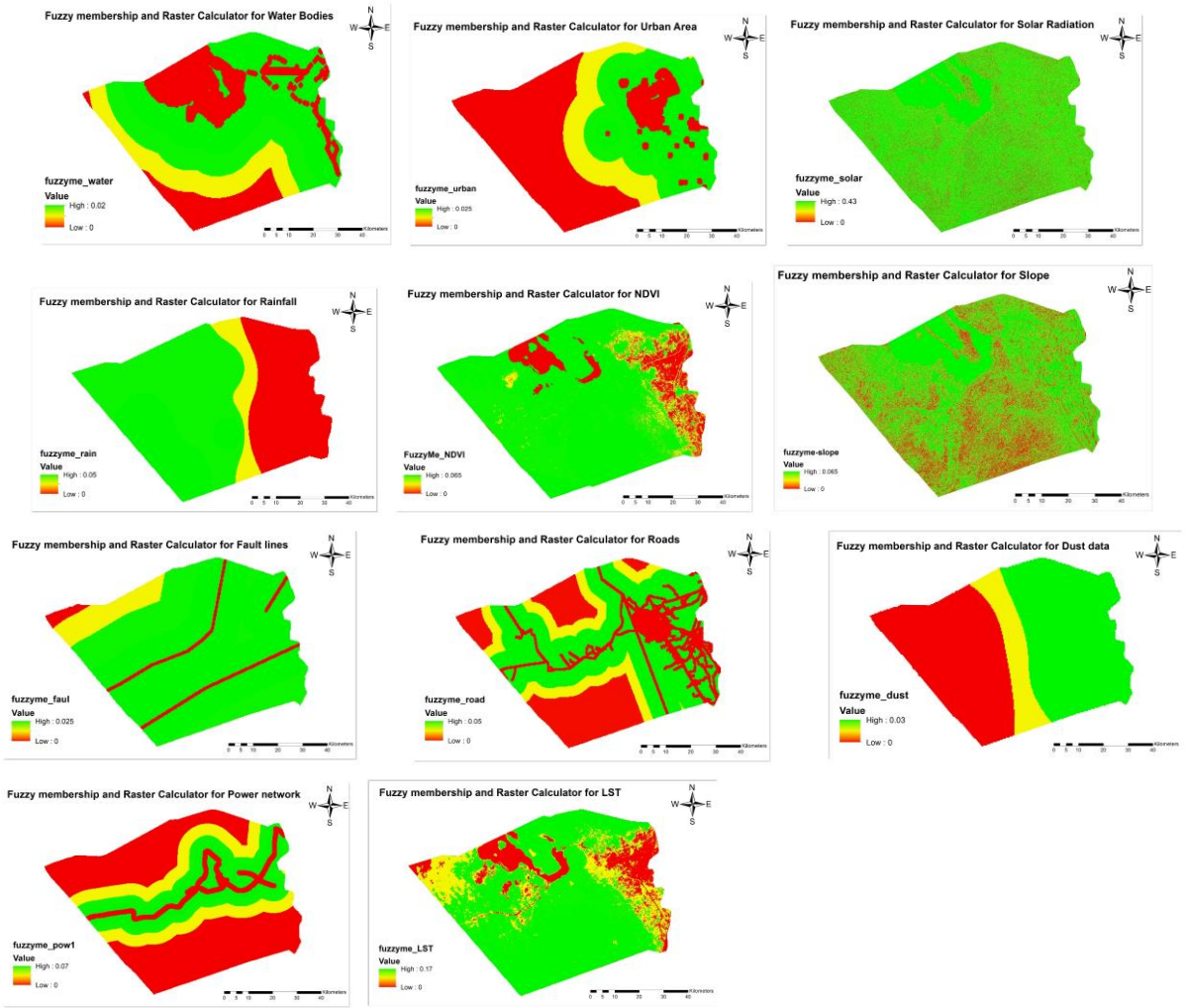

Figure 30-40: Constraint fuzzy layers

4. Results

4.1 fuzzy overlay analysis

Fuzzy overlay analysis, a crucial method used in the results area, was made possible by the fuzzy weighted overlay tool. This technique was used to create an appropriate model that accounts for several variables affecting the choice of a solar power plant webpage. The input layers include slope, distance from the grid, distance from water bodies, solar radiation, distance from urban areas, distance from road networks, LST, NDVI, rainfall, annual dust, and distance from fault lines. To facilitate a cogent analysis and align these entry criteria with a standard preference measure, they were categorized. Because they show the criterion weights of each criterion, the results in Table 3 represent the main findings of this investigation. The most important factors affecting site suitability, according to the FAHP analysis, were slope and solar radiation, followed by proximity to the power grid and urban areas. While elements like precipitation and NDVI were relatively less significant, other criteria like distance from water bodies and fault lines were of moderate importance. The order of significance for each criterion in the site selection process is clearly indicated by this ranking."

By adopting this exhaustive approach, fuzzy overlay analysis integrates the distinct influences, offering an in-depth perspective of the ideal sites for locating solar power plants. This procedure leverages the reclassified input conditions and their respective weights to yield indispensable insights into the most promising areas for implementing solar power plants.

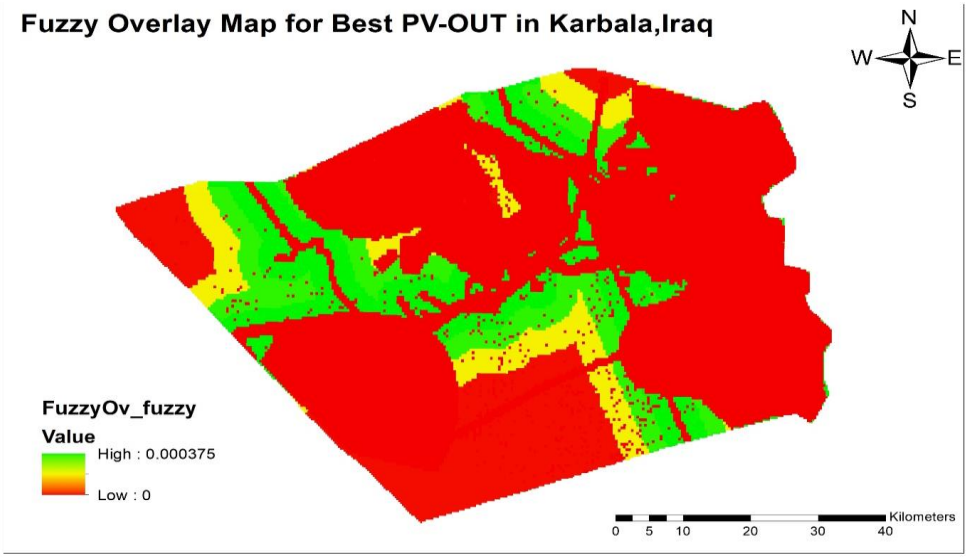

Figure 41: **Fuzzy overlay map**

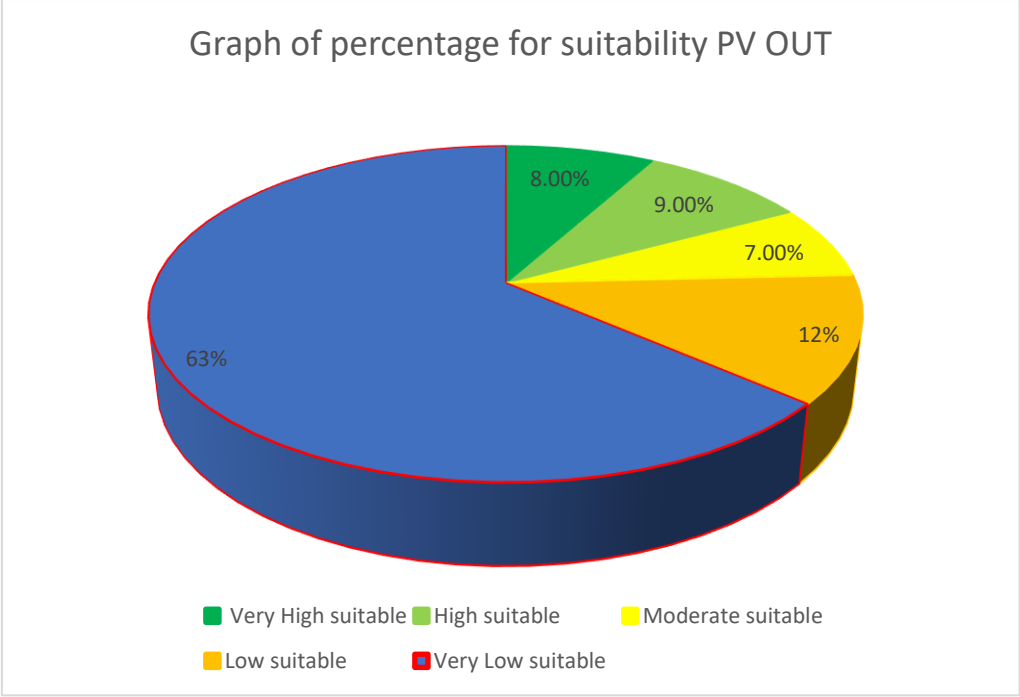

Figure 42*:* Graph of percentage for final suitability PV OUT

4--2 Final Suitability Map

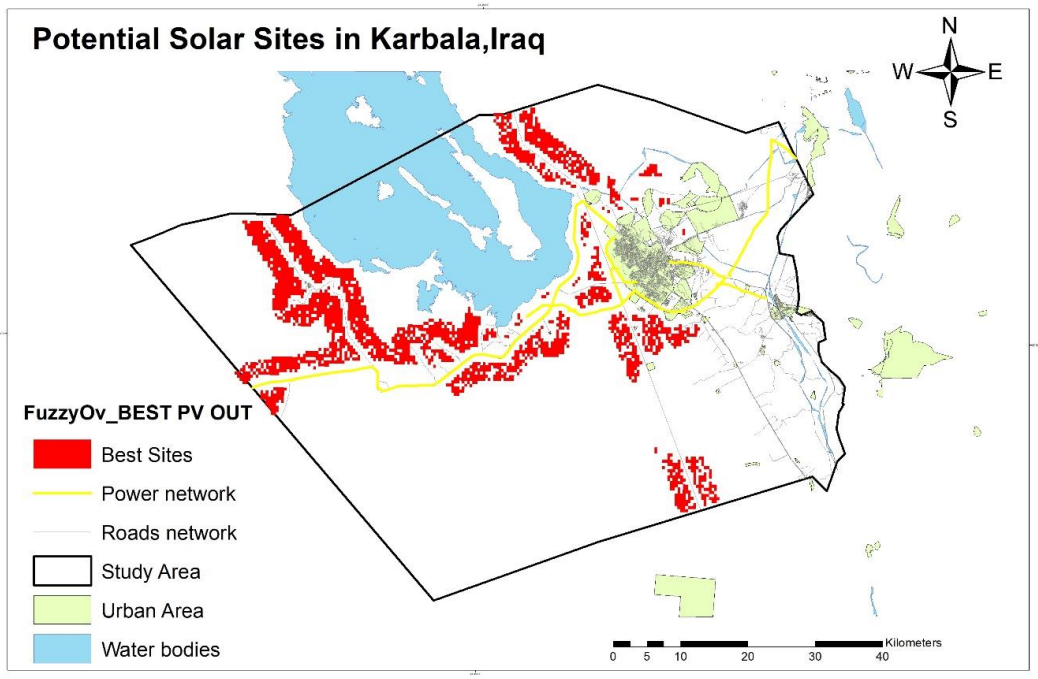

Figure 43: Potential solar sites.

The weighted factor layer produced the final matching map (Figure 41).
This Final Suitability Map has five distinct values, denoted by the numbers 1 through 5. A preferred value of 1 indicates areas with restrictions, making them unsuitable for solar farm development. At the top, a suitability value of 5 indicates maximum suitability, indicating ideal locations for a solar farm. Relevance values of 3 and 4 indicate "somewhat relevant" status, while a value of 2 indicates no relevance.
Once the highest level of suitability was determined, the criteria for selecting potential sites extended to considerations of site size. According to guidance provided by the US Department of Energy's National Renewable Energy Laboratory (2012), utility-scale solar power plant projects typically begin at 5 MW. A similar standard is being adopted in the United Kingdom, where the distinction between small and large-scale solar farms is often defined by a 5-megawatt (MW) threshold.
Research indicates that a 5 MW solar installation requires approximately 0.1011715 km²and can generate enough energy to support an average of 1,515 households per year. (Solar Trade Association, 2016). The analysis shows that within the total study area, 432km2 (8%) have features that meet the "most suitable" classification. Furthermore, an area of 478 km2, 9% falls in the category of "moderately suitable" for the implementation of ground-based solar PV plants. On the other hand, 83% of the study area is classified as unsuitable for the solar farm development. The distribution of ideal Sites is concentrated in the central part of the study area, where power lines exert a great influence. This is due to the region's solar radiation being close to and consistent with the Earth's surface temperature.
In all, an area of 432 km2 (8%) was identified and reserved as potential sites for solar farms for this research study. The percentage distribution of these feasible locations is illustrated in a diagram form in (Figure_ 42)

4-3 Discussion

In this paper, the site suitability assessment for the solar farm development of Iraq was made using a GIS-based FAHP method. The results identify promising sites, which are located in the center of the study area, due to high solar radiation and existing infrastructure. Environmental and economic factors like slope, temperature, rainfall, dust, and proximity to power lines will be considered. This research highlights that a multi-criteria decision-making approach, supported by accurate data, is important. Specific national regulations necessary to support future solar energy investments and encourage large-scale photovoltaic deployment in Iraq are also stressed.

4-4 Contribution of This Study to Advancing Solar Siting Methods

Findings from the current research help develop the way of selecting a solar farm site in countries where large-scale planning is only in its infancy. Combining GIS with the Fuzzy-AHP way offers a versatile, precise approach to the analysis of possible locations, considering a broad range of factors and variables. The usage of fuzzy logic in managing uncertainties and weighted multi-criteria evaluations also makes a special contribution to innovative methods, which may be easily used in other countries with the same infrastructure and resource facilities. This provides a useful example of how to speed up the strategic planning of solar facilities and, therefore, the efficient identification of locations and the reduction of the risks posed by the failure to plan sites.

5- Summary of Conclusions, Limitations, and Recommendations

Findings of this research indicate that a reasonable place where utility-scale solar PV farms can be installed in Karbala Governorate, Iraq, covering an area of 432 km 2 (or about 8% of the study area), exists. The research has successfully identified the right locations for high solar radiation with the least slope and their nearness to infrastructure using a Fuzzy-AHP methodology based on GIS. This was an effective methodology for multi-criteria decision making, as it was flexible and clear.

The Republic of Iraq has been very unsuccessful in harnessing the potential of solar energy, and in particular, vis-a-vis other similar nations in the Middle East. This paper discusses research on the assessment of suitable locations for large-scale PV solar power plants in the Karbala Governorate of central Iraq.

Nevertheless, this study had several limitations: field validation was lacking, land ownership data were not considered, and default radiation values were used, which omits cloud cover. Digital elevation models can give inaccurate estimates of terrain slope.

The on-site assessment, consideration of economic and environmental factors, updating models with technological progress, and evaluation of the impact of policies and coordination of urban planning would significantly contribute to the improvement of further research. This shall ultimately offer a more detailed, viable, and sustainable growth of solar power development in the area.

They already have solar energy projects in Iraq, such as the Karbala Solar Project, which can serve as a viable reference point in matching sites that are viable for solar energy in the country. Secondly, they consulted five experts who were well-versed in solar energy and urban planning. The experts have been requested to evaluate whether the chosen locations were appropriate and whether the criteria used in this research were relevant. The comparative analysis, coupled with expert consultation, contributed to confidence in the final findings to allow believing that the locations that are chosen do have the realistic potential on the ground to implement solar energy projects. The 30-m DEM and 10-m Landsat images used in this study are suitable for most analyses, but their relatively low resolution can decrease the accuracy of site suitability analysis, particularly in densely populated cities or along major

roads. High-resolution data or the combination of local data can be used in future research to improve the credibility of findings.

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