



EMPIRICAL MODELING OF PHOTOSYNTHETICALLY ACTIVE RADIATION (PAR) USING WIND SPEED AND AEROSOL DATA IN MAKURDI, NIGERIA

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ABSTRACT

This study introduces a novel data-driven approach to PAR estimation by integrating wind speed and aerosol dynamics, addressing gaps in tropical Savannah regions in Nigeria. Recognizing the critical role of PAR in agricultural productivity and ecological dynamics, the research investigates the reliability of using wind speed and aerosol concentrations including PM_{2.5}, black carbon and dust as predictive variables for PAR estimation. Eight empirical models were developed using statistical modeling and validated with statistical metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Pearson's correlation coefficient, R. Results obtained show that Model 4 emerged as the most accurate and reliable, exhibiting the lowest error values and strongest correlation with observed data. In contrast, some models with high theoretical correlation, such as Model 5, performed poorly in prediction accuracy, underscoring the complexity of atmospheric interactions affecting PAR. The findings highlight the significance of model validation and selection tailored to local climatic conditions. This research contributes to the advancement of cost-effective PAR estimation methods and provides valuable insights for agricultural planning, environmental monitoring, and climate-smart strategies in sub-Saharan Africa.

Keywords: Photosynthetically Active Radiation, Empirical Modeling, Aerosol Concentration, Wind Speed, Tropical Savanna Climate, Model Validation

INTRODUCTION

Photosynthetically Active Radiation (PAR), defined as solar radiation ranging from 400 to 700 nanometers, is a key driver of photosynthesis, impacting plant development, agricultural yield, and overall ecosystem dynamics (Smith *et al.*, 2022). Quantifying PAR is critical for a wide range of applications, including agricultural planning, ecological modeling, and climate monitoring estimation (Ogunjobi *et al.*, 2019). As a result, empirical models have been constructed to estimate PAR using more routinely measured solar factors, including Global Solar Radiation (GSR) (Xu *et al.*, 2022). These models provide practical answers by establishing statistical correlations between PAR and GSR, allowing for more comprehensive geographical and temporal assessments (Adediran *et al.*, 2021). The performance and reliability of empirical relationships are contingent upon local atmospheric conditions, latitude, altitude, and climatic regimes (Johnson *et al.*, 2017). Recent research has concentrated on creating empirical models for estimating Photosynthetically Active Radiation (PAR) using meteorological parameters, including global solar radiation (GSR), temperature (Akpootu, 2023), cloud cover index, relative humidity (RH) (Wang *et al.*, 2016), aerosol concentration (PM_{2.5}) and sunshine hours (Zhang, 2019). These models seek to offer cost-effective alternatives to direct PAR measurements, facilitating estimations in regions with limited data availability for researchers, farmers, and policy-maker.

Aerosols are suspensions of fine solid particles and/or droplets of liquid uniformly distributed in the air. It comprises of particulate matter and gases pollutants in the air. These particles have diameters in the range of 0.002 to 100 micrometers and are classified as colloids i.e. homogeneous mixture where particles of one substance are suspended in another (Hinds, 1999). Aerosols are both natural and anthropogenic (man-made). Examples of natural aerosols include: fog, mist, volcanic ash, sea salt, pollen grains and dust while anthropogenic aerosols include: smoke and black

carbon from exhausts of industries and vehicles, cement dust, spray-paints, deodorants and air fresheners, herbicides, pesticides, nitrates, sulphates etc. which result from the burning of fossil fuels, infrastructural, industrial and agricultural activities. Aerosols usually do not settle down quickly as they remain suspended for extended periods of time blocking the sun's rays from reaching the earth and thus reducing the intensity of solar radiation illuminating the earth. The larger particles usually settle down faster while the gases condense at cooler periods especially at night and settle on the ground, buildings and leaves of plants (Encyclopedia Britannica, 2025). However, studies have shown that aerosols enhance photosynthesis by increasing diffuse radiation as increased aerosol concentration leads to aerosol-induced direct radiative forcing (ADRF) in the atmosphere which in turn changes the vegetation photosynthesis at global scales (Xue *et al.*, 2021; Zhou *et al.*, 2021).

Makurdi town which is located in the Guinea savanna belt of central Nigeria, exhibits a tropical savanna climate marked by distinct wet and dry seasons, varying cloud cover, aerosol concentrations, and seasonal variations in solar radiation intensity. These climatic and environmental factors provide a unique opportunity to assess the empirical relationships between Photosynthetically Active Radiation (PAR) and aerosol concentration which is dispersed by wind (Obafemi *et al.*, 2024). Despite increasing interest in PAR modeling in sub-Saharan Africa, there exists a notable deficiency in localized research aimed at validating PAR estimation models (Lawal *et al.*, 2022). In relation to sustainable agriculture and climate-smart practices, accurately estimating PAR through readily available meteorological data and air pollutants could enhance resource manage (Ajayi *et al.*, 2023). Thus, this study aims to conduct a quantitative assessment and verification of empirical correlations between PAR and wind speed/aerosol concentration over Makurdi, utilizing satellite observational data. The objectives of the research include: (i) evaluate the trend and correlation of PAR with wind speed and aerosol

concentration from 2015-2022; (ii) develop various empirical models for estimating PAR based on wind speed and aerosol concentrations (PM_{2.5}, PM₁₀, and black carbon); and (iii) validate the models and identify the most effective model for estimating PAR in Makurdi.

MATERIALS AND METHODS

Study Area

Makurdi, the capital of Benue State, Nigeria, is located in the North-Central region of the country. Geographically, it lies between latitudes 7° 44' N and 7° 50' N, and longitudes 8° 24' E and 8° 38' E, and occupies a land area of approximately 16 km². It also has an altitude of 104 m and is situated along the banks of the River Benue, one of the major rivers in Nigeria (Tikyaa et al., 2018). Makurdi is characterized by two distinct seasons: the rainy season which spans from April to October, and the dry season, from November to March. Rainfall in Makurdi averages between 1,200 mm and 1,500 mm annually, with peaks typically occurring between July and

September (Adakole et al., 2019). During the dry season, the region experiences Harmattan, a dry and dusty wind originating from the Sahara Desert, which significantly lowers humidity levels and reduces visibility. The temperatures in Makurdi range from 22°C to 34°C, with the hottest months usually being March and April, just before the onset of the rainy season (Chikwendu and Igori, 2020).

The vegetation in and around Makurdi consists primarily of Guinea Savannah, which features a mixture of grasses, shrubs, and scattered trees. The natural vegetation has been largely altered due to farming activities, urbanization, and infrastructural development. However, pockets of natural savanna vegetation still exist on the outskirts of the town. These savanna regions are interspersed with gallery forests, particularly along the floodplains of the River Benue. These forests serve as important ecological zones, supporting biodiversity and helping in soil conservation (Okwori and Abah, 2020).

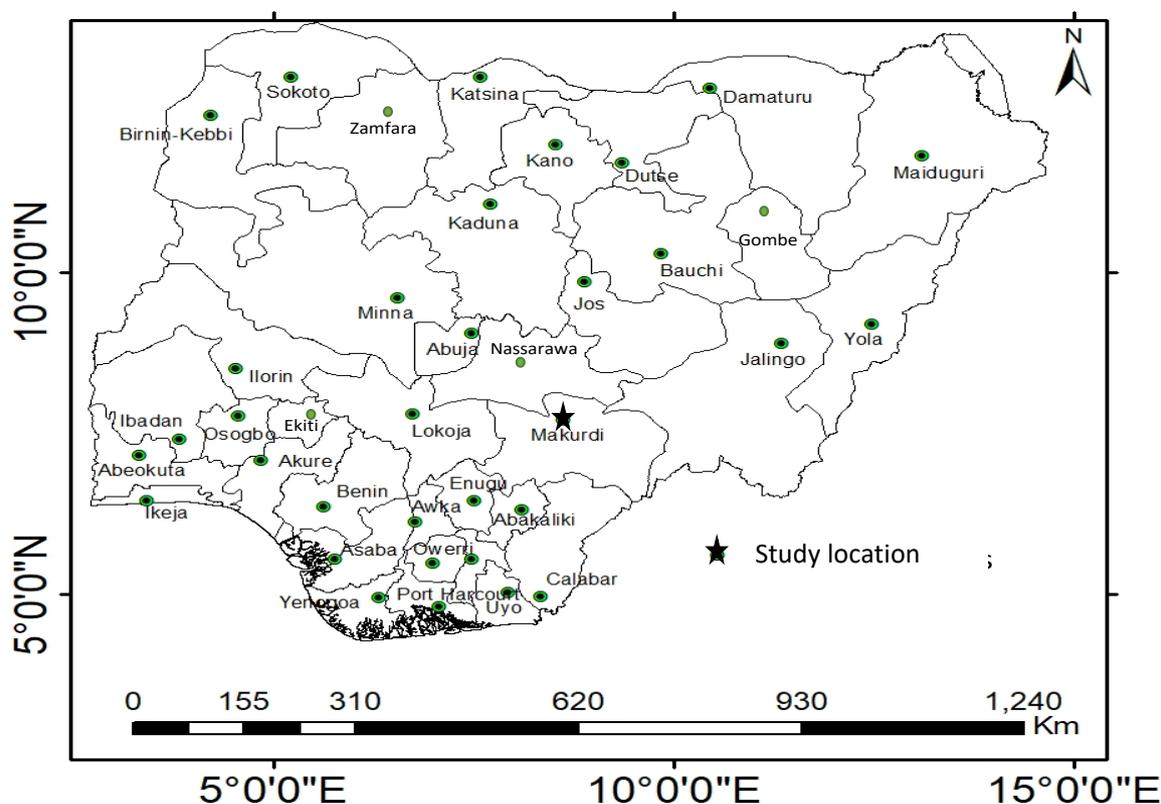


Figure 1: Map of Nigeria showing the study area - Makurdi

Data Sources

The secondary data required for this study was sourced from satellite maps of the Modern Era Retrospective Reanalysis (MERRA-2) of the National Aeronautical and Space Administration (NASA). The meteorological data contains monthly averages of Photosynthetically Active Radiation, PAR (MJ/m²/day) and Extraterrestrial PAR (MJ/m²/day), wind speed at 10 m (m/s), PM_{2.5}, dust and black carbon concentrations (µg/m³) over Makurdi, Nigeria from 2015 – 2022 (Galero et al., 2017).

The model equation

The empirical model equations for estimating PAR using wind speed and aerosol concentration are presented in Table 1. These models were chosen out of the many others after several trials; with temporal correlations between the dependent parameter PAR and independent variables (wind and aerosol concentrations and its functionals) being considered. These error metrics of these 8 model equations had the highest values of Pearson's correlation coefficient, R (closest to 1) and lowest values of the statistical error metrics (RMSE, MAE and MAPE).

Table 1: Empirical model equations used in the study

Model	Model Equations	Model Parameters
Model 1	$\frac{PAR}{PAR_0} = a + bW + cPM + d BC + e DST$	W, PM, BC & DST
Model 2	$\frac{PAR_0}{PAR} = a + bW^{0.5} + c \ln(PM) + d DST^2$	W, PM & DST
Model 3	$\frac{PAR_0}{PAR} = aPM + bW + c \ln(BC + DST)$	W, PM, DST & BC
Model 4	$\frac{PAR_0}{PAR} = aW + bBC^2 + cPM^{0.5} + dDST^2$	W, PM, DST & BC
Model 5	$\frac{PAR_0}{PAR} = a + b \exp(\frac{W}{DST}) + c \exp(\frac{W}{PM}) + d \exp(\frac{W}{BC})$	W, PM, DST & BC
Model 6	$\frac{PAR_0}{PAR} = a + b \log_{10}(\frac{n}{PM}) + c \log_{10}(\frac{n}{DST}) + d \log_{10}(\frac{n}{BC})$	PM, BC, DST & n
Model 7	$\frac{PAR_0}{PAR} = a + b \exp(\frac{n}{BC}) + c \exp(\frac{n}{PM}) + d \exp(\frac{n}{DST})$	PM, BC, DST & n
Model 8	$\frac{PAR_0}{PAR} = a + b \exp(\frac{n}{BC})^{0.5} + c \exp(\frac{n}{PM})^{0.5} + d \exp(\frac{n}{DST})^{0.5}$	PM, BC, DST & n

Where n is the month index; i.e. 1-12 for January to December, PAR is the Photosynthetically Active Radiation, PAR₀ is the extra-terrestrial PAR, PM is the particulate matter of diameter 2.5 μm, BC is the Black carbon concentration and DST is the Dust concentration. Also, a, b, c, d & e are the regression coefficients to be estimated.

Curve fitting and model evaluation

Multivariate regression analysis was conducted to assess the relationship between the multiple independent variables (wind and aerosol concentration) and the dependent variable (PAR) using the different model equations in Table 1. The regression constants (a – e) were evaluated using nonlinear least square fitting method. The Levenberg-Marquardt algorithm (Garvin, 2024) was deployed in training and fitting

the empirical models empirical models using the MATLAB Curve Fitting Toolbox (cftool); allowing for the estimation of regression coefficients and evaluation of each predictor's contribution to the model (Tikyaa et al., 2018).

In order to assess the predictive capability of the developed models, several performance evaluation metrics were calculated. These included the Root Mean Square Error (RMSE), Sum of Squared Errors (SSE), and the Coefficient of Determination (R²). These statistical indicators provided a robust framework for validating the accuracy and reliability of each model, enabling a thorough comparison of their effectiveness in estimating Photosynthetically Active Radiation. The equations are presented in Table 2 (Tikyaa et al., 2019).

Table 2: Model performance evaluation functions

Function	Algorithm
Root mean squared error, RMSE	$\sqrt{\frac{1}{n} \sum_{i=1}^n (y_a(i) - y_p(i))^2}$
Mean absolute error, MAE	$\frac{1}{n} \sum_{i=1}^n y_a(i) - y_p(i) $
Pearson’s correlation coefficient, R	$\frac{n \sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2} \sqrt{n(\sum y^2) - (\sum y)^2}}$
Coefficient of determination, D	R^2
Sum Squared error, SSE	$\sum_{i=1}^n (X_i - \bar{X})^2$

RESULTS AND DISCUSSION

The mean monthly time series of Photosynthetically Active Radiation (PAR) and its trend over Makurdi from 2015 to

2022 is presented in Figure 2. The plot shows a weak increasing but insignificant trend over the period of study.

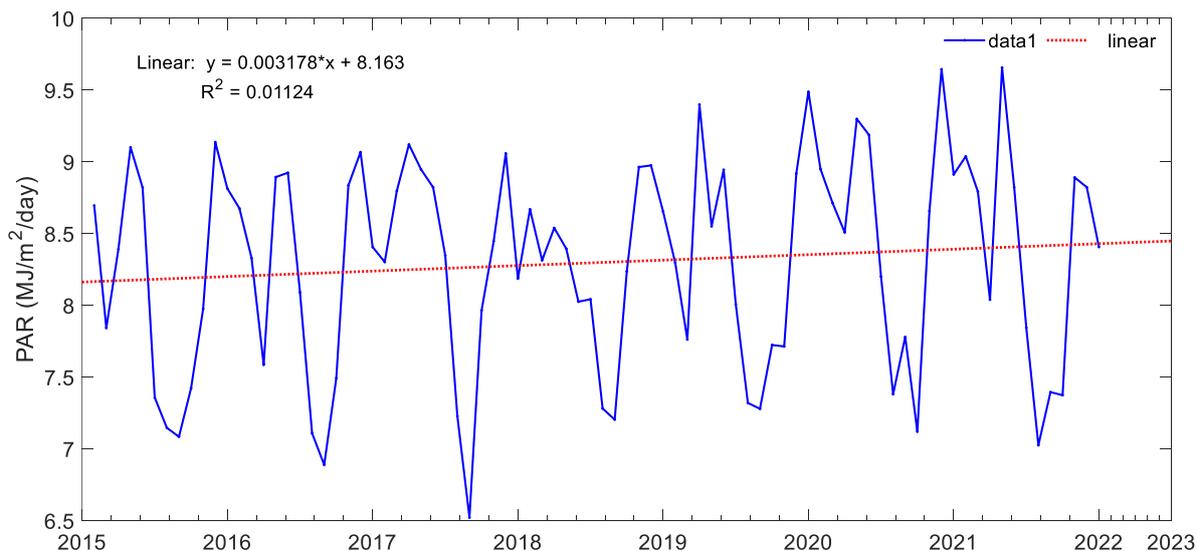


Figure 2: Mean monthly PAR trend over Makurdi from 2015 – 2022

The graph in Figure 2 shows the monthly time series of Photosynthetically Active Radiation (PAR) from 2015 to 2021. The result shows a weak increasing trend of irregular monthly values of PAR over the eight-year period. This increase could be attributed to climate change and global warming as a result of human anthropogenic activities.

Tables 3: Pearson’s Correlation coefficient between PAR and month index, wind speed, PM_{2.5}, Dust and black carbon concentration in Makurdi

Variable	Pearson’s Correlation coefficient (R)	p-value	Trend	Significance
Month index, n	-0.0841	0.415	Decreasing	Not significant
Wind speed, W	0.0397	0.701	Increasing	Not significant
PM _{2.5}	0.4536	0.000	Increasing	Significant
Dust, DST	0.4157	0.000	Increasing	Significant
Black carbon, BC	0.3189	0.0015	Increasing	Significant

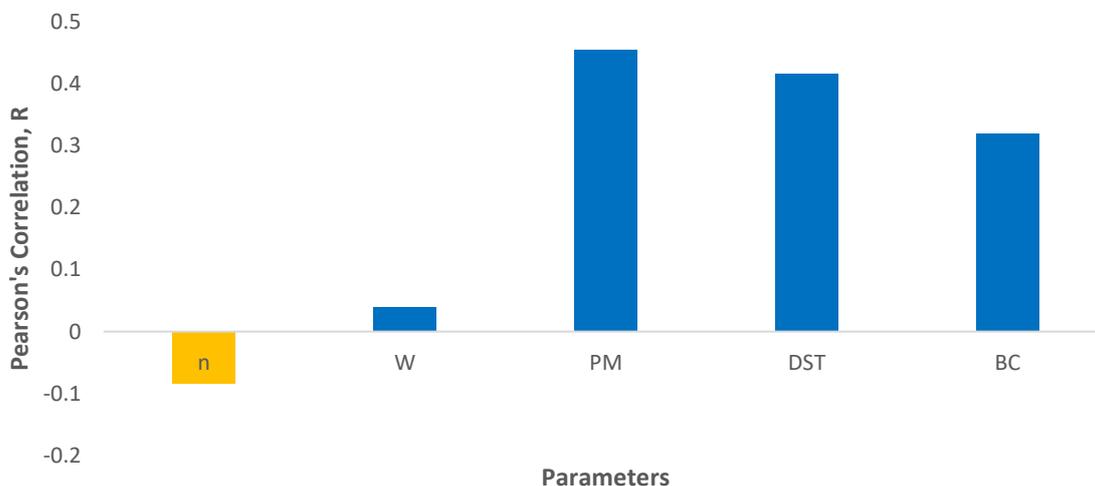


Figure 3: Correlation of Pearson coefficients between monthly PAR, monthly index, wind speed and aerosol concentration in Makurdi

The results of the correlation analysis contradict the earlier assumption as it is observed that an increase in aerosol concentration increases the amount of PAR reaching the plants. This could be attributed to the reflection of diffuse PAR back to the earth’s surface (aerosol-induced direct and diffuse radiative forcing effect) trapping it there and making it available for plants to absorb and grow (Xue et al., 2021). As for wind speed, the insignificant trend observed is because the wind does not affect the PAR intensity directly but

disperses the aerosols gradually from one location to another in a random manner.

The results in Table 4 provide a complete overview of the efficacy of eight wind speed and aerosol-based models for predicting Photosynthetically Active Radiation (PAR). The efficiency of each model is assessed using several regression coefficients and error metrics, which are used to inform the model rankings with the model parameters estimated tested at 95% confidence interval i.e. 5% level of significance, $\alpha =$

0.05. The values of the regression coefficients (a, b, c, d & e) obtained for the eight (8) wind speed and aerosol based models for prediction PAR using mean monthly data for wind speed, PM_{2.5}, dust and black carbon from 2015 – 2021 were then inputted in the model equations together with the

monthly values of the input parameters for 2022 to obtain the PAR prediction for 2022. The estimated and observed values of PAR for 2022 are plotted in Figures 4 while the three best performing models are plotted in Figure 5.

Table 4: Regression coefficients and error validation of the eight (8) wind speed and aerosol based model for PAR prediction

Models	Regression Coefficients						RMSE	MAE	MAPE (%)	R	Rank
	a	b	c	D	e	f					
Model 1	0.0895	-0.3196	0.0840	-0.9069	-0.0739	--	0.7398	0.6052	7.2799	0.5394	5
Model 2	0.4237	-0.0821	0.0834	0.000	--	--	0.7874	0.6741	8.0367	0.5174	7
Model 3	-0.0031	0.0662	0.1666	--	--	--	0.6888	0.5133	6.0638	0.7666	3
Model 4	0.06969	0.0057	0.0625	0.000	--	--	0.6197	0.4834	6.0538	0.7922	1
Model 5	1.4724	0.0211	-0.8347	-0.0002	1.000	--	0.7849	0.6777	8.0609	0.5289	8
Model 6	0.5879	0.1922	-0.2187	0.0438	--	--	0.7564	0.6753	8.0355	0.5396	6
Model 7	0.9499	-0.3323	0.000	0.0667	--	--	0.6866	0.6359	7.5071	0.6577	4
Model 8	0.6387	-0.0962	1.000	0.0019	--	--	0.6302	0.5768	6.8335	0.7243	2

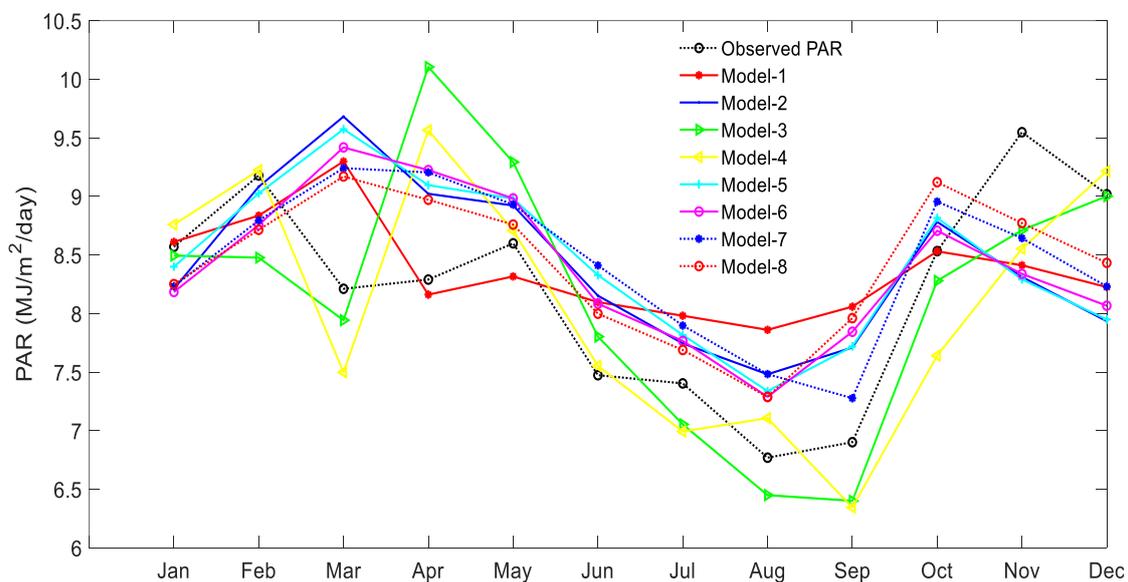


Figure 4: Plot of the predicted and Observed PAR for 2022 using the eight (8) wind speed and aerosol based models

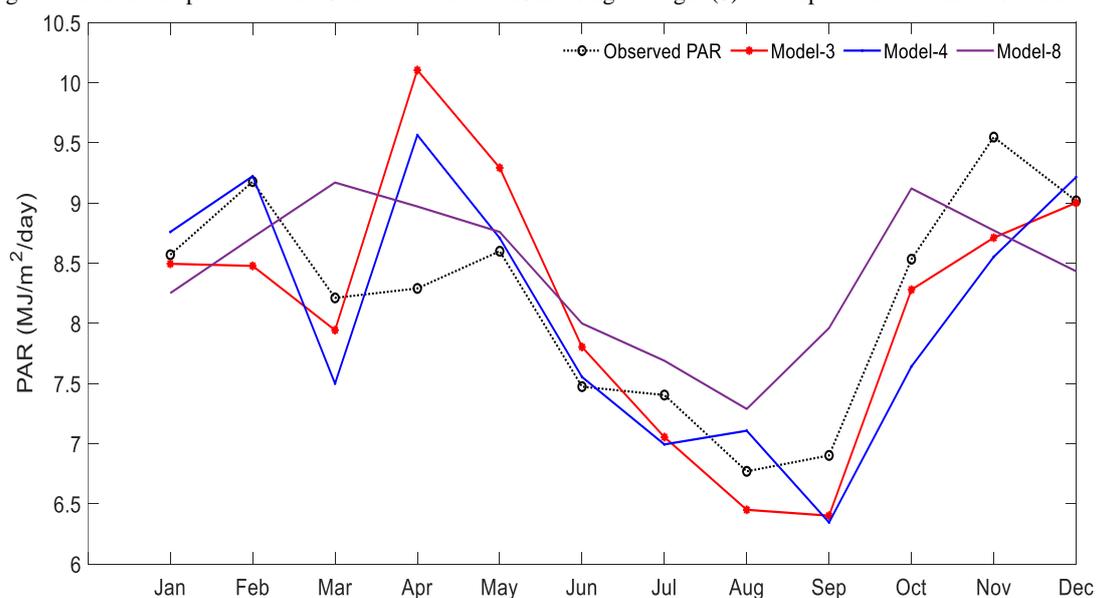


Figure 5: Plot of the three (3) best performing wind speed and aerosol based models for the prediction of Monthly PAR in 2022

In assessing the error validation, the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Pearson's correlation coefficient (R) give information about the goodness of fit of each model; with a lower value of RMSE, MAE and MAPE indicating a better fit while a higher value of R closest to 1 also indicating a better fit. In this work, the RMSE was considered as the key criterion for the ranking in Table 4. Thus, according to this criteria, Model 4 emerged the best performing model with RMSE and R values of 0.6197 and 0.7922, and is followed by Model 8 having RMSE and R values of 0.6302 and 0.7243 respectively while in third place is Model 3 with RMSE and R values of 0.6888 and 0.7666. Similarly, the least performing model is Model 5 in 8th place with RMSE and R values of 0.7849 and 0.5395, Model 2 in 7th place with RMSE and R values of 0.7874 and 0.8174 while Model 6 is in 6th place with RMSE and R values of 0.7564 and 0.5396 respectively. It is worthy to note that all the models performed well with their MAPE all being within the recommended limit of $\leq \pm 10\%$ (Akpootu and Sulu, 2015); with the best and least models having MAPE values of 6.0538 % and 8.0609 % respectively.

However, these wind speed and aerosol based models performed less than the temperature based models proposed by Akpootu *et al.* (2023) which recorded a RMSE of 0.3415 and R value of 0.8994 because atmospheric temperature correlates better than wind speed and aerosol concentration. Thus, it is recommended that in order to boost the performance of the wind speed and aerosol based models, hybrid models be developed to incorporate more meteorological parameters such as atmospheric temperature, relative humidity and precipitation which have proven to correlate better with PAR.

CONCLUSION

This study focused on evaluating various empirical models to estimate Photosynthetically Active Radiation (PAR) in Makurdi, using wind speed and aerosol concentration as primary predictors. Eight model equations were developed and validated using PAR, wind speed and aerosol (PM_{2.5}, dust and black carbon) data from 2015 to 2022, and the resultant model parameters obtained were then applied to the model equations to predict PAR over Makurdi in 2022. The results revealed that although all models showed some alignment with actual PAR data, their accuracy varied considerably. Model 4 stood out as the most dependable, achieving the lowest error values and highest correlation with observed measurements. This indicates that wind speed and aerosol concentration play significant roles in estimating PAR. On the other hand, Model 5, despite having a high regression coefficient, underperformed in terms of predictive accuracy highlighting the complex nature of atmospheric processes influencing PAR. These findings offer valuable contributions to PAR modeling, with practical implications for agriculture, ecology, and climate studies especially in areas like Makurdi where light availability is vital for crop production.

ACKNOWLEDGEMENT

The authors wish to appreciate the NASA MERRA-2 database for allowing us access to the meteorological variables and aerosol data used in this work. We also acknowledge the Department of Physics, Joseph Sarwuan Tarka University Makurdi for their technical and moral support.

REFERENCES

- Adakole, J. A., Akinyemi, B. A., and Umar, T. (2019). Climatic characteristics and rainfall patterns in Makurdi, Benue State, Nigeria. *International Journal of Climatology and Weather Studies*, 17(2), 112-123. <https://doi.org/10.1016/j.ijcws.2019.01.003>
- Adediran, A. A., Ogunjobi, K. O. and Eze, J. C. (2021). Relationship between Photosynthetically Active Radiation and Global Solar Radiation in Akure, Nigeria. *Journal of Environmental Science and Technology*, 14(4), 213-225.
- Ajayi, A. O., Ogunleye, O. and Ojo, J. A. (2023). Performance Assessment of Empirical Models for Estimating Photosynthetically Active Radiation in Akungba-Akoko, Nigeria. *Meteorological Applications*, 30(1), 21-34.
- Akinwande, I., Eze, J. C. and Ogunjobi, K. O. (2022). Climate and Agricultural Potential of Makurdi, Benue State, Nigeria. *Journal of Agricultural Science and Technology*, 24(1), 45-58.
- Akpootu, D.O. and Sulu, H.T. (2015) A Comparative Study of Various Sunshine based Models for Estimating Global Solar Radiation in Zaria, North-Western, Nigeria. *International Journal of Technology Enhancements and Emerging Engineering Research*, 3(12):1- 5.
- Akpootu, D. O., Isah, A. K., Abdulsalam, M. K., Aliyu, M. A., Kola, T. A., Yusuf, A., Salifu, S. I. and Bello, G. (2023). Estimation and Investigation of Photosynthetically Active Radiation Using Meteorological Parameters over Ikeja, Nigeria. *Journal of Energy Research and Reviews*, 15(4), 51-62. <https://doi.org/10.9734/JENRR/2023/v15i4324>
- Chikwendu, I. M. and Igori, G. I. (2020). Temperature and humidity variations in Makurdi, Benue State, Nigeria: Impact of the harmattan season. *African Journal of Meteorology and Climatology*, 14(4), 233-241. <https://doi.org/10.1029/2020AJP45>
- Encyclopedia Britannica.* (2025). *Aerosols.* <https://www.britannica.com/science/aerosol>. Accessed on 2 May 2025
- Gelaro, R. and Coauthors (2017) The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2). *J. Climate*, 30, 5419-5454, <https://doi.org/10.1175/JCLI-D-16-0758.1>.
- Garvin, H.P. (2024) The Levenberg-Marquardt algorithm for nonlinear least squares curve-fitting problems. Seminar series, Department of Civil and Environmental Engineering, Duke University.
- Hinds, W.C. (1999). *Aerosol Technology* (2nd ed.). New Jersey: Wiley – Interscience, p. 32. ISBN 978-0-471-19410-1
- Johnson, H. A., Smith, J. P., & Lee, R. (2017). The Role of Photosynthetically Active Radiation in Plant Growth in Tropical Rainforests. *Ecosystem Dynamics*, 12(2), 100-115.

- Lawal, A. O., Adeyemi, A. A. and Ojo, J. A. (2022). Investigating the Relationship between PAR and Satellite-Derived Solar Radiation Data for Ibadan, Nigeria. *International Journal of Climatology*, 42(5), 2345-2357.
- Obafemi, A. A., Ayanlade, A. and Eze, J. C. (2024). Estimating Photosynthetically Active Radiation Using Convolutional Neural Networks for Lagos, Nigeria. *Remote Sensing Applications: Society and Environment*, 25, 101073.
- Ogunjobi, K. O., Akinwande, I. and Eze, J. C. (2019). Challenges in Measuring Photosynthetically Active Radiation: Insights from Nigeria. *Environmental Science and Policy*, 92, 172-180.
- Okwori, A. L. and Abah, G. O. (2020). Vegetation Dynamics and Ecological Zones of Makurdi, Benue State: Impact of Urbanization and Agriculture. *Journal of Environmental and Ecological Studies*, 13(5), 98-108. <https://doi.org/10.1016/j.jes.2020.04.007>
- Smith, J. P., Thompson, L. R. and Harris, M. (2022). Understanding the Role of Photosynthetically Active Radiation in Crop Yield. *Agronomy for Sustainable Development*, 42(3), 1-12. 14(2), 45-58.
- Tikyaa, E.V., Echi, M.A., Isikwue, B.C. and Amah, N. (2018). A Hybrid SARIMA-NARX Nonlinear Dynamics Model for Predicting Solar Radiation in Makurdi. *International Journal of Mathematics and Computational Science*, 4(2), 35-47. <http://www.aiscience.org/journal/ijmcs>
- Tikyaa, E.V., Akinbolati, A. and Shehu, M. (2019). Assessment of Empirical Models for Estimating Mean Monthly Global Solar Radiation in Katsina. *FUDMA Journal of Sciences (FJS)*, 3(1), 333-344.
- Wang, Y., Zhang, X. and Li, Y. (2016). Development of a Photosynthetically Active Radiation Model Using Remote Sensing Data and Ground-Based Measurements. *Remote Sensing*, 8(6), 449.
- Xu, X., Zhao, X. and Wang, Y. (2022). Application of Machine Learning in Estimating Photosynthetically Active Radiation: A Case Study. *Computers and Electronics in Agriculture*, 195, 106825.
- Xue, W., Zhang, J., Ji, D. Che, Y., Lu, T., deng, X., Li, X., Tian, Y. and Wei, X. (2021). Aerosol-Induced Direct Radiative Forcing Effects on Terrestrial Ecosystem Carbon over China, *Environmental Research*, 200, 111464. <https://doi.org/10.1016/j.envres.2021.111464>
- Zhang, Q. and Li, X. (2019). Estimating Photosynthetically Active Radiation Using Meteorological and Remotely Sensed Data in Agricultural Areas. *Agricultural Sciences*, 10(3), 219-230.
- Zhou, H., Yue, X., Lei, Y., Tian, C., Ma, Y. and Cao, Y. (2021). Aerosol Radiative and Climative Effects on Ecosystem productivity and Evapotranspiration. *Current Opinion in Environmental Science and Health*, 29(2021), 100218. <https://doi.org/10.1016/j.coesh.2020.10.006>

