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GIS-Based Multi-Criteria and Machine Learning Assessment of Rooftop Photovoltaic Deployment Potential in Selected Nigerian Cities

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ABSTRACT

Nigeria's abundant solar resource contrasts sharply with persistent electricity shortages, underscoring the need for robust spatial frameworks to guide rooftop photovoltaic (PV) deployment. This study developed an integrated Geographic Information System (GIS)-based approach for assessing rooftop solar suitability across twelve selected Nigerian cities by combining satellite-derived Global Horizontal Irradiance (GHI), Global Human Settlement Layer (GHSL) data, rooftop geometry proxies, and a density-based shading index. A multi-criteria suitability index was constructed using the Analytic Hierarchy Process (AHP) and validated through Random Forest regression to evaluate model reliability. Results reveal a pronounced north–south gradient in rooftop PV suitability, with northern cities exhibiting greater potential owing to higher solar irradiation and lower atmospheric attenuation. GHI (0.504) and rooftop area (0.245) emerged as the most influential suitability criteria, while urban density and shading significantly moderated local photovoltaic potential. The validation model demonstrated high predictive accuracy (R^2 = 0.87, RMSE = 0.041, MAE = 0.032), confirming the robustness of the proposed framework. Spatial suitability mapping further highlighted substantial intra-urban variability, emphasizing the importance of integrating urban morphology into rooftop solar assessments. The proposed framework provides a scalable geospatial decision-support tool for prioritizing rooftop PV investments and supporting evidence-based renewable energy planning in Nigeria and other data-constrained urban environments.

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INTRODUCTION

Nigeria is strategically located within the global tropical solar belt, where high levels of incoming solar radiation provide one of the country's most abundant renewable energy resources. According to the Global Solar Atlas (World Bank Group & Solargis, 2020), satellite-derived estimates indicate that annual Global Horizontal Irradiance (GHI) ranges from approximately 1,600 to 2,200 kWh/m²/year, corresponding to average daily values between 4.5 and 6.2 kWh/m²/day depending on latitude, atmospheric conditions, and seasonal variability (World Bank Group & Solargis, 2020). These values are considerably higher than the minimum solar resource thresholds required for economically viable photovoltaic (PV) electricity generation and position Nigeria among the countries with the greatest technical potential for solar energy deployment in sub-Saharan Africa (International Renewable Energy Agency [IRENA], 2022; International Energy Agency [IEA], 2023).

Despite this enormous renewable energy endowment, electricity generation and supply remain critically inadequate. According to the International Energy Agency (2023) and the World Bank (2022), available grid generation rarely exceeds 5 GW against an estimated national demand exceeding 20 GW, resulting in persistent electricity shortages across residential, commercial, and industrial sectors (IEA, 2023; World Bank, 2022). Consequently, households and businesses increasingly depend on decentralized diesel and petrol generators to supplement unreliable public electricity supply. As reported by Akinyele and Rayudu (2014) and the International Renewable Energy Agency (2022), besides imposing substantial operational costs on consumers, this dependence contributes significantly to greenhouse gas emissions, particulate pollution, environmental degradation, excessive noise, and adverse public health outcomes (Akinyele & Rayudu, 2014; IRENA, 2022). The resulting energy deficit continues to constrain economic productivity, industrial competitiveness, sustainable urban development, and progress toward Nigeria's commitments under the Sustainable Development Goals (SDGs), particularly SDG 7 on affordable and clean energy (United Nations, 2015).

The persistence of this paradox, abundant solar resources coexisting with chronic electricity shortages, suggests that the principal challenge is no longer resource availability but rather the absence of scientifically robust spatial planning frameworks capable of identifying where solar technologies can be deployed most efficiently. Traditional solar resource assessments generally rely on coarse-resolution irradiation datasets that provide regional averages but neglect the significant spatial variability introduced by urban morphology, rooftop geometry, surrounding obstructions, and local atmospheric conditions (Šúri et al., 2007; Hofierka & Kaňuk, 2009; Freitas et al., 2015). Consequently, they frequently overestimate practical photovoltaic potential by assuming uniform exposure across heterogeneous urban landscapes.

Urban environments exhibit substantial spatial heterogeneity arising from differences in settlement density, building height, roof configuration, land-use characteristics, and street orientation. These factors directly influence the amount of solar radiation that ultimately reaches rooftop surfaces available for photovoltaic installation. According to Hofierka and Kaňuk (2009), dense urban development often experience substantial shading from adjacent buildings, while roof orientation and inclination further modify the effective incident solar radiation received by photovoltaic modules. Previous investigations have reported that urban shading alone may reduce annual photovoltaic electricity generation by between 10% and 35%, depending on building configuration and local urban geometry (Redweik et al., 2013; Freitas et al., 2015). Consequently, rooftop solar suitability cannot be evaluated solely from solar irradiation measurements but requires integrated assessment of both climatic and morphological characteristics.

Rapid urbanization in Nigeria further amplifies this complexity. According to the United Nations Human Settlements Programme (UN-Habitat, 2022) and the World Bank (2022), cities such as Lagos, Port Harcourt, Ibadan, Benin City, Abuja, Kano, Maiduguri, and Makurdi continue to experience accelerated population growth accompanied by extensive horizontal and vertical expansion, much of which occurs with limited adherence to comprehensive urban planning regulations. The resulting urban forms are characterized by highly heterogeneous building densities, irregular settlement patterns, varying roof geometries, and significant differences in solar accessibility. Such spatial variability implies that photovoltaic potential may differ substantially not only between cities but also within individual neighbourhoods, thereby necessitating high-resolution geospatial analysis for informed energy planning.

Recent advances in remote sensing, Geographic Information Systems (GIS), and geospatial analytics have considerably improved the ability to characterize rooftop solar potential at multiple spatial scales. Satellite-derived solar irradiation products now provide continuous raster representations of solar resources with high spatial resolution, while datasets such as the Global Human Settlement Layer (GHSL) developed by the Joint Research Centre (JRC) of the European Commission (Pesaresi et al., 2016), enable detailed characterization of urban morphology, settlement density, and built-up extent (Corbane et al., 2018; Pesaresi & Politis, 2023; Pesaresi et al., 2016). The integration of these complementary datasets within GIS facilitates spatially explicit modelling of rooftop photovoltaic suitability through simultaneous consideration of solar resource availability, rooftop geometry, urban density, and shading effects (Hofierka & Zlocha, 2012; Freitas et al., 2015).

Furthermore, recent developments in machine learning (Gaboitaolelwe et al., 2023; Akhter et al., 2019) have significantly strengthened geospatial energy modelling by providing powerful techniques for capturing complex nonlinear relationships among environmental, climatic, and structural variables. Algorithms such as Random Forest regression have demonstrated superior predictive performance for solar resource estimation, photovoltaic performance prediction, and suitability assessment because of their ability to model variable interactions while remaining relatively insensitive to multicollinearity and noisy input datasets (Breiman, 2001; Kumar et al., 2026; Datta et al., 2023). Consequently, integrating GIS-based multi-criteria analysis with machine learning validation provides a scientifically rigorous framework for evaluating rooftop solar suitability in complex urban environments.

Although several international studies have demonstrated the effectiveness of integrated GIS-based rooftop solar assessment frameworks (Hofierka & Zlocha, 2012; Redweik et al., 2013; Mainzer et al., 2014; Freitas et al., 2015), comparable studies in Nigeria remain relatively limited. Existing investigations have primarily focused on regional solar resource mapping, rooftop potential estimation, or isolated city-level analyses, with limited integration of rooftop-specific characteristics, urban morphology, shading effects, multi-criteria decision analysis, and machine learning within a unified analytical framework (Ayompe et al., 2011; Ohunakin et al., 2014; Chanchangi et al., 2022). Moreover, comparative assessments involving multiple Nigerian cities that represent diverse climatic and urban development zones remain scarce, thereby limiting the evidence base for national-scale urban renewable energy planning. This limitation has important policy implications because photovoltaic deployment strategies, investment decisions, urban planning initiatives, and renewable energy programmes may not fully optimize available solar resources in the absence of robust spatial decision-support tools. As emphasized by the International Renewable Energy Agency (IRENA, 2023), evidence-based geospatial planning is fundamental to accelerating distributed renewable energy deployment, while the International Energy Agency (IEA, 2023) highlights the importance of spatially explicit planning for strengthening urban energy resilience and optimizing clean electricity investments. To address these gaps, this study develops an integrated GIS-based framework that combines satellite-derived Global Horizontal Irradiance (GHI), Global Human Settlement Layer (GHSL) data, rooftop geometry proxies, and a density-based shading index within an Analytic Hierarchy Process (AHP) for multi-criteria suitability assessment, while employing Random Forest (RF) to evaluate the robustness of the resulting suitability model. By integrating expert-driven weighting with data-driven model assessment, the proposed framework provides a reliable and scalable approach for identifying priority rooftop photovoltaic deployment areas in data-constrained urban environments and is readily transferable to other rapidly urbanizing regions facing similar geospatial data constraints.

The contributions of this study are threefold. First, it develops an integrated GIS-based multi-criteria framework for assessing rooftop photovoltaic deployment potential across representative Nigerian cities. Second, it incorporates urban morphology through GHSL-derived settlement density and a density-based shading index, thereby improving the realism of rooftop suitability assessment in data-constrained environments. Third, it demonstrates the robustness of the proposed framework through Random Forest-based model assessment, providing a transferable geospatial decision-support approach for decentralized photovoltaic planning in rapidly urbanizing regions.

MATERIALS AND METHODS

Data Sources

To ensure consistency during spatial analysis, all raster datasets were harmonized to a common spatial resolution of approximately 1 km. The Global Solar Atlas (GSA), and Global Horizontal Irradiance (GHI) dataset provides satellite-derived solar irradiation estimates at approximately 1 km spatial resolution, whereas the Global Human Settlement Layer (GHSL) settlement density dataset is available at 250 m resolution and was aggregated to match the GHI grid prior to analysis. All spatial datasets were projected to the National Geospatial-Intelligence Agency 2014 geographic coordinate system to ensure spatial compatibility during raster overlay and subsequent GIS processing in accordance with the Global Solar Atlas geospatial framework and NASA POWER data standards (World Bank Group & Solargis, 2020; NASA POWER Project, 2024).

Solar irradiation data were obtained from the Global Solar Atlas (GSA), developed under the World Bank Group Energy Sector Management Assistance Program (ESMAP) in collaboration with Solargis (World Bank Group & Solargis, 2020). The dataset is generated using physically based radiative transfer models that integrate atmospheric parameters including aerosol optical depth, water vapour concentration, cloud cover, and surface elevation. These satellite-derived products are particularly appropriate for Nigeria, where the spatial distribution of ground-based solar monitoring stations remains limited.

Global Horizontal Irradiance (GHI) was selected as the principal climatic variable because it represents the total incoming solar radiation available on a horizontal surface and is widely recognized as the primary determinant of photovoltaic energy production (Duffie & Beckman, 2013; Huld, Müller, & Gambardella, 2012). Nevertheless, satellite-derived irradiation products may contain uncertainties arising from seasonal atmospheric variability, especially within the humid coastal regions of southern Nigeria. To improve data reliability, auxiliary climatological datasets obtained from NASA POWER and the World Meteorological Organization (WMO) were used for cross-validation and consistency checks (NASA POWER Project, 2024; World Meteorological Organization, 2024). Data from the Global Solar Atlas (GSA) were used, where GHSL settlement metrics were unavailable at the required resolution, built-up density estimates were supplemented using national urban statistics and visual interpretation of high-resolution satellite imagery to maintain consistency across the study cities.

Urban morphology and settlement density information were obtained from the GHSL (Pesaresi et al., 2016). Because comprehensive cadastral datasets describing rooftop geometry are unavailable for most Nigerian cities, GHSL settlement density was adopted as a proxy for estimating rooftop distribution and urban compactness. This approach is consistent with previous GIS-based rooftop solar assessment studies where remotely sensed urban morphology is used to approximate building characteristics (Hofierka & Zlocha, 2012; Freitas, Catita, Redweik, & Brito, 2015).

To improve local applicability, satellite-derived datasets were complemented with ground-based observations from the 2025 Nigerian Meteorological Agency (NiMet) review and demographic information obtained from the 2023 National Bureau of Statistics (NBS). NiMet observations were used to verify regional solar radiation patterns, while NBS urban statistics assisted in refining estimates of settlement distribution and building density. The integration of these national datasets improves model reliability by accounting for the heterogeneous characteristics of Nigerian cities, including rapidly expanding informal settlements.

Estimated rooftop area, average roof tilt, roof azimuth, and shading index were derived from GHSL settlement density, published building morphology characteristics for Nigerian urban environments, and GIS-based geometric approximations following the methodology described in Section 2.2.

The variables extracted for the analysis are summarized in Table 1, which presents the representative secondary datasets used in computing rooftop solar suitability across the selected cities.

Table 1: Input Data Used for Rooftop Solar Suitability Computation

City	GHI (kWh/m²/day)	Built-up Density (%)	Estimated Roof Area (m²)	Avg Tilt (°)	Avg Azimuth (°)	Shading Index	Data Source
Lagos	4.8	72	120	5	180	0.30	GSA, GHSL, NiMet
Abuja	5.5	60	150	7	175	0.20	GSA, GHSL
Kano	5.8	65	100	4	185	0.35	GSA, GHSL
Port Harcourt	4.5	75	130	6	182	0.40	GSA, GHSL
Benin City	4.9	68	140	6	180	0.28	GSA, GHSL
Minna	5.6	55	160	8	178	0.22	GSA, GHSL
Makurdi	5.4	58	155	7	180	0.25	GSA, GHSL
Sokoto	6.2	50	110	5	185	0.30	GSA
Ibadan	5.0	66	135	6	180	0.27	GSA, GHSL
Jalingo	5.7	57	145	7	178	0.23	GSA
Bauchi	5.9	59	125	5	182	0.29	GSA
Maiduguri	6.1	52	115	4	185	0.26	GSA

Table 1 summarizes the principal input variables used in the GIS-based rooftop solar suitability analysis for the selected Nigerian cities. The datasets represent the climatic, geometric, and urban morphological parameters incorporated into the multi-criteria suitability model. Global Horizontal Irradiance (GHI) exhibits a clear latitudinal gradient, increasing from the humid coastal cities toward the northern regions, consistent with the spatial distribution of solar resources reported by the Global Solar Atlas (World Bank Group & Solargis, 2020). Built-up density and the derived shading index vary considerably among cities, reflecting differences in urban form and settlement patterns. These variations provide the basis for evaluating how climatic conditions and urban morphology jointly influence rooftop photovoltaic suitability across diverse environmental settings.

Following data preparation, the analytical workflow adopted for integrating the various datasets into the GIS environment is presented in Figure 1.

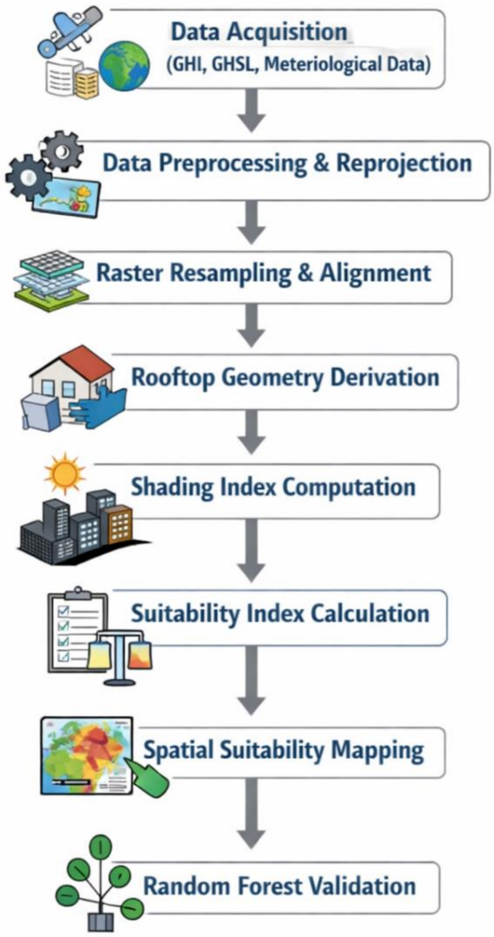

Figure 1: GIS Workflow for Rooftop Solar Suitability Modeling

GIS Modelling Framework

The GIS modelling framework integrated solar irradiation, urban morphology and rooftop geometric characteristics to estimate rooftop photovoltaic suitability. Raster layers representing Global Horizontal Irradiance (GHI) were imported into the GIS environment and served as the primary climatic input describing the spatial distribution of solar energy across the study area (World Bank Group & Solargis, 2020).

Settlement density derived from the Global Human Settlement Layer (GHSL) was subsequently overlaid on the GHI raster to characterize urban compactness and rooftop distribution. This integration enabled the simultaneous consideration of solar resource availability and urban form within a common spatial framework (Pesaresi et al., 2016; Freitas et al., 2015).

Rooftop characteristics were estimated using geometric approximations. Rooftop area (A_r) was estimated from settlement density and land-use characteristics, while roof tilt (θ_{tilt}) and roof azimuth ($\theta_{azimuth}$) were assigned using typical residential and commercial roof configurations commonly observed within Nigerian cities. These parameters influence the amount of solar radiation intercepted by rooftop surfaces (Duffie & Beckman, 2013).

The effective solar irradiance received by an inclined rooftop was approximated as

$$G_{eff} = GHI \cdot cos(\theta_{tilt}) \cdot cos(\theta_{azimuth}) \quad (1)$$

where G_{eff} denotes the effective solar irradiance after accounting for rooftop orientation. Equation (1) represents the physical transformation of horizontal irradiance into the usable irradiance incident on an inclined photovoltaic surface.

Potential obstruction from neighbouring buildings was represented using a shading index,

$$S = \frac{\sum_{i=1}^{n} Hi/di}{n} \quad (2)$$

where H_i denotes the height of the neighbouring structure, d_i is its distance from the rooftop under consideration, and n is the number of surrounding buildings included in the analysis. Equation (2) defines a dimensionless proxy shading index that captures the combined influence of surrounding building height and separation distance on potential rooftop obstruction, rather than a direct radiative transfer model.

The processed raster layers were subsequently combined using weighted overlay analysis to generate a continuous rooftop solar suitability surface for each study location. Weighted overlay analysis has been widely applied in multi-criteria spatial decision analysis because it enables the integration of heterogeneous environmental variables into a common suitability framework (Malczewski, 1999; Malczewski & Rinner, 2015).

Variable Normalization

Because the evaluation criteria are measured in different units and numerical ranges, all continuous variables were normalized to the interval (0, 1) before weighted overlay analysis using min-max normalization

$$V_{norm} = \frac{V - V_{min}}{V_{max} - V_{min}} \quad (3)$$

For shading

$$S_{norm} = \frac{S - S_{min}}{S_{max} - S_{min}} \quad (4)$$

where higher normalized values correspond to greater obstruction and therefore reduce suitability. The normalized variables were subsequently combined using the weighted suitability index.

Rooftop Solar Suitability Index

The rooftop solar suitability index (SI) was developed as a weighted multi-criteria model integrating climatic, geometric and environmental variables influencing photovoltaic performance. The index is expressed as

$$SI = 0.504(GHI) + 0.245(A_r) + 0.102cos(\theta_{tilt}) + 0.102cos(\theta_{tazimuth}) - 0.046(S) \quad (5)$$

where *GHI* is the Global Horizontal Irradiance, A_r is rooftop area, θ_{tilt} and $\theta_{azimuth}$ denote roof tilt and azimuth, respectively, while S represents the shading index.

Equation (5) is an AHP-based decision model, whereas Equation (1) is a physical engineering model describing the transformation of horizontal irradiance into effective irradiance. Accordingly, Equation (1) serves as the physical basis for the orientation terms in Equation (5) rather than as a direct algebraic replacement. The AHP procedure produced normalized positive weights for the benefit criteria. The shading index was subsequently incorporated as a penalty factor because shading negatively affects photovoltaic performance. Consequently, the final suitability model combines normalized AHP weights with a deductive penalty coefficient for shading. If Equation (1) is substituted into Equation (5), the orientation variables become embedded within the effective irradiance term,

$$SI = 0.504G_{eff} + 0.245(A_r) - 0.046(S) \quad (6)$$

thereby reducing the number of explicit decision variables from five to three. This apparent reduction in explicit weighting (from approximately 1.00 to 0.795) does not indicate a loss of criterion importance. Instead, the roof tilt and azimuth weights (0.102 each) are implicitly incorporated within G_{eff} through the physical transformation defined in Equation (1). Consequently, the reduction results from criterion aggregation rather than loss of explanatory power. Retaining the orientation terms separately in Equation (5) preserves their independently derived AHP priorities and avoids obscuring their individual contributions to rooftop suitability.

The suitability model is based on the physical relationship governing photovoltaic energy generation, where energy yield is proportional to the available rooftop area, incident solar irradiance, roof orientation, and shading effects (Duffie & Beckman, 2013):

$$E \propto A_r . GHI \cdot cos(\theta_{tilt}) \cdot cos(\theta_{azimuth}) . (1 - S) \quad (7)$$

or equivalently,

$$E \propto A_r . G_{eff} . (1 - S)$$

Because the objective of this study is to estimate relative rooftop suitability rather than exact energy output, this relationship was linearized into a weighted suitability index for computational efficiency within the GIS environment. The cosine terms account for the angular dependence of incident solar radiation on inclined rooftop surfaces.

The formulation reflects the physical processes governing photovoltaic energy generation, in which solar resource availability, installation area, rooftop orientation and shading jointly determine rooftop solar potential. Although photovoltaic output is inherently nonlinear, the weighted linear representation provides computational efficiency for raster-based GIS implementation while preserving the relative contribution of each variable.

The weighting coefficients were determined using the Analytic Hierarchy Process (AHP) developed by Saaty (1980). Pairwise comparisons were conducted based on published evidence and engineering judgement to quantify the relative importance of each criterion. The consistency of the pairwise comparison matrix was evaluated using

$$CR = \frac{CI}{RI} \quad (8)$$

and

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (9)$$

where *CR* is consistency ratio, *CI* is the consistency index, *RI* is the random index corresponding to the order of the pairwise comparison matrix, λ_{max} is the principal (maximum) eigenvalue of the pairwise comparison matrix, and *n* is the number of evaluation criteria used in the AHP model.

A consistency ratio (CR) of less than 0.10 was considered acceptable, indicating that the pairwise comparison judgments were sufficiently consistent for deriving reliable criterion weights (Saaty, 2008; Saaty, 1987). The derived AHP weights were incorporated into a weighted overlay analysis within the GIS environment to compute a normalized rooftop solar suitability index ranging from 0 (least suitable) to 1 (most suitable). The normalized index facilitated spatial comparison of rooftop photovoltaic suitability across the selected Nigerian cities.

Machine Learning Validation

The robustness of the developed suitability index was evaluated using Random Forest regression, an ensemble machine-learning algorithm widely applied in geospatial prediction because of its ability to model complex nonlinear relationships while minimizing overfitting (Breiman, 2001; Belgiu & Drăguț, 2016).

The model used Global Horizontal Irradiance (GHI), rooftop area, roof tilt, roof azimuth, and shading index as predictor variables, while the computed suitability index served as the response variable. Random Forest constructs multiple decision trees using bootstrap samples of the input data and combines their predictions through ensemble averaging, thereby improving prediction stability and reducing model variance (Breiman, 2001).

Model performance was evaluated using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). These performance indicators quantify the proportion of variability explained by the model and the magnitude of prediction errors, providing an objective assessment of model reliability before interpreting the suitability maps presented in the Results and Discussion section (James ET AL., 2021).

Statistical Analysis

Descriptive and inferential statistical analyses were performed to evaluate the spatial variability of rooftop solar suitability among the selected Nigerian cities. Descriptive statistics, including minimum, maximum, mean, and standard deviation, were computed for the principal variables to summarize their spatial characteristics and identify regional differences in solar resource availability and urban morphology (Montgomery, Peck, & Vining, 2021).

The performance of the suitability model was assessed using three standard statistical indicators: the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The coefficient of determination was used to quantify the proportion of variation in the suitability index explained by the predictor variables, whereas RMSE and MAE measured the average magnitude of prediction errors and overall model accuracy (Willmott & Matsuura, 2005).

To further evaluate model consistency, variable importance rankings generated by the Random Forest algorithm were compared with the weights assigned through the Analytic

Hierarchy Process (AHP). Agreement between the two approaches provided an independent assessment of the robustness of the weighting scheme and strengthened confidence in the suitability model. Similar hybrid AHP–Random Forest frameworks have been successfully applied in spatial suitability modelling and renewable energy planning (Gigović et al., 2016; Arabameri et al., 2019). All GIS processing, spatial analysis, and weighted overlay operations were carried out within a Geographic Information System environment, while statistical computations and model validation were performed using standard machine-learning and statistical analysis tools.

RESULTS AND DISCUSSION

Spatial Distribution of Solar Irradiation

The spatial distribution of Global Horizontal Irradiance (GHI) across Nigeria is presented in Figure 2. The rasterized GHI surface, derived from the Global Solar Atlas and cross-validated using NASA POWER climatological data (World Bank Group & Solargis, 2020; NASA POWER Project, 2024), reveals a distinct north–south gradient in solar resource availability. Higher irradiation values occur across the Sahel and Sudan–Savannah ecological zones, whereas comparatively lower values are observed in the humid southern coastal belt where cloud cover and atmospheric moisture are more persistent.

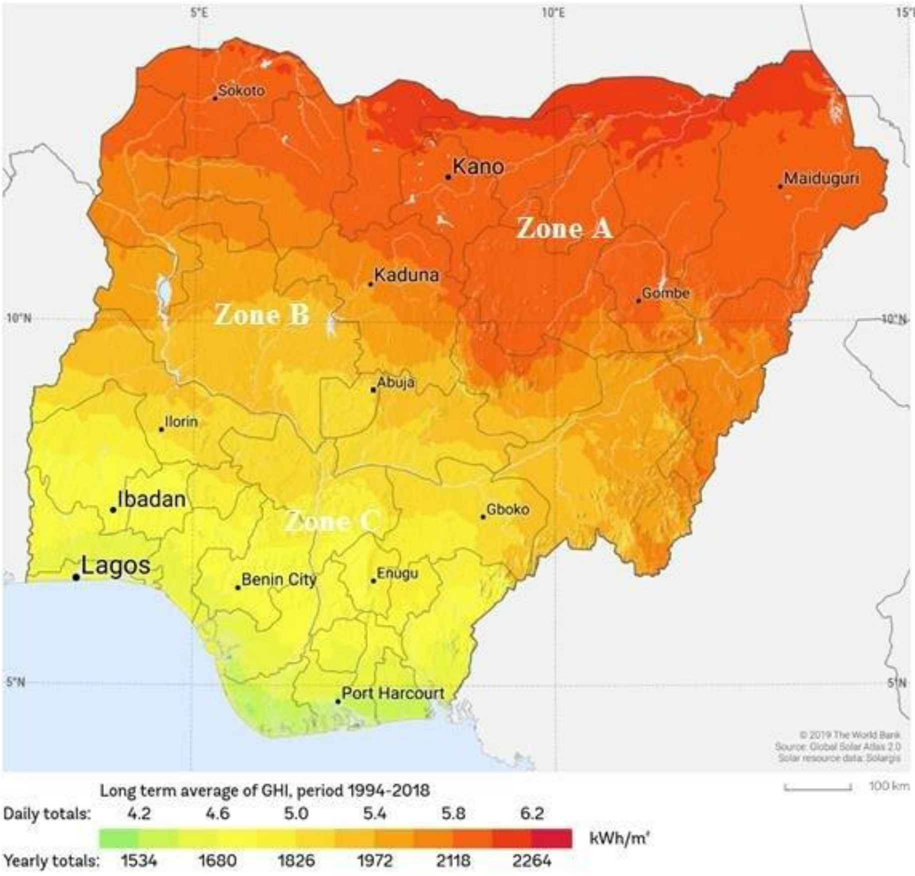

Figure 2: Spatial Distribution of Global Horizontal Irradiance in Nigeria (Source: World Bank Group & Solargis, 2020; NASA POWER Project, 2024).

To summarize the spatial variability observed in Figure 2, representative GHI ranges for the major climatic zones are presented in Table 2.

Table 2: Regional Global Horizontal Irradiance (GHI) Ranges across Nigerian Climatic Zones

Region	GHI Range (kWh/m²/day)
Sahel	6.0 – 6.2
Savannah	5.2 – 5.8
Coastal	4.5 – 5.0

Source: Adapted from World Bank Group and Solargis (2020) and NASA POWER Project (2024)

The results indicate that northern Nigeria receives approximately 20–30% higher solar irradiation than the southern coastal region. This spatial gradient provides the climatic basis for the rooftop photovoltaic suitability assessment developed in this study.

AHP Weighting Results

The Analytic Hierarchy Process (AHP) applied in this study assigned the greatest importance to Global Horizontal Irradiance (0.504), followed by rooftop area (0.245). Roof tilt and roof azimuth contributed equally (0.102 each), whereas the shading index received a negative weight (–0.046), reflecting its adverse influence on photovoltaic performance.

Table 3: AHP-Derived Weights for Rooftop Solar Suitability Criteria

Criterion	Weight
Global Horizontal Irradiance	0.504
Rooftop Area	0.245
Roof Tilt	0.102
Roof Azimuth	0.102
Shading Index	–0.046

The weighting structure confirms that solar resource availability and rooftop area are the dominant determinants of rooftop photovoltaic suitability, while roof orientation and shading provide secondary adjustments to overall performance. The derived weights satisfied the Analytic Hierarchy Process consistency requirement (CR < 0.10), indicating acceptable consistency of the pairwise comparison judgments (Saaty, 1987; Saaty, 2008).

Model Validation Results

The Random Forest validation model demonstrated strong predictive performance, with a coefficient of determination of $R^2 = 0.87$, indicating close agreement between predicted and computed suitability values. Prediction errors were low, with a Root Mean Square Error (RMSE) of 0.041 and a Mean Absolute Error (MAE) of 0.032, confirming the robustness of the proposed suitability framework. Feature importance analysis further identified Global Horizontal Irradiance and rooftop area as the most influential predictor variables, consistent with the weighting structure of the suitability index.

Table 4: Random Forest Validation Statistics

Performance Metric	Value
Coefficient of Determination (R^2)	0.87
Root Mean Square Error (RMSE)	0.041
Mean Absolute Error (MAE)	0.032

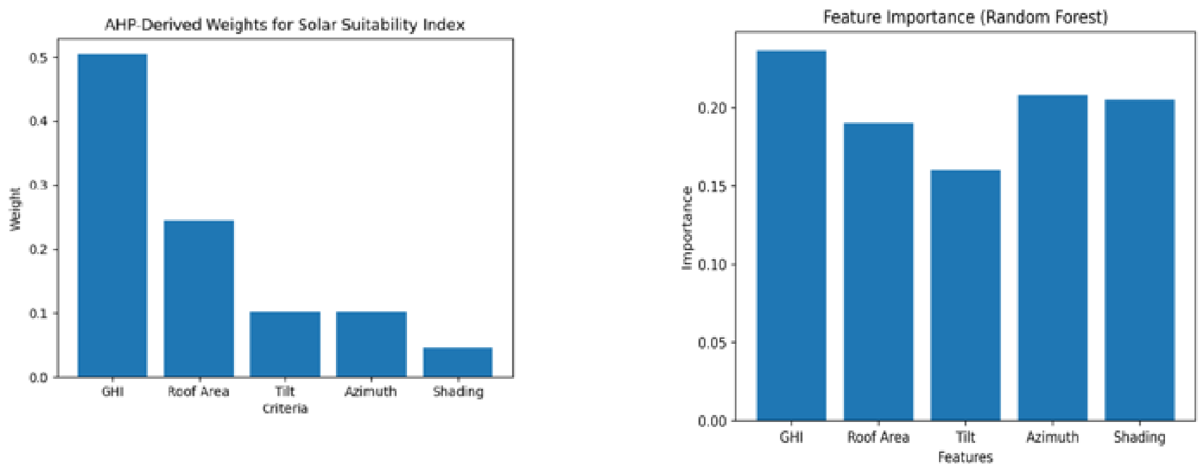

Figure 3: Comparison of AHP-Derived Criterion Weights and Random Forest Feature Importance for Rooftop Photovoltaic Suitability Assessment. (Source: Adapted from Hofierka & Zlocha, 2012; Freitas et al., 2015).

The validation statistics demonstrate that the proposed suitability model provides reliable predictions of rooftop photovoltaic suitability. The high coefficient of determination ($R^2 = 0.87$) indicates that the selected predictor variables explain a substantial proportion of the observed variability in suitability values. Likewise, the relatively low RMSE (0.041) and MAE (0.032) indicate limited prediction error and good agreement between computed suitability indices and model predictions. These results support the robustness of the integrated GIS and machine-learning framework for spatial assessment of rooftop solar potential.

Influence of Urban Density on Photovoltaic Performance

Although solar resource availability determines the theoretical photovoltaic potential of a location, the effective performance of rooftop systems is strongly influenced by the surrounding built environment. Figure 4 illustrates the relationship between urban density and estimated photovoltaic output reduction resulting from increased rooftop shading. Dense urban configurations produce greater obstruction angles, thereby limiting solar access and reducing system efficiency (Hofierka & Zlocha, 2012; Freitas et al., 2015).

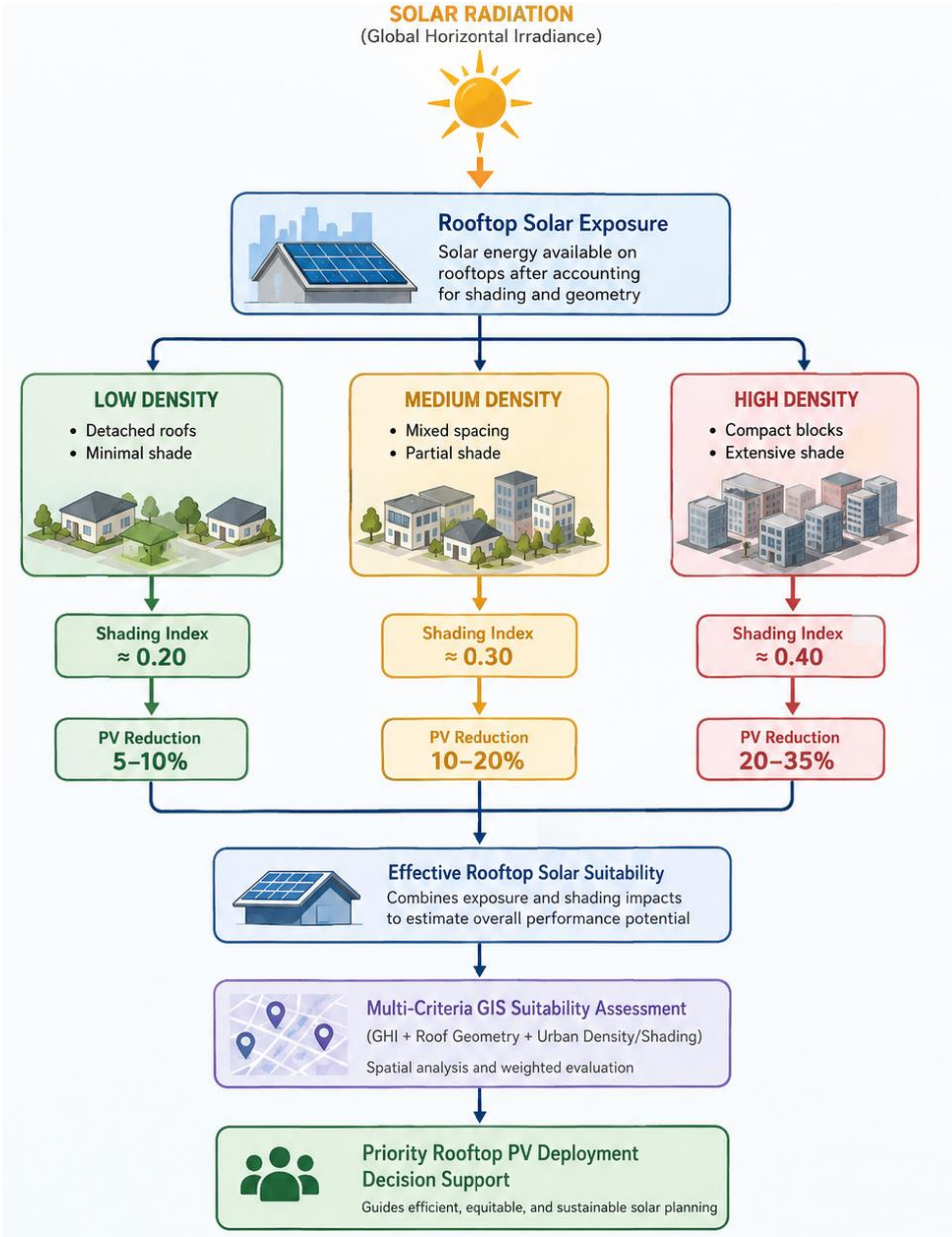

Figure 4: Conceptual relationship between urban density, rooftop shading, and photovoltaic output reduction. (Source: Author's conceptualization based on the literature.)

Representative shading indices and associated photovoltaic output reductions for different urban density classes are summarized in Table 5.

Table 5: Relationship between Urban Density, Shading Index, and Photovoltaic Output Reduction

Density Level	Shading Index	PV Reduction (%)
Low	0.20	5–10
Medium	0.30	10–20
High	0.40	20–35

The results indicate that high-density urban environments may experience photovoltaic output reductions exceeding 30% because of shading. This finding highlights the importance of incorporating urban morphology into rooftop solar suitability assessments.

Solar Path Considerations for Rooftop Orientation

In addition to solar irradiation and shading, rooftop orientation influences the amount of solar energy intercepted by photovoltaic panels. Figure 5 presents the annual solar path diagram for Benin City (Latitude 6.34°N; Longitude 5.22°E), illustrating seasonal variations in solar altitude and azimuth.

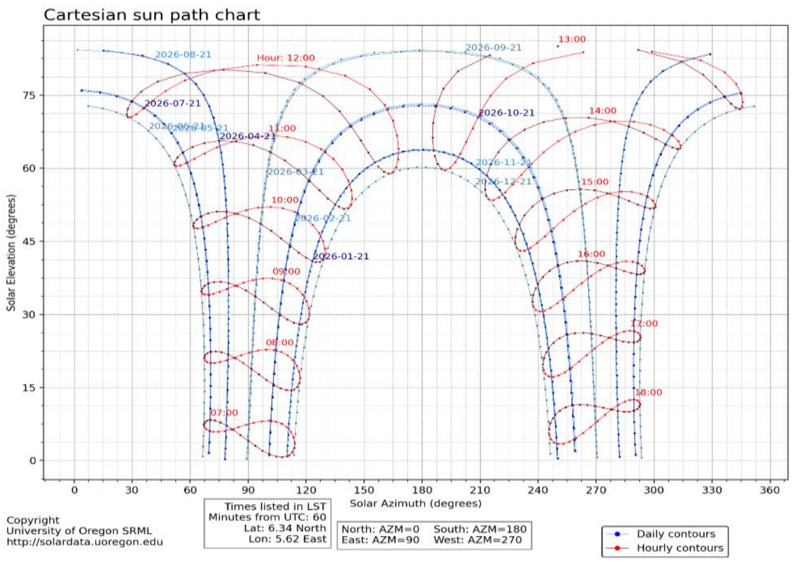

Figure 5: Annual Solar Path Diagram for Benin City (Source: Generated with University of Oregon SRML Software)

The solar path demonstrates that Nigeria's proximity to the equator results in consistently high solar elevations throughout the year, with peak solar altitude occurring around the equinoxes. These conditions favour rooftop installations oriented close to due south (approximately 180° azimuth) with relatively low tilt angles. The solar path diagram complements the GIS-derived suitability assessment by illustrating the geometric basis of the roof orientation factors incorporated into the suitability index.

City-Level Rooftop Solar Suitability

The rooftop solar suitability index was computed for twelve representative Nigerian cities spanning different climatic and urban settings. The resulting rooftop characteristics and suitability indices are presented in Table 6.

Table 6: Computed Rooftop Solar Suitability Parameters and Suitability Index

City	Roof Area (m^2)	Tilt (°)	Azimuth (°)	Shading	GHI ($kWh/m^2/day$)	SI
Lagos	120	5	180	0.30	4.8	0.72
Abuja	150	7	175	0.20	5.5	0.78
Kano	100	4	185	0.35	5.8	0.68
Port Harcourt	130	6	182	0.40	4.5	0.65
Benin City	140	6	180	0.28	4.9	0.74
Minna	160	8	178	0.22	5.6	0.80
Makurdi	155	7	180	0.25	5.4	0.77
Sokoto	110	5	185	0.30	6.2	0.82
Ibadan	135	6	180	0.27	5.0	0.75
Jalingo	145	7	178	0.23	5.7	0.79
Bauchi	125	5	182	0.29	5.9	0.76
Maiduguri	115	4	185	0.26	6.1	0.81

Suitability indices ranged from 0.65 in Port Harcourt to 0.82 in Sokoto. Northern cities generally exhibited higher suitability values because of greater solar irradiation, whereas southern coastal cities recorded comparatively lower suitability owing to reduced irradiation and higher shading conditions. Cities within the Middle Belt, including Minna and Makurdi, also demonstrated favourable suitability resulting from a balance between solar resource availability and moderate urban density.

Spatial Mapping of Rooftop Solar Suitability

The integration of solar irradiation, rooftop geometry proxies, and shading indices within the GIS environment produced a continuous rooftop solar suitability surface, presented in Figures 6 and 7.

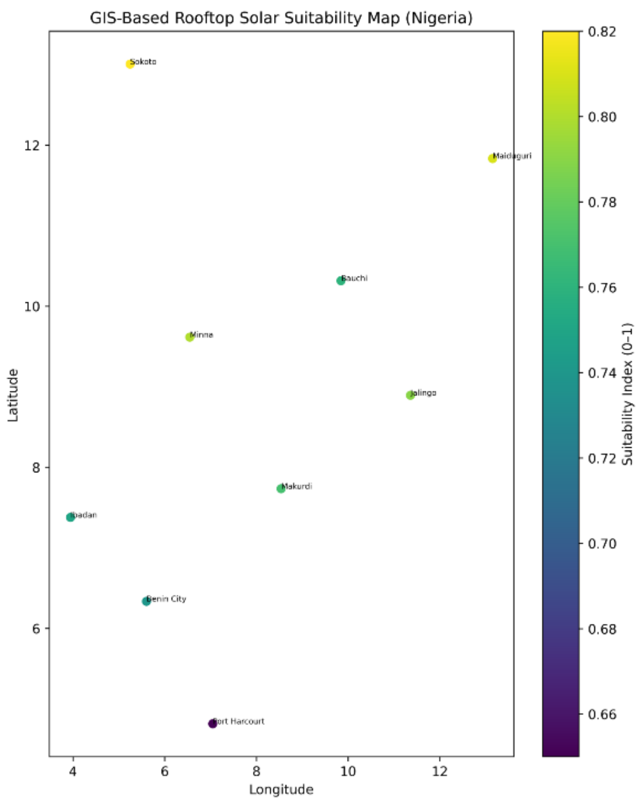

Figure 6: Spatial Distribution of Rooftop Photovoltaic Suitability Index across Selected Nigerian Cities. (Source: World Bank Group & Solargis, 2020; NASA POWER Project, 2024).

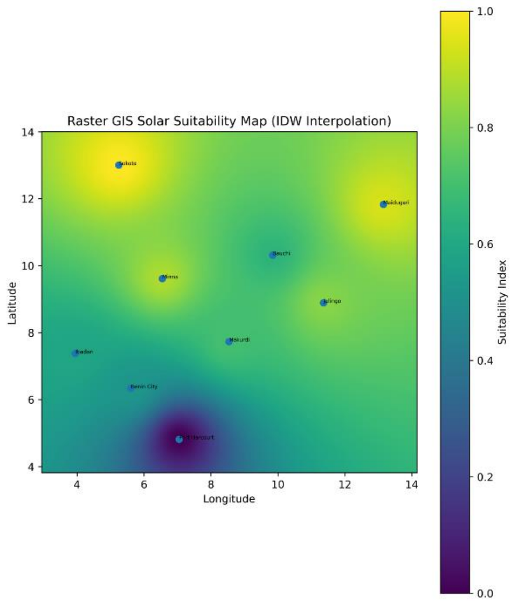

Figure 7: GIS-Based Rooftop Solar Suitability Map (Source: World Bank Group & Solargis, 2020; NASA POWER Project, 2024)

The suitability map was classified into four categories: high (0.80–1.00), moderate (0.65–0.79), marginal (0.50–0.64), and low (<0.50) suitability. High-suitability areas were characterized by strong solar irradiation, minimal shading, and favourable rooftop orientation, whereas low-suitability zones reflected combinations of reduced solar resource, dense urban development, and greater shading effects.

The resulting spatial pattern reveals substantial intra-urban variability in rooftop photovoltaic potential across the study area. The generated suitability map provides a practical geospatial framework for identifying priority locations for rooftop photovoltaic deployment and supports evidence-based planning for decentralized solar energy development in Nigeria.

Discussion

The findings demonstrate that rooftop photovoltaic suitability in Nigeria is governed by the interaction between solar resource availability and urban morphology rather than by solar irradiation alone. The dominance of Global Horizontal Irradiance (GHI) in the Analytic Hierarchy Process (AHP) weighting structure (50.4%) (Saaty, 2008) confirms its fundamental role in determining photovoltaic energy yield, while the substantial contribution of rooftop area (24.5%) highlights the importance of available installation space in urban environments. According to Duffie and Beckman (2013), solar irradiation remains the principal determinant of photovoltaic electricity production, while available installation area directly constrains the practical energy that can be harvested from rooftop systems. The comparatively smaller contributions of roof tilt, azimuth, and shading indicate that these factors primarily refine system performance after the available solar resource has been established.

The spatial distribution of suitability closely follows the established north–south climatic gradient in Nigeria. Northern cities exhibited higher suitability because of greater solar irradiation and relatively lower atmospheric attenuation, whereas southern coastal cities recorded lower suitability due to persistent cloud cover and increased atmospheric moisture. These findings agree with previous studies reporting significant spatial variability in solar resources across tropical Africa and Nigeria (World Bank Group & Solargis, 2020; Huld, Müller, & Gambardella, 2012; International Renewable Energy Agency [IRENA], 2022). Similar north–south variations in solar resource availability have also been reported by Ohunakin et al. (2014), who observed that northern Nigeria possesses considerably higher photovoltaic generation potential than the humid coastal regions.

Urban morphology also exerted a significant influence on rooftop photovoltaic potential. Cities characterized by high settlement density, particularly Port Harcourt, exhibited higher shading indices resulting from closely spaced buildings and reduced rooftop solar exposure. This observation supports previous findings that building density, rooftop accessibility, and obstruction effects are important determinants of photovoltaic performance in urban environments (Hofierka & Zlocha, 2012; Freitas et al., 2015). Redweik et al., (2013) further demonstrated that incorporating urban geometric characteristics substantially improves rooftop photovoltaic assessment compared with approaches based solely on solar irradiation. The incorporation of a density-based shading index therefore improves the realism of rooftop suitability assessment in rapidly urbanizing cities where detailed three-dimensional building datasets are unavailable.

The Random Forest validation further demonstrates the robustness of the proposed framework. The high coefficient of determination ($R^2 = 0.87$) and the relatively low prediction errors (RMSE = 0.041; MAE = 0.032) indicate that the selected variables adequately explain the observed spatial variation in rooftop suitability. Furthermore, the close agreement between Random Forest feature importance rankings and the AHP-derived weights provides evidence of internal consistency between the expert-based weighting procedure and the data-driven validation approach. This convergence strengthens confidence in the suitability model and supports its application for strategic energy planning. Similar advantages of Random Forest for geospatial prediction and environmental modelling have been reported by Breiman (2001) and Belgiu and Drăguț (2016), who demonstrated that ensemble learning algorithms effectively capture nonlinear interactions among environmental variables while maintaining high predictive accuracy.

An important contribution of this study is the integration of Geographic Information Systems (GIS), multi-criteria decision analysis, and machine learning within a single analytical framework. Unlike conventional solar resource assessments that rely primarily on irradiation maps, the proposed framework simultaneously considers climatic conditions, rooftop geometry, and urban morphology to produce a spatially explicit suitability index. This integrated approach provides a more realistic representation of rooftop photovoltaic potential and supports informed decision-making for decentralized renewable energy development. Malczewski (1999) and Malczewski and Rinner (2015) emphasized that GIS-based multi-criteria decision analysis provides an effective framework for integrating heterogeneous spatial datasets into objective decision-support systems. More recently, Gigović et al. (2016) demonstrated that combining multi-criteria evaluation with machine-learning techniques substantially enhances spatial suitability assessment and improves decision reliability.

Although the framework demonstrates strong predictive capability, previous Nigerian rooftop PV studies have relied mostly on Google Earth imagery, GIS analyses, DSM/DEM products, and building footprint extraction for rooftop suitability assessment (Ayodele et al., 2021; Ugbong et al., 2023). Taken together, these methodological choices reflect the broader challenge of limited availability of comprehensive building footprint and LiDAR datasets for many Nigerian cities. Rooftop geometry was therefore represented using settlement-density proxies. Rooftop geometry was represented using settlement-density proxies because comprehensive building footprint and LiDAR datasets are not currently available for most Nigerian cities. Consequently, local variations in roof architecture may not be fully represented. Similar limitations have been acknowledged in previous GIS-based rooftop solar studies conducted in data-constrained environments (Lodhi et al., 2025; Hofierka & Zlocha, 2012; Jaczewska et al., 2025; Freitas et al., 2015). Future studies should integrate high-resolution building footprint data, digital surface models, and UAV-derived elevation data to improve rooftop characterization and shading estimation. Incorporating time-series photovoltaic performance observations would further strengthen model calibration and facilitate long-term validation under varying climatic conditions.

Overall, the study demonstrates that rooftop solar suitability in Nigeria is highly location-specific and should therefore be considered within regionally differentiated energy planning strategies. The proposed framework provides a scalable methodology that can be readily adapted to other data-constrained cities across sub-Saharan Africa and similar developing regions. Its integration of satellite-derived solar resources, GIS-based urban morphology, multi-criteria evaluation, and machine learning offers a practical decision-support tool capable of supporting evidence-based renewable energy planning where conventional building datasets remain limited.

Policy and Planning Implications

The findings provide important evidence for strengthening rooftop photovoltaic deployment strategies in Nigeria. The spatial suitability maps developed in this study enable governments and energy planners to prioritize locations where rooftop photovoltaic investments are likely to achieve the highest technical performance and economic returns. Such spatial prioritization can improve the efficiency of renewable energy investment programmes by directing financial incentives, tax credits, and subsidy schemes toward areas with the greatest photovoltaic potential.

The framework also offers practical support for urban planning and sustainable city development. Integrating rooftop solar suitability assessment into building approval processes, urban development plans, and municipal energy strategies would encourage solar-ready building designs while reducing future retrofitting costs. State governments and planning authorities could incorporate the suitability maps into Geographic Information System databases to guide zoning decisions and promote distributed renewable energy infrastructure within expanding urban areas.

For electricity distribution companies and national energy regulators, the suitability framework provides a valuable decision-support tool for identifying areas where distributed rooftop photovoltaic systems could complement grid expansion, reduce transmission losses, improve supply reliability, and enhance urban energy resilience. The approach is particularly relevant for rapidly growing cities where conventional electricity infrastructure is unable to keep pace with increasing demand.

At the national level, widespread application of the proposed framework could support implementation of Nigeria's Energy Transition Plan, National Renewable Energy and Energy Efficiency Policy, and Sustainable Development Goal 7 by promoting evidence-based renewable energy planning. Because the methodology relies primarily on publicly available satellite datasets and transferable geospatial techniques, it offers a cost-effective approach for supporting decentralized electricity generation in Nigeria and other data-constrained developing countries.

CONCLUSION

This study developed and validated an integrated GIS-based framework for assessing rooftop photovoltaic suitability across selected Nigerian cities by combining satellite-derived Global Horizontal Irradiance, urban morphology indicators, rooftop geometry proxies, density-based shading assessment, Analytic Hierarchy Process (AHP), and Random Forest machine learning. The framework successfully captured the spatial variability of rooftop photovoltaic potential across diverse climatic and urban environments while providing a robust decision-support system for renewable energy planning.

The results demonstrate that rooftop photovoltaic suitability in Nigeria is primarily controlled by the combined influence of solar resource availability and urban morphology. Global Horizontal Irradiance and rooftop area emerged as the most influential suitability criteria, while urban density and shading substantially modified local photovoltaic potential. The Random Forest validation confirmed the reliability of the proposed framework, indicating that the integrated geospatial methodology provides accurate and consistent predictions of rooftop suitability across the study area.

The principal contribution of this research lies in demonstrating that the integration of GIS, multi-criteria decision analysis, and machine-learning validation offers a practical and scientifically robust approach for rooftop photovoltaic assessment in data-constrained urban environments. By combining expert knowledge with data-driven validation, the framework improves confidence in suitability mapping and provides a transferable methodology for supporting decentralized renewable energy planning.

To maximize the practical value of the proposed framework, future studies should incorporate high-resolution building footprints, LiDAR or UAV-derived elevation datasets, and measured photovoltaic generation data to improve rooftop characterization and long-term model validation. Policymakers should also consider integrating GIS-based rooftop suitability mapping into urban planning, renewable energy investment strategies, and building development regulations to accelerate rooftop photovoltaic deployment and strengthen Nigeria's transition toward a more sustainable and resilient energy system.

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