

Spatiotemporal Variability and Trend Analysis of Solar Radiation in North-Central Nigeria (Federal Capital Territory, Abuja and Nasarawa State), using Non-parametric Statistical Methods

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ABSTRACT

This study assessed the spatiotemporal variability and temporal trends of mean daily global solar radiation in the Federal Capital Territory (FCT), Abuja, and Nasarawa State (NS), Nigeria, using complementary nonparametric methods. Monthly average daily global solar radiation data for 2014–2023 were analyzed using descriptive statistics, coefficient of variation, Radiation Anomaly Index (RAI), Mann-Kendall (M-K) test, Sen's slope estimator, Spearman rank correlation, and Innovative Trend Analysis (ITA). The results revealed pronounced seasonal and interannual variability at both locations. FCT recorded its highest and lowest monthly mean radiation in February (17.56 MJm⁻²day⁻¹) and August (10.12 MJm⁻²day⁻¹), respectively, whereas NS recorded corresponding values of 24.87 MJm⁻²day⁻¹ in January and 15.64 MJm⁻²day⁻¹ in July. NS generally exhibited higher radiation levels, while FCT showed greater relative variability. The strongest positive RAI occurred in 2021 at both locations, with values of 2.00 for FCT and 1.27 for NS; the strongest negative anomalies were recorded in 2014 for FCT (−1.22) and 2018 for NS (−1.69). Annual M-K results indicated no statistically significant trend in FCT ($Z = 1.43$, $p = 0.156$; Sen's slope = 0.1083) or NS ($Z = 0.54$, $p = 0.601$; Sen's slope = 0.0094). Following adjustment for multiple monthly tests using the Holm-Bonferroni correction, the previously identified significant monthly trends did not remain statistically significant. ITA further indicated month-dependent changes rather than a uniform temporal pattern. Overall, both locations possess favorable solar resources, although seasonal and interannual variability should be incorporated into photovoltaic resource assessment, system design, and renewable-energy planning.

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INTRODUCTION

The growing demand for reliable, affordable, and environmentally sustainable electricity has accelerated global interest in renewable energy resources. Among these resources, solar energy has emerged as a major component of the global energy transition because photovoltaic (PV) technology converts solar radiation directly into electricity without fuel combustion during operation. Technological advances, economies of scale, and declining generation costs have further improved the competitiveness of solar PV, making it increasingly important for expanding electricity access and diversifying energy systems (IEA, 2024; IRENA, 2024). This potential is particularly relevant in developing countries, where decentralized renewable-energy systems can complement unreliable or inadequate grid electricity and support socioeconomic development (Agbo et al., 2021). Africa possesses abundant solar resources, with extensive areas receiving high levels of solar irradiation throughout the year. Consequently, solar energy is considered an important resource for improving electricity access and supporting the continent's energy transition (IRENA, 2023). However, solar radiation is neither spatially nor temporally uniform. Variations in latitude, atmospheric moisture, cloud cover, aerosols, rainfall, and other atmospheric conditions influence the amount of radiation reaching the Earth's surface. Nigeria,

owing to its tropical location, has considerable solar-energy potential, but pronounced dry- and wet-season contrasts can produce substantial temporal changes in surface radiation (Chanchangi et al., 2023; Adelakun and Adelakun, 2024). The limited distribution of radiation-monitoring stations further emphasizes the need for location-specific assessment of solar resources (Andah et al., 2020; Mamman et al., 2020). Previous investigations show that solar radiation varies considerably across Nigerian locations and seasons. In Nasarawa State (NS), Mamman et al. (2020) reported substantial variation in solar radiation in Akwanga, highlighting the importance of local-scale resource assessment. Similarly, studies involving the Federal Capital Territory, Abuja (FCT), and other Nigerian locations have identified significant differences in global solar-radiation characteristics and clearness indices, demonstrating that national or regional averages may conceal important local conditions (Amadi et al., 2020). Such variability is particularly important for PV planning because system performance depends not only on the average amount of radiation available but also on its seasonal distribution, interannual stability, and occurrence of anomalous conditions. The identification of unusually high or low radiation years is therefore important for evaluating the reliability of solar resources and estimating PV energy yield. Long-term

averages can mask substantial departures from normal conditions, potentially resulting in unrealistic expectations of system performance (Okono et al., 2022). Moreover, changes in cloudiness and atmospheric conditions can produce substantial short-term and seasonal fluctuations in solar radiation, with implications for solar-power forecasting and system operation (Carpentieri et al., 2023). Satellite and reanalysis datasets can provide valuable spatial coverage, but differences from ground observations may introduce uncertainties into resource assessment (Carpentieri et al., 2022). Consequently, observed station data remain important for characterizing local radiation regimes.

Trend analysis offers an additional way to assess whether solar-radiation conditions show systematic temporal changes. Environmental time series may exhibit non-normal distributions, outliers, missing observations, seasonality, and serial dependence, which can limit the suitability of conventional parametric methods (Vrac et al., 2020). Non-parametric approaches are therefore valuable because they make fewer assumptions about the underlying data distribution. The Mann-Kendall (M-K) test is widely used to detect monotonic trends in meteorological time series, while Sen's slope estimator quantifies the magnitude and direction of an identified trend (Wang et al., 2020). Spearman's rank correlation provides a complementary measure of monotonic association and can strengthen the interpretation of temporal behavior (Garba and Udokpoh, 2023; Abdullahi et al., 2023). Innovative Trend Analysis (ITA) offers a graphical complement to these statistical techniques by comparing ranked observations from the earlier and later portions of a time series. It can visually indicate whether radiation values have shifted upward or downward during the study period. Nevertheless, ITA is best interpreted as a complementary diagnostic rather than a substitute for formal statistical tests, given ongoing methodological discussions about its interpretation (Serinaldi et al., 2020). The combined application of these approaches can therefore provide a more comprehensive understanding of solar-radiation dynamics than reliance on a single trend test.

Despite increasing research on solar resources in Nigeria, relatively little attention has been given to a consistent comparative assessment in North-Central Nigeria (FCT and NS) using a common observation period and multiple complementary non-parametric techniques. This study addresses that gap by analyzing monthly average daily global solar-radiation data for 2014–2023 to evaluate spatial, monthly, seasonal, and annual variability. Descriptive statistics and the coefficient of variation characterize radiation magnitude and stability; seasonal indices assess monthly contributions to the annual radiation regime; and the Radiation Anomaly Index (RAI) identifies unusually high and low radiation years. The M-K test and Sen's slope estimator evaluate the significance, direction, and magnitude of temporal trends, while Spearman's rank correlation and ITA provide complementary statistical and graphical perspectives. By integrating these approaches, the study moves beyond a simple assessment of solar-resource magnitude to provide a multidimensional characterization of resource availability, variability, stability, anomalous behavior, and temporal change. The resulting evidence is expected to improve understanding of the spatial differences and temporal dynamics of solar radiation across FCT and NS and to provide information relevant to PV-system sizing, energy-yield assessment, resource forecasting, site selection, and renewable-energy planning in North-Central Nigeria.

MATERIALS AND METHODS

Study Area

The solar-radiation data used in this study were obtained from the Nigerian Meteorological Agency (NiMet), Abuja, and covered the period January 2014 to December 2023. The dataset comprised observations from two meteorological stations: Abuja, located in the Federal Capital Territory (FCT), and Lafia, located in Nasarawa State (NS). The Abuja station is situated at 9.02033°N and 7.2746°E, with an elevation of 354 m above sea level, while the Lafia station is located at 8.506°N and 8.5227°E, with an elevation of 135 m above sea level. At both stations, solar radiation was measured using a solarimeter. These station-level details were used to establish the provenance and geographical context of the radiation records analyzed in the study.

The original records were examined before statistical analysis to assess data completeness and consistency. The quality-control procedure included checks for missing observations, duplicate records, and unusually extreme values. Missing observations were identified during the initial screening of the dataset, while duplicate observations were checked and removed where identified. Potentially anomalous observations were further examined using the interquartile range (IQR) method and boxplots. The IQR was calculated as:

$$IQR = Q_3 - Q_1 \quad (1)$$

where Q_1 and Q_3 represent the first and third quartiles, respectively.

Observations below ($Q_1 - 1.5(IQR)$) or above ($Q_3 + 1.5(IQR)$) were flagged as potential outliers. However, an observation was not removed solely because it met the statistical outlier criterion; removal was considered only where there was evidence that the observation resulted from an error or data-quality problem. This approach was adopted to avoid eliminating genuine extreme solar-radiation observations.

For temporal aggregation, the original radiation observations were processed to obtain monthly average daily global solar radiation, expressed in $\text{MJ m}^{-2}\text{day}^{-1}$. Thus, each monthly value represents the average daily solar radiation for that particular month and does not represent the total radiation received during the month. The annual value for each year was subsequently calculated as the arithmetic mean of the twelve monthly average daily radiation values for that year. Consequently, each annual observation represents the mean daily global solar radiation for the corresponding year. Seasonal values were derived from the monthly observations using the predefined seasonal classification, with the dry season defined as November–April and the wet season as May–October. Following the quality-control and aggregation procedures, the resulting dataset provided 120 monthly observations for each station, covering the ten years from 2014 to 2023. The processed dataset was subsequently used for descriptive statistics, coefficient of variation, Radiation Anomaly Index (RAI), M-K trend analysis, Sen's slope estimation, Spearman rank analysis, and Innovative Trend Analysis.

Data Source and Period

The dataset comprises a continuous 10-year record of 120 monthly observations for each location, with solar radiation expressed in $\text{MJ m}^{-2}\text{day}^{-1}$. The data were analyzed separately for both locations to characterize location-specific monthly, seasonal, and interannual radiation patterns before conducting comparative assessments. The continuous observation period provides a consistent basis for evaluating solar radiation variability, anomalies, and temporal trends using the statistical methods applied in this study.

Descriptive Statistical Analysis

The standard deviation was calculated to measure the dispersion of solar-radiation observations around their arithmetic mean using

$$\delta = \sqrt{\frac{\sum (X - \mu)^2}{N-1}}; \quad \mu = \frac{\sum_{i=1}^n X}{n} \quad (2)$$

where δ is the standard deviation, μ is the arithmetic mean, X is the observed radiation for a year or a specific monthly observation, and n is the number of observations (Montgomery & Runger, 2018).

Monthly and Seasonal Variability

Coefficient of Variation

The coefficient of variation (CV) was used to quantify the relative variability of solar radiation and was computed as:

$$CV = \left(\frac{\delta}{\mu} \right) \times 100 \quad (3)$$

Seasonal Index

A seasonal index was calculated to identify the relative strength of each month compared with the annual radiation level:

$$SI = \frac{\mu_m}{\mu_a} \quad (4)$$

where μ_m and μ_a denote the mean radiation for a particular month and the annual or long-term mean radiation. $SI > 1$ indicates that radiation in the corresponding month is above the annual mean, whereas $SI < 1$ indicates radiation below the annual mean (Wilks, 2019).

Rainfall Anomaly Index (RAI) Evaluation

The Rainfall Anomaly Index was calculated to identify positive and negative departures from the long-term radiation condition:

$$RAI = \frac{Y - \beta}{\delta} \quad (5)$$

where Y is the observed solar-radiation value, β is the long-term mean solar radiation, and δ is the standard deviation. An annual RAI was also calculated using the annual mean radiation series to identify years with above- or below-normal overall radiation conditions.

Dry Season: The dry season is defined as the period from November to March, characterized by relatively low rainfall, lower atmospheric moisture, and generally clearer skies. These conditions can result in relatively higher solar-radiation availability.

Wet Season: The wet season is defined as the period from April to October, characterized by increased rainfall, higher atmospheric moisture, greater cloud cover, and more frequent precipitation. These conditions generally reduce the amount of incoming solar radiation reaching the Earth's surface. This classification was adopted to examine seasonal variations in solar radiation and associated meteorological conditions across FCT and NS.

M-K Trend Test

The non-parametric M-K test was employed to assess the presence and significance of monotonic trends in monthly solar-radiation series. The M-K statistic was calculated as:

$$S = \sum_{i=1}^n \sum_{j=i+1}^n \text{sgn}(X_j - X_i) \quad (6)$$

The variance was determined by accounting for tied observations. The standardized test statistic was subsequently calculated. At the 5% significance level, a trend was considered statistically significant when positive and negative values indicate increasing and decreasing trends, respectively (Mann, 1945; Kendall, 1975).

$$\text{sgn}(X_j - X_i) = \begin{cases} +1, & X_j - X_i > 0 \\ 0, & X_j - X_i = 0 \\ -1, & X_j - X_i < 0 \end{cases} \quad (7)$$

Thus, every later observation (X_j) is compared with every earlier observation (X_i). A positive difference contributes (+1), a negative difference contributes (-1), and a tied observation contributes zero. For sufficiently large samples, the standardized test statistic was calculated as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & S < 0 \end{cases} \quad (8)$$

The variance of S ($\text{Var}(S)$), accounting for tied observations, was calculated using:

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{p=1}^q tp(tp-1)(2tp+5)}{18} \quad (9)$$

where tp is the number of observations in the p^{th} group of tied values. The M-K test was conducted separately for each month to identify specific months exhibiting significant temporal changes. Annual and seasonal trend analyses were also performed to provide broader temporal interpretation.

Sen's Slope Estimator

Sen's slope estimator was employed to quantify the magnitude and direction of trends in monthly solar radiation. The slope between each pair of observations was calculated as:

$$Q_{ij} = \frac{X_j - X_i}{j - i} \quad (10)$$

where X_j and X_i represent observations at times j and i , respectively. All possible pairwise slopes were ranked, and the median slope was adopted as Sen's slope estimate. Positive values indicate increasing trends, whereas negative values indicate decreasing trends (Sen, 1968). The Sen's slope estimates were interpreted alongside the M-K test to determine both the magnitude and the statistical significance of the observed trends.

Innovative Trend Analysis

Innovative Trend Analysis (ITA) was applied as a complementary graphical trend-detection method. For each selected monthly series, the ten-year observations were divided into two equal sub-series: (2014-2018) and (2019-2023) using:

$$ITA = \frac{2}{n} \sum_{i=1}^{n/2} (Y_i - X_i) \quad (11)$$

where X_i represents the ranked value from the first (earlier) sub-series, Y_i indicates the corresponding ranked value from the second (later) sub-series, and n is the total number of observations. Each sub-series was independently arranged in ascending order. The ranked observations from the first sub-series were plotted against those from the second sub-series. A 1:1 reference line was then introduced. The interpretation was based on the position of the plotted points relative to the reference line. Points predominantly above the line indicate an increasing tendency, while points predominantly below the line indicate a decreasing tendency. Points distributed around the 1:1 line indicate weak or no systematic change.

Spatial Comparison between FCT and NS

Spatial variability was assessed by comparing the radiation characteristics of FCT and NS. The comparison included differences in monthly, seasonal, and annual mean radiation. The absolute mean difference was calculated as:

$$PD = \left(\frac{A-B}{(A+B)/2} \right) \times 100 \quad (12)$$

This measure expresses the difference between the two locations relative to their combined mean. Spatial

interpolation techniques such as Inverse Distance Weighting or Ordinary Kriging were considered appropriate only where sufficient geographically distributed stations were available.

Spearman Rank Correlation Analysis

Spearman's rank correlation coefficient was used to evaluate monotonic relationships between solar radiation and available meteorological variables. The coefficient was calculated as:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (13)$$

where d_i is the difference between the ranks of paired observations, and the value of ρ ranges from (-1) to (+1). A positive value indicates a positive monotonic relationship, while a negative value indicates an inverse relationship. Values close to zero indicate weak or negligible monotonic association. The significance of the correlation coefficients was evaluated at $\alpha = 0.05$, corresponding to a 95% confidence level.

RESULTS AND DISCUSSION

Monthly Variation in Mean Daily Global Solar Radiation

Figure 1 shows a pronounced seasonal cycle in mean daily global solar radiation (MDGSR) at both FCT (Abuja) and NS during 2014–2023, with consistently higher values in NS. In FCT, radiation increased from January, peaked at $17.56 \text{ MJm}^{-2}\text{day}^{-1}$ in February, and then declined to a minimum of $10.12 \text{ MJm}^{-2}\text{day}^{-1}$ in August. Radiation subsequently recovered from September and remained relatively high through November and December. This seasonal pattern aligns with previous observations for FCT, where radiation generally decreases during the wet season and reaches its lowest values around August. The pronounced reduction in FCT radiation from May to August reflects the influence of the wet-season atmospheric regime. Increased cloud cover reduces incoming shortwave radiation through reflection and absorption, while atmospheric water vapor and aerosols further attenuate solar

radiation (NASA, 2024; WMO, 2024). The August minimum therefore reflects the combined effect of seasonal atmospheric attenuation rather than a reduction in the availability of extraterrestrial solar energy. The subsequent increase from September toward December suggests improving atmospheric transmission as the wet season weakens.

NS recorded substantially higher radiation throughout the year, ranging from $15.64 \text{ MJm}^{-2}\text{day}^{-1}$ in July to $24.87 \text{ MJm}^{-2}\text{day}^{-1}$ in January. The decline toward July and subsequent increase toward December indicate a strong seasonal cycle similar to FCT, though at a higher magnitude. Comparable seasonal variability has been reported in NS (Mamman et al., 2020). The consistently higher values observed in the present NS series suggest greater solar-resource availability during every month of the study period; however, the underlying causes of this spatial difference cannot be established from radiation data alone and may involve differences in local atmospheric and geographical conditions.

The variability statistics further distinguish radiation stability between the two locations, as summarized in Tables 1 and 2. FCT recorded monthly coefficients of variation (CVs) of 1.56–10.65%, with the highest variability in June and the lowest in December. This indicates that radiation conditions were less stable during the transition into the wet season, whereas December was more consistent. In contrast, NS recorded substantially lower CVs of 0.47–3.42%, suggesting greater stability during the study period. The seasonal reduction in radiation at both locations broadly corresponds with the wet season, when increased cloudiness and atmospheric moisture can attenuate incoming solar radiation. Overall, the results demonstrate strong intra-annual seasonality, consistently higher radiation in NS, and greater relative stability there than in FCT. These spatial and temporal differences are important for PV resource assessment, energy-yield estimation, and system planning in the region.

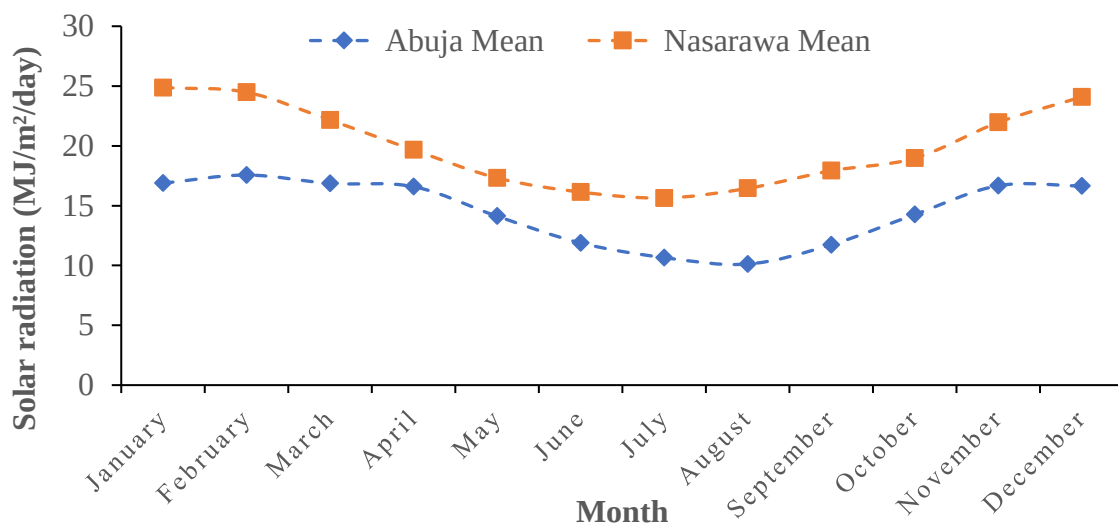


Figure 1: Monthly Variation in MDGSR for FCT (Abuja) and Nasarawa State (NS)

Table 1: Descriptive Statistics of Monthly Solar Radiation for FCT (Abuja)

Month	Mean	SD	Var	CV%	S	Var(S)	Z	p-value	Trend
Jan	16.88	0.44	0.19	2.59	7	123	0.54	0.60	Not Significant
Feb	17.56	0.87	0.75	4.94	17	120.33	1.46	0.15	Not Significant
Mar	16.86	0.75	0.56	4.44	10	121.33	0.82	0.42	Not Significant
Apr	16.59	0.76	0.58	4.58	6	119.33	0.46	0.66	Not Significant
May	14.12	1.10	1.21	7.78	12	124.00	0.99	0.33	Not Significant
Jun	11.88	1.27	1.60	10.65	24	121.33	2.09	0.03	Significant*

Month	Mean	SD	Var	CV%	S	Var(S)	Z	p-value	Trend
Jul	10.66	0.62	0.39	5.85	6	124.00	0.45	0.66	Not Significant
Aug	10.12	0.75	0.56	7.42	11	116.33	0.93	0.36	Not Significant
Sep	11.73	0.76	0.58	6.47	-7	123.00	-0.54	0.60	Not Significant
Oct	14.26	1.35	1.82	9.47	12	124.00	0.99	0.33	Not Significant
Nov	16.67	0.51	0.26	3.05	9	120.33	0.73	0.48	Not Significant
Dec	16.65	0.26	0.07	1.56	3	120.33	0.18	0.86	Not Significant

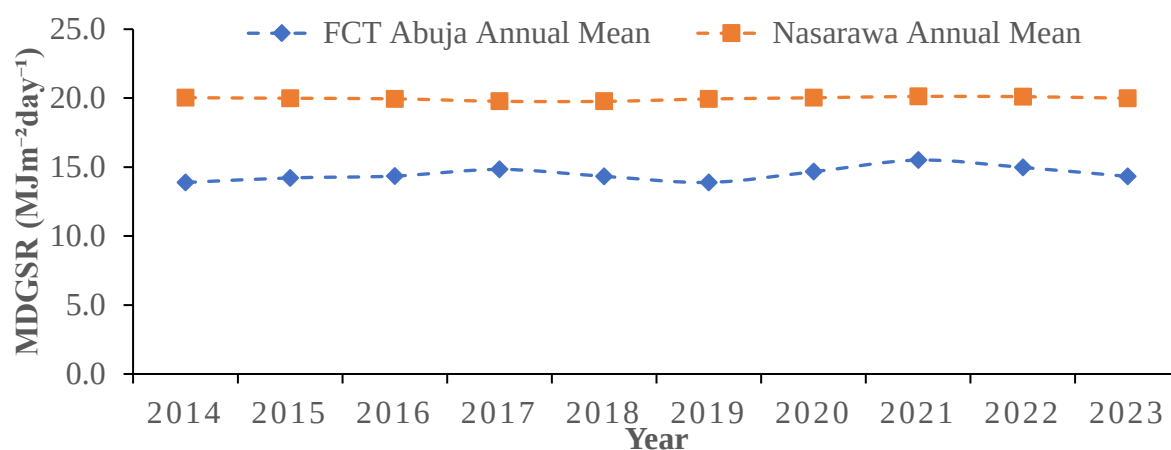
Table 2: Descriptive Statistics of Monthly Solar Radiation for NS

Month	Mean	SD	Var	CV%	S	Var(S)	Z	p-value	Trend
Jan	16.88	0.44	0.19	2.59	7	123	0.54	0.60	Not Significant
Feb	17.56	0.87	0.75	4.94	17	120.33	1.46	0.15	Not Significant
Mar	16.86	0.75	0.56	4.44	10	121.33	0.82	0.42	Not Significant
Apr	16.59	0.76	0.58	4.58	6	119.33	0.46	0.66	Not Significant
May	14.12	1.10	1.21	7.78	12	124.00	0.99	0.33	Not Significant
Jun	11.88	1.27	1.60	10.65	24	121.33	2.09	0.03	Significant*
Jul	10.66	0.62	0.39	5.85	6	124.00	0.45	0.66	Not Significant
Aug	10.12	0.75	0.56	7.42	11	116.33	0.93	0.36	Not Significant
Sep	11.73	0.76	0.58	6.47	-7	123.00	-0.54	0.60	Not Significant
Oct	14.26	1.35	1.82	9.47	12	124.00	0.99	0.33	Not Significant
Nov	16.67	0.51	0.26	3.05	9	120.33	0.73	0.48	Not Significant
Dec	16.65	0.26	0.07	1.56	3	120.33	0.18	0.86	Not Significant

Annual Variation in Mean Daily Global Solar Radiation (MDGSR)

Figure 2 presents the interannual variability of mean daily global solar radiation (MDGSR) across the FCT and NS during 2014–2023. The results reveal distinct differences in radiation magnitude, alongside relatively stable annual patterns at both locations. NS consistently recorded higher MDGSR values, ranging approximately from 19.6 to 20.1 $\text{MJm}^{-2}\text{day}^{-1}$, compared with 13.8–15.3 $\text{MJm}^{-2}\text{day}^{-1}$ in FCT. This persistent disparity suggests spatial heterogeneity in solar radiation availability across the study area. At FCT, MDGSR exhibited noticeable interannual fluctuations, increasing from approximately 13.8 $\text{MJm}^{-2}\text{day}^{-1}$ in 2014 to a

maximum of 15.3 $\text{MJm}^{-2}\text{day}^{-1}$ in 2021, before declining to about 14.2 $\text{MJm}^{-2}\text{day}^{-1}$ in 2023. Conversely, NS demonstrated comparatively limited variability, maintaining values close to 20.0 $\text{MJm}^{-2}\text{day}^{-1}$ throughout the observation period. The contrasting amplitudes suggest greater temporal variability in FCT than NS (Ohunakin et al., 2015). Nevertheless, the observed fluctuations do not independently establish statistically significant trends. Accordingly, the subsequent M-K test and Sen's slope estimator are essential for distinguishing persistent monotonic changes from natural interannual variability and quantifying their respective directions and magnitudes.

**Figure 2: Annual Variation of MDGSR for FCT and NS**

Annual RAI

Figure 3(a-b) shows marked interannual fluctuations in the Radiation Anomaly Index (RAI) for FCT and NS during 2014–2023. FCT exhibited both positive and negative departures, with the strongest positive anomaly in 2021 ($\text{RAI} = 2.00$) and the strongest negative anomaly in 2014 ($\text{RAI} = -1.22$), followed closely by 2019 ($\text{RAI} = -1.20$) (Figure 3a). The alternation between positive and negative values indicates that annual radiation varied considerably around the

study-period mean rather than following a uniform pattern (Table 3). NS also displayed substantial interannual variability, but its most pronounced negative conditions occurred during 2017–2019, with the minimum RAI of approximately -1.69 in 2018 (Figure 3b). This was followed by a shift toward positive anomalies, culminating in 2021 ($\text{RAI} = 1.27$). The simultaneous positive anomalies in 2021 at both locations coincide with the highest annual radiation recorded at the two sites, suggesting that this year represented

an unusually favorable radiation condition relative to their respective study-period means. Conversely, negative anomalies identify years when radiation availability fell below the respective baseline. The contrasting anomaly magnitudes indicate that interannual departures were not spatially uniform, despite the broadly similar temporal pattern. Such variability is consistent with previous studies reporting significant interannual variability of solar irradiance

across Nigeria (Ohunakin et al., 2015). Current research also shows that radiation variability can affect PV energy production and the reliability of resource estimates. The RAI results demonstrate that reliance on mean radiation alone may obscure unusually favorable or unfavorable years. Incorporating anomalous conditions into solar-resource assessment can therefore improve the reliability of PV energy-yield estimates and system planning.

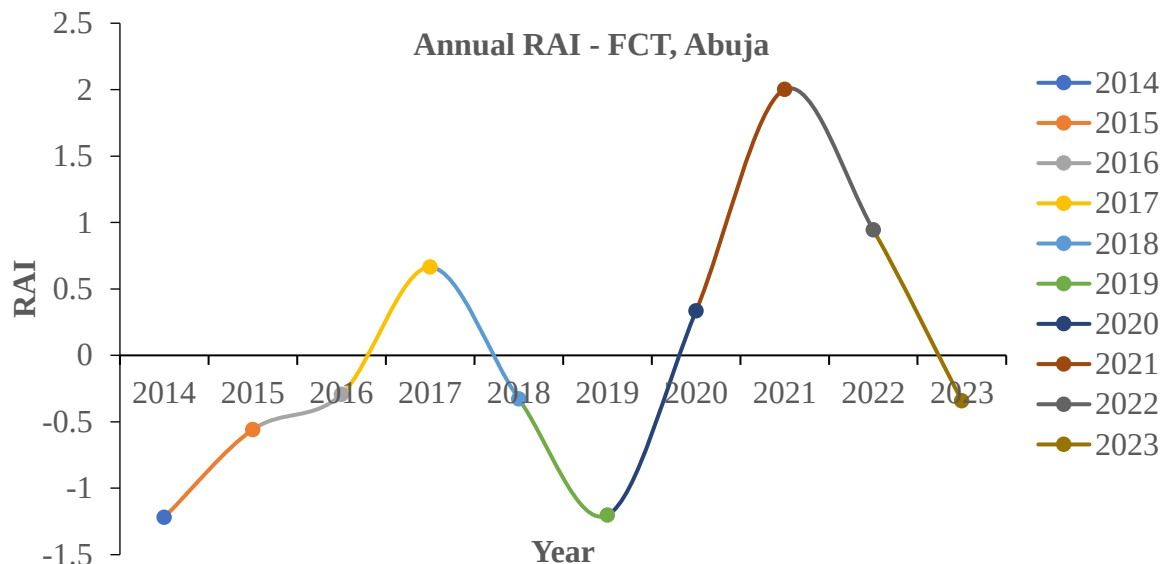


Figure 3a: Annual RAI for FCT, Abuja

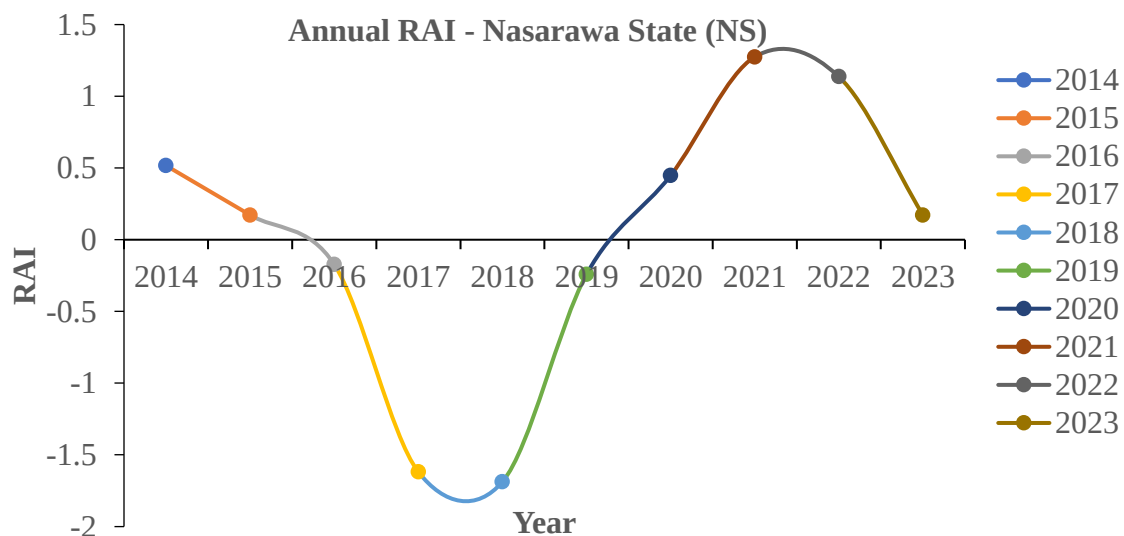


Figure 3b: Annual RAI for NS

Table 3: Annual RAI for FCT and NS

Year	RAI, FCT	Classification	RAI, NS	Classification
2014	-1.22	Negative	0.52	Positive
2015	-0.56	Negative	0.17	Positive
2016	-0.29	Negative	-0.17	Negative
2017	0.66	Positive	-1.62	Negative
2018	-0.33	Negative	-1.69	Negative
2019	-1.20	Negative	-0.24	Negative
2020	0.33	Positive	0.45	Positive
2021	2.00	Strong positive	1.27	Positive
2022	0.94	Positive	1.14	Positive
2023	-0.34	Negative	0.17	Positive

Sen's Slope Analysis

Figure 4 illustrates the magnitude and direction of monotonic changes in annual MDGSR across the FCT and NS during 2014–2023. Sen's slope, a robust non-parametric estimator derived from the median of pairwise slopes, provides a reliable measure of temporal change in environmental datasets (Sen, 1968). FCT exhibited a positive Sen's slope of $+0.1083 \text{ MJm}^{-2}\text{day}^{-1}\text{year}^{-1}$, indicating an upward tendency in annual solar radiation. In contrast, NS recorded a substantially smaller positive slope of $+0.0094 \text{ MJm}^{-2}\text{day}^{-1}\text{year}^{-1}$, suggesting comparatively stable radiation conditions throughout the observation period. Despite these positive estimates, the corresponding Mann–Kendall (M–K) statistics

(FCT: $S = 17$, $p = 0.156$; NS: $S = 7$, $p = 0.601$) indicate that neither location exhibited a statistically significant monotonic trend at the 5% significance level. The contrasting slope magnitudes therefore represent differences in estimated temporal tendencies rather than statistically established increases. Importantly, integrating Sen's slope with the M-K test provides complementary insights into trend magnitude and statistical significance. These findings underscore the importance of distinguishing apparent directional changes from statistically supported long-term trends when evaluating solar radiation variability and its implications for regional solar-energy assessment (Sen, 1968; Garba & Udokpoh, 2023).

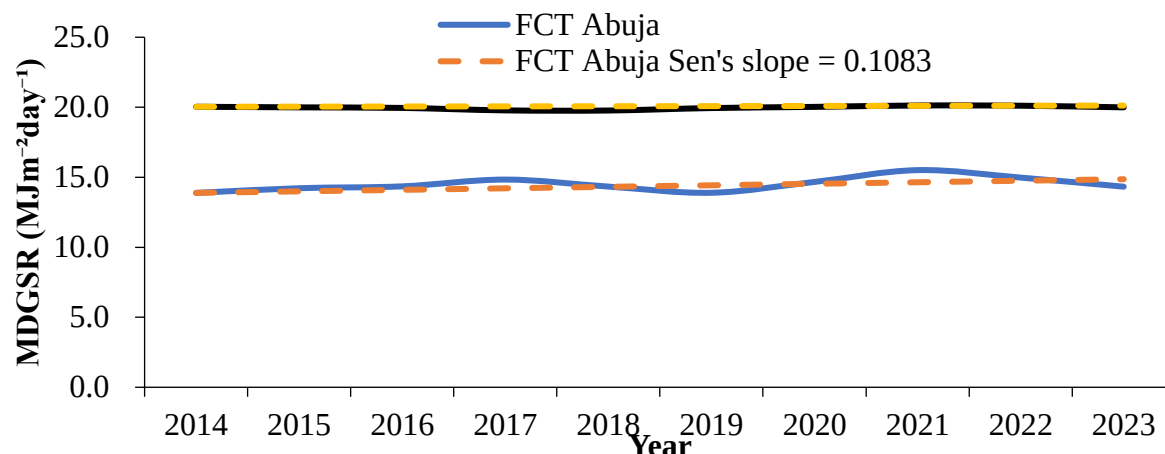


Figure 4: Sen's Slope Trend for Annual Solar Radiation for FCT and NS

Spearman's Rank Correlation Analysis

The two locations show broadly similar seasonal patterns, with relatively high radiation values occurring during the drier months and lower values concentrated around the middle of the year. This pattern is consistent with the pronounced seasonal cycle identified in Figure 5(a–b), particularly the reduction in solar radiation during the wet-season months. Similar seasonal behavior has been reported for the FCT and other locations in Nigeria, where increased cloudiness and atmospheric moisture during the rainy season have been associated with reductions in surface solar radiation (Isikwue et al., 2014; Olasope et al., 2023). Although the overall seasonal cycles at the two locations are comparable, differences in the magnitude of monthly radiation indicate that the two observation records do not respond identically

throughout the year. These differences are particularly useful for the present study because the objective is not only to describe the seasonal pattern but also to compare the temporal behavior of the two observation locations. Figure 5(a–b) is therefore included to demonstrate the consistency and differences in the monthly ordering and seasonal behavior of radiation between FCT and NS. Rather than using rank correlation as a separate measure of trend, the rank patterns provide a complementary descriptive perspective on the strong seasonality already identified through the monthly and seasonal analyses. The findings reinforce that solar radiation at both locations is strongly seasonal, while also demonstrating that the magnitude and timing of monthly variations are not completely identical between the two observation records.

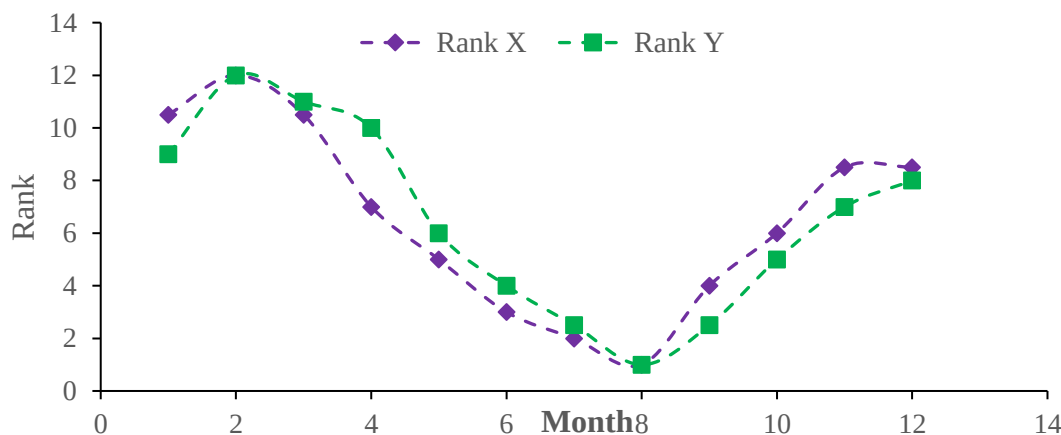


Figure 5a: Spearman's Ranked Monthly Solar-radiation Observations for FCT

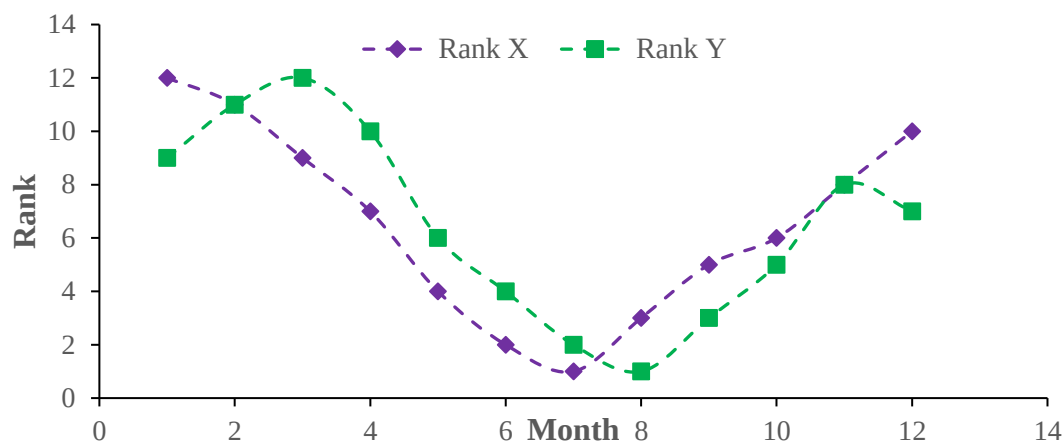


Figure 5b: Spearman's Ranked Monthly Solar-radiation Observations for NS

Innovative Trend Analysis (ITA)

Figure 6 presents ITA results for January, April, July, and October, spanning different phases of the annual radiation cycle. The analysis compares the first half of the record (2014–2018) with the second half (2019–2023), with the 1:1 line indicating no change between the two periods (Table 4). This approach provides a graphical assessment of shifts in the distribution of radiation values between the two sub-periods (Şen, 2012). The results indicate month-dependent changes rather than a uniform shift throughout the year. In FCT, January and April showed slight increases in mean radiation from 16.84 to 16.92 $\text{MJm}^{-2}\text{day}^{-1}$ and 16.56 to 16.62 $\text{MJm}^{-2}\text{day}^{-1}$, respectively (Figure 6a-b; Table 5). July declined slightly from 10.76 to 10.56 $\text{MJm}^{-2}\text{day}^{-1}$, whereas October increased from 14.10 to 14.42 $\text{MJm}^{-2}\text{day}^{-1}$ (Figure 6c-d). NS exhibited predominantly stable-to-increasing behavior, with January increasing from 24.58 to 25.16 $\text{MJm}^{-2}\text{day}^{-1}$, April from 19.56 to 19.76 $\text{MJm}^{-2}\text{day}^{-1}$, and July from 15.60 to 15.68 $\text{MJm}^{-2}\text{day}^{-1}$, as shown in Figure 6(e-g). October showed virtually no change (18.96 to 18.98 $\text{MJm}^{-2}\text{day}^{-1}$) (Figure 6h).

The contrasting monthly responses indicate that changes in solar radiation were seasonally heterogeneous, with FCT showing both upward and downward shifts and NS exhibiting generally weaker changes. This finding complements the M-K and Sen's slope results by showing that temporal behavior can vary across months even when the annual series shows only a weak overall tendency. Similar applications of ITA to solar-radiation data have demonstrated the value of examining monthly behavior rather than relying exclusively on annual aggregates. However, the ITA results should be interpreted cautiously because the analysis is based on only five observations in each sub-period. Methodological studies have shown that ITA plots are closely related to two-sample quantile-quantile plots and that their interpretation can be sensitive to sample size, distributional characteristics, and serial dependence (Serinaldi et al., 2020). Accordingly, the present ITA results are best regarded as graphical evidence of distributional shifts between the two periods, while the M-K test and Sen's slope provide the principal basis for formal trend assessment.

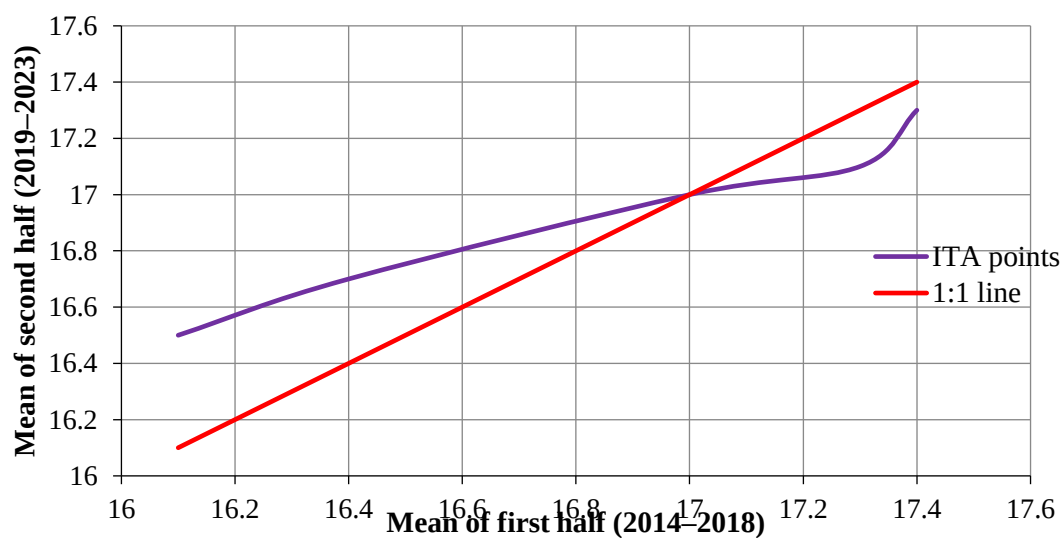


Figure 6a: ITA of Monthly Solar Radiation in FCT for January (2014–2023)

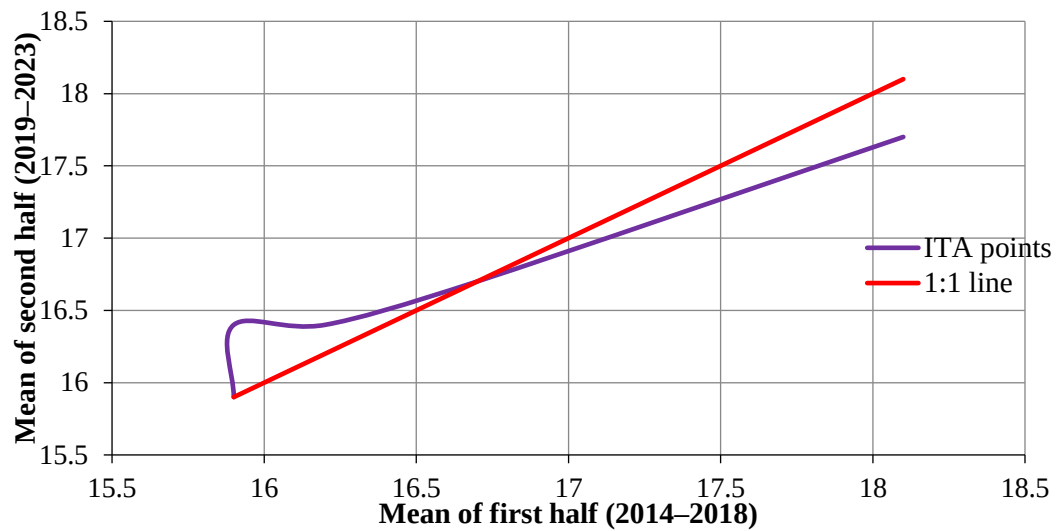


Figure 6b: ITA of Monthly Solar Radiation in FCT for April (2014–2023)

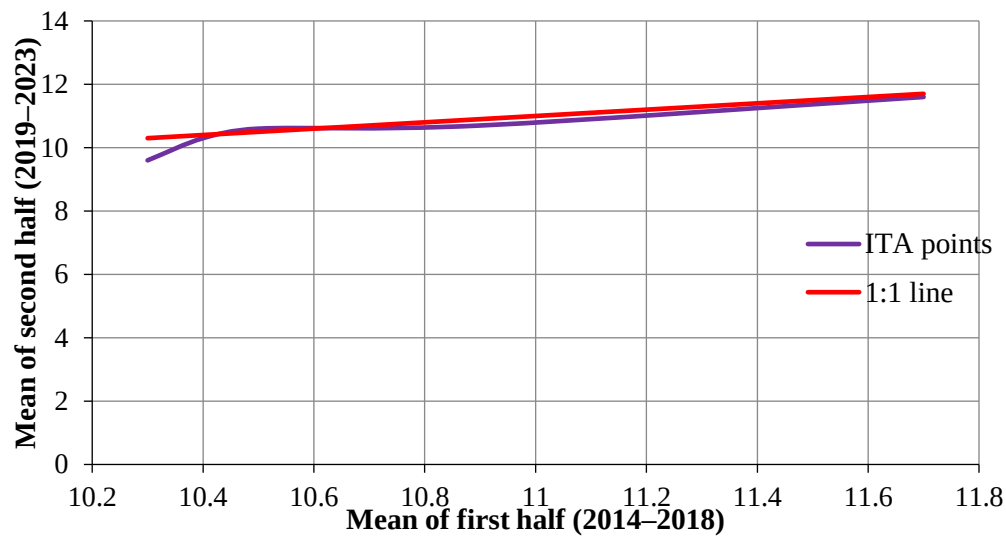


Figure 6c: ITA of Monthly Solar Radiation in FCT for July (2014–2023)

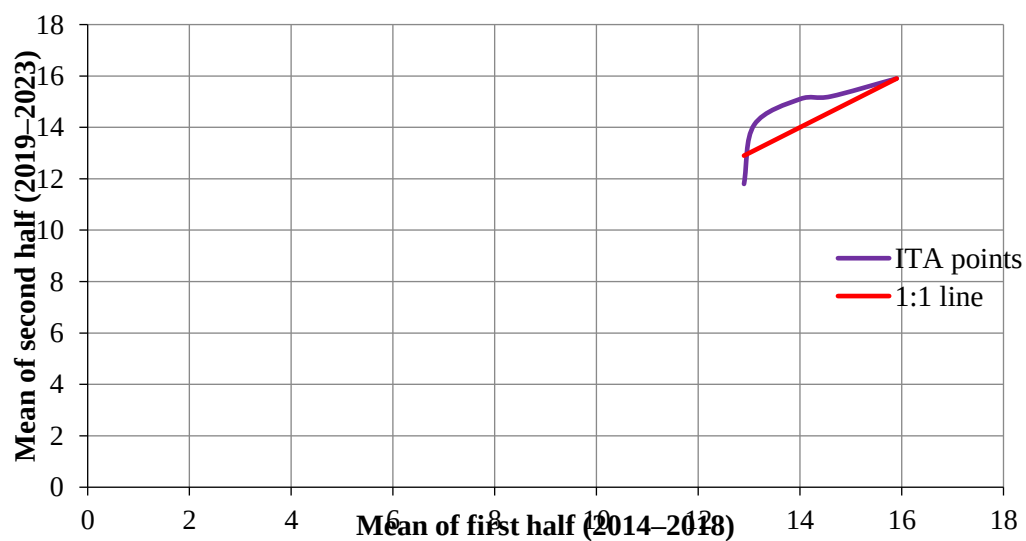


Figure 6d: ITA of Monthly Solar Radiation in FCT for October (2014–2023)

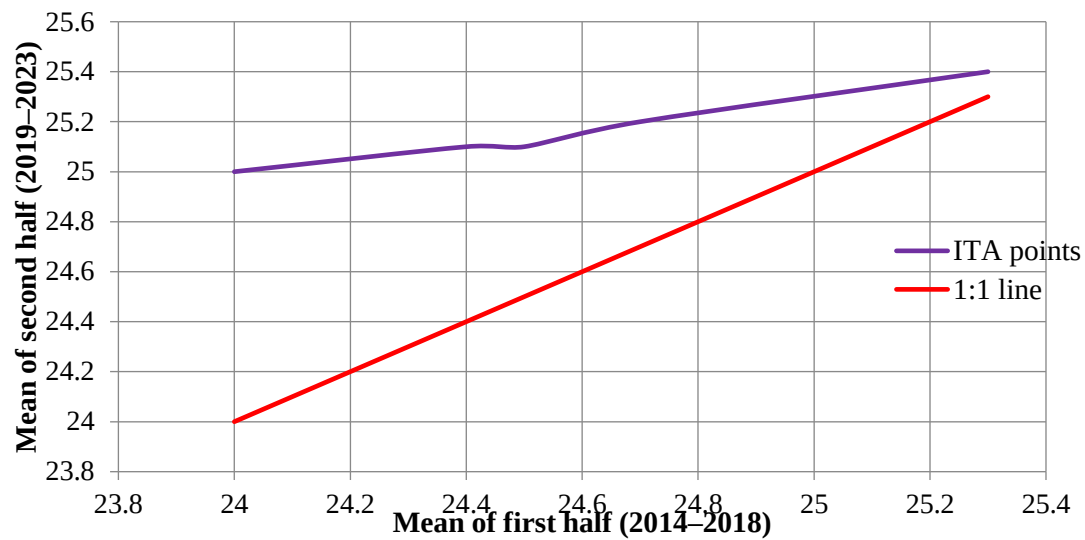


Figure 6e: ITA of Monthly Solar Radiation in NS for January (2014–2023)

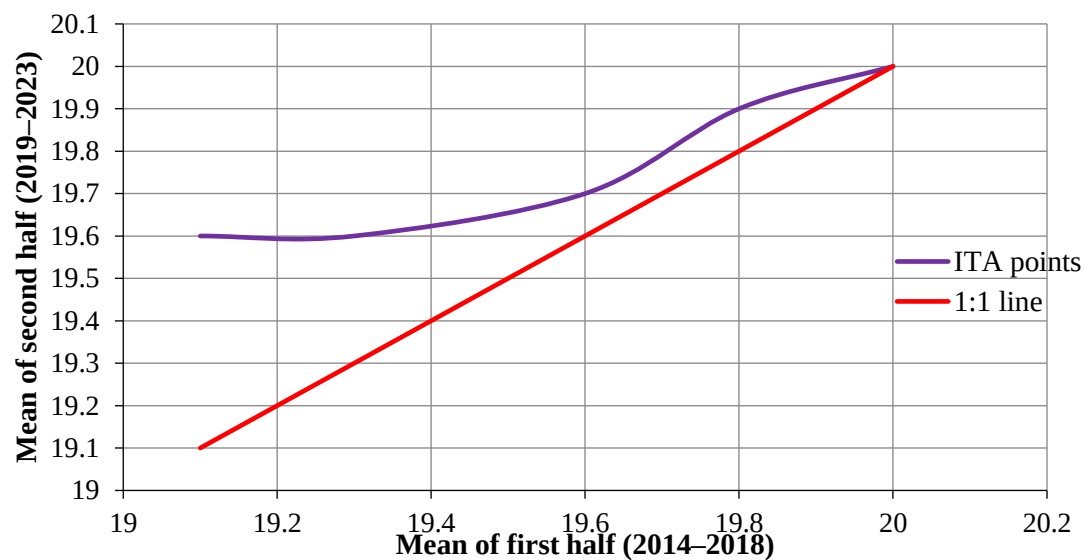


Figure 6f: ITA of Monthly Solar Radiation in NS for April (2014–2023)

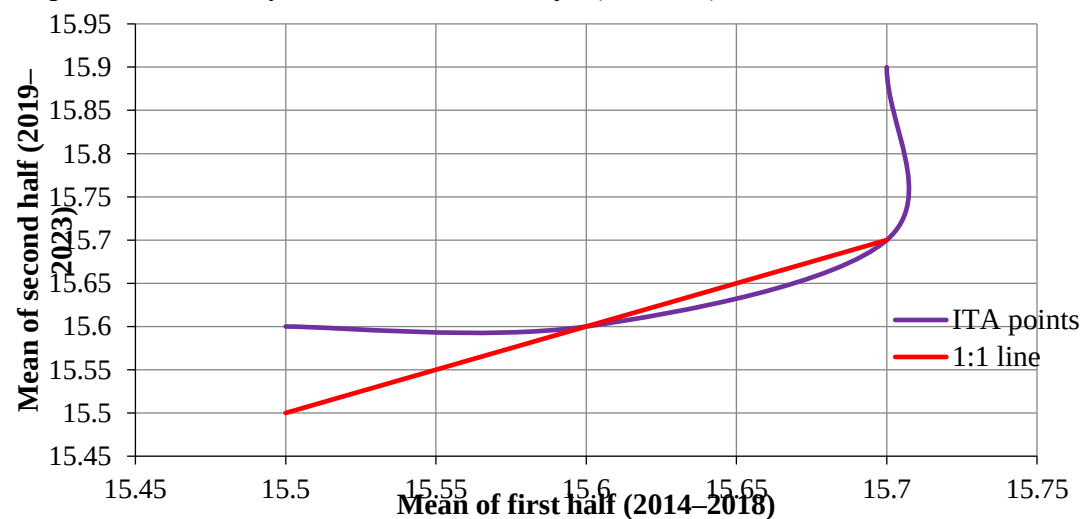


Figure 6g: ITA of Monthly Solar Radiation in NS for July (2014–2023)

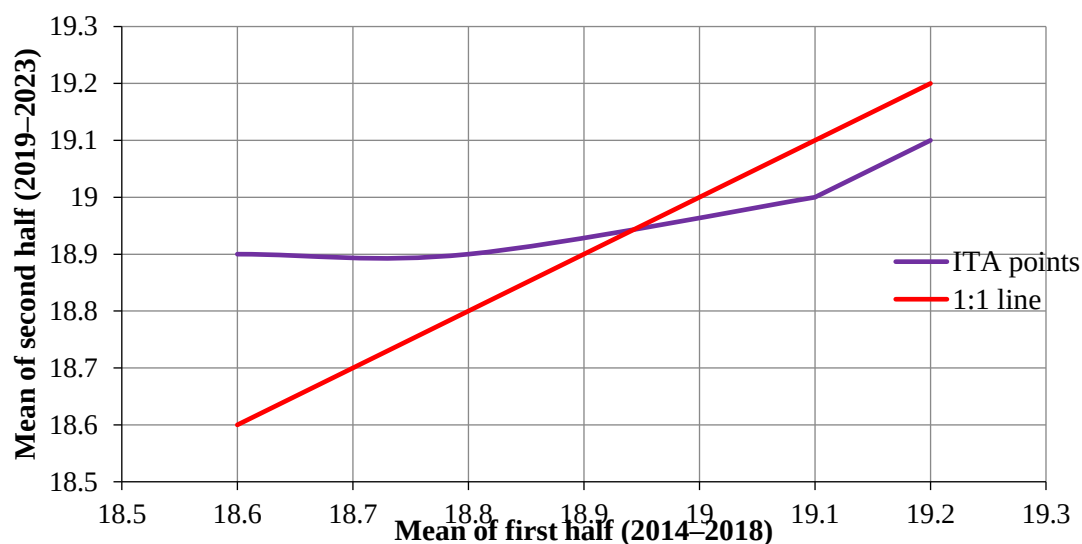


Figure 6h: ITA of Monthly Solar Radiation in NS for October (2014–2023)

Table 4: ITA of Solar Radiation for January, April, July, and October in FCT and NS (2014–2023)

Location	Month	First-half mean	Second-half mean	ITA interpretation
FCT	January	16.84	16.92	Increasing
FCT	April	16.56	16.62	Increasing
FCT	July	10.76	10.56	Decreasing/No increase
FCT	October	14.1	14.42	Increasing
NS	January	24.58	25.16	Increasing
NS	April	19.56	19.76	Increasing
NS	July	15.6	15.68	Increasing
NS	October	18.96	18.98	Increasing

Seasonal Distribution and Variability

Figure 7(a-c) shows a clear separation between dry- and wet-season solar radiation in both FCT and NS. Radiation was consistently higher during the dry season and lower during the wet season, confirming the seasonal pattern observed in the monthly analysis. This behavior aligns with observations from other Nigerian locations, where increased cloud cover and atmospheric humidity during the wet season substantially attenuate incoming solar radiation, while comparatively clearer conditions favor higher surface radiation during the dry season (Soneye et al., 2019). The magnitude of the seasonal contrast differed between the two locations. FCT showed a more pronounced separation between dry- and wet-season radiation, particularly in years with relatively high wet-season values (Figure 7a). In contrast, NS maintained a

higher and more stable radiation regime across both seasons (Figure 7b). This finding aligns with previous investigations in NS that reported substantial seasonal differences in solar radiation, including markedly lower values during July–August (Mamman et al., 2020). The seasonal comparison demonstrates that solar-resource availability cannot be adequately represented by annual averages alone (Figure 7c). The persistence of higher dry-season and lower wet-season radiation has direct implications for seasonal photovoltaic energy yield, system sizing, and energy-management strategies. The results confirm seasonality as a dominant characteristic of the solar-radiation regime in both study locations, while also revealing meaningful differences in the magnitude and stability of the seasonal resource.

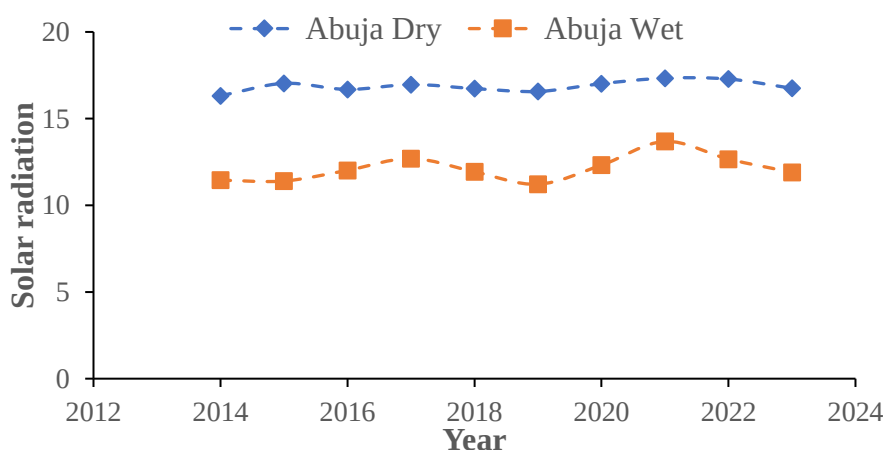


Figure 7a: Seasonal Distribution and Variability in FCT, Abuja

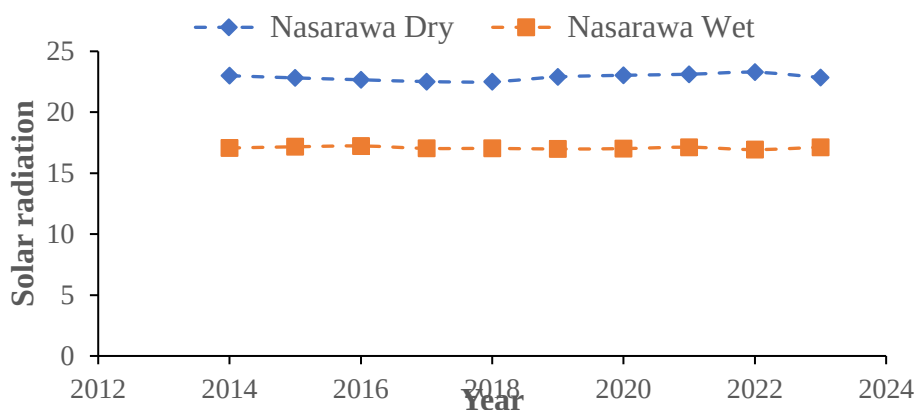


Figure 7b: Seasonal Distribution and Variability in Nasarawa State (NS)

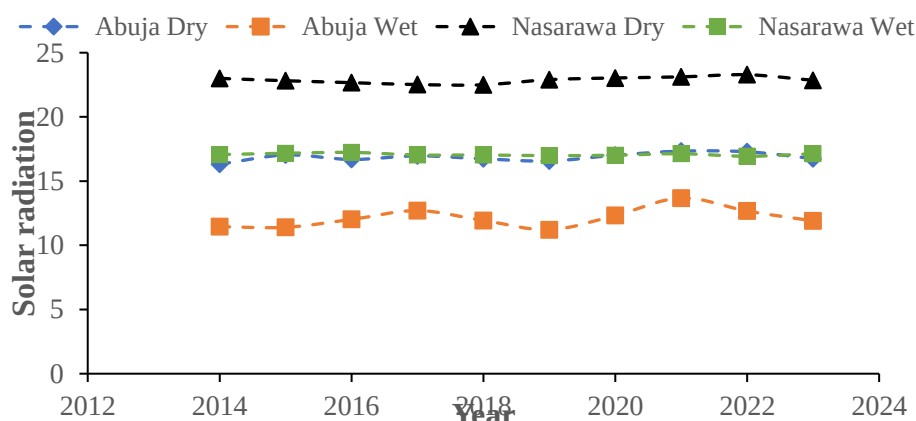


Figure 7c: Comparison of Seasonal Distribution and Variability in FCT, Abuja and Nasarawa State (NS)

M-K Trend Analysis

Table 5 presents the annual M-K trend statistics and Sen's slope estimates for MDGSR across the FCT and NS during 2014–2023. The results reveal positive but statistically non-significant monotonic tendencies at both locations. FCT recorded an M-K statistic of $S = 17$, $Z = 1.431$ and $p = 0.156$, with a Sen's slope of $+0.1083 \text{ MJm}^{-2}\text{day}^{-1}\text{year}^{-1}$. Conversely, NS exhibited $S = 7$, $Z = 0.537$ and $p = 0.601$, with a considerably smaller slope of $+0.0094 \text{ MJm}^{-2}\text{day}^{-1}\text{year}^{-1}$. Since both p-values exceed the 0.05 significance threshold, the null hypothesis of no monotonic trend cannot be rejected at either location. Although FCT demonstrated a greater

estimated rate of increase, this difference does not establish a statistically significant contrast between the locations. The positive slopes indicate directional tendencies rather than confirmed long-term increases (Sen, 1968; Garba & Udokpoh, 2023). Furthermore, the Holm-Bonferroni-adjusted monthly results revealed no statistically significant trends at the 5% family-wise error level. Collectively, these findings indicate that the observed radiation fluctuations are not supported by statistically significant monotonic trends, highlighting the importance of combining M-K significance testing with Sen's slope estimation for robust environmental trend assessment.

Table 5: M-K Trend and Sen's Slope Results for FCT and NS

Location	M-K (S)	Var (S)	Z	Exact p-value	Sen's slope	Trend
FCT	17	125	1.431	0.156	+0.1083	Increasing (Not significant)
NS	7	125	0.537	0.601	+0.0094	Increasing (Not significant)

CONCLUSION

Solar radiation across FCT and NS exhibited pronounced seasonal and interannual variability during 2014–2023, with generally higher values during the dry season. Although positive Sen's slopes were observed at both locations, M-K tests revealed no statistically significant annual trend. At the monthly scale, some apparent significant trends were identified before adjustment; however, none remained statistically significant after Holm-Bonferroni correction for multiple testing. Thus, the observed monthly variations do not constitute robust evidence of persistent month-specific trends. Nevertheless, the radiation regime demonstrates considerable potential for photovoltaic applications in North-Central

Nigeria. Longer, quality-controlled datasets are recommended for more robust assessment of future solar-resource changes.

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