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Original Article

Wavelet power spectrum analysis applied for solar radiation investigations over Nigeria

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Abstract

Wavelet power spectrum (WPS) techniques were used to evaluate the temporal structure of the clearness index and relative sunshine duration, using monthly values of clearness index and relative sunshine duration between 1995 and 2010. The significant years are featured by high wavelet coefficients of both the clearness index and relative sunshine duration. Low wavelet coefficients noticed during the selected years might emerge from the increase in turbidity and cloudiness, indicating that cloudiness has the greater impact on the solar radiation resulting in weak sky condition. Bootstrap method was also used to acquire regression correlations between clearness index and relative sunshine duration. The correlation coefficient between the monthly values of clearness index and relative sunshine duration for ABK (0.32), ENU (0.31), JOS (0.40), MAID (0.46), OWE (0.25), PH (0.46), SOK (0.65), YOL (0.58). The climatic condition and weather patterns of locations have an impact on the amount solar energy received.

Keywords: clearness index, solar irradiance, wavelet power spectrum, relative sunshine duration and bootstrap

1. Introduction

Solar energy plays a significant role in the green source of energy and is presently under development in many countries, especially in Africa. Solar energy has different technological relevancies such as photovoltaic power generation. An accurate evaluation of solar energy production involves the exact calculation of solar radiation using various atmospheric parameters such as relative humidity, cloud cover, surface temperature, sunshine duration, rainfall, precipitation, wind speed and water vapour (Inman, Pedro, & Coimbra, 2013; Khatib, Mohamed, Mahmoud, & Sopian, 2012; Rehman, & Mohandes, 2009; Sozen, Erol, & Mehmet, 2004).

Several studies have investigated the Angstrom type regression model for predicting global solar irradiance (Akpabio, Udo, & Etuk, 2004; Fagbenle, 1990; Falayi & Rabiu, 2005; Sambo, 1985; Mohamed & Rehman, 2013; Okogbue & Adedokun, 2002; Rehman, 1999; Rehman, & Mohandes, 2012; Sayigh, 1993). According to Akpabio and Etuk (2002); Falayi, Adepitan, and Rabiu (2008); Bocco, Willington, and Arias (2010); Falayi, Rabiu, and Teliat (2011) developed a multiple linear regression model using different atmospheric variables to estimate global solar radiation. Also, artificial intelligence techniques such as neural networks (NN) have been developed as a predictive model for solar radiation (Krishnaiah, 2007; Mohandes, Balghonaim, Kassas, Rehman, & Halawani, 2000; Rehman & Mohamed, 2008). Studies have shown the forecast of solar radiation using machine learning techniques, such as support vector machines (SVMs) applied for the prediction of solar radiation problems from meteorological predictive variables (Chen, Liu, Wu, & Xie, 2011; Dong, Yang, Zhang, & Li, 2014; Zeng & Qiao, 2013;).

In the recent years, exploitation of solar energy has improved due to the development of solar panel efficiency. The performance of the solar panel is significantly influenced by daily variation of the solar radiation. The solar panel also known as photovoltaic (PV) power lessen the grid power consumption and carbon dioxide emission. Prediction of solar energy is important for efficient management of the power grid and enhanced exploitation of solar in residential and commercial deployments. Forecasting the power output of

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solar photovoltaic system using wavelet transform and artificial intelligence techniques as a prediction model based on solar irradiation is measured as an efficient technique in practical applications (Sahin, Rehman, & Al-Sulaiman, 2017; Tao, Shanxu, & Changson 2010; Yona, Senjyu, & Funabashi, 2007).

Wavelet transform as a mathematical tool was used to acquire a time-frequency wavelet spectrum that efficiently offered a localized frequency energy spectrum for each data point in a given time series (Farge, 1992; Liu, 1993; Liu, 2000; Percival & Walden, 2000; Yang, Yao, Wang, & Wang 2015). Numerous fields have used to wavelet transform in time series analysis of meteorology, climatology, astronomy and geophysics signals and therefore producing information on both the amplitude of any signals within the series, and how this amplitude varies with time. Santos, Galvao, Suzuki, and Trigo (2001) used the wavelet power spectrum to examine the monthly variation of rainfall of Matsuyama city. It was noted that the more power concentration between the 8–16 month-bands has a strong annual signal. Pisoft, Jaroslava, & Rudolf (2004) measured cycles and trends in the Czech temperature series using wavelet transforms for the time period between 1930 and 2001. It was observed that the increase in temperatures was pronounced between 12-14yrs. Falayi, Usikalu, and Omotosho (2017) employed wavelet transform based approach to investigate the meteorological parameters over Covenant University, Ota, Nigeria. It is observed that between 256 and 540 periods show the more power concentration of high temperature from November to March. Also, Silsirivanish (2017) used wavelet transformation to examine the fluctuation characteristics effect analysis of solar irradiation data. It was noted that the components of irradiating signal are fast displayed all time scales of fluctuation from variation period.

In this paper, we investigate the global solar radiation using clearness index and relative sunshine duration time series. Section 2 gives an overview of the study area and analysis methods. We investigate the wavelet power spectrum of clearness index and relative sunshine duration in section 3. Section 4 provides a bootstrap method, regression correlations between clearness index and relative sunshine duration time series. In Section 5 we discuss the results and Section 6 gives the conclusions

2. Data Analysis and Methods

The monthly values of terrestrial solar radiation and hours of bright sunshine were obtained from the Archives of the Nigerian meteorological Agency Oshodi, Lagos State, Nigeria. Eight Nigerian meteorological stations (Abeokuta, Enugu, Jos, Maiduguri, Owerri, Port-Harcourt, Sokoto and Yola) are considered in this study. The geographical coordinates, altitudes data range of studied stations are listed in Table 1.

The clearness index (KT) referred to as a clearness index (KT) which is the relation of the quantity of terrestrial solar radiation at the ground (H) to the extraterrestrial solar radiation (H_O) (Falayi & Rabiu 2005; Okogbue, & Adedokun, 2002). KT is used to express the level of cloudiness, water vapour and aerosol of the atmosphere (Diabate, Blanc, &Wald, 2004; Poudyal, Bhattarai, Sapkota, & Kjeldstad, 2012). Also, KT is the transmittance of the overlaying sky and a measure of the quantity of solar radiation available at the study locations.

Table 1. Geographical coordinate’s altitudes and data range of studied stations

S/No	Stations	Latitude (°N)	Longitude (°E)	Altitude (m)	Data Range
1.	Abeokuta (ABK)	07.01	03.20	104	1995-2010
2.	Enugu (ENU)	06.28	0.733	141.8	1995-2003
3.	Jos (JOS)	09.52	08.45	192.2	1995-2010
4.	Maiduguri (MAID)	11.5	13.05	353.8	1995-2010
5.	Owerri (OWE)	05.29	07.00	91.0	1995-2003
6.	Port-Harcourt (PH)	04.51	07. 01	19.50	1995-2003
7.	Sokoto (SOK)	13.01	05.15	350	1995-2010
8.	Yola (YOL)	09.14	12.28	186.1	1995-2010

H is the monthly mean of daily terrestrial solar radiation falling on the ground surface at the study locations measured in MJ/m^2. While H_O is obtained from Equation (2) measured in MJ/m^2 (Duffie & Beckman, 1994).

$$H_O = \frac{24\times 3600}{\pi} Gsc\left(1+0.33 Cos\frac{360n}{365}\right)\left(Cos\phi Cos\delta Sin W_s + \frac{2\pi Ws}{360} Sin\phi Sin\delta\right) \tag{1}$$

where Gsc denotes Solar constant approximately 1367 W/m^2, Ws is the sunset hour angle for the typical day n for each month in degrees expressed in Equation (2)

$$Ws = Cos^{-1}\left(-\tan\phi \tan\delta\right) \tag{2}$$

where ϕ is the latitude of the selected locations on the Earth surface in degrees, and δ represents declination angle of the Earth in degrees. The declination angle is calculated from Equation 3 and n is the number for the Julian day of the year.

$$\delta = 23.45 Sin\left(360\left(\frac{284+n}{365}\right)\right) \tag{3}$$

The relative sunshine duration (Rs) is computed from Equation 4.

$$R_s = \frac{S}{S_{max}}, \tag{4}$$

where S is the monthly mean daily hours of bright sunshine, while S_{max} is the possible daily maximum number of hours of insolation Equation 5 defines the S_{max} as

$$S_{max} = \frac{2}{15}\cos^{-1}\left(-\tan\phi\tan\delta\right) \quad (5)$$

2.1 Wavelet power spectrum

We used wavelet power spectrum (WPS) in order to evaluate the temporal structure of the clearness index and relative sunshine duration. Equation (7) is a function ψ (a, x) (t) obtained from the mother wavelet ψ (t) during dilation and translation (Torrence & Compo, 1988).

$$\psi(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-x}{a}\right), \quad (7)$$

where a stands for scaling variable that estimate the level of compression and x is the translation variable that determine the time position of the wavelet. Equation 8 is the convolution integral of the mother wavelet ψ (t)

$$W_{(a,b)} = \frac{1}{\sqrt{a}}\int \psi^{*}\left(\frac{t-x}{a}\right)\psi(t)dt \quad (8)$$

where ψ^{*} is the conjugate of ψ and the morlet wavelet ψ_o is expressed in Equation 9

$$\psi_o(\eta) = \pi^{-\frac{1}{4}}\exp(iw_o t)\exp\left(-\frac{t^2}{2}\right) \quad (9)$$

$\psi_o(\eta)$ refers to as wavelet value at non-dimensional time t, and W_o is the non-dimensional frequency. Figures 1 (a-h) show the WPS of the clearness index variations for the selected stations in Nigeria.

Figures 2. (a-h) display the WPS of the clearness index variations for the selected stations in Nigeria between 1995 and 2010.

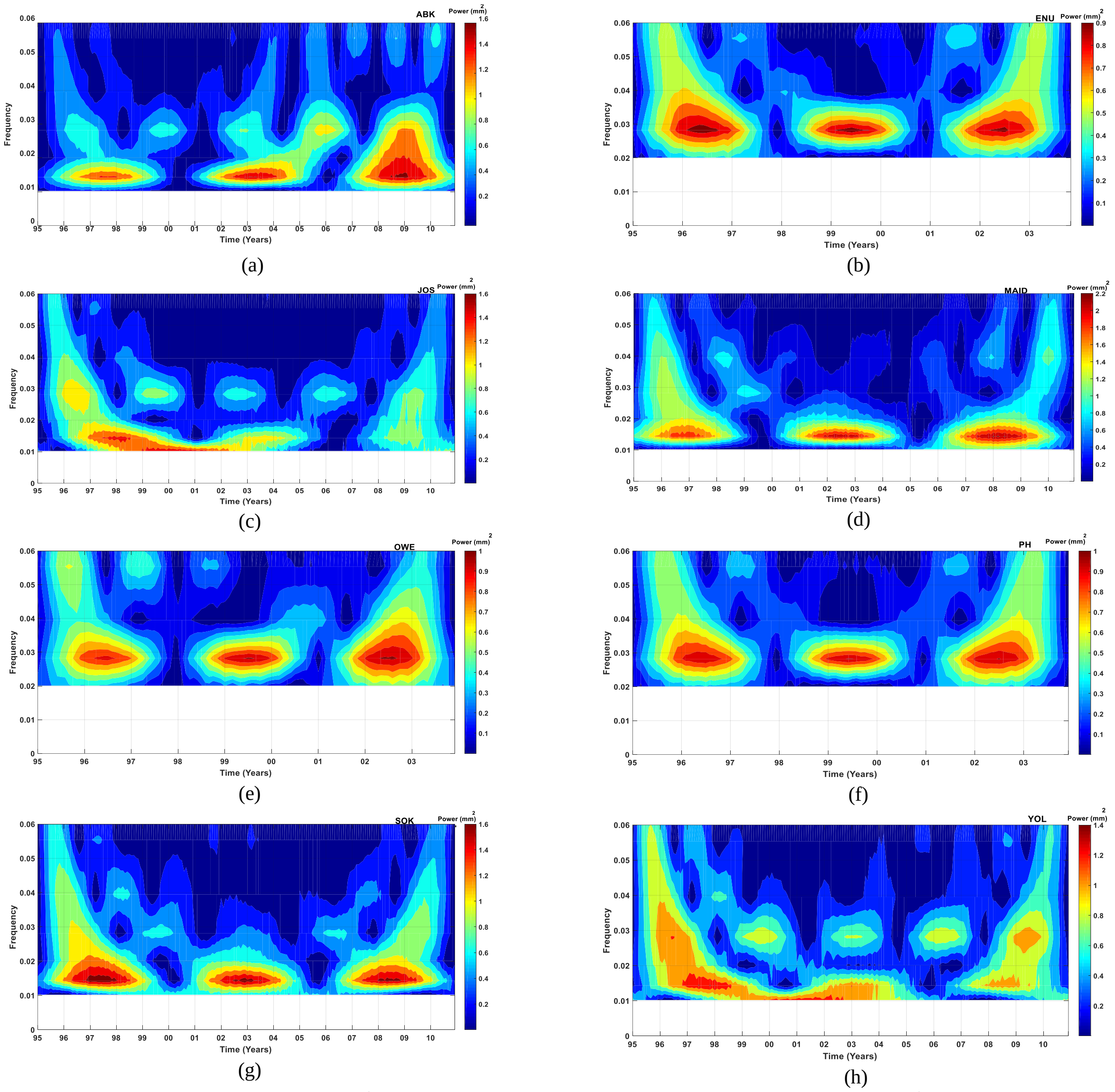

Figure 1. (a-h) Wavelet power spectrum of clearness index at (a) ABK (b) ENU (c) JOS (d) MAID (e) OWE (f) PH (g) SOK (h) YOL

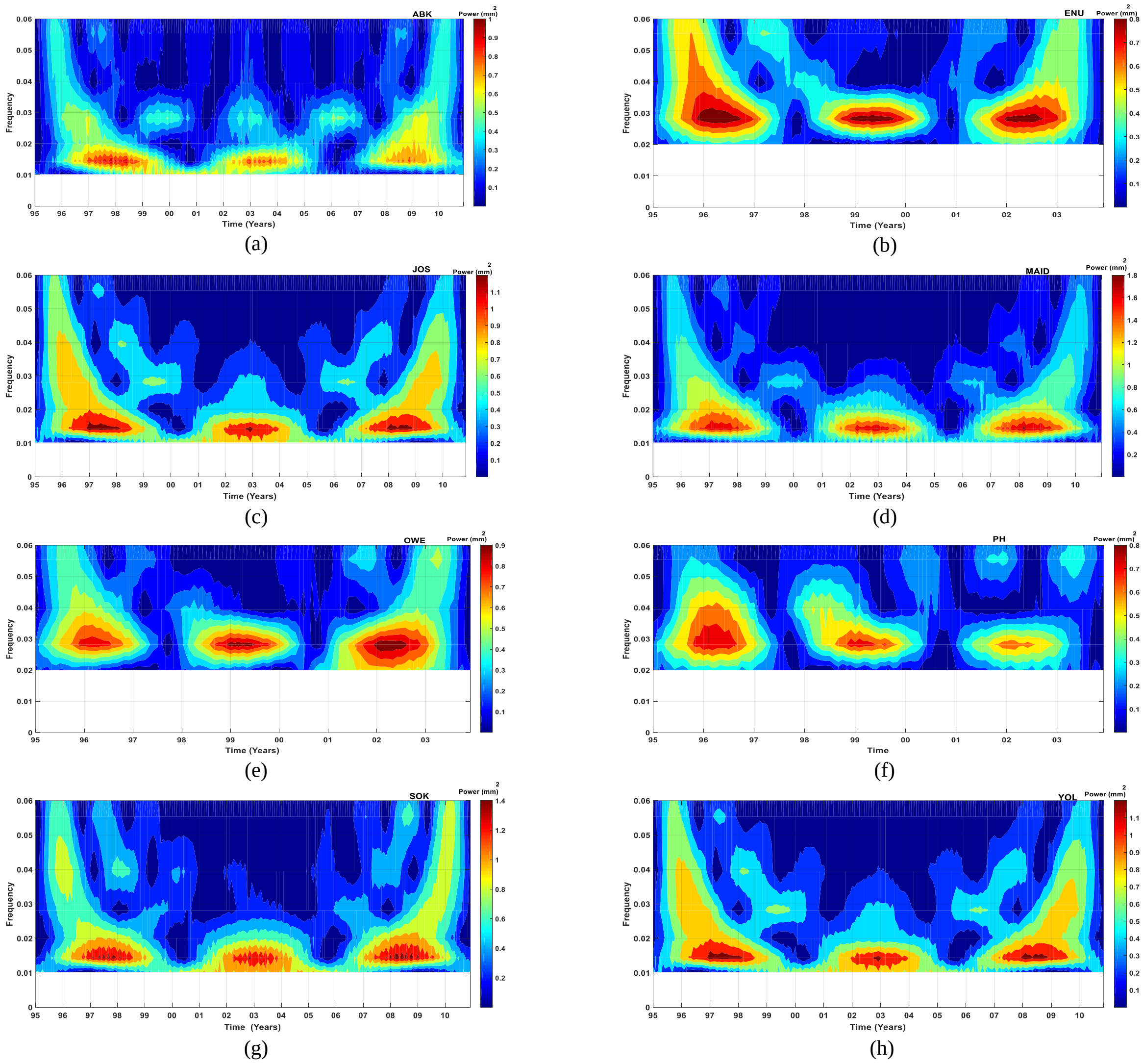

Figure 2. (a-h) Wavelet power spectrum of relative sunshine duration at (a) ABK (b) ENU (c) JOS (d) MAID (e) OWE (f) PH (g) SOK (h) YOL

2.2 Bootstrap estimates of the regression coefficients

This section uses the bootstrap method to obtain an estimate of the regression coefficients between the clearness index and relative sunshine duration from Equations (2) and (5). The strong relationship between the parameters indicated that the subsamples outliers generates powerful correction close to one, while lower values of correlation coefficient, suggesting a weak relationship between the parameters (Trauth, 2010).

3. Discussion of the Results

The wavelet analysis of both clearness index and relative sunshine duration would be useful to examine the power fluctuation levels. Statistical and wavelet time series analysis would describe the significance of local and large scale fluctuations on energy analyses. The monthly clearness indices and relative sunshine duration with WPS describes the event phase of small and large scale fluctuations at eight different geographical locations in Nigeria. From the wavelet power spectrum of clearness index time series, Figure 1 (a-h), is non-stationary with the periodicities irregular that is available at sometimes and missing in other years. The wavelet power spectrum of ABK, the western Nigeria clearness variability in Figure 1a reveals a significant power concentration at interannual time scales of 1997-1999, 2002-2004 and 2008-2010 years with power magnitude of 1.2 mm^2, at 16 year time scales. Figure 1 (b, e and f) displays similar pattern of variation with power concentration of clearness index between the years 1996-1997, 1999-2000 and 2002-2003. It was noticed that the magnitude of ENU, OWE and PH varies with values of 0.9, 1.0 and 1.0 mm^2 respectively. In Figure 1c, the magnitude of power concentration is 1.4 mm^2 and concentration of wavelet power spectrum was observed between 1997 and 2002. The same patterns of variation were noticed in Figure 1d and g with high concentration power between the year 1996-1998, 2001-2004 and 2007-2010. The magnitude of power concentration of MAID and SOK are 2.2 and 1.6 mm^2. A dominant amplitude mode is also seen

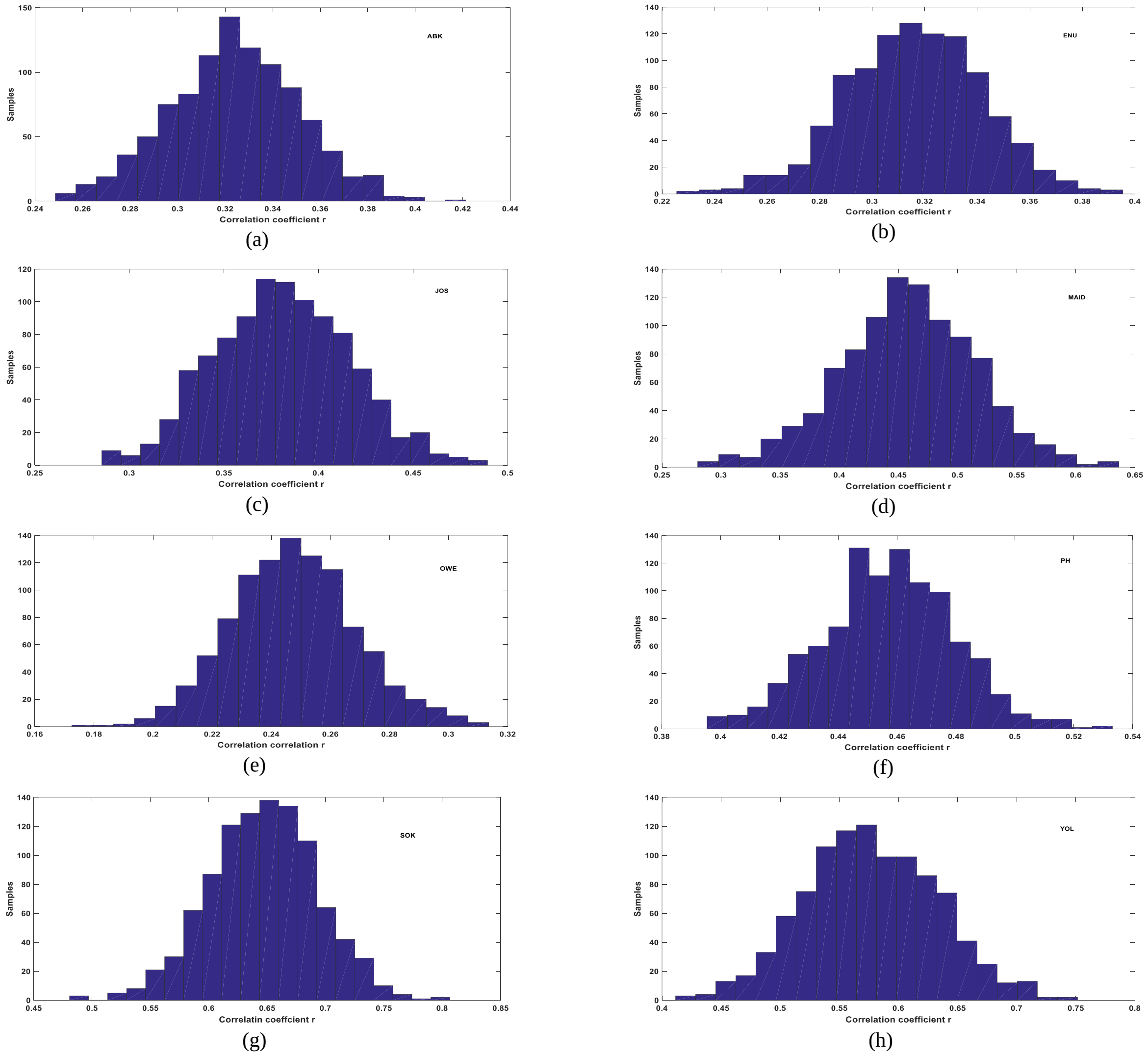

Figure 3. (a-h) Bootstrap method regression correlations between the clearness index and relative sunshine duration at (a) ABK (b) ENU (c) JOS (d) MAID (e) OWE (f) PH (g) SOK (h) YOL

between 1997 and 2002 in Figure 1c for 16 years (at periods 1995–2010). Figure 1h displays significant peaks in the selected years and the magnitude of power concentration is 1.4 mm^2. We observed that the regions with higher latitudes receive a high magnitude of wavelet coefficient in both solar radiation and sunshine duration stationed at cloud free climate (SOK, YOL, MAID and JOS) and less magnitude of wavelet coefficient were noticed at stations near the coast region (ENU, OWE, PH and ABK). The clearness index values decrease as cloudiness increases in a southward region like ABK, ENU, OWE and PH. While the SOK, YOL, MAID and JOS have higher values of clearness index with low values of cloudiness (Figure 1(a-h). The clearness indices and sunshine duration with wavelet analysis to give details of the occurrence period of minimum and maximum scale fluctuations at different geographical regions. These analyses examine the suitability of investing in solar energy potential in Nigeria. The design and performance of solar appliances such as PV require accurate information on solar radiation accessibility.

Figure 2 shows the wavelet power spectrum of the entire year record at ABK, ENU, JOS, MAID, OWE, PH, SOK, YOL stations for the relative sunshine duration. We observed that the magnitudes of the solar radiation correspond to the relative sunshine duration which depends on the stations from Figure 2, it is obvious that for the solar radiation, the yearly periodicity is dominant, which follow the same pattern for the relative sunshine duration. This confirmed by the wavelet power spectrum analysis (see Figure 2). We observed that the significant years are featured by high wavelet coefficients of both the solar radiation and relative sunshine duration. Low wavelet coefficients noticed during the selected years might emerge from the increase in turbidity and cloudiness, indicating that cloudiness has the greater impact on the solar radiation resulting in weak sky condition. The amount of solar radiation obtained on the ground surface relies much on the solar elevation, turbidity in the atmosphere and cloudiness; see Figures 1 (a-h) and 2 (a-h). The Figures 1 and 2 clearly demonstrates that the intensity of relative sunshine duration and clearness index in selected stations in

Nigeria is adequate to sustain solar energy application in this stations and can be utilized in the designing of solar energy applications. The clearness index and relative sunshine duration are a genuine technique in the description of sky conditions over a particular region. It is noted that SOK, YOL, MAID and JOS are hotter than other stations, while other stations are colder (ABK, OWE, PH and ENU) with slightly moderate weather condition. This implies that differences in the geographical location of the stations on the Earth's surface lead to variation in solar radiation received on the Earth's surface. We perceived that WPS is a better mathematical technique to evaluate time series variability, which gives an impartial and steady assessment.

Figure 3 depicts the sample distribution of correlation coefficients for the selected years. The bootstrap samples were obtained from the random sample, we consider the interrelationship based on the sample between the solar radiation and relative sunshine duration. The correlation coefficient between the monthly values of clearness index and relative sunshine duration for ABK (0.32), ENU (0.31), JOS (0.40), MAID (0.46), OWE (0.25), PH (0.46), SOK (0.65), YOL (0.58). It was noticed that each of the effects produces distinct annual variability patterns and hence their contribution could be identified from the data. The stations characteristics of variation in solar radiance possibly identify requirements for devices or increased additional power generation in a given station. The climatic condition and weather patterns of the stations have an impact on the amount solar energy received.

4. Conclusions

This study examines the variability of monthly global solar radiation using clearness index and relative sunshine duration time series in Nigerian city (ABK, ENU, JOS, MAID, OWE, PH, SOK, YOL) using wavelet analysis. The correlation coefficients were developed between clearness index and relative sunshine duration for ABK (0.32), ENU (0.31), JOS (0.40), MAID (0.46), OWE (0.25), PH (0.46), SOK (0.65), YOL (0.58) using the bootstrap method which will allow the solar energy researchers and project designer to estimate solar radiation intensity. We noticed from Figures 1 and 2 that variation in clearness index and relative sunshine duration might be due to variations in the atmospheric movement. The cloud cover has an impact on the clearness index values, while a decrease in cloud cover result to increase in the values of the clearness index.

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