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Performance Analysis of Temperature Models for Environmental Monitoring in Southwest Nigeria

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Abstract

Temperature is a major meteorological parameter driving most of the atmospheric processes vis-à-vis climate change. Therefore, a consistent model is necessary to achieve sustainable development goal 13 (SDG 13) known as climate action. Long-term monthly averages of surface temperature obtained from six southwest states in Nigeria were subjected to five mathematical models, namely the sum of two-Gaussians, the sum of two-Lorentzians, Fourier on four harmonics, Sine wave and Fourth-order polynomial functions. Statistical tools were used to examine the accuracy and fitness of the models. The evaluation showed that the Gaussian and Lorentzian models are good fits of the observed data. Furthermore, the performance indicators such as mean bias error (MBE), root mean square error (RMSE), mean percentage error (MPE) recorded the lowest values for Fourier on the fourth harmonic model. Similarly, its correlation coefficient, R, was the highest ranging from 0.95 to 1. Consequently, the Fourier model presented the best correlation with the observed data and hence recommended for predicting the temperature at the selected locations.

Keywords: Temperature models, Predictive models, Surface temperature, Statistical test, Annual variation.

1. Introduction

Measurement, archiving as well as modelling of atmospheric meteorological variables are essential scientific tasks required for analysis and planning in the design, development and implementation of various application systems. These applications may range from meteorology and weather forecasting, climate change prediction, geography and agricultural systems. Other human endeavours in which these variables also find application are satellite and terrestrial radio propagation and renewable energy conversion systems. Project design tools such as energy management and simulation software for energy efficiency, commercial agriculture/farm management software products and a host of others, require hourly, daily or monthly predicted or true values obtained from mathematical implementation of modelling functions. Radio propagation models also contain radio refractivity estimates, which are derived from pressure temperature and relative humidity. Energy software and thermal heating systems also require approximations of solar radiation and temperature resource observed at the location where the system is to be installed (Ohunakin et al., 2015; Hussein, 2012; Mubiru, 2011; Okundamiya and Nzeako, 2010; Gopinathan and Soler, 1995; Gopinathan,

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1992; Davies and McKay, 1982; Majumdar et al., 1972). Among all the meteorological variables, temperature plays a pivotal role in determining the variations of the other variables. Previous studies have made efforts to obtain empirical models for the estimation of meteorological parameters at the earth's surface in Nigeria (Akinbobola et al., 2018; Okundamiya et al., 2016; Ajayi et al., 2014; Umoh et al., 2014; Kolebaje and Mustapha, 2012; Ogolo, 2010; El-Metwally, 2009; Augustine and Nnabuchi, 2010, 2009; Akpabio et al., 2005; Yang and Koike, 2002; A. and M., 2000; Togrul and Onat, 1999; Ododo and Usman, 1996; Fagbenle, 1993, 1992; Bindi and Miglietta, 1991; Balogun, 1981; Sabbagh et al., 1977). These models have been developed from records of databases archived by meteorological weather stations in different regions of the country. A majority of these predictive models are based on existing empirical models that were proposed and developed by individual researchers.

2. Research Objectives

In this work, curve fitting models that use mathematical expressions of sum of two-Gaussians, sum of two-Lorentzians, Fourier on fourth harmonic (depicted as Fourier FH in the plots), sine wave and 4th order polynomial functions to best fit the monthly average data points for six cities in the Southwest zone of Nigeria were used to estimate the atmospheric temperature. A monthly set of predicted data is returned when the observed data were fed into the functions. The deviations of the returned data from the observed were then assessed using standard error analysis to test the accuracy of the function. The evaluation of the performance accuracy of these models was validated using mean bias error (MBE), root mean square error (RMSE) and mean percentage error (MPE) in order to determine the best fit for the variables.

3. Temperature

Temperature is one of the two most important driving forces of precipitation. However, atmospheric temperature models are largely affected by relative humidity compared to seasonality. Atmospheric temperature offers an important, attractive and practical alternative in the absence of data of sunshine hours for global solar radiation because of the wide availability of air temperature data. Temperature is an important atmospheric variable in the determination of rainfall, as a rise in temperature will increase the amount of rain and the amount of rainy days. As temperature rises and the air becomes warmer, thereby increasing the rate of evaporation of moisture into the atmosphere. Higher moisture content in the atmosphere means an expectation of more rain and more heavy down pours. In effect, it leads to adverse effects such as coastal flooding in Nigeria, landslides in erosion prone areas, increase in health issues especially in the northern Nigeria, deforestation as a result of the relocation of people from the flooded areas among others. Hence, knowledge of the temperature data of a location forms the basis on which a range of climatological variables is determined. Temperature with humidity data has been used to estimate the distribution of monthly mean of precipitable water vapour, precipitation efficiency and solar radiation (Udoh and Okujagu, 2014; Yang and Koike, 2002; Ojo, 1970). Knowledge of the mean profiles of these variables is of relevance for the optimum design and prediction of the performances of many systems such as communication systems (Kolebaje and Mustapha, 2012; Willoughby et al., 2002). Amadi et al. (2014) used 1950-2012 monthly mean maximum and minimum temperature data collected from 20 NIMET stations to reveal the spatial and temporal pattern of long-term trends in these variables. Statistical techniques such as time-series plots, correlation analysis, descriptive statistics and Mann-Kendall's test were used for the analysis. The results showed latitudinal dependence of basic temperature characteristics with the northern part of the country exhibiting higher temperature variability than the south. At significance level of 0.01, the Mann-Kendall tests indicate that 17 stations (representing 85%) showed significant increasing trends in the minimum temperature. On the other hand, 16 stations (representing 80%) showed significant increasing trends in the maximum temperature at the 0.01 and 0.05 significance levels. Port Harcourt and Ikeja had the greatest trend coefficients among the 20 stations. The minimum temperatures have higher trend coefficients than the maximum temperatures for almost all the stations.

Table 1. Geographical coordinates of the stations.

S/N	Station	Geo. Coordinates
1	Abeokuta in Ogun	7°9′ N, 3 °21′ E
2	Ado-Ekiti in Ekit	7°37′ N, 5 °13′ E
3	Ibadan in Oyo	7°22′ N, 3 °54′ E
4	Ikeja in Lagos	6°35′ N, 3 °20′ E
5	Ilorin in Kwara	8°30′ N, 4 °32′ E
6	Osogbo in Osun	7°46′ N, 4 °34′ E

4. Methodology

4.1. Data Acquisition

Twenty-one years averaged data (1981-2012) obtained from Nigerian Meteorological agency (NIMET) were used in the model assessment. Figure 1 shows the geographical location of each of the stations in the southwest region of Nigeria. The average of these parameters were computed and used in the correlation formulas.

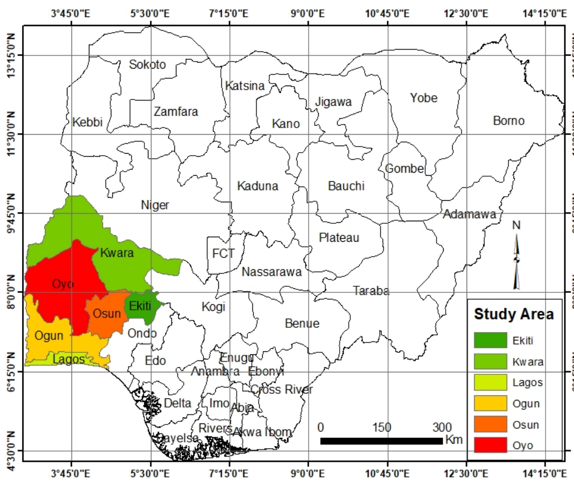

Figure 1. Map showing the study area in the southwest region.

4.2. Prediction Models

Curve fitting models are mathematical functions that provide the best mathematical description or fit to a set of data points. The function returns a set of predicted data based on observed or experimental data. For the prediction formula to be appreciably accurate the deviations from the observed data points must be as small as possible. A measure of deviation commonly used to test the effectiveness of the model is to find the minimum root mean square error. The trends of temperature display a dip midyear, indicating reduced mean values, usually between June and September. This periodic variation was analysed using four model functions to assess the goodness of fits of the models with the observed data. The models, namely Gaussian, Lorentzian, Fourier, sine and polynomial functions and their corresponding correlation coefficients were used. Widely used among the models are Gaussian and Lorentzian non-linear regression functions for fitting bell shaped curves with peaks, although the Lorentzian has a wider 'tail'spread.

The general forms of the empirical relationships employed in predicting the parameters as a function of time are listed below:

4.2.1. Sum of two-Gaussian distributions:

$$y = a + b\exp\left[-0.5\left(\frac{x-c}{d}\right)^2\right] + g\exp\left[-0.5\left(\frac{x-h}{k}\right)^2\right] \quad (1)$$

where b and g are the amplitudes or height of the centre of the distribution in x units, x representing month of the year; c and h represent the means or centres of the distribution and d and k are the measure of the widths or standard deviations of the distribution, and where the area under the curve = $bd/0.399$ or = $gk/0.399$.

4.2.2. Sum of two-Lorentzian distributions:

$$y = a + \frac{b}{\left[1+\left(\frac{x-c}{d}\right)^2\right]} + \frac{g}{\left[1+\left(\frac{x-h}{k}\right)^2\right]} \quad (2)$$

where b and g represent amplitudes; c and h represent centres and d and k represent widths.

4.2.3. Fourier function on four harmonics:

$$f(x) = a_0 + \sum_{n=0}^{\infty}\left(a_n\cos\frac{n\pi x}{l} + b_n\sin\frac{n\pi x}{l}\right) \quad (3)$$

Eqn. (3) represents a periodic variable reconstructed from cosine and sine waves with frequencies that are multiples of the fundamental frequency, f. Eqn. (3) can be expanded such that, the following series is obtained:

$$y = a + c_1\cos(bx) + d_1\sin(bx) + c_2\cos(2bx) + d_2\sin(2bx) + c_3\cos(3bx) + d_3\sin(3bx) + c_4\cos(4bx) + d_4\sin(4bx) \quad (4)$$

where, $c_1\cos(bx) + d_1\sin(bx)$ represents the fundamental, $c_2\cos(2bx) + d_2\sin(2bx)$ represents the second harmonic, $c_3\cos(3bx) + d_3\sin(3bx)$, the third harmonic and $c_4\cos(4bx) + d_4\sin(4bx)$ the fourth harmonic. Fourier on four and five harmonics were found suitable in giving a very good approximation of the observed data, the fourth was preferred as it gave better prediction in most cases (Rahoma and Hassan, 2007).

4.2.4. Sine wave function:

$$y = a + b\sin\left[\frac{\pi(x-c)}{d}\right] \quad (5)$$

where, a is the y-Intercept, b is the amplitude, c is the phase shift and d is the wavelength.

4.2.5. Fourth order polynomial function:

$$y = a + bx + cx^2 + dx^3 + gx^4 \quad (6)$$

where a, b, c, d and g are the polynomial coefficients to be deduced.

4.3. Performance indicators (statistical tests)

Three statistical tests, the Mean Bias Error (MBE), the Root Mean Square Error (RMSE), and the Mean Percentage Error (MPE) have been utilised colour for assessment of the accuracy of the function to predict the data. They are defined below:

4.3.1. Mean Bias Error (MBE):

This is a non-dimensional measure of overall bias error or systematic error.

$$MBE = \left[\frac{\sum_{i=1}^{n}(Y_{est,i} - Y_{obs,i})}{n}\right] \quad (7)$$

4.3.2. Root Mean Square Error (RMSE):

This is the square root of the mean squared error and is a measure of the deviations or residual differences between values predicted by a model or function and the actual values measured or observed and it is non-dimensional. It depicts how concentrated the predicted data is around the line of best fit as well as representing the quality of the fit. In the following equations, $Y_{obs,i}$ are the observed data and $Y_{est,i}$ are the estimated values of the variable from the model, n the number of values. For more accurate estimation, lower values of RMSE should be obtained (Akpabio and Etuk, 2002). However a few large errors in the sum can produce a significant increase in RMSE.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_{est,i} - Y_{obs,i})^2}{n}} \tag{8}$$

4.3.3. Mean Percentage Error (MPE):

$$MPE = \frac{\sum_{i=1}^{n}(\frac{Y_{est,i}-Y_{obs,i}}{Y_{obs,i}} \times 100)}{n} \tag{9}$$

where, for the three tests, $Y_{obs,i}$ and $Y_{est,i}$ are the *ith* observed and estimated values of data respectively, n is the number of data points. The lower the values of the three errors, the better the fit. Ideally, zero values are desirable. Positive MBE and MPE values are indications of overestimation while negative values are suggestive of underestimation. A zero RMSE is ideal but it is usually positive (Ahmad and Tiwari, 2008; Kolebaje and Mustapha, 2012). This test can be used to compare a type of model performance to that of other predictive models. For a long-term performance of the regression equations, MPE is preferred. Similar to MBE, a positive value of MPE indicates over-estimation in the estimated values, while the negative value indicates under-estimation (Akpabio and Etuk, 2002).

5. Results and Discussion

The comparison between the modelled and observed temperature data are shown in Figures 2(a)-(f) across all the stations. The figures show that temperature decreases during the rainy season and reaches the minimum between June and July in Abeokuta and Ado-Ekiti, July and August in Ibadan, Ilorin and Osogbo. However, in the coastal city of Lagos, temperature reaches its minimum in August. Consequently, the decrease in temperature results in an increase in relative humidity due to the reduced evaporation during this period. The temperature peaks are observed between January and May, and November and December (dry seasons) when there is little or no rainfall. For each of the locations, Fourier model gives a better correlation, with slight deviations in January and December. The deviations in values of the Gaussian and Lorentzian models are larger than those of the Fourier model, thus, reducing their accuracies. Marked largest deviations were observed with the sine and polynomial models, exhibiting the poorest prediction and hence curve. Table 3 presents the results of the statistical indicators for the performance level of each of the models for temperature in the selected locations. The RMSE values, which are a measure of the accuracy of the models, vary between 0 and 7.76 in Abeokuta, 0 and 7.74 in Ado-Ekiti, 0 and 7.59 in Ibadan, 0 and 7.61 in Ikeja, 0 and 7.79 in Ilorin, 0 and 7.56 in Osogbo. In each case, the Fourier model has the lowest RMSE values and the Gaussian and Lorentzian models have the highest RMSE values. The MPE values are negative for sine, Lorentzian and Gaussian models. The values show that the models underestimate the temperature values in each of the cities. The Polynomial model under estimates MPE values in Abeokuta, Ado-Ekiti and Ibadan and overestimates in Ilorin and Osogbo.

5.1. Statistical Test Results:

The performance of each model was assessed statistically by computing the mean bias error (MBE), root mean square (RMSE) and mean percentage error (MPE). The standard error (SE) for each model is also presented. For accurate estimation, lowest MBE, RMSE, MPE, SE values and correlation coefficient, R, value close to 1 are desired. Table 2 presents the performance indicators of the models for radiation in each location. It is observed that for Abeokuta, Fourier FH has the lowest MBE, RMSE and MPE (%). It has the lowest standard error and highest correlation coefficient R of 0.037 and 0.997 respectively. This is followed by the sine wave model, which has standard error of 0.105. The fourth order polynomial correlation formula has the highest standard error of 0.234. Also for

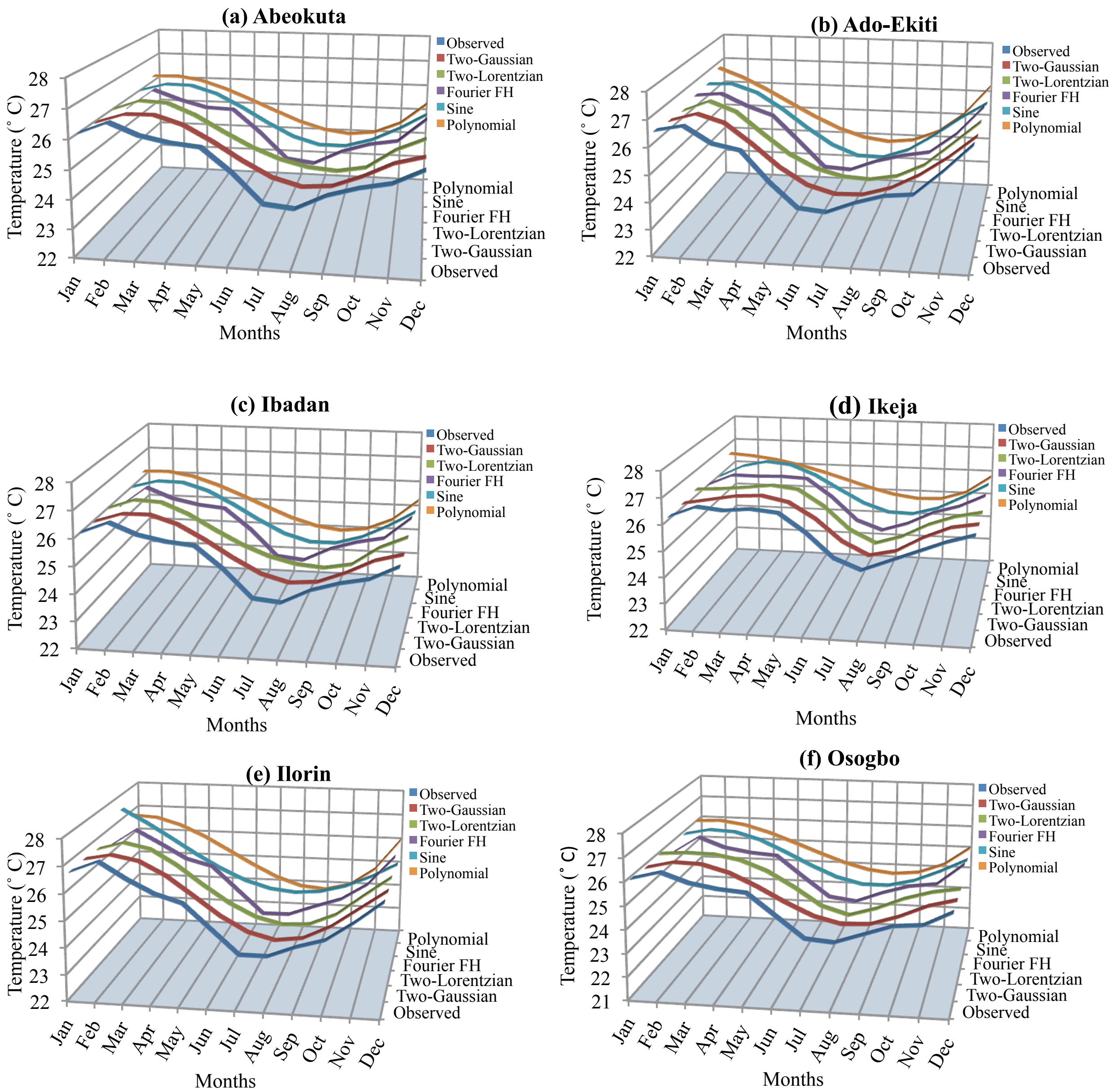

Figure 2. (a)-(f) Observed and modelled temperature at the stations

the all regions, Fourier FH has the lowest MBE, RMSE, and MPE (%), which indicates a much better correlation with the observed data. Table 3 gives a summary of the performance indicators of the models for temperature in the selected states. Figures 2(a)-(f) show that the estimated values of the models exhibit a good variation trend along with the observed data except the fourth order polynomial model, which shows the least goodness of fit with the observed values. From the observed data for each of the figures, Figures 2(a)-(f), it is evident that the temperature decreases during the rainy season and increases during the dry season. Also, for each of the locations, Fourier model gives a very good correlation, except in January and December. The other models do not show a good fit with the observed data, particularly the sine and polynomial models, which exhibit the least degree of fit curves.

6. Conclusion

Five mathematical models were used to estimate the daily temperature of the selected southwestern states in Nigeria. The estimated values of the models were compared with the values of the observed data. Statistical performance indicators showed the accuracies of each of the models, namely mean bias error (MBE), root mean square error (RMSE), mean percentage error (MBE), correlation coefficient, R and standard error (SE). Evidently, the polynomial model estimates of temperature at the selected locations showed the least correlations with the observed data from the statistical performance indicators as well as the comparison of the plots the observed and modelled data. On the other hand, the sine model had fairly good correlations. The results showed that the Polynomial model is not suitable for the prediction of atmospheric temperature in the selected southwestern states of Nigeria. Considering the correlation coefficients, the Gaussian and Lorentzian models performed better than the sine and polynomial models. The Fourier model had the least estimate errors when compared with the other models. Fourier also gave the highest correlation coefficient values R in each of the cities, ranging from 0.95 to 1, thereby indicating high accuracy in the estimated data. Thus, from the summary of the results, the Fourier model is recommended as the most suitable model for the estimation of the daily temperature in the selected locations.

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Table 2. Regression coefficients for temperature at all the stations

TEMPERATURE

Location	Models	Regression Coefficients									
		a	b	c	d	g	h	k			
Abeokuta	Sum of two Gaussians	22.48	3.83	2.42	3.38	2.69	12.17	2.29			
	Sum of two Lorentzians	22.63	3.70	2.26	4.09	2.22	11.71	1.35			
	Sine wave	25.13	1.14	0.705	6.077	-	-	-			
	4th order Polynomial	25.96	0.40	-0.15	0.08	1E-04	-	-			
	Fourier 4 Harmonics	a	b	c_1	c_2	c_3	c_4	d_1	d_2	d_3	d_4
		25.1	0.57	-.01	1.14	.03	-.07	-.03	-.01	-.02	-.05
Ado-Ekiti	Sum of two Gaussians	23.23	3.37	1.88	2.32	5.16	15.68	3.62			
	Sum of two Lorentzians	22.11	4.36	1.87	3.17	3.94	12.37	2.32			
	Sine wave	25.14	-1.42	4.49	5.93	-	-	-			
	4th order Polynomial	26.93	-0.08	-0.13	0.01	-8.84	-	-			
	Fourier 4 Harmonics	a	b	c_1	c_2	c_3	c_4	d_1	d_2	d_3	d_4
		25.0	0.57	0.6	1.2	-.22	.05	-.01	.24	-.07	.01
Ibadan	Sum of two Gaussians	22.48	3.83	2.42	3.38	2.69	12.17	2.29			
	Sum of two Lorentzians	22.62	3.69	2.26	4.10	2.22	11.70	1.35			
	Sine wave	25.13	1.14	0.71	6.08	-	-	-			
	4th order Polynomial	25.96	0.39	-0.15	0.01	1E-04	-	-			
	Fourier 4 Harmonics	a	b	c_1	c_2	c_3	c_4	d_1	d_2	d_3	d_4
		25.1	.57	.01	1.15	.03	-.07	-.3	.01	-.02	-.05
Ikeja	Sum of two Gaussians	25.86	0.76	4.25	2.38	-1.66	7.89	1.51			
	Sum of two Lorentzians	26.21	1.03	4.81	2.26	-2.18	7.79	2.25			
	Sine wave	25.65	1	0.38	5.41	-	-	-			
	4th order Polynomial	26.56	-0.01	-0.01	-0.01	6E-04	-	-			
	Fourier 4 Harmonics	a	b	c_1	c_2	c_3	c_4	d_1	d_2	d_3	d_4
		25.7	0.57	-.15	.99	.19	-.12	-.14	-.02	-.01	-.03
Ilorin	Sum of two Gaussians	22.25	4.56	1.91	3.42	4.14	13.4	2.83			
	Sum of two Lorentzians	19.54	6.97	1.84	5.18	5.16	12.51	2.88			
	Sine wave	26.16	-1.94	3.08	9.79	-	-	-			
	4th order Polynomial	26.59	0.34	1.64	0.08	0.003	-	-			
	Fourier 4 Harmonics	a	b	c_1	c_2	c_3	c_4	d_1	d_2	d_3	d_4
		25.2	0.57	0.23	1.44	-.03	.08	-.26	.08	.02	-.04
Osogbo	Sum of two Gaussians	22.04	4.08	2.29	3.6	2.89	12.29	2.34			
	Sum of two Lorentzians	25.19	1.24	3.23	4.5	2.26	7.67	2.35			
	Sine wave	24.93	1.17	-0.89	6.21	-	-	-			
	4th order Polynomial	25.74	0.46	-0.17	0.01	7E-05	-	-			
	Fourier 4 Harmonics	a	b	c_1	c_2	c_3	c_4	d_1	d_2	d_3	d_4
		24.9	.57	-.01	1.18	.02	-.06	-.29	.03	-.05	-.08

Table 3. Statistical tests for solar radiation and temperature at all the stations

		TEMPERATURE				
Location	Models	MBE	RMSE	MPE (%)	SE	R
Abeokuta	Sum of two Gaussians	-2.19	7.59	-0.73	0.20	0.07
	Sum of two Lorentzians	-2.19	7.59	-0.73	0.26	0.07
	Fourier on four harmonics	0.00	0.00	0.00	0.15	0.97
	Sine wave	-0.37	1.29	-0.12	0.22	0.25
	4th order Polynomial	0.00	0.01	0.00	0.29	0.01
Ado-Ekiti	Sum of two Gaussians	25.15	7.74	-0.74	0.19	0.12
	Sum of two Lorentzians	25.15	7.74	-0.74	0.22	0.12
	Fourier on four harmonics	0.00	0.00	0.00	0.05	1.00
	Sine wave	-0.41	1.44	-0.14	0.22	0.52
	4th order Polynomial	-0.02	0.07	-0.01	0.29	0.38
Ibadan	Sum of two Gaussians	-2.19	7.59	-0.73	0.19	0.00
	Sum of two Lorentzians	-2.19	7.59	-0.73	0.26	0.00
	Fourier on four harmonics	0.00	0.00	0.00	0.15	0.97
	Sine wave	-0.37	1.27	-0.12	0.22	0.25
	4th order Polynomial	0.00	0.01	0.00	0.29	0.01
Ikeja	Sum of two Gaussians	-2.19	7.61	-0.71	0.08	0.03
	Sum of two Lorentzians	-2.19	7.61	-0.71	0.08	0.03
	Fourier on four harmonics	0.00	0.00	0.00	0.06	0.99
	Sine	-0.32	1.12	-0.10	0.19	0.81
	4th order Polynomial	0.00	0.01	0.00	0.34	0.01
Ilorin	Sum of two Gaussians	-2.25	7.79	-0.74	0.16	0.14
	Sum of two Lorentzians	-2.25	7.79	0.74	0.17	0.14
	Fourier on four harmonics	0.00	0.00	0.00	0.13	0.99
	Sine wave	-0.62	2.15	-0.20	0.38	0.08
	4th order Polynomial	0.00	0.00	0.00	0.26	0.03
Osogbo	Sum of two Gaussians	-2.18	7.56	-0.73	0.19	0.11
	Sum of two Lorentzians	-2.18	7.56	-0.73	0.14	0.11
	Fourier on four harmonics	0.00	0.00	0.00	0.17	0.96
	Sine wave	-0.65	2.25	-0.21	0.21	0.79
	4th order Polynomial	0.01	0.00	0.00	0.27	0.00

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