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EVALUATION OF NEW DEVELOPED MODELS FOR ESTIMATION OF DIFFUSE SOLAR RADIATION OVER IKEJA, LAGOS STATE, NIGERIA

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ABSTRACT

This study investigates the estimation of diffuse solar radiation in Ikeja, Nigeria (6.58°N, 3.33°E, 39.40m above sea level). Employing a 22-year dataset (2001-2022) of monthly average climatic data from NASA website, nineteen new models were developed to predict diffuse solar radiation. These models incorporated various meteorological parameters including global solar radiation, wind speed, temperature, pressure, and relative humidity. A categorized approach was used, with models falling into five groups: modified Page, Liu and Jordan; clearness index with one additional variable; two-variable; three-variable; and a four-variable model. Evaluation using five statistical tests tools of Mean Bias Error (MBE), Root Mean Square Error (RMSE), Mean Percentage Error (MPE), t-test, and Coefficient of determination (R^2) identified Equation 28h (the model relating diffuse radiation to clearness index and temperature) as the most suitable model out of all the models in each of the five categories for estimation of diffuse solar radiation for Ikeja. Hence, emphasizing the importance of considering both atmospheric clarity and temperature for accurate diffuse solar radiation estimation in this coastal location.

Keywords: Clearness index, Diffuse solar radiation, Ikeja, Meteorological parameters, Models, Statistical test

INTRODUCTION

Energy usage worldwide has seen a notable rise, while the availability of fossil fuels is dwindling. The combustion of these fuels has hastened environmental deterioration (Sabzpooshani *et al.*, 2014). This situation has increased the demand for the harnessing of renewable energy sources. Among these, solar energy stands out as a pivotal source. Precise knowledge of the solar energy available, encompassing both direct and diffuse components in a specific location, holds paramount significance for the design and dimensioning of solar energy conversion systems (Hussain *et al*., 1999; Torres *et al*., 2010). Solar power, noted for its abundance, cost-effectiveness, and eco-friendliness (Li *et al*., 2010), is hindered only by its unpredictable intermittence. Remarkably, as the primary extraterrestrial energy source, solar energy governs numerous atmospheric phenomena crucial to land productivity, such as river flow regulation and material exchange between the surface and atmosphere. Precise ground measurements play a pivotal role in estimating the required solar component accurately (Sabziparvar, 2009). Solar energy measurements can be acquired through various methods: direct measurement (Benchrifa *et al*., 2019), remote sensing, or simulation techniques (Trenberth *et al*., 2007). Additionally, artificial neural networks offer another avenue for estimation (Loufti *et al*., 2017; Zhang *et al*., 2017; Rocha *et al*., 2019), along with satellite data analysis (Yoem *et al*., 2016). The solar radiation reaching the Earth's surface annually surpasses the world's proven fossil fuel reserves by 160 times (Yoshida *et al*., 2013). Nigeria, in particular, enjoys a bountiful supply of sunshine, boasting approximately 3000 hours of sunlight annually (Burari and Sambo, 2001). Solar radiation measurements employs a device known as the Pyrheliometer. However, as noted by Olatona (2018), its installation can incur substantial costs and requires delicate handling. Consequently, its installations are infrequent and widely dispersed across Nigeria. Therefore, alternative methods must be devised to derive solar radiation data, utilizing commonly monitored meteorological parameters in areas lacking dedicated solar radiation measuring instruments (Osinowo *et al*., 2015). To address these challenges, modeling techniques have been utilized to assess global solar radiation using more readily available meteorological data. Hence, many researchers have developed empirical connections to forecast diffuse irradiance in the sky using various input parameters, with the clearness index (kt) being among the foremost (Akpootu and Mustapha 2015; Despotovic *et al*., 2016; Wang *et al.*, 2016; Zhang *et al*., 2017). Liu and Jordan were among the researchers who pioneered the initial model for estimating diffuse solar radiation (Duffie and Beckman 2013). Their model established a correlation between the diffuse fraction (Hd/H) and the clearness index (K_T), where the diffuse fraction represents the ratio of diffuse radiation to global radiation, and the clearness index denotes the ratio of global radiation to extraterrestrial radiation. Subsequently, in a series of studies spanning various regions and climates, researchers have developed and validated models for estimating daily and monthly mean diffuse solar radiation, vital for enhancing solar energy system designs. Yao *et al.* (2017) focused on fog and haze-prone areas, particularly Beijing, where they utilized 55 years of solar radiation data (1957-2013) to improve diffuse solar radiation models through AQI-based modifications. Their validation using recent data (2013-2016) underscored the enhanced accuracy of these models, especially after AQI adjustments, showing significant improvements in regions like Shenyang. Jamil and Akhtar (2017) evaluated diffuse solar radiation estimation models in Aligarh, India, over three years (2013-2016), developing 42 new empirical models. Their comprehensive analysis, leveraging global performance indices, suggested that models incorporating both sky-clearness index and relative sunshine period offered superior accuracy, recommending these dual-input models for more precise estimates. Fan *et al*. (2019) assessed 72 models across various Chinese climatic regions, finding that models combining sunshine duration and global solar radiation inputs generally outperformed others. They identified best-performing models specific to each region, emphasizing the importance of model selection according to climatic conditions for accurate diffuse solar radiation estimation. More recently, Salifu *et al*. (2024) conducted a comprehensive study on the development of new models for estimating diffuse solar radiation in Benin, Nigeria. Utilizing a 22-year dataset from NASA, including various meteorological parameters, they developed 19 new models categorized into five groups. Statistical evaluation using five validation indices identified the most effective models in each category. Notably, the quadratic regression model ranked as the most suitable for accurate estimation, particularly for Benin's climatic conditions. This suggests its applicability for estimating diffuse solar radiation in Benin and similar locations. The study aims to: (i) identify optimal models for estimating diffuse solar radiation in Ikeja, adapting Page, Liu, and Jordan models, (ii) create correlation models by combining two to four variables for diffuse solar radiation estimation, (iii) rank these models to determine the most accurate one, and (iv) analyze correlations between estimated and measured values, offering a thorough assessment of model performance.

MATERIALS AND METHODS

Data collection

This research acquired twenty-two years' worth (2001-2022) of monthly average climatic data for Ikeja, situated in the coastal region of Nigeria, with coordinates of Latitude 6.58°N, Longitude 3.33°E, and an elevation of 39.40 meters above sea level. The dataset encompasses measurements of various parameters including all-sky surface shortwave diffuse irradiance, global solar radiation, wind speed, mean temperatures, surface pressure, and relative humidity. These data were sourced from the National Aeronautics and Space Administration (NASA) website.

The average daily extraterrestrial radiation on a horizontal surface, represented by H_o and measured in units of $MJm^{-2}day^{-1}$, can be approximated for each day within a month by averaging the daily values throughout that month (Iqbal, 1983; Zekai, 2008; Saidur *et al*., 2009). This computation relies on the formulas introduced by Iqbal (1983) and Zekai (2008) as reported by Sa'id *et al*., 2019; Akpootu and Abdullahi (2022) and Salifu *et al*., 2024

$$H_o = \left(\frac{24}{\pi}\right) I_{sc} \left[1 + 0.033\cos\left(\frac{360n}{365}\right)\right]\left[\cos\phi\cos\delta\sin\omega_s + \left(\frac{2\pi\omega_s}{360}\right)\sin\phi\sin\delta\right] \quad (1)$$

where $I_{SC} = 1367 Wm^{-2}$

The values of I_{sc}, ϕ, δ, and ω_s, which stand for the solar constant, site latitude, solar declination, and mean sunrise hour angle respectively, are employed in the equation to ascertain H_O Moreover, n, representing the number of days in a year from January 1st to December 31st, is factored into the computation. The determination of solar declination and mean sunrise hour angle relies on the methods outlined by Iqbal (1983) and Zekai (2008) as reported by Sa'id *et al*., 2019; Akpootu and Abdullahi (2022) and Salifu *et al*., 2024 are given by

$$\delta = 23.45\sin\left\{360\left(\frac{284+n}{365}\right)\right\} \quad (2)$$

$$\omega_s = \cos^{-1}(-\tan\phi\tan\delta) \quad (3)$$

The clearness index, denoted by K_T, offers crucial insights into the presence of solar radiation at a specified location. A K_T value of one (1) signifies entirely clear skies, with maximum solar radiation reaching the Earth's surface. Conversely, a K_T value of zero (0) denotes complete cloud cover, resulting in no solar radiation reaching the Earth's surface. K_T values generally fall between 0.2 and 0.8, with higher values indicating clearer skies and greater solar radiation availability (Iqbal, 1983). Below is the mathematical representation of the clearness index as reported by Akpootu *et al*. 2023; Salifu *et al*., 2024:

$$K_T = \frac{H_m}{H_o} \quad (4)$$

Developed Diffuse Solar Radiation Models

The proposed models of diffuse solar radiation based on the modified Page; Liu and Jordan models are:

$$\frac{H_d}{H_m} = a + bK_T \quad (5)$$

$$\frac{H_d}{H_m} = a + bK_T + cK_T^2 \quad (6)$$

$$\frac{H_d}{H_m} = a + bK_T + cK_T^2 + dK_T^3 \quad (7)$$

$$\frac{H_d}{H_m} = a + bK_T + cK_T^2 + dK_T^3 + eK_T^4 \quad (8)$$

To capture the influence of all potential factors, the multiple linear regression was employed. This approach will incorporate all four meteorological parameters $\{WS$, monthly average daily wind speed (ms^{-1}); T_{mean}, monthly average mean temperature (^OC); RH, monthly average daily relative humidity (%), PS), and monthly average daily atmospheric pressure (hPa)} as independent variables and $\frac{H_d}{H_m}$ as the dependent variable. This study also proposed other diffuse solar radiation models, that involves correlations of the linear Page model with meteorological parameters as follows:

$$\frac{H_d}{H_m} = a + b\frac{H}{H_o} + cWS \quad (9)$$

$$\frac{H_d}{H_m} = a + b\frac{H}{H_o} + cRH \quad (10)$$

$$\frac{H_d}{H_m} = a + b\frac{H}{H_o} + cPS \quad (11)$$

$$\frac{H_d}{H_m} = a + b\frac{H}{H_o} + cT_{mean} \quad (12)$$

The proposed two variables models are:

$$H_d = a + bWS + cRH \quad (13)$$

$$H_d = a + bWS + cT_{mean} \quad (14)$$

$$H_d = a + bWS + cPS \quad (15)$$

$$H_d = a + bRH + cT_{mean} \quad (16)$$

$$H_d = a + bRH + cPS \quad (17)$$

$$H_d = a + bT_{mean} + cPS \quad (18)$$

The proposed three variables correlation models are:

$$H_d = a + bWS + cRH + dT_{mean} \quad (19)$$

$$H_d = a + bWS + cT_{mean} + dPS \quad (20)$$

$$H_d = a + bWS + cPS + dRH \quad (21)$$

$$H_d = a + bRH + cT_{mean} + dPS \quad (22)$$

The proposed four variables correlations model is:

$$H_d = a + bWS + cRH + dT_{mean} + ePS \quad (23)$$

The algebraic constants a, b, c, d, and e in the equations (5) to (23), are termed empirical constants or coefficients.

The Minitab software package, version 21.2, was utilized to analyze the model parameters required for determining the empirical constants. Origin 2018 version software was employed to plot the correlation graphs.

Accuracy of the Models

To assess each model's accuracy, statistical tests were applied. These tests included Mean Bias Error (MBE), Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and a t-test. The equations for calculating MBE, RMSE, and MPE, based on modifications to the method proposed by El-Sebaii *et al.*, (2005) as proposed by Akpootu *et al*., (2015) are presented as follows:

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(H_{d_{i,cal}} - H_{d_{i,meas}}\right) \quad (24)$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left(H_{d_{i,cal}} - H_{d_{i,meas}}\right)^2\right]^{\frac{1}{2}} \quad (25)$$

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{H_{d_{i,meas}} - H_{d_{i,cal}}}{H_{d_{i,meas}}}\right) \text{x } 100 \quad (26)$$

In line with Bevington's (1969) explanation, we employed the t-test to assess the average values produced by our models. This statistical method relies on a specific variable denoted as "t," which incorporates the concept of degrees of freedom. According to (Akpootu *et al*., 2019c, d; Akpootu *et al*., 2023) t –test is a non-dimensional parameter and it can be mathematically expressed as follows:

$$t = \left[\frac{(n-1)(MBE)^2}{(RMSE)^2 - (MBE)^2}\right]^{\frac{1}{2}} \quad (27)$$

The variables $H_{d_{i,meas}}$ and $H_{d_{i,cal}}$ denotes i^{th} the measured and i^{th} calculated values of daily diffuse solar radiation, respectively, along with the total number of observations denoted by n, as derived from equations (24), (25), and 26). Lower values of MBE, RMSE, MPE, and t-test signifies superior model performance. These statistical measures assess the accuracy of a model's predictions compared to actual observed values. Positive values of MPE and MBE quantify the average degree of overestimation in the model's predictions, while negative values indicate underestimation (Akpootu *et al*., 2023). According to research by Merges *et al.* (2006), Gana *et al.* (2013a, b), Akpootu *et al.* (2014), Akpootu and Sulu (2015), and Olomiyesan *et al*. (2021), a model's performance is deemed better when it exhibits a low Mean Percentage Error (MPE), and errors within the range of -10 % to +10 % are considered acceptable. Additionally, studies by Halouani *et al*., (1993), Almorox *et al*., (2005), and Chen et al. (2004) suggest that an ideal model should have a Mean Bias Error (MBE) value close to zero, and a low Root Mean Square Error (RMSE) value is desirable. These measures provide valuable insights into the model's biases and limitations.

For a more precise data modeling outcome, it's crucial that the coefficient of determination (R^2) tends towards the value 1, ideally reaching 100 % (Akpootu and Iliyasu 2015a, b; Akpootu *et al*., 2019a, b). This signals a robust correlation between predicted and observed values, reflecting a well-fitting model.

RESULTS AND DISCUSSION

The results of the Page, Liu and Jordan models; clearness index and one variable models; two variables model; three variables models and four variables model for Ikeja based on equations (5) to (23) are:

$$\frac{H_d}{H_m} = 1.0140 - 0.9441K_T \quad (28a)$$

$$\frac{H_d}{H_m} = 0.062 + 3.21K_T - 4.47{K_T}^2 \quad (28b)$$

$$\frac{H_d}{H_m} = 7.66 - 46.20K_T + 101.8{K_T}^2 - 75.60{K_T}^3 \quad (28c)$$

$$\frac{H_d}{H_m} = -17.9 + 178K_T - 630{K_T}^2 + 982{K_T}^3 - 570{K_T}^4 \quad (28d)$$

$$\frac{H_d}{H_m} = 0.812 - 0.686\frac{H}{H_o} + 0.0367WS \quad (28e)$$

$$\frac{H_d}{H_m} = 1.132 - 0.998\frac{H}{H_o} - 0.00109RH \quad (28f)$$

$$\frac{H_d}{H_m} = 17.07 - 1.2348\frac{H}{H_o} - 0.01579PS \quad (28g)$$

$$\frac{H_d}{H_m} = 0.737 - 1.0746\frac{H}{H_o} + 0.01279T_{mean} \quad (28h)$$

$$H_d = 8.53 + 0.232WS + 0.0048RH \quad (28i)$$

$$H_d = -8.74 + 1.018WS + 0.603T_{mean} \quad (28j)$$

$$H_d = 540.5 + 1.379WS - 0.5299PS \quad (28k)$$

$$H_d = -9.83 + 0.0799RH + 0.471T_{mean} \quad (28l)$$

$$H_d = 437 + 0.1254RH - 0.435PS \quad (28m)$$

$$H_d = 163 + 0.142T_{mean} - 0.156PS \quad (28n)$$

$$H_d = -9.16 + 0.983WS + 0.0058RH + 0.603T_{mean} \quad (28o)$$

$$H_d = 577 + 1.388WS - 0.052T_{mean} - 0.565PS \quad (28p)$$

$$H_d = 558.9 + 1.112WS - 0.5519PS + 0.0511RH \quad (28q)$$

$$H_d = 640 + 0.1389RH - 0.271T_{mean} - 0.630PS \quad (28r)$$

$$H_d = 702 + 1.089WS + 0.0624RH - 0.195T_{mean} - 0.690PS \quad (28s)$$

Modified Page, Liu and Jordan Models

Below are the statistical analysis summary of the models Eqn 28a to Eqn 28d

Table 1: **Modified Page, Liu and Jordan Models Statistical Error indicators**

Models	R^2	MBE	RMSE	MPE	t
Eqn 28a	91.84%	-0.0062	0.2659	-0.0888	0.0776
Eqn 28b	96.53%	-0.0022	0.1702	-0.0117	0.0435
Eqn 28c	97.67%	0.0257	0.1403	-0.2934	0.6173
Eqn 28d	97.91%	2.5195	2.5814	-26.7558	14.8694

Table 1 presents a condensed overview of the statistical validation test conducted on the modified Page, Liu and Jordan models for this study. Among the models, the modified equation 28d, a polynomial of degree 4, exhibits the highest R^2 value of 97.91 %. Notably, the quadratic equation (Eqn 28b) has the lowest MBE, MPE, and t-test values with underestimation of 0.0022 $MJm^{-2}day^{-1}$ and 0.0117 % in its estimated values and 0.0435 respectively. The results equally shows that MPE values for all the developed models excluding equation 28d are within the acceptable range of $\pm$10 %. The t-test values for all the models are significant at 95% and 99% while the model equation 28d isn't.

Table 2: **Ranks obtained from the estimated modified Page, Liu and Jordan Models for Ikeja**

Models	R^2	MBE	RMSE	MPE	t	Rank
Eqn 28a	4	2	3	2	2	13
Eqn 28b	3	1	2	1	1	**8**
Eqn 28c	2	3	1	3	3	12
Eqn 28d	1	4	4	4	4	17

Table 2 provides a summary of the ranks derived from the estimated modified Page, Liu and Jordan models for Ikeja. It is evident from the table that the ranks achieved by each model range from 8 to 17. The comprehensive findings indicate that the quadratic regression model, as defined in equation 28b, proves to be more accurate in estimating diffuse solar radiation in Ikeja when compared to the other four models.

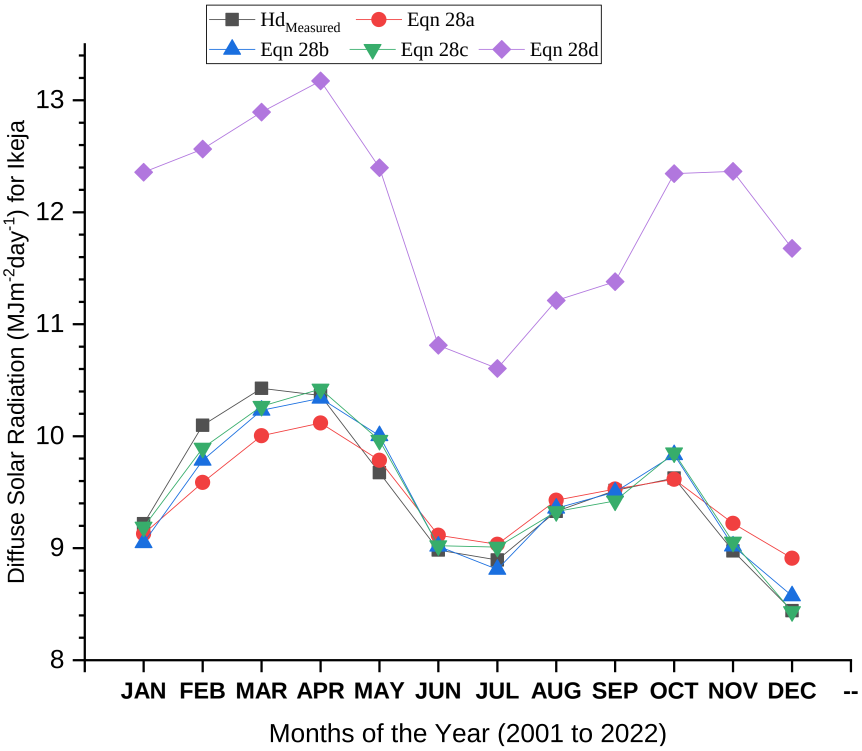

Figure 1: Comparison between the measured diffused solar radiation and estimated modified Page, Liu and Jordan models for Ikeja

Figure 1 shows the comparison between the measured diffuse solar radiation and estimated models based on the modified Page, Liu and Jordan Models for Ikeja. It appears evidently from the figure that the developed polynomial model of degree 4 (Eqn 28d) overestimated the measured diffuse solar radiation and other developed models from the month of January to December. The quadratic model (Eqn 28b) followed similar pattern of variation with the measured diffuse solar radiation and was reported to be the most suitable model for estimating diffuse solar radiation in Ikeja based on the modified Page, Liu and Jordan models as compared to other estimated models in this category.

Clearness Index and One Variable Correlation Models

Table 3: Clearness Index and One Variable Models Statistical Error indicators

Models	**R^2**	**MBE**	**RMSE**	**MPE**	**t**
Eqn 28e	92.74%	-0.0040	0.2471	-0.0913	0.0543
Eqn 28f	91.99%	-0.0147	0.2631	-0.0030	0.1856
Eqn 28g	97.89%	0.0486	0.1434	-0.5329	1.1936
Eqn 28h	94.80%	-0.0002	0.2078	-0.0780	0.0030

Table 3 provides a summarized overview of the statistical validation tests conducted on the Clearness index and a single variable model in this study. Among these models, modified equation 28g stands out with the highest R^2 value at 97.89 % and the lowest RMSE value of 0.1434 $MJm^{-2}day^{-1}$. Notably, Equation 28h exhibits the lowest values for both MBE and t-test, recording an underestimation of 0.0002 $MJm^{-2}day^{-1}$ in its estimated value and 0.0030 respectively. Regarding MPE, equation 28f achieves the lowest value at 0.0030 %, with thus an underestimation of 0.0030 % in its estimated value. Furthermore, the results indicate that the MPE values for all developed models fall within the acceptable range of ± 10%. Additionally, the t-test values for all models are statistically significant at both 95% and 99%.

Table 4: Ranks obtained from the estimated Clearness Index and One Variable correlation Models for Ikeja

Models	**R^2**	**MBE**	**RMSE**	**MPE**	**t**	**Rank**
Eqn 28e	3	2	3	3	2	13
Eqn 28f	4	3	4	1	3	15
Eqn 28g	1	4	1	4	4	14
Eqn 28h	2	1	2	2	1	**8**

Table presents a concise summary of the rankings obtained from the estimated clearness index and one variable models for Ikeja. The table clearly shows that the ranks attained by each model fall within the range of 8 to 15. The overall findings concludes that, in estimating diffuse solar radiation in Ikeja, model equation 28h demonstrates greater performance and accuracy compared to the other three models.

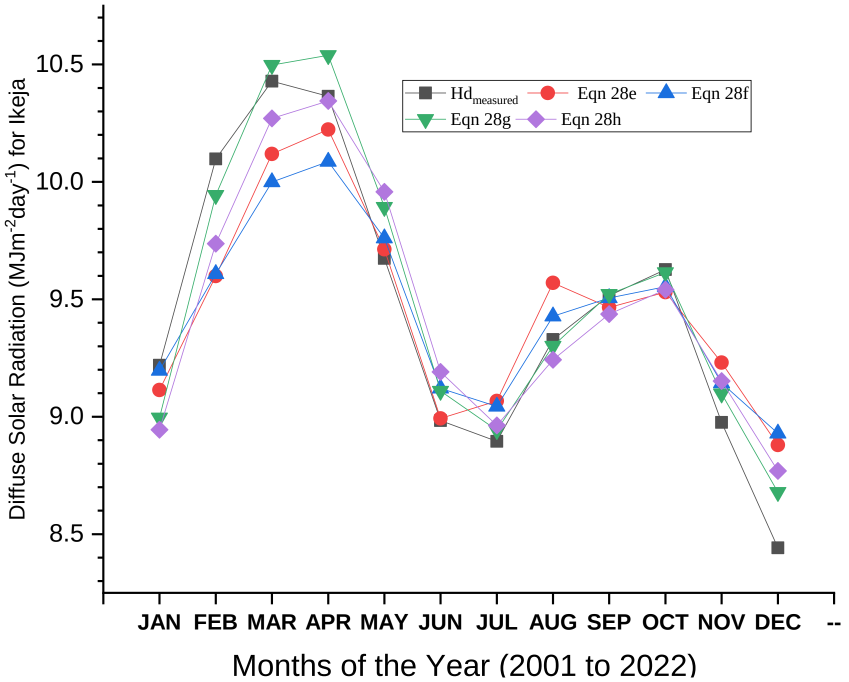

Figure 2: Comparison between the measured diffused solar radiation and estimated clearness index and a single variable models for Ikeja.

Figure shows the comparison between the measured diffuse solar radiation and estimated models based on the clearness index and a single variable Models for Ikeja. It is evident that the model equation 28g overestimated the measured diffuse solar radiation and other estimated models in the month of March and April. The model Eqn 28h followed similar pattern of variation with the measured diffuse solar radiation and was reported to be the most suitable model for estimating diffuse solar radiation in Ikeja based on the clearness index and a single variable models as compared to other estimated models.

Two Variables Correlation Models

Table 5: Two variables Models Statistical Error indicators for Ikeja

Models	R^2	MBE	RMSE	MPE	t
Eqn 28i	3.31%	-0.0007	0.5770	-0.3614	0.0043
Eqn 28j	63.14%	0.0013	0.3563	-0.1619	0.0123
Eqn 28k	81.85%	-0.0717	0.2601	0.6836	0.9510
Eqn 28l	46.02%	-0.0049	0.4312	-0.1599	0.0373
Eqn 28m	63.49%	-0.2399	0.4281	2.4007	2.2440
Eqn 28n	30.79%	0.0202	0.4886	-0.4863	0.1370

Table 5 provides a summarized overview of the statistical validation tests conducted on the two variable models in this study. Among these models, equation 28k stands out with the highest R^2 and the lowest RMSE values of 81.85 % and 0.2601 % $MJm^{-2}day^{-1}$ respectively. Notably, Equation 28i exhibits the lowest for MBE and t-test values, recording an underestimation of 0.0007 $MJm^{-2}day^{-1}$ in its estimated value and 0.0043 respectively. While equation 28l has the lowest MPE value of 0.1599 %, thus, with an underestimation of 0.1599 % in its estimated value. Furthermore, the results indicate that the MPE values for all developed models fall within the acceptable range of ± 10%. Additionally, the t-test values for all models are statistically significant at both 95% and 99%.

Table 6: Ranks obtained from the estimated Two Variables Correlation models for Ikeja

Models	R^2	MBE	RMSE	MPE	t	Rank
Eqn 28i	6	1	6	3	1	17
Eqn 28j	3	2	2	2	2	**11**
Eqn 28k	1	5	1	5	5	17
Eqn 28l	4	3	4	1	3	15
Eqn 28m	2	6	3	6	6	23
Eqn 28n	5	4	5	4	4	22

Table 6 provides a summary of the ranks derived from the estimated two variables models for Ikeja. It is evident from the table that the ranks achieved by each model range from 11 to 23. The comprehensive findings indicate that the model equation 28j, proves to be more accurate in estimating diffuse solar radiation in Ikeja when compared to the other five models in terms of the two variable correlation models above.

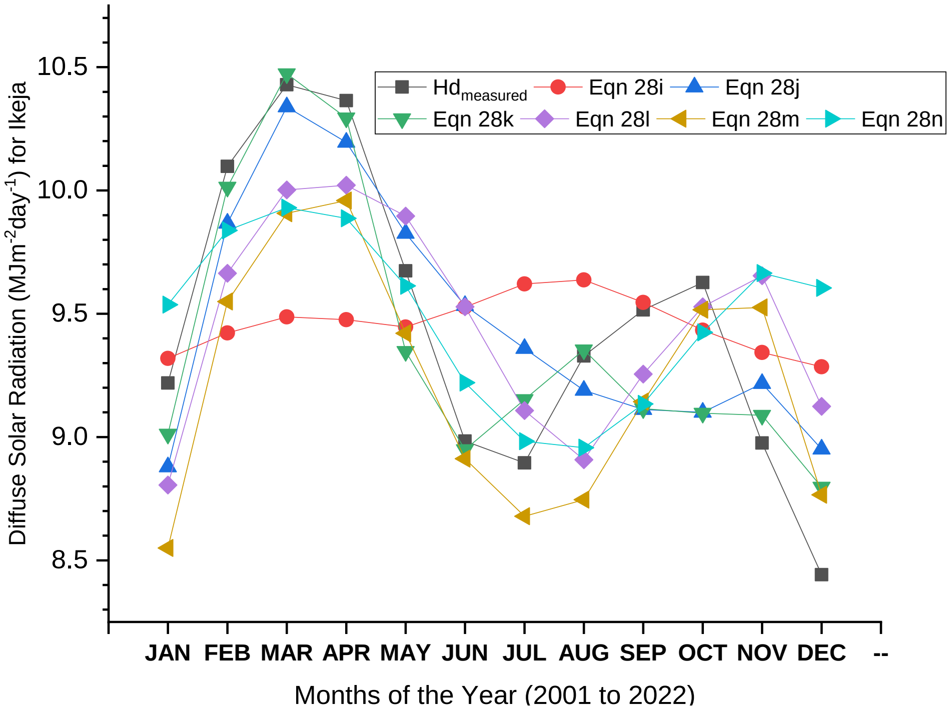

Figure 3: Comparison between the measured diffused solar radiation and estimated two variables models for Ikeja.

Figure 3 shows the comparison between the measured diffuse solar radiation and estimated models based on the two variable models for Ikeja. The model equation 28i overestimated the measured diffuse solar radiation and other developed models from the month of July to August. The model with equation 28i also underestimated from February to April. The model Eqn 28j followed similar pattern of variation with the measured diffuse solar radiation and was reported to be the most suitable model for estimating diffuse solar radiation in Ikeja based on the two variable models as compared to other estimated models in this category.

Three Variables Models

Table 7: Three Variable Models Statistical Error indicators for Ikeja

Models	R^2	MBE	RMSE	MPE	t
Eqn 28o	63.19%	0.0002	0.3560	-0.1499	0.0021
Eqn 28p	81.94%	-0.3094	0.3974	3.2055	4.1146
Eqn 28q	85.46%	-0.0669	0.2335	0.6472	0.9909
Eqn 28r	65.71%	0.1796	0.3877	-2.0407	1.7340

Table 7 presents a condensed overview of the statistical validation test conducted on the three variables correlation models for this study. Among the models, the equation 28q, exhibits the highest R^2 and lowest RMSE values of 85.46 % and 0.2335 MJm^{-2}day^{-1} respectively. Notably, the model equation 4.3o has the lowest for MBE, MPE, and t-test values with overestimation of 0.0002 MJm^{-2}day^{-1} in its estimated value, an underestimation of 0.1499 % in its estimated value and 0.0021 respectively. The results equally shows that MPE values for all the developed models are within the acceptable range of ± 10 %. The t-test values for all models are significant at 95% and 99% except for model equation 28p.

Table 8: **Ranks obtained from the estimated Three Variables Correlation models for Ikeja**

Models	R^2	MBE	RMSE	MPE	t	Rank
Eqn 28o	4	1	2	1	1	9
Eqn 28p	2	4	4	4	4	18
Eqn 28q	1	2	1	2	2	**8**
Eqn 28r	3	3	3	3	3	15

Table 8 above provides a summary of the ranks derived from the estimated three variable correlation models for Ikeja. It is evident from the table that the ranks achieved by each model range from 8 to 18. The comprehensive findings indicate that the model equation 28q, proves to be more accurate in estimating diffuse solar radiation in Ikeja when compared to the other three models.

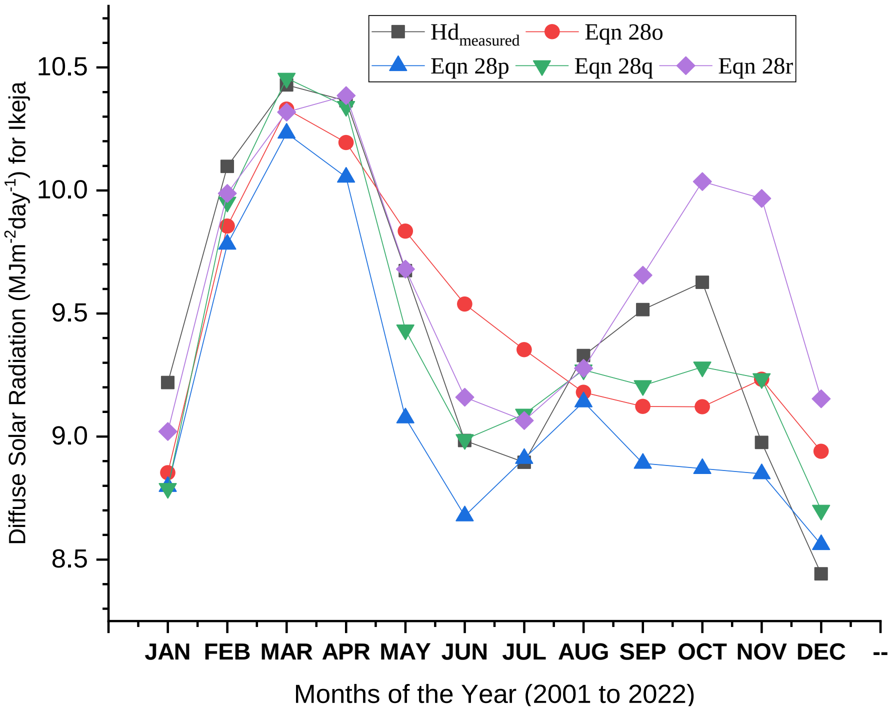

Figure 4: Comparison between the measured diffused solar radiation and estimated three variables models for Ikeja.

Figure 4 shows the comparison between the measured diffuse solar radiation and estimated models based on the three variable Models for Ikeja. The model equation 28r overestimated the measured diffuse solar radiation and other developed models from the month of September to December. While the model equation 28p underestimated the measured diffuse solar radiation and other developed models in the month of March to June and in September to November. The model equation 28q followed similar pattern of variation with the measured diffuse solar radiation and was reported to be the most suitable model for estimating diffuse solar radiation in Ikeja based on the three variable models as compared to other estimated models.

Four Variables Model

Table 9: **Four Variable Statistical Error indicators for Ikeja**

Model	R^2	MBE	RMSE	MPE	t
Eqn 4.3s	86.61%	-0.4190	0.4708	4.3883	6.4710

Table 9 shows that the model equation 28s has an underestimation of 0.4190 $MJm^{-2}day^{-1}$ and overestimation of 4.3883 $MJm^{-2}daay^{-1}$it in estimated value. The t-test value is not significant at 95% and 99%.

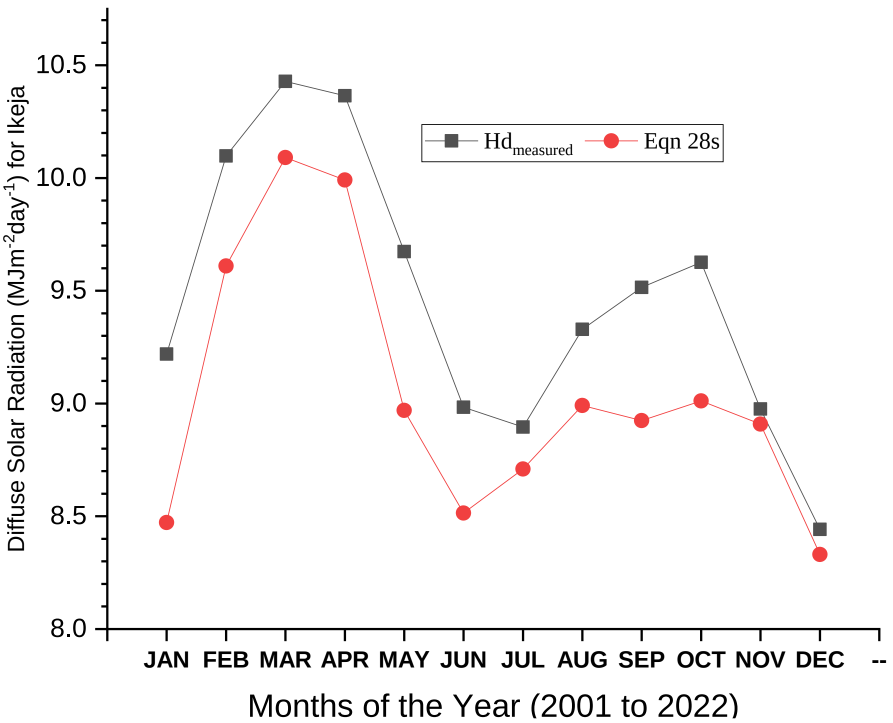

Figure 5: Comparison between the measured diffused solar radiation and estimated Four variables models for Ikeja.

Figure 5 shows the comparison between the measured diffuse solar radiation and estimated four variable model for Ikeja. The model equation 28s underestimated the measured diffuse solar radiation from the month of January to December.

Comparison of all Categories of Models

Table 10: Statistical summary of better performed models across each category for Ikeja

Models	R^2	MBE	RMSE	MPE	t
Eqn 28b	96.53%	-0.0022	0.1702	-0.0117	0.0435
Eqn 28h	94.80%	-0.0002	0.2078	-0.0780	0.0030
Eqn 28j	63.14%	0.0013	0.3563	-0.1619	0.0123
Eqn 28q	85.46%	-0.0669	0.2335	0.6472	0.9909
Eqn 28s	86.61%	-0.4190	0.4708	4.3883	6.4710

Table 11: Ranks obtained for the performed models across each category for Ikeja

Models	R^2	MBE	RMSE	MPE	t	Rank
Eqn 28b	1	3	1	1	3	9
Eqn 28h	2	1	2	2	1	**8**
Eqn 28j	5	2	4	3	2	16
Eqn 28q	4	4	3	4	4	19
Eqn 28s	3	5	5	5	5	23

From Table 12, equation 28h of the clearness index and one variable model category was found to perform best in estimating diffuse solar radiation for Ikeja.

CONCLUSION

In this study, a dataset spanning twenty-two years (2001 to 2022) encompassing measured monthly average daily global solar radiation, diffuse solar radiation, relative humidity, atmospheric pressure, wind speed, and mean temperature was employed. This dataset were utilized to develop 19 (nineteen) novel models for estimating diffuse solar radiation. These models are of five categories namely; modified Page, Liu and Jordan models; clearness index and one variable models; two variable models; three variable models and four variable model and statistically tested using five validation indices of MBE, RMSE, MPE, t-test and R^2.

The results obtained based on the models developed for Ikeja, in modified Page, Liu and Jordan models, equations 28b was found to be appropriate; equation 28h was found appropriate for the clearness index and one variable models category; equation 28j was found appropriate for the two variable models category; equation 28q was found appropriate for the three variable category. The ranking of all the better performed developed models from each categories indicated that the model that relates the diffuse solar radiation with clearness index and temperature (Eqn.28h) performed most appropriate for estimation of diffuse solar radiation for Ikeja.

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