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ASSESSMENT OF EMPIRICAL MODELS FOR ESTIMATING MEAN MONTHLY GLOBAL SOLAR RADIATION IN KATSINA

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ABSTRACT

Solar energy occupies the most significant position among the various renewable energy sources in the world today. Global solar radiation data in various locations across the country is not accessible due to unavailability of the required equipment to measure it. This work sought to estimate the mean monthly global solar radiation in Katsina using different empirical models. Daily data of meteorological parameters obtained from the Nigeria meteorological agency (NiMet) was converted into monthly data and fitted using MATLAB curve fitting toolbox to determine the regression coefficients. Models based on temperature, sunshine and hybrid parameters were developed, tested and validated using statistical error indicators such as mean absolute error (MAE), root mean square error (RMSE), mean percentage error (MPE) and coefficient of determination (R^2). The prediction results show that the model with the best performance is a temperature-based model with RMSE, MAE, MPE and R^2 values of 1.0811, 0.8961, 4.005 and 0.9463 which is within the acceptable prediction error range. However, one of the hybrid parameter–based models also showed good performance with RMSE, MAE, MPE and R^2 values of 1.3105, 1.0506, 4.4069 and 0.9280 respectively. Furthermore, the entire prediction results for all the sunshine-based models fitted to the data did not yield acceptable results as the R^2 value were not up to 0.5 and the RMSE and MPE were all found to greater than 10%. This could be as a result of the unreliability of the sunshine hour's data obtained from NiMet. It is recommended that Government, non-governmental organizations and individuals should step up their effort in harnessing this renewable energy form in order to boost the economy and standard of living in the country.

Keywords: Solar energy, global solar radiation, meteorological parameters, statistical error indicators, empirical models.

INTRODUCTION

Energy plays a vital role in the current societies, accelerate economics development and has been thought to be one of the critical issues in the last decades (Saeed *et* al., 2019).Renewable energy is consider as the key source for the future as it is the vital and essential ingredients for all human transactions and without them human activities of all kind will not be progressive at all (Medugu and Yakubu, 2011). According to the World Energy Council (2017), the potential of solar energy that could be used by humans differs from the amount of solar energy present near the surface of the planets because factors such as geography, time variation, cloud cover and the land available to humans limit the amount of solar energy that we can acquire.

Measurements of solar radiation are important because of the increasing number of solar heating and cooling applications and the need for accurate solar irradiation data to predict performance. Experimental determination of the energy transferred to a surface by solar radiation required instrument which will measure the heating effect of direct solar radiation and diffuse solar radiation (Jatto *et al*., 2015). Solar radiation is a major contributor for stability in the weather-system and climate-atmosphere mechanism. Keeping a tab on its variability therefore helps in understanding the weather and climate conditions of an environment and ultimately at a global scale (Said *et al*., 2015). Solar energy is mainly utilized in the design and installation of solar energy devices or systems (Saeed *et al*., 2019), radiant floor cooling systems (Feng *et al*., 2016), environmental and agricultural studies (Kaufmann and Hagermann, 2015) and managing the effect of global warming (Ming *et al*., 2014). Despite the various applications of solar energy, in some countries solar radiation cannot be measured directly. However in some regions, the sensors of solar radiation are not installed in the meteorological stations, even some stations with these sensors the measured data could be inaccurate or blank due to some technical problems (Saeed, 2019; Augustine and Nnabuchi, 2010 and Jatto *et al*., 2015). Because of the cost implication, maintenance and expertise involved in ground measurement of solar radiation data, several models were proposed across the world that can estimate global solar radiation without considering the cost of the instrument needed (Etuk *et al*., 2016; Nwokolo, 2017).

In the North-western part of Nigeria, not much work has been done in this area. Tijjani (2011) compared the performance of the Angstrom-type correlation of the first and second order via correlationin estimating the mean monthly global solar radiation using sunshine hours for Katsina using SPSS software to determining the regression coefficients. The results obtained showed that the second order model (R=0.702) performed better than the first order model (R=0.345). Olomiyesan *et al.* (2017) assessed the performance of four global solar radiation models in three locations: Gusua, Yelwa and Katsina, all in North-western Nigeria and developed a new model for estimating global solar radiation. The models were tested and validated using twenty-two years' meteorological data collected from the Nigerian Meteorological Agency (NiMeT) from 1984 to 2005. The results obtained showed that the Olomiyesan and Oyedum model gave the lowest RMSE values in all the locations (1.240 for Gusau, 0.659 for Yelwa and 0.997 for Katsina) and the highest R^2 values (0.582 for Gusau,0.793 for Yelwa and 0.889 for Katsina).

In this study, different models for estimating mean monthly global solar radiation in Katsina will be developed based on Sunshine hours, temperature, relative humidity and hybrid parameters. The first empirical correlation using the idea of employing sunshine hours for the estimation of global solar radiation was proposed by Angstrom in 1924 which was later modified by Prescott in 1940 (Tijjani, 2011).The Angstrom-Prescott model is given by (Olomiyesan *et al.*, 2017):

$$\frac{H}{H_0} = a + b\frac{S}{S_0} \quad (1)$$

and

$$k_t = \frac{H}{H_0} \quad (2)$$

where: K_t = clearness index

H = monthly average daily global radiation on a horizontal surface ($MJm^{-2}day^{-1}$);

H_o= monthly average daily extra-terrestrial radiation on a horizontal surface ($MJm^{-2}day^{-1}$);

S = monthly average daily number of hours of bright sunshine;

S_o= monthly average daily maximum number of hours of possible sunshine;

a,b = regression constants.
H_o can be calculated using the equation developed by Dufien and Beckman (1991) given by:

$$H_0 = \frac{24\times 3600}{\pi} \times I_{SC} \left[1 + 0.033cos\left(\frac{360dn}{365}\right)\right] \times \left[cos\emptyset cos\delta \sin\omega_s + \frac{\pi}{180}\omega_S \sin\delta\sin\emptyset\right] \quad (3)$$

Where ω_s is the sunset hour angle and is given by:

$$\omega_s = cos^{-1}(-tan\emptyset tan\delta) \quad (4)$$

The daily light hours S_o is given by:

$$S_o = \frac{24\omega_S}{\pi} \quad (5)$$

$\boldsymbol{\delta}$ is the declination angle given as:

$$\delta = 23.45\sin\left(\frac{360}{365}\right)(284 + d_n) \quad (6)$$

where; $\emptyset$ is the latitude of the location and d_n is the Julian days.
For January 1st, d_n = 1 and d_n = 365 for December 31st or 366 for a leap year. I_{sc} is the solar constant with numerical value; $1367Wm^{-2}$.
Temperature-based models are adaptations of Angstrom-Prescott model for estimating global solar radiation especially where sunshine hour data are not available. The basis of temperature-based models is that the differences between maximum and minimum temperature is directly proportional to the fraction of extra-terrestrial solar radiation received at the surface of the earth. Hargreaves and Samani (1982) propose the first temperature based model expressed as:

$$\frac{H}{H_0} = a + b\sqrt{\Delta T} \quad (7)$$

where $\Delta T = (T_{max} - T_{min})$ is the difference between monthly average of daily maximum and minimum temperature.
Relative humidity-based models are an adoption of Angstrom-Prescott-Page type model for predicting global solar radiation. This is primarily due to the availability of the meteorological variable in most standard weather stations in Africa especially where sunshine hour and temperature data are not readily available. The relative humidity based model are expressed in the form (Falayi *et al*., 2008):

$$\frac{H}{H_0} = a + b(RH) \quad or \quad \frac{H}{H_0} = a + b\left(\frac{RH}{100}\right) \quad (8)$$

These empirical models make use of a combination of two or more meteorological parameters such as relative humidity, atmospheric pressure, sunshine hour, air temperature, precipitation, and cloud cover etc. to estimation global solar radiation. The hybrid parameters-based models can be represented as (Soufi *et al*., 2014):

$$\frac{H}{H_0} = a + b\left(\frac{S}{S_0}\right) + c\,(T_{mean}) \text{ or } \frac{H}{H_0} = a + b\left(\frac{S}{S_0}\right) + c(RH) \quad (9)$$

where a, b and c are regression constants.
Thus in this work, some of these models will be assessed in order to select the best model equation for estimating the monthly global solar radiation in Katsina city. Also new model equations will be developed and tested to see if they perform better than the existing model equations.

Study Area, Data Source and Methodology
The Study Area
Katsina City is the capital of Katsina State and is located within the Sudan Savannah zone in the North-western part of Nigeria with geographical coordinates: $12^0\ 59'\ 52''$N;$7^0\ 35'\ 57''$E. The climate of Katsina is dominated by two counteracting air masses: the maritime and tropical continental winds. The tropical maritime wind is moist and blows from the Atlantic Ocean, predominantly blowing during the rainy season whereas the tropical continental is a dry windwhich blows from the Sahara desert and is predominant during the dry season (Tijjani, 2011).

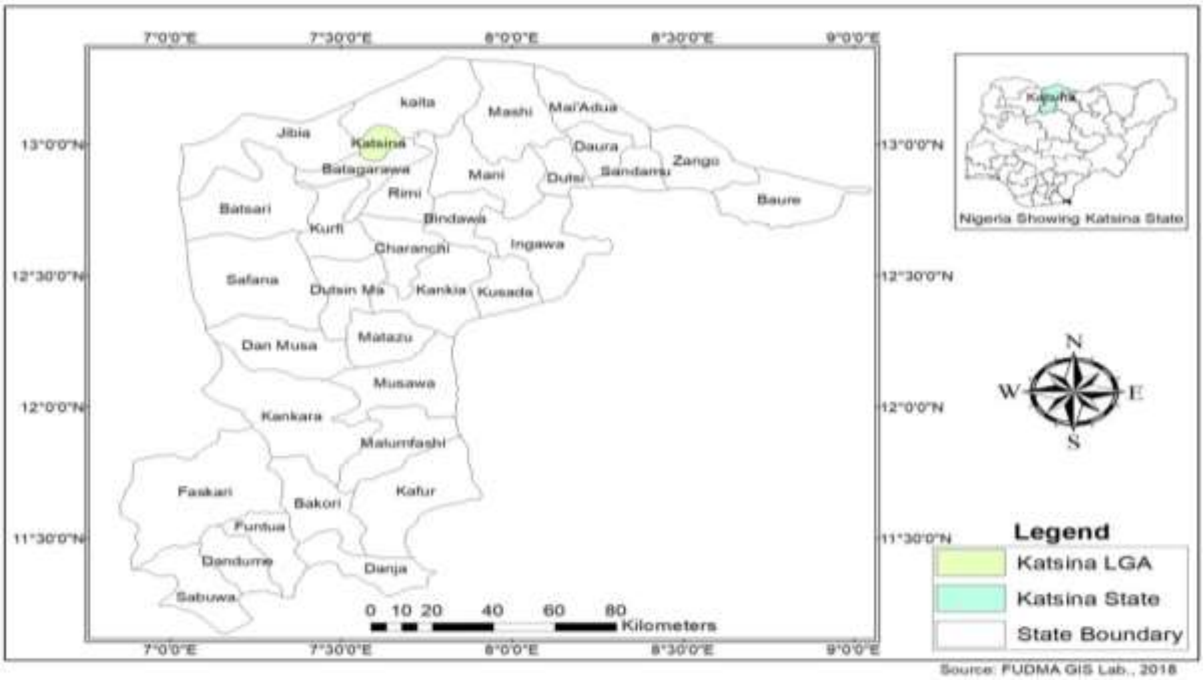

Fig. **1**: Map of Katsina state showing the study area (Source: GIS Lab. FUDMA, 2018)

Data Sources

Secondary data of time series of meteorological variables recorded over Katsina was collected from the Nigerian Meteorological Agency (NiMet) Abuja, Nigeria. It comprises the daily averages of sunshine hour (hr), solar radiation (MJm^{-2}day^{-1}), minimum and maximum temperature(℃) and mean relative humidity (%) for a period of eleven years i.e. 2006 to 2016. The air temperature, T was evaluated using the expression (FAO.org, 2018):

$$T = \frac{T_{max} + T_{min}}{2} \qquad (10)$$

Methodology

The fitting and the prediction results obtained using MATLAB R2013a curve fitting toolbox (cftool) are displayed in the tables and discussed. The secondary meteorological data which comprises of monthly averages of solar radiation (MJ/m^2/day), sunshine hours (hrs), relative humidity (%), maximum and minimum temperature (℃) were divided into two datasets. The method deployed by Balarabe *et al.* (2016) was applied in this work and extended to nonlinear model equations as well; the first dataset (January, 2006 to December, 2015) was employed to establish the models using regression analysis using MATLAB cftool. The optimal values of empirical coefficients corresponding to the actual data for Katsina were obtained and recorded. The second dataset (January, 2016 to December, 2016) was employed to predict the monthly global solar radiation using the model equations and the actual values of their empirical coefficients and validated/assessed using different statistical error indicators. The six statistical error indicators used to validate the model equations include:

Model accuracy evaluations

i. Mean absolute error (MAE): this is the average of the absolute differences (deviations) between the monthly average monthly solar radiation estimated by a model and the actual measured values measured. The mathematical expression for the mean absolute error is (Olomiyesan *et al.,* 2017):

$$MAE = \sum_J^n \left|\frac{H_{i,cal} - H_{i,meas}}{n}\right| \qquad (11)$$

ii. Mean percentage error (MPE): The mean percentage error is the percentage deviation of the monthly average daily solar radiation values estimated by the model used from the measured values (Gadilawa *et al.,* 2013). The mean percentage error in is expressed as (Olomiyesan *et al.,* 2017):

$$MPE = \left(\frac{1}{n}\right)\sum_I^n \left(\frac{H_{i,cal} - H_{i,meas}}{H_{i,meas}}\right) X\ 100\% \qquad (12)$$

iii. Root mean square error (RMSE): The Root Mean square Error gives the same result of the divergence between the monthly average daily radiation values estimated by the model used and the measured values. The RMSE in MJm^{-2}day^{-1} is calculated by the expression given as (Augustine and Nnabuchi, 2010):

$$RMSE = \sqrt{\sum_I^n \left(\frac{H_{i,cal} - H_{i,meas}}{n}\right)} \qquad (13)$$

iv. Sum Squared Error (SSE): this is the sum of the squared differences between each observation and its group's mean. It is often used as a measure of variation within a cluster of data. If all pairs of data within a cluster have identical values, the SSE would then be equal to 0. SSE is expressed as (Ward, 2019):

$$SSE = \sum_{i=1}^n (x_i - \bar{x})^2 \qquad (14)$$

v. Coefficient of Determination (R^2): The coefficient of determination is the square of the correlation coefficient. The correlation coefficient is a statistical measurement which determines the amount of linear relationship between$H_{i,cal}$ *and* $H_{i,meas}$. The value of R satisfies the inequality $-1 \le R \le 1$.The correlation coefficient is given by the expression as (Rahimikhoob *et al.,* 2013; Olomiyesan *et al.,* 2017):

$$R = \frac{\left|\sum_i^n (H_{i,cal} - \bar{H}_{i,cal})(H_{i,meas} - \bar{H}_{i,meas})\right|}{\sqrt{\sum_i^n (H_{i,cal} - \bar{H}_{i,cal})^2 \sum_i^n (H_{i,meas} - \bar{H}_{i,meas})^2}} \quad (15)$$

where; $H_{i,cal}$ is the calculated (predicted or estimated) value of solar radiation.
$H_{i,meas}$ is the measured value of solar radiation.
$\bar{H}_{i,cal}$ is the mean value of calculated solar radiation.
$\bar{H}_{i,meas}$ is the mean value of the measured solar radiation.
n is the total number of observations.
The value R^2 ranges from 0 to 1; an R^2 of 0 means that the calculated variable cannot be predicted from the observed variable, while an R^2 of 1 means the calculated variable can be perfectly predicted from the observed variable. In general, an R^2 value between 0 and 1 indicates the degree to which the calculated variable is predictable (Stattrek.com/statistics, 2018).

RESULTS AND DISCUSSIONS

A total of fifteen (15) temperature-based models were analysed in this work; the first nine models (1-9) were from those proposed by Hassan *et al.* (2016) while the last six models (10-15) are presented as new models developed from this study. The models are listed in Table 1 as follows:

Table 1: Temperature-based models and their equations

Model No.	Model equation
1	$\frac{G}{G_o} = a + bT$
2	$\frac{G}{G_o} = a + bT + cT^2$
3	$\frac{G}{G_o} = a\exp(bT^C)$
4	$\frac{G}{G_o} = a\Delta T^b + c$
5	$\frac{G}{G_o} = (a + b\Delta T)\Delta T^c$
6	$\frac{G}{G_o} = (a + b\Delta T + c\Delta T^2)\Delta T^d$
7	$\frac{G}{G_o} = (a + bT)\Delta T^c$
8	$\frac{G}{G_o} = (a + bT + cT^2)\Delta T^d$
9	$\frac{G}{G_o} = (a + b\Delta T + c\Delta T^2)\Delta T^{0.5} + d$
10	$\frac{G}{G_o} = a\Delta T^b$
11	$\frac{G}{G_o} = a + b\Delta T + c\Delta T^2$
12	$\frac{G}{G_o} = a(1 + 2.7X10^{-5}T)\Delta T^{0.5}$
13	$\frac{G}{G_o} = a\exp(b\Delta T^c)$
14	$\frac{G}{G_o} = a + b\Delta T + c\Delta T^2 + dT^3$
15	$\frac{G}{G_o} = a + b\Delta T + cT^2 + dT^3$

where T, ΔT and G_o are the air temperature (℃), temperature range (℃) and extraterrestrial solar radiation on a horizontal surface (MJ/m^2/day) respectively while a, b, c, and d are the regression coefficients.

Table 2: Fitting results showing the regression constants for the temperature-based models

Model No.	a	b	c	d	SSE	RMSE	R^2
1	0.4606	0.04079			0.56	0.06889	0.5552
2	0.05556	0.1414	-0.005695		0.08923	0.02762	0.9291
3	0.00024	7.411	0.04249		0.4347	0.06095	0.6547
4	64.8	0.009202	-65.63		0.8249	0.08397	0.3336
5	-8.36	1.691	-1.131		0.2181	0.04317	0.8268
6	894.1	-228.7	17.33	-2.747	0.1279	0.03321	0.8984
7	0.08703	-0.003436	0.9472		0.09124	0.02793	0.9275
8	894.9	-457.8	69.37	-2.747	0.1279	0.03321	0.8984
9	0.2474	0.4216			0.3953	0.05788	0.6861
10	-0.2144	0.02062	-0.0004064	0.7753	0.07431	0.02531	0.941
11	0.05556	0.07069	-0.001424		0.08923	0.02762	0.9291
12	0.2006				0.4272	0.05992	0.6607
13	0.02237	2.637	0.1088		0.4269	0.0604	0.6609
14	0.4105	0.004317	0.009018	-5.77e-05	0.0742	0.02529	0.9411
15	0.4105	0.004317	0.009018	-0.0004616	0.0742	0.02529	0.9411

From Table 2 it was observed that models 14 and 15 have similar value of RMSE (0.02529) and highest values of R^2 (0.9411) and their RMSE is small. Also model 10 showed a large value of R^2 (0.941) and small value of RMSE (0.02531). The worst performance is displayed by models 1 and 4 which recorded the lowest R^2 values of 0.5552 and 0.3336 respectively.
Fifteen (15) sunshine–based models were fitted using cftool in MATLAB and the following results were obtained as displayed in Table 3.

Table 3: Sunshine-based models and their equations

Model No.	Model equation
1	$\frac{G}{G_0} = a + b\left(\frac{S}{S_0}\right)$ (Angstrom, 1924)
2	$\frac{G}{G_O} = a + b\left(\frac{S}{S_0}\right) + c\left(\frac{S}{S_0}\right)^2$ (Olgelman *et al.*,1984)
3	$\frac{G}{G_O} = a + b\left(\frac{S}{S_0}\right) + c\left(\frac{S}{S_0}\right)^2 + d\left(\frac{S}{S_0}\right)^3$ (Samuel, 1991)
4	$\frac{G}{G_O} = a\left(\frac{S}{S_0}\right)^b$ (Gana and Akpootu, 2013)
5	$\frac{G}{G_O} = a + b\log\left(\frac{S}{S_0}\right)$ (Ayodele and Ogunjuyigbo, 2010)
6	$\frac{G}{G_O} = a + b\exp\left(\frac{S}{S_0}\right)$ (Ulgen and Hapbasli, 2016)
7	$\frac{G}{G_O} = a\exp\left[b\left(\frac{S}{S_0}\right)\right]$ (new model)

8	$\frac{G}{G_O} = a\sqrt{\left(\frac{S}{S_0}\right)}$(new model)
9	$\frac{G}{G_O} = a + b\log\left(\frac{S}{S_0}\right) + c$(new model)
10	$\frac{G}{G_O} = a + b\exp\left(\frac{S}{S_0}\right) + c$ (new model)
11	$\frac{G}{G_O} = a\exp[0.5\left(\frac{S}{S_0}\right)]$ (new model)
12	$\frac{G}{G_O} = a\left(\frac{S}{S_0}\right)$ (new model)
13	$\frac{G}{G_O} = a\left(\frac{S}{S_0}\right)^2$ (new model)
14	$\frac{G}{G_O} = a\left(\frac{S}{S_0}\right) + b$ (new model)
15	$\frac{G}{G_O} = a\left(\frac{S}{S_0}\right) + b\log\left(\frac{S}{S_0}\right)$(new model)

Table 4: Fitting results showing the regression constants for the sunshine-based models

Model No.	a	b	c	d	SSE	RMSE	R^2
1	0.5378	0.2941			1.135	0.09808	0.09844
2	1.041	-1.349	1.286		1.032	0.09392	0.1803
3	1.183	-2.186	2.78	-0.8339	0.031	0.09426	0.1814
4	0.9494				1.513	0.1128	-0.2017
5	0.7951	0.1361			1.181	0.1001	0.06173
6	0.4072	0.166			1.113	0.09713	0.1159
7	0.671				1.182	0.09966	0.06123
8	0.8866				1.291	0.1042	0.02549
9	0.5572	0.1361	0.2378		1.181	0.1005	0.06173
10	0.4222	0.166	-0.01505		1.113	0.09754	0.1159
11	0.5467	0.4375			1.125	0.09765	0.1062
12	1.036				1.943	0.1278	-0.5436
13	0.9494				1.513	0.1128	-0.2017
14	0.2941	0.5378			1.135	0.09808	0.09844
15	0.8719	-0.4584			1.062	0.09488	0.15 63

From the results in Tables 3 and 4 it was observed that all the sunshine-based models fitted to the data did not yield acceptable results as the R and R^2 values were not up to 0.5. This could be as a result of the unreliability of the sunshine hour data obtained from NiMet. However, model 2 has the smallest value of RMSE (0.09808) and R^2 (0.1803) followed by model 3 with RMSE and R^2 values of 0.09426 and 0.1814 respectively. In addition the worst performance is displayed by models 4, 12 and 13 which have a negative value of R^2 -0.2017, -0.5436 and -0.2017 respectively which indicates lack of convergence of the models leading to negative correlations. Thus, these models cannot be used in estimating the monthly global solar radiation. Nine (9) new hybrid parameters – based models were developed and fitted using cftool in MATLAB. The fitting results are displayed in Tables 5 and 6.

Table 5: Hybrid parameters based-models and their equations

Model No.	Model equation
1	$\frac{G}{G_O} = a + b\left(\frac{S}{S_0}\right) + cT_{max}$
2	$\frac{G}{G_O} = a + b\left(\frac{S}{S_0}\right) + cT$
3	$\frac{G}{G_O} = a + b\left(\frac{S}{S_0}\right) + c\left(\frac{RH}{100}\right)$
4	$\frac{G}{G_O} = a + bT + c\left(\frac{RH}{100}\right)$
5	$\frac{G}{G_O} = a + b\left(\frac{RH}{100}\right)G_0$
6	$\frac{G}{G_O} = a + b\left(\frac{T_{max}}{RH}\right)$
7	$\frac{G}{G_O} = a + b\left(\frac{T_{max}}{RH}\right) + c\left(\frac{T_{max}}{RH}\right)^2$
8	$\frac{G}{G_O} = a + b\left(\frac{S}{S_0}\right) + c\Delta T$
9	$\frac{G}{G_O} = a + \left(\frac{S}{S_0}\right)^b + \Delta T^C$

Table 6: Fitting results showing the regression constants for the hybrid parameter based- models

Model No.	A	b	c	SSE	RMSE	R^2
1	0.3282	0.2846	0.00636	1.087	0.09638	0.138
2	0.4098	0.08763	0.03922	0.5581	0.06857	0.5631
3	0.8865	0.06176	-0.4337	0.1743	0.0386	0.8616
4	0.8616	0.007416	-0.3945	0.1688	0.03799	0.8659
5	0.9332	-0.01474		0.1813	0.0392	0.856
6	0.6183	11.47		0.4536	0.062	0.6397
7	0.504	31.41	-615.9	0.2091	0.04228	0.8339
8	0.4098	0.08736	0.01961	0.5501	0.06857	0.5631
9	-1.946	9.327e-5	0.2012	0.3458	0.05436	0.7254

From Tables 5 and 6 it was observed that model 4 has the lowest value of RMSE (0.03799) and highest value of R^2 (0.8659) followed by model 3 having RMSE and R^2 values of 0.0386 and 0.8616 respectively. The worst performance is displayed by model 1 which has the greatest value of RMSE (0.09638) and least value of R^2 (0.138).

Validation of the predicted monthly global solar radiation values in Katsina for the year 2016

The equations generated from the different models were used to predict the monthly global solar radiation over Katsina for 2016. The results were validated using the actual measured values of monthly global solar radiation for 2016 obtained from NiMet by computing the RMSE, MAE, MPE, R and R^2 values. The models were then ranked according to their performance and the best performing model ranked number 1 and having the least value of root mean square error and greatest value of coefficient of determination.

Validation of temperature-based models

The result of the predictions of monthly global solar radiation in Katsina for 2016 using the temperature-based models in Table 1 is presented in Table 7.

Table 7: Prediction results from temperature –based model

Model No.	RMSE	MAE	MPE	R	R^2	Rank
1	1.6178	1.4594	6.3981	0.9510	0.9044	13
2	1.1799	0.9857	4.4020	0.9674	0.9358	3
3	1.5648	1.4385	6.3463	0.9597	0.9209	12
4	2.2145	1.7835	8.7071	0.9664	0.9340	14
5	1.1884	1.0392	4.7435	0.9669	0.9348	5
6	1.0865	0.9004	4.0181	0.9728	0.9463	2
7	1.1917	1.0013	4.5015	0.9679	0.9369	6
8	**1.0811**	**0.8961**	**4.0005**	**0.9728**	**0.9463**	**1**
9	1.3859	1.1876	5.0878	0.9605	0.9225	10
10	23.3483	3.3325	105.5224	0.9564	0.9147	15
11	1.1837	0.9890	4.4162	0.9674	0.9358	4
12	1.3689	1.0481	4.3720	0.9603	0.9221	9
13	1.4877	1.3350	5.8163	0.9591	0.9198	11
14	1.2948	1.0271	4.4195	0.9538	0.9097	7
15	1.2948	1.0271	4.4195	0.9538	0.9097	7

The prediction result in Table 7 shows that model 8 exhibits the best performance with an RMSE value of 1.0811 and MPE value of 4% which is within the acceptable prediction error range of $\pm 10\%$ (Hassan *et al.*, 2016) and also has the joint highest value of R^2 (0.9463).

The runners up are models 6, 2 and 11 successively, with error statistic (RMSE, MPE, R^2) values of (1.0865, 4.0181, 0.9463), (1.72199, 4.4020, 0.9358) and (1.1837, 4.4162, 0.9358) respectively. In addition models 6, 2 and 11 have slight variation in their performance with excellent R^2 values. On the other hand models 4 and 10 showed a good value of R^2 with the largest values of RMSE and MPE which indicates a poor fitting and their values are far away from the optimal values. Hence models are not quite suitable for estimating mean monthly global solar radiation and thus are excluded due to their inaccurate prediction. The results of the five best temperature-based model predictions are displayed in Figure 2.

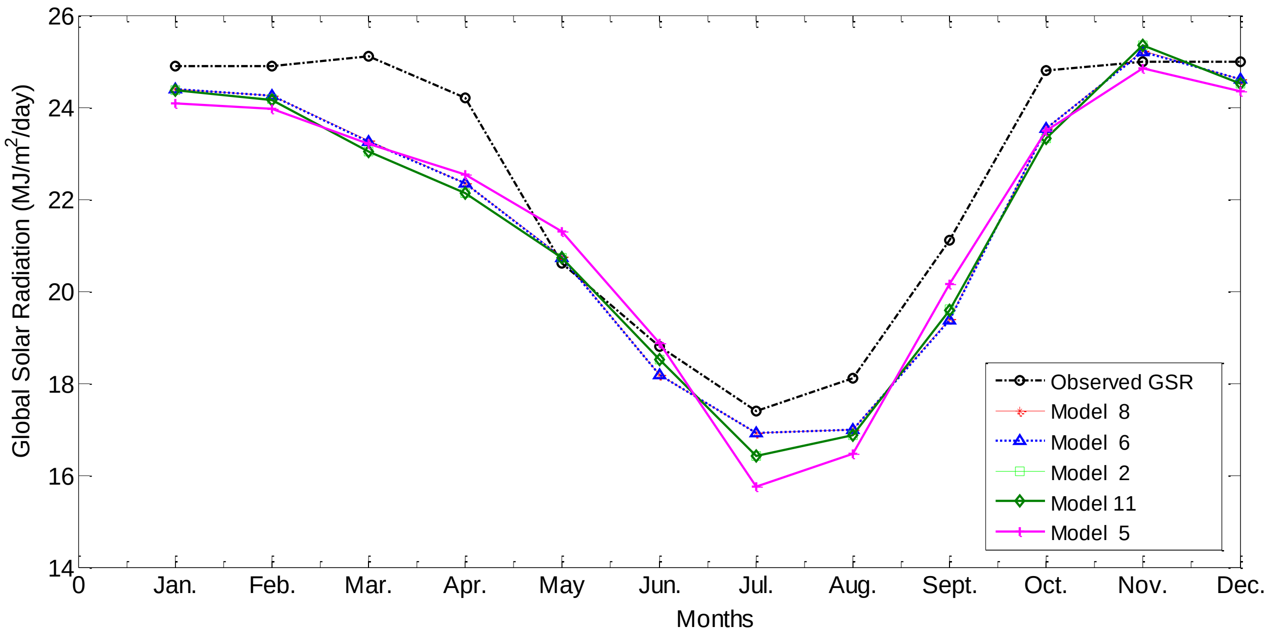

Fig. 2: Plot of the five best temperature-based model predictions of global solar radiation in Katsina for 2016.

Validation of sunshine-based models

The result of the predictions of monthly global solar radiation in Katsina for 2016 using the sunshine-based models is presented in Table 8.

Table 8: Prediction results from sunshine –based model

Model No.	RMSE	MAE	MPE	R	R^2
1	2.9640	2.7024	12.5028	0.1071	0.0115
2	2.9873	2.6290	11.9331	0.2146	0.0461
3	10.0404	9.5596	41.6819	0.2332	0.0544
4	3.2919	2.7378	12.4080	0.1069	0.0114
5	2.9522	2.7329	12.7093	0.0735	0.0054
6	2.9679	2.6846	12.3853	0.1267	0.0161
7	6.5707	5.7831	28.0201	0.1190	0.0142
8	3.0943	2.6696	12.2399	0.0990	0.0098
9	2.9960	2.6236	12.7345	0.0479	0.0023
10	2.9681	2.6849	12.3855	0.1267	0.0167
11	2.9696	2.6913	12.4302	0.1163	0.0135
12	3.6630	2.9587	13.1246	0.1161	0.0135
13	3.2919	2.7378	12.4080	0.1069	0.0114
14	4.1903	3.5719	14.8388	0.1245	0.0155
15	2.9569	2.7229	12.6456	0.0823	0.0065

The prediction result in Table 8 shows that all the sunshine-based models fitted to the data did not yield acceptable results as the R and R^2 values were not up to 0.5 and the RMSE and MPE were all found to greater than 10%. This could be as a result of the unreliability of the sunshine hours data obtained from NiMet. Hence the sunshine hour based models are not quite suitable for estimating mean monthly global solar radiation and thus are excluded due to their inaccurate prediction. The results of the three best sunshine-based model predictions are displayed in Figure 3.

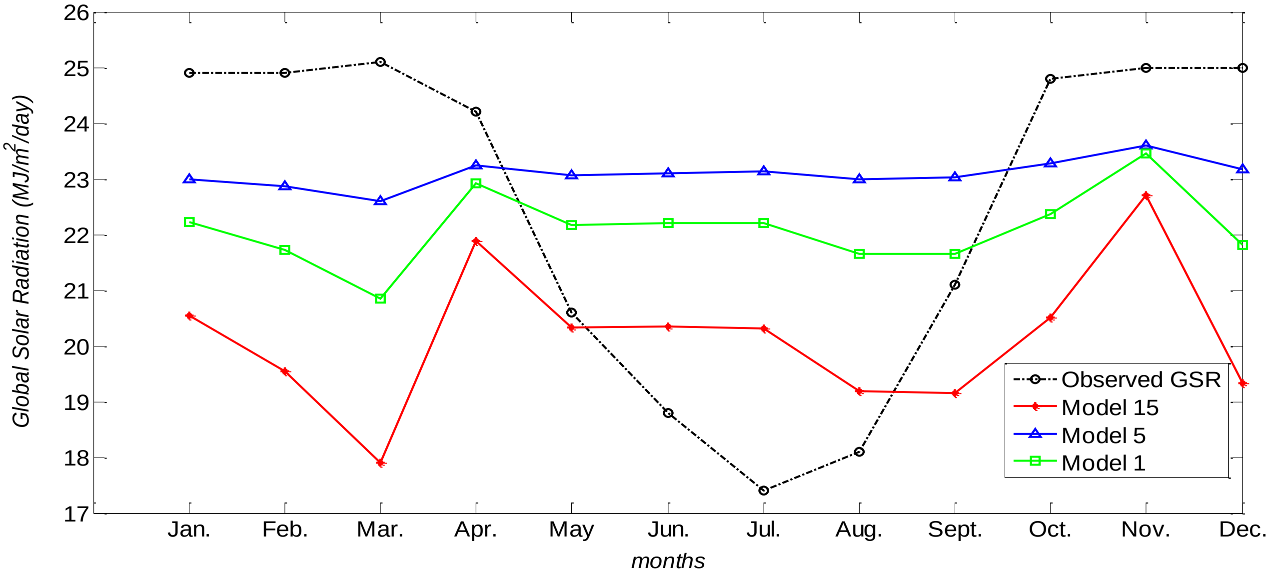

Fig. 3: Plot of the top-three sunshine-based model predictions of global solar radiation in Katsina for 2016.

Validation of hybrid parameters-based models

The result of the predictions of monthly global solar radiation in Katsina for 2016 using the hybrid parameters-based models is presented in Table 9.

Table 9: Prediction results from hybrid parameter models

Model No.	RMSE	MAE	MPE	R	R^2	Rank
1	2.9036	2.5926	11.9960	0.2123	0.0451	8
2	8.6867	8.1973	35.2860	0.3219	0.1036	9
3	2.3586	1.7838	8.0028	0.6581	0.4331	4
4	2.0136	1.5780	7.3955	0.7283	0.5304	3
5	2.2342	1.7687	8.3285	0.6567	0.4313	5
6	2.3930	2.1628	9.7943	0.5900	0.3481	7
7	2.2996	2.0064	9.0956	0.6505	0.4231	6
8	1.6942	1.5742	6.6387	0.9342	0.8727	2
9	**1.3105**	**1.0506**	**4.4069**	**0.9633**	**0.9280**	**1**

The prediction result in Table 49 shows that Model 9 exhibits the best performance with an RMSE value of 1.3105 and MPE value of 4% which is within the acceptable prediction error range of $\pm$10% (Hassan *et al.*, 2016) and also has highest value of R^2 (0.9280). The runners up are models 8 and 4 successively, with error statistic (RMSE, MPE, R^2) values of (1.6942, 6.6387, 0.8727) and (2.0136, 7.3955, 0.5304) respectively. The worst performing models are models 1 and 2 which have R and R^2 values not up to 0.5, hence they are not quite suitable for estimating mean monthly global solar radiation and thus are excluded due to their inaccurate prediction. The predictions of the best three models are displayed in Figure 4.

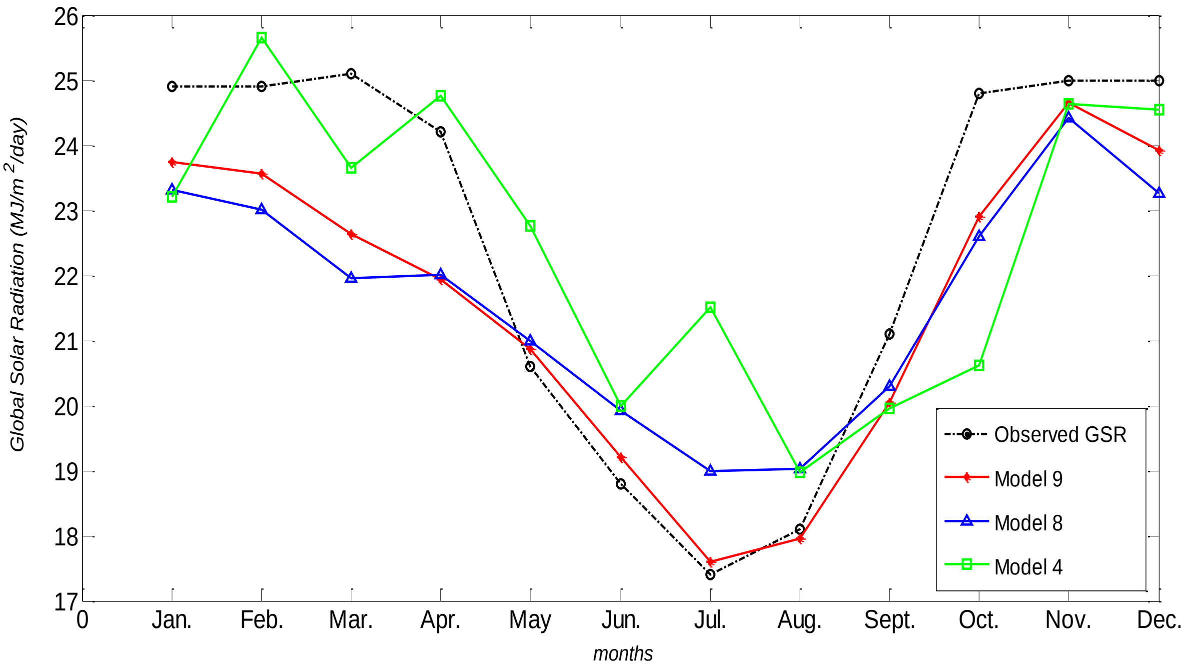

Fig. **4**: Plot of the results of the three best hybrid parameters-based models of global solar radiation in Katsina for 2016

Comparison with Previous works

This work has served as a continuing research in the assessment of empirical models for estimating global solar radiation in Katsina. The use of Matlab cftool has added more flexibility and computational accuracy in estimating more linear and nonlinear models with special exponential and logarithmic functions inclusive. The best model result obtained is from the temperature-based Model 8 with RMSE value of 1.0811, R value of 0.973 and R^2 value of 0.946 for prediction of GSR value for 2016 while the Olomiyesan and Oyedum model which predicted GSR up to 2015 obtained a RMSE value of 0.997, R value of 0.943 and R^2 value of 0.889. The Angstrom type model of second order used by Tijjani (2011) however, obtained an R value of 0.702 and R^2 value of 0.493. Thus it can be seen that this work apart from replicating the computational accuracy of the previous models has assessed more models of estimating GSR in Katsina using a wider spectrum of meteorological variables thereby opening the door for further research in this area.

CONCLUSION

In this work, the mean monthly global solar radiation in Katsina was estimated using different empirical models. Different empirical models were deployed and new models for estimating global solar radiation in Katsina were developed. All the results obtained from this research shows that the temperature-based models are more efficient in estimating the global solar radiation in Katsina while the sunshine and the hybrid parameters models were found to be unsuitable for estimating global solar radiation in Katsina due to the poor performance. This could be attributed to the poor quality of sunshine hours and relative humidity data obtained from NiMet. It is recommended that the facilities for observation of meteorological variables such as global solar radiation, sunshine hours, relative humidity, precipitation and cloud cover should be made available in our tertiary institutions so that accurate data can be obtained directly from them for research of this nature while government should improve their funding of NiMet so as to enable them obtain more accurate records of meteorological data for research and forecasting.

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REFERENCES

Angstrom, A.S. (1924). Solar and terrestrial radiation. *Meteorological Society,* 50:121-126.

Augustine, C., Nnabuchi, M.N. (2010). Analysis of some meteorological data for some selected cities in the Eastern and Sourthern zone of Nigeria. *African Journal of Environmental and Technology*, 4: 92 – 99.

Anyakoha, M.W. (2007). New School Physics. Africana First Published Limited.

Ayodele, T.R., Ogunjuyigbe, A. (2016). Performance assessment of empirical models for prediction of daily and monthly average global solar radiation: the case study of Ibadan, Nigeria. *International Journal of Ambient Energy.*

Balarabe, M., Abdullah, K., Nawawi, M. and Khalil, A. E. (2016). Monthly Temporal-Spatial Variability and Estimation of Absorbing Aerosol Index Using Ground-Based Meteorological Data in Nigeria. *Atmospheric and Climate Sciences*, 6, 425-444. http://dx.doi.org/10.4236/acs.2016.63035

Dufien, J.A. and Beckman, W.A. (1991). Solar Engineering of Thermal Processes, 2nd Edition. John Wiley and Sons, New York, 944pp.

Etuk, S.E, Nwokolo, S.C. Okechukwu E.A, John-Jaja S.A., (2016). Analysis of photosynthetically active radiation over six tropical ecological zones in Nigeria. *Journal of Geography, Environment and Earth Science International,* 7:1–15.

Falayi, E.O, Adepitan, J.O., Rabiu, A.B. (2008) Empirical models for the correlation of global solar radiation with meteorological data for Iseyin, Nigeria. *International Journal of Physical science,* 3: 210–216.

Feng, H., Schiavon, S., & Bauman, F. (2016). New method for the design of radiant floor cooling systems with solar radiation. *Energy and Buildings*, *125*, 9–18.

Gana, N.N., Akpootu, D.O. (2013). Angstrom type empirical correlation for estimating global solar radiation in North-Eastern Nigeria. *International Journal of Engineering and Science,* 2: 58–78.

Gadiwala, M.S., Usman, A., Akhtar, M., Jamil, K. (2013). Empirical Models for the Estimation of Global Solar Radiation with Sunshine Hours on Horizontal Surface in Various Cities of Pakistan. *Pakistan Journal of Meteorology,* 9*(*18): 43

Hassan, I., Onimisi, M.Y. (2013). Assessment of the Global Solar EnergyPotential at Nigerian Defence Academy (NDA) Permanent Site Afaka Kaduna, Nigeria. *American Chemical Science Journal,* 3(3): 232-246*.*

Hargreaves, G.H., Sammani, Z. (1982). Estimating potential evapo-transpiration. *Journal of irrigation and drainage engineering,* 108: 225 – 230.

Hassan,G.E., Youseef, M.E., Mohamed, Z.E., Ali, M.A. and Hanafy, A.A. (2016).New Temperature-Based Models for Predicting Global Solar Radiation. *Journal of Applied energy,* 179(2016) 437- 450.

International Energy Agency (2011). Technology Roadmap: Solar photovoltaic Energy. iea.org.IEA. Archieved.

Jatto, M.A., Shuaibu, A.Y., Garba, I. (2015). Investigation of the global solar energy potential in Potiskum, Yobe state Nigeria. Proceedings of theInternational Academic Conference for Sub-Sahara African Transformation & Development.

Kaufmann, E., Hagermann, A. (2015). Penetration of solar radiation into pure and Mars-dust contaminated snow. *Icarus*, *252*, 144–149.

Medugu, D.W, Yakubu, D. (2011). Estimation of mean monthly global solar radiation in Yola, Nigeria. *International Journal of Energy and Enviromental Engineering,* 2: 41-47.

Ming, T., De_Richter, R., Liu,W., & Caillol, S. (2014). Fighting global warming by climateengineering: Is the earth radiation management and the solar radiation management any option for fighting climate change? *Renewable and Sustainable Energy Reviews*, *31*, 792–834.

Nwokolo, S.C. (2017). A comprehensive review of empirical models for estimating global solar radiation in Africa. Renewable and Sustainable Energy Reviews, 78: 955–995.

Okonkwo, G.N., Nwokoye, A.O.C. (2014). Estimating global solar radiation from temperature data in Minna location. *European Scientific Journal,* 10: 1857–7431.

Olomiyesan, B.M., Oyedum, O.D., Ugwuoke, P.E., Abolarin, M.S. (2017) Evaluation of Some Global Solar Radiation Models in Selected Locations in Northwest, Nigeria. *Open Access Journal of Photo energy*, 1(1): 00001.DOI:15406/oajp.2017.01.0000110.

Prescott, J.A. (1940). Evaporation from water surface in relation to solar radiation. Transactions of Royal Society, South Australia, 64: 114–118.

Samuel, T. (1991). Estimation of Global Radiation for Sri Lanka. *Solar Energy,* 47(5): 333–337.

Saeed S., Abolfazl M.H., Sultan N.Q., Ozgur K., hahaboddin S., Kwok W. C. (2019) Daily global solar adiationmodeling using data-driven techniques and empirical equations in a semi-arid climate, Engineering Applications of omputational Fluid Mechanics, 13:1, 142-157.

Said, R.S., Gabriel, F. I, Garba, M.B., Najib, G.Y. (2015). Variation of Solar Radiation and its Correlation with Weather Parameters using Statistical Analysis at Yola, North-Eastern Nigeria. *Nigerian Association of Mathematical Physics Journal,* 29: 319 – 324.

Stattrek.com (2018). Statistics: Coefficient of Determination. https://stattrek.com/statistics/dictionary.aspx?definition=coefficient_of_determination. Retrieved on 12/03/2019 at 10:23 AM.

Tijjani, B.I. (2011). Comparison between first and second order Angstrom type models for sunshine hours at Katisna, Nigeria. Bayero *Journal of Pure and Applied Science,* 4(2): 24–27. http://dx.doi.org/10.4314/bajopas.v4i2.5

Ward, J.H. (2017). Error Sum of Squares. https://hlab.stanford.edu/brian/error_sum_of_ squares.html. Retrieved on 25/03/2019 at 11:50 AM.