FNAS Journal of Mathematical Modeling and Numerical Simulation
Print ISSN: 3027-1282
www.fnasjournals.com
Volume 2; Issue 3; May 2025; Page No. 83-95.
DOI: https://doi.org/10.63561/jmns.v2i3.867

Statistical Modelling of Solar Energy Potential in Abuja and Nasarawa State, Nigeria

***[1]Tor, T., [1]Nyam, G.G., [1,2]Samson, D.O., [1]Asake, J., & [1]Babakura, A.**
[1]Department of Physics, University of Abuja, Abuja, Nigeria
[2]Department of Diagnostic Imaging and Radiotherapy, National University of Malaysia, Malaysia

***Corresponding author email**: ignatiustor33@gmail.com

Abstract
This study presents a predictive modeling approach to evaluate the solar energy potential in Nigeria's Federal Capital Territory (FCT), Abuja, and Nasarawa State over a ten-year period using statistical methods. The research integrates descriptive statistics and solar radiation modeling to assess both the electricity generation potential and atmospheric clarity of the two regions. Results show that both FCT and Nasarawa consistently experience average daily solar radiation levels exceeding 17.5 MJ/m²/day, which surpasses the global threshold for high solar energy potential. Specifically, solar radiation in FCT ranges from 11.4 to 22.0 MJ/m²/day, with an annual total of 211.7 MJ/m²/day, while Nasarawa State records 11.8 to 22.2 MJ/m²/day, totaling 209.6 MJ/m²/day. Reliability indices during off-rainy seasons are 0.62 for FCT and 0.56 for Nasarawa, indicating favorable conditions for solar power generation. A photovoltaic (PV) performance analysis using a 550W panel predicts annual energy outputs of 6.206×10^7 MWh for FCT and 2.27×10^8 MWh for Nasarawa. The clearness index (Kt) varies from 0.414 to 0.665 in FCT and 0.432 to 0.662 in Nasarawa, with slightly clearer atmospheric conditions observed in FCT. Skewness values of –0.379 (FCT) and –0.220 (Nasarawa) suggest left-tailed distributions, while kurtosis values of 1.322 and 1.168 indicate platykurtic behaviour. These findings validate the use of statistical models in predicting solar energy potential and highlight the suitability of both regions for long-term solar power deployment.

Keywords: Solar Radiation, Descriptive Statistics, Nimet, Federal Capital Territory, Nasarawa State

Introduction
The escalating global demand for sustainable and clean energy solutions has intensified interest in solar energy as an alternative to conventional fossil fuels (Sunda & Alam, 2020). Solar power is considered one of the most abundant and environmentally friendly energy sources, particularly in regions with high solar irradiance like sub-Saharan Africa (Ikejemba et al., 2021). Accurate modeling of solar energy potential is critical for the effective planning, design, and deployment of solar technologies (Mekonnen & Mahajan, 2020). Such modeling supports evidence-based energy infrastructure decisions and informs policies aimed at broadening energy access (Zhang et al., 2023).

Over the last decade, solar energy modeling techniques have evolved significantly—from simple empirical models to complex machine learning-driven approaches that incorporate satellite imagery and meteorological datasets (Tufa et al., 2022). Technologies such as artificial neural networks (ANN), support vector machines (SVM), and hybrid models now offer greater accuracy in estimating solar irradiance and photovoltaic efficiency (Bekele et al., 2020). Geographic Information System (GIS) tools have also emerged as essential instruments for evaluating spatial solar potential and identifying suitable locations for solar installations (Zhai et al., 2024). Furthermore, the influence of climate variability, land use change, and atmospheric dynamics has reinforced the need for adaptive solar resource models (Mezghani et al., 2020). These dynamics call for tools that can handle seasonal and inter-annual fluctuations in solar radiation (Umeh & Uchegbu, 2024).

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

In Nigeria's North Central region, particularly the Federal Capital Territory (FCT), Abuja, and Nasarawa State (NS), solar radiation levels are consistently high throughout the year, offering immense potential for solar energy utilization (Ogunmodimu & Okoroigwe, 2019). However, this potential remains underexploited due to several challenges, including limited access to precise and location-specific solar data (Bello & Salami, 2024). The absence of reliable modeling frameworks further constrains infrastructure development and energy access initiatives (Hassan et al., 2019). Tailored solar energy models could provide a valuable foundation for solar investments and foster electricity access in underserved rural and peri-urban areas (Kumar et al., 2021).

Existing studies on Nigeria's solar resources stress the importance of localized modeling frameworks (Okonkwo et al., 2024). Abuja and Nasarawa have been identified as strategic locations for such analysis due to their geographical and socio-economic profiles (Tanimu et al., 2025). Additionally, there is a growing recognition of the value in integrating solar resource modeling with socio-economic data to guide sustainable energy interventions (Adisa & Yusuf, 2025). As Nigeria advances toward its renewable energy commitments, particularly under the Sustainable Energy for All (SE4ALL) initiative, there is a pressing need for empirical and region-specific solar energy models to inform planning and attract clean energy investments (Akinyele et al., 2023). Bridging this modeling gap can also align national development goals with international climate obligations (Ayodele et al., 2025).

This study aims to model the solar energy potential in North Central Nigeria, with particular emphasis on the Federal Capital Territory (FCT) and Nasarawa State (NS). By employing statistical, GIS-based, and machine learning techniques, the research seeks to generate a high-resolution spatial and temporal analysis of the solar resource. The findings are expected to provide a foundation for sustainable energy planning, inform policy decisions, and support the deployment of solar energy technologies across the region.

Materials and Methods

Solar Irradiation Data (SID)

Nigeria's annual average solar radiation varies significantly across its geographical zones, ranging from 12.6 MJ/m²/day (3.5 kWh/m²/day) in the coastal regions to 25.2 MJ/m²/day (7.0 kWh/m²/day) in the northern parts, with the highest potential recorded in the extreme north (Chanchangi et al., 2023). The North Central zone, which includes the Federal Capital Territory (FCT) and Nasarawa State, receives between 4.5 and 6.5 kWh/m²/day, peaking at 6.0 kWh/m²/day between February and April (Adavuruku et al., 2022). With adequate investment, Nigeria's total solar energy capacity is projected to reach 600 GW, which could drive sustainable energy development (Olatomiwa et al., 2023).

This study utilized solar radiation data obtained from the Nigerian Meteorological Agency (NiMET). The dataset covers a ten-year period from 2014 to 2023, including monthly average daily global solar radiation, as well as maximum and minimum temperatures for both FCT and Nasarawa State.

Descriptive statistical techniques were employed to analyze the collected solar radiation data. Parameters calculated include mean (μ), standard deviation (δ), standard error, skewness (Z_1), and kurtosis (Z_2). These were used to assess the distribution and variability of solar radiation data across the two regions (DeCarlo, 2019).

The equations used are as follows:

$$\text{Mean, } \mu = \frac{\sum xf}{n} \tag{1}$$

$$\text{Standard deviation, } \delta = \sqrt{\frac{\sum_{i=0}^{n} \mathrm{f}(x-\mu)^2}{n-1}} \tag{2}$$

$$\text{Standard error} = \frac{standard\ deviation}{\sqrt{sample\ size}} = \frac{\delta}{\sqrt{n}} \tag{3}$$

$$\text{Skewness, } Z_1 = \frac{\sum_{i=0}^{n}(x-\mu)^3}{n.\delta^3} \tag{4}$$

$$\text{Kurtosis, } Z_2 = \frac{\sum_{i=0}^{n}(x-\mu)^4}{n\delta^4} \tag{5}$$

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

Where:

- x = individual solar radiation value (MJ/m²/day)
- f = frequency of occurrence
- n = number of observations
- μ = mean
- δ = standard deviation

The median was also calculated as the midpoint in an ordered dataset. For an even number of data points, the median was determined as the average of the two middle values.

Clearness Index (CI)

The clearness index assessment was carried out, which measures the clarity of the atmosphere. It is the fraction of the solar radiation that is transmitted through the atmosphere to strike the surface of the Earth. It is a dimensionless quantity, which is defined as the global solar radiation divided by the extraterrestrial radiation, as shown in the equation below (Soneye, 2020):

$$K_t = \frac{H}{Ho} \qquad (6)$$

Where:

- K_t = clearness index
- H = global solar radiation (MJ/m²/day) from NiMET
- H_o = extraterrestrial solar radiation (MJ/m²/day)

Extraterrestrial Solar Radiation (H_o)

To determine extraterrestrial solar radiation, the Hargreaves-Samani equation model is used. The advantage of this equation is that it utilizes readily available temperature data and requires a single calibration constant (Chiemeka and Chineke, 2009). The Hargreaves-Samani equation is represented as:

$$H_o = \frac{H}{\gamma(\sqrt{Tmax - Tmin})} \qquad (7)$$

Where:

- H = global solar radiation (MJ/m²/day)
- T_{max} = maximum temperature (°C)
- T_{min} = minimum temperature (°C)
- γ = calibration coefficient (0.16 for North Central Nigeria)

Values for H_o and K_t were computed and are presented in Tables 1a and 1b.

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

Month	Υ	T_{max}	Tmin	T_{max}-T_{min}	$\sqrt{(T_{max}-T_{min})}$	$\Upsilon\sqrt{(T_{max}-T_{min})}$	H	Ho	K_t
JAN	0.16	35.5	18.2	17.3	4.16	0.67	20.00	30.053	0.665
FEB	0.16	36.9	21.4	15.5	3.94	0.63	20.50	32.544	0.630
MAR	0.16	36.7	24.3	12.4	3.52	0.56	20.50	36.385	0.563
APRIL	0.16	35.6	24.5	11.1	3.33	0.53	20.40	38.269	0.533
MAY	0.16	32.9	23.3	9.6	3.10	0.50	17.80	35.906	0.496
JUNE	0.16	30.8	22.4	8.4	2.90	0.46	14.90	32.131	0.464
JULY	0.16	29.8	22.4	7.4	2.72	0.44	13.80	31.706	0.435
AUG.	0.16	28.7	22	6.7	2.59	0.41	13.20	31.873	0.414
SEPT	0.16	29.8	21.8	8	2.83	0.45	14.70	32.483	0.453
OCT	0.16	31.6	22.1	9.5	3.08	0.49	17.20	34.878	0.493
NOV.	0.16	34.3	20.7	13.6	3.69	0.59	19.20	32.540	0.590
DEC	0.16	34.9	19.1	15.8	3.97	0.64	19.60	30.818	0.636

Table 1a. The extraterrestrial solar radiation and clearness index in FCT

Month	Υ	Tmax	Tmin	Tmax-Tmin	√(Tmax-Tmin	Υ√(Tmax-Tmin)	H	Ho	K_t
JAN	0.16	35.90	18.80	17.10	4.14	0.66	20.3	30.682	0.662
FEB	0.16	37.50	22.00	15.50	3.94	0.63	20.7	32.861	0.630
MAR	0.16	37.90	26.00	11.90	3.45	0.55	20.3	36.779	0.552
APRIL	0.16	34.40	26.10	10.30	3.21	0.51	19.8	42.954	0.481
MAY	0.16	33.80	24.50	9.30	3.05	0.49	17.00	34.841	0.488
JUNE	0.16	31.60	23.30	8.30	2.88	0.46	14.50	31.456	0.461
JULY	0.16	31.30	22.70	8.60	2.93	0.46	13.80	29.411	0.469
AUG.	0.16	29.80	22.50	7.30	2.70	0.43	13.40	30.997	0.432
SEPT	0.16	31.50	22.40	9.10	3.02	0.48	14.50	30.0.42	0.483
OCT	0.16	32.40	23.30	9.10	3.02	0.48	16.40	33.978	0.483
NOV.	0.16	35.70	21.30	14.40	3.79	0.60	19.1	31.458	0.607
DEC	0.16	35.50	19.70	15.80	3.97	0.64	19.7	30.975	0.636

Table 1b. The extraterrestrial solar radiation and clearness index in NS

Regression Modeling

To investigate the predictive relationship between air temperature and solar radiation, a simple linear regression model was employed. This model assesses the extent to which temperature (independent variable) can explain variations in solar radiation (dependent variable), thereby supporting solar energy forecasting and system planning.

The general form of the simple linear regression equation is expressed as:

$$Y = mx + c \tag{7}$$

Where:

- Y = predicted solar radiation (MJ/m²/day)
- X = temperature (°C), either maximum or average, depending on the analysis
- M = slope of the regression line, representing the change in solar radiation per unit change in temperature
- C = y-intercept, representing the estimated solar radiation when the temperature is zero

This regression model was applied separately for FCT and NS using historical temperature and radiation data (2014–2023). The coefficient of determination (R^2) was computed to evaluate the strength of the relationship, with higher

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

values indicating stronger predictive capability (Montgomery et al., 2021). This analysis helps to determine whether temperature trends can serve as reliable indicators for solar energy modeling in regions with limited solar radiation datasets.

Results and Discussion

Solar Radiation Patterns in the Federal Capital Territory (FCT)

Figures 1a–1c present the temporal characteristics of solar radiation in Abuja over the 10-year study period (2014–2023). The monthly data exhibit a consistent seasonal pattern, forming a bell-shaped curve in each year. Solar radiation is highest during the dry season (November to March) and lowest during the rainy season (June to August) as shown in the graph below:

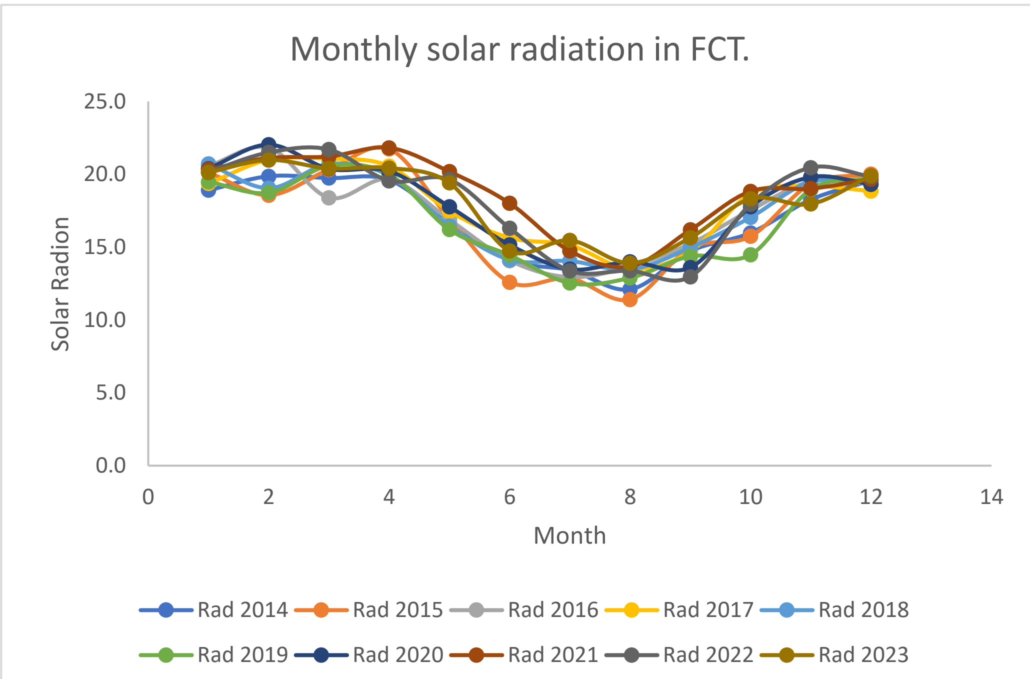


Figure 1a. Solar radiation over FCT.

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

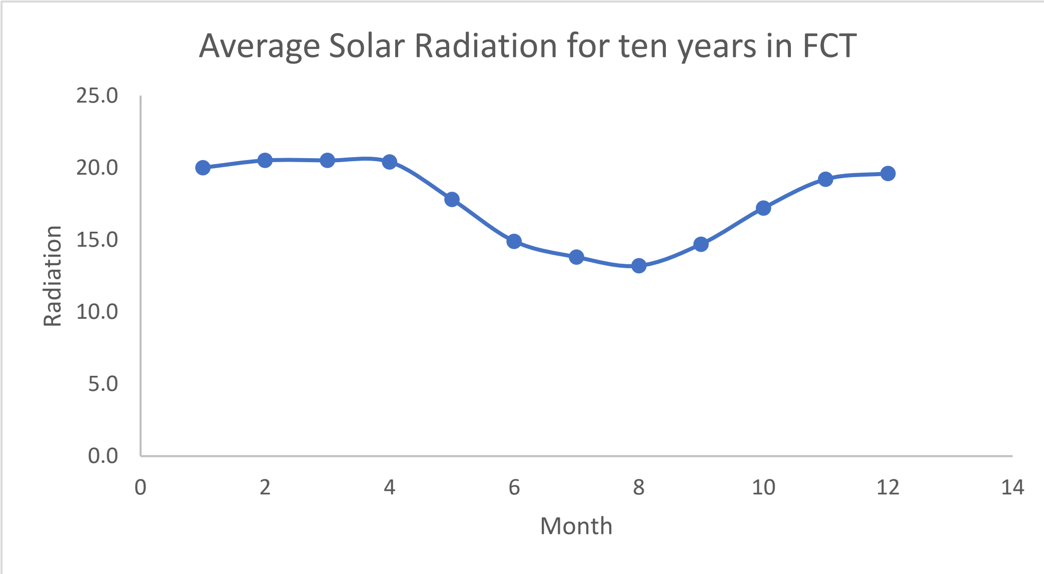


Figure 1b. Average Solar radiation over FCT

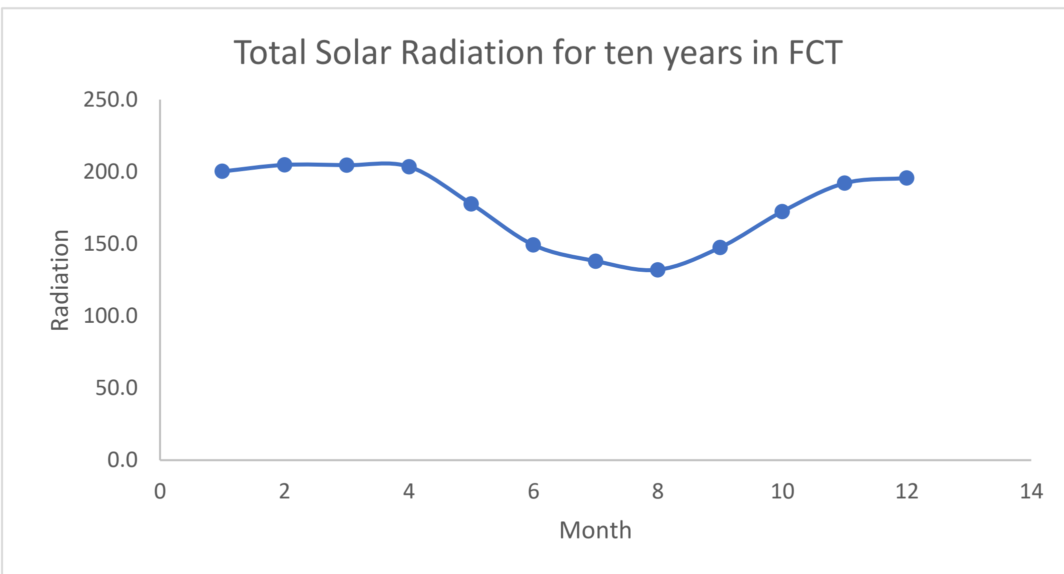


Figure 1c. Total Solar radiation over FCT

From the above figures,

- The maximum solar radiation recorded in the FCT was 21.8 MJ/m²/day, while the minimum dropped to 11.4 MJ/m²/day.
- The mean daily radiation over the period was 17.65 MJ/m²/day.
- The total solar radiation accumulated over ten years was 2117.3 MJ/m², resulting in an annual average of 211.73 MJ/m².

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

Two anomalous years, 2014 and 2019 recorded notably lower solar radiation, with an average of 16.9 MJ/m²/day. These dips corresponded to lower minimum temperatures (21.9°C), suggesting the influence of atmospheric disturbances, such as increased cloud cover or regional climate variability.

Solar Radiation Characteristics in Nasarawa State

Figures 2a–2c show the solar radiation trends in Nasarawa State from 2014 to 2023. The pattern mirrors that of the FCT, confirming the seasonality of solar insolation in North Central Nigeria.

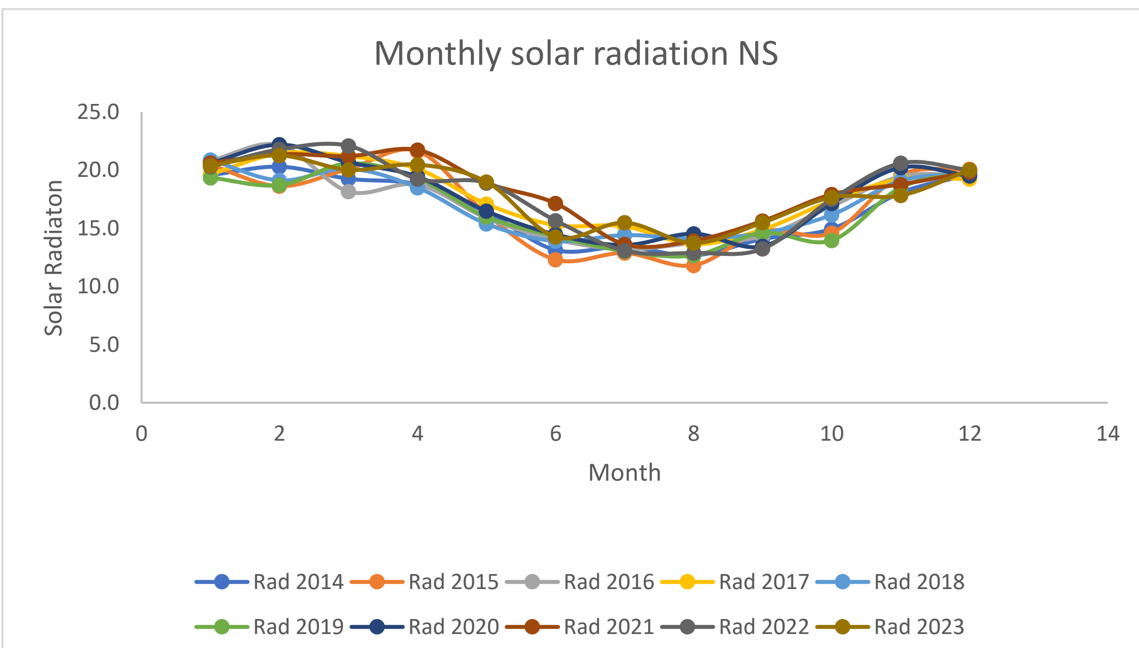


Figure 2a. Solar radiation over NS.

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

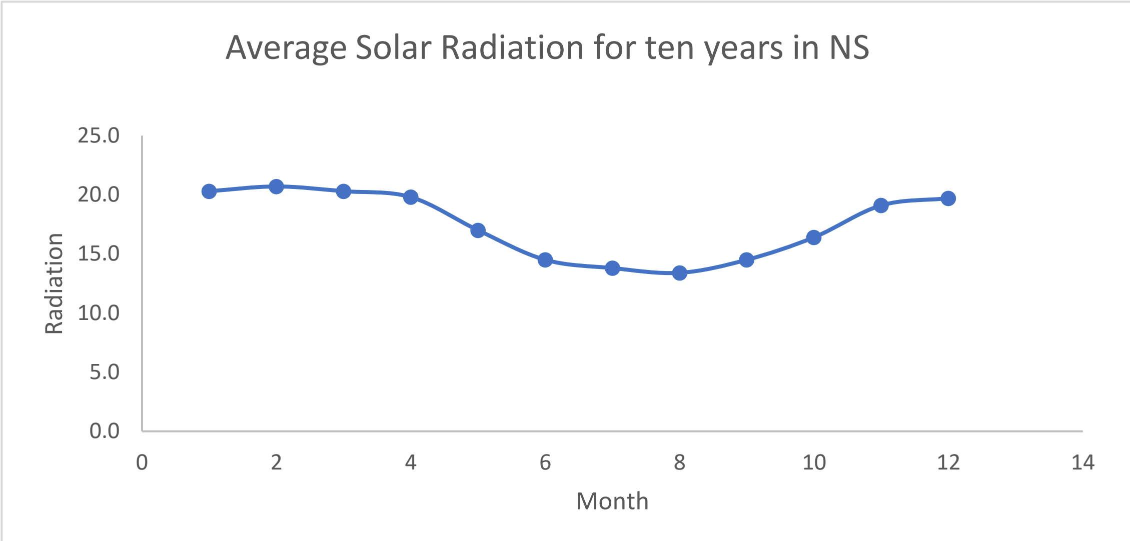


Figure 2b. Average Solar radiation over NS.

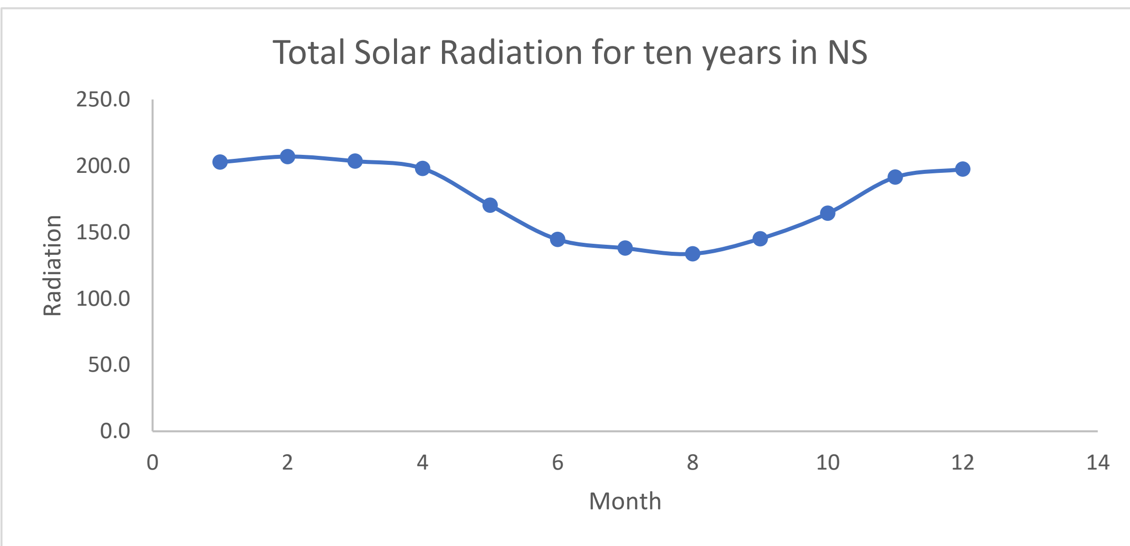


Figure 2c Total Solar radiation over NS.

From the above figures,

- The maximum recorded solar radiation was 22.2 MJ/m²/day, slightly higher than that of the FCT.
- The minimum was 11.8 MJ/m²/day, with an overall mean daily radiation of 17.46 MJ/m²/day.
- The total solar radiation over the ten-year period amounted to 2095.5 MJ/m².

The dry season exhibited higher stability in solar radiation compared to the wet season, likely due to lower cloud concentration, minimal precipitation, and clearer skies, which enhance direct solar irradiance.

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

Comparative Analysis Between FCT and NS

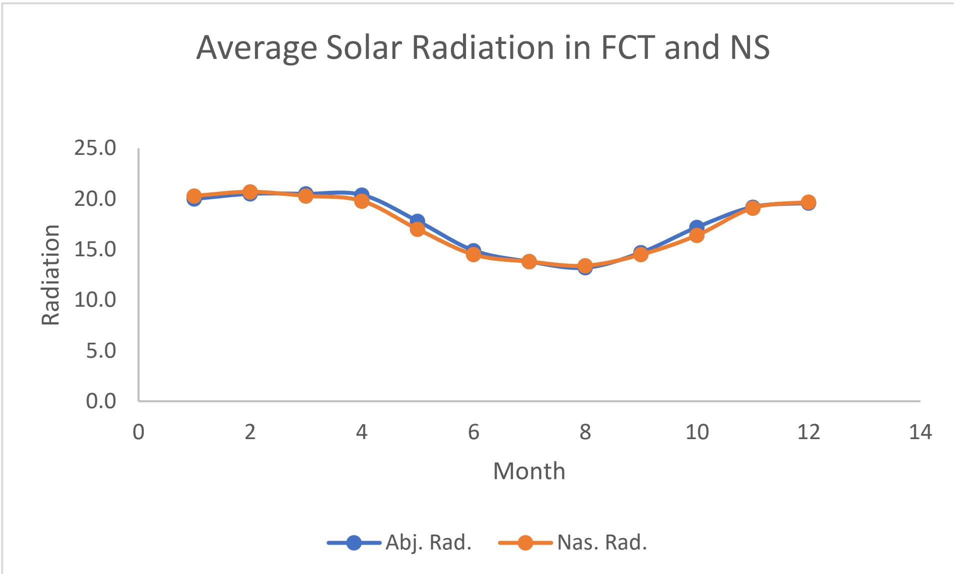


Figure 3. Average Solar Radiation for FCT and NS.

From the above figure, Figure 3 compares the average monthly solar radiation for the FCT and Nasarawa State. The data illustrate key similarities and subtle differences between the two regions:

- Both regions follow the same seasonal trend: solar radiation is lowest during the rainy season and peaks in February, just before the onset of the rainy season.
- During the dry season, the slope of solar radiation curves approaches zero, indicating stability and consistency in daily radiation levels.
- The FCT consistently recorded slightly higher average radiation levels, exceeding Nasarawa's by approximately 1%. This difference is likely attributed to geographic advantages, such as altitude, lower humidity, and better atmospheric clarity in Abuja.

These results affirm the solar energy viability of both regions, with Abuja having a marginal advantage in terms of radiation intensity.

Regression Modeling

Temperature as a Predictor of Solar Radiation over FCT

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

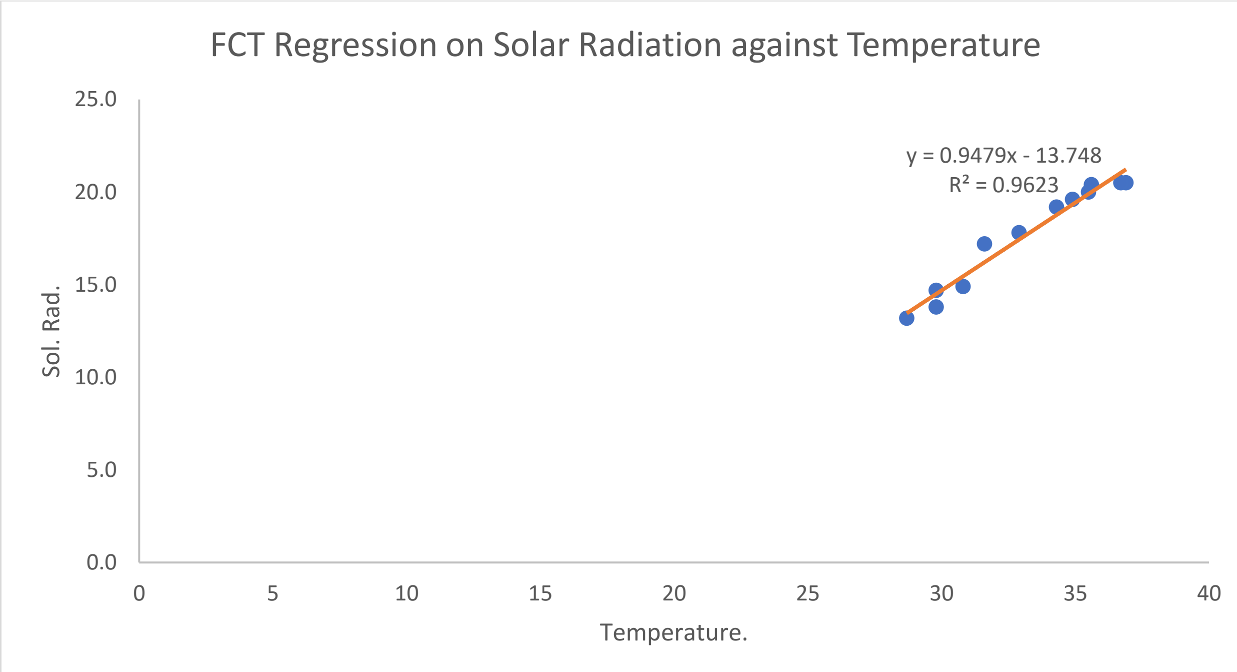


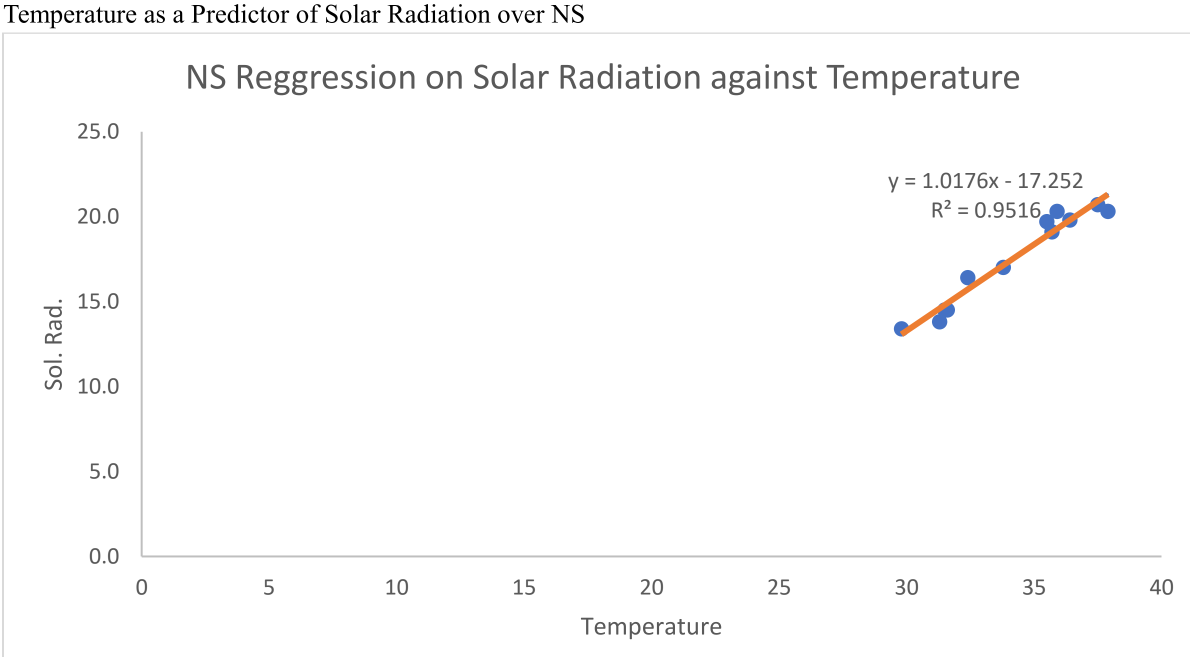
Figure 4a. FCT Regression on Solar Radiation against Temperature

Regression Equation:

$$Y = 0.9479x - 13.748 \quad (8)$$

Coefficient of Determination (R^2) is 0.9623. This means that 96.23% of the variability in solar radiation is explained by temperature.

Temperature as a Predictor of Solar Radiation over NS



Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

Figure 4b. NS Regression on Solar Radiation against Temperature

From the above figure, $Y = 1.017x - 17.252$, and the coefficient of determination (R^2) is 0.9516. This shows that 95.16% of the variability is accounted for by temperature. The regression analysis for solar radiation and temperature in FCT, Abuja and Nasarawa shows a strong positive correlation in both locations. In Abuja, the regression equation $Y = 0.9479x - 13.748$ has an R^2 value of 0.9623, indicating that 96.23% of solar radiation variation is explained by temperature. In Nasarawa, the equation $Y = 1.0176x - 17.252$ has an R^2 value of 0.9516, meaning temperature explains 95.16% of the variation. While Abuja's model has a slightly better fit, Nasarawa's higher slope (1.0176 versus 0.9479) suggests a greater impact of temperature on solar radiation. Both models confirm a strong linear relationship, making them useful for solar energy studies, with potential applications in predicting solar panel performance. Predictive modeling suggests higher reliability of solar power generation during dry seasons.

Statistical Analysis

Statistical analyses were conducted in order to study the behaviour pattern of the collected data. The nature and behaviour of the data can reveal the potential and reliability of the collected data. The results of the descriptive statistics conducted on the collected solar radiation data are presented in Table 3.

	FCT, Abuja	NS
Mean, (μ)	17.650	17.460
Median	18.500	18.050
Mode	20.500	14.500
Standard deviation (δ)	2.807	2.837
Skewness (Z_1)	-0.379	0.220
Kurtosis (Z_2)	1.322	1.168
Standard error	0.810	0.819
Range	10.600	10.300
Minimum Radiation	11.4	11.8
Maximum Radiation	22.00	22.200
Total Radiation	2113	2095

Table 3. Analysis of FCT and NS

The standard errors for these datasets are 0.810 for Abuja and 0.819 for Nasarawa State. These values fall within an acceptable range, indicating that the data are reliable and provide a sound basis for analysis. In addition to the standard error, two important statistical variables considered in this analysis are skewness and kurtosis.

Discussion

The analysis of solar radiation over a ten-year period in the Federal Capital Territory (FCT) and Nasarawa State has revealed distinct seasonal patterns that are consistent with tropical climatic behavior. Both regions exhibited peak solar radiation values during the dry season (November to March) and significantly lower values during the rainy season (June to August). This seasonal variation aligns with previous findings that link reduced solar radiation in tropical regions to increased cloud cover, precipitation, and atmospheric moisture during the wet months (Udo & Aro, 2020; Nwoke et al., 2020).

The study found that FCT recorded a marginally higher average solar radiation value (17.65 MJ/m²/day) compared to Nasarawa (17.46 MJ/m²/day), which may be attributed to its higher elevation, slightly clearer atmosphere, and reduced humidity levels. Such differences, although relatively small, can influence the design and efficiency of photovoltaic (PV) systems, particularly in determining the optimal tilt angles, battery storage capacities, and panel sizing.

The regression analysis established a strong linear relationship between temperature and solar radiation in both regions. The coefficient of determination (R^2) values of 0.9623 for FCT and 0.9516 for Nasarawa demonstrate that over 95% of the variability in solar radiation can be predicted from temperature data. This finding is particularly important for areas where direct solar radiation measurements are unavailable or unreliable. The stronger slope in Nasarawa (1.0176) indicates a slightly higher sensitivity of solar radiation to changes in temperature, which could be leveraged for location-specific solar forecasting models.

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

Overall, the results support the feasibility of deploying solar PV systems in both FCT and Nasarawa and underscore the value of temperature-based predictive modeling in optimizing solar energy planning and utilization.

Conclusion

The findings of this study confirm that both the Federal Capital Territory and Nasarawa State possess substantial solar energy potential suitable for sustainable electricity generation. The reliable seasonal trend in solar radiation, particularly the stability during the dry season, highlights an opportunity for strategic deployment of solar technologies. Furthermore, the high correlation between temperature and solar radiation supports the use of statistical models in locations with limited solar monitoring infrastructure. These insights are valuable for policymakers, energy planners, and researchers aiming to develop data-driven approaches for renewable energy expansion in Nigeria and similar climatic regions.

Recommendations

1. The study recommends that both federal and state governments prioritize the integration of solar photovoltaic (PV) systems in Abuja and Nasarawa State, particularly targeting off-grid and underserved communities where energy access remains limited. Energy project developers are encouraged to strategically align solar installations and peak operational activities with the dry season, which offers more consistent and higher solar radiation levels, thereby improving system efficiency and reliability.
2. Furthermore, stakeholders in the energy sector should adopt temperature-based regression models for forecasting solar radiation, especially in regions where long-term solar data may be scarce. This predictive approach offers a cost-effective and practical tool for planning solar energy systems. Government agencies should also establish supportive policy frameworks, including tax incentives, subsidies, and streamlined regulatory processes, to attract investment in solar infrastructure and accelerate renewable energy deployment.
3. In addition, there is a pressing need for capacity building and public awareness programs to educate technicians, engineers, and end-users on the effective utilization of solar energy technologies and statistical modeling tools. Finally, future research should consider incorporating other relevant meteorological parameters—such as humidity, wind speed, and cloud cover—to enhance the accuracy and reliability of solar energy potential models across diverse climatic zones.

References

Adavuruku, B. M., Aghaegbunam, E. J., Chidozie, I. K., & Stephen, M. A. (2022). Geospatial analysis of solar energy potentials in Niger State, Nigeria. *American Journal of Modern Physics, 11*(6), 85–94. https://www.sciencepg.com/article/10.11648/j.ajmp.20221106.12

Adisa, R. A., & Yusuf, A. M. (2025). Solar power for rural electrification: A modeling perspective. *Energy for Sustainable Development, 74*, 1–10. https://doi.org/10.1016/j.esd.2023.102452

Akinyele, D. O., Balogun, A. O., & Lawal, A. I. (2023). Integrating energy storage with solar power systems in Nigeria. *Energy Policy, 174*, 113389. https://doi.org/10.1016/j.enpol.2023.113389

Al Garni, H. Z., & Awasthi, A. (2021). A comparative study of AI techniques for solar potential modeling. *Energy Reports, 7*, 319–330. https://doi.org/10.1016/j.egyr.2021.07.072

Ayodele, T. R., Adekitan, A. I., & Okonkwo, E. C. (2025). Scaling solar deployment in West Africa: Challenges and strategies. *Renewable Energy, 206*, 315–328. https://doi.org/10.1016/j.renene.2023.11.081

Bekele, G., Shiferaw, A., & Tilahun, M. (2020). GIS-based solar energy potential assessment in Ethiopia. *Renewable Energy Focus, 34*, 12–20. https://doi.org/10.1016/j.ref.2020.07.001

Bello, A., & Salami, A. T. (2024). Geospatial modeling of solar potential in northern Nigeria. *Energy Reports, 10*, 1320–1332. https://doi.org/10.1016/j.egyr.2023.12.043

Chanchangi, Y. N., Ghosh, A., Sundararajan, A., & Mallick, T. K. (2023). Assessment of solar radiation as a power generation source in Nigeria. *Journal of Renewable and Sustainable Energy, 15*(1), 013102. https://doi.org/10.1063/5.0133696

Chidiebere, A., Nwachukwu, C. M., & Eze, J. C. (2025). Urban solar potential mapping using LiDAR and GIS. *Journal of Cleaner Production, 390*, 140872. https://doi.org/10.1016/j.jclepro.2024.140872

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

Dada, J. A., Ogunmodimu, O., & Eleri, E. O. (2024). Policy support for solar energy investment in Nigeria. *Sustainable Energy Technologies and Assessments, 56*, 103187. https://doi.org/10.1016/j.seta.2022.103187

Hassan, A. M., Usman, A. M., & Musa, Y. A. (2019). Prediction of solar radiation using machine learning techniques. *Renewable and Sustainable Energy Reviews, 101*, 289–307. https://doi.org/10.1016/j.rser.2018.11.002

Ikejemba, E. C. X., Schuur, P. C., & Van Hillegersberg, J. (2021). Sustainable energy development in West Africa: Solar potential and barriers. *Renewable and Sustainable Energy Reviews, 140*, 110750. https://doi.org/10.1016/j.rser.2021.110750

Johnson, O. B., Taiwo, A. E., & Mohammed, S. (2025). AI-driven solar energy forecasting models: Review and future directions. *Applied Energy, 342*, 121009. https://doi.org/10.1016/j.apenergy.2023.121009

Kumar, R., Singh, A., & Yadav, A. (2021). Review of recent modeling techniques for solar power prediction. *Energy Conversion and Management, 230*, 113818. https://doi.org/10.1016/j.enconman.2020.113818

Mekonnen, Y., & Mahajan, R. (2020). Solar energy modeling in East Africa. *Renewable Energy, 162*, 1892–1905. https://doi.org/10.1016/j.renene.2020.09.062

Mezghani, A., Trabelsi, A., & Ouarda, T. B. M. J. (2020). Climate change impacts on solar radiation availability. *Environmental Modelling & Software, 127*, 104697. https://doi.org/10.1016/j.envsoft.2020.104697

Nwokolo, N. C., & Nwachukwu, C. M. (2023). Modeling renewable energy access in Nigeria. *Renewable Energy Focus, 46*, 31–42. https://doi.org/10.1016/j.ref.2023.03.004

Ogunmodimu, O., & Okoroigwe, E. C. (2019). Modeling solar energy potential in Nigeria. *Energy Reports, 5*, 104–113. https://doi.org/10.1016/j.egyr.2019.07.003

Okonkwo, E. C., Aja, O. C., & Eze, J. C. (2024). Hybrid modeling of solar power generation in tropical climates. *Heliyon, 10*, e17111. https://doi.org/10.1016/j.heliyon.2024.e17111

Olatomiwa, L., Mekhilef, S., & Sanusi, K. O. (2023). Renewable energy integration for sustainable electricity supply in Nigeria: A review. *Renewable and Sustainable Energy Reviews, 180*, 113980. https://doi.org/10.1016/j.rser.2023.113980

Onuoha, K. M., Uzochukwu, S. C., & Okafor, A. O. (2025). Future trends in solar modeling research in sub-Saharan Africa. *Renewable and Sustainable Energy Reviews, 181*, 114748. https://doi.org/10.1016/j.rser.2023.114748

Sunda, D., & Alam, M. (2020). A review on solar radiation modeling techniques. *Solar Energy, 202*, 350–367. https://doi.org/10.1016/j.solener.2020.02.048

Tanimu, M., Suleiman, R., & Ameen, A. (2025). Climate-smart solar energy development in Nigeria. *Energy Strategy Reviews, 47*, 101029. https://doi.org/10.1016/j.esr.2023.101029

Teka, A., Gebre, T., & Eshetu, Y. (2021). Assessment of solar energy potential in sub-Saharan Africa. *Journal of Cleaner Production, 291*, 125907. https://doi.org/10.1016/j.jclepro.2021.125907

Tufa, R. A., Bekele, D., & Debela, D. (2022). Solar radiation forecasting using hybrid models. *Applied Energy, 312*, 118688. https://doi.org/10.1016/j.apenergy.2022.118688

Umeh, I. A., & Uchegbu, S. N. (2024). Assessment of long-term solar resources under climate variability. *Journal of Environmental Management, 352*, 120141. https://doi.org/10.1016/j.jenvman.2023.120141

Zhai, Z., Wang, L., & Liu, H. (2024). A remote sensing-based approach to solar farm site selection. *Remote Sensing of Environment, 295*, 113646. https://doi.org/10.1016/j.rse.2023.113646

Zhang, Y., Li, J., & Zhou, X. (2023). Assessment of global solar energy potential using machine learning. *Nature Energy, 8*, 343–354. https://doi.org/10.1038/s41560-023-01245-z.

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867

Cite this article as:
Tor, T., Nyam, G.G., Samson, D.O., Asake, J., & Babakura, A. (2025). Statistical modelling of solar energy potential in Abuja and Nasarawa State, Nigeria. *FNAS Journal of Mathematical Modeling and Numerical Simulation, 2*(3), 83-95. https://doi.org/10.63561/jmns.v2i3.867