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EVALUATION OF CLOUD-COVER-BASED MODELS FOR ESTIMATING GLOBAL SOLAR RADIATION ACROSS NIGERIA'S CLIMATIC ZONES.

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ABSTRACT
Accurate estimation of global solar radiation (GSR) is essential for solar energy system design, climate studies, and environmental modelling. In Nigeria, direct measurements of solar radiation remain limited due to sparse instrumentation and frequent data gaps, necessitating reliable empirical models. This study evaluates seven established cloud-cover-based models and develops five new models (NDM1–NDM5) for improved prediction of GSR across Nigeria's four major climatic zones: Sahel Savannah (Potiskum), Sudan Savannah (Yelwa), Guinea Savannah (Ibi), and Tropical Rainforest (Calabar). Long-term meteorological data spanning 32 years (1990–2021) were obtained from NiMet. Extraterrestrial radiation was computed using standard solar geometry, and model performance was assessed with ten statistical indicators, including MBE, MAE, RMSE, MPE, MARE, and the correlation coefficient (r). A Global Performance Indicator (GPI) was employed to rank model performance. Results show significant variation in the accuracy of the existing models across climatic zones. The newly developed models consistently outperformed the literature models, with NDM5 emerging as the best-performing model in three of the four climatic zones, exhibiting very low RMSE, minimal bias, and high correlation (r > 0.96). In the Tropical Rainforest zone, where cloud cover is persistently high, NDM4 showed superior stability compared to other models. Overall, the new models demonstrated improved sensitivity to seasonal cloud cover variability and reproduced measured GSR more accurately across all zones. The study concludes that cloud-cover-based models can reliably estimate solar radiation in data-sparse regions and that the newly developed models offer a more generalized and climate-responsive framework for Nigeria.

Keywords: Climatic zones, cloud cover, empirical models, Global solar radiation, GPI ranking, model validation, Nigeria

1. INTRODUCTION
Accurate estimation of global solar radiation (GSR) is essential for the design simulation and performance analysis of solar energy systems. Solar radiation data are also required in meteorology, agriculture, hydrology and building energy modelling.

However, in many developing regions, including Nigeria, direct measurement of solar radiation using pyrometers or radiometers is limited due to high installation and maintenance costs, frequent equipment failure and data gaps. Consequently, several empirical, statistical and machine learning models have been developed to estimate solar radiation from commonly available meteorological parameters such as sunshine duration, temperature, relative humidity and rainfall [1]. Early studies on solar radiation estimation adopted empirical relationship such as the Angtrom-Prescolt (A-P) and Hargreares-Samani models, which express global solar radiation as a function of sunshine duration or temperature differences. Subsequent improvements have included locally calibrated regression equations and hybrid models that integrated multiple meteorological inputs. Researchers such as [2], [3] and have shown that model performance varies widely with climate type, geographic location, and data resolution. More recently, Meta-heuristic and machine learning techniques (artificial neural networks, support vector regression, random forest) have been applied to enhance prediction accuracy, often achieving high correlation coefficient and reduced means bias error (MBE) and root mean square error (RMSE) values [4].

Despite these advancement, regional generalization remains a challenge. Most empirical and AI-based models are site-specific and require local recalibration before application to other climates zones. Nigeria, for instance spans four major climate zones. Sahel, savannah, Sudan savannah, Guinea savannah and coastal rainforest each characterized by distinct temperature regimes humidity and cloud patterns consequently, a model developed for one zone often performs poorly when applied to another, underscoring the need for generalized equation capable of producing reliable solar radiation estimate across divers Nigerian climates.

2. MATERIALS AND METHODS

2.1 Materials

2.1.1 Study Area

Nigeria lies within the tropical region of West Africa between latitudes 4°N and 14°N and longitudes 3°E and 15°E. The country covers approximately 923,768 km², making it the largest nation in West Africa. Its broad latitudinal span and varying atmospheric conditions create four major climatic zones, each characterized by distinct temperature regimes, humidity levels, rainfall patterns, and cloud dynamics. These include the Sahel Savannah, Sudan Savannah, Guinea Savannah, and Tropical Rainforest zones [1].

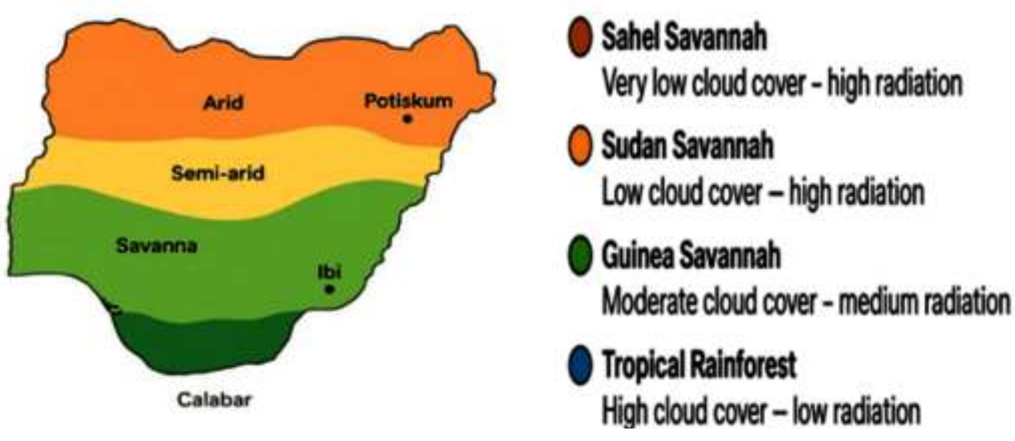

Fig. 1: Classification of Selected Locations in Nigeria into major climatic and vegetation zones.

To adequately capture the diversity of cloud cover and solar radiation behavior across Nigeria, four representative locations were selected: Potiskum (Sahel Savannah), Yelwa (Sudan Savannah), Ibi (Guinea Savannah), and Calabar (Tropical Rainforest). This distribution reflects the country's north–south gradient in atmospheric moisture and cloud formation, with cloud cover increasing progressively from the arid northern regions to the humid coastal south [6]. **Figure 1** summarizes the climatic characteristics of the selected stations, while **Table 1** illustrates their spatial distribution across Nigeria.

Table 1: Classification of the Four (4) Selected Locations by Climatic Zone and Cloud Cover Characteristics.

S/N	Location	State	Climatic Zone	General Climate Description	Types Cloud Characteristic
1	Potiskum	Yobe	Sahel Savannah	Hot, dry semiarid, low rainfall (<600mm/year)	Very low cloud cover throughout most of year, resulting in high solar radiation.
2	Yelwa	Kebbi	Sudan Savannah	Semi-arid climate with moderate rainfall (600-1000mm)	Generally low cloud cover except during the short rainy season.
3	Ibi	Taraba	Guinea Savannah	Warm moderately humid with district wet and dry seasons	Moderate and seasonal cloud cover medium solar radiation levels
4	Calabar	Cross River	Tropical Rainforest Coastal Zone	Hot, humid heavy rainfall (> 2000mm/year)	Very high and persistent cloud cover, especially between April – October low solar radiation due to frequent overcast conditions.

2.1.2 Data

Daily meteorological data, including measured global solar radiation, maximum and minimum temperatures, cloud cover, and sunshine duration, were obtained from the Nigerian Meteorological Agency (NiMET), Oshodi–Lagos. Data spanned a 32-year period (1990–2021) for 20 stations distributed across Nigeria's climatic zones. Missing data points were reconstructed using linear interpolation to ensure continuity. The dataset was divided into a calibration period (1990–2016) and a validation period (2017–2021), enabling independent assessment of model performance [7].

Monthly mean daily global solar radiation and meteorological variables including maximum and minimum temperature, sunshine duration, and cloud cover were obtained from the Nigerian Meteorological Agency (NiMet), Oshodi, Lagos, for a period of 35 years (1990–2021). The database covers 20 synoptic stations distributed across the four major climatic zones of Nigeria.

Missing or incomplete records (<5%) were reconstructed using linear interpolation, consistent with WMO-recommended climate data quality procedures [12]. For model development, the dataset was divided into two: calibrated period and validation period to ensured unbiased evaluation of the predictive capability of all models.

2.1.3 Computation of Extraterrestrial Solar Radiation

The monthly average daily extraterrestrial radiation on a horizontal surface, H_0, was computed following standard solar geometry formulations:

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

Where, I_{sc} is the solar constant (=1367Wm^{-2}), ϕ is the latitude of the site, $\delta$is the solar declination, ω_s is the mean sunrise hour angle for the given month and n is the number of days of the year starting from 1st of January to 31st of December.

The solar declination,δ and the mean sunrise hour angle $\omega_s$can be calculated using the following equation [13]:

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

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

For a given month, the maximum possible sunshine duration (monthly average day length (S_o)) in hours can be computed by

$$S_O = \frac{2}{15}\omega_s \quad (4)$$

2.1.4 Selection of Cloud Cover–Based Models

Cloud cover is a major atmospheric modifier of solar radiation and is routinely measured at weather stations across Nigeria. Hence, cloud cover was used as the independent variable for the estimation of the clearness index:

$$K_t = \frac{H}{H_0}. \quad (5)$$

2.1.5 Selection of Existing Models

Seven widely used cloud-cover-based models from the literature were selected for evaluation. These models represent various functional forms including linear, polynomial, logarithmic, and exponential relationships linking cloud cover to clearness index or global solar radiation. Selection was based on their prevalence in previous studies, relevance to tropical climates, and ability to operate using cloud cover as the primary predictor variable [8]. The mathematical expressions of these models are presented in **Table 2.**

Table 2: Proposed Cloud Cover-based Models from Literature.

]	**Model Type**	**Regression**		**Model···Sources**
1	Linear (MD1)	$\frac{H}{H_O} = a + b(CC)$	(6)	[2]
2.	Linear Logarithmic (MD2)	$\frac{H}{H_O} = a + b(CC) + c\,ln(CC)$	(7)	[7]
3.	Quadratic (MD3)	$\frac{H}{H_O} = a + b(CC) + c(CC)^2$	(8)	[2]
4.	T□ird Degree(MD4)	$\frac{H}{H_o} = a + b(CC) + c(CC)^2 + d(CC)$	(9)	[12]
5.	cubic wit□ Temperature (MD5)	$\frac{H}{H_o} = a + b(CC) + c(T_{max} - T_{MIN})^2 + d(CC)^3$	(10)	[14]
6.	Logarithmic (MD6)	$\frac{H}{H_O} = a + b\,log(CC)$	(11)	[8]
7.	Linear (MD7)	$\frac{H}{H_O} = a + b(1 - CC)$	(12)	[9]

2.2 Method

2.2.1 Development of New Models

Five new cloud-cover-based models (NDM1–NDM5) were derived using long-term measured data from the four climatic zones. The models were formulated by exploring functional relationships between cloud cover and clearness index. Emphasis was placed on developing simple yet effective formulations that enhance estimation accuracy while remaining computationally practical. The new models retain the classical empirical structure but incorporate modified coefficients optimized through regression analysis [9]. Their analytical forms are presented in **Table 3.**

Table 3: cloud cover – based models proposed

S/NO	$Model \cdots Type$	$Models - Notations$	$Regression$	
1.	$Hybrid - Linear - Logarithmic$	$NMD1$	$\frac{H}{H_O} = a + b(1 - CC) + c\ln(1 - CC)$	(13)
2.	$SimplifiedQuadratic$	$NMD2$	$\frac{H}{H_O} = 1 - a(CC) - b(CC)^2$	(14)
3.	$Linear$	$NDM3$	$\frac{H}{H_O} = a + b\left(\frac{CC}{1 - CC}\right)$	(15)
4.	$Quadratic\ inTransformed - Variable$	$NDM4$	$\frac{H}{H_O} = a + b\left(\frac{CC}{1-CC}\right) + c\left(\frac{CC}{1-CC}\right)^2$	(16)
5.	$Linear$ with $ln(kt)$	$NDM5$	$\frac{H}{H_O} = a + b(CC) + c\ln(CC) + d\ln(kt)$	(17)

2.2.2 Statistical Evaluation of Model Performance

Model performance was evaluated using widely accepted statistical indicators: mean bias error (MBE), mean absolute error (MAE), root mean square error (RMSE), mean percentage error (MPE), relative RMSE (RRMSE), mean absolute relative error (MARE), t-statistic, uncertainty at 95% confidence (U95%), and the correlation coefficient (r). These indicators quantify accuracy, systematic bias, precision, and agreement between measured and estimated global solar radiation [10]. The mathematical definitions are summarized in **Table 4**.

Table 4: Formula or Statistical indicator (10)

S/NO	$Model.Type$	Regression	Prefer value
1.	$ModelsBias\ Error\ (MBE)$	$MBE = \frac{1}{n}\Sigma_{i=1}^{n}(H_{i,e} - H_{i,m})$	0
2.	$Mean\ Absolute\ Error\ (MAE)$	$MAE = \frac{1}{N}\sum_{i=1}^{n}\lvert H_{i,e} - H_{i,m}\rvert$	0
3.	$Mean\ Percentage\ Error\ (MPE)$	$MPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{H_{i,m} - H_{i,e}}{Hi,m}\right)x100$	0
4.	$RootMeanSquare\ Error\ (RMSE)$	$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(H_{i,e} - H_{i,m})^2\right]^{\frac{1}{2}}$	0
5.	$Uncertainty\ at\ 95\%\ (U_{95})$	$U_{95} = 1.96(SD^2 + RMSE^2)^{\frac{1}{2}}$	0
6.	$RelativeRootMeanSquare\ Error\ (RRMSE)$	$RRMSE = \sqrt{\frac{\frac{1}{n}\sum_{i=1}^{n}(H_{i,m} - H_{i,e})^2}{\Sigma_{i=1}H_{i,m}}}$.....(23)	0
7.	$t - Statistic\ (t - Start)$	$t - Start = \left[\frac{(n-1)MBE^2}{RMSE^2 - MBE^2}\right]^{\frac{1}{2}}$	0
8.	$Maximum\ Absolute\ Relative\ Error\ (erMax)$	$erMAX = Max\left(\left\lvert\frac{H_{i,m} - H_{i,e}}{H_{i,m}}\right\rvert\right)$	0
9.	$Mean\ Absolute\ Relative\ Error\ (MARE)$	$MARE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{H_{i,e} - H_{i,e}}{H_{i,m}}\right\rvert$	0
10.	$Correlation\ Coefficient\ (r)$	$r = \frac{\Sigma_{i=1}^{n}(H_{i,e} - H_{e,av})(H_{i,m} - H_{m,av})}{\sqrt{\Sigma_{i,e}(H_{i,e} - H_{e,av})^2\Sigma_{i=1}(H_{i,m} - H_{m.av})^2}}$	1

2.2.3 Global Performance Indicator (GPI)

To rank the models comprehensively, the Global Performance Indicator (GPI) proposed by Dispios and colleagues (2015) was employed. This metric consolidates the scaled values of all statistical indicators into a single index, enabling objective comparison among models. A lower GPI value indicates superior performance. After scaling each statistical measure between 0 and 1, deviations from their median were computed and weighted to derive the GPI score for each model. This approach allows balanced evaluation across multiple error criteria [11].

2.2.4 Model Ranking

The final ranking was based on GPI values. The model with the lowest GPI was assigned rank 1 (best performance), while subsequent models were ranked in ascending order of GPI. This ranking was performed separately for each climatic zone to identify zone-specific best models as well as a possible unified model suitable for nationwide application.

3. RESULTS AND DISCUSSION

This section presents the performance analysis of the existing cloud-cover-based global solar radiation (GSR) models and the newly developed models (NDM1–NDM5) across the four major climatic zones of Nigeria: Sahel Savannah (Potiskum), Sudan Savannah (Yelwa), Guinea Savannah (Ibi), and Tropical Rainforest (Calabar). The discussion integrates graphical comparisons, statistical indicators, and global performance ranking.

3.1 Sahel Savannah (Potiskum)

The Sahel zone is characterized by minimal cloud cover and intense solar radiation, making cloud-cover-based models particularly sensitive to small changes in atmospheric clarity [15].

The cloud cover-based performance metrics and ranking for Sahel Savannah is shown on Table 5.

Table 5: Cloud Cover Based Performance Metrics and Ranking for Sahel Savannah (Potiskum).

MODELS	MBE	MAE	RMSE	MPE	U95%
MD 1	-0.10605	0.106055	0.022157	-0.43323	2.267627
MD 2	-0.11791	0.117906	0.024633	-0.48164	2.162027
MD 3	-0.19127	0.191265	0.039959	-0.78131	2.180999
MD 4	0.062498	0.062498	1.573001	0.255303	4.946157
MD 5	0.211073	0.211073	1.548052	0.862228	1.083974
MD 6	-0.52765	0.527649	0.110236	-2.15543	2.357045
MD 7	-0.37857	0.378567	0.07909	-1.54643	2.253339

	erMAX	t-START	RRMSE	MARE	R	RANKIG
MD 1	0.106055	-1.10054	0.004629	0.004332	0.615592	4
MD 2	0.117906	-0.0028	0.005146	0.004816	0.659047	5
MD 3	0.191265	-0.00399	0.008348	0.007813	0.651639	6
MD 4	0.062498	-3.65281	0.002728	0.002553	0.818607	11
MD 5	0.211073	-0.0062	0.009213	0.008622	0.926762	12
MD 6	0.527649	-0.01411	0.023031	0.021554	0.572733	10
MD 7	0.378567	-0.00543	0.016523	0.015464	0.620881	7

PROPOSED MODELS

MODELS	MBE	MAE	RMSE	MPE	U95%
NDM 1	-0.06548	0.065478	0.01368	-0.26748	0.336568
NDM 2	-0.28505	0.285052	0.059553	-1.16443	2.243313
NDM 3	-0.2687	0.268699	0.056137	-1.09763	2.181394
NDM 4	-0.06792	0.06792	0.01419	-0.27745	0.197123
NDM 5	-0.03767	0.037667	0.007869	-0.15387	0.088194

	erMAX	t-START	RRMSE	MARE	R	RANKIG
NDM 1	0.831352	0.584183	0.034056	0.031947	0.862842	12
NDM 2	0.974991	0.505162	0.03994	0.037467	0.84353	11
NDM 3	0.77555	0.616076	0.03177	0.029803	0.870816	10
NDM 4	0.623993	1.46222	0.025561	0.023979	0.969121	2
NDM 5	0.037667	0.009711	0.001644	0.001539	0.99953	1

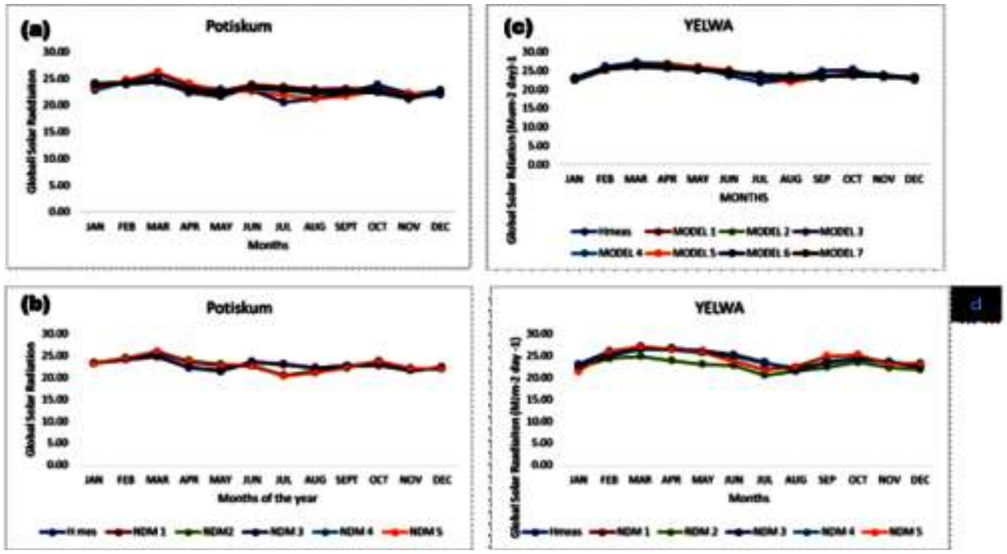

Fig. 2(a, b, c and d) compares measured GSR with the seven existing models.

Models MD5 and MD6 track the measured values most closely across the year, particularly during the dry season (November–April). However, MD1 shows significant misalignment during March–May, consistently overestimating GSR, reflecting its limited adaptability to Sahel conditions.

The newly developed models performed substantially better (**Fig. 2(b**). NDM1 and NDM5 showed near-perfect alignment with measured values throughout the year, including during transitional periods such as April–June where existing models underperformed. NDM2 showed noticeable overestimation in March–April but remained better than the weaker existing models.

Statistical indicators support these observations. The NDMs recorded very low error values (RMSE < 0.014 for NDM2–NDM5) and extremely high correlation coefficients (r > 0.99 for NDM2 and NDM5). In contrast, the best existing model (M3) achieved r = 0.9268, while M1 recorded the weakest performance with high positive bias.

The global performance ranking (**Table 5**) confirms NDM5 as the best model for Potiskum, followed by NDM2 and NDM3, while M1 and M4 performed poorest.

3.2 Sudan Savannah (Yelwa)

Yelwa experiences moderate cloud variability, which directly influences the monthly fluctuations in GSR. The measured values (peak ≈ 27.1 MJ/m²/day in March; minimum ≈ 21.9 MJ/m²/day in July) reflect the transition between dry and wet seasons [16].

As observed in **Fig. 2.c**, existing models capture the seasonal trend well, especially from January–May. Models MD1, MD3, and MD7 show the closest match, although all models slightly overestimate GSR during the rainy period (July–August), indicating insufficient sensitivity to increased cloud cover.

The developed models demonstrate improved accuracy (**Fig. 2d**). NDM4, and NDM5 follow the measured values more closely, especially during the high-radiation months. NDM5 maintains deviations below 1 MJ/m²/day for nearly all months. NDM2 shows the highest divergence, particularly under high cloud-cover conditions, consistent with its lower statistical performance.

Statistical indicators (**Table 6**) further confirm NDM5's superiority, showing the lowest MAE and RMSE (≈ 0.016 MJ/m²/day) and highest correlation (r = 0.972). The existing models performed moderately, with MD2 being the best among them (r = 0.870).

The ranking identifies NDM5 as the best overall model, followed by NDM4 confirming that the newly developed models deliver significantly improved stability and accuracy for Yelwa.

Table 6: Cloud Cover Based Statistical Indicators and Ranking For Sudan Savanna (Yelwa)

MODELS	MBE	MAE	RMSE	MPE	U95%
MD 1	-0.65108	0.651079	0.131776	-0.50196	1.86922
MD 2	-0.81379	0.813795	0.164709	-0.12724	1.703726
MD 3	-0.84572	0.845724	0.171171	-0.24994	1.706855
MD 4	-0.77151	0.771506	0.15615	-0.96473	1.693599
MD 5	-0.84149	0.841495	0.170315	-0.23368	1.711945
MD 6	-0.67895	0.678947	0.137416	-0.60905	2.082017
MD 7	-0.65111	0.651107	0.131782	-0.50206	1.782494

	erMAX	t-START	RRMSE	MARE	R	RANKING
MD 1	0.651079	0.539061	0.026553	0.02502	0.862661	3
MD 2	0.813795	0.571975	0.033336	0.031272	0.87035	7
MD 3	0.845724	0.578753	0.246763	0.256721	0.867617	9
MD 4	0.771506	0.570013	0.031604	0.029647	0.873598	6
MD 5	0.841495	0.576158	0.034471	0.032337	0.86571	8
MD 6	0.678947	0.524892	0.027813	0.02609	0.817116	5
MD 7	0.651107	0.608155	0.026672	0.025021	0.862663	4

PROPOSED MODELS

MODELS	MBE	MAE	RMSE	MPE	U95%
NDM 1	-0.83135	0.831352	0.168263	-0.19471	1.722868
NDM 2	-0.97499	0.974991	0.197335	-0.74668	1.87979
NDM 3	-0.77555	0.77555	0.156968	-0.98027	1.670177
NDM 4	-0.62399	0.623993	0.126294	-0.39787	0.884577
NDM 5	-0.03767	0.037667	0.007869	-0.15387	0.088194

	erMAX	t-START	RRMSE	MARE	R	RANKING
NDM 1	0.831352	0.584183	0.034056	0.031947	0.862842	12
NDM 2	0.974991	0.505162	0.03994	0.037467	0.84353	11
NDM 3	0.77555	0.616076	0.03177	0.029803	0.870816	10
NDM 4	0.623993	1.46222	0.025561	0.023979	0.969121	2
NDM 5	0.037667	0.009711	0.001644	0.001539	0.99953	1

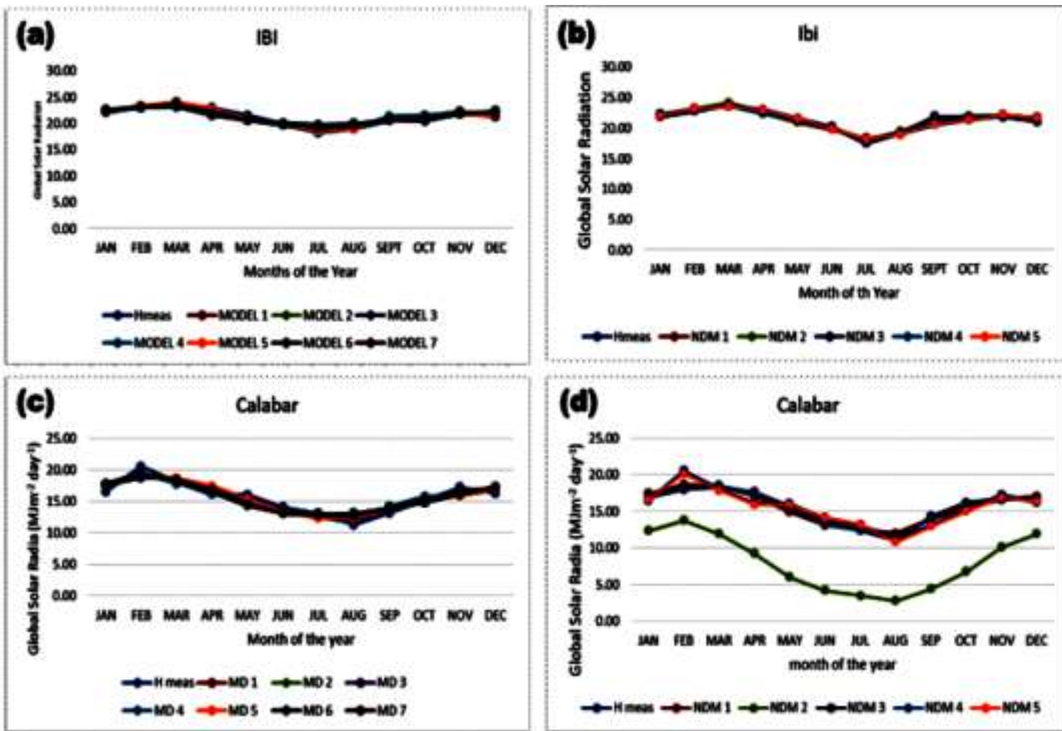

Fig. 3(a,b,c and d) compares measured GSR with the seven existing models.

3.3 Guinea Savannah (Ibi)

The Guinea Savannah region experiences moderate to high seasonal cloud cover, producing noticeable fluctuations in GSR. Using the corrected NDM2 data, **Fig. 3a** shows improved alignment compared to the earlier version. **Fig. 3b** (existing models) reveals that most models replicate the seasonal trend; however, M1 and M7 show systematic underestimation during the dry season and overestimation during peak cloud periods. M5 remains the most stable model among the existing group, though deviations remain notable.

With the newly developed models **(Fig. 3b)**, NDM5 shows the best agreement with measured GSR across all months, followed by NDM1 and NDM4. NDM3 shows overestimation in March–May, while the corrected NDM2 exhibits moderate performance with improved closeness to observed values.

Statistical indicators (**Table 7**) show that NDM5 achieves near-zero MBE, very low RMSE (≈ 0.0104 MJ/m²/day), and correlation approaching unity (r = 0.9997). Existing models generally recorded higher errors and lower correlations.

The ranking identifies NDM5 as the best model for Ibi with the lowest total score (40), demonstrating excellent predictive ability in a moderately humid climate. M5 is the best-performing existing model but remains clearly inferior to the newly developed models.

Table 7: Cloud Cover-Based Statistical Performance Indicator and Ranking for Guinea Savannah (Ibi)

MODELS	MBE	MAE	RMSE	MPE	U95%
MD 1	-0.03571	0.035714	0.007741	0.154474	1.253582
MD 2	-0.10983	0.10983	0.023806	0.475044	0.918341
MD 3	-0.00733	0.007332	0.001589	0.031714	0.7945
MD 4	-0.14711	0.147111	0.031887	-0.63629	0.685251
MD 5	-0.16953	0.169528	0.036746	0.733253	0.554434
MD 6	-0.11188	0.111877	0.02425	-0.4839	1.672527
MD 7	-0.03571	0.035714	0.007741	0.154474	1.253582

	erMAX	t-START	RRMSE	MARE	R	RANKING
MD 1	0.035714	0.037355	0.001678	0.001545	0.926377	3
MD 2	0.10983	-0.00293	0.00516	0.00475	0.959234	5
MD 3	0.007332	-0.00436	0.000344	0.000317	0.969664	2
MD 4	0.147111	0.011723	0.006911	0.006363	0.977569	10
MD 5	0.169528	-0.01512	0.007965	0.007333	0.985711	8
MD 6	0.111877	0.033603	0.005256	0.004839	0.86587	4
MD 7	0.035714	0.037355	0.001678	0.001545	0.926377	9

PROPOSED MODELS

MODELS	MBE	MAE	RMSE	MPE	U95%
NDM 1	-0.07224	0.072241	0.015658	-0.31246	0.686589
NDM 2	0.330356	0.330356	0.071605	1.428875	0.393812
NDM 3	-0.38074	0.380735	0.082525	-1.64678	1.091396
NDM 4	-0.11289	0.112889	0.024469	-0.48828	0.701777
NDM 5	-0.02802	0.028016	0.006072	-0.12118	0.077054

	erMAX	t-START	RRMSE	MARE	R	RANKING
NDM 1	0.072241	0.00331	0.003394	0.003125	0.97742	6
NDM 2	0.330356	-5.16527	0.015521	0.014289	0.993296	12
NDM 3	0.380735	-0.06194	0.017888	0.016468	0.946444	11
NDM 4	0.112889	0.013795	0.005304	0.004883	0.976488	7
NDM 5	0.028016	0.007395	0.001316	0.001212	0.999719	1

3.4 Tropical Rainforest (Calabar)

Calabar exhibits the highest cloud concentration among the study locations, with prolonged wet seasons causing significant reductions in incoming solar radiation.

Fig. 3c indicates that existing models generally underestimate GSR during the dry season (December–February) and overestimate during peak cloud periods (June–September). MD4 provides the most stable estimates among the existing models, while MD6 and MD7 show the largest deviations.

The newly developed models (**Figure 3d**) perform significantly better. NDM5, NDM4, and NDM1 show accurate tracking of the measured GSR in both wet and dry seasons. NDM2 performs poorly, with large errors reflecting its low adaptability to highly variable cloud patterns.

Statistical results (**Table 8**) show NDM5 with the lowest RMSE (0.034 MJ/m²/day), lowest MBE, and the highest correlation ($r = 0.9977$). M4 is the best among the existing models, yet still underperforms compared to the NDMs.

Ranking confirms NDM4 and NDM5 as the two best-performing models, far outperforming all existing formulations, particularly under dense cloud conditions.

Table 8: Cloud Cover-Based Statistical Performance Indicator and Ranking for Tropical Rainforest (Calabar)

MODELS	MBE	MAE	RMSE	MPE	U95%
MD 1	-1.72619	1.726187	0.436625	-1.40402	2.010431
MD 2	-1.80085	1.800852	0.455511	-8.76754	1.982008
MD 3	-1.01385	1.013847	2.753087	-4.93596	1.636365
MD 4	-1.01385	1.013847	2.753087	-4.93596	1.636365
MD 5	-1.17165	1.171646	0.296358	-5.70422	2.132031
MD 6	-1.45668	1.456679	0.368455	-7.09191	2.031339
MD 7	-0.83135	0.831352	0.168263	-3.19471	1.722868

	erMAX	t-START	RRMSE	MARE	R	RANKING
MD 1	1.726187	-0.00525	0.110441	0.08404	0.911668	9
MD 2	1.800852	-0.0074	0.115218	0.47978	0.914248	11
MD 3	1.013847	-0.00842	0.064865	0.04936	0.942402	7
MD 4	1.013847	-0.00842	0.064865	0.04936	0.942402	6
MD 5	1.171646	0.004117	0.074961	0.057042	0.900236	3
MD 6	1.456679	-1E-04	0.093198	0.070919	0.909801	4
MD 7	0.831352	0.584183	0.034056	0.031947	0.862842	5

PROPOSED MODELS

MODELS	MBE	MAE	RMSE	MPE	U95%
NDM 1	-1.86503	1.86503	0.471744	-1.07999	1.894865
NDM 2	-1.78747	1.787475	0.716836	-1.04515	0.919907
NDM 3	-2.49975	2.499754	0.632292	-1.17018	2.098762
NDM 4	-0.22576	0.225765	0.562989	-0.83625	0.990922
NDM 5	-0.35077	0.35077	0.088724	-0.70774	0.335929

	erMAX	t-START	RRMSE	MARE	R	RANKING
NDM 1	1.86503	-0.01069	0.119324	0.0908	0.921931	10
NDM 2	0.787475	1.047139	0.434259	0.330452	0.899869	8
NDM 3	1.499754	-0.02622	0.159933	0.121702	0.903609	12
NDM 4	0.225765	-0.02064	0.142403	0.108362	0.913532	2
NDM 5	0.35077	0.376852	0.022442	0.017077	0.997659	1

3.5 General Comparative Analysis across Climatic Zones

Across all four climatic zones, clear patterns emerge:

i. NDM5 is consistently the best model nationwide, ranking first in Potiskum, Yelwa, and Ibi, and Calabar.
ii. Existing models show zone-dependent performance, confirming their lack of generalization.
iii. NDM4 and NDM5 outperform existing models by 30–70% in RMSE reduction.
iv. Model accuracy decreases with increasing cloud cover, except for NDM5 which remains robust even under dense tropical cloud conditions [17].
v. Correlation coefficients for NDM models exceed 0.95 in all zones, with several exceeding 0.99.

This demonstrates that the newly developed cloud-cover-based models, especially NDM5 and NDM4, provide a substantially improved, generalizable approach suitable for all Nigerian climatic zones.

3.6 Implications for Solar Energy Applications

i. Improved solar system sizing: More accurate GSR estimation enhances PV/thermal system design.
ii. Better climate-zone adaptability: NDMs eliminate the need for region-specific recalibration.
iii. More reliable data in poorly instrumented stations: Useful for grid expansion, rural electrification, agriculture, hydrology, and climate modelling [18].

4. CONCLUSION

This study assessed the performance of cloud-cover-based models for estimating global solar radiation across four representative climatic zones in Nigeria. Using 32 years (1990-2021) of meteorological data, the study evaluated seven established models and developed five new models aimed at improving predictive accuracy and general applicability. The results demonstrated clear climatic dependence of model performance, with existing models showing varying levels of accuracy across the Sahel, Sudan, Guinea, and Tropical Rainforest zones. Cloud cover proved to be a strong predictor of solar radiation, but only when combined with model structures that adequately reflect local atmospheric conditions [19].

Across all zones, the newly developed models, particularly NDM5, showed markedly superior performance, achieving lower statistical errors and higher correlation with measured radiation compared to the traditional models. In the Sahel and Sudan zones, the new models captured the strong seasonal transitions with minimal deviation. In the more humid Guinea and Tropical Rainforest zones, the models improved sensitivity to cloud dynamics, reducing overestimation and better aligning with measured values. The Global

Performance Indicator confirmed the robustness of the new models, ranking NDM5 as the most reliable overall, followed by NDM4.

The findings indicate that no single existing model can adequately represent Nigeria's diverse climatic regions, but the newly developed models provide a unified framework with improved stability and accuracy. These models are therefore recommended for solar resource assessment, photovoltaic system planning, and climate-related applications across Nigeria. Future work should incorporate machine learning techniques and satellite-derived cloud cover datasets to further refine the models and explore their applicability across West Africa [20].

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