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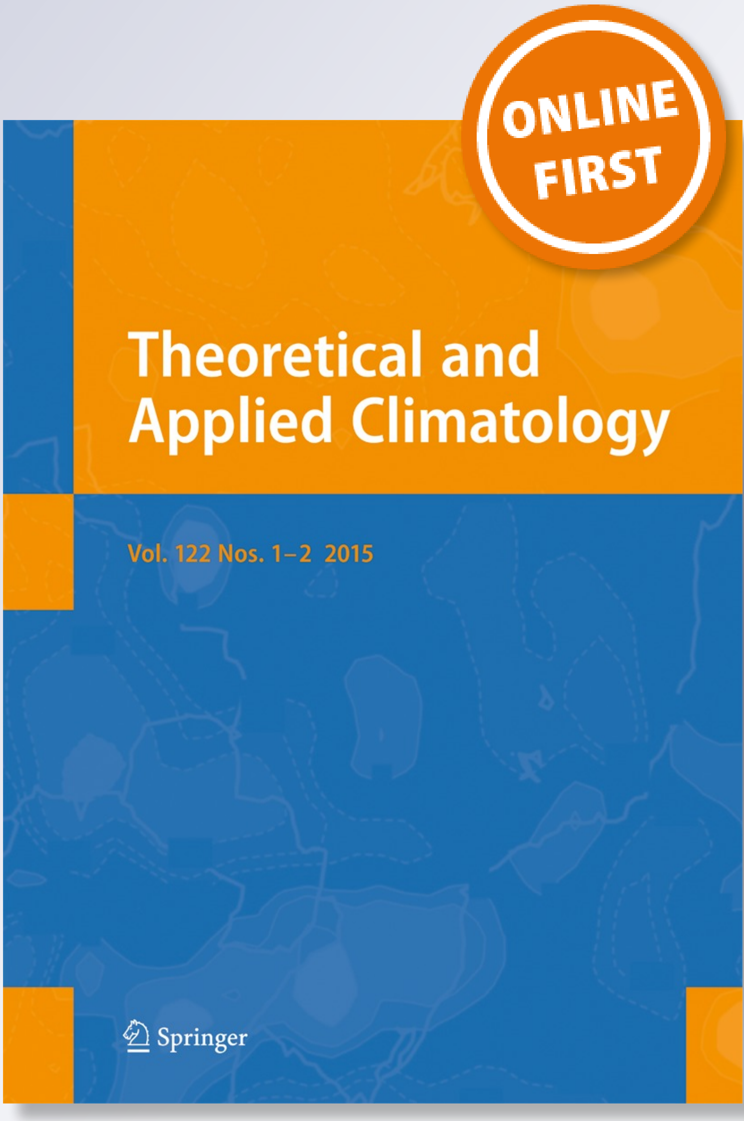

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ORIGINAL PAPER

Investigating chaotic features in solar radiation over a tropical station using recurrence quantification analysis

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Abstract The use of solar energy for power generation and other uses is on the increase. This demand necessitate a better understanding of the underlying dynamics for better prediction. Nonlinear dynamics and its associated tools readily lend itself for such analysis. In this paper, nonlinearity in solar radiation data is tested using recurrence plot (RP) and recurrence quantification analysis (RQA) in a tropical station. The data used was obtained from an ongoing campaign at the Federal University of Technology, Akure, Southwestern Nigeria using an Integrated Sensor Suite (Vantage2 Pro). Half hourly and daily values were tested for each month of the year. Both were found to be nonlinear. The dry months of the year exhibit higher chaoticity compared to the wet months of the year. The daily average values were found to be mildly chaotic. Using RQA, features due to external effects such as harmattan and intertropical discontinuity (ITD) on solar radiation data were uniquely identified.

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1 Introduction

The finite nature of existing non-renewable energy has necessitated the search for newer and more reliable energy sources. One of the most promising source is solar energy. This is the radiant energy from the sun. It is the source of energy that sustains the earth and greatly influence weather and climate. Various estimates of the amount of solar radiation reaching the earth abound, but the earth receives about 173 Petawatts of insolation Agbo and Oparaku (2006). Accounting for loss to clouds, reflection from surfaces, and absorbtion by the atmosphere, the earth still receives an enormous amount of solar radiation.

The increase in quest for solar energy are in essence due to its reduced cost, relative abundance, environmental effects associated with fossil fuels, and low maintenance cost. However, this source of energy is not without its drawbacks which include fluctuations due to location (more around the equator), strongly affected by climatic conditions (cloud and fog), efficiency of converters (< 20 %), and so on. Solar radiation varies with the atmospheric conditions as well as with seasons and is very difficult to predict. A good knowledge of the local solar radiation is essential for the proper design of building energy systems, solar energy systems, and a good evaluation of thermal environment within buildings (Wong and Chow 2001). Due to many reasons (equipment, location, etc.), solar radiation data are usually not readily available. Hence, many researchers depend on models to study this important atmospheric parameter. A nonlinearity test is necessary before further analysis with linear or nonlinear tools can be applied (Gan et al. 2012).

Investigation of daily solar radiation using nonlinear tools has been done by several authors using Neuro-fuzzy approach (Omid et al. 2012), hidden Markov models (Hocaoglu 2011), artificial neural network (Sozen et al.

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2004), swarm-optimized neural network (Lazzus 2011), autoregressive integrated moving average (ARIMA) (Wu and Chee 2011), and parametric models are described in Katiyar and Pandey (2013). Gan et al. (2012) tested for nonlinearity in solar radiation data using the method of fast surrogate test and revealed that the 5-min, hourly, daily global solar radiation time series exhibit apparently nonlinearity while the monthly time series does not. Many other works have been carried out on atmospheric time series using nonlinear quantifiers such as Lyapunov exponents, correlation dimension, etc., however, none of these attempted to use nonlinear tools to characterize solar radiation data in any form. In this paper, variation in monthly and daily solar radiation data were tested using recurrence plot and recurrence quantification analysis.

2 Chaos theory

A suitable nonlinear analysis tool can be found in chaos theory. This theory initially was developed to study dynamical models and has been extended to the study of time series data. Some of the methods developed for the analysis of times series data include correlation dimension, Lyapunov exponent, Kolmogorov entropy, recurrence quantification analysis, and fractal dimension. The use of nonlinear dynamical tools in analyzing natural time series data is not new. Due to its ability to reveal the dynamics of a data set, it has been used in investigating several natural time series such as insect population (Ogunjo et al. 2013b), temperature (Povedo-Jaramillo and Puente 1993; Fraedrich 1986), financial time series (Fuwape and Ogunjo 2013), atmospheric dynamics (Waelbroeck 1995; Mukherjee et al. 2013), refractivity (Adediji and Ogunjo 2014), and many others.

The long data length requirement of conventional dynamical tools make them inadequate in the study of natural time series which tend to be short. Eckmann et al. (1987) introduced the concept of recurrence plot to visualize the time-dependent behavior of the dynamics of systems, which can be pictured as a trajectory in the phase space. This is done based on the recurrence matrix $R_{i,j}$ (Thiel et al. 2002)

$$\mathbf{R}_{i,j} = \Theta(\varepsilon - \|\mathbf{x}_i - \mathbf{j}_j\|), \quad i, j = 1, \cdots, N. \tag{1}$$

where $\mathbf{x}_i$ stands for the point in phase space at which the system is situated at time i, and ε is a predefined threshold. $\Theta(x)$ is the Heaviside function. The matrix consists of the values 1 and 0 only. The graphical representation is an $N \times N$ grid of points, which are encoded as black for 1 and white for 0. A black point in the RP means that the system returns to an ε-neighborhood of the corresponding point in phase space (Thiel et al. 2002). The recurrence plot is a very versatile nonlinear tool as other dynamical measures such as correlation sum, Shannon entropy, correlation dimension, and Lyapunov exponent can be derived. Furthermore, it can be used for both stationary and non-stationary time series. It shows certain dynamical features such as bifurcation and synchronization (Marwan et al. 2007) and distinguish between chaotic systems and noise in short data lengths (Zbilut et al. 2000).

The graphical difficulty and the need to quantify the structures in recurrence plot led to the development of recurrence quantification analysis (RQA) by Zbilut and Webber (1992) and Webber and Zbilut (1994). Several quantities were defined to quantify the deterministic structure and complexity of the plot. The recurrence rate (RR) is the density of recurrence points.

$$RR = \frac{1}{N^2}\sum_{i,j=1}^{N} \mathbf{R}_i j \tag{2}$$

where N is the total number of data points and $R_{i,j}$ is the recurrence matrix. It quantifies the amount of cyclic behavior. This variable can range from 0 % (no recurrent points) to 100 % (all points recurrent). The recurrence rate has been used to successfully estimate dynamical invariants such as correlation dimension and second-order Renyi entropy (Thiel et al. 2002).

Determinism (DET) is the ratio of recurrence points forming diagonal structures to all recurrence points.

$$DET = \frac{\sum_{l=l_{min}}^{N} l P^{\epsilon}(l)}{\sum_{i,j}^{N} R_{i,j}^{D_E}} \tag{3}$$

where ϵ is the threshold, $P^{\epsilon}(l)$ is the histogram of the length l of the diagonal structures. Periodic signals (e.g., sine waves) will give very long diagonal lines. Chaotic signals (e.g., Henon attractor) will give very short diagonal lines, and stochastic signals (e.g., random numbers) will give no diagonal lines (Webber and Zbilut 2005). It has been used to quantify how deterministic a system is (Webber and Zbilut 1994).

Entropy (ENT), that is, the Shannon information entropy, is a measure of signal complexity. It shows the richness of deterministic structuring. Trend (TND) quantifies the degree of system stationarity. Linemax (LMAX) is defined as the length of the longest diagonal line segment in the plot, excluding the main diagonal line of identity. This particular variable is important as it has been shown to be related to the Largest Lyapunov Exponent. Other parameters based on the structure of the recurrence plots have been developed and reported in Marwan et al. (2007) with several applications in physics, engineering, biology and others.

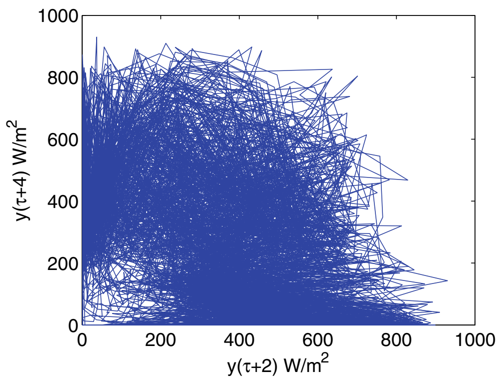

Fig. 1 Phase space plot of second and fourth component of solar radiation data with $m = 8$ and $\tau = 2$ using Taken's theorem (Eq. 6)

One of the parameters defined by Marwan et al. (2007) is Laminarity (LAM). This quantity is analogous to DET but the measure uses the vertical lines instead of diagonal lines.

$$LAM = \frac{\sum_{\nu=\nu_{min}}^{N} \nu P(\nu)}{\sum_{\nu=1}^{N} \nu P(\nu)} \tag{4}$$

where $P(\nu)$ is the total number of vertical lines of the length ν in the recurrence plot. Laminarity represents the occurrence of laminar states in the system. It allows for the investigation of chaos-chaos transitions in short and stationary time series such as revealed by a bifurcation diagram (Facchini et al. 2007).

To construct the phase space and recurrence plots for the solar radiation data and understand the multidynamical aspect of the data, it is necessary to compute the time delay and embedding dimension. There exist two very popular approaches to computing the optimal time delay (τ): autocorrelation method and mutual information approach. The amount of information $I(\tau)$ obtained about the time series y_n by observing $y_{b+\tau}$, is given by Eq. 5

$$I(T) = \sum_{n=1}^{N} P(y_n, y_{n+\tau}) log_2 \frac{P(y_n, y_{n+\tau})}{P(y_n)P(y_{n+\tau})} \tag{5}$$

where $P(y_n, y_{n+\tau})$ is the probability of observing y_n and $y_{n+\tau}$ and $P(y_n)$ is the probability of observing y_n. If the time delayed mutual information shows a marked minimum, the value can be considered as a reasonable time delay (τ) (Fraser and Swinney 1986). Furthermore, it is essential to obtain the embedding dimension for the data. According to Rabarimanantsoa et al. (2007), a recurrence plot analysis is optimal when the trajectory is embedded in a phase space reconstructed with an appropriate dimension m. Such a dimension can be well estimated using a false nearest neighbor technique as introduced by Kennel et al. (1992).

After choosing the appropriate time delay (τ) and embedding dimension (m), the time series y can be written according to Takens theorem (Takens 1981) as

$$y(t) = [y(t), y(t+\tau), \ldots, y(t+(m-1)\tau)] \tag{6}$$

The remainder of the paper is as follows: In Section 3 the study area, instrumentation and recurrence quantification analysis used are described. The results obtained are presented and discussed in Section 4 while conclusions are made in Section 5.

3 Research site and methods

The city of Akure lies in the southwestern part of Nigeria (5.19° E, 7.25° N). The Akure climate is basically tropical; it is a zone where warm, moist air from the Atlantic converges with hot, dry and often dust-laden air from Sahara

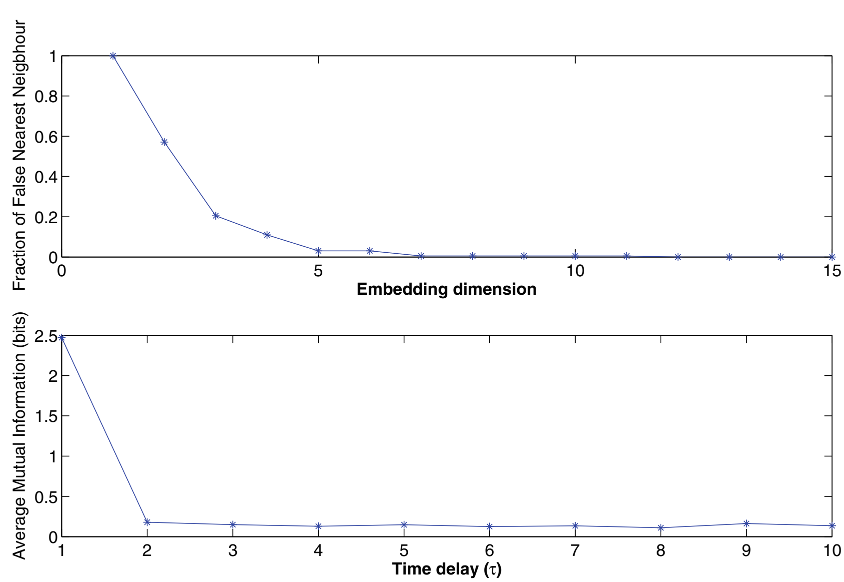

Fig. 2 (*Upper plot*) Determination of embedding dimension using the method of false nearest neighbor. (*Lower plot*) Average mutual information as a function of time delay

called the "harmattan." This moist air could be a factor for the prevalence of wind over solar radiation in the area as reported by Ogunjo et al. (2013a). The region exhibit two clear climatic seasons (dry and wet) every year. The dry period is usually from November to March while the wet season months are usually from April to October every year.

Data used for this study was obtained from the on-going measurement of some weather parameters by the Communication Physics Research Group of the Department of Physics, Federal University of Technology, Akure, Nigeria. The instrument consists of a Davis 6162 Wireless Vantage Pro2 equipped with the integrated sensor suite (ISS), a solar panel (with an alternative battery source) and a wireless console. The ISS houses several sensors including that of pressure, temperature, relative humidity, UV index, solar radiation, among others. The observatory is located about 26 km by road from the campus of the Federal University of Technology, Akure (FUTA) and about 11.5 km on line of sight from Akure. The data is logged throughout the day at 30-min interval. Data from January, 2010–December, 2011 (2 years) was used for this study. Very few data points were missing and these were filtered. Few extreme and false outliers were replaced by the mean of the data set. The data analysis was divided into the following categories:

1. Daily average data
2. 30-min monthly data analyzed each month for the 2-year period
3. 30-min seasonal data over the 2-year period

All computations were done using the CRP toolbox in Matlab by Marwan et al. (2007) and available at http://www.agnld.uni-potsdam.de/marwan/toolbox). Except otherwise stated, a threshold $\varepsilon = 0.1$ and Euclidean norm were used throughout this research work. The data was also normalized to zero mean and standard deviation of one.

4 Results and discussion

4.1 Daily average data

The phase space plot of solar radiation data according to Taken's theorem is shown in Fig. 1. The phase space plot is typical of chaotic systems with an attractor-like shape in the lower part of the figure but this is not enough to infer chaos in the data set. In a periodic system, the phase space will spread out to occupy the phase plane. The embedding dimension ($d = 8$) and time delay ($\tau = 2$ days) used in obtaining the phase space were obtained using the methods of false nearest neighbor and average mutual information respectively (Fig. 2).

Features of solar radiation in the study area can be obtained by using laminarity plot. This is shown in Fig. 3 (lower plot). The time series data of the daily average solar

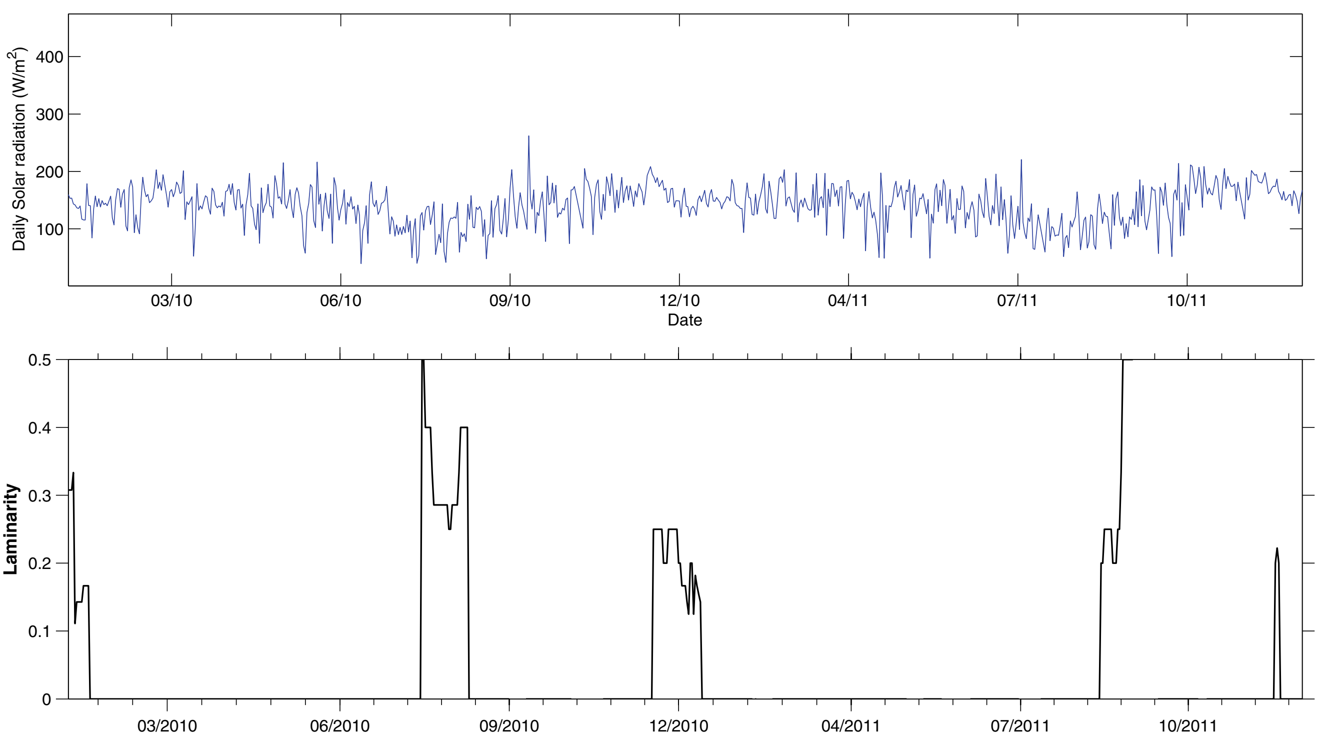

Fig. 3 Daily solar radiation data over the study location in the period January 2010–December, 2011 (*upper plot*) and the laminarity plot using a window size of 31 to represent a month and window shift of 1, indicating a shift of 1 day

Table 1 Values of monthly recurrence rate and L_{max} for the years 2010 and 2011

	Mean (W/m^2)		RR		L_{max}	
Month	2010	2011	2010	2011	2010	2011
Jan	140.9	149.1	0.0996	0.0996	235	285
Feb	154.9	152.4	0.0998	0.0998	197	137
Mar	148.3	149.3	0.0995	0.0995	103	143
Apr	144.7	136.9	0.0994	0.0994	124	169
May	144.7	148.3	0.0995	0.0995	108	90
Jun	133.3	135.8	0.0994	0.0994	76	88
Jul	109.7	119.9	0.0995	0.0999	79	74
Aug	106.9	97.7	0.0995	0.0996	72	103
Sep	126.5	124.1	0.0997	0.0995	87	133
Oct	141.5	142.9	0.0992	0.0996	92	67
Nov	160.7	173.6	0.0998	0.0996	110	96
Dec	167.5	169.4	0.0995	0.0996	367	436

radiation data is shown in the upper plot of Fig. 3. Comparing with the upper plot of daily solar radiation, five peaks are seen. The peaks indicate transition between states in the data. The first, third, and fifth peaks correspond to the effect of harmattan at the beginning of the year. The second and fourth peaks can be attributed to the effect of intertropical discontinuity (ITD) in the month of August. From Table 1, it can be inferred that dry months have high values of Lmax and determism while dry season in the region has low values of Lmax and determism.

The recurrence plot of the time series is also shown in Fig. 4, and the following recurrence quantification analysis parameters were obtained from the distribution of points around the central diagonal: recurrence rate (0.0991), %DET (21.15), LMAX (59.0), and entropy (2.2958). These values indicate determinism (albeit, low) in the daily solar radiation data. This can be used to explain the errors usually associated with empirical formulae used in obtaining solar radiation data.

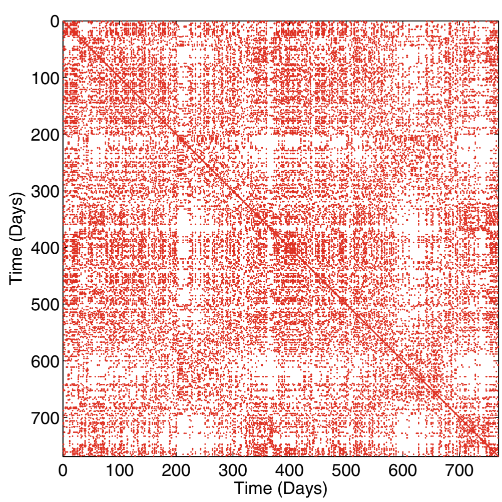

Fig. 4 Recurrence plot of average daily solar radiation for the study location. Every *red point* (ones) indicates distance between two points in phase space that is smaller than the threshold while *white spaces* (zeros) denotes distance between two points in phase space that are larger than the given threshold

4.2 Monthly and seasonal analysis

To study the monthly variability in the recurrence parameters, data values of the monthly solar radiation were investigated and the results presented in Table 1 for the embedding dimension, recurrence rate (RR), and L_{max} while determinism (DET) and entropy (ENT) are shown in Figs. 5 and 6 respectively. A time delay of 2 and embedding dimension of 6 were chosen (using the method of average mutual information and false nearest neigbhor) for all the months.

From Table 1, the value of L_{max} can be seen to be very high at the beginning of each year with a gradual decrease towards the middle of the year (August) before rising again at the return of the dry season (August, 2010 and July, 2011). It can be said that the dry months exhibit lower chaoticity than the wet months (as L_{max} is inversely proportional to the largest Lyapunov exponent). This trend is seen to occur in the mean solar radiation for each month under study. The lowest values in August 2010 and July 2011 can be attributed to the effect of the intertropical discontinuity which affects the region during these periods. The values of recurrence rate is in the range 0.0992–0.0998 which indicate that the recurrence matrix is sparse. The low values of RR in January of both years can be as the result of harmattan common in the area around December–January which causes great fluctuations in the value of solar radiation.

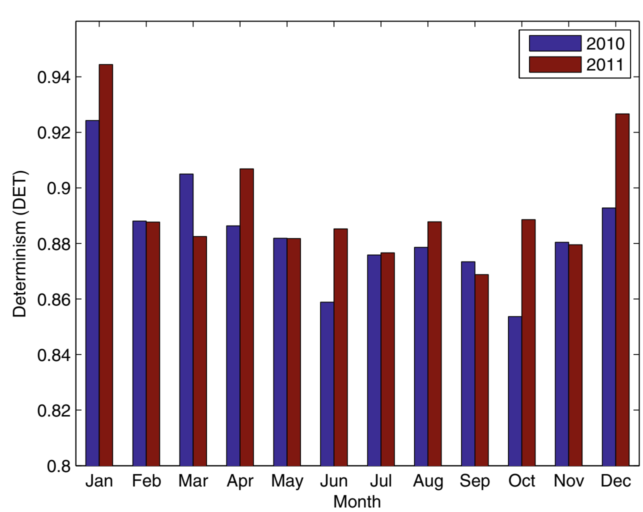

Fig. 5 Determinism of monthly solar radiation data over a tropical station during the years 2010 and 2011 with $m = 8$ and $\tau = 2$

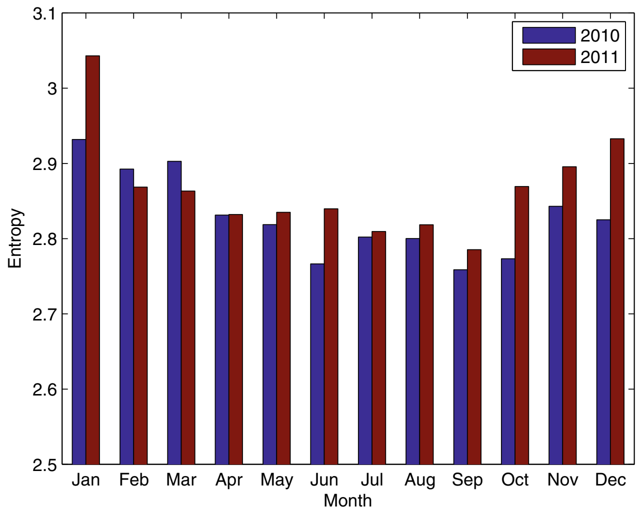

Fig. 6 Entropy of the monthly solar radiation data over the study area for the years 2010–2011 with $m = 8$ and $\tau = 2$

From Figs. 5 and 6, the same trend is seen in the determinism and entropy, with high values during the dry months and low values in wet months. The values of determinism for each of the months are greater than 0.85 showing that most of the recurrent points present are found in deterministic structures. Recurrence quantification analysis has been able to reveal variations in solar radiation caused by ITD and harmattan in the region.

5 Conclusion

Recent clamor for affordable renewable energy has necessitated the study of solar radiation data for better modeling and prediction. Several models have been proposed on harnessing solar radiation for energy generation, especially during the dry season. This study extends the use of recurrence quantification analysis to studying features of solar radiation data in the tropics. From various quantifiers, solar radiation data for the region was found to be chaotic. Thus, long-term predictability of solar radiation for power generation within the region is limited to a few days ahead. The results also show that the dry season exhibit more chaoticity than wet season for daily solar radiation data. This was confirmed by investigating the data on a monthly basis using RQA parameters. Higher chaotic nature of solar radiation during the harmattan season implies that predictability is higher during harmattan than during the wet season. Solar radiation during harmattan is subject to rapid and unpredictable fluctuations which will hamper available solar energy. Furthermore, by use of RQA, features such as effect of harmattan and ITD has been extracted. Significant transmission is found to occur at the interface of harmattan-wet, wet-harmattan, and "little dry" season in the tropical station under consideration. It, therefore, becomes imperative that these effects be taken into account when modeling solar radiation for the tropics.

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