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GIS-BASED FUZZY AHP APPROACH FOR SOLAR FARM SITE SUITABILITY ANALYSIS IN EGOR, BENIN CITY, NIGERIA

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ABSTRACT

The increasing demand for sustainable energy solutions in Nigeria has necessitated the exploration of alternative energy sources, particularly solar power. This study presents a cost-effective suitability analysis for siting a solar photovoltaic (PV) farm in Egor Local Government Area of Edo State, Nigeria, using an integrated Geospatial Information System (GIS) and Fuzzy Analytical Hierarchy Process (FAHP) framework. Eight critical factors were evaluated: solar radiation, elevation, slope, temperature, relative humidity, land use/land cover, distance to roads, and distance to residential areas. Each factor was standardized using fuzzy membership functions, weighted using the AHP pairwise comparison method, and overlaid using fuzzy summation to generate a final suitability map. Validation was performed by cross-checking spatial outputs with existing physical features and confirming consistency with known land use characteristics. The results reveal that solar radiation and elevation are the most influential criteria, with weighted sums of 5.802 and 3.204, respectively. The analysis identifies Evbuotubu and surrounding zones as highly suitable for solar farm development. This study demonstrates that the combination of GIS and FAHP provides a robust decision-support tool for identifying optimal locations for solar energy infrastructure in urbanizing environments. The findings offer practical insights for policymakers, planners, and energy developers aiming to expand renewable energy infrastructure in Nigeria.

Keywords: Solar Farm Siting, Fuzzy AHP, Terrain Analysis, Suitability Analysis, Benin City

INTRODUCTION

The global demand for clean and renewable energy has intensified due to rising concerns over climate change, fossil fuel depletion, and the increasing need for sustainable energy alternatives. Among renewable energy sources**,** solar energy is considered one of the most promising and accessible, particularly in regions with high solar insolation, such as Sub-Saharan Africa. Nigeria, situated within the equatorial zone, receives abundant solar radiation, making it a viable state for large-scale solar energy generation (Giwa *et al*., 2017). Despite this natural advantage, the country continues to face acute energy supply challenges. More than 40% of Nigeria's population lacks access to electricity, while those connected to the national grid often experience frequent and prolonged power outages (Ozuegwu *et al*., 2017). These energy challenges reflect a broader global concern over energy sustainability. However, Nigeria's situation is uniquely severe, considering its high solar potential and yet low renewable energy utilization. Therefore, understanding localized solutions like solar PV development is crucial.

In Nigeria, electricity generation is predominantly dependent on thermal and hydroelectric sources, which are insufficient to meet the growing energy demand of the rapidly expanding population and urban centers. With a population exceeding 200 million by projection, Nigeria's economic productivity and quality of life are significantly hampered by unreliable power supply (Aliyu *et al*., 2015). The Egor Local Government Area (LGA) in Edo State, home to key institutions such as the University of Benin, exemplifies the nationwide crisis of energy inadequacy. Recurrent blackouts, escalating electricity tariffs from distribution companies like the Benin Electricity Distribution Company (BEDC), and infrastructural vulnerabilities such as vandalism of electrical installations underscore the urgent need for energy diversification and localized, renewable alternatives.

In this context, solar photovoltaic (PV) systems provide an environmentally sustainable, economically viable, and technically feasible solution. The application of Geospatial Information System (GIS) technology in combination with Multi-Criteria Decision Analysis (MCDA) methods offers a powerful tool for identifying optimal locations for solar energy development. GIS facilitates the spatial analysis of multiple factors including solar radiation, terrain, land use, and infrastructure proximity, while MCDA methods, such as the Fuzzy Analytical Hierarchy Process (Fuzzy-AHP**)**, enable the integration of expert judgment and uncertainty into the decision-making framework (Asakereh *et al*., 2017; Noorollahi, 2016).

The Fuzzy-AHP approach enhances the conventional AHP by incorporating the fuzziness inherent in human judgment, thereby yielding more robust and realistic weight assignments for criteria (Zadeh, 1965). This makes it especially suitable for renewable energy planning, where input data and stakeholder preferences often contain degrees of uncertainty. In the present study, this methodology was employed to assess the suitability of sites for solar farm installation in Egor LGA, with key criteria including solar radiation, slope, elevation, relative humidity, temperature, land use/land cover, proximity to roads, and residential areas.

Previous studies on solar farm siting across the globe have demonstrated the effectiveness of GIS-based MCDA in decision support for renewable energy projects. For instance, Sanjeevi (2014) developed a geospatial model incorporating slope and land cover for solar park location analysis in India, while Chaves and Bahil (2019) employed an algorithm integrating elevation, slope, and irradiance in site selection. Similarly, in Nigeria, Ulu and Aigbayboa (2019) and Oyedepo (2018) highlighted regional variations in solar potential, the study reveal the necessity of localized assessments in energy planning as supported by (Kalogirou *et al*., 2016; Ohunakin *et al*., 2004).

Despite Nigeria's favorable solar radiation profile, ranging from 3.5 to 7.0 kWh/m²/day across various regions, solar energy remains grossly underutilized. This underperformance is largely attributed to poor planning, weak policy frameworks, and the absence of spatially explicit, data-driven feasibility studies (Mas'ud *et al*., 2017). Egor, with its urban infrastructure, relatively high solar irradiance, and critical energy needs, presents a good case for such an assessment.

This study, therefore, aims to apply a GIS-based Fuzzy-AHP model to identify the most suitable locations for solar farm development in Egor LGA. By integrating geospatial and multi-criteria decision-making techniques, the study provides a replicable methodology for sustainable energy planning in urban and peri-urban Nigerian communities.

This research contributes to the body of knowledge in geospatial energy planning and supports the broader Sustainable Development Goals (SDGs)**,** particularly Goal 7: "Affordable and Clean Energy." It also offers practical guidance for policymakers, energy developers, and urban planners seeking to expand solar infrastructure in southern Nigeria and similar regions.

MATERIALS AND METHODS

Study Area Description

The study was conducted in Egor Local Government Area (LGA) of Edo State, Nigeria, located between latitudes 6°16'N and 6°24'N and longitudes 5°32'E and 5°39'E. Egor lies in the humid tropical zone characterized by a wet and dry season, making it well-suited for solar energy capture. The LGA covers an area of approximately 93 km² and has a population of over 330,000 (NPC, 2006). Egor hosts significant public infrastructure, including the University of Benin, and faces challenges related to unreliable grid electricity, hence making it an ideal location for evaluating solar PV deployment. The map of the study area is shown in Figure 1.

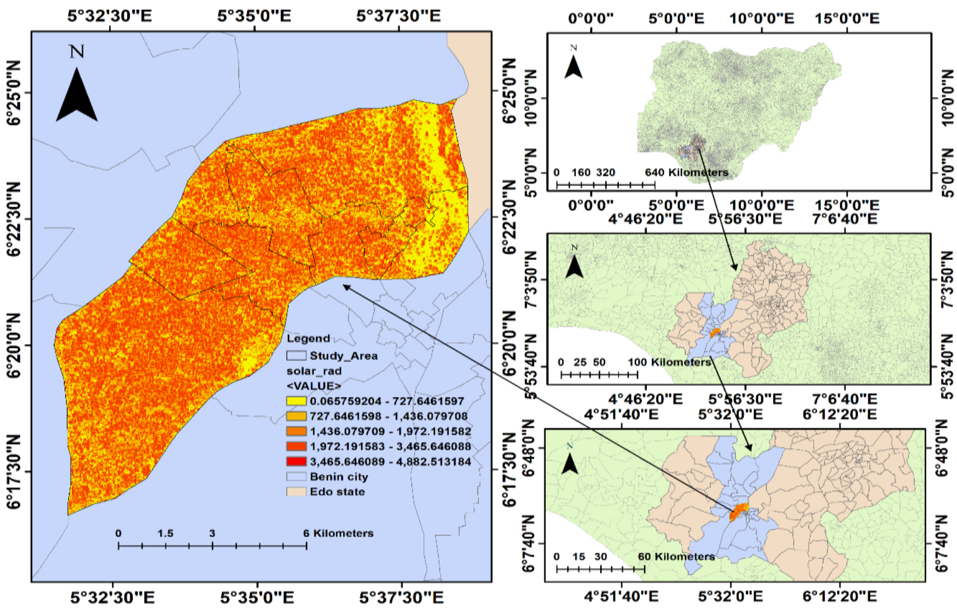


Figure 1: Map of the study area

Overview of Approach

This study employed an integrated methodology combining Geospatial Information System (GIS) and Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) within a Multi-Criteria Decision Analysis (MCDA) framework. The process involved five key steps: selecting relevant spatial and climatic criteria; acquiring and pre-processing data; standardizing inputs using fuzzy membership functions; deriving weights through AHP pairwise comparison; and performing a weighted fuzzy overlay to generate the final site suitability map. The general flow diagram for the process is summarized as shown in Figure 2.

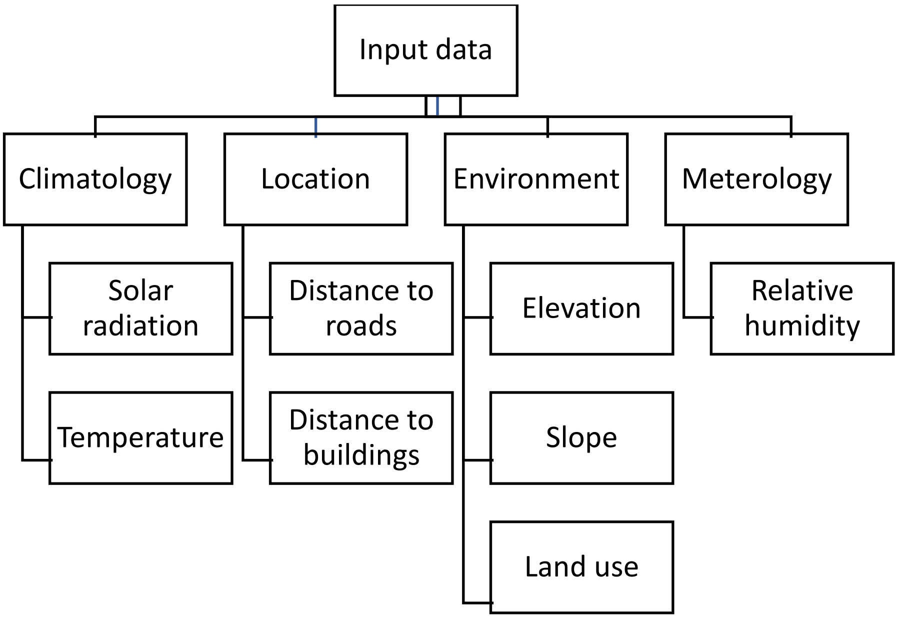


Figure 2: Flow diagram of the procedures for location of solar PV plants

Criteria Selection
Feasibility and site-specific peculiarity informed the identification of eight (8) criteria which were selected based on literature and expert consultation. Table 1 shows the list of these nine criteria and the justification for selecting them for the research.

Table 1: Criterial for Solar Farm Suitability Analysis

No	Criteria	Justification
1	Solar Radiation	Primary energy source
2	Elevation	Affects irradiance and flood risk
3	Slope	Influences installation feasibility
4	Temperature	Affects PV efficiency
5	Relative Humidity	Influences panel performance
6	Land Use / Land Cover	Indicates available land types
7	Distance to Roads	Reflects infrastructure cost
8	Distance to Buildings	Prevents shading and safety issues

Data Sources and Preprocessing
The data used for this research was derived from different sources as itemized below.

i. Solar Radiation, Temperature, Humidity was downloaded from the NASA POWER Data Portal at (https://power.larc.nasa.gov).
ii. The Digital Elevation Model was downloaded from the Shuttle Radar Topographic Mission (SRTM 30m resolution) from the United State Geological Survey (USGS) (https://earthexplorer.usgs.gov/) for elevation variable processing.
iii. For land use land cover, Sentinel-2 satellite imagery was used to classify the study area into five classes, the data was also obtained from (https://earthexplorer.usgs.gov/) USGS website
iv. Roads and Buildings were extracted from the topographic maps and OpenStreetMap at https://www.openstreetmap.org/#map=6/9.12/8.67
v. The coordinate system adopted for all the maps to aid smooth analysis was the WGS 1984, UTM Zone 31N.

All spatial layers were resampled to a 30m resolution and projected into a uniform spatial reference for overlay operations in ArcGIS 10.2.

Fuzzy Membership Standardization
Each criterion was normalized using fuzzy membership functions (MF) to transform raw data into a common scale [0, 1]. The trapezoidal membership function was used due to its flexibility and simplicity. This function was chosen because it effectively models gradual transitions in suitability and can accommodate both increasing and decreasing criteria trends. Compared to sigmoid or linear functions, it provides a balance between simplicity and accuracy (Oladosu *et al*., 2025). The general form of the trapezoidal fuzzy membership function is presented in equation 1 adapted from (Zadeh, 1965).

$$\mu(z) = \begin{cases} 0 & z \leq a \\ \frac{z-a}{b-a} & \alpha < z \leq d \\ 1 & b < z \leq c \\ \frac{d-z}{d-c} & c < z \leq d \\ 0 & z > d \end{cases} \quad (1)$$

Where: z represents the input value (such as, elevation, slope), [a,b,c,d] are the control points defining the shape of the fuzzy function, $\mu(z) \in [0,1]$ is the degree of suitability.

The trapezoidal MF accommodates both "increasing" and "decreasing" suitability trends, depending on the criterion. For instance, solar radiation and elevation were modeled as increasing functions because more is better while slope and distance to buildings were modeled as decreasing functions because less is better. Model builder was used in ArcGIS 10.2 to carry out analysis as shown in Figure 3. Table 1 is the fuzzy membership function and rankings.

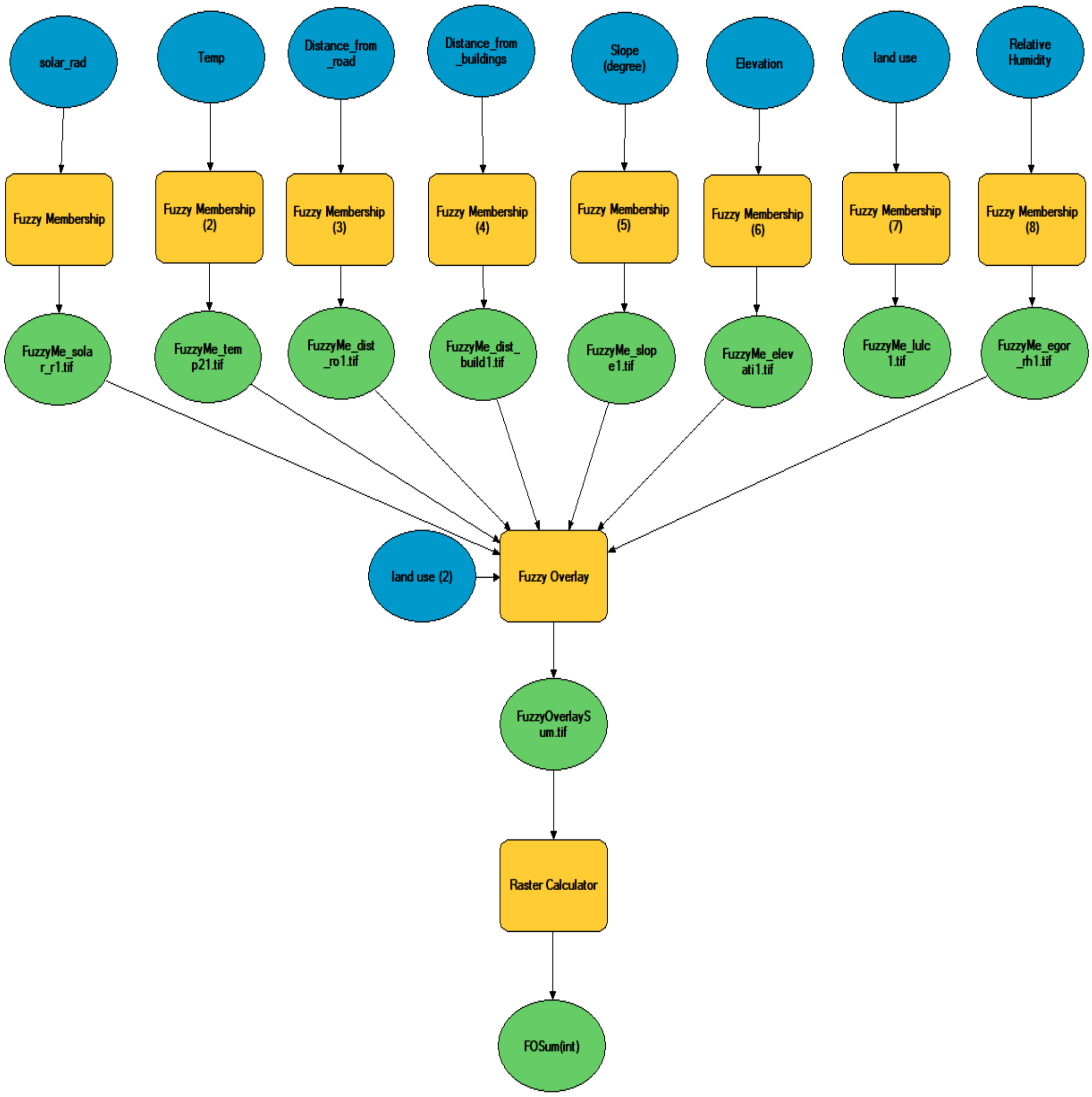


Figure 3: A model of fuzzy membership and fuzzy overlay

Table 2: Fuzzy membership for solar farm site selection for the case study

Criteria	Fuzzy Membership	Ranking
Land use	Water	1
	Trees	2
	Rangeland	3
	Built-up Area	4
	Bare ground	5
Elevation	0 - 0.31372549	1
	0.31372549 - 0.48627451	2
	0.48627451 - 0.615686275	3
	0.615686275 - 0.760784314	4
	0.760784314 - 1	5
Slope	0 - 0.090196078	1
	0.090196078 - 0.160784314	2
	0.160784314 - 0.239215686	3
	0.239215686 - 0.360784314	4
	0.360784314 - 1	5
Solar radiation	0 - 0.149019608	1
	0.149019608 - 0.294117647	2
	0.294117647 - 0.403921569	3
	0.403921569 - 0.709803922	4
	0.709803922 - 1	5
Temperature	0 - 0.184313704	5

	0.184313704 - 0.345097998	4
	0.345097998 - 0.517646997	3
	0.517646997 - 0.717646973	2
	0.717646973 - 0.999999881	1
Distance to roads	0	4
	0 - 0.149019608	3
	0.149019608 - 0.6	2
	0.6 - 1	1
Distance to buildings	0.030303031 - 0.231847891	1
	0.231847891 - 0.456209151	2
	0.456209151 - 0.688175877	3
	0.688175877 - 0.897326203	4
	0.897326203 - 1	5
Relative humidity	0.000003362 - 0.094120693	5
	0.094120693 - 0.313727798	4
	0.313727798 - 0.517648681	3
	0.517648681 - 0.674510898	2
	0.674510898 - 1	1

The relative importance of each criterion was evaluated using the AHP developed by Saaty (1980). The pairwise comparisons were conducted by a panel of three experts: a renewable energy specialist, a GIS analyst, and a regional planner with solar farm siting experience. Their consensus ensured a multidisciplinary and context-specific weighting of criteria. The process includes the construction of a pairwise comparison matrix $A = [a_{ij}]$, where: a_{ij} indicates how much more important criterion i is compared to criterion j, using a scale of 1 to 9. Table 3 shows the criteria and the pair-wise matrix of the situation.

Table 3: Pair-Wise Comparison Matrix

Criteria	SR	Elev.	Slope	Temp.	Dist. Roads	Dist. Build	RH	LULC
SR	1	3	5	7	7	7	5	5
Elev.	0.333	1	3	5	5	5	3	3
Slope	0.2	0.333	1	3	3	3	1	1
Temp.	0.143	0.2	0.333	1	3	3	1	1
Dist. Roads	0.143	0.2	0.333	0.333	1	3	1	1
Dist. Build	0.143	0.2	0.333	0.333	0.333	1	0.333	0.333
RH	0.2	0.333	1	1	1	3	1	1
LULC	0.2	0.333	1	1	1	3	1	1
Total	2.362	5.599	11.999	18.666	21.333	28	13.333	13.333

Normalization of the matrix was done using equation 2:

$$\bar{a}_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \quad (2)$$

The computation of priority weights (W) as the average of each row in the normalized matrix was carried out while the consistency Index (CI) is computed by adopting equation 3 (Saaty, 1980). Table 4 shows the preliminary results from the normalized data while Table 5 shows the randomized index values.

Table 4: Normalized Pair-Wise Comparison Matrix

Criteria	SR	Ele	Slope	Temp	Dist. Roads	Dist. Build	RH	LULC
SR	0.412	0.5	0.357	0.41	0.388	0.259	0.263	0.263
Elev.	0.137	0.167	0.214	0.293	0.278	0.185	0.158	0.158
Slope	0.082	0.056	0.071	0.176	0.167	0.111	0.053	0.053
Temp	0.059	0.033	0.024	0.059	0.167	0.111	0.053	0.053
Dist. Roads	0.059	0.033	0.024	0.02	0.056	0.111	0.053	0.053
Dist. Build	0.059	0.033	0.024	0.02	0.019	0.037	0.018	0.018
RH	0.082	0.056	0.071	0.176	0.167	0.111	0.053	0.053
LULC	0.082	0.056	0.071	0.176	0.167	0.111	0.053	0.053

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (3)$$

Where: λ_{max} refers to the maximum eigenvalue of matrix *A*, *n* is the number of criteria.

Table 5: Randomized Index for *n*- Criteria

N	1	2	3	4	5	6	7	8	9	10
Random Index (RI)	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

The consistency ratio (CR) was determined using equation 5. Table 6 presented the preliminary results used to determine the maximum eigen value of the designed matrix A.

Table 6: Consistency of the Criteria Results to Obtain the λ_{max}.

Criteria	SR	Ele	SL	Temp	Dist. Roads	Dist. Builds	RH	LU LC	Weighted sum	Criteria weight	
SR	0357	0.594	0.430	0.357	0.273	0.196	0.430	0.430	3.067	0.357	8.59
Elev.	0.119	0.198	0.258	0.255	0.195	0.140	0.258	0.258	1.681	0.198	8.49
Slope	0.071	0.066	0.086	0.153	0.117	0.084	0.086	0.086	0.749	0.086	8.71
Temp	0.051	0.040	0.029	0.051	0.117	0.084	0.086	0.086	0.544	0.051	10.67
Dist. Roads	0.051	0.040	0.029	0.017	0.039	0.084	0.086	0.086	0.432	0.039	11.08
Dist. Build	0.051	0.040	0.029	0.017	0.013	0.028	0.027	0.27	0.232	0.028	8.29
RH	0.071	0.066	0.086	0.051	0.039	0.084	0.086	0.086	0.569	0.086	6.62
LULC	0.071	0.066	0.086	0.051	0.039	0.084	0.086	0.086	0.569	0.086	6.62

Note: Where applicable in Tables 3-4, and 6: LULC is Land use and land cover, Elev. is the Elevation, SL is the Slope, SR is the Solar radiation, Temp. is the Temperature, Dist.Roads is the Distance to roads, Dist.Build is the Distance to buildings, RH is the Relative humidity.

To get the value for CR, equation 4 was used. According to Saaty (1980), If CR<0.10, the judgment matrix is considered consistent. The preliminary results of the CR is as presented in Table 7.

$$CR = \frac{CI}{RI} \quad (4)$$

Where: RI is the Random Index depending on n (see Table 5).

Table 7: Calculation of Criteria Index

S/No	Calculation	Solution
λmax	(8.59+8.49+8.71+10.67+11.08+8.29+6.62+6.62)/8	8.641
CI	(λmax-m)/(m-1) = (8.641- 8)/ (8-1)	0.092
RI	1.41	
CR	CI/RI = (0.092/1.41)	0.065
CR%		6.5%

Note: λmax is the consistency vector's average consistency vector's average, CI is the consistency ratio RI is the random index

Fuzzy Overlay Analysis

After standardizing and weighting the layers, a Fuzzy Overlay (SUM operator) was applied to integrate the criteria using equation 5.

$$S(x,y) = \sum_{i=1}^{n} w_i \times \mu_i(x,y) \quad (5)$$

Where: S(x,y) refers to the suitability score at pixel location (x,y), w_i is the weight of criterion i, μ_i (x,y) = fuzzy membership value of criterion i at location (x,y), and n is the total number of criteria.

The output is a suitability map where pixel values range between 0 (unsuitable) and 1 (highly suitable).

Classification and Site Selection

The final suitability map was classified into five categories: Very High Suitability (0.8–1.0), High Suitability (0.6–0.79), Moderate Suitability (0.4–0.59), Low Suitability (0.2–0.39), and Unsuitable (0.0–0.19) The "Very High" and "High" zones were extracted using spatial queries in ArcGIS to identify potential locations for solar farm installation.

Validation and Interpretation

The preliminary results were validated through, cross-checking the spatial outputs with physical features (e.g., avoiding dense built-up areas and forests). Comparing identified sites with known solar project locations in similar geographic settings, and through logical consistency check based on expected patterns (e.g., high solar radiation correlating with high suitability).

RESULTS AND DISCUSSION

Overview of Suitability Analysis

The integrated GIS and Fuzzy-AHP approach yielded a spatially explicit suitability map for solar farm development across Egor Local Government Area. Each criterion was individually analyzed and reclassified using fuzzy membership functions. These layers were then aggregated using the fuzzy overlay SUM operator, resulting in a composite suitability surface with values ranging from 0 (least suitable) to 1 (most suitable).

Individual Criteria Maps and Interpretations

The following are the individual map produced and the interpretation of the results pertaining to them.

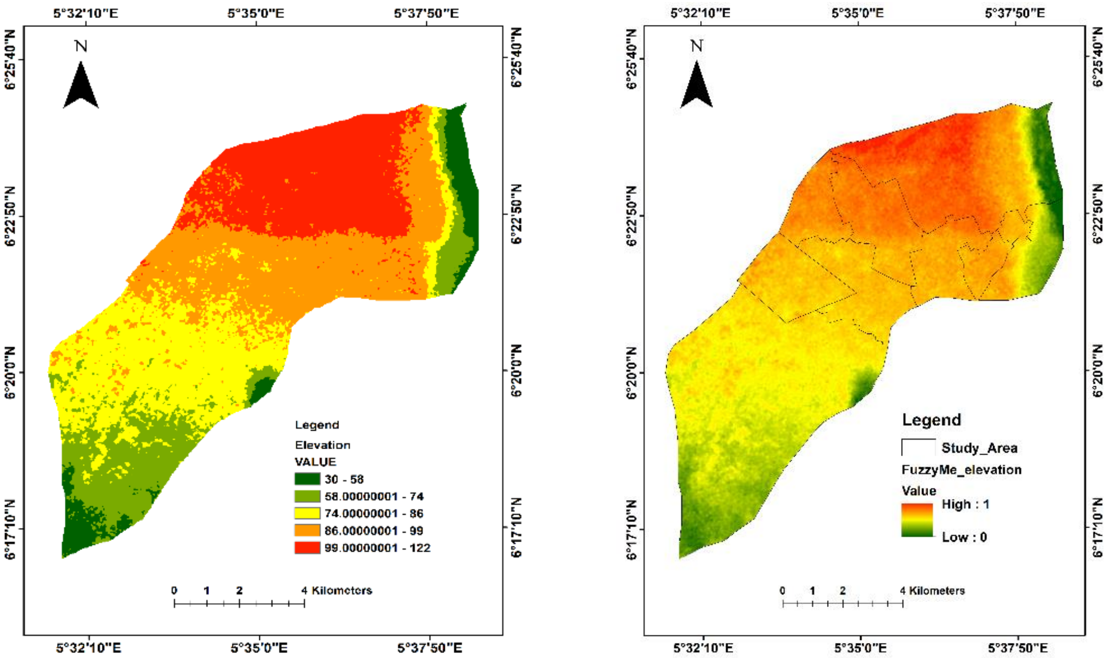
Elevation

Figure 4a and b show the elevation maps and the reclassified map respectively. Elevation influences solar farm siting primarily through its impact on flood risk, temperature, and atmospheric clarity. Higher elevations tend to offer better air quality and are typically less vulnerable to seasonal flooding, making them more reliable for long-term solar infrastructure investment.

In this study, elevation data from the SRTM DEM were reclassified using a fuzzy increasing membership function, where higher elevations were rated as more suitable.

The analysis revealed that northeastern and north-central parts of Egor, particularly around Evbuotubu and Oghedaivbiobaa, had elevations above 150 meters, making them ideal candidates for solar PV installation. Lower-lying areas in the southern and central zones, such as Ugbowo and Useh, were considered less suitable due to greater susceptibility to flooding and slight thermal elevation effects.

These areas were assigned lower fuzzy membership values. Elevation was the second most influential criterion in the pairwise AHP comparison, with a normalized weight of 3.204, underscoring its importance in ensuring site stability, safety, and resilience in solar farm development.



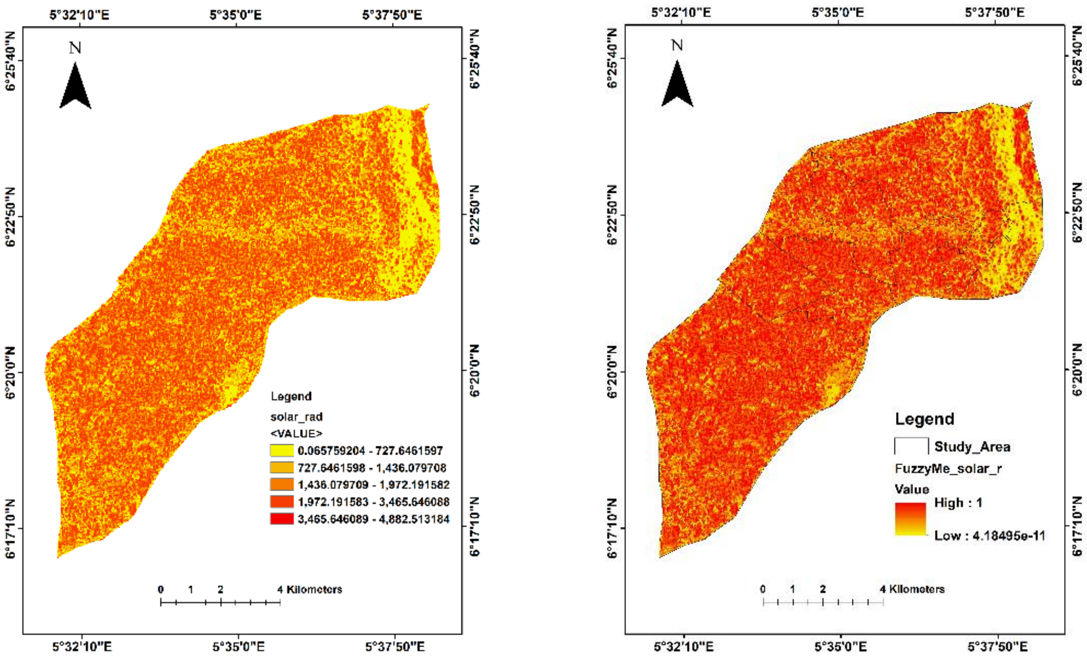
(a) (b)

Figure 4: (a) Elevation and (b) Reclassified elevation map of Egor L.G.A.

Solar Radiation

Solar radiation is the most critical factor in solar photovoltaic (PV) farm siting, as it directly determines the amount of energy a location can generate. Higher solar irradiance ensures greater power output and improved return on investment for PV installations.

In this study, average annual solar radiation data were sourced from the NASA POWER database and reclassified using a fuzzy increasing membership function, where higher radiation levels received greater suitability scores. The analysis revealed that most of Egor LGA consistently receives radiation above 1900 kWh/m²/year, which falls within the optimal range for PV deployment. The north-central and northeastern regions, including Evbuotubu, Uwelu, and parts of Oghedaivbiobaa, showed slightly higher irradiance levels, earning fuzzy membership scores close to 1.0. This uniformity in radiation across the LGA underscores Egor's strong potential for solar energy development. Solar radiation had the highest weight (5.802) in the AHP analysis, reinforcing its role as the primary driver of solar site suitability. Its dominant influence helped anchor the suitability model by identifying zones with the greatest energy generation potential. Figure 5 a and b show the solar radiation map of the study area.



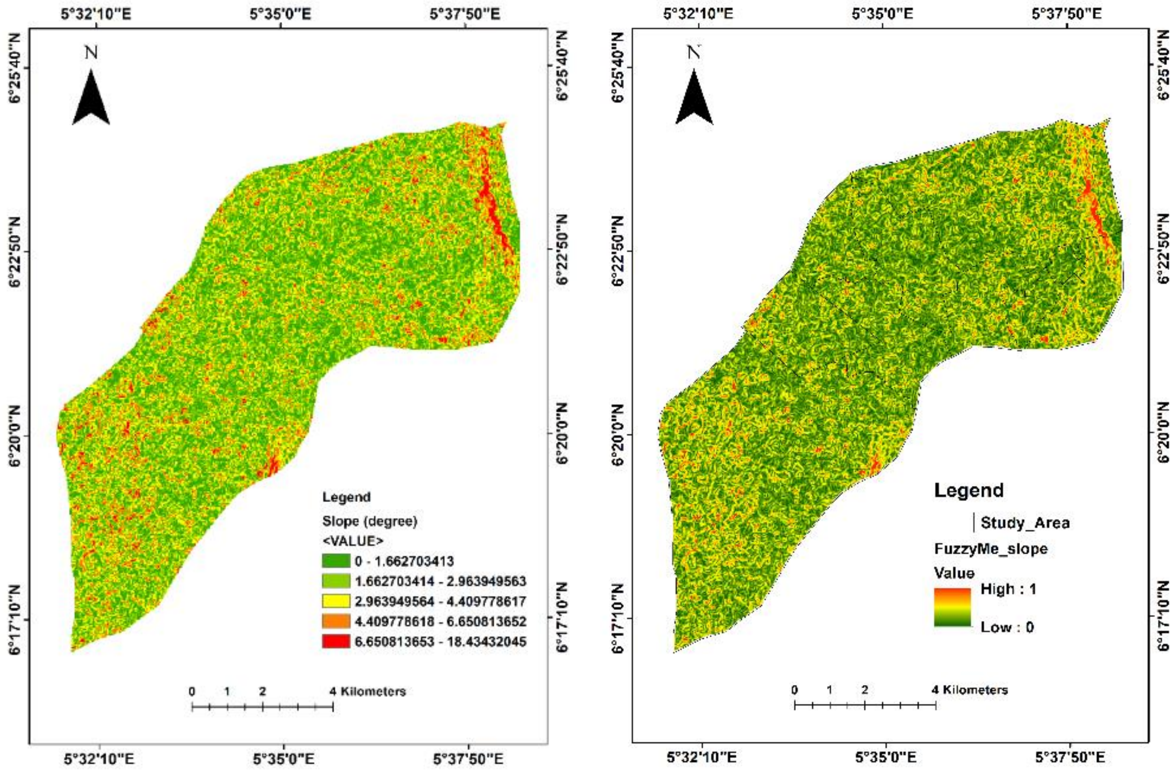
(a) (b)

Figure 5: (a) Solar radiation and (b) Reclassified solar radiation map of Egor L.G.A.

Slope

Slope is a vital topographic parameter in solar farm siting, as it affects both the constructability and operational efficiency of solar PV systems. Flat or gently sloped terrain reduces site preparation costs, minimizes shading between panel rows, and improves panel alignment flexibility (Wheatbelt Development Commission, 2010). Slopes above 10% are generally considered less favorable due to increased engineering complexity and installation cost (Uyan, 2013). In this study, slope was derived from the SRTM DEM and reclassified using a fuzzy decreasing membership function, where lower slopes (0–5%) were assigned higher suitability scores. The analysis showed that over 80% of Egor's terrain falls within the 0–4% slope range, particularly in the central and northeastern areas such as Uwelu and Evbuotubu, making these zones highly suitable for solar installations.

Areas with steeper slopes, mostly localized in northwestern fringes, were assigned lower fuzzy membership values due to the increased difficulty and cost of solar farm construction on inclined surfaces. By incorporating slope into the model, the analysis ensured that selected locations are technically feasible, cost-effective, and less susceptible to construction-related constraints. The slope map of the study is represented by Figure 6 a and b.



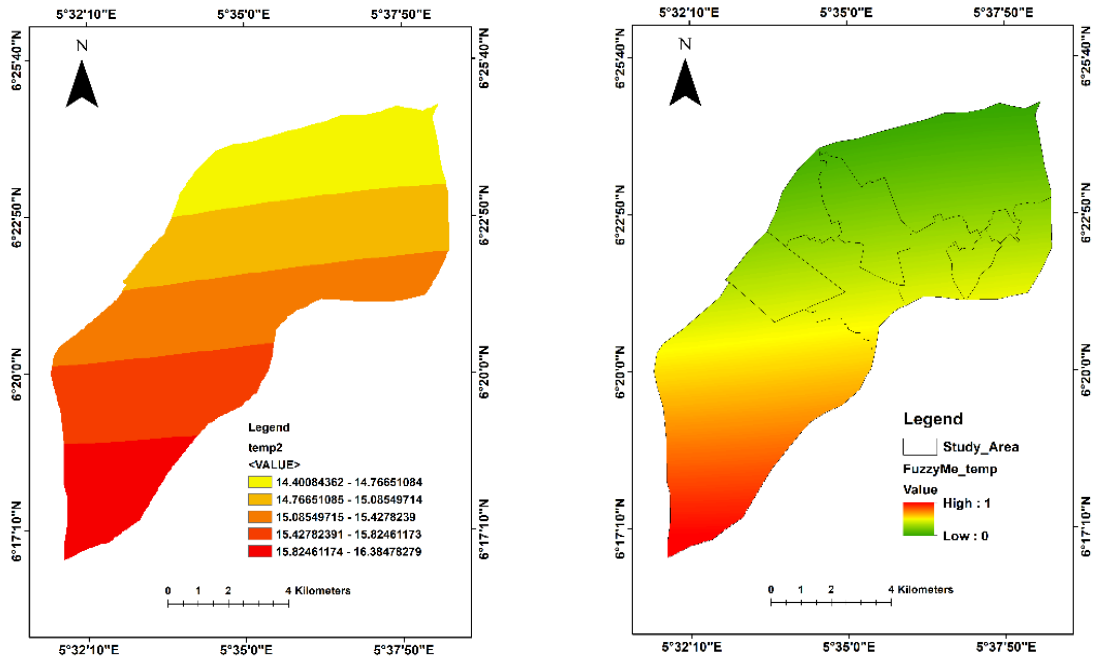
(a) (b)

Figure 6: (a) Slope and (b) Reclassified slope map of Egor L.G.A.

Temperature

Temperature plays a moderating role in the performance of solar photovoltaic (PV) systems. While sunlight is essential for electricity generation, excessively high ambient temperatures can reduce the efficiency of PV modules by increasing internal resistance and causing energy losses. Research shows that PV efficiency typically declines by 0.4–0.5% for each degree Celsius above 25°C (Huld *et al.*, 2015). In this study, monthly average temperature data were obtained from the NASA POWER database and standardized using a fuzzy decreasing membership function, giving higher scores to cooler areas. The analysis revealed that the northern and northeastern parts of Egor, particularly Evbuotubu and Oghedaivbiobaa, recorded lower average temperatures (26–28°C) and were thus rated more suitable. In contrast, southern areas, including Ugbowo, experienced higher average temperatures (above 30°C), which could reduce PV output and were therefore assigned lower fuzzy suitability values.

Though not as dominant as solar radiation, temperature was an important refinement factor in the model, helping distinguish between areas of similar irradiance but differing PV efficiency potential. The map of temperature around the study area is as presented in Figure 7 a and b.



(a) (b)

Figure 7: (a) Temperature and (b) Reclassified temperature map of Egor L.G.A.

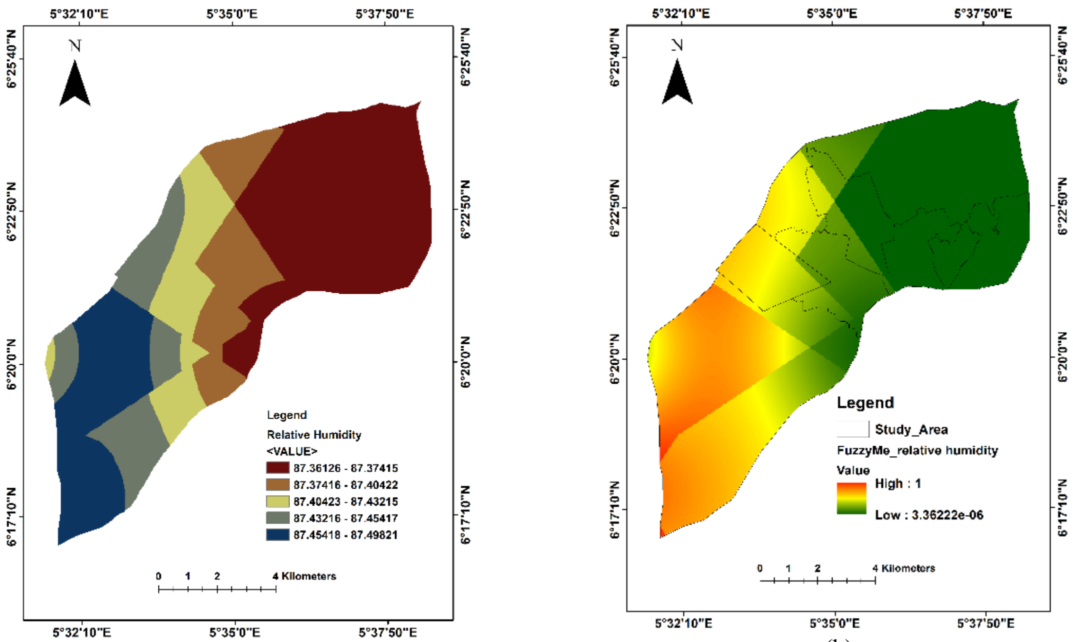
Relative Humidity

Relative humidity influences the efficiency and durability of solar photovoltaic (PV) systems by affecting the level of moisture in the atmosphere, which can reduce solar irradiance and cause condensation on panels. Areas with consistently high humidity often experience more cloud cover, which reduces the direct solar radiation reaching the panels and may lead to corrosion or soiling issues over time (Mas'ud *et al.*, 2017).

In this study, monthly average relative humidity data obtained from the NASA POWER dataset were reclassified using a fuzzy decreasing membership function, assigning higher suitability scores to drier areas. The analysis showed that northern and northeastern parts of Egor, such as Evbuotu and Useh, recorded lower relative humidity levels (below 70%), making them more suitable for solar PV deployment. These areas were assigned fuzzy membership values close to 1.0.

Conversely, central and southern parts of the LGA, especially around Ugbowo and densely vegetated zones, exhibited higher humidity levels (above 80%) and were therefore assigned lower fuzzy suitability scores (0.2–0.4).

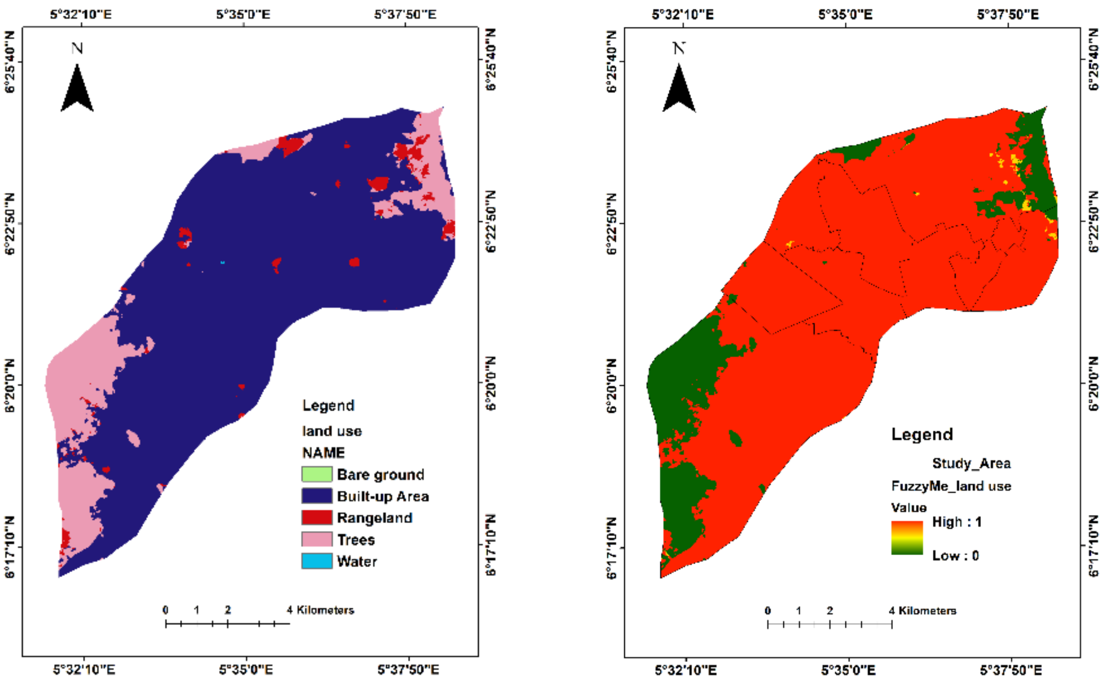
Although not the most dominant factor, relative humidity served as a moderating criterion, helping to fine-tune the suitability ranking by identifying areas less prone to solar energy loss due to atmospheric moisture. Figure 8 a and b show the maps of humidity derived for the study area.



(a) (b)

Figure 8: (a) Relative humidity and (b) Reclassified relative humidity map of Egor L.G.A.

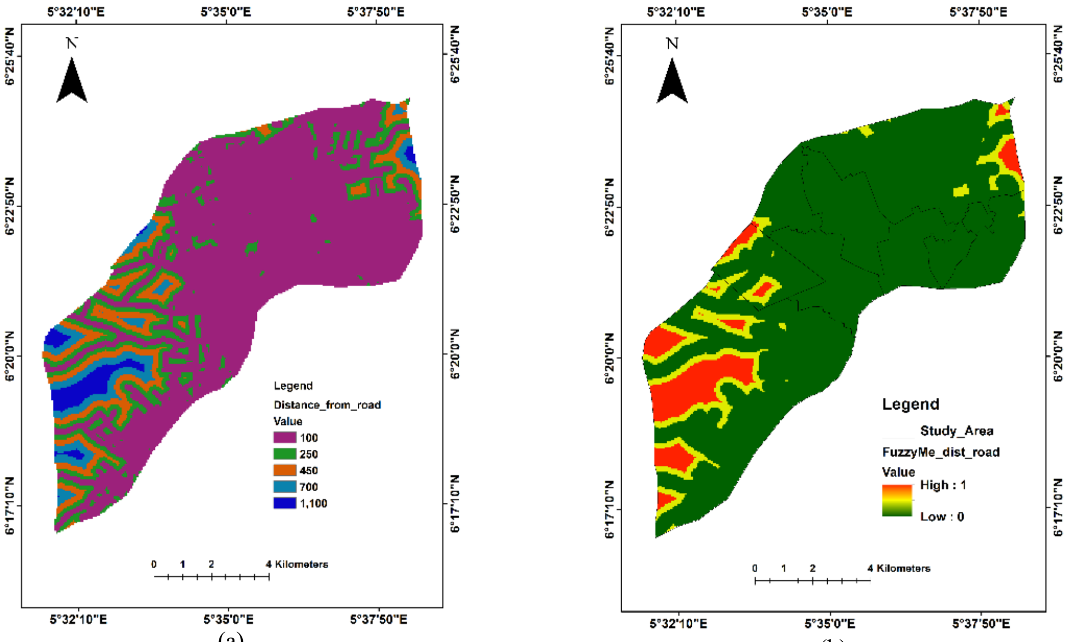
Land Use/Land Cover (LULC)
Land use and land cover (LULC) play a pivotal role in determining the physical feasibility and sustainability of solar farm installations. LULC affects the availability of open space, the potential for land-use conflict, and the cost of land acquisition and preparation. For this study, Sentinel-2 imagery was classified into five major land cover categories: Built-Up Areas, Forest, Agricultural Land, Bare Land, and Rangeland.
Using a supervised classification technique with a maximum likelihood algorithm in ArcGIS, the resulting LULC map indicated that Built-Up Areas and Forests dominate the central and southern regions of Egor, particularly around Ugbowo, Oghedaivbiobaa, and parts of Uwelu, making them unsuitable due to limited space, shading, and high land conversion costs. These areas were assigned low fuzzy membership values (0–0.3).
In contrast, Bare Land and Rangeland areas, primarily located in the northern and northeastern zones, including Evbuotu, Oghedaivbiobaa outskirts, and Useh, were identified as the most favorable. These land classes offer minimal obstruction, relatively low land-use conflict, and typically require less site clearing and preparation. Accordingly, they were assigned high fuzzy membership values (0.7–1.0).
Agricultural land, covering a moderate portion of the LGA, received medium suitability scores (0.4–0.6). While technically feasible, solar development in these areas could result in the displacement of food production activities, posing socioeconomic concerns. Hence, agricultural zones were considered only under limited trade-off scenarios.
The incorporation of LULC ensures that the model identifies sites that are not only technically suitable but also compatible with existing land uses, reducing the risk of future encroachments, legal disputes, or ecological degradation. By prioritizing underutilized or non-competitive land classes such as bare lands and degraded rangelands, the analysis supports a sustainable and conflict-sensitive solar farm siting strategy. The land use land cover map is presented in Figure 9 a and b.



(a) (b)

Figure 9: (a) LULC and (b) Reclassified LULC map of Egor L.G.A.

Distance to Roads
The distance to roads criterion plays a critical role in determining the economic feasibility and accessibility of solar farm development. Proximity to existing transportation infrastructure reduces the cost of equipment transportation, construction logistics, and long-term maintenance (Uyan, 2013). In this study, a buffer threshold of 5 kilometers from major and secondary roads was established, with areas closer to roads assigned higher fuzzy suitability scores.
The reclassified distance-to-roads map revealed that areas within central and eastern Egor, especially around Uwelu, Evbareke, and Use, were well-connected to a network of major and minor roads. These zones received higher fuzzy membership values due to their accessibility and cost advantages. On the other hand, isolated areas in the northwestern and southwestern parts of the LGA, which are relatively far from primary road networks, scored lower due to anticipated infrastructure investment required to enable access.
This layer helped refine the final suitability output by ensuring that proposed solar farm sites are logistically accessible, which is vital for construction mobilization, routine inspection, and emergency response. Areas identified as highly suitable for solar PV development generally coincided with zones that are within close proximity to motorable roads, thus meeting both technical and practical criteria for site selection. Figure 10 a and b show the maps of distance to road as produced from the work

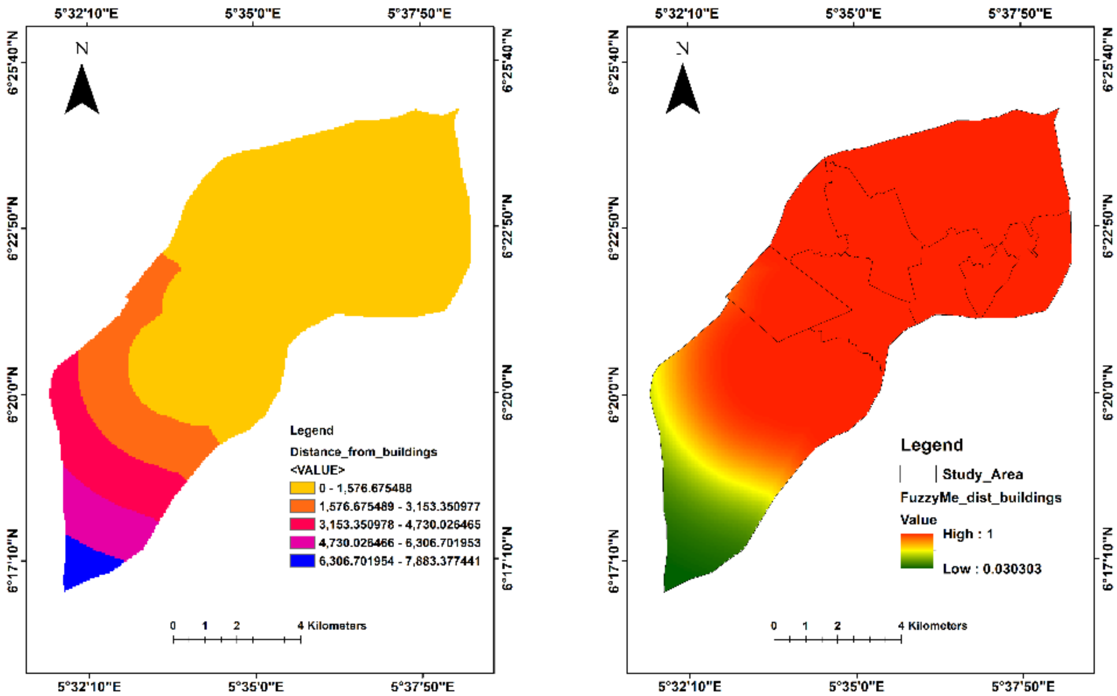


(a) (b)

Figure 10: (a) Distance to road and (b) Reclassified distance to road map of Egor L.G.A.

Distance to Buildings

The distance to buildings criterion was assessed to prevent land-use conflicts and minimize shading effects, which can significantly reduce solar panel efficiency and system safety. A minimum buffer distance of 500 meters from residential areas was established, consistent with solar farm zoning standards in peri-urban environments (Gerbo *et al*., 2022). The reclassified raster layer showed that the central and southern parts of Egor LGA, particularly around Ugbowo and Oghedaivbiobaa, had high building densities and were thus marked as low suitability zones. Conversely, northwestern and northeastern areas, such as Evbuotubu and parts of Uwelu, contained open lands located farther from dense settlement clusters. These zones were assigned higher fuzzy membership values due to their compliance with setback distance requirements. This layer contributed to refining the final suitability map by filtering out areas that might face community opposition, legal encumbrances, or technical difficulties related to shading and safety. Integrating this factor helped ensure that identified solar farm sites were not only environmentally suitable but also socially and operationally viable. Figure 11 is the produced distance to building map.



(a) **(b)**

Figure 11: (a) Distance to buildings and (b) Reclassified distance to buildings map of Egor L.G.A.

Final Suitability Map

The integration of all eight standardized and weighted criteria, solar radiation, elevation, slope, temperature, relative humidity, land use/land cover, distance to roads, and distance to buildings, through the Fuzzy Overlay (SUM) operation produced the final solar farm suitability map for Egor Local Government Area. This final output map of the suitability study is presented in Figure 12.

The resulting map displays a continuous surface of suitability values ranging from 0 (completely unsuitable) to 1 (highly suitable). To aid interpretation and planning, these values were classified into five categories. Conversely, southern and central Egor, particularly around Ugbowo, were classified as Low to Unsuitable due to dense built-up areas, high temperature and humidity levels, and limited open land.

The final suitability map serves as a decision-support tool for energy planners and developers by spatially identifying the most technically, environmentally, and infrastructurally favorable locations for solar farm deployment. It also provides a replicable model for solar siting in other local government areas with similar urban-periurban characteristics. It is important to acknowledge potential sources of uncertainty in this analysis. For example, the use of 30-meter resolution DEM and satellite imagery may not capture micro-scale topographic variations or highly localized land use features. Similarly, atmospheric distortions or seasonal effects may affect climate data accuracy. These limitations, while not critical at the LGA scale, may influence fine-grained site decisions.

The results validate the usefulness of combining GIS and Fuzzy-AHP for solar farm site selection. The significant influence of solar radiation, elevation, and land cover underscores the necessity of incorporating both climatic and spatial parameters in energy planning. While solar radiation had a uniform distribution, the actual feasibility of installation was limited by factors like land use and accessibility.

The use of fuzzy logic allowed the incorporation of gradual transitions between suitability levels rather than rigid thresholds, which more closely reflects real-world conditions. For example, slightly sloped lands were not outright excluded but assigned lower weights, enhancing the flexibility of the model.

Furthermore, the pairwise comparison in AHP provided a transparent and quantitative basis for integrating expert judgment. The resulting Consistency Ratio (CR) of 0.06 confirmed the reliability of the weight assignment process.

This study confirms similar findings from earlier works. For instance, Uyan (2013) and Noorollahi *et al.* (2016) emphasized the influence of terrain, proximity to infrastructure, and climate factors in their GIS-MCDM analyses. Similar methodologies have been applied in other Sub-Saharan countries. Again, Gerbo *et al.* (2022) conducted a GIS-based solar siting study in Ethiopia and found that elevation, proximity to roads, and solar irradiance were top determinants which closely aligning with our findings in Egor. This suggests broader regional applicability of the GIS-Fuzzy AHP approach. However, unlike those studies, this work incorporated uncertainty handling via fuzzy logic and applied the methodology to a dense urban-periurban interface, making it a novel contribution in the Nigerian context.

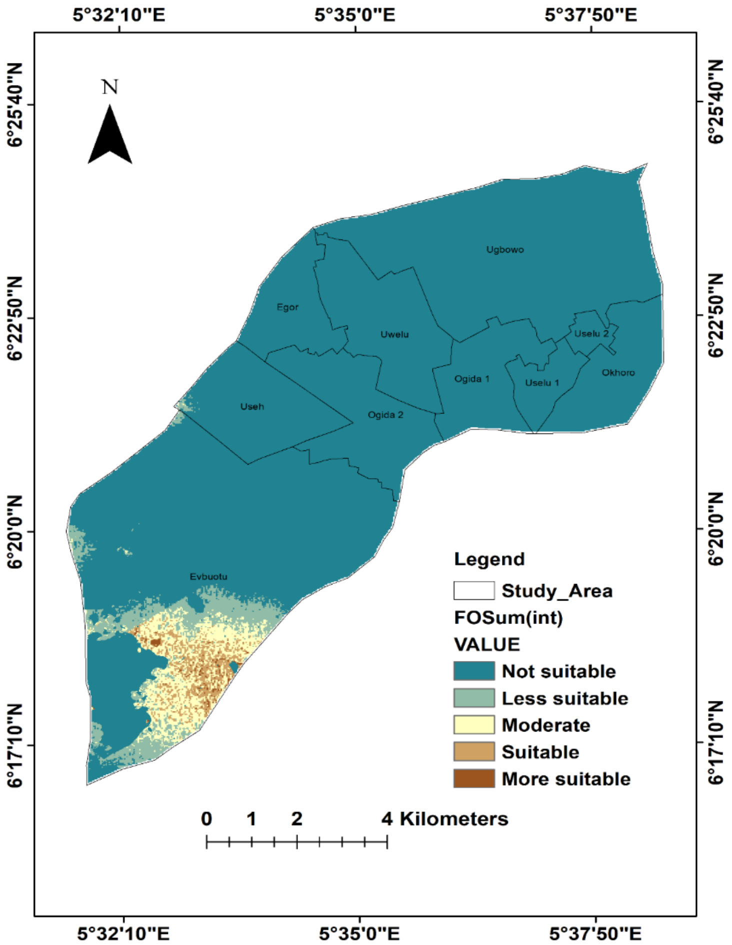


Figure 12: Final suitability map

Table 8: Summary of Suitability Characteristics

Suitability Class	Value Range	Area Coverage (%)
Very High	0.80–1.00	14.2%
High	0.60–0.79	24.6%
Moderate	0.40–0.59	34.8%
Low	0.20–0.39	18.7%
Unsuitable	0.00–0.19	7.7%

The "Very High" and "High" suitability areas are predominantly located in Evbuotubu, community and surroundings. These areas are relatively elevated, have open land cover, have near access roads, and are exposed to strong solar radiation with low relative humidity.

CONCLUSION

This study employed a hybrid GIS and Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) approach to assess the spatial suitability of Egor Local Government Area, Edo State, Nigeria, for solar photovoltaic (PV) farm development. By integrating eight critical environmental and infrastructural factors, including solar radiation, slope, elevation, land use, temperature, humidity, and proximity to roads and buildings, the study produced a comprehensive suitability map highlighting optimal locations for solar energy infrastructure. The findings indicate that approximately 39% of the total land area in Egor falls within the "High" to "Very High" suitability categories, with the most promising zones identified in Evbuotubu and surrounding communities. Solar radiation and elevation emerged as the most influential parameters, confirming their dominant role in PV site optimization. The integration of fuzzy logic enabled nuanced modeling of suitability, capturing uncertainties often ignored in traditional MCDA approaches.

The findings of this study reveal the potential of geospatial decision-support systems in renewable energy planning. The resulting suitability map serves not only as a technical tool for developers and urban planners but also as a strategic asset for government agencies and policymakers seeking to accelerate the energy transition in Nigeria.

This approach contributes to the ongoing discourse on sustainable energy development and aligns with global efforts to meet Sustainable Development Goal 7 (Affordable and Clean Energy) and Goal 13 (Climate Action) by promoting decentralized, low-carbon energy systems. The research strongly supports SDG 7: "Affordable and Clean Energy," by enabling spatially optimized siting of solar infrastructure, which is critical to ensuring equitable access to energy in developing urban centers.

Based on the results and findings, the following recommendations are proposed:

i. Policy integration involving local and state governments in Edo to adopt geospatial tools such as GIS and Fuzzy-AHP in energy infrastructure planning. These tools will enhance transparency, precision, and stakeholder engagement in renewable energy decision-making.

ii. Pilot implementation should consider the identified high-suitability zones, especially around Evbuotubu, as priority for pilot solar farm projects. Doing so would validate the findings of this model in practice and provide scalable templates for other LGAs.

iii. We recommend data improvement for future research which should incorporate real-time solar monitoring stations and economic cost layers (such as, land value, transmission costs) to enhance the resolution and practicality of the model.

iv. Inclusion of socioeconomic criteria is recommended since this study focused primarily on physical and climatic factors. Future assessments could integrate social acceptance, land tenure, and grid connection capacity to provide a more holistic evaluation.

v. Replication in other regions should be made by adapting the methodology developed in this research for other LGAs in Nigeria and Sub-Saharan Africa with similar challenges. This would facilitate nationwide planning for solar energy infrastructure using spatially intelligent models.

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