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ABSTRACT

Integrating renewable energy sources is essential for sustainable development and addressing inconsistencies in power supply. This study evaluates and compares the Fuzzy Overlay and Analytic Hierarchy Process (AHP) models for siting a solar photovoltaic (PV) plant in Ondo West LGA, Nigeria. Five key criteria influencing optimal solar energy generation were considered: solar irradiance, slope, land use/land cover, proximity to transmission lines, and proximity to road networks. The study utilised solar global horizontal irradiance (GHI) data, a digital elevation model (DEM), Landsat 8 imagery, power grid data, and road network data. Geographic Information Systems (GIS), remote sensing, and multi-criteria decision-making (MCDM) techniques were applied to assess solar resources, topography, land use, accessibility, and infrastructure. The northeastern region of the study area is the most suitable area for siting Solar PV plant. The Fuzzy Overlay model identified a highly suitable area of 2,017.42 ha, while the AHP model indicated 3,239.61 ha. Statistical analysis (t-test, $\alpha = 0.05$) revealed no significant difference between the two models. However, Fuzzy MCDM is less influenced by subjective weighting, making it more effective in refining highly suitable areas. The study provides critical spatial insights to support strategic planning and decision-making in optimising solar PV deployment for enhanced energy sustainability.

Keywords: AHP, Fuzzy overlay, Geographic Information Systems, Multi-criteria decision analysis, Renewable energy, Site Selection.

1. INTRODUCTION

Suitability analysis is a versatile tool used across various sectors to identify optimal locations for different functions. It is essential in determining the best sites for energy-generating systems like wind farms and solar photovoltaic (PV) plants [31]. Beyond energy, suitability analysis helps assess risks such as pollution, earthquakes, and criminal activity and is also used to identify ideal locations for commercial hubs to accommodate growing populations and alleviate pressure on agricultural lands [12]; [15]; [27]. Geospatial techniques, including multicriteria decision analysis (MCDA), artificial intelligence, and geographic information systems (GIS), have been at the forefront of advancements in land-use suitability analysis for over four decades. These methods are essential in urban, regional, and environmental planning [21]. Fuzzy set theory, a key element in these analyses, allows for handling data with gradual transitions rather than clear boundaries, improving the accuracy of land-use mapping [3].

Therefore, conducting a suitability analysis for specific areas is crucial to identifying optimal locations for solar PV installations. Among various Multi-Criteria Decision Making (MCDM) methods, the Analytic Hierarchy Process (AHP) is the most commonly used due to its simplicity and effectiveness in addressing site suitability challenges, as evidenced in numerous studies [2]; [39]. Consequently, exploring a geospatial fuzzy MCDM approach for site selection is an important area for further research [10]. The fuzzy overlay technique is used in various fields, such as geographic information systems (GIS), image processing, and pattern recognition, to combine and analyse data that may be imprecise or ambiguous [18]. The fuzzy overlay technique uses fuzzy logic principles to handle uncertainty and imprecision in data [40]. This technique is beneficial when dealing with data that cannot be precisely classified into distinct categories. In GIS, fuzzy overlay combines multiple layers of spatial data, each representing different criteria or attributes, to generate a composite layer that reflects varying degrees of suitability or risk [41]. For example, it might evaluate land suitability for development based on proximity to roads, elevation, and land use. The technique relies on fuzzy sets, allowing for partial category membership. Unlike binary logic, where elements are either in or out of a set, fuzzy logic assigns a degree of membership ranging from 0 to 1, reflecting the degree to which an element belongs to a set.

Solar PV systems are Africa's most widely adopted renewable energy source, with solar energy seen as a reliable, cost-effective, and eco-friendly option compared to other sources like wind or biomass [34]. Advancements in solar panel technology and efficiency drive the increasing adoption of solar PV. In countries like Nigeria, solar PV is viewed as a key solution to achieving sustainable development goals despite the underutilisation of renewable resources [9]. Despite the vast solar potential, many developing countries like Nigeria struggle to harness this energy due to a lack of information on suitable locations for solar PV plants and other essential factors. The proximity of existing electrical grids, Global Horizontal Irradiance (GHI), Slope, Proximity to Road infrastructure, Land use/ Land cover (LULC) and more are criteria to be considered when seeking suitable locations for solar PV plants under factors like Environmental, spatial, economical, technical and climatic [1]; [43]; [38]; [44].

This study aims to compare fuzzy overlay and AHP models in determining a site suitable for a solar photovoltaic plant in Ondo West LGA, Nigeria, to showcase the potential of solar renewable

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energy sources within the study area. The study's objectives are to identify factors that influence solar PV sites, identify suitable sites for solar PV plants using the geospatial fuzzy overlay model, and perform comparative analysis using the geospatial fuzzy overlay model and the Analytical Hierarchical Process (AHP).

2. THE STUDY AREA

The study area is Ondo West local government area of Ondo State, Nigeria, with Ondo City being home to its headquarters, which is located at Ondo West Local Government Office, Akinsowon Folajimi Ave, Ondo City, Ondo State. Figure 1 shows the study area, which lies between latitudes 6°50'40.8"N and 7°13'09.1"N and longitudes 4°32'51.2"E and 4°55'50.0". The geographic site is within an approximate area of 840.1km², with a population of 288,868 according to the 2006 census, a projected population of 475,000 and a growth rate of 3.26% by 2023; it is the second-largest Local Government Area in Ondo State in terms of population and commerce, after Akure South LGA [35]. The area's economy is mainly agrarian, with a significant portion of the population farming and growing crops such as cocoa, oil palm, kola nut, plantain, yam, cassava, and cocoyam. These agricultural activities contribute to food security and play a key role in the national economy by producing cash crops.

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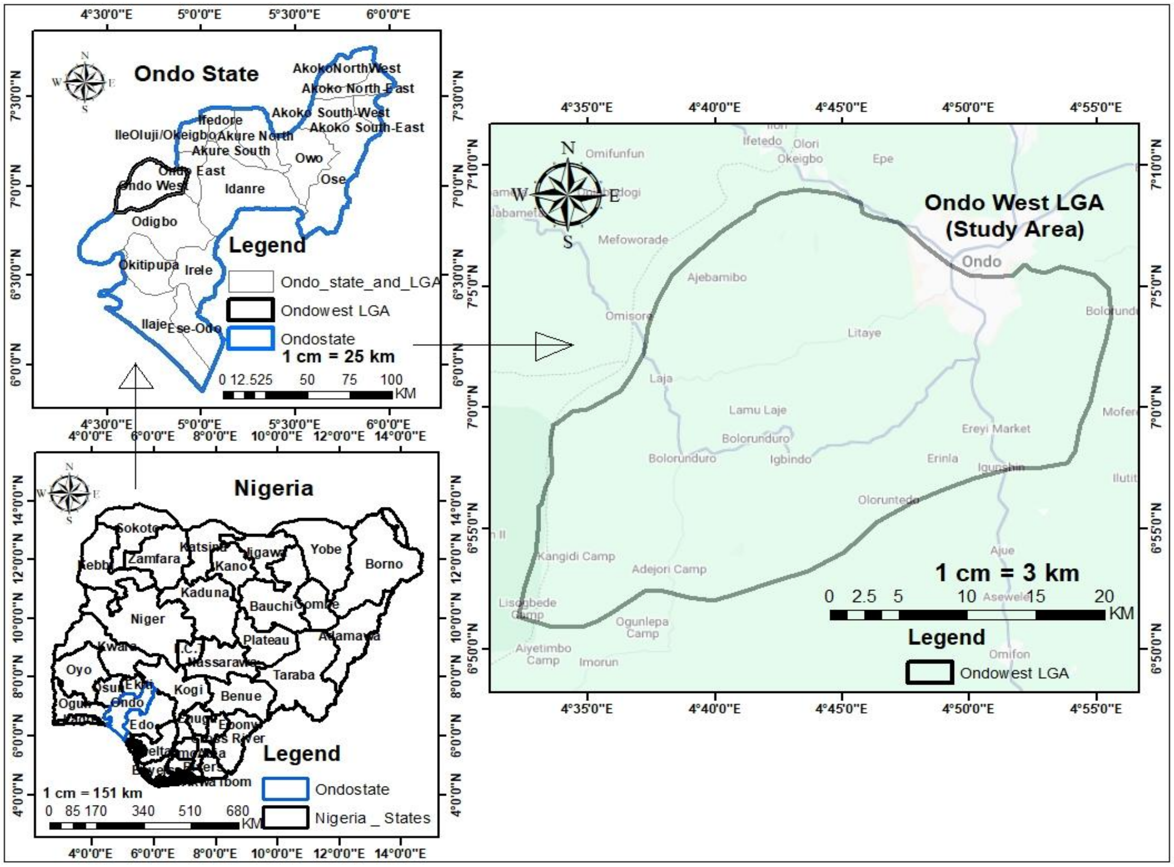

Figure 1: Map showing the study area

3. MATERIALS AND METHOD

3.1 Data Acquisition

Several literatures reviewed in the initial planning stages highlight a series of criteria contributing to this decision, criteria including global horizontal irradiance [17], slope [11]; [26], land use/land cover [23]; [28], distance to Transmission lines [16]; [29], distance to roads [20], proximity to water bodies [5] among others. Data derivations for the MCDM were achieved by developing spatial data layers using GIS techniques with ArcGIS 10.5 software. These criteria then undergo an assessment with the help of ArcGIS (GIS software) to make a comprehensive geographical study of the area and select each location suitable for optimal solar harvestable energy. The various data used for this research were acquired as follows and shown in Table 1:

Table 1: Datasets acquired for the research

Datasets	Source	Resolution	Period of data collection	Description	Application in the study

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Global Horizontal irradiance (GHI)	SolarGIS (originator) The World Bank (owner)	Distance: 9.0 arcsec (250 m)	-	The long-term yearly average of global horizontal irradiation (GHI) [kWh/m2]	Solar irradiance data
Landsat 8 satellite imagery	United States Geological Survey (USGS)	30 m spatial resolution except band 8 (panchromatic) with 15 m resolution	23-12-2023	11 bands of multispectral images were collected with an operational land imager (OLI) and thermal infrared sensor (TIRS) onboard the Landsat 8 satellite.	Land use / Land cover mapping
Digital Elevation Model (DEM)	ASTER Global Digital Elevation Map	30 m spatial resolution	2020	Raster digital elevation model (DEM) with global coverage	Surface Analysis: slope
Electricity grid data	Grid3 Nigeria **https://grid3.gov.ng/**	-	2018-08-03	Information on the transmission line and substations within the study area	Proximity to grid connection
Road Network	Grid3 Nigeria **https://grid3.gov.ng/**	-	2020-12-22	Polygon shapefiles WGS84	Proximity to Road.

The study area was evaluated using criteria modified from standards suggested by expert studies to examine and map locations appropriate for installing solar PV plants. The suitability indices for this study are highly suitable, suitable, moderately suitable, low suitability, and unsuitable. Table 8 shows the criteria used to classify the research area's suitability depending on the amount of solar energy obtained on its surface, proximity to road networks, grid connections, slope, and land cover.

Table 8: Criteria modified from standards suggested by expert studies [33].

Standard	**GHI [kWh/m²]**	**Grid connection [m]**	**Road Network [m]**	**Slope [%]**	**Land cover**
Unsuitable	< 1680	> 15000	> 8000	21 – 47	Built-up
Low suitability	1680 - 1698	7000 – 15000	5000 – 8000	14 – 21	Rock Outcrops
Moderately suitable	1698 - 1717	5000 – 7000	3000 – 5000	9 – 14	Thick vegetation
Suitable	1717 - 1735	3000 - 5000	1000 - 3000	5 – 9	Light vegetation
High suitability	> 1753	< 3000	<1000	< 5	Bare lands

After the study area evaluation using guided standards, the MCDM technique adopted for the decision-making process in the study is Fuzzy overlay and AHP. Fuzzy Overlay model was chosen due to the significance of the research, the ability to handle uncertainty, better representation even in the absence of expert opinion, a combination of diverse data types (quantitative or qualitative and also adaptability to changes that may occur over time in the study area [32]; [13]; [36]. The

AHP was chosen because of the reliability and flexibility of the technique described in past and recent studies, which has gained popularity in site suitability assessment [24].

3.1 Mapping Site suitable for Solar PV using Fuzzy Overlay Technique

The foundation of fuzzy overlay analysis is set theory, which states that a set typically corresponds to a class. The data values are reclassified or converted using fuzzy overlay analysis to a similar scale (0–1). However, the transformed values indicate the likelihood of falling into a particular spectrum. Unlike weighted overlay and weighted sum, which have values on a ratio scale of preference, with greater values being more preferred, fuzzy overlay has membership possibilities. The combining analysis stage in fuzzy overlay analysis estimates each location's likelihood of belonging to defined sets drawn from distinct input raster. The fuzzy Gaussian function equation is as follows:

$$\mu\,(x) = e^{-f_1*(x-f_2)^2} \quad (1)$$

μ(x): The membership function, e: Euler's number, approximately 2.718, f_1 and f_2 are the spread and the midpoint, respectively, x is the input value [14]

A user-defined value with a fuzzy membership of 1 can serve as the midpoint. By default, the midpoint of the input raster's value range is used. The membership of the Gaussian function is defined by spread. Typically, it falls between 0.01 and 1. The fuzzy membership curve steepens as the dispersion increases. Based on membership value, fuzzy overlay analysis estimates each cell's or location's chances of falling into a given set.

3.2 Mapping Site suitable for Solar PV using Analytical Hierarchical Process

The Analytical Hierarchical Process (AHP) is a structured technique for organising and analysing complex decisions. The AHP process involves breaking down a complex decision into a hierarchy of more manageable parts; it includes some key components: the hierarchical structure, the pairwise comparison and the mathematical analysis [22]. It is based on the practical determination of weights. Thus, this research generated weights for five variables using the Pairwise Comparison Analysis, as seen in Table 2. It evaluates each pair of elements based on relative importance or preference, usually using a scale [8].

Table 2: Fundamental scale of pairwise comparison

Degree of Importance	Definition	Explanation
1	Equal Importance	Criterion equally crucial to the objective
3	Moderate importance	One criterion is slightly more critical than another
5	Strong importance	One criterion is enormously more important than another
7	Extreme importance	One criterion is very strongly more important than another

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9	Extreme importance	One criterion is hugely more important than another
2, 4, 6, and 8	Intermediate values	A compromise is needed

The pairwise comparison matrix was derived by comparing each criterion with the next to determine which is more important based on each expert's opinion.

Here, the first step in normalising the decision-maker matrix for a solar PV farm is obtained by summing up each matrix column and dividing it by the column elements. This was calculated using Equation 2:

$$N = \frac{c}{\sum j} \tag{2}$$

where N is the normalised value, j is the column of the matrix, and c is each column element.

The pairwise comparison of weighting, the criteria used in the AHP to determine the relative importance (weights) of different criteria when assessing the suitability of sites for solar PV plants, is presented in Table 3. Each cell in the matrix represents a comparison between two criteria. A value of 1 on the diagonal indicates that a criterion is equally essential as itself. Values greater than 1 indicate that the row criterion is more important than the criterion in the column. Values less than 1 indicate that the criterion in the row is less important than the criterion in the column.

Table 3: Decision-maker (Pairwise comparison) matrix of a solar PV plant

Criteria	Solar irradiance	Slope	Land cover	Grid connection	Road Proximity
Solar irradiance	1	8	9	9	9
Slope	1/8	1	3	2	2
Land cover	1/9	1/3	1	2	2
Grid connection	1/9	1/2	1/2	1	1
Road Proximity	1/9	1/2	1/2	1	1
Total	1.4583333	10.33333	14	15	15

Source: adapted from [33]

Once all the criteria maps were normalised, the weights assigned to each criterion were computed and presented in Table 4. These weights are then used in the AHP to prioritise the criteria used to assess site suitability for wind farms, and the final weights give the relative importance of each criterion in the decision-making process. Higher weights in Table 4 indicate more important criteria: solar irradiance having the highest weight, followed by slope and Land cover. The lower weights indicate less important criteria compared to others in the table: grid connection and road proximity.

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Table 4: Normalized pairwise comparison (decision-maker matrix) and weights of the criteria

Criteria	Solar irradiance	Slope	Land cover	Grid connection	Road Proximity	Weight	%
Solar irradiance	0.686	0.774	0.643	0.6	0.6	0.6606	66.06
Slope	0.09	0.10	0.21	0.13	0.13	0.1327	13.27
Land cover	0.08	0.03	0.07	0.13	0.13	0.0893	8.93
Grid connection	0.08	0.05	0.04	0.07	0.07	0.0587	5.87
Road Proximity	0.08	0.05	0.04	0.07	0.07	0.0587	5.87
Total						1	100.00

Comparative site suitability analysis

Comparative analysis may be characterised as a set of analytical procedures that allow comparisons between distinct elements and their sets, including scenarios in which a comparison cannot be made using human intelligence [4]. Comparative analysis uses quantitative and qualitative methods to examine and contrast the two MCDMs to identify similarities, differences, and relationships. The method used to compare between AHP and fuzzy overlay MCDMs are;

1. Sensitivity analysis in comparative analysis for solar PV plant siting is a crucial method for assessing how variations in input parameters impact the suitability scores of different potential locations [45]. Sensitivity analysis assesses the stability and reliability of the models under varying input parameters
2. Computational Complexity - Evaluate and compare the ease of implementation, computational time, and resource requirements: AHP involves creating pairwise comparison matrices, which may become cumbersome for many criteria. Fuzzy Overlay may require fine-tuning membership functions and fuzzy operators, which can be more computationally intensive.
3. Quantitative Analysis / Evaluation—Normalize the AHP and Fuzzy Overlay outputs to a standard scale to facilitate comparisons. Compare the ranking results of both models using statistical tests like the T-test for paired comparisons. Compare the ease of understanding and interpreting the results of each model. Due to its hierarchical structure, AHP is often easier to explain to decision-makers. Fuzzy Overlay might require more expertise in fuzzy logic.

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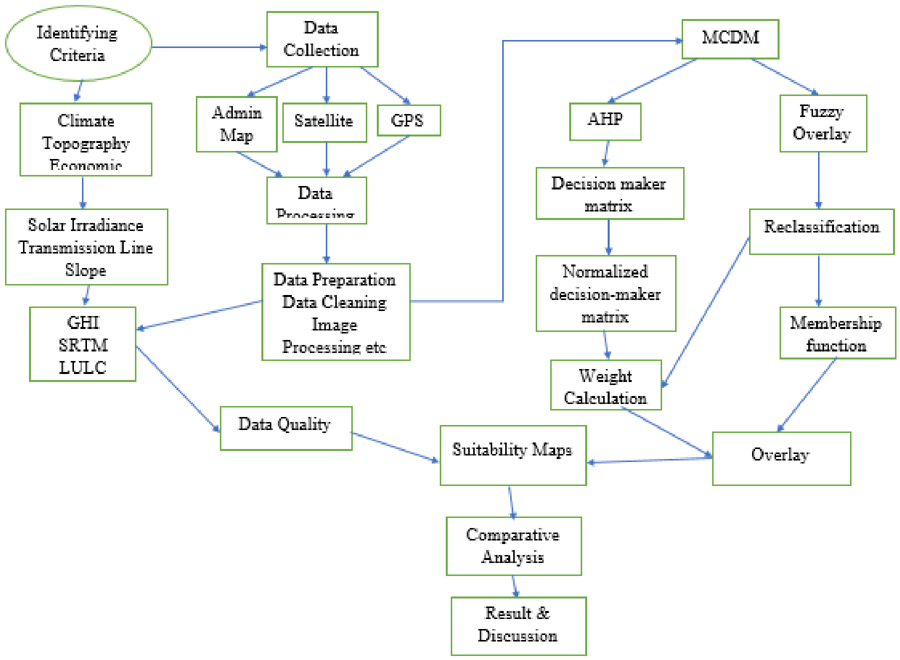

Figure 2: Flowchart of the methodology adopted by the study (Author)

4. RESULTS AND DISCUSSION

A geospatial assessment to identify areas with optimal solar power involves analysing various geographic, climatic, and environmental factors to determine the most suitable locations for solar energy production. Five criteria that reclassified spatial data layers of factors considered in this study are overlayed and adopted in the methodology, which resulted in the findings of this study. The categorisation of the study area based on Solar-GHI is presented based on the reclassified map in Figure 3, which is based on the standards and the suitability index of the solar resource of the study area. The geographical factors include terrain analysis and proximity analysis. The terrain analysis helps to produce the slope map of the study area in order to identify areas with higher elevation, ridges and valleys. Since this topography influences solar irradiance and, ultimately, the productivity of any site located there. Figure 4 shows the reclassified slope map of the study area. Cutting across the entire study area was performed using Euclidean distance, showing the straight-line distance from the grid connection transmission line and the road network. Figure 5 shows the reclassified image according to the proximity to the grid, and Figure 6 shows the reclassified image according to the proximity to the road. Land use land cover analysis is necessary to identify areas with minimal human disturbance, bare lands, or thin vegetation (agricultural lands) suitable for solar PV plant development. An accurate assessment of the land cover analysis was carried out, and ground truthing was carried out to ascertain the result achieved. Figure 7 shows the pictorial information on the land cover of the study area, and Table 5 shows the extent of the land use types and changes in land use in the study area. The suitability of the study area for installing solar PV

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is mapped in Figure 8 and Figure 9 using both AHP and Fuzzy overlay MCDM, with tables 6 and 7 showing the breakdown of their suitability classes, respectively.

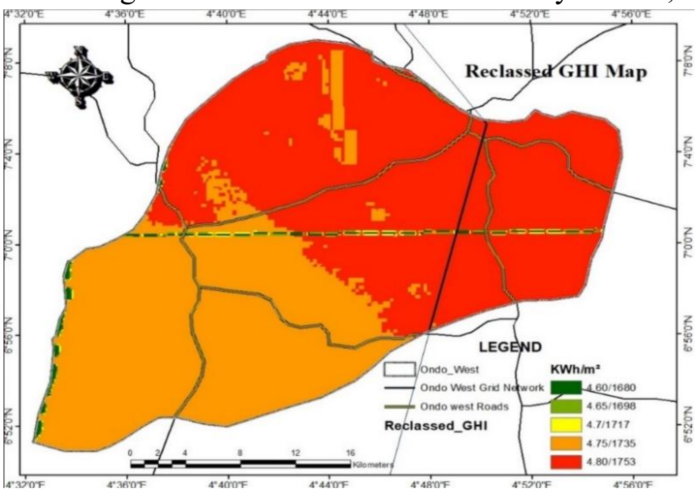

Figure 3: Reclassified GHI map of the study area

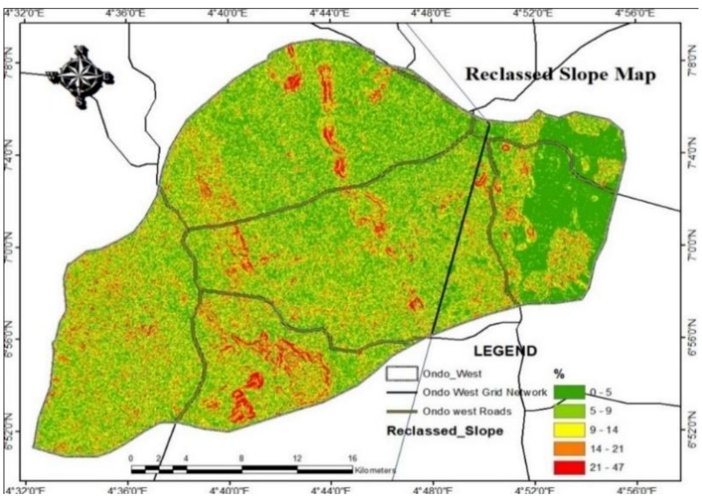

Figure 4: Reclassified slope map of the study area

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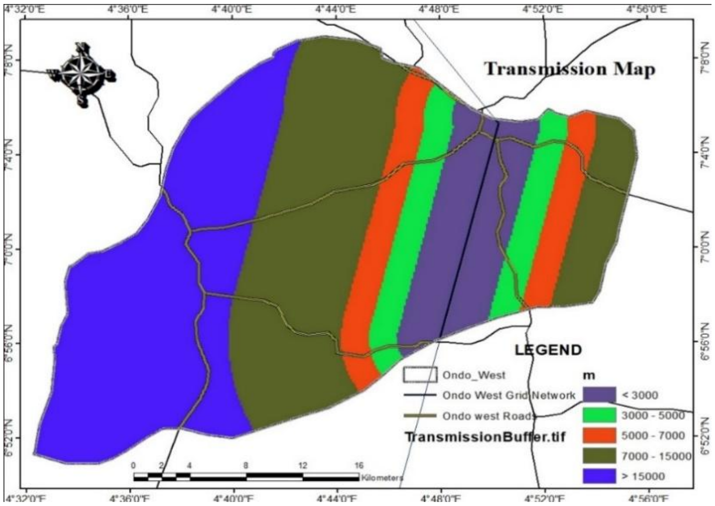

Figure 5: Reclassified transmission map of the study area

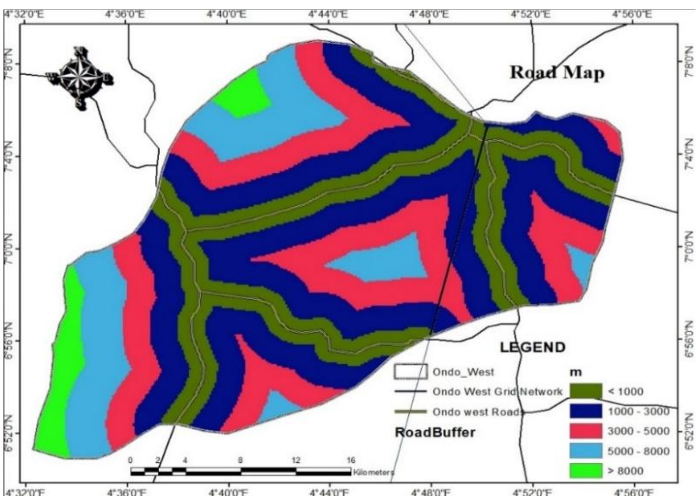

Figure 6: Reclassified distance to Road network map

Table 5: Area and percentage extent of land use

LULC Classes	Area (ha)	Percentage (%)
Bare land	2128.71	3
Rock Outcrop	50898.55	61
Built-up	4554.18	5
Light vegetation	12515.61	15
Thick vegetation	13978.15	17
Grand Total	84075.2	100

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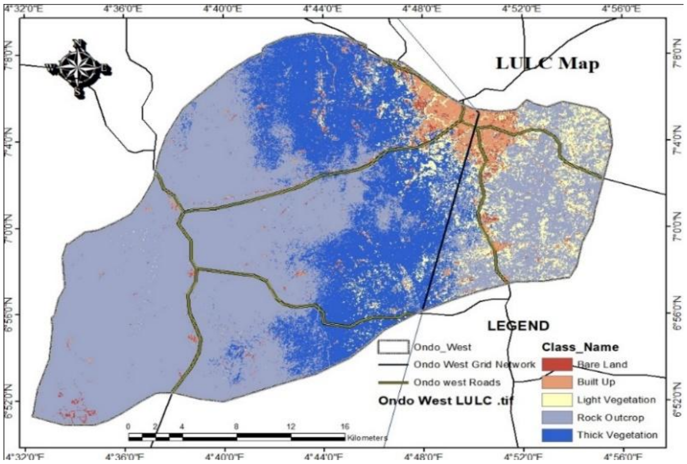

Figure 8: Land use/land cover of the study area

4.1 Suitability map

The suitability map of different areas within the study area for solar PV plant development in Figure 9 shows the AHP, and Figure 10 shows the fuzzy overlay. The suitability is classified into 5 categories: The high suitability areas, AHP (blue), fuzzy overlay (red) are concentrated towards the northern parts of the study area, indicating areas where favourable condition converges; Moderately suitable areas: AHP (green), fuzzy overlay (yellow) suggest an area where not all condition is favourable; While the unsuitable areas: AHP (brown), fuzzy overlay (green) are located towards the southern parts of the study area denoting conditions not suitable for the establishment of solar PV plant. Tables 6 and 7 summarise the area for each suitability class to get the total area classified.

Table 6: Breakdown of the suitability classes

Suitability class	Area (ha)	Percentage (%)
Unsuitable	189.3	0
Low suitability	1002.3	1
Moderately suitable	39002.0	46
Suitable	40642.0	48
High suitability	3239.6	4
Total	84075.2	100

Table 7: Breakdown of the suitability classes for Fuzzy overlay

Suitability class	Area (ha)	Percentage (%)
Unsuitable	37102.271	44
Low suitability	26892.175	32
Moderately suitable	12900.493	15

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Suitable	5162.842	6
High suitability	2017.417	2
Total	84075.198	100

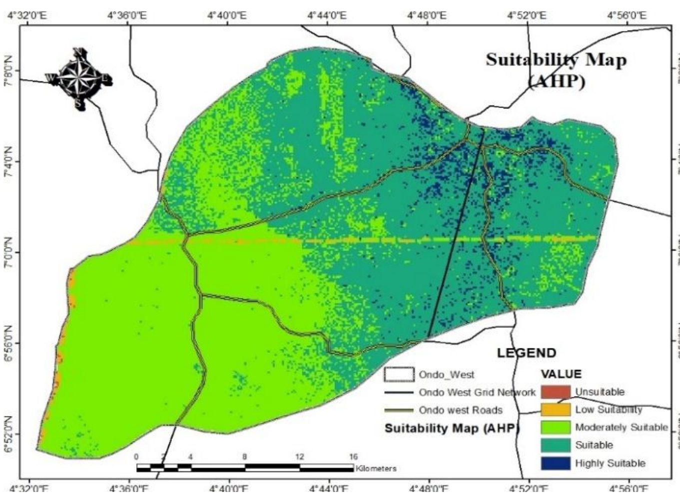

Figure 9: AHP suitability map for Solar PV plant

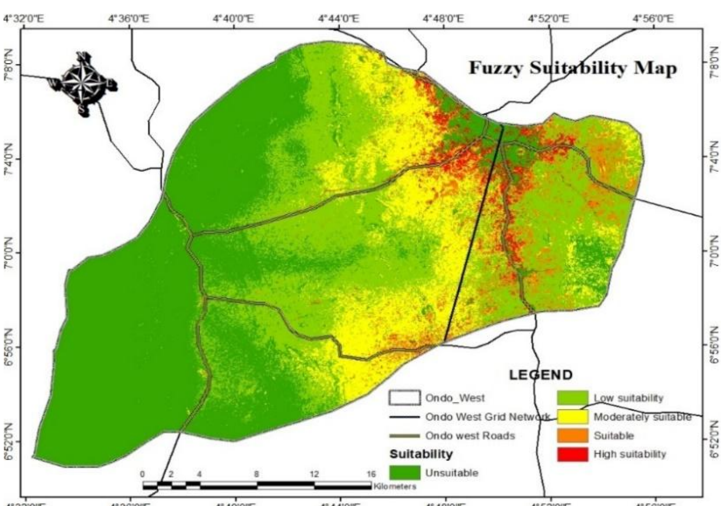

Figure 10: Fuzzy suitability map for solar PV plant

Comparative site suitability analysis using MCDM

Comparing the results of both MCDMs, Table 8 shows the difference in the suitable area for each MCDM. With a difference of 1200ha to the AHP area, the Fuzzy overlay MCDM captures a lesser area for the best possible area for siting Solar PV plant in the study area.

Table 8: Comparing areas from both AHP and Fuzzy overlay MCDM

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MCDM / class	Unsuitable (ha)	Low suitability (ha)	Moderately suitable (ha)	Suitable (ha)	High suitability (ha)
AHP	189.32	1002.30	39001.97	40642.01	3239.61
Fuzzy overlay	37102.27	26892.18	12900.49	5162.84	2017.42

Sensitivity analysis is a technique used to determine how different values of an input variable impact the output of a model. Fuzzy overlay assesses how changes in fuzzy parameters (like membership functions) influence overall suitability or decision-making outcomes. Table 9 shows the area of suitability in the different fuzzy overlay types.

Table 9: Breakdown of the suitability classes area in the different overlay types

Overlay /suitability	Unsuitable (Ha)	Low suitability (Ha)	Moderately suitable (Ha)	Suitable (Ha)	High suitability (Ha)
Gamma	2377.79	5839.82	15602.02	37272.56	22983.01
Product	37102.27	26892.18	12900.49	5162.84	2017.42
Sum	2377.79	5839.82	15602.02	37272.56	22983.01
Or	2520.85	4035.31	49611.94	21570.90	6338.65
And	55959.22	20457.77	788.09	2444.09	4426.03

For AHP, it assesses how changes in weight parameters for each criterion, as suggested by expert opinions, influence the overall suitability or decision-making outcomes. Taking the normalised pairwise comparison (decision-maker matrix) and weights of the criteria according to Table 4, each criterion is assumed to weigh 20%. Tables 10 and 11 show the results of the analysis.

Table 10: Breakdown of the suitability classes area of different criteria for AHP

Criteria /suitability	Unsuitable (Ha)	Low suitability (Ha)	Moderately suitable (Ha)	Suitable (Ha)	High suitability (Ha)
AHP	189.3195506	1002.30	39001.97	40642.01	3239.61
Equal	182.280755	6253.24	45284.09	30268.58	2025.41

Table 11: Comparison of the scores or ranking results derived from both models using a statistical test

statistical test	AHP	Fuzzy Overlay
Mean	16815.04	16815.04
Variance	442683561	220796869
Observations	5	5
Hypothesised Mean Difference	0	
Df	7	

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t Stat	-6.9447E-12
P(T<=t) one-tail	0.5
t Critical one-tail	1.89457861
P(T<=t) two-tail	1
t Critical two-tail	2.36462425

For a two-tailed test at α=0.05, the absolute value of t-Stat must exceed this value to indicate a significant difference.

Discussion

In this research, two MCDM techniques were employed, with the fuzzy overlay method as the major one, while the AHP is supported to compare results from both methods. The fuzzy overlay approach yielded results with fuzzy values ranging from 0 to 1; the result is given five separate classifications, with 0 signifying unsuitable and 1 meaning high suitability. The resulting suitability map shows that the northeastern region of the study area has the highest suitability value of 2017.42ha compared to other regions. In comparison, the southern region of the study area is unsuitable (37102.27ha) for siting a solar PV plant. The AHP technique also produced a similar result to the fuzzy overlay; it shows that the area with the highest suitability (3239.606ha) is also around the northeastern region of the study area while the unsuitable region (187.32ha) remains towards the south side.

The region with the highest suitability to optimally generate energy through Solar PV plants, i.e., the study area's northeastern region, comes from associating criteria. The region is an intersection of associating criteria like GHI, about 1753kWh/m², the highest irradiance quantity available in the study area [37]. Another criterion is the Land Use/Land Cover (LULC), which accounts for bare lands and supports establishing Solar PV plants without clearing existing structures, infrastructures or farmlands [6]. Areas with less than 1000m proximity to grids/transmission lines were prioritised to aid the distribution of energy generated to consumers without spending money on establishing an independent distribution network [19]. Road networks help periodically transport construction materials, equipment needed by the plant, and other maintenance materials to aid the smooth running of the plant. With a slope of about 0 – 5%, the highly suitable area maintains a relatively gentle slope, which aids the angle of exposure of the Photovoltaic (PV) panels to solar irradiance and also suggests that these areas are not susceptible to erosion [42].

However, there are distinct differences in the techniques, which makes each technique unique in its own right; the fuzzy overlay model accounts for the complexity of the real-world environment using the dataset, while the AHP model takes the author's perception of the real-world environment through the level of importance of criteria. Both MCDMs have a standard method of operation; in fuzzy overlay, all criterion is expected to be converted to fuzzy values (0 - 1) through various membership functions (Mssmall, Near, Gaussian, Mslarge, Large, Small, Linear). At the same time, the AHP employs weight, which is made through human perception (Expert opinion) of the importance of one criterion over the other [30].

The two MCDM models affect different subjectivity due to their respective algorithms and methods flow. AHP relies on precise weights and Experts' opinions on the level of importance [33]. The fuzzy overlay is known for handling uncertainty, reclassifying to a standard scale, and less human involvement in the flow of methods, and it quantifies each location's possibility of belonging to specified sets from various input raster [25]. AHP takes the author's perception of the level of importance the criteria pose to the research without the uncertainty that such poses to the real world. Fuzzy overlay accounts for the complexity of the real-world environment of the dataset presented [7].

Since the Fuzzy overly model is not susceptible to human perception of the level of importance of one criterion over the other, the suitability map becomes smaller than the AHP. Rather than prioritise one criterion over the other, it considers areas with fuzzy values closer to 1 (which denotes highly suitable) in all criteria. The fuzzy suitability map also shows that the far end of the northeastern side of the study area is suitable for siting solar PV plants while AHP remains clustered away from the edges. The size of the suitability area: While AHP has a lesser size (3239.606ha) than the fuzzy produced map, the fuzzy suitability map has a much bigger size (2017.41ha) than the AHP.

Relatively, the region of highly suitable PV plants is similar in the fuzzy overlay types, AHP and Equal weight AHP, which denotes that all methods help achieve some level of suitability depending on the objectives and aim of the research. Sensitivity analysis shows that the fuzzy overlay MCDM (product overlay type) is relatively similar in the highly suitable areas (2017.41ha) to the Equal AHP highly suitable area (2025.41ha), which denotes that fuzzy overlay takes each criterion as equal weight compared to AHP that gives a level of importance to each criterion. It also shows that when there is an error in the human perception of the importance of each criterion to the research, there is a significant influence on the result.

The means of AHP and Fuzzy Overlay are identical, so the T-test results confirm no significant difference. Variance differences are notable but do not affect the comparison of the mean. However, the variance shows that the fuzzy overlay is more accurate in coining highly suitable areas since its variance is much closer to the mean than that of the AHP.

5. CONCLUSION AND RECOMMENDATION

The development of a solar-PV plant in Nigeria is of immense benefit to the nation's energy sector and also to the citizens; Ondo West LGA is not left out of the crisis rocking the national grid and is characterised by its exploitation in the areas of industrialisation, education, food processing, all of which needs a sustainable source of power generation. This study shows that AHP, Fuzzy overlay MCDM, and GIS can be successfully utilised for site suitability of Solar PV plants to reduce the mismanagement of resources and minimise the adverse effects of such plants in the environment. Compared to weighted overlay analysis, most regions suggested by fuzzy overlay analysis meet the requirements for possible locations. Also, when considering the current input layers, such as land use/land cover (LULC), GHI, and slope, the fuzzy overlay function-derived spatial distribution of suggested regions of the research area map is determined to be more appropriate than the weighted overlay function. Fuzzy overlay analysis produces more accurate and reliable findings than weighted overlay analysis, although computationally more expensive. Fuzzy overlay is a superior substitute for other overlay functions.

This research and its findings are recommended as a key to unlocking and harnessing the underlying potential solar PV plants could provide to solve the study area's power sector inconsistencies. It is recommended that the Fuzzy overlay MCDM be used when there is little human involvement in the entire suitability process because the prospective locations were either overstated or underestimated via weighted overlay analysis. The scarcity of data from public archives, image resolution of acquired satellite imagery, and seasonal variation of GHI were among the numerous challenges faced in this research. Further study is required to ensure that the selected site is viable long-term, considering future land use and technology changes. Secondly, the market conditions are essential for the enduring success of solar PV research.

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