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Assessment of solar radiation resource from the NASA-POWER reanalysis products for tropical climates in Ghana towards clean energy application

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Abstract:

In order to expand the output of solar power systems for efficient integration into the national grid, solar energy resource assessment at site is required. A major impediment however, is the widespread scarcity of radiometric measurements, which can be augmented by satellite observation. This paper assessed the suitability of satellite-based solar radiation resource retrieved from the NASA-POWER archives at $0.5^\circ \times 0.5^\circ$ spatial resolution over Ghana - West Africa, to develop a long-term source reference. The assessment is based on the criteria of comparison with estimations from sunshine duration measurement for 22 synoptic stations. Overall, the satellite-based data compared well with ground-based estimations by $r = 0.6 - 0.94 \pm 0.1$. Spatiotemporally, the agreement is strongest over the northern half Savannah-type climate during March-May, and weakest over the southern half Forest-type climate during June-August. The assessment provides empirical framework to support solar energy utilization in the sub-region.

Keywords: NASA-POWER; Global solar radiation; Solar energy; Ghana-West Africa

1. Introduction

Solar energy resource assessment is critical for accurate evaluation of the quantity of incoming solar radiation available to develop, install, and operationalize highly efficient solar power technologies [1, 2]. The task primarily involves development of a comprehensive climatological solar radiation and related parameters database at short-time intervals, an in-depth grasp of the spatiotemporal distribution and correlations, and accurate forecasts to ascertain precisely the performance of solar power systems and the technical effect of solar radiation variability on national electric grids. However, due to sparse or non-existent solar radiation measurement stations in many parts of the world, the gap between installation and performance modeling widens [3 - 6]

In the last recent decade, retrieving satellite products for solar energy resource assessment has become a state-of-the-art technique to bridge the gap of insufficient or non-existent solar radiation measurement stations [3, 4, 7], especially as satellite products have the advantage of wide coverage [8 - 10]. Many studies have used satellite-based observations to predict solar radiation and develop estimation models especially in areas where insolation measurement stations are completely non-existent, towards efficient power generation [4, 8, 10, 11, 12, 13]. However, despite the promising potentials of wide-coverage and quick-time earth observations associated with satellite-based datasets, a major application challenge immediately confronting the scientific community is resolution and local climate-specific representation viz. data accuracy. For example, Dubovik [14] and Kim [15] have clearly identified the limitation of high-orbit geostationary satellites in capturing surface phenomena at high resolution despite the advantage of wide spatial coverage over their Low-Earth Orbit satellite counterparts. Thus generally, wider spatial capture results in poor spatial resolution. Owing to this, reliance on satellite-based observations require synergistic support from ground data in the form of validation, merging, and reanalysis [14].

Over the years, the National Aeronautics and Space Administration (NASA) has made significant efforts to improve satellite atmospheric observation data on a global scale, especially tailored to the needs of the renewable energy industry [16, 17]. For example, development of the Surface Meteorological and Solar Energy (SSE) climatological resource database needed by the photovoltaic and renewable energy industries, was especially targeted at optimizing electric power from renewable energy systems, and ultimately towards the successful integration of the technology into conventional power generation systems [16, 17]. Currently, under the NASA

Science Mission Directorate Applied Science National Application program, the Prediction of Worldwide Energy Resource (POWER) project has been initiated to further improve the SSE database, augment with products retrieved from new satellites, and develop forecast models to serve specifically as decision support tools for the energy sector [18, 19]. Looking forward, the NASA-POWER project is expected to expand with strong stakeholder involvement and industry support [16, 20 - 22].

With this background, the objective of this paper is to assess the suitability of the NASA-POWER Global solar radiation (GSR) products over Ghana in West Africa, which is expected to provide a comprehensive high density network GSR database for a solar resource assessment, as currently no regularized solar measurement stations are reported. Firstly, 35 years sunshine duration measurement datasets were used to estimate and develop a climatological monthly mean GSR dataset, in order to provide a statistical comparative reference for the NASA-POWER climatological GSR datasets. The study will serve a valuable tool to further develop forecasting models for performance enhancement of solar technologies.

2. Methodology

2.1. Geography and climatology of study area

The area of study, Ghana, is on the coastal edge of tropical West African, bounded in latitude 4.5° N and 11.5° N and longitude 3.5° W and 1.5° E, and characterized by a tropical monsoon climate system [23, 26]. Figure 1 shows map of the study area indicating the selected twenty two (22) sunshine measurement stations distributed across the four main climatological zones and Table 1 summarizes the geographical positions of selected stations.



Figure 1: Map of the study area showing all twenty two (22) synoptic stations distributed in four main climatological zones countrywide. Adapted from Asilevi et. al. (2019)

Atmospheric clarity over the area is closely connected to cloud amount distribution and rainfall activities, largely determined by the oscillatory migration of the Inter-Tropical Discontinuity (ITD), accounting for the West African Monsoon (WAM) [27, 28].

Table 1: Geographical position and elevation for selected sites

| Station | Latitude (°) | Longitude (°) | Elevation (m) |
|----------------|---------------------|----------------------|----------------------|
| Wa | 10.05 | -2.5 | 305 |
| Navrongo | 10.9 | -1.1 | 197 |
| Bole | 9.33 | -2.483 | 246.94 |
| Tamale | 9.417 | -0.85 | 152 |
| Yendi | 9.45 | -0.167 | 157 |
| Wenchi | 7.75 | -2.1 | 299 |
| Sunyani | 7.33 | -2.33 | 305 |
| Kete Krachi | 7.817 | -0.33 | 92 |
| Kumasi | 6.717 | -1.6 | 256 |
| Sefwi Bekwai | 6.2 | -2.33 | 186.5 |
| Oda | 5.933 | -0.983 | 151 |
| Abetifi | 6.667 | -0.75 | 601 |
| Koforidua | 6.833 | -0.25 | 199 |
| Ho | 6.6 | 0.467 | 154 |
| Akuse | 6.1 | 0.117 | 107.63 |
| Axim | 4.9 | -2.25 | 71 |
| Takoradi | 4.883 | -1.767 | 74 |
| Salt Pond | 5.2 | -1.67 | 77 |
| Accra | 5.6 | -0.167 | 91 |
| Tema | 5.617 | 0 | 79 |
| Ada | 5.7833 | 0.63 | 15.29 |
| Akatsi | 6.117 | 0.8 | 66.48 |

Owing to the highly variable spatiotemporal distribution of cloud amount vis-à-vis rainfall activities, resulting in contrasting climatic conditions in different parts of the region, the country is partitioned by the Ghana Meteorological Agency (GMet) into four main agro-ecological zones namely, the Savannah, Transition, Forest and Coastal zones as shown in Figure 1 [23]. As a result, the region experiences an estimated Global solar radiation (GSR) intensity peaks in April-May and

then in October-November, with the highest monthly average of $22 \text{ MJm}^{-2}\text{day}^{-1}$ over the savannah climatic zone and the lowest monthly average of $13 \text{ MJm}^{-2}\text{day}^{-1}$ over the forest climatic zone [24].

2.2. Research datasets

The main datasets used for the study comprised of long-term sunshine duration measurements and satellite-derived Global solar radiation (GSR) spanning equal periods of 1983-2018. Daily sunshine duration measurements recorded by the Campbell–Stokes sunshine recorder mounted at the twenty-two (22) selected sites, were used to estimate GSR. Satellite-derived Global solar radiation (GSR) for all 22 stations were retrieved from the National Aeronautics and Space Administration - Prediction of Worldwide Energy Resources (NASA-POWER) reanalysis datasets based on the Modern Era Retrospective-Analysis for Research and Applications (MERRA-2) assimilation model products, which provided climatological reanalysis archive as point datasets spanning equal study period and made accessible via a user friendly web based mapping portal: <https://power.larc.nasa.gov/data-access-viewer/>, at daily and monthly mean temporal scales and $0.5^\circ \times 0.5^\circ$ spatial resolution.

The POWER Project analyzes, synthesizes and makes available data parameters on a global scale, Primarily from NASA's World Climate Research Programme (WCRP), Global Energy and Water cycle Experiment (GEWEX), Surface Radiation Budget (SRB) project (Version 2.9) and the Global Modeling and Assimilation Office (GMAO) [17]. The datasets are widely used in renewable energy application [16, 20], agricultural modelling of crop yields [29], crop simulation exercises [30], and plant disease modelling [31].

2.3. Sunshine measurement based GSR estimation

The climatological estimated GSR datasets (H) was developed from the Angstrom-Prescott sunshine duration model in Equation 1 using previously established model constants and the long-term sunshine duration measurements sourced from the selected synoptic stations [24].

$$H = \left[a + b \frac{n}{N} \right] H_0 \quad (1)$$

were H_0 ($\text{kWhm}^{-2}\text{day}^{-1}$) is the daily extraterrestrial solar radiation on an horizontal surface, n is the daily sunshine duration measurements obtained from the Ghana Meteorological Agency (GMet),

and N is the maximum possible daily sunshine duration or the day length in hours. H_0 was calculated from astronomical parameters by Equation 2:

$$H_0 = \frac{24 \cdot 60}{\pi} \cdot G_{sc} \cdot d_r [\omega_s \sin \varphi \sin \delta + \cos \varphi \cos \delta \sin \omega_s] \quad (2)$$

where G_{sc} is the Solar constant in $\text{MJm}^{-2}\text{min}^{-1}$, d_r is the relative Earth – Sun distance in meters (m), ω_s is the sunset hour angle (angular distance between the meridian of the observer and the meridian whose plane contains the sun), δ is the angle of declination in degrees ($^\circ$) and φ is the local latitude. A detailed presentation of the calculation was published in a previous work [24].

2.4. Statistical assessment analysis

For the purpose of assessing the NASA-POWER derived monthly mean GSR (GSR_n) datasets in comparison with the estimated Global Solar Radiation (GSR_e) datasets used in this paper, the following deviation and correlation methods in Equations 3 - 9, each showing a complimentary result were used: Standard deviation (σ), residual error (RE), Root mean square error (RMSE), Mean bias error (MBE), Mean percentage error (MPE), Pearson's correlation coefficient (r), and Willmott index of agreement (d) for n observations [32 - 36]. GSR_e , GSR_n , and RE represent the estimated GSR, NASA-POWER GSR, and the residual error between GSR_e and GSR_n respectively. A positive RE indicates that sunshine-based estimated GSR is larger than the NASA-POWER reanalysis dataset, while a negative RE indicates that sunshine-based estimated GSR is smaller than the NASA-POWER reanalysis dataset. The arithmetic mean of any dataset is μ .

The standard deviation (σ) was used to check the upper and lower limits of distribution around the mean deviations between GSR_e and GSR_n in order to ascertain violations between both datasets [34]. The RMSE is a standard statistical metric to quantify error margins in meteorology and climate research studies, and by definition is always positive, representing zero in the ideal case, plus a smaller value signifying a good marginal deviation [32]. The MBE is a good indicator for under-or overestimation in observations, with MBE values closest to zero being desirable. The MPE further indicates the percentage deviation between the GSR_e and GSR_n individual datasets [36].

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (GSR - \mu)^2} \quad (3)$$

$$RE = GSR_e - GSR_n \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (RE)^2} \quad (5)$$

$$MBE = \frac{1}{n} \sum_{i=1}^n (RE) \quad (6)$$

$$MPE = \frac{1}{n} \sum_{i=1}^n \left(\frac{RE}{GSR_e} \times 100\% \right) \quad (7)$$

$$r = \frac{\sum_{i=1}^n (GSR_e - \sigma_e)(GSR_n - \sigma_n)}{(n-1)\sigma_e\sigma_n} \quad (8)$$

$$d = 1 - \left[\frac{\sum_{i=1}^n (GSR_e - GSR_n)^2}{\sum_{i=1}^n (|GSR_e - GSR_{n_{ave}}| + |GSR_n - GSR_{n_{ave}}|)^2} \right] \quad (9)$$

Further, as with other statistical studies in meteorology [37], the Pearson's correlation coefficient (r) was used to quantify the strength of correlation between GSR_e and GSR_n . Finally, the Willmott index of agreement (d) commonly used in meteorological literature computed from Equation 7 is used to assess the degree of GSR_e / GSR_n agreement [35].

3. Results and discussions

3.1. Comparison of estimated GSR and NASA-POWER satellite-based GSR

This section compared the time and space variations of climatological estimated monthly mean Global Solar Radiation (GSR_e) and the NASA-POWER Global Solar Radiation (GSR_n) datasets across the study area, in order to ascertain similarities. From Figure 2, it is seen that both GSR_e (Figure 2a) and GSR_n (Figure 2b) show similarity in spatiotemporal distribution countrywide. That is peak insolation between February - May ($GSR_e = 5.5 - 5.7 \text{ kWhm}^{-2}\text{day}^{-1}$; $GSR_n = 5.3 - 5.7 \text{ kWhm}^{-2}\text{day}^{-1}$) with the highest over the Savannah climatic zone, and lowest insolation during the June - September season ($GSR_e = 4.4 - 4.9 \text{ kWhm}^{-2}\text{day}^{-1}$; $GSR_n = 4.4 - 4.7 \text{ kWhm}^{-2}\text{day}^{-1}$), the Forest climatic zone receiving the least in both datasets. Therefore even with slight variations, both datasets show significantly very good spatiotemporal arrangements countrywide. However on a daily scale comparison, relatively higher variations may be expected largely due to the complexities in atmospheric dynamics which have not been well parameterized in the observation satellite sensor [14, 15].

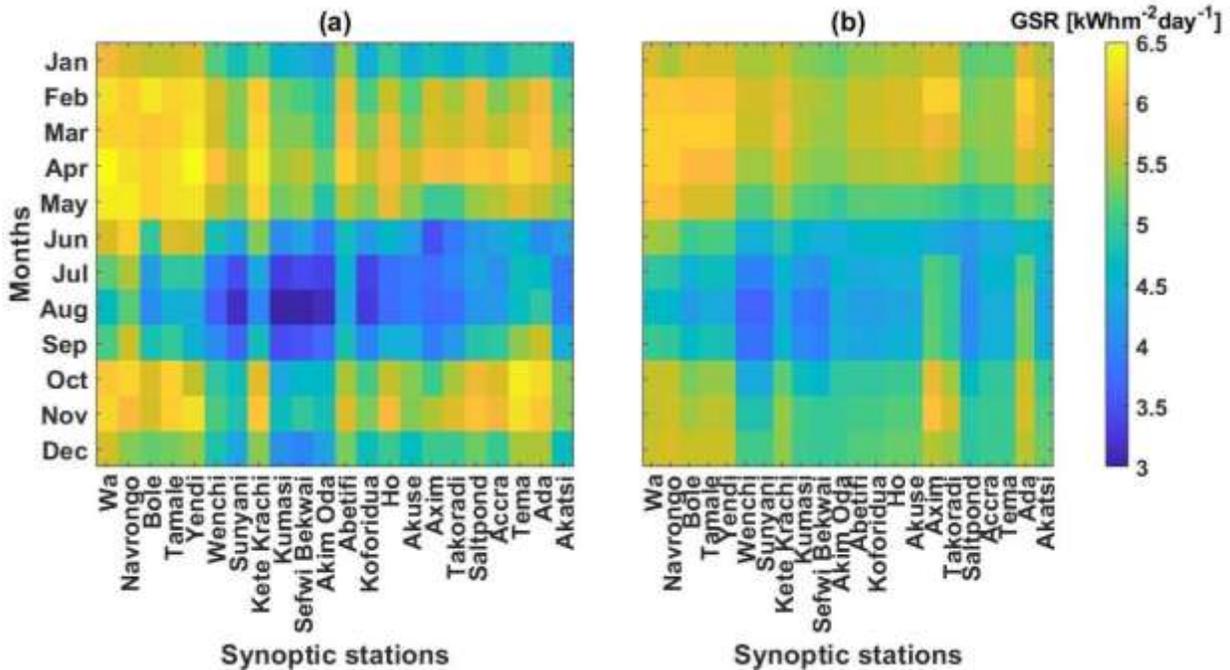


Figure 2: Space and time distribution of (a) estimated monthly mean Global Solar Radiation (GSR_e) and (b) NASA-POWER derived monthly mean GSR (GSR_n)

In a further comparison, Figure 3 shows the total annual GSR and daily maximum-minimum GSR for both datasets in 2018 at four (4) synoptic stations (Accra, Kumasi, Kete Krachi, and Wa) representative of the Coastal, Forest, Transition, and Savannah climatic zones respectively. As seen in Figure 3a, the variation range in annual GSR for both datasets for all four stations is 33.1 - 109 kWhm⁻²day⁻¹, with only the Forest climatic zone showing slight over-estimation in the satellite data.

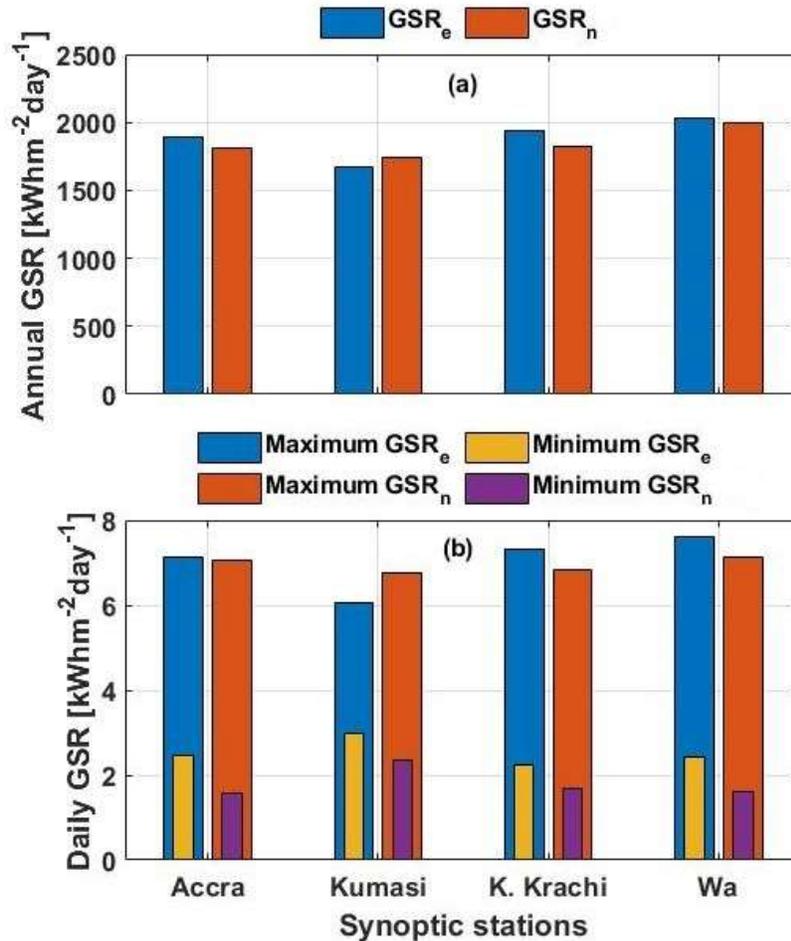


Figure 3: Comparing estimated and NASA-POWER GSR in 2018 on (a) annual total and (b) daily scales at four stations (Accra, Kumasi, Kete Krachi, and Wa) representing the Coastal, Forest, Transition, and Savannah climatic zones respectively.

Again with Figure 3b, the variation range in maximum daily GSR for both datasets for all four stations is 0.09 - 0.71 kWhm⁻²day⁻¹ with similar over-estimation situation for the Forest climatic

zone. Meanwhile, the variation range in minimum daily GSR all showed under-estimation in the satellite datasets with the range of $0.57 - 0.9 \text{ kWhm}^{-2}\text{day}^{-1}$. Under normal circumstances, satellite data rarely shows any exactness with ground measurements. However, considering that the reference GSR in this study was estimated and not a direct measurement, such slight variations are expected. For example, Sayago [18] observed in comparing daily solar radiation retrieved from the NASA-POWER archives with ground measurements in Spain that, high coefficient of correlations was mainly associated with high solar radiation especially on clear days, and the opposite is true. Comparatively in this study, the best similarities are seen with the stations and seasons where high insolation occurs. Monteiro [21] also reported good similarity of correlation coefficient and index of agreement to be 0.71 and 0.92 respectively when the NASA-POWER solar radiation datasets were compared with ground measurements over Brazil.

Meanwhile, in comparison with other studies which assessed a broader range of parameters including relative humidity, precipitation, and wind speeds, it is apparent that the NASA-POWER datasets show more consistency and accuracy with solar radiation related parameters [22].

3.2. Statistical analysis of the $\text{GSR}_e / \text{GSR}_n$ pairwise datasets

This section discussed various statistical approaches targeted at quantifying the strength of similarity between the $\text{GSR}_e / \text{GSR}_n$ pairwise datasets. Figures 4a and 4b show the boxplots for climatological monthly mean seasonal GSR_e and GSR_n datasets respectively. It is evident from the plots that, both GSR_e and GSR_n show semblance in inter-seasonal variation but some significant intra-seasonal variations. Inter-seasonally, both GSR_e ($\mu = 5.135 \pm 0.08 \text{ kWhm}^{-2}\text{day}^{-1}$) and GSR_n ($\mu = 5.137 \pm 0.07 \text{ kWhm}^{-2}\text{day}^{-1}$) show maximum insolation of $6.1 \text{ kWhm}^{-2}\text{day}^{-1}$ and $6.2 \text{ kWhm}^{-2}\text{day}^{-1}$ respectively during March-April-May (MAM) season hence only 0.78% deviation. For both datasets, peak GSR is in MAM. This inter-seasonal variation is obviously related to the annual migration of the ITCZ discussed in under the spatiotemporal comparison [23]. The seasonal variation in GSR distribution across the study area has been discussed by Asilevi [24].

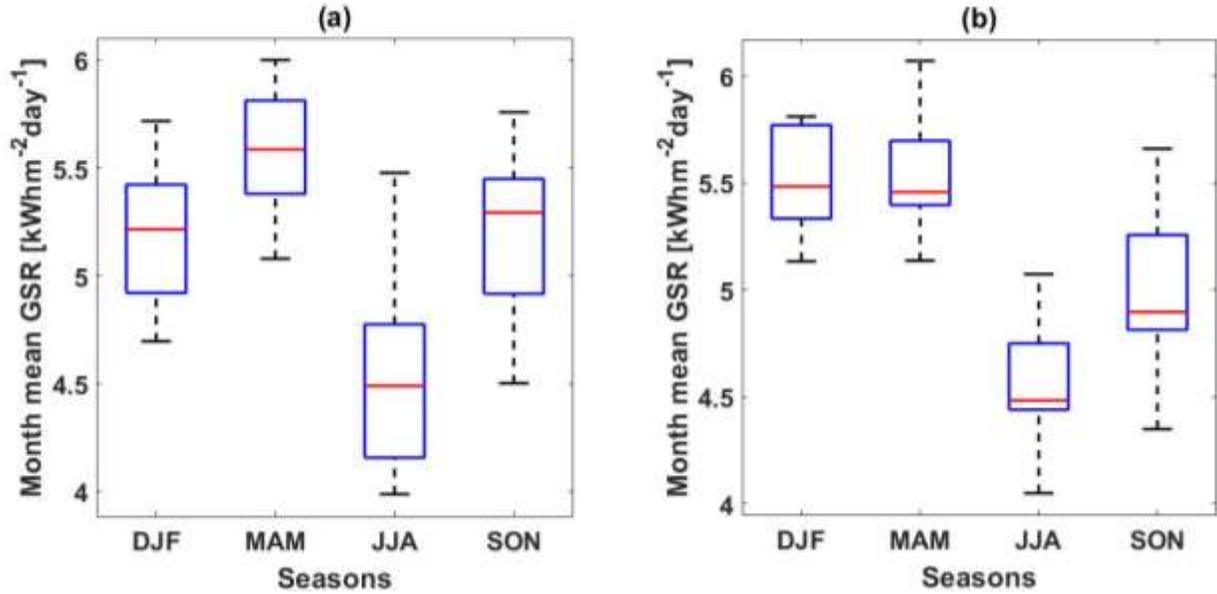


Figure 4: Boxplots showing seasonal variation in (a) estimated Global Solar Radiation (GSR_e) and (b) NASA-POWER derived monthly mean GSR (GSR_n). Seasons are December-January-February (DJF), March-April-May (MAM), June-July-August (JJA), and September-October-November (SON).

Intra-seasonally, the GSR_e and GSR_n datasets show remarkable differences in median and standard deviation. For example, each seasonal set in the GSR_n dataset show comparatively smaller interquartile ranges (IQR) of DJF = 0.44, MAM = 0.3, JJA = 0.31, and SON = 0.44 suggesting stronger relation within the satellite data than seasonal IQR in the GSR_e dataset of DJF = 0.5, MAM = 0.4, JJA = 0.62, and SON = 0.53. Again, the GSR_n dataset show relatively lower medians compared with the GSR_e datasets except of the DJF season, suggesting frequent under-estimations in the satellite data. These may be due to resolution and local climate specificity challenges with satellite observation data addressed by Dubovik [14] and Kim [15]. Indeed similar variations were reported in the previous study by Asilevi et al. [24] comparing estimated monthly mean GSR over Ghana with GSR data retrieved from the German Aerospace Centre (DLR) at a spatial resolution of 10 km by 10 km.

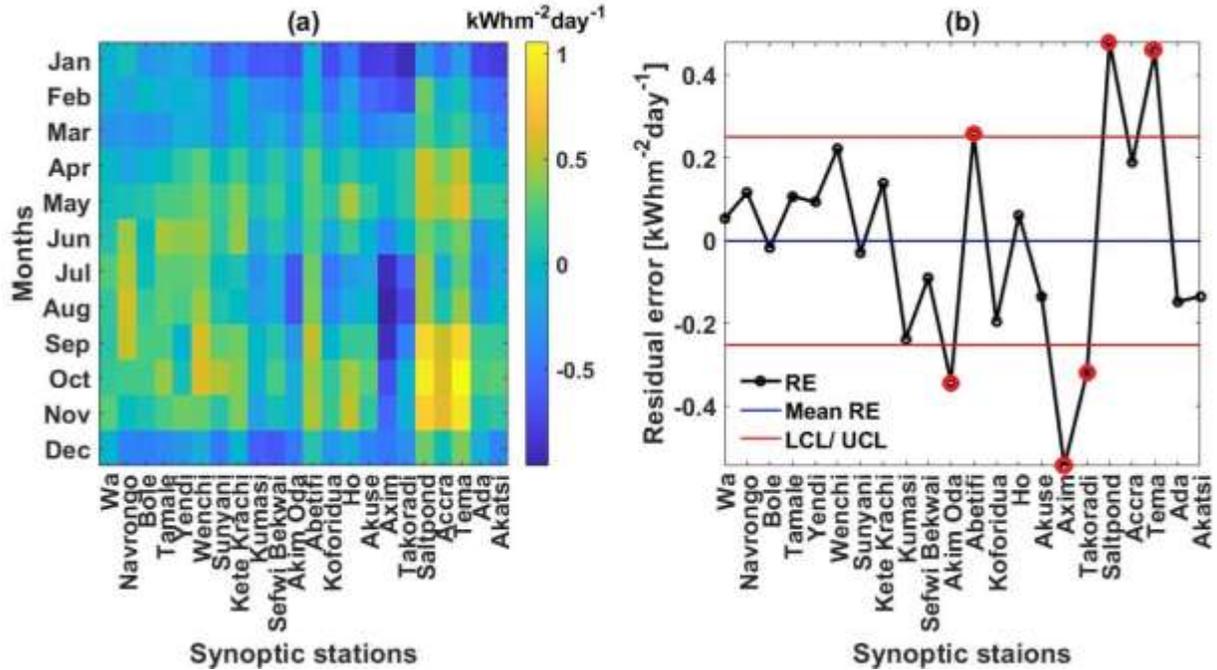


Figure 5: (a) Color plot depicting the climatological time and space variations of RE in the climatological $\text{GSR}_e/\text{GSR}_n$ pairwise datasets and (b) control chart depicting the station-by-station variation in mean climatological RE within the lower control limit (LCL) and upper control limit (UCL) of the standard deviation of RE

To further analyze the pairwise datasets, the climatological residual errors (RE) between GSR_e and GSR_n datasets was calculated based on Equation 4. The time and space variations of RE is shown in Figure 5a. The absolute RE range in the pairwise datasets is $0.002 - 1.06 \text{ kWhm}^{-2}\text{day}^{-1}$, with 51.1% positive REs and 48.9% negative REs indicating more higher GSR_e against GSR_n as depicted in Figure 5a. The lowest absolute RE is in the northern half Savannah climatic zone during the MAM season while the highest is in the southern half Coastal climatic zone during the SON season, which can be attributed to the high and low atmospheric clarity during the MAM and SON seasons respectively, and the consequential high and low insolation in the respective seasons [24]. Additionally, the control chart in figure 5b shows that $\sim 73\%$ of station-by-station REs agree with the standard deviation of ± 0.25 around the mean RE, while only 27% is out of standard deviation range. This further demonstrates close semblance in the datasets.

Figure 6 further shows an interesting trend in the Pearson's correlation coefficients (r) comparing GSR_e and GSR_n with significant p -values < 0.05 . As seen, r decreases towards the

coastal south of the study area where r values (0.59 – 0.75) are predominantly below the mean $r = 0.83$. Similar trend was reported in the previous comparison with the GSR data retrieved from the German Aerospace Centre (DLR) by Asilevi [24]. This has been attributed to the complex ocean-atmosphere-land interactions over the southern half, and the consequential frequent convective turbulences characterizing coastal tropics [25]. Undoubtedly, these conditions create significant satellite signal retrieval challenges. On the contrary, the northern half characterized by the highest atmospheric clarity indices of ~ 0.6 have a more stable atmosphere dynamics.

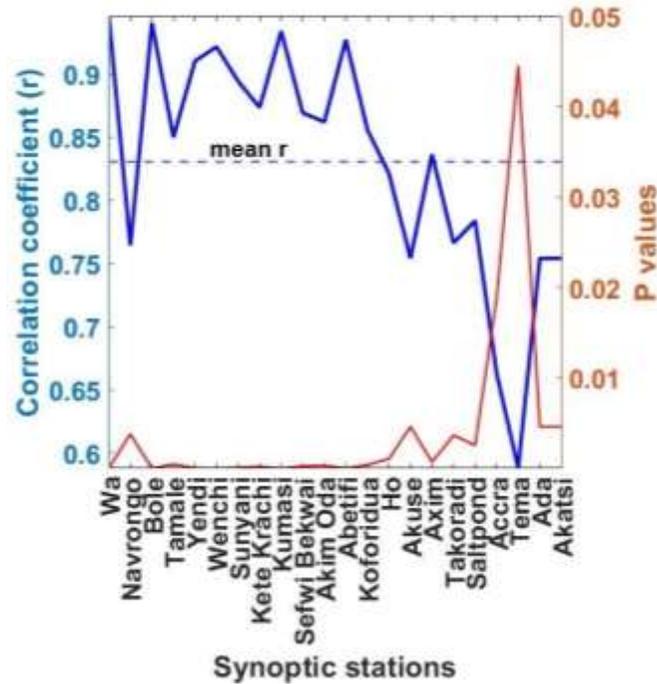


Figure 6: Station-by-station Pearson’s correlation coefficients (r) and their corresponding p -values for the climatological GSR_e/GSR_n pairwise datasets.

Table 2 summarizes all the statistical indices used in the comparisons. On the overall, the absolute ranges of RMSE = 0.13 - 0.46, MBE = 0.01 - 0.3, MPE = 1.11 - 6.34, $r = 0.59 - 0.94$, and $d = 0.95 - 0.99$ for all synoptic stations.

Table 2: Summary of statistical indices comparing estimated GSR and NASA POWER derived GSR for all stations in the four ecological zones. Root mean square error (RMSE), mean bias error (MBE), mean percentage error (MPE), Pearson's correlation coefficient (r), and Willmott index of agreement (d).

| Stations | RMSE | MBE | MPE | r | d |
|--------------|-------|--------|--------|-------|-------|
| Wa | 0.126 | 0.028 | 0.548 | 0.946 | 0.998 |
| Navrongo | 0.257 | 0.063 | 1.160 | 0.764 | 0.991 |
| Bole | 0.157 | -0.010 | -0.114 | 0.941 | 0.997 |
| Tamale | 0.219 | 0.058 | 1.088 | 0.850 | 0.993 |
| Yendi | 0.173 | 0.050 | 0.923 | 0.910 | 0.996 |
| Wenchi | 0.274 | 0.121 | 2.585 | 0.922 | 0.989 |
| Sunyani | 0.236 | -0.017 | -0.243 | 0.894 | 0.993 |
| Kete Krachi | 0.212 | 0.075 | 1.354 | 0.873 | 0.992 |
| Kumasi | 0.232 | -0.130 | -2.864 | 0.934 | 0.993 |
| Sefwi Bekwai | 0.224 | -0.049 | -1.144 | 0.869 | 0.993 |
| Oda | 0.303 | -0.186 | -4.259 | 0.862 | 0.982 |
| Abetifi | 0.234 | 0.140 | 2.708 | 0.927 | 0.986 |
| Koforidua | 0.248 | -0.107 | -2.407 | 0.856 | 0.987 |
| Ho | 0.229 | 0.033 | 0.488 | 0.821 | 0.989 |
| Akuse | 0.253 | -0.074 | -1.555 | 0.754 | 0.984 |
| Axim | 0.464 | -0.297 | -6.342 | 0.836 | 0.963 |
| Takoradi | 0.343 | -0.174 | -3.702 | 0.766 | 0.977 |
| Salt Pond | 0.423 | 0.261 | 4.967 | 0.784 | 0.968 |
| Accra | 0.284 | 0.102 | 1.830 | 0.663 | 0.977 |
| Tema | 0.426 | 0.248 | 4.476 | 0.588 | 0.953 |
| Ada | 0.238 | -0.081 | -1.655 | 0.754 | 0.989 |
| Akatsi | 0.253 | -0.074 | -1.555 | 0.754 | 0.984 |

Respectively in the order of Savannah, Transition, Forest, and Coastal zones, the mean absolute RMSE = 0.19, 0.24, 0.29, and 0.3, MBE = 0.04, 0.07, 0.15, and 0.13, MPE = 0.77, 1.39, 3.04, and 2.38, r = 0.88, 0.89, 0.84, and 0.69, and d = 0.99, 0.99, 0.98, and 0.97, depicting higher RMSE,

MBE, and MPE over the southern half and lower over the northern half, while r and d are higher over the northern half and lower over the southern half.

Conclusion

A statistical suitability assessment of the National Aeronautics and Space Administration - Prediction of Worldwide Energy Resources (NASA-POWER) satellite-derived solar radiation archives is presented. The NASA-POWER climatological datasets were compared with measured sunshine duration based estimated Global solar radiation (GSR) for 22 synoptic stations across four climatic zones in Ghana - West Africa. The results reveal that, the NASA-POWER monthly mean GSR (GSR_n) ranging $3.69 - 6.15 \pm 0.07 \text{ kWhm}^{-2}\text{day}^{-1}$ showed good statistical semblance with sunshine duration based estimated GSR (GSR_e) ranging $3.68 - 6.1 \pm 0.08 \text{ kWhm}^{-2}\text{day}^{-1}$ by correlation coefficient = 0.59 - 0.94, rmse = 0.13 - 0.46 and Willmott's index of agreement = 0.95 - 0.99. Furthermore, both agree in zonal and seasonal GSR intensity distribution patterns with high and low zonal ranges in the Savanna ($GSR_n = 4.46 - 6.11 \pm 0.53 \text{ kWhm}^{-2}\text{day}^{-1}$, $GSR_e = 4.77 - 5.98 \pm 0.4 \text{ kWhm}^{-2}\text{day}^{-1}$) and Forest ($GSR_n = 4.36 - 5.66 \pm 0.48 \text{ kWhm}^{-2}\text{day}^{-1}$, $GSR_e = 4.11 - 5.57 \pm 0.5 \text{ kWhm}^{-2}\text{day}^{-1}$) respectively, and the peak and low seasonal ranges in March-May ($GSR_n = 6.1 \text{ kWhm}^{-2}\text{day}^{-1}$, $GSR_e = 6 \text{ kWhm}^{-2}\text{day}^{-1}$) and June-August ($GSR_n = 5.1 \text{ kWhm}^{-2}\text{day}^{-1}$, $GSR_e = 5.4 \text{ kWhm}^{-2}\text{day}^{-1}$) respectively. It is expected that, as the results have shown good agreement between the estimated and satellite derived datasets, the NASA-POWER archives can be used extensively to develop a comprehensive solar energy resource assessment for the effective application of solar power systems and integration into the national grid. The results hereby provides empirical framework to develop a support system for the solar energy resource assessment task in the sub-region.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Author contributions

P. J. A., A. Q., F.D., and P. B., L. D., and Y. A. S. N conceptualized the work, retrieved and quality controlled station and satellite data, design the statistical evaluations, performed the computations, and wrote the manuscript text. S. O. K. and P. M supervised the findings of this work. All authors discussed the results and contributed to the final manuscript

Competing interests

The authors declare no competing interests.