

Analysis of Downward Longwave Radiation Models Under Clear Sky Condition across the Guinea Savannah Climatic Zone of Nigeria

Agidi O. E¹, Akpootu D. O^{1*}

¹Department of Physics, Usmanu Danfodiyo University, Sokoto, Nigeria

DOI: <https://doi.org/10.36348/sjet.2026.v11i09.001>

| Received: 27.06.2026 | Accepted: 20.08.2026 | Published: 02.09.2026

*Corresponding author: Akpootu D. O

Department of Physics, Usmanu Danfodiyo University, Sokoto, Nigeria

Abstract

Accurate estimation of Downward Longwave Radiation (DLR) is essential for climate modeling, hydrology, agriculture, and renewable energy applications, yet the reliability of widely used empirical DLR models across different climatic zones remains uncertain. This study evaluated eleven existing clear-sky DLR empirical models and developed five new locally calibrated regression models for Ibadan and Makurdi, within the Guinea Savannah climatic zone of Nigeria. Forty years (1984-2023) of monthly mean air temperature, relative humidity, and DLR data were used, with thirty-two years for model development and eight years for validation. Model performance was assessed using Mean Bias Error, Root Mean Square Error, Mean Percentage Error, t-statistic, Index of Agreement, and correlation coefficient, followed by a composite ranking procedure. Results showed that, among existing models, Kruk *et al.*, performed best at Ibadan while Idso was most suitable for Makurdi. Among the newly developed models, the modified Guest model gave the highest accuracy at Ibadan, while the modified Dilley and O'Brien model performed best at Makurdi, with all modified models outperforming their existing counterparts. Seasonal analysis revealed that DLR was consistently higher during the rainy season, driven predominantly by atmospheric water vapour and cloud cover rather than temperature. These findings demonstrate that site-specific calibration substantially improves DLR estimation accuracy and provide validated, region-appropriate models recommended for practical application across the Guinea Savannah climatic zone of Nigeria in the absence of direct pyrgeometer measurements.

Keywords: Clear-Sky Conditions, Downward Longwave Radiation, Guinea Savannah Climatic Zone, Modified Models, Statistical Test Indicators.

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1. INTRODUCTION

Downward Longwave Radiation (DLR) is the thermal infrared radiation emitted by atmospheric constituents, including water vapour, carbon dioxide (CO₂), methane (CH₄), clouds, and aerosols, towards the Earth's surface. It is a fundamental component of the Earth's surface radiation budget because it regulates the exchange of energy between the atmosphere and the land surface, thereby influencing surface temperature, evapo transpiration, atmospheric stability, hydrological processes, and climate variability [1, 2]. As one of the major components of the surface energy balance, DLR contributes significantly to the greenhouse effect by reducing the amount of longwave energy lost from the Earth's surface to the atmosphere. Consequently, accurate estimation of DLR is indispensable for climate change studies, weather forecasting, agricultural

planning, hydrological modeling, environmental monitoring, and renewable energy applications [3, 4]. The physical basis of downward longwave radiation is governed by the theory of thermal radiation, which states that every object with a temperature above absolute zero (0 K) continuously emits electromagnetic radiation. The total longwave radiation emitted by an ideal blackbody is described by the Stefan–Boltzmann law as [5].

$$L = \sigma T_A^4 \quad (1)$$

where L is the emitted longwave radiation (Wm⁻²), $\sigma = 5.670 \times 10^{-8} \text{ Wm}^{-2}\text{K}^{-4}$ is the Stefan–Boltzmann constant, and T is the absolute temperature (K). Since the atmosphere is not a perfect blackbody but behaves as a grey body, the downward longwave radiation received at the Earth's surface is expressed as [5, 6].

$$L \downarrow = \epsilon_A \sigma T_A^4 \quad (2)$$

Citation: Agidi, O. E., & Akpootu, D. O. (2026). Analysis of Downward Longwave Radiation Models Under Clear Sky Condition across the Guinea Savannah Climatic Zone of Nigeria. *Saudi J Eng Technol*, 11(9), 749-766. <https://doi.org/10.36348/sjet.2026.v11i09.001>

where ε_A the effective atmospheric emissivity and T_A is the near-surface air temperature (K). Atmospheric emissivity depends primarily on atmospheric water vapour, greenhouse gases, aerosols, and cloud cover. An increase in atmospheric moisture enhances infrared absorption and re-emission by greenhouse gases, resulting in higher downward longwave radiation. Conversely, a reduction in atmospheric water vapour decreases atmospheric emissivity and lowers DLR reaching the Earth's surface [7, 8]. The accurate estimation of DLR is therefore indispensable for meteorological forecasting, agricultural planning, climate modeling, and the assessment of the surface energy balance [3]. Accurate knowledge of DLR at the surface is therefore every important for a wide range of scientific and engineering applications, from agricultural water-use modeling and hydrological cycle simulations to photovoltaic system energy balance analysis and regional climate change impact assessment [9, 10].

The earliest empirical relationship for estimating DLR under a clear-sky conditions based on Equation (1), was proposed by Ångström in [11]. Since then, many researchers have introduced additional empirical formulations, including those developed by Swinbank [12], Idso and Jackson [13], Deacon [14], Brutsaert [15], Idso [16], Garratt [17], Prata [18], Dilley and O'Brien [19], and Guest [20]. These models have subsequently been applied in different climatic environment and locations to parameterize DLR flux under varying atmospheric conditions [5-21]. The application of all the developed empirical models to parameterized the flux at both the regional and global scales are unknown. In this regard, there is need to carry out an investigation to find out if this universally accepted models are very suitable for estimation of DLR in all regions in Nigeria. Recently, Agidi *et al.*, [22], developed new DLR models for estimating DLR across the coastal climatic zone of Nigeria, their result revealed that the modified Dilley and O'Brien regression model and the modified Guest regression model were found to be the most reliable and accurate for DLR estimation at Ikeja and Warri respectively. In another study, Akpootu *et al.*, [23], developed new DLR model across the Midland climatic zone of Nigeria their result indicated that the modified Idso regression model and the modified Guest regression model was found most reliable and accurate for DLR estimation for Minna and Zaria respectively. The quest for the most suitable models for estimating DLR necessitated the need to develop new models. This study is aimed at evaluating and calibrating the DLR radiation under a clear sky in Ibadan and Makurdi located across the Guinea Savannah climatic zone with the objectives outlined as follows (i) To access the performance of the existing widely used empirical DLR models (ii) To develop and compare five (5) new DLR models for Ibadan and Makurdi (iii) To rank the eleven (11) existing DLR models and the five (5) modified newly developed DLR models to ascertain

which reliably estimate DLR in the Guinea Savannah zone (iv) to compare the models through the different validation indicators to ascertain the suitability and applicability of the models (v) To investigate the impact of DLR on relative humidity and temperature in the Guinea Savannah zone.

2. METHODOLOGY

2.1 Acquisition of Data

According to the World Meteorological Organization [24], also in Ojo and Adeyemi [25], mentioned that reliable climate modeling requires data records extending for at least thirty (30) years or more. The monthly average daily data for relative humidity, air temperature and DLR employed in this study covers forty (40) years (1984-2023) period and were sourced from the National Aeronautics and Space Administration (NASA). Thirty-two (32) (1984-2015) years data was used to develop the DLR based empirical models while eight (8) years (2016-2023) data was used for the validation of the models. This study employed the same approach adopted by Akpootu and Abdullahi [26], Akpootu *et al.*, [27], and Soneye-Arogundade [28], where approximately 80% of the total years of the data were used for the development of models and 20% for validation of models. The locations under investigation are Ibadan (Latitude 7.37°N and Longitude 3.91°N) and Makurdi (Latitude 7.73°N and Longitude 8.53°N) located across the Guinea Savannah climatic zones of Nigeria.

2.2 Clear- Sky Downward Longwave Radiation Models

Eleven (11) previously published empirical models were applied to estimate the downward longwave radiation flux under clear sly conditions. The existing models are presented below:

(1) Ångström [11] estimated longwave irradiance from air temperature and water vapor pressure with an equation of the form:

$$L_{lcl} = (0.83 - 0.18 \times 10^{-0.067e_0}) \sigma T_A^4 \quad (3)$$

L_{lcl} is the atmospheric longwave irradiance

where e_0 is water vapor in hectopascals (hPa) and is given by:

$$e_0 = \frac{RH}{100} \left\{ 1.33322368 \left[\exp \left(\frac{20.386 - 5132}{T_A} \right) \right] \right\}$$

$$\sigma = \text{Stefan Boltzmann constant } (5.67 \times 10^{-8} \text{ Wm}^{-2} \text{ K}^{-4})$$

where RH is the relative humidity in percentage; and T_A is the air temperature.

(2) Swinbank [12], developed an equation for estimating downward longwave atmospheric irradiance that only depended on screen-level air temperature. It is given by the expression:

$$L_4 = (0.94 \times 10^{-5} T_A^2) \sigma T^4 \quad (4)$$

(3) Idso and Jackson [13] estimated longwave irradiance from air temperature which is given by the expression:

$$L_1 = \{1 - 0.261 \exp[-7.77 \times 10^{-4} (273 - T_A)]^2\} \sigma T_A^4 \quad (5)$$

(4) Deacon [14] equation estimated longwave atmospheric irradiance from air temperature and altitude as:

$$L_{\downarrow} = (0.94 \times 10^{-5} T_A^2) - \left[0.035 \left(\frac{z}{1000} \right) \right] \sigma T_A^4 \quad (6)$$

where z is the altitude of the meteorological sites in meters

(5) Brutsaert [15], proposed an equation in which emissivity is a function of water vapor pressure and temperature. It is given by the expression:

$$L_{\downarrow Cl} = 0.643 \left(\frac{e_0}{T_A} \right)^{\frac{1}{7}} \sigma T_A^4 \quad (7)$$

(6) Idso [16], estimated longwave irradiance from air temperature and water vapor pressure with an equation of the form:

$$L_{\downarrow Cl} = [0.7 + 5.95 \times 10^{-7} e_0 \exp(1500/T_A)] \sigma T_A^4 \quad (8)$$

(7) Garratt [17], estimated longwave irradiance from air temperature and water vapor pressure with an equation of the form:

$$L_{\downarrow Cl} = [0.79 - 0.174 \exp(-0.095 e_0)] \sigma T_A^4 \quad (9)$$

(8) Prata [18], proposed an equation in which emissivity is a function of precipitable water and temperature. It is given by the expression:

$$L_{\downarrow Cl} = (1 - [(1 + w) \exp(-(1.2 + 3.0w)^{0.5})]) \sigma T_A^4 \quad (10)$$

where w is the precipitable water content in kgm^{-2} and $w = 0.465(e_0/T_A)$

(9) Dille and O'Brien [19], proposed an equation in which emissivity is a function of precipitable water and temperature at screen level. It is given by the expression:

$$L_{\downarrow Cl} = 59.38 + 113.7(T_A/273.16)^6 + 96.96 \sqrt{\frac{w}{25}} \quad (11)$$

(10) Guest [20], estimated longwave irradiance from air temperature and relative humidity with an equation of the form:

$$L_{\downarrow Cl} = \sigma T_A^4 \times 1.0438 + 0.2486 RH - 113.6 \quad (12)$$

(11) Kruk *et al.*, [29], estimated longwave irradiance from air temperature and water vapor pressure with an equation of the form:

$$L_{\downarrow Cl} = \left[0.576 \left(\frac{e_0}{T_A} \right)^{0.202} \right] \sigma T_A^4 \quad (13)$$

2.3 Validation of Models

The estimated values of the DLR obtained from the empirical models for both the existing and modified were compared with the measured DLR for Ibadan an Makurdi by calculating the Mean Bias Error (MBE), Root Mean Square (RMSE), Mean percentage Error (MPE), t-test, Index of Agreement (IA) while the correlation coefficient (R) for the proposed modified models was determined from scattered plots using origin

2018software. The regression analysis was done using Minitab software. The MBE, RMSE, and MPE were calculated using the equation [30].

$$MBE = \frac{1}{n} \sum_{i=1}^n (Et_i - Md_i) \quad (14)$$

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n ((Et_i - Md_i))^2 \right]^{\frac{1}{2}} \quad (15)$$

$$MPE = \frac{1}{n} \sum_{i=1}^n \left(\frac{(Md_i - Et_i)}{Md_i} \right) \times 100 \quad (16)$$

In line with the explanation provided by [31], the t test was utilized to evaluate the mean values generated by the developed models. This statistical technique is based on a parameter represented by "t," which incorporates the degree of freedom in its computation. The t-test is a non-dimensional parameter and it can be mathematically expressed as follows [32, 33].

$$t = \left[\frac{(n-1)(MBE)^2}{(RMSE)^2 - (MBE)^2} \right]^{\frac{1}{2}} \quad (17)$$

The location was statically tested at the $(1-\alpha)$ confidence levels of significance of 95% and 99%. For the critical t-value, i.e., at α level of significance and degree of freedom, the calculated t-value must be less than the critical value ($t_{critical}=2.20$, $df = 11$, $p<0.05$ for 95% and ($t_{critical}=3.12$, $df = 11$, $p<0.01$) for 99%.

The index of agreement (IA) was calculated using the below equation [34]

$$IA = 1 - \frac{\sum_{i=1}^n (Et_i - Md_i)^2}{\sum_{i=1}^n (|Et_i - \bar{Md}| + |Md_i - \bar{Md}|)^2} \quad (18)$$

In equation (14) - (18), i represent the i th observed and corresponding i th predicted values of DLR, while n denotes the total number of observations. The $\bar{Md}$ indicates the mean measured DLR. Studies by [35, 36] indicate that MBE value approaching zero is ideal, whereas lower RMSE and MPE value are preferred for accurate model prediction. Generally, smaller magnitudes of MBE, RMSE, MPE, and the t-statistic signify superior model performance. Positive MBE and MPE values indicate that the model tends to overestimate the calculated results, while negative values suggest underestimation. For reliable performance, the MPE should remain small, and percentage errors within the range of -10% to + 10% are considered acceptable, as reported by Merges [37].

Moreover, Akpootu *et al.*, [32, 33], noted that higher values of R, and IA correspond to improved model accuracy, as R and IA values approaches 1.0 (100%) reflects strong predictive agreement. In terms of measurement units, MBE and RMSE are expressed in Wm^{-2} ; MPE, R, and IA in percentage when multiply by 100, whereas t-test is dimensionless. Proposed models under a clear sky condition is shown in Table 1.

Table 1: DLR based models proposed in this study

Model No.	Model Type	Regression equation
1	Modified Angstrom	$L_{\downarrow Cl} = (a + b \times 10^{ce_0}) \sigma T^4$
2	Modified Deacon	$L_{\downarrow Cl} = \left[a T_A^2 + b \left(\frac{Z}{1000} \right) \right] \sigma T^4$
3	Modified Idso	$L_{\downarrow Cl} = \left(a + b e_0 \exp \left(\frac{1500}{T_A} \right) \right) \sigma T^4$
4	Modified Dilley and O'Brien	$L_{\downarrow Cl} = a + b \left(\frac{T_A}{273.16} \right)^6 + c \sqrt{\frac{W}{25}}$
5	Modified Guest	$L_{\downarrow Cl} = [a \sigma T^4 + b RH + c]$

The proposed models which were developed through the regression analysis are modified form of the existing DLR based models. The modification of the existing models was to attest if the accuracies of the

models are improved or not through statistical validation when compared to the existing models.

3. RESULTS AND DISCUSSION

3.1 Statistical Analysis Summary of DLR for Ibadan

Table 2: Statistical error indicators for the eleven estimated DLR over Ibadan

Models	MBE	RMSE	MPE	t	IA
Angstrom	-34.1533	35.4799	8.3531	11.7853	0.3153
Swinbank	-31.4443	32.9843	7.6902	10.4698	0.3378
Idso&Jackson	-29.2982	30.9679	7.1623	9.6868	0.3529
Deacon	-34.4092	35.8196	8.4202	11.4669	0.3193
Brutsaert	-11.6082	13.3708	2.8297	5.8023	0.6632
Idso	17.4639	18.2828	-4.3067	10.7048	0.5442
Garratt	-52.0925	52.9696	12.7698	17.9979	0.2353
Prata	-14.8554	16.3531	3.6264	7.2066	0.5935
Dilley&O'Brien	-114.7611	115.0602	28.2085	45.9095	0.1254
Guest	-30.8186	31.9290	7.5421	12.2456	0.3604
Kruk	-3.6199	7.0397	0.8749	1.9885	0.8758

Table 2 summarized the different statistical validation test for the eleven estimated DLR models for Ibadan. From the table 2, the existing Kruk *et al.*, [29], had the lowest value MBE and MPE with underestimation of 3.6199 Wm⁻² and overestimation of 0.8749% respectively. Kruk *et al.*, [29], also had the lowest values of RMSE and t statistic of 7.0397 Wm⁻² and 0.3802 respectively indicating that the Kruk *et al.*, [29], performed better when compared to other models in this study. The model Kruk *et al.*, [29], also show the highest IA values 0.8758 confirming its superior predictive accuracy relative to the other models. In contrast, the Dilley and O'Brien [19], model exhibited the poorest performance, with the largest MBE of 114.7611 Wm⁻², RMSE of 115.0602 Wm⁻², MPE of 28.2085 %, and t-statistic of 45.9095, alongside the lowest IA 12.5487 %. The result of the existing models indicated that all the MPE values are within the

acceptable range of (MPE ≤ ± 10%) apart from Garratt [17], and Dilley and O' Brien [19], existing models. The Kruk *et al.*, [29], is significant at both 95% and 99% confidence level. The superior performance of the Kruk *et al.*, [29], model in this study is consistent with findings from other regions. In a clear-sky evaluation across two desert sites in Qatar, Bachour *et al.*, [38], found that models incorporating both air temperature and water vapour pressure outperformed models relying on either variable alone, a category that includes the Kruk *et al.* [29], model. Similarly, in Baghdad, Iraq, Al-Ansari *et al.*, [39], reported that parameterizations combining vapour pressure and air temperature returned the lowest bias and RMSE values, with the Kruk *et al.*, [29], model ranking among the better performers, while temperature-only models such as Swinbank [12], and Idso and Jackson [13], produced the largest errors.

Table 3: Ranking of the eleven estimated DLR over Ibadan

Models	MBE	RMSE	MPE	t	IA	RANK
Angstrom	8	8	8	8	9	41(8)
Swinbank	7	7	7	5	7	33(7)
Idso & Jackson	5	5	5	4	6	25(5)
Deacon	9	9	9	7	8	42(9)
Brutsaert	2	2	2	2	2	10(2)
Idso	4	4	4	6	4	22(4)

Models	MBE	RMSE	MPE	t	IA	RANK
Garratt	10	10	10	10	11	51(10)
Prata	3	3	3	3	3	15(3)
Dilley&O'Brien	11	11	11	11	10	54(11)
Guest	6	6	6	9	5	32(6)
Kruk	1	1	1	1	1	5(1)

Table 3 summarized the ranks obtained from the eleven estimated DLR models over Ibadan. The rank obtained by each of the models varies between the value 5 and 51. Kruk *et al.*, [29], model, is ranked as the best overall based on the statistical accuracy assessment test

which is consistent across all the five test particularly in its low MBE and better t-test with lowest ranking value of 5 and its was found more accurate in the estimation of DLR in Ibadan as compared to other models.

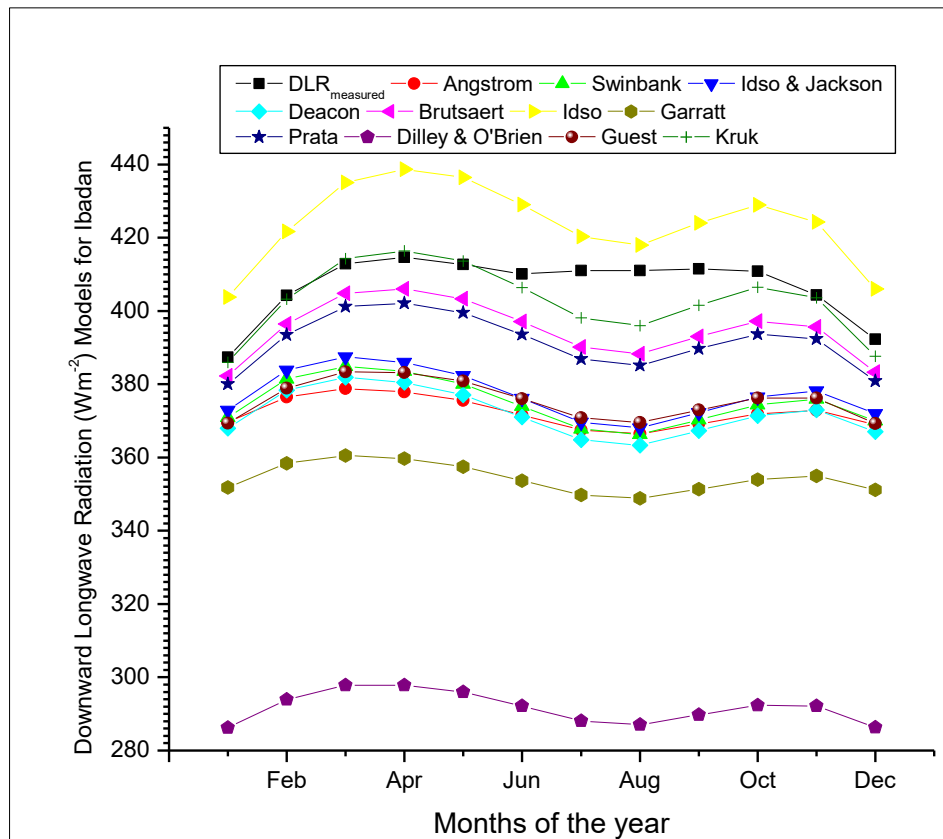


Figure 1: Monthly Variation of measured DLR with the eleven estimated DLR models over Ibadan

It was observed in Figure 1 that the Idso [16], model overestimated the measured DLR and all other evaluated DLR models throughout the entire period from January to December, consistently plotting above the measured curve. The Ångström [11], Swinbank [12], Idso and Jackson [13], and Deacon [14], models formed a closely clustered mid-range band that consistently underestimated the measured values to a lesser degree, reflecting their limited suitability for humid tropical climates where atmospheric moisture plays a dominant role in modulating DLR. The Kruk *et al.*, [29], model showed a comparable pattern of variation with the measured DLR throughout the year and was found to be the most appropriate model for estimating DLR over Ibadan when compared with the other models.

This superior performance of the Kruk *et al.*, [29], model is consistent with findings by Tian *et al.*,

[40], which showed that downward longwave radiation is governed by the radiative properties of the entire atmospheric column, principally water vapour, alongside clouds and other greenhouse gases, as well as the heat stored in the atmosphere. This reinforces that DLR estimation accuracy is strongly contingent on incorporating both air temperature and atmospheric moisture as input variables, which explains the consistently poorer performance of temperature-only models such as Swinbank [12], and Idso and Jackson [13], relative to the Kruk *et al.*, [29], model. This finding also aligns with earlier comparative results from, Al-Ansari *et al.*, [39], which demonstrated that parameterizations combining temperature and moisture-related variables generally outperformed single-variable formulations under arid climatic conditions.

3.2 Downward Longwave Radiation Proposed Based Models for Ibadan

The results of the proposed DLR regression models for Ibadan are shown below

$$DLR(Wm^{-2}) = 308 + 0.042610 \times 10^{0.067e_0} \quad (19)$$

$$DLR(Wm^{-2}) = -96 + 0.00566 \times T^2 \quad (20)$$

$$DLR(Wm^{-2}) = 184 + 0.0401 \times e_0 + 0.750 \exp\left(\frac{1500}{T}\right) \quad (21)$$

$$DLR(Wm^{-2}) = 268 - 43.0 \left(\frac{T}{273.16}\right)^6 + 516 \sqrt{w/25} \quad (22)$$

$$DLR(Wm^{-2}) = -40.1 + 0.758 \sigma T^4 + 1.26 \times RH \quad (23)$$

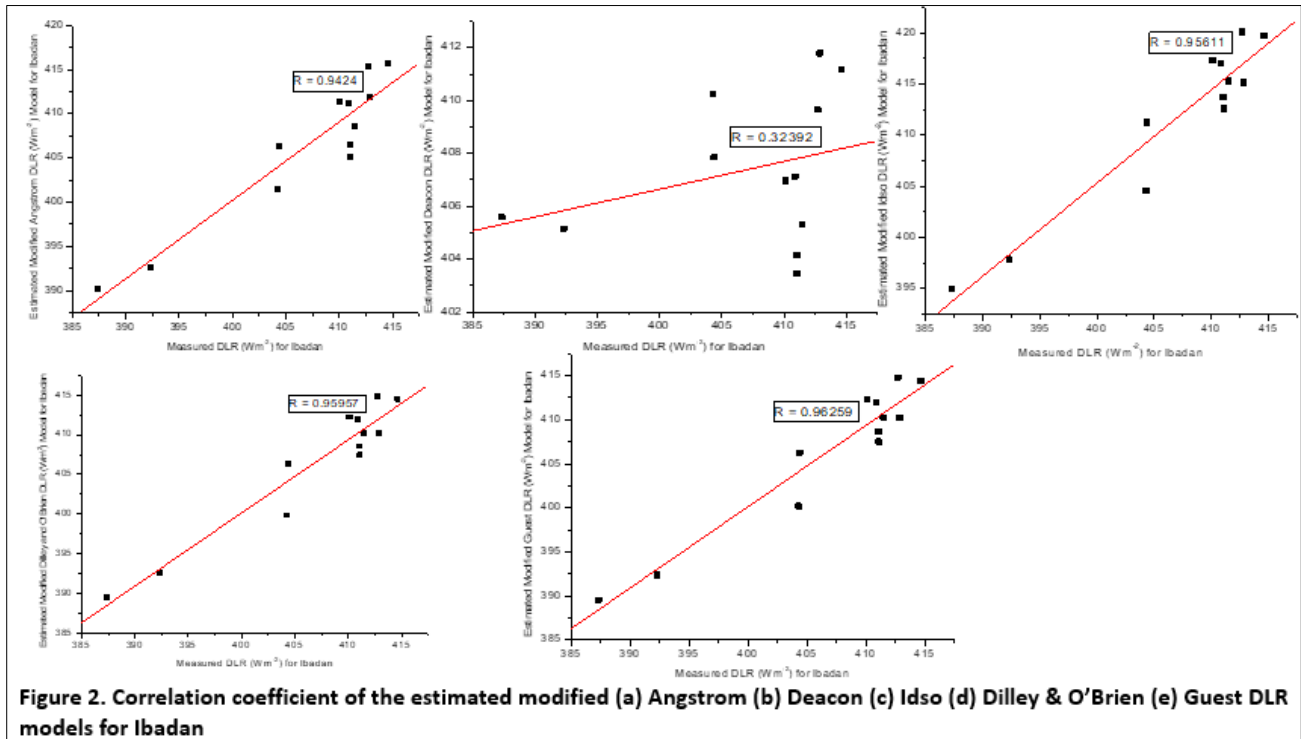


Table 4: Statistical error indicators for the estimated modified DLR models over Ibadan

Models	R	MBE	RMSE	MPE	t	IA
Modified Ångström	0.9424	-0.0286	4.0297	-0.0113	0.0235	0.9480
Modified Deacon	0.3239	0.9813	9.6568	-0.3006	0.3388	0.3575
Modified Idso	0.9561	5.2352	6.4180	-1.3061	4.6768	0.8813
Modified Dilley & O'Brien	0.9596	0.1444	3.6057	-0.0496	0.1237	0.9591
Modified Guest	0.9626	0.1315	3.5334	-0.0512	0.1330	0.9608

Figure 2 shows the correlation coefficient (R) of the estimated modified models for Ibadan which varies from 0.3239 (modified Deacon) to 0.9626 (modified Guest).

Table 4 summarized the different statistical validation test for the estimated modified DLR models for Ibadan. The modified Guest model recorded the lowest coefficient of correlation and RMSE value of 0.9625 and 3.5334 Wm^{-2} respectively. The modified Guest model also achieved the highest coefficient correlation value 0.9626 and the highest IA value of 0.9608. This finding is consistent with results from Ile-Ife, Nigeria, where the calibrated Guest [20], model gave the lowest errors and performed best among all eleven empirical models [28]. Also, the modified Ångström has the lowest value MBE, MPE and t-statistic of underestimation 0.0286 Wm^{-2} , underestimation of 0.0113 Wm^{-2} and 0.0235 respectively. In contrast, the

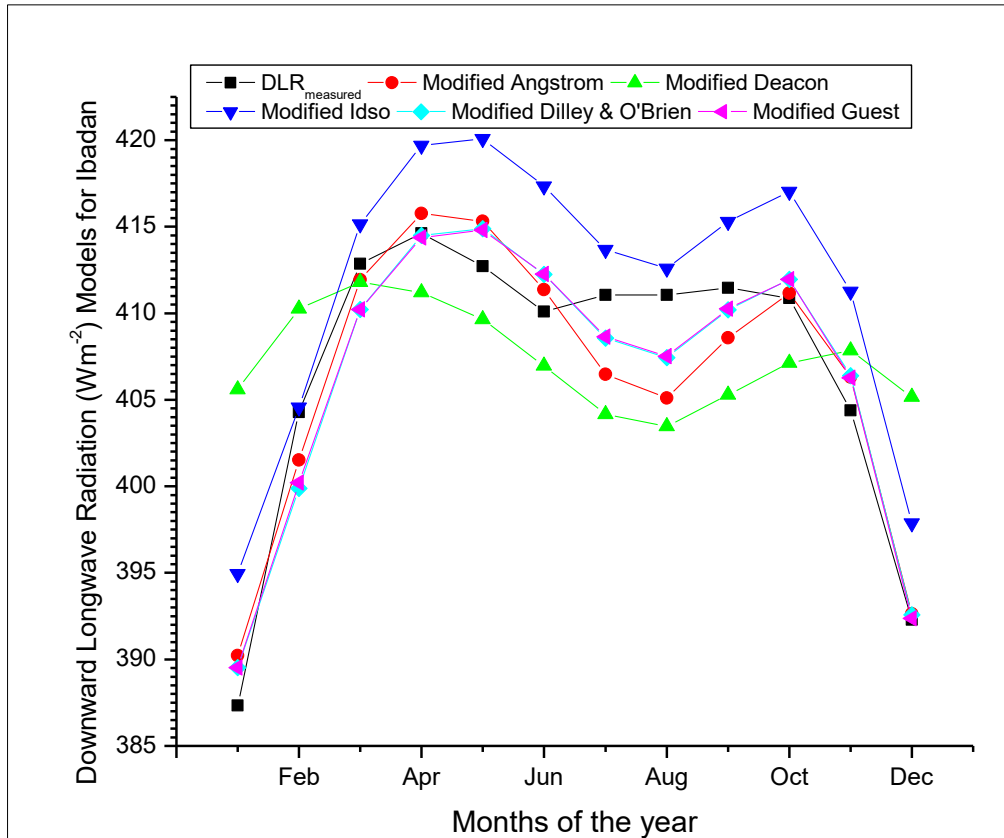
modified Deacon model recorded the poorest performance among the models evaluated, with the lowest coefficient correlation value 0.3239 and the highest RMSE and MBE value of 9.6568 Wm^{-2} and 0.9813 Wm^{-2} respectively. This is attributed to the structural limitations of the Deacon formulation, which relies primarily on-air temperature and does not explicitly incorporate water-vapour pressure, a critical driver of atmospheric emissivity in the humid tropical climate of Ibadan. This is further supported by Yang *et al.*, [41], who demonstrated, using long-term baseline surface radiation measurements in China, that parameterizations incorporating vapour pressure alongside air temperature substantially improved the accuracy of clear-sky DLR and atmospheric emissivity estimates relative to single-variable formulations. The results for the modified models indicated that all MPE values were within the acceptable range ($MPE \leq \pm 10\%$).

Table 5: Ranking of the estimated modified DLR model over Ibadan

Models	R	MBE	RMSE	MPE	t	IA	Total
Modified Angstrom	4	1	3	1	1	3	13(2)
Modified Deacon	5	4	5	4	4	5	27(5)
Modified Idso	3	5	4	5	5	4	26(4)
Modified Dilley & O'Brien	2	3	2	2	2	2	13(2)
Modified Guest	1	2	1	3	3	1	11(1)

Table 5 summarized the ranks obtained from the modified DLR models over Ibadan. The rank obtained by each of the models varies between the value 11 and 27. The overall results for Ibadan showed that the

modified DLR regression model as given in equation 23 which is the modified Guest DLR model was found more accurate for estimating DLR in Ibadan as compared to another model.

**Figure 3: Monthly Variation of the measured DLR with the modified DLR models over Ibadan**

It was observed in Figure 3 that the modified Deacon DLR model consistently underestimated the measured DLR and all other modified DLR models throughout the entire period from April to October. The divergence of the modified Deacon curve from the measured DLR and from the other modified models was conspicuous across all months, with modified Deacon values falling substantially below the rest of the modified DLR curves. This persistent underestimation is attributed to structural limitations inherent in the Deacon formulation, which is essentially a temperature-only parameterization and does not explicitly incorporate water-vapour pressure, consistent with findings reported by Soneye-Arogundade [28]. In contrast, the modified Idso model consistently overestimated the measured DLR and other evaluated models throughout the year from April to November, forming the uppermost curve

and diverging most visibly from the measured values during the March to April peak period, which corresponds to the transition from the dry season to the onset of the wet season, a period characterized by rising temperature and increasing atmospheric humidity that jointly enhance atmospheric emissivity and elevate DLR, as supported by the findings of Tian *et al.*, [40].

The modified Guest model, meanwhile, displayed closely similar and nearly overlapping patterns of variation throughout the year, clustering tightly around the measured DLR curve across nearly all months. Among these, the modified Guest model tracked closest to the measured DLR and followed an almost identical pattern of variation, confirming it as the most suitable model for estimating DLR over Ibadan, consistent with its superior statistical performance.

3.3 Comparison between the Best Existing DLR Model and the Best Modified DLR Model for Ibadan

Table 6: Statistical error indicators for the best existing and modified DLR over Ibadan

Models	MBE	RMSE	MPE	t	IA
Kruk	-3.6199	7.0397	0.8749	1.9885	0.8758
Modified Guest	0.1315	3.5334	-0.0512	0.1330	0.9608

Table 6 summarized the different statistical validation test for the best existing estimated and modified DLR models for Ibadan. The modified Guest has the lowest MBE, RMSE, MPE, t statistic and IA

value of overestimation of 0.1315 Wm^{-2} , 3.5334 Wm^{-2} , underestimation of 0.0512%, 0.1330 and 0.9608 respectively when compared with existing Kruk *et al.*, [29].

Table 7: Ranking of the best existing estimated and modified DLR model over Ibadan

Models	MBE	RMSE	MPE	t	IA	Total
Kruk	2	2	2	2	2	10
Modified Guest	1	1	1	1	1	5

Table 7 summarized the ranks obtained from the best existing estimated and modified DLR models over Ibadan. The rank obtained by each of the models varies between the value 5 and 10. The overall results for Ibadan showed that the modified DLR regression model as given in equation 23 which is the modified Guest was found more accurate for estimating DLR in Ibadan as compared to existing estimated model.

3.4 Variation of measured DLR with Meteorological Parameters over Ibadan

The variation of measured Downward Longwave Radiation (DLR) with meteorological parameters of Temperature (T) and Relative Humidity (RH) for Ibadan are shown in the figures below.

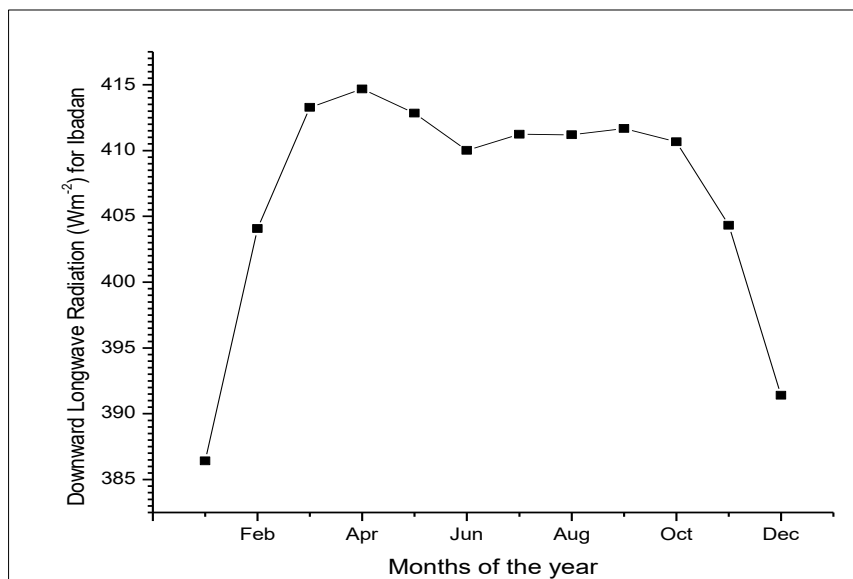


Figure 4: Monthly Variation of the measured DLR over Ibadan

It was observed in figure 4, that DLR in Ibadan shows a gradual increase from a minimum value of 386.4167 Wm^{-2} in the month of January until it gets to its peak at 414.6667 Wm^{-2} in the month of April and decreases gradually until it gets to 411.2396 Wm^{-2} in June. It abruptly increases and reaches another high value of 411.6771 Wm^{-2} in the month of September and significantly drops to 391.4063 Wm^{-2} in December. The maximum value of DLR was noticed in April with a value of 414.667 Wm^{-2} and the minimum value was noticed in month of January with a value of 386.4167 Wm^{-2} . The result shows that high values of DLR are observed during the rainy season with an average value

of 411.7574 Wm^{-2} and low values are observed during the dry season, with an average value of 399.8938 Wm^{-2} . The slightly decrease in the value of DLR for Ibadan in June corresponds with a period of convective cloud cover. The high values which were observed during the rainy season (April-October) suggests maximum atmospheric radiative emission, due to a combination of high humidity and increased cloud cover, both of which are efficient emitters of longwave radiation back to the surface resulting to a significant increase of DLR which was observed in Ibadan with a value of 414.667 Wm^{-2} in the month of April that is been emitted towards the earth's surface. While the lower values in Ibadan were

during the dry seasons (November-March) due to seasonal changes in atmospheric circulation, reductions in precipitable water vapour, even though temperatures

may remain relatively high thereby reducing atmospheric emissivity leading to lower DLR.

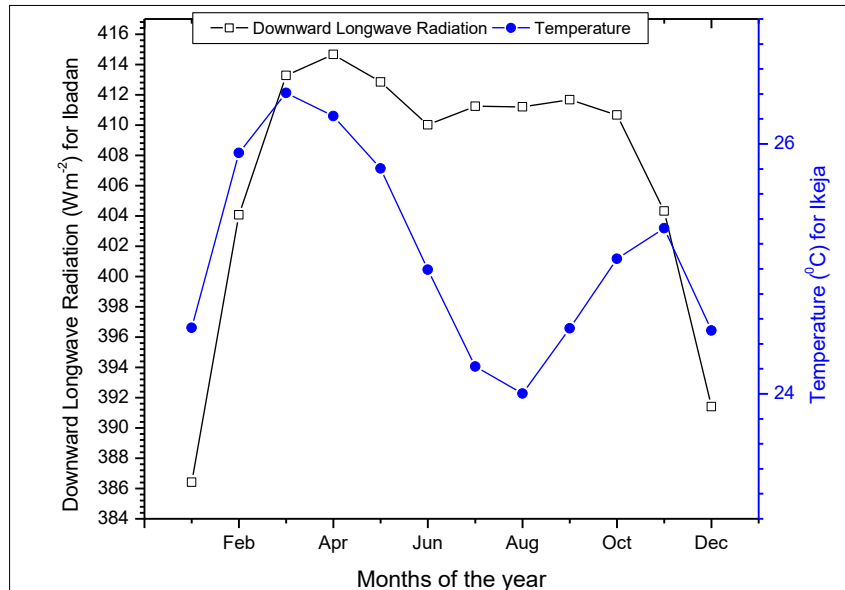


Figure 5: Monthly Variation of measured DLR with Temperature over Ibadan

Figure 5 shows the monthly variations of the measured DLR with temperature for Ibadan during the period of study. Clear observations shows that both the measured DLR and temperature increased from the month of January and reaches its highest point with value 414.667 Wm⁻² and 26.4072 °C in the month April and March respectively. The DLR and temperature experienced a decreased with a value of 410.0104 Wm⁻² and 24.0032 °C respectively in the month of June and August. The average value of the measured DLR during the rainy and dry seasons are 411.7574 Wm⁻² and

399.8938 Wm⁻² while the average value of temperature during the rainy and dry season are 24.9778 °C and 25.3390 °C respectively. This shows that the measured DLR remains relatively high during the rainy season despite the low temperatures due to increased cloud cover and atmospheric water vapour. While during the dry season, the measured DLR is low with significant increase in temperature because of low humidity and low cloud cover there by resulting in low DLR when compared to the rainy season.

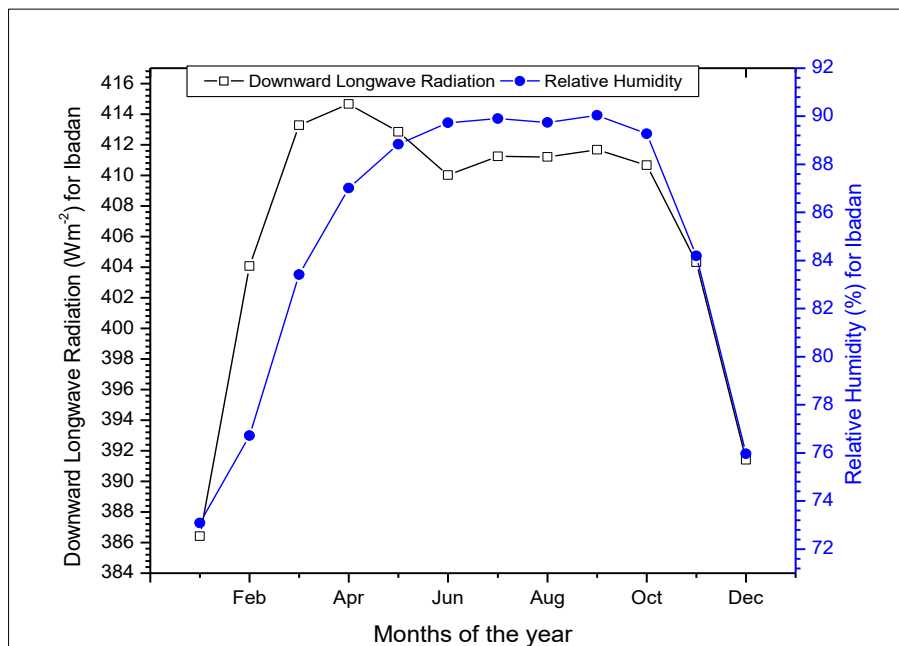


Figure 6: Monthly variation of measured DLR with RH over Ibadan

Figure 6 shows the monthly variations of the measured DLR with RH for Ibadan during the period of study. Clear observations shows that both the measured DLR and RH increased from the month of January and reaches its highest point with value 414.667 Wm^{-2} and 89.8985% in the month of April and July respectively. The average value of the measured DLR during the rainy and dry seasons are 411.7574 Wm^{-2} and 399.8938 Wm^{-2}

while the average value of RH during the rainy and dry season are 89.2187% and 78.6759% respectively, indicating that RH is higher during the rainy season than in the dry season.

3.5 Statistical Analysis Summary of DLR for Makurdi

Table 8: Statistical error indicators for the eleven estimated DLR over Makurdi

Models	MBE	RMSE	MPE	t	IA
Angstrom	-35.6985	37.9494	8.5931	9.1959	0.4617
Swinbank	-31.8995	33.9253	7.6905	9.1618	0.5158
Idso&Jackson	-29.6274	31.7582	7.1385	8.5918	0.5375
Deacon	-33.9709	35.8833	8.1963	9.7479	0.4995
Brutsaert	-16.7644	17.2555	4.0690	13.6032	0.7962
Idso	9.4250	10.5109	-2.2697	6.7186	0.9257
Garratt	-53.7380	55.2963	12.9982	13.6733	0.3639
Prata	-19.6708	20.2354	4.7689	13.7452	0.7437
Dilley&O'Brien	-117.9960	118.4606	28.7228	37.3343	0.2101
Guest	-33.5380	34.8887	8.1006	11.5699	0.5228
Kruk	-10.3172	10.9487	2.5372	9.3375	0.9159

Table 8 presents the statistical error indicators for the eleven existing downward longwave radiation (DLR) models evaluated over Makurdi. From table 6, the Idso [16], has the lowest MBE, MPE, RMSE and t-statistic value overestimation of 9.4250 Wm^{-2} , underestimation of 2.2697% , 10.5109 Wm^{-2} and 6.7186 respectively, the Idso [16], also has the highest Index of Agreement value of 92.5770% . The superior performance of the Idso [16], model can be attributed to its dependence on air temperature, one of the dominant controls of atmospheric longwave emission. According to the Stefan-Boltzmann law, longwave radiation emitted by the atmosphere increases approximately with the fourth power of absolute temperature. Makurdi experiences relatively warm and humid tropical conditions throughout much of the year, allowing the

temperature-based parameterization adopted by Idso [16], to effectively represent atmospheric emissivity and downward longwave radiation. The result of the existing models indicated that all the MPE values are within the acceptable range of ($\text{MPE} \leq \pm 10\%$) apart from Garratt [17], and Dilley and O'Brien [19], existing models. The findings agree with Soneye-Arogundade *et al.*, [28], who reported that empirical DLR models calibrated for Nigerian climatic conditions generally produce lower RMSE and higher agreement statistics than uncalibrated models. Similar conclusions were reported by Carmona *et al.*, [21], and Guo *et al.*, [20], who showed that temperature-based parameterizations perform well in warm climates where air temperature strongly controls atmospheric longwave emission.

Table 9: Ranking of the eleven estimated DLR over Makurdi

Models	MBE	RMSE	MPE	t	IA	RANK
Angstrom	9	9	9	9	9	45(9)
Swinbank	6	6	6	3	7	28(5)
Idso & Jackson	5	5	5	2	5	22(4)
Deacon	8	8	8	8	8	40(7)
Brutsaert	3	3	3	8	3	20(3)
Idso	1	1	1	1	1	5(1)
Garratt	10	10	10	10	10	50(10)
Prata	4	4	4	10	4	26(5)
Dilley&O'Brien	11	11	11	11	11	55(11)
Guest	7	7	7	7	6	34(7)
Kruk	2	2	2	5	2	13(2)

Table 9 summarized the ranks obtained from the eleven estimated DLR models over Makurdi. The rank obtained by each of the models varies between the value 5 and 55. Idso *et al.* [16] model, is ranked as the best overall based on the statistical accuracy assessment

test which is consistent across all the five test particularly in its low MBE and better t-test with lowest ranking value of 5 and its was found more accurate in the estimation of DLR in Makurdi as compared to other models.

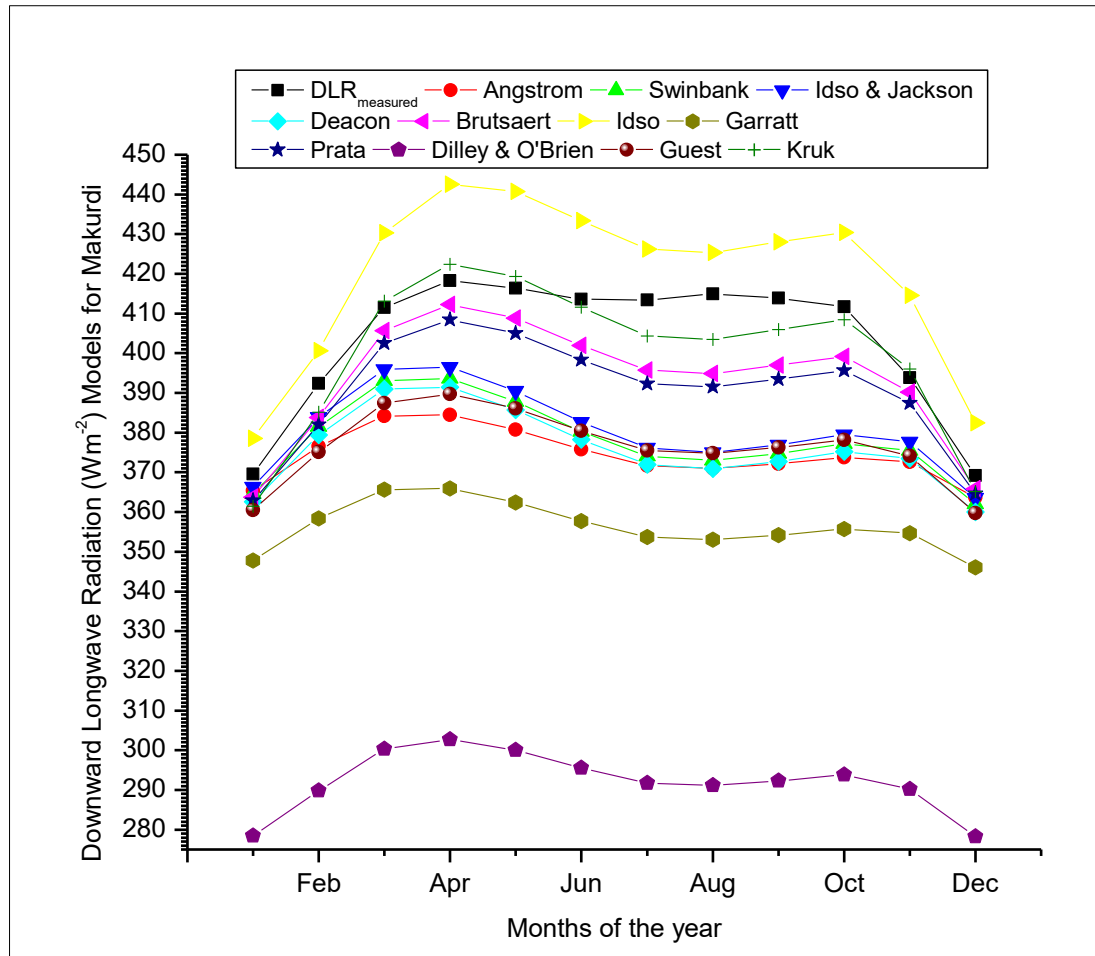


Figure 7: Monthly variation of measured DLR with the eleven estimated DLR models over Makurdi

It was observed in Figure 7, that the Idso [16], model consistently overestimated the measured downward longwave radiation (DLR) and other evaluated models throughout the entire study period from January to December. However, it depicts closed values with the measured DLR from January to March. The model successfully captured the gradual increase in DLR from January to April, the relatively stable values during the rainy season, and the decline towards December. This superior performance suggests that the Idso model effectively represents the combined influence of atmospheric water vapour, air temperature, and near-surface meteorological conditions on downward longwave radiation, making it more suitable for humid tropical environments such as Makurdi. The findings of this study are consistent with those of Wang *et al.*, [42], who reported that atmospheric water vapour exerts the strongest control on downward longwave radiation and that incorporating humidity-related variables significantly improves the performance of empirical DLR models. Likewise, Jiang *et al.*, [43], demonstrated

that parameterizations incorporating both air temperature and atmospheric water vapour pressure provide more accurate DLR estimates than models based solely on temperature. Furthermore, Soneye-Arogundade *et al.*, [28], found that empirical models calibrated under Nigerian climatic conditions produced more reliable DLR estimates across different ecological zones because they better represented regional atmospheric characteristics.

3.6 Downward Longwave Radiation proposed based models for Makurdi

The results of the proposed DLR regression models for Makurdi are shown below

$$DLR(Wm^{-2}) = 302.11 + 0.04631 \times 10^{0.067e_o} \quad (24)$$

$$DLR(Wm^{-2}) = -1030 + 0.01607 \times T^2 \quad (25)$$

$$DLR(Wm^{-2}) = 440.7 + 0.03558 \times e_o - 0.843 \exp\left(\frac{1500}{T}\right) \quad (26)$$

$$DLR(Wm^{-2}) = 115.6 + 66.6 \left(\frac{T}{273.16}\right)^6 + 438.4 \sqrt{w/25} \quad (27)$$

$$DLR(Wm^{-2}) = -217.2 + 1.179\sigma T^4 + 1.137 \times RH \quad (28)$$

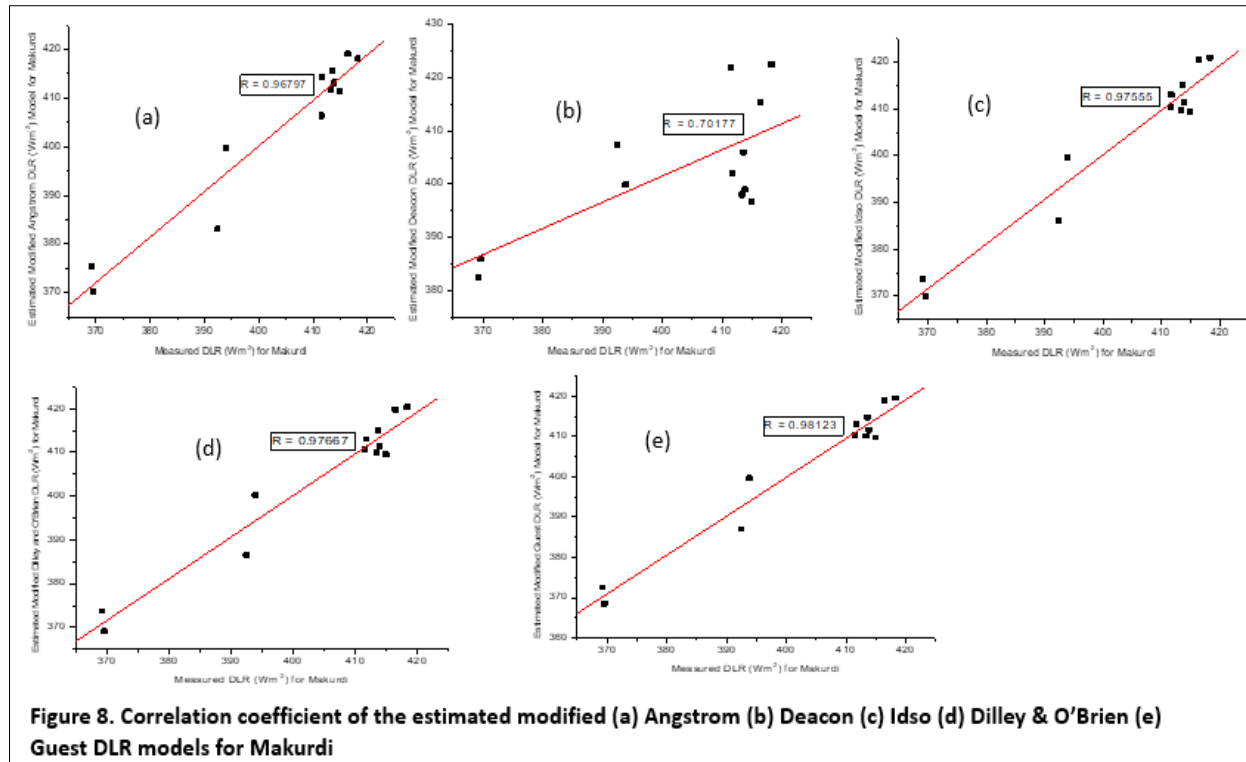


Figure 8 shows the correlation coefficient (R) of the estimated modified models for Makurdi which varies from 0.7018 (modified Deacon) to 0.9812 (modified Guest)

Table 10: Statistical error indicators for the estimated modified DLR models over Makurdi

Models	R	MBE	RMSE	MPE	t	IA
Modified Ångström	0.9680	-6.8032	8.1486	1.6517	5.0307	0.9431
Modified Deacon	0.7018	-6.8697	12.9785	1.5953	2.0692	0.8152
Modified Idso	0.9756	-6.7357	7.4574	1.6394	6.9805	0.9524
Modified Dille & O'Brien	0.9767	-6.7211	7.4298	1.6362	7.0390	0.9528
Modified Guest	0.9812	-7.0522	7.7458	1.7179	7.3005	0.9491

In table 10, it was observed that the modified Dille & O'Brien DLR model had the lowest value for MBE and RMSE with an underestimation of 6.7211 Wm^{-2} and 7.4298 Wm^{-2} respectively and also recorded the highest IA values of 0.9528 confirming its superior predictive performance among all the modified models evaluated over Makurdi based on IA. Also, the modified Deacon has a lowest value of MPE and t-statistic of overestimation of 1.5953 % and 2.0692 respectively while the modified Guest has the highest coefficient of correlation vale of 0.9812. The superior performance of the modified Dille and O'Brien model can be attributed to its physical formulation, which accounts for the effects of atmospheric water vapour on longwave radiation. Makurdi lies within the Southern Guinea Savanna

climatic zone, where seasonal variations in atmospheric moisture strongly influence atmospheric emissivity and downward longwave radiation. Consequently, models that adequately represent atmospheric moisture are expected to perform better than those based primarily on-air temperature. This finding agrees with Yang *et al.*, [41], who reported that empirical DLR models incorporating atmospheric moisture consistently outperform temperature-based models under varying climatic conditions. A similar observation was reported by Soneye-Arogundade [28], who found that calibrated DLR models developed for Nigerian stations significantly improved prediction accuracy by adapting the empirical coefficients to local climatic conditions.

Table 11: Ranking of the estimated Modified DLR Model over Makurdi

Models	R	MBE	RMSE	MPE	t	IA	Total
Modified Angstrom	4	3	4	4	2	4	25
Modified Deacon	5	4	5	1	1	5	21
Modified Idso	3	1	2	3	3	2	14
Modified Dille & O'Brien	2	2	1	2	4	1	12
Modified Guest	1	5	3	5	5	3	22

Table 11 summarized the ranks obtained from the modified DLR models over Makurdi. The rank obtained by each of the models varies between the value 12 and 22. The overall results for Makurdi showed that

the modified DLR regression model as given in equation 27 which is Modified Dilley & O'Brien was found more accurate for estimating DLR in as compared to another model.

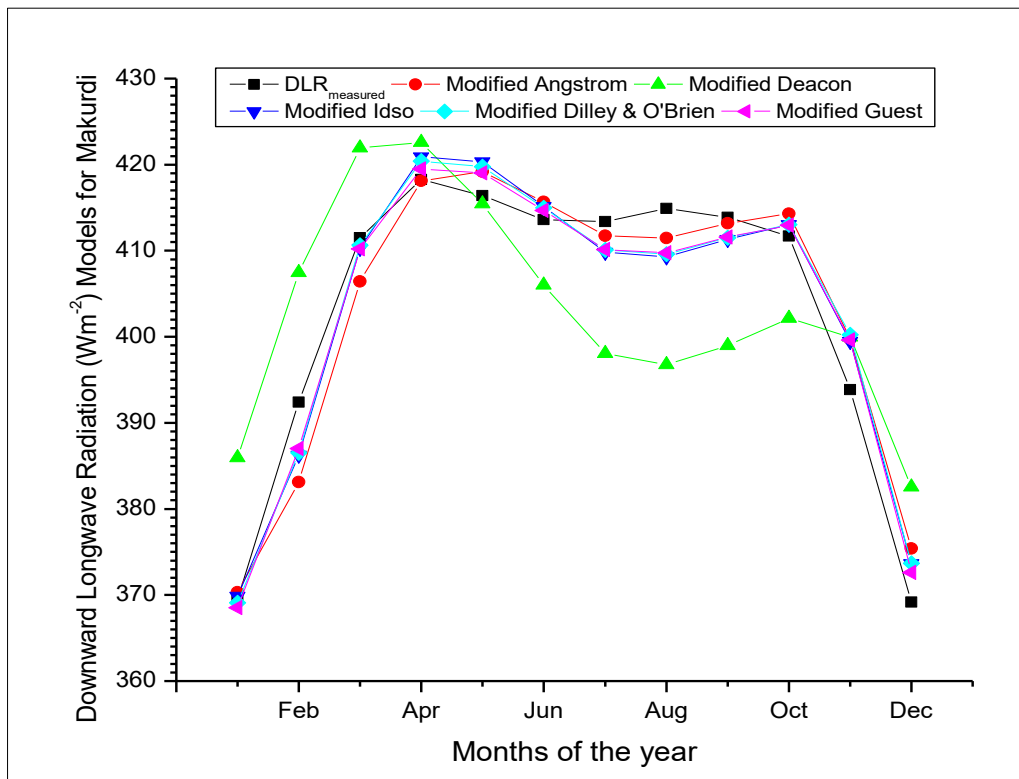


Figure 9: Monthly variation of the measured DLR with the modified DLR models over Makurdi

It was observed in Figure 9 that the modified Deacon DLR model generally overestimated the measured DLR and other evaluated model during the late dry season (January to April), reaching its highest values when the measured DLR was comparatively lower, before underestimating the measured DLR and other evaluated model from June to October during the peak wet season. This divergence from both the measured DLR and the other modified models indicates that the modified Deacon model was unable to adequately reproduce the seasonal variability of atmospheric longwave radiation in Makurdi. The relatively poor performance of the modified Deacon model may be attributed to the inherent limitation of the Deacon formulation, which relies predominantly on-air temperature and does not sufficiently account for the strong influence of atmospheric water vapour on emissivity. Since water vapour is the principal greenhouse gas responsible for atmospheric longwave emission, models that inadequately represent its effect are expected to exhibit larger seasonal deviations, particularly in humid tropical environments. Similar observations were reported by Soneye-Arogundade *et al.*, [28], who found that empirical DLR models with limited representation of atmospheric moisture performed less satisfactorily across different climatic zones of Nigeria. Among the modified models, the modified Dilley & O'Brien DLR model followed the

measured DLR most closely throughout the annual cycle. The model successfully reproduced both the seasonal maxima and minima with only slight deviations, indicating that its regression coefficients effectively captured the local atmospheric characteristics of Makurdi. Its superior agreement with the measured DLR suggests that the local calibration improved the representation of atmospheric emissivity by accounting for the combined influence of temperature and moisture conditions peculiar to the Guinea Savannah climate. Similar improvements obtained through local calibration of empirical DLR models have been reported by Sridhar and Elliott [44], and Carmona *et al.*, [21], who demonstrated that site-specific modification of empirical models substantially enhances prediction accuracy compared with the original formulations. Likewise, Soneye-Arogundade *et al.*, [29], reported that locally calibrated empirical models consistently outperform their original counterparts across Nigerian climatic regions because they better represent regional atmospheric conditions. Overall, the close agreement between the modified Dilley & O'Brien model and the measured DLR demonstrates that local calibration significantly improves empirical DLR estimation. The findings further confirm that empirical models incorporating both atmospheric temperature and moisture information provide more reliable estimates of

downward longwave radiation than models relying primarily on temperature alone.

3.7 Comparison between the Best Existing DLR Model and the Best Modified DLR Model for Makurdi

Table 12: Statistical error indicators for the best existing and modified DLR over Makurdi

Models	MBE	RMSE	MPE	t	IA
Idso	9.4250	10.5109	-2.2697	6.7186	0.9257
Modified Dilley & O'Brien	-6.7211	7.4298	1.6362	7.0390	0.9528

Table 12 summarized the different statistical validation test for the best existing estimated and modified DLR models for Makurdi. The modified Dilley & O'Brien has the lowest MBE, RMSE, MPE and IA

value of underestimation of 6.7211 Wm^{-2} , 7.4298 Wm^{-2} , overestimation of 1.6362% and 0.9528 respectively when compared with existing Idso [16].

Table 13: Ranking of the best existing estimated and modified DLR model over Makurdi

Models	MBE	RMSE	MPE	t	IA	Total
Idso	2	2	2	1	2	9
Modified Dilley & O'Brien	1	1	1	2	1	6

Table 13 summarized the ranks obtained from the best existing estimated and modified DLR models over Makurdi. The rank obtained by each of the models varies between the value 6 and 9 the overall results for Makurdi showed that the modified DLR regression model as given in equation 27 which is the modified Dilley & O'Brien was found more accurate for

estimating DLR in Makurdi as compared to existing estimated model.

3.8 Variation of Measured DLR with Meteorological Parameters over Makurdi

The Variation of measured Downward Longwave Radiation (DLR) with meteorological parameters of Temperature (T) and Relative Humidity (RH) for Makurdi are shown in the figures below.

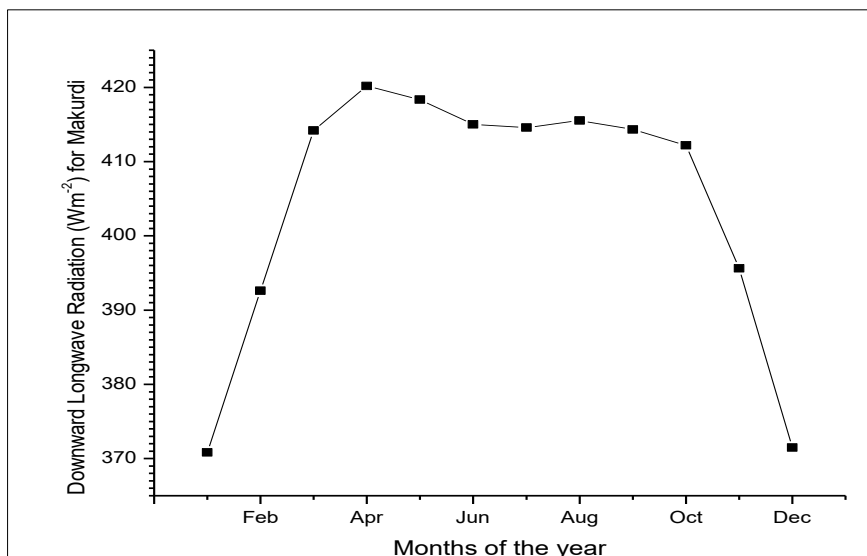


Figure 10: Monthly variation of the measured DLR over Makurdi

It was observed in figure 10, that DLR in Makurdi shows a gradual increase from a minimum value of 370.8333 Wm^{-2} in the month of January until it gets to its peak at 420.1875 Wm^{-2} in the month of April and decreases gradually until it gets to 414.5938 Wm^{-2} in July. It abruptly increases and reaches another high value of 415.5313 Wm^{-2} in the month of August and significantly drops to 371.4792 Wm^{-2} in December. The maximum value of DLR was noticed in April with a value of 420.1875 Wm^{-2} and the minimum value was noticed in month of January with a value of 370.8333

Wm^{-2} . The result shows that high values of DLR are observed during the rainy season with an average value of 415.7440 Wm^{-2} and low values are observed during the dry season, with an average value of 388.9500 Wm^{-2} . The high values which were observed during the rainy season (April-October) suggests maximum atmospheric radiative emission, due to a combination of high humidity and increased cloud cover, both of which are efficient emitters of longwave radiation back to the surface resulting to a significant increase of DLR which was observed in Makurdi with a value of 420.1875 Wm^{-2}

in the month of April that is been emitted towards the earth's surface .while the lower values in Makurdi was during the dry seasons (November-March) due to seasonal changes in atmospheric circulation, reductions

in precipitable water vapour, even though temperatures may remain relative high thereby reducing atmospheric emissivity leading to lower DLR.

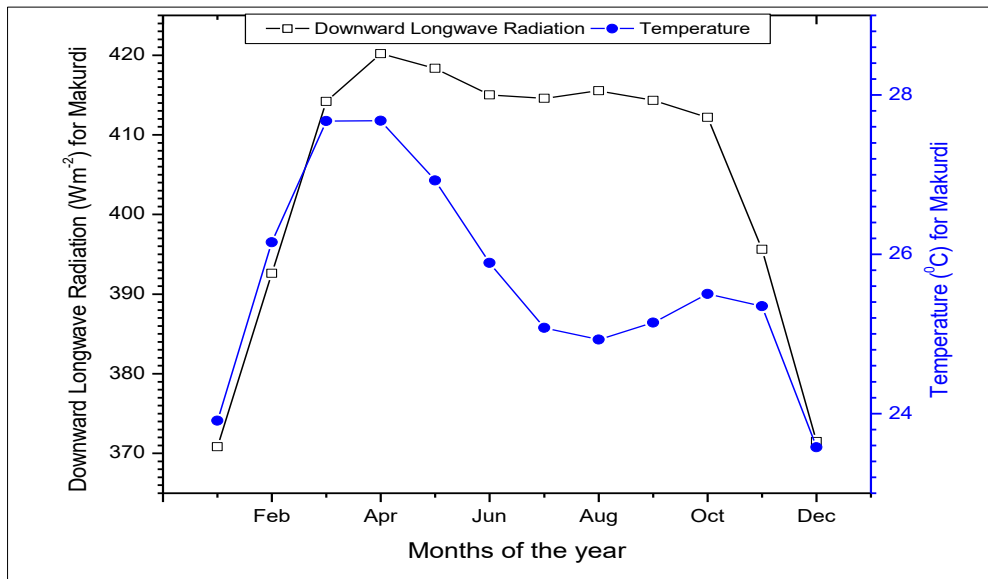


Figure 11: Monthly Variation of measured DLR with Temperature over Makurdi

Figure 11 shows the monthly variations of the measured DLR with temperature for Makurdi during the period of study. Clear observations shows that both the measured DLR and temperature increased from the month of January and reaches its highest point with value 420.1875 Wm⁻² and 27.6765 °C in the month April respectively. The DLR and temperature experienced a decreased with a value of 414.5938 Wm⁻² and 24.9287 °C respectively in the month of July and August. The average value of the measured DLR during the rainy and dry seasons are 415.7440 Wm⁻² and 388.9500 Wm⁻²

while the average value of temperature during the rainy and dry season are 25.8775 °C and 25.3316 °C respectively. This shows that the measured DLR remains relatively high during the rainy season despite the low temperatures due to increased cloud cover and atmospheric water vapour. While during the dry season, the measured DLR is low with significant increase in temperature because of low humidity and low cloud cover there by resulting in low DLR when compared to the rainy season.

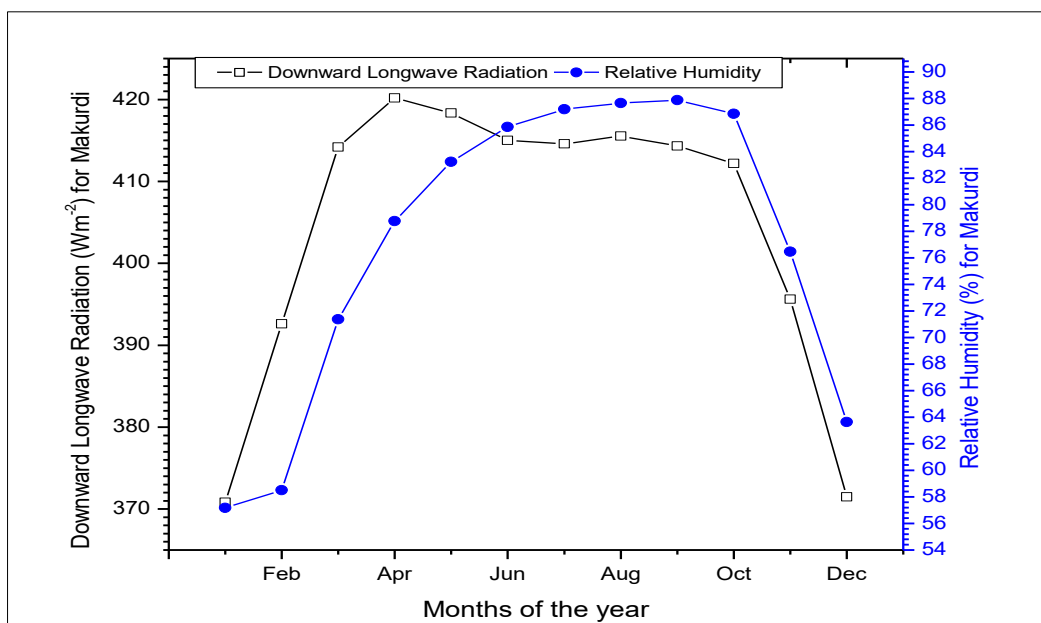


Figure 12: Monthly Variation of measured DLR with RH over Makurdi

Figure12 shows the monthly variations of the measured DLR with RH for Makurdi during the period of study. Clear observations shows that both the measured DLR and RH increased from the month of January and reaches its highest point with value 420.1875 Wm⁻² and 87.8700% in the month of April and September respectively. The average value of the measured DLR during the rainy and dry seasons are 415.7440 Wm⁻² and 388.9500 Wm⁻² while the average value of RH during the rainy and dry season are 85.3381% and 65.4286 % respectively, indicating that RH is higher during the rainy season than in the dry season. Therefore, DLR increased with increased in RH during rainy season and vice-versa.

4. CONCLUSION

In this study, eleven (11) distinctive existing clear-sky DLR empirical models and five (5) locally developed modified regression models were evaluated and compared through the statistical validation test indicators of MBE, RMSE, MPE, t-test, IA, and R. The models were subjected to a comprehensive ranking procedure to determine the suitability, reliability, and accuracy of each model for DLR estimation in from Ibadan and Makurdi located across the Guinea Savannah climatic zone of Nigeria and also the variation of DLR with meteorological parameters were investigated. The results of the study show that:

- i. The evaluation of the eleven existing empirical downward longwave radiation (DLR) models showed that model performance varied across the Guinea Savannah climatic zone. The Kruk *et al.*, [30], model was the most suitable existing model for Ibadan, while the Idso [14], model performed best for Makurdi.
- ii. Five modified empirical DLR models were successfully developed through regression analysis. The modified Guest model provided the best prediction accuracy in Ibadan, whereas the modified Dilley and O'Brien model performed best in Makurdi, demonstrating that local calibration significantly improves estimation accuracy.
- iii. Ranking of both existing and modified models showed that Kruk *et al.*, [30], and Idso [16], were the highest-ranked existing models for Ibadan and Makurdi respectively. Among the calibrated models, the modified Guest model ranked first in Ibadan, while the modified Dilley and O'Brien model ranked first in Makurdi.
- iv. Validation using MBE, RMSE, MPE, t-test, correlation coefficient (R) and Index of Agreement (IA) confirmed that the modified models consistently outperformed the original empirical models and are more suitable for estimating DLR in the Guinea Savannah climatic zone.
- v. Seasonal analysis showed that DLR was highest during the rainy season because of increased atmospheric moisture and cloud cover, despite

relatively lower temperatures. This demonstrates that atmospheric water vapour and relative humidity have a stronger influence on DLR than air temperature alone.

Overall, the findings of this study confirm that locally calibrated DLR models significantly improved the predictive performance of empirical DLR models. The modified models developed in this study are therefore recommended for practical DLR estimation at Ibadan and Makurdi in the absence of direct pyrgeometer measurements.

ACKNOWLEDGEMENTS

The authors are grateful to the management and staff of National Aeronautics and Space Administration (NASA) for making the data used in this study available online.

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