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COMPREHENSIVE ANALYSIS AND MODELING OF MULTIVARIATE DIFFUSE SOLAR RADIATION USING KEY METEOROLOGICAL PARAMETERS IN YELWA, KEBBI STATE, NIGERIA

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ABSTRACT

This study analyzes a 35-year dataset (1990–2024) of monthly average weather data for Yelwa, Nigeria, including global solar radiation, diffuse shortwave radiation reaching the surface, air temperature, wind speed, relative humidity, and air pressure, sourced from NASA. Using multiple linear regression, the research develops nineteen models grouped into modified Page and Liu-Jordan models, clearness index models, and single- to four-variable models. The independent variables are air pressure, relative humidity, air temperature, and wind speed. Each model's accuracy was tested with statistical measures: Mean Bias Error (MBE), Root Mean Square Error (RMSE), Mean Percentage Error (MPE), t-test, and coefficient of determination (R^2). Among the modified Page and Liu-Jordan models, a quadratic regression model of degree two performed best. In the clearness index and single-variable category, the model linking diffuse solar radiation to clearness index and relative humidity showed the highest accuracy. For two-variable models, the combination of relative humidity and air temperature was most effective. In the three-variable category, the model using wind speed, relative humidity, and air temperature stood out. Overall, the model combining clearness index and relative humidity proved most accurate for estimating diffuse solar radiation in Yelwa's tropical climate. By relying on simple relative humidity measurements, this model avoids the need for advanced tools like pyrheliometers, providing a practical and accurate method for estimating diffuse solar radiation, useful for solar energy planning and climate studies in similar regions.

Keywords: Diffuse solar radiation, Clearness index , Relative humidity, Multiple linear regression, Yelwa.

1.0 Introduction

The steady rise in global energy demand, alongside the rapid depletion of fossil fuel reserves, has intensified the need for renewable energy sources that are both sustainable and environmentally responsible. Conventional fuels have long driven economic growth, but their extensive use has also accelerated environmental degradation, increased greenhouse gas emissions, and heightened the urgency of mitigating climate change (Sabzpooshani and Mohammadi, 2014; Zhou *et al*., 2021; Chen *et al*., 2024). Consequently, renewable energy has become central to global clean-energy transitions, with solar power standing out as one of the most promising alternatives because of its abundance, accessibility, and minimal ecological footprint (Torres *et al*., 2010; Khalil and Rahoma, 2021; Kassem *et al*., 2023; Mwigereri *et al*., 2025; Rajagukguk and Lee, 2025;).

Africa's inability to harness sufficient renewable energy keeps millions reliant on fossil fuels, fueling poverty, limiting development, and worsening diseases tied to pollution (Alex-Oke *et al*., 2025; Ember, 2025). Despite rapid growth in capacity—

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solar rising from 0.5 GW in 2015 to 20 GW by 2025—renewables still account for just 25% of electricity, far below the global average (Eze, 2025).

Accurate assessment of solar radiation—comprising its global, direct, and diffuse components—is crucial for the design, sizing, and optimization of solar-energy conversion systems(Paulescu and Paulescu, 2022). Beyond energy applications, solar radiation influences a range of atmospheric and ecological processes, including evapotranspiration, temperature regulation, and primary productivity(Sabziparvar, 2009; Latifah *et al*., 2025). However, direct measurement using instruments such as pyrheliometers and pyranometers is often limited in developing regions due to high equipment and maintenance costs(Olatona, 2018). As a result, empirical and statistical modeling approaches have become indispensable for estimating solar radiation from commonly available meteorological variables like temperature, humidity, pressure, and wind speed (Osinowo *et al*., 2015; Salifu, D. O., *et al*., 2024).

Nigeria, situated within the tropical belt, is particularly well-positioned to exploit solar energy, receiving about 3,000 hours of sunshine annually and mean daily solar radiation values ranging from 3.5 to 7.0 kWh m^{-2} day^{-1} (Burari and Sambo, 2001; Elehinafe *et al*., 2021). Despite this vast potential, spatially distributed solar radiation data remain scarce. This gap has motivated the development of empirical models that estimate solar components based on meteorological parameters. A central concept in such modeling is the clearness index (K_t)—the ratio of global solar radiation to extraterrestrial radiation—which serves as a key predictor of diffuse solar radiation (Akpootu and Mustapha, 2015; Despotovic *et al*., 2016; Wang et al., 2016).

The foundational work of Liu and Jordan established a robust correlation between the diffuse fraction (Hd/H) and the clearness index (K_t), a relationship that continues to underpin modern solar-radiation modeling (Iqbal, 1983; Duffie and Beckman, 2013). Subsequent refinements, through regional calibrations and climatic validations, have improved model accuracy under different atmospheric conditions (Fan *et al*., 2019; Lu *et al*., 2023). For instance, (Yao *et al*., 2020) enhanced model precision in haze-prone areas by incorporating the Air Quality Index (AQI), while (Jamil and Akhtar, 2017) demonstrated that dual-variable models combining the clearness index and relative sunshine duration produce more reliable estimates.

Recent advances in data-driven modeling—such as artificial neural networks (ANNs) and machine-learning techniques—have further improved diffuse-radiation prediction by capturing complex nonlinear relationships among meteorological variables (Mustafa *et al*., 2022; Lu *et al*., 2023). These hybrid models are especially useful in data-limited regions, offering adaptable and transferable predictive frameworks (Khalil and Rahoma, 2021; Q. Qi *et al*., 2024; Y. Qi *et al*., 2024; Puspita *et al*., 2025).

In Nigeria, similar modeling frameworks have been applied across various climatic zones. Studies by (Akpootu and Salifu, 2024; Salifu, Akpootu, and Kola, 2024; Salifu, D. O., *et al*., 2024) developed and validated nineteen empirical models using a 22-year NASA dataset for both coastal and inland regions. Their findings revealed that temperature-based models—especially those integrating the clearness index and mean temperature—yield the most accurate diffuse-radiation estimates for locations such as Benin, Ogoja, and Ikeja. These results highlight the value of multi-variable models for improving solar-radiation prediction in tropical and coastal climates.

Building on this foundation, the present study focuses on Yelwa (Kebbi State), Nigeria, with the objectives to: evaluate the performance of Page, Liu, and Jordan models in estimating diffuse solar radiation; develop and test new multi-variable correlation models incorporating up to four meteorological parameters; rank and

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validate model performance using statistical indicators such as RMSE, MBE, MPE, R^2, and t-tests; and assess variations in model accuracy to deepen understanding of solar-radiation dynamics across the scope of this study.

2.0 MATERIALS AND METHODS

2.1 Study Area

Yelwa (Latitude 10.8351° N, Longitude 4.7424° E; Elevation ≈ 244. 0 m) lies within Yauri Local Government Area of Kebbi State, Northwestern Nigeria. The town occupies part of the Sudano–Sahelian ecological zone, characterized by tropical savanna climate (Aw) under the Köppen–Geiger classification (Galadima *et al*., 2019).



Figure 1: The Study Area as shown on Map of Nigeria

2.2 Data Collection

A 35 years (1990-2024) monthly average climatic data for Yelwa, Nigeria (Latitude 10.8351° N, Longitude 4.7424° E; Elevation ≈ 244. 0 m) was utilized. These data are global solar radiation, all-sky surface shortwave diffuse irradiance, mean temperatures, wind speed, relative humidity and surface pressure, sourced from the NASA website. The data output file was in CSV.

According to Iqbal, 1983 H_0 measured in $MJm^{-2}day^{-1}$ is the mean daily extraterrestrial radiation on a horizontal surface and can be estimated for each day of a month by averaging the daily values over that month. Also, based on the equations presented by (Zekai S., 2008):

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

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

Symbolically, the site latitude, solar constant, mean sunrise hour angle and solar declination are respectively denoted by φ, I_{sc}, ω_s and δ are utilized (in equation 1) to determine H_0 likewise, n, (i.e the total number of days that makes a year from January 1st to December 31st) is also incorporated into the calculation. The mean sunrise hour angle and solar declination are determined using the methods presented by Iqbal (1983) and Zekai (2008) as reported by (Sa'id *et al*., 2020); (Akpootu and Abdullahi, 2022) and (Salifu, Akpootu, and Kola, 2024) as shown in the below equations:

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

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

The clearness index, K_T, according to (Iqbal, 1983)and reported by (Li *et al*., 2020; Ding *et al*., 2024) is the ratio of the global solar radiation to the extraterrestrial solar radiation. It does provide valuable information about the availability of solar radiation at any specific location. When K_T outcome is one (1), the sky is completely clear indicating that maximum amount of solar radiation is reaching the Earth's surface and when zero (0), it denotes a complete overcast of the sky, which means the solar radiation is not reaching the Earth's surface. Clearness index typically ranges between 0.2 and 0.8, whereby the higher values denotes clearer skies and more available solar radiation (Iqbal, 1983). The clearness index as reported by Akpootu *et al*., 2023; Akpootu and Salifu (2024); Salifu, D. O., *et al*., 2024) is expressed as:

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

H_m, measure in $MJm^{-2}day^{-1}$, is global solar radiation.

2.3 Data Processing

The diffuse solar radiation and global solar radiation data were obtained from the NASA website in $Kwhm^{-2}day^{-1}$ which was converted to $MJm^{-2}day^{-1}$ according to the conversion factor: 1 $Kwhm^{-2}day^{-1}$ = 3.6 $MJm^{-2}day^{-1}$ (Salifu, Akpootu, Kola, *et al*., 2024).

The surface pressure in kPa was multiplied with 10 converting it to hPa. The wind speed is in ms^{-1}, mean temperature in (°C) and relative humidity in (%). The Minitab software (version 22.2.1) package was employed to obtain the empirical constants, while the Origin Pro 2024 software version (10.1.0.178) was employed for plotting of the graphs.

2.4 Regression Analysis

The proposed models based on the modified Page; Liu and Jordan models are:

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

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

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

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

The multiple linear regression approach was employed, using as independent variables the four meteorological parameters of (WS, T_{mean}, RH, PS) and the dependent variable been $\frac{H_d}{H_m}$

.

Where

PS measured in (hPa) is the monthly average daily atmospheric pressure;

RH is the monthly average daily relative humidity measured in ($\%$);

T_{mean} being the monthly average mean temperature (^{O}C);

WS denotes the monthly average daily wind speed (ms^{-1}).

The other proposed models developed in this study, 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 2 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 3 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 4 variables correlations model is:

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

The algebras a, b, c, d, and e above (in Eqn 5 to Eqn 23) are referred to as empirical coefficients or constants.

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2.5 Accuracy of the Models

The statistical indices of Mean Bias Error (MBE), Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and t-test were employed to test the effectiveness of each of the models. The formulae used in obtaining MBE, RMSE, and MPE, based on modifications to the method proposed by (El-Sebaii and Trabea, 2005) and reported by (Akpootu *et al.*, 2024)are presented as follows:

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

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

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

According to (Bevington, 1969), the t-test, is amongst the statistical methods used to evaluate mean values, utilizes a random variable denoted as t, possessing $n-1$ degrees of freedom. It is a non-dimensional parameter according to (Akpootu and Salifu, 2024; Salifu, Akpootu, and Kola, 2024) and it is mathematically written as:

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

As seen in eqns (24), (25), and 26), $H_{d_{i,meas}}$ and $H_{d_{i,cal}}$ denotes i^{th} measured and i^{th} calculated values of daily diffuse solar radiation, while n represents the total number of observations. Lower values of RMSE, t-test, MPE, and MBE denotes superior model performance. These statistical tools are used to test the accuracy of a model's predictions compared to actual observed values. According to (Salifu, Akpootu, and Kola, 2024), positive values of MPE and MBE quantify the average degree of overestimation in a model's prediction, while negative values denotes underestimation. In addition, (Merges *et al*., 2006; Akpootu and Sulu, 2015) when a model exhibits a low Mean Percentage Error (MPE), and errors are within the range of -10 % to +10 % , then the model is deemed to perform best. Additionally, Akpootu *et al.*, 2024 and Salifu *et al.*, 2024, opined that a model would be an ideal model when the model has a Mean Bias Error (MBE) value close to zero, and a low Root Mean Square Error (RMSE) value that is desirable. A more reliable and accurate data modeling outcome will be achieved if the coefficient of determination (R^2) approaches a value of 1 i.e. 100% (Akpootu and Salifu, 2024), indicating a robust correlation between estimated and observed values, which reflects a well-fitting model.

3.0 RESULTS AND DISCUSSION

The results obtained according to the different categories of models for Yelwa based on equations (5) to (23) are:

$$\frac{H_d}{H_{mea}} = 1.0970 - 1.0438K_T \quad (28a)$$

$$\frac{H_d}{H_{mea}} = 0.260 + 2.11K_T - 2.92K_T^2 \quad (28b)$$

$$\frac{H_d}{H_{mea}} = 8.06 - 41.1K_T + 76.1K_T^2 - 47.8K_T^3 \quad (28c)$$

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$$\frac{H_d}{H_{mea}} = -69.7 + 539K_T - 1533K_T^2 + 1926K_T^3 - 902K_T^4 \quad (28d)$$

$$\frac{H_d}{H_m} = 1.1442 - 1.205K_T + 0.0231WS \quad (28e)$$

$$\frac{H_d}{H_m} = 1.3516 - 1371K_T - 0.001088RH \quad (28f)$$

$$\frac{H_d}{H_m} = 8.14 - 1.163K_T - 0.00711PS \quad (28g)$$

$$\frac{H_d}{H_m} = 1.027 - 1.092K_T + 0.00371T_{mean} \quad (28h)$$

$$H_d = 5.33 + 1.13WS + 0.0400RH \quad (28i)$$

$$H_d = 1.55 - 0.634WS + 0.366T_{mean} \quad (28j)$$

$$H_d = 385 - 0.739WS - 0.381PS \quad (28k)$$

$$H_d = -0.88 + 0.0208RH + 0.3610T_{mean} \quad (28l)$$

$$H_d = 538 + 0.0342RH - 0.540PS \quad (28m)$$

$$H_d = -906 + 0.751T_{mean} + 0.913PS \quad (28n)$$

$$H_d = -2.19 + 0.469WS + 0.0310RH + 0.352T_{mean} \quad (28o)$$

$$H_d = -965 + 0.150WS + 0.771T + 0.972PS \quad (28p)$$

$$H_d = 539 + 1.18WS - 0.545PS + 0.0601RH \quad (28q)$$

$$H_d = -1252 - 0.0152RH + 0.892T_{mean} + 1.264PS \quad (28r)$$

$$H_d = -1528 - 0.939WS - 0.0435RH + 1.030T_{mean} + 1.545PS \quad (28s)$$

3.1 Modified Page, Liu and Jordan Models

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

Models	R^2	MBE	RMSE	MPE	t
M.Eqn28a	93.22%	-0.0456	0.4590	0.0746	0.3313
M.Eqn28b	92.19%	0.0036	0.3962	-0.1909	0.0298
M.Eqn28c	94.11%	-0.2255	0.4146	2.2035	2.1493
M.Eqn28d	95.30%	8.3562	8.5005	-85.2906	17.7695

Table 2: Ranks obtained from **Table 1**

Models	R^2	MBE	RMSE	MPE	t	Rank
M.Eqn28a	3	2	3	1	2	11
M.Eqn28b	4	1	1	2	1	9
M.Eqn28c	2	3	2	3	3	13
M.Eqn28d	1	4	4	4	4	17

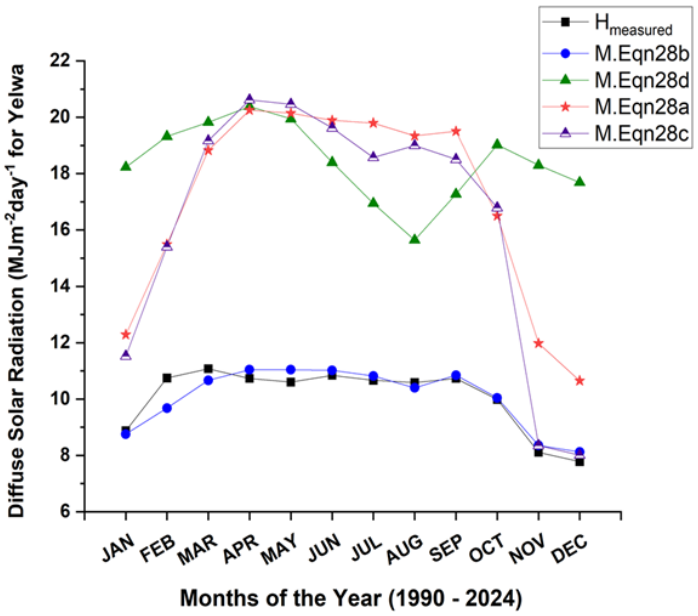

Figure 2: Comparison Between the Measured Diffused Solar Radiation and Estimated Modified Page, Liu and Jordan Models for Yelwa.

Table 1 is a summary of the statistical validation tests conducted on the developed models for this category. Among these models, equation M.Eqn28d stands out with the highest R^2 at 95.30 %. While, M.Eqn28b has the lowest MBE, RSME and t-test values with overestimation of 0.0036 $MJm^{-2}day^{-1}$, 0.3962 $MJm^{-2}day^{-1}$ in its estimated value and 0.0298 respectively. Also, M.Eqn28a has the lowest MPE of 0.1909 %. The MPE values for all developed models are within the acceptable range of ± 10%.

Table 2 is the summary of the ranks deduced from the estimated modified Page, Liu and Jordan models for Yelwa. From the table the ranks achieved by each model ranges from 9 to 17. Notably, the quadratic regression model, as defined in equation M.Eqn28b, proves to be best in estimating diffuse solar radiation in Yelwa when compared to the other three models.

Figure 2: is a comparison of measured and predicted diffuse solar radiation in Yelwa showed that models M.Eqn28a, M.Eqn28c, and M.Eqn28d consistently overestimated the measured values. Despite individual variances, all models followed the same seasonal pattern as observed data,it is M.Eqn28 that showed the closest alignment with actual measurements in both magnitude and seasonal pattern. This suggests it most accurately reflects the region's climatic influences on diffuse solar radiation, hence, M.Eqn28 is considered the most suitable for estimating solar radiation in Yelwa.

3.2 Clearness Index and One Variable Correlation Models

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

Models	R^2	MBE	RMSE	MPE	t
M.Eqn28e	91.84%	-0.0037	0.4001	-0.2251	0.0310
M.Eqn28f	94.30%	-0.0063	0.3289	-0.1511	0.0631
M.Eqn28g	91.27%	-0.0294	0.4217	0.0897	0.2321
M.Eqn28h	91.39%	-0.0023	0.4188	-0.1622	0.0183

Table 4: Ranks obtained from **Table 3**

Models	R^2	MBE	RMSE	MPE	t	Rank
M.Eqn28e	2	2	2	4	2	12
M.Eqn28f	1	3	1	2	3	10
M.Eqn28g	4	4	4	**1**	4	17
M.Eqn28h	3	1	3	3	1	11

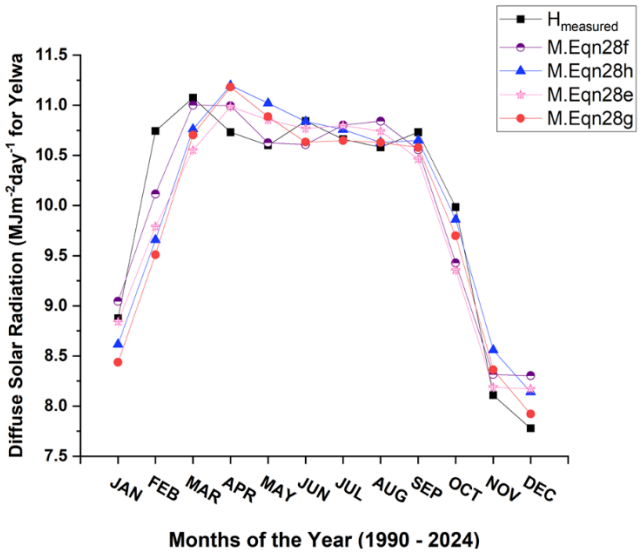

Figure 3: Comparison Between the Measured Diffused Solar Radiation and Estimated Clearness Index and a Single Variable Models for Yelwa.

Table 3 is the summary of the statistical validation tests conducted on the Clearness index and a single variable model in this study. The M.Eqn28f possesses the highest R^2 value at 94.30% and lowest RMSE value with overestimation of 0.3289 $MJm^{-2}day^{-1}$ in its estimated value; while equation M.Eqn28h, has the lowest MBE and t-test with underestimations of 0.0023 $MJm^{-2}day^{-1}$ and 0.0183 respectively. While M.Eqn28g exhibits the lowest for MPE recording an underestimation of 0.0897 % in it estimated value. The MPE values for all developed models are within the acceptable range of ± 10% and all models have t-test values that are statistically significant at both 95% and 99%.

Table 4 presents a summary of the ranks obtained from the estimated Clearness index and one variable models for Yelwa. As seen, the ranks attained by each model are within 10 to 17. In conclusion, to estimate diffuse solar radiation in Yelwa, M.Eqn28f shows greater accuracy and performance compared to the other three models.

3.3 Two Variables Correlation Models

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Table 5: Two variables Models Statistical Error indicators for Yelwa

Models	R^2	MBE	RMSE	MPE	t
M.Eqn28i	13.40%	0.00113	1.01791	-1.198594	0.00367
M.Eqn28j	57.83%	0.00827	0.71033	-0.672773	0.03863
M.Eqn28k	16.06%	-0.2982	1.04557	1.8473034	0.98705
M.Eqn28l	63.87%	-0.0021	0.65749	-0.483524	0.01077
M.Eqn28m	33.77%	0.31447	0.94413	-4.081547	1.17162
M.Eqn28n	82.89%	-0.3335	0.56207	3.1167647	2.44516

Table 6: Ranks obtained from **Table 5**

Models	R^2	MBE	RMSE	MPE	t	Rank
M.Eqn28i	6	1	5	3	1	16
M.Eqn28j	3	3	3	2	3	14
M.Eqn28k	5	4	6	4	4	23
M.Eqn28l	2	2	2	1	2	9
M.Eqn28m	4	5	4	6	5	24
M.Eqn28n	1	6	1	5	6	19

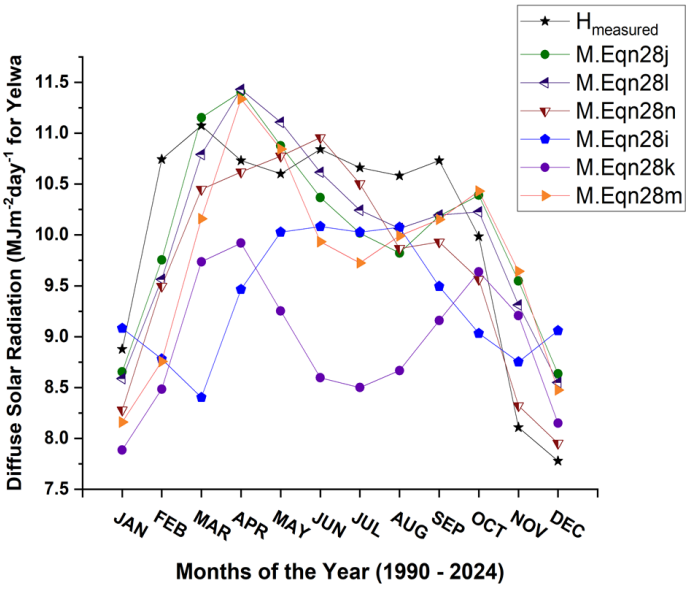

Figure 4: Comparison between the Measured Diffused Solar Radiation and estimated Two Variable Models for Yelwa.

Table 5 represents the statistical validation tests done on the two variable models in this study for Yelwa. As evidently seen, M.Eqn28n possesses the highest R^2 of value 82.89%, lowest RMSE with value 0.56207 $MJm^{-2}day^{-1}$ a clear overestimation in its estimated value while M.Eqn28i has the lowest MBE and t-test values with an overestimation of 0.00113 $MJm^{-2}day^{-1}$ and 0.00367 respectively. The results also indicate that the MPE values of developed models are within the acceptable range of ± 10%. Additionally, all models t-test values are statistically significant at both 95% and 99%.

Table 6 above provides a summary of the ranks derived from the estimated two variables models for Yelwa. It is evident from the table that the ranks achieved by each model range from 9 to 24. The comprehensive findings indicate that M.Eqn28l, proves to be more accurate in estimating diffuse solar radiation in Yelwa when compared to the other five models in terms of the two variable correlation models above.

3.4 Three Variables Models

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Table 7: Three Variable Models Statistical Error indicators for Yelwa

Models	R^2	MBE	RMSE	MPE	t
M.Eqn28o	64.84%	0.01729	0.64879	-0.664466	0.08844
M.Eqn28p	83.19%	-0.619	0.7644	5.9967851	4.57744
M.Eqn28q	40.14%	0.3749	0.92559	-4.604054	1.4693
M.Eqn28r	85.42%	0.82806	0.92745	-8.558221	6.57489

Table 8: Ranks obtained from **Table 7**

Models	R^2	MBE	RMSE	MPE	t	Rank
M.Eqn28o	3	1	1	1	1	7
M.Eqn28p	2	3	2	3	3	13
M.Eqn28q	4	2	3	2	2	13
M.Eqn28r	1	4	4	4	4	17

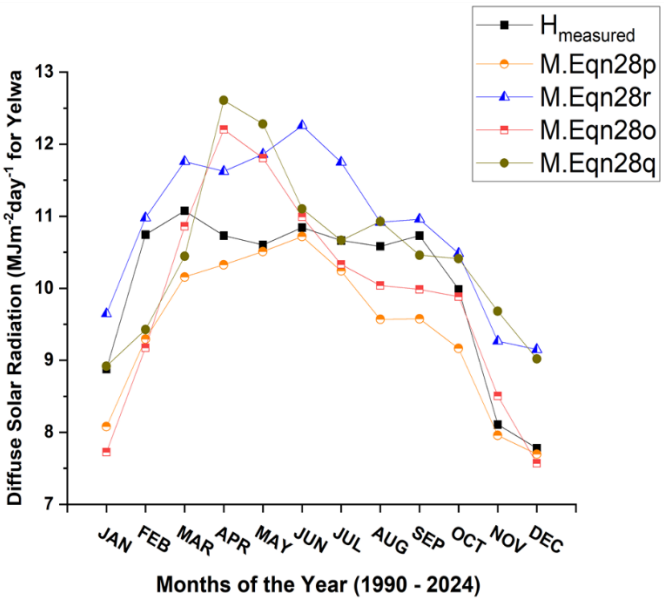

Figure 5: Comparison between the Measured Diffused Solar Radiation and estimated Three Variables Models for Yelwa.

Table 7 shows a summarized statistical validation test done for this model category in this study. The model equation M.Eqn28r, has the highest R^2 of 85.42 %; while M.Eqn28o has the lowest MBE, RMSE, MPE and t-test values with an overestimation of 0.01729 $MJm^{-2}day^{-1}$ in its estimated value, 0.646879 $MJm^{-2}day^{-1}$, an underestimation of 0.664466 % in its estimated value and 0.0840 respectively. The MPE values for all the developed models equation are within the acceptable range of $\pm$ 10 %. The t-test values for the models are significant at 95% and 99% .

Table 8 provides a summary of the ranks derived for this category. As seen above, the ranks achieved by each model are from 7 to 17. In conclusion, M.Eqn28o, proves to be the most accurate in estimating diffuse solar radiation in Yelwa when compared to the other four models in terms of the three variable correlation models above.

3.5 Four Variables Model

Below are the statistical analysis summary of the models Eqn 28s

Table 9: Four Variable Model Statistical Error indicators for Yelwa

Models	R^2	MBE	RMSE	MPE	t
M.Eqn28s	88.26%	0.547	0.66308	-5.686	4.84079

The above table indicates that the four variables model (M.Eqn 28s) has an underestimation of 5.686 % and overestimation of 0.547 $MJm^{-2}day^{-1}$ in its estimated value.

3.6 Comparison of all Categories of Models

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

Models	R^2	MBE	RMSE	MPE	t
M.Eqn28b	92.19%	0.0036	0.3962	-0.1909	0.0298
M.Eqn28f	94.30%	-0.0063	0.32894	-0.1511	0.06311
M.Eqn28l	63.87%	-0.0021	0.65749	-0.4835	0.01077
M.Eqn28o	64.84%	0.01729	0.64879	-0.6645	0.08844
M.Eqn28s	88.26%	0.547	0.66308	-5.686	4.84079

Table 11: Ranks obtained from **Table 10**

Models	R^2	MBE	RMSE	MPE	t	Rank
M.Eqn28b	2	2	2	2	2	10
M.Eqn28f	1	3	1	1	3	9
M.Eqn28l	5	1	4	3	1	14
M.Eqn28o	4	4	3	4	4	19
M.Eqn28s	3	5	5	5	5	23

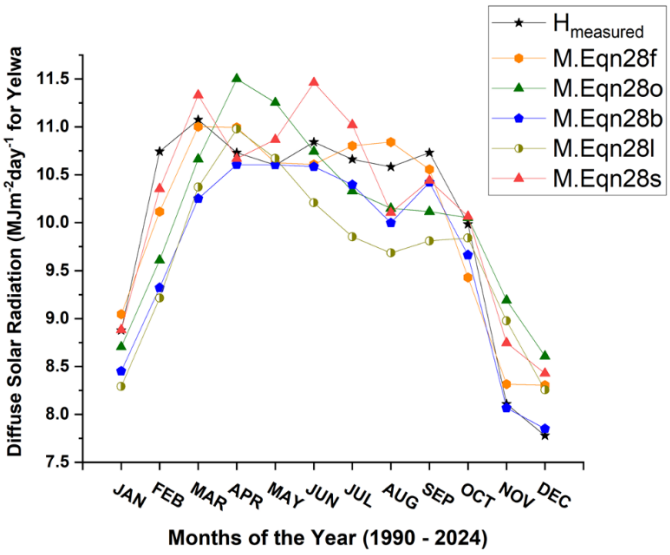

Figure 6: Comparison between the Measured Diffused Solar Radiation and Best performed models across all category for Yelwa.

From table 11, M.Eqn28f of the clearness index and one variable model category was found to perform best in amongst all the categories of models that was developed for estimating diffuse solar radiation for Yelwa.

4.0 CONCLUSION

The study clearly shows that diffuse solar radiation in Yelwa can be predicted with confidence using simple, routinely measured weather variables like temperature, humidity, wind speed, and surface pressure. All the developed models passed strict statistical checks, with percentage errors staying within ±10% and significance tests confirming that the estimates closely match real observations.

Although several model groups were tested, some stood out. A quadratic regression (M.Eqn28b) performed best among the modified Page, Liu and Jordan models, while M.Eqn28f was the strongest of the clearness-index-based equations. For models using two and three meteorological variables together, M.Eqn28l and M.Eqn28o gave the most reliable results.

When all categories were compared side by side, the clearness-index model **M.Eqn28f** emerged as the overall best performer. In real terms, this work provides Yelwa and similar Sudano–Sahelian locations with a tested tool for estimating diffuse solar radiation without expensive instrumentation i.e with a simple hygrometer measurement for a given period be it daily or monthly, if integrated into **M.Eqn28f** one will know the diffuse solar radiation for the given period in Yelwa, Nigeria.

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