Journal of Materials and Environmental Science
ISSN : 2028-2508
e-ISSN : 2737-890X
CODEN : JMESCN

J. Mater. Environ. Sci., 2025, Volume 16, Issue 9, Page 1641-1654

http://www.jmaterenvironsci.com

Linear Temperature-Based Modelling of Monthly Solar Irradiation: A Five-Site Case Study in Mississippi (USA)

Anwaoy Pandit [1] *

[1]*Department of Physics and Astronomy, University of Southern Mississippi, Hattiesburg, MS, USA*

**Corresponding author, Email address: Anwaoy.Pandit@usm.edu*

Received *24 May 2025,*
Revised *04 Aug 2025,*
Accepted *05 Aug 2025*

Citation*: Anwaoy P. (2025) Linear Temperature-Based Modeling of Monthly Solar Irradiation: A Five-Site Case Study in Mississippi (USA), J. Mater. Environ. Sci., 16(9), 1641-1654.*

Abstract:

This study investigates the applicability of a simple linear temperature-based model to estimate monthly average global solar irradiation using data from five selected locations in Mississippi, USA, over the period 2019–2023. The model employs an empirical linear relationship between air temperature and solar irradiation, with its performance evaluated through statistical indicators, including the coefficient of determination (R^2), root mean square error (RMSE), and regression slope analysis. The results demonstrate strong linear correlations across all five sites, with R^2 values ranging from 0.74 to 0.81 and regression slopes approaching unity. Residual diagnostics, including monthly residual boxplots and 1:1 comparison plots between observed and predicted irradiation values, further confirm the model's reliability and minimal seasonal bias. These findings suggest that the linear temperature-based approach offers a practical, low-data-requirement method for estimating monthly solar irradiation.

Keywords: *Solar irradiation; Temperature-based model; Residual analysis; Empirical model; Energy assessment*

1. Introduction

Solar energy has emerged as one of the most promising and sustainable sources of renewable energy, contributing significantly to the global transition toward clean energy systems (Maka & Alabid, 2022; Güney, 2021; Obaideen *et al.*, 2023; Novas *et al.*, 2021; Karzazi & Arbouch, 2014; Ahmed, 2025). The accurate estimation of solar irradiation is essential for the design, planning, and optimization of solar energy systems (AlFaraj *et al.*, 2024; Byiringiro *et al.*, 2025a). In regions where ground-based solar radiation measurements are sparse or nonexistent, empirical models offer practical and accessible methods for estimating solar irradiation using readily available meteorological variables (Atsbeha *et al.*, 2025; Byiringiro *et al.*, 2025b). Accurate solar radiation data is indispensable for a variety of environmental and biophysical modeling frameworks. These include hydrological models for simulating runoff and soil moisture dynamics (Beven, 2012), wildfire risk assessment tools (Chuvieco *et al.*, 2002), and agro-meteorological models used to optimize irrigation and yield forecasting. Given its foundational role, solar radiation must be reliably estimated or measured to support the development and validation of predictive models in climate science, agriculture (Gourdo *et al*., 2018), and natural resource management. Among the various empirical approaches, temperature-based models have gained widespread attention due to the extensive availability and reliability of air temperature data compared to other parameters such as sunshine duration or cloud cover (Kómar & Kocifaj, 2016; Gandoman *et al*., 2018). The Hargreaves-Samani model (Hargreaves & Samani, 1982) and its derivatives are well-known examples of such models, where a linear or exponential relationship is established between air temperature and solar irradiation. These models have been successfully applied across different climatic zones, including arid, humid, and subtropical regions, with varying levels of accuracy (Jamil *et al*., 2016; Almorox *et al*., 2015). Indeed, a substantial body of research has concentrated on quantifying atmospheric turbidity and assessing its influence on solar irradiance.

It's suitable to add a bibliometric analysis to measure quantitatively and qualitatively the scientific production to get more information on the prolific authors and the corresponding countries, as well as the cooperation (Salim *et al*., 2022; N'diaye *et al*., 2022; Laita *et al*., 2024; You *et al*., 2024). Scopus, Web of Science, and Publish or Perish… offer various data and analysis during a given period and multiple indicators (Pranckutė *et al*., 2021; Lrhoul *et al*., 2023; Chakir *et al*., 2023).

Several studies have emphasized the importance of site-specific calibration of empirical models to improve their predictive performance, as the influence of local climate and atmospheric conditions can significantly affect model parameters (Sabbagh *et al*., 2023). Additionally, the broader utility of empirical modeling approaches using meteorological parameters has been reinforced by recent studies in atmospheric and environmental physics (Oyewole *et al*., 2025). This highlights the flexibility and scientific relevance of using simple yet effective empirical models in scenarios where direct measurements are limited or inaccessible.

In this context, the present study investigates the use of a simple linear temperature-based model to estimate monthly mean daily global solar irradiation for five representative sites in Mississippi, USA. The model was calibrated using five years of observational data (2019–2023), and its performance was rigorously evaluated using statistical metrics such as the coefficient of determination (R^2), regression slope, root mean square error (RMSE), and residual analysis. Additionally, the model's predictive capabilities were assessed using 1:1 comparison plots and monthly residual boxplots to evaluate any systematic biases. The outcomes of this study aim to contribute to simplified and low-data-demanding methods for solar resource estimation, supporting preliminary solar energy planning in Mississippi and similar climatic regions.

Bibliometric analysis

Solar irradiation and energy have been primarily studied in literature to be quantified by 19,132 papers from 1953 to 2024. The massive increase from one paper in 1953 to 2233 articles indicated the importance of this field (**Figure 1**). **Figure 2** explicitly shows the high concern of researchers and industries using several areas for the realization and exploitation of solar energy.

More than 95% of the published documents on Scopus are journal articles, conference papers, reviews, book chapters… (**Figure 3**). The importance of this topic prompted researchers to identify journals with high impact factors, as illustrated in **Figure 4**. The "*Solar Energy*" journal, published by Elsevier, is a highly ranked publication with an IF of 6.6. Also, having an H-index of 6.6, "*Renewable energy*" is the second target Elsevier journal for researchers on the application of solar energy. The third one, "Chemical Engineering Journal" with IF = 13.1, is a more attractive Elsevier journal.

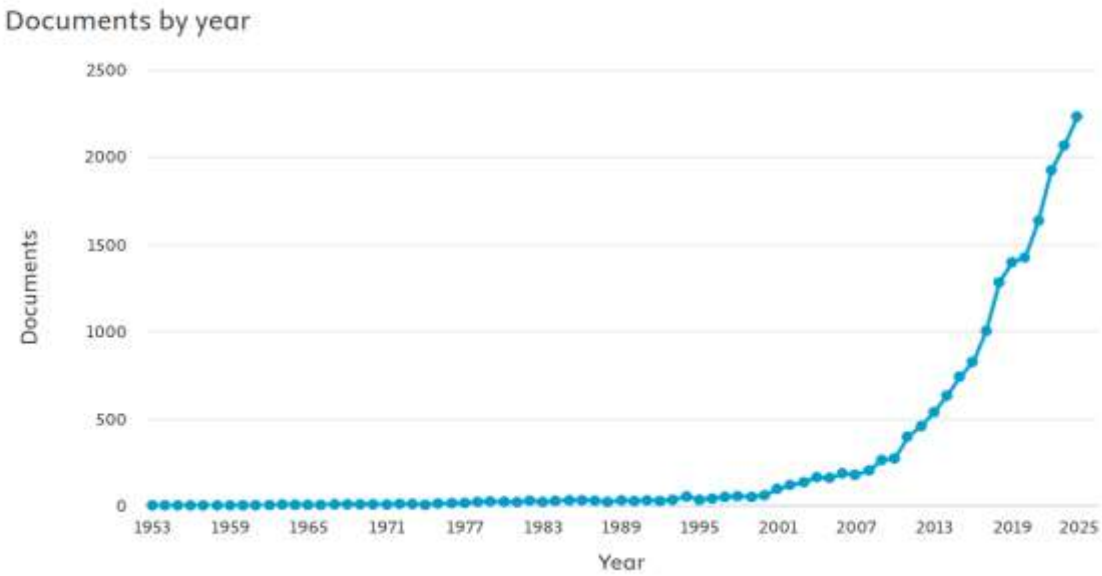

Figure 1: The evolution of articles from 1953 to 2024

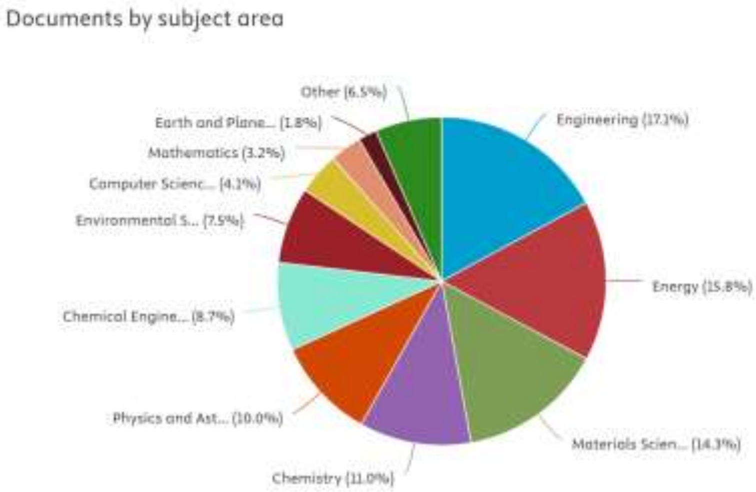

Figure 2: The repartition of articles by area

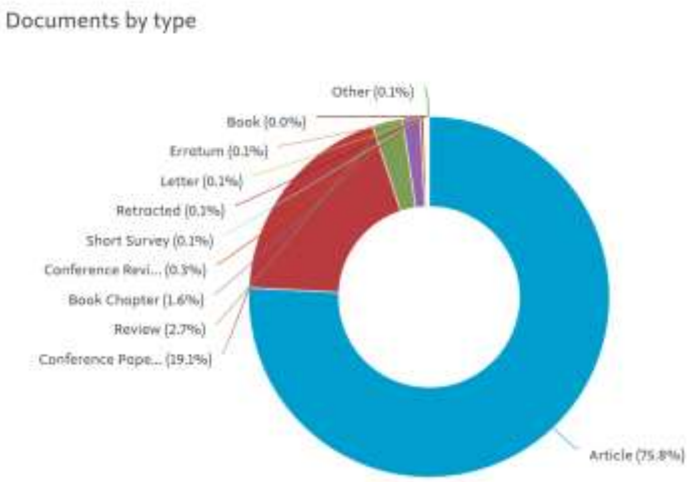

Figure 3: The kind of articles by article journal or others

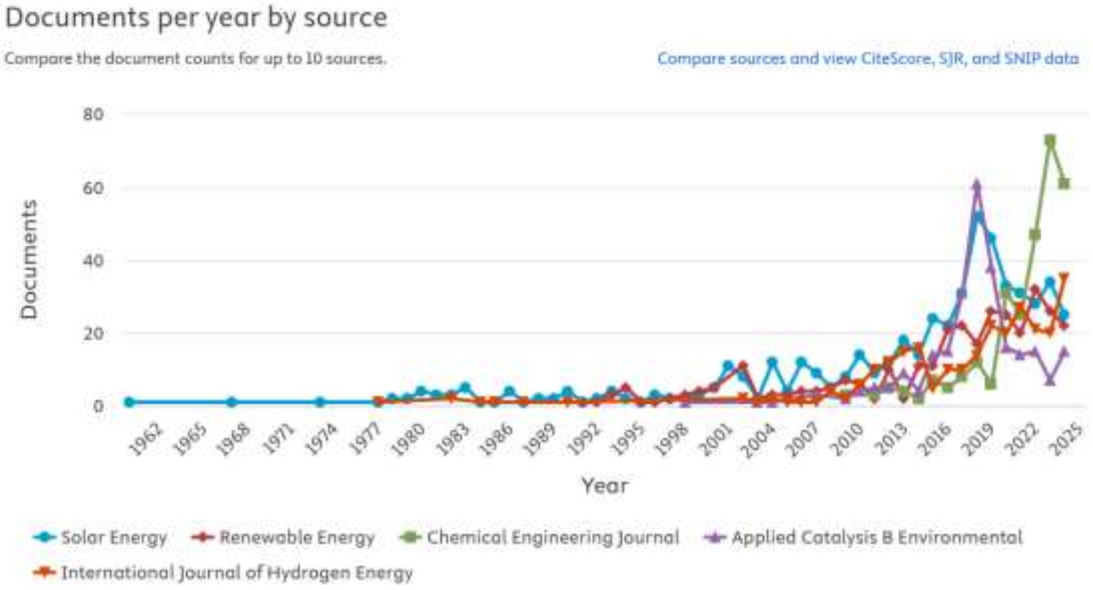

Figure 4: The most chosen journals by researchers

China, India, and the US are major players in solar energy, with significant solar irradiation levels and increasing solar power generation. China leads in solar power generation, followed by the US and India. All three countries are expanding their solar capacity, with China seeing the most significant growth in recent years. In this way, the top concerned countries are listed in **Figure 5**, followed by Japan, Germany, South Korea… The most productive authors in *Solar Irradiation and Energy* research were identified (**Figure 6**). According to the analysis, No Author ID Found indicates that different groups of researchers published more than 70 articles. Imaizumi M. emerged as the most productive author, with 65 publications, followed by Ihshima T. with 56 publications and Yamaguchi M. with 53 publications, and Steinfeld A., Iqbal M., Wu J. having less than 50 publications.

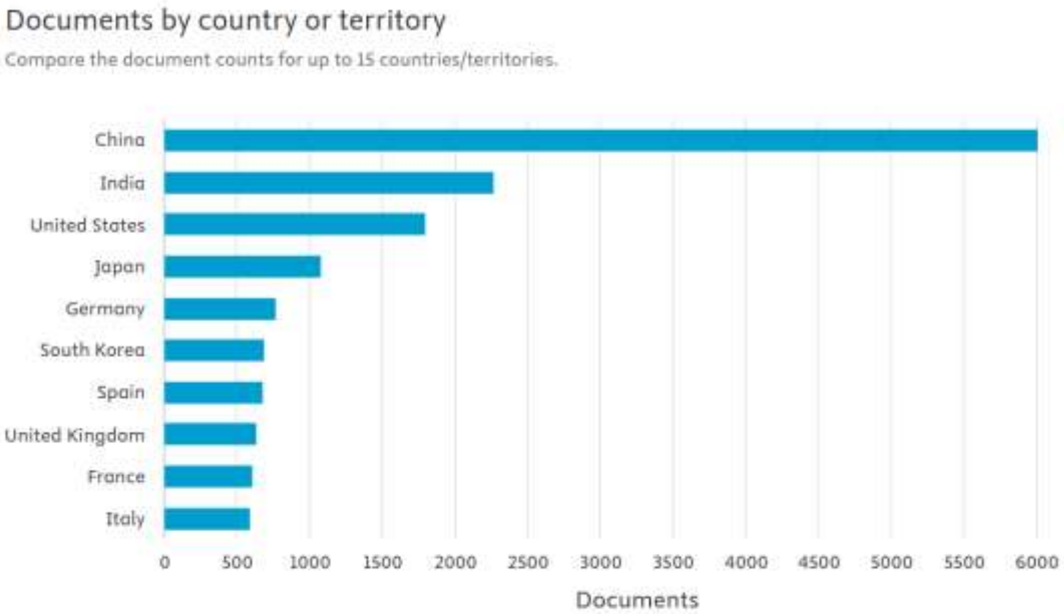

Figure 5: The ten most countries contributing from 1953 to 2024

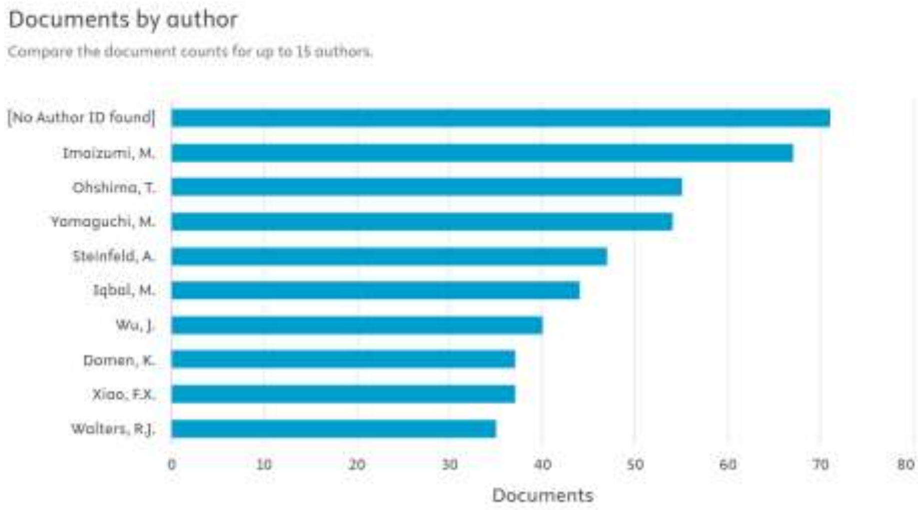

Figure 6: The ten profiled authors.

2. Sites and Measurement

Despite the proven potential of temperature-based models, limited studies have been conducted to assess their applicability and performance in the southeastern United States (Kafka *et al.,* 2019), particularly in Mississippi. This knowledge gap underscores the need for comprehensive, site-specific calibration and validation of empirical models using long-term datasets to enhance solar resource assessment capabilities in the region.

Mississippi has a humid-subtropical climate, characterized by long, warm-to-hot summers and short, generally mild winters. Average summer daytime highs range from 31 – 34 °C across most of the state, with sultry humidity frequently pushing heat-index values above 40 °C during July and August. Winters are comparatively gentle: mean January temperatures hover around 8 – 10 °C in the north and 10 – 12 °C along the Gulf Coast, with sub-freezing nights and light freezes mainly confined to occasional Arctic outbreaks. Overall, Mississippi's warm, humid climate and high irradiation make it well suited for studies of temperature–based solar-irradiance modeling.

Ground-based pyranometer networks provide the most accurate records of solar irradiations, yet their spatial and temporal coverage remains sparse because the instruments are costly to install, require frequent calibration, and demand continuous maintenance. According to the new SolarStations.org catalogue, only about 60 multi-component irradiance stations are currently active across all North America—and just one of them is located in Mississippi, whereas more than 200 active sites are listed for Asia, the majority in India (Jensen *et al.*, 2025). To overcome this observational gap, the present study relies on the NASA Prediction of Worldwide Energy Resources (POWER) database, which blends satellite irradiance with ground observations to generate consistent global fields (Zhang *et al.*, 2008; Boughamrane *et al.*, 2016). Monthly average daily global solar irradiation (H_{obs}) and corresponding air-temperature (T) series for 2019–2023 were extracted from POWER for each Mississippi site we studied. Recent validation under Brazilian conditions has shown that POWER's temperature-humidity indices—and, by extension, its meteorological variables—match national weather-station data with high fidelity (Carrara *et al.*, 2023), confirming the suitability of this hybrid satellite–model data set for regional solar-resource studies.

This study was conducted at five representative locations across the state of Mississippi, USA. The selected sites Starkville, Hattiesburg, Oxford, Gulfport, and Jackson were chosen to capture a range of geographical and climatic conditions, including inland, coastal, and urban environments. These sites are distributed across northern, central, and southern Mississippi, covering variations in temperature, humidity, and solar exposure patterns. Their precise geographical coordinates and altitudes are presented in **Table 1.**

Table 1. Geographical characteristics of the study sites.

Site	Latitude (°N)	Longitude (°W)	Altitude (m)
Starkville	33.4500	-88.8184	101
Hattiesburg	31.3271	-89.2903	47
Oxford	34.3665	-89.5192	146
Gulfport	30.3674	-89.0928	6
Jackson	32.2988	-90.1848	89

Monthly-mean data were selected for this analysis due to their optimal balance between physical relevance and statistical robustness in empirical solar resource modeling. Aggregating solar and temperature data to the monthly scale significantly reduces the influence of high-frequency noise caused by transient cloud cover, instrumental anomalies, and sporadic data gaps—factors that often obscure the underlying temperature–irradiance relationship when using daily or hourly datasets. Furthermore, monthly average daily irradiation values are the standard reference in most photovoltaic (PV) and solar thermal system design studies. This is because system sizing, tilt angle optimization, and economic performance metrics such as Levelized Cost of Energy (LCOE) are typically evaluated over monthly or annual periods rather than over short-term variability.

Monthly aggregation also improves the resilience of the analysis to missing data. A limited number of absent hours or even days have a minimal impact on monthly averages, whereas they can significantly skew regression models based on finer temporal resolutions. Notably, prior studies that have demonstrated strong temperature-based irradiance correlations also rely on monthly or seasonal mean data (Ertekin & Evrendilek,2007; Fan et al.,2018).

Both solar irradiation and temperature data were carefully processed and cross-checked for consistency. The solar irradiation data were expressed in kilowatt-hours per square meter per day (kWh $m^{-2} Day^{-1}$), while air temperature was measured in degrees Celsius (°C). These datasets formed the basis for model calibration, validation, and performance evaluation steps carried out in this research.

3. Methodology

3.1 Model Formulation

The primary objective of this study is to estimate monthly average daily global solar irradiation (H) using a simple linear relationship with monthly average air temperature (T). The empirical model adopted in this study is of the form:

$$H = a + b\,T$$

a and b are the empirical coefficients to be determined through linear regression.

This approach is based on well-established temperature-based models that have been applied globally due to their simplicity and low data requirements (Hargreaves & Samani, 1982; Almorox *et al*., 2015). The rationale behind this model is that higher air temperatures are generally associated with clearer skies and higher solar irradiance, although this relationship can vary with local atmospheric conditions (Sabbagh *et al*., 2023).

3.2 Data Processing and Model Calibration

For each of the five selected sites, the observed solar irradiation (H_{obs}) and corresponding air temperature (T) data for the years 2019 to 2023 were used to calibrate the model. The coefficients a and b were determined by minimizing the sum of squared errors (SSE) using the ordinary least squares (OLS) regression method. The best-fit line was obtained by minimizing the residuals:

$$Residual_i = H_{obs,i} - H_{pred,i}$$

Where, $H_{pred,i}$ is the predicted solar irradiation for month i. Monthly residuals (H_{obs} - H_{pred}) were computed and analyzed using boxplots to check for systematic seasonal biases and ensure that residuals behaved like random noise.

3.3 Model Evaluation Metrics

The performance of the model was evaluated using the following statistical metrics:

Coefficient of Determination (R^2):

$$R^2 = 1- \frac{\sum_{i=1}^{n}(H_{obs,i} - H_{pred,i})^2}{\sum_{i=1}^{n}(H_{obs,i} - \overline{H}_{obs})^2}$$

Where, $\overline{H}_{obs}$ is the mean of the observed solar irradiation. An R^2 value close to 1 indicates a strong correlation between observed and predicted values.

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_{obs,i} - H_{pred,i})^2}$$

RMSE provides an estimate of the average error between observed and predicted values.

Regression-slope Analysis:

To quantify how closely the predicted values follow the measured ones, we performed an additional simple-linear-regression of the form

$$H_{pred} = \beta_0 + \beta_1 H_{obs}$$

where β_1 is the slope and β_0 is the intercept. An ideal model would reproduce every observation exactly, the benchmark of perfect agreement is a slope β_1 equal to 1 and an intercept β_0 equal to 0; under that condition all points would fall on the one-to-one line H_{pred}= H_{obs}.

3. Results and Discussion

The temperature based linear model was calibrated for each of the five selected sites using the dataset from 2019 to 2023. Relationship between solar irradiation and temperature is shown in **Figure** 7. **Table 2** presents the obtained model parameters (a and b), the coefficient of determination ($\boldsymbol{R^2}$) and the RMSE for each site.

Table 2. Model parameters and performance metrics for the five study sites.

Site	a	b	R^2	RMSE
Starkville	1.71	0.161	0.740	0.74
Hattiesburg	1.32	0.173	0.735	0.72
Oxford	1.65	0.169	0.711	0.74
Gulfport	1.12	0.177	0.711	0.71
Jackson	1.34	0.179	0.770	0.71

The results indicate that the linear temperature-based model performed consistently well across all five sites, with R^2 values ranging between 0.711 and 0.77, aligning with previous findings where similar models were applied in different climatic zones (Almorox *et al*., 2015; Sabbagh *et al*., 2023; Fan *et al*., 2018).

Starkville exhibited a model with a=1.71 and b=0.161, achieving an R^2 of 0.740 and an RMSE of 0.74 kWh/m²/day. Hattiesburg showed a slightly lower interception of a=1.32 and a marginally higher slope of b=0.173, resulting in an R^2 = 0.735 and RMSE = 0.72. Oxford's regression parameters were a=1.65 and b=0.169, with an R^2 value of 0.711 and RMSE = 0.74. Gulfport recorded the lowest intercept among the sites (a=1.12) but the highest slope (b=0.177), with an R^2 of 0.711 and RMSE = 0.71. Jackson demonstrated the strongest correlation, with R^2= 0.770, and maintained relatively low error (RMSE = 0.71) with coefficients a=1.34 and b=0.179. These results collectively indicate that a simple linear temperature-based model can capture a substantial portion of the variance in monthly solar irradiation across diverse Mississippi climates. The relatively consistent slopes (ranging from 0.161 to 0.179) suggest that temperature serves as a robust proxy variable. The RMSE values (ranging between 0.71 and 0.74) confirm that prediction errors remain within an acceptable margin for monthly-scale solar resource estimation. Jackson's superior R^2 value may reflect more stable atmospheric conditions or a stronger temperature–irradiance coupling compared to the other locations.

The RMSE values, mostly below 0.72 kWh $m^{-2}Day^{-1}$, reflect an acceptable level of error, corroborating earlier studies where temperature-based models provided satisfactory accuracy with minimal data input (El-Sebaii et al., 2005). **Figure 8** displays the scatter plots of observed versus predicted solar irradiation for each site, along with the 1:1 reference line. The regression lines were nearly parallel to the 1:1 line with slopes, β_1, in the range of **0.97 to 0.98**, suggesting a slight underestimation during higher irradiation months. Nevertheless, the residual spread remains narrow, indicating strong model robustness across various climatic conditions of Mississippi.

Residual analysis was conducted by generating monthly residual boxplots (**Figure 9**) aggregated for all sites. The boxplots show that residuals are symmetrically distributed around zero, with minor dispersion in the colder months of January and December, possibly due to cloud cover and other local atmospheric effects not captured by the simple temperature model. The residual patterns showed no significant seasonal bias, confirming the adequacy of the model in reflecting monthly variations without systematic errors. Overall, the findings reaffirm the usefulness of the temperature-based linear model as a quick and reliable approach for solar irradiation estimation, especially in regions where detailed solar datasets are unavailable. Such models, when calibrated with local data, can serve as practical tools for preliminary solar resource assessment, supporting energy planning and policy. However, it is acknowledged that the model does not account for other influencing parameters (Nalina *et al*., 2014) such as humidity (Behar *et al*., 2019), cloud cover, or precipitation (Winslow *et al*., 2001), which could affect irradiation levels, particularly during transitional months.

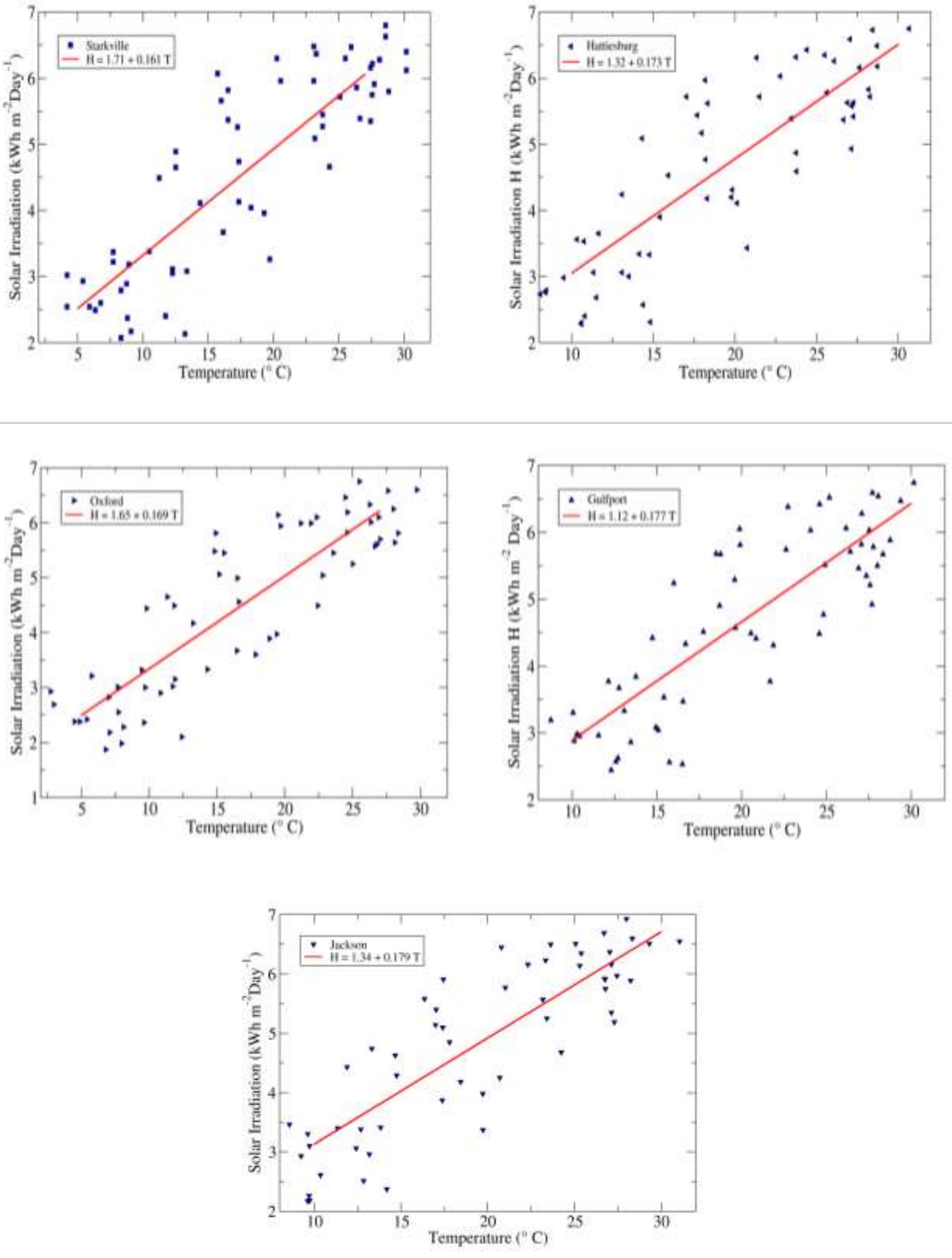

Figure 7. Monthly temperature–irradiation relationship at five Mississippi sites (2019–2023)

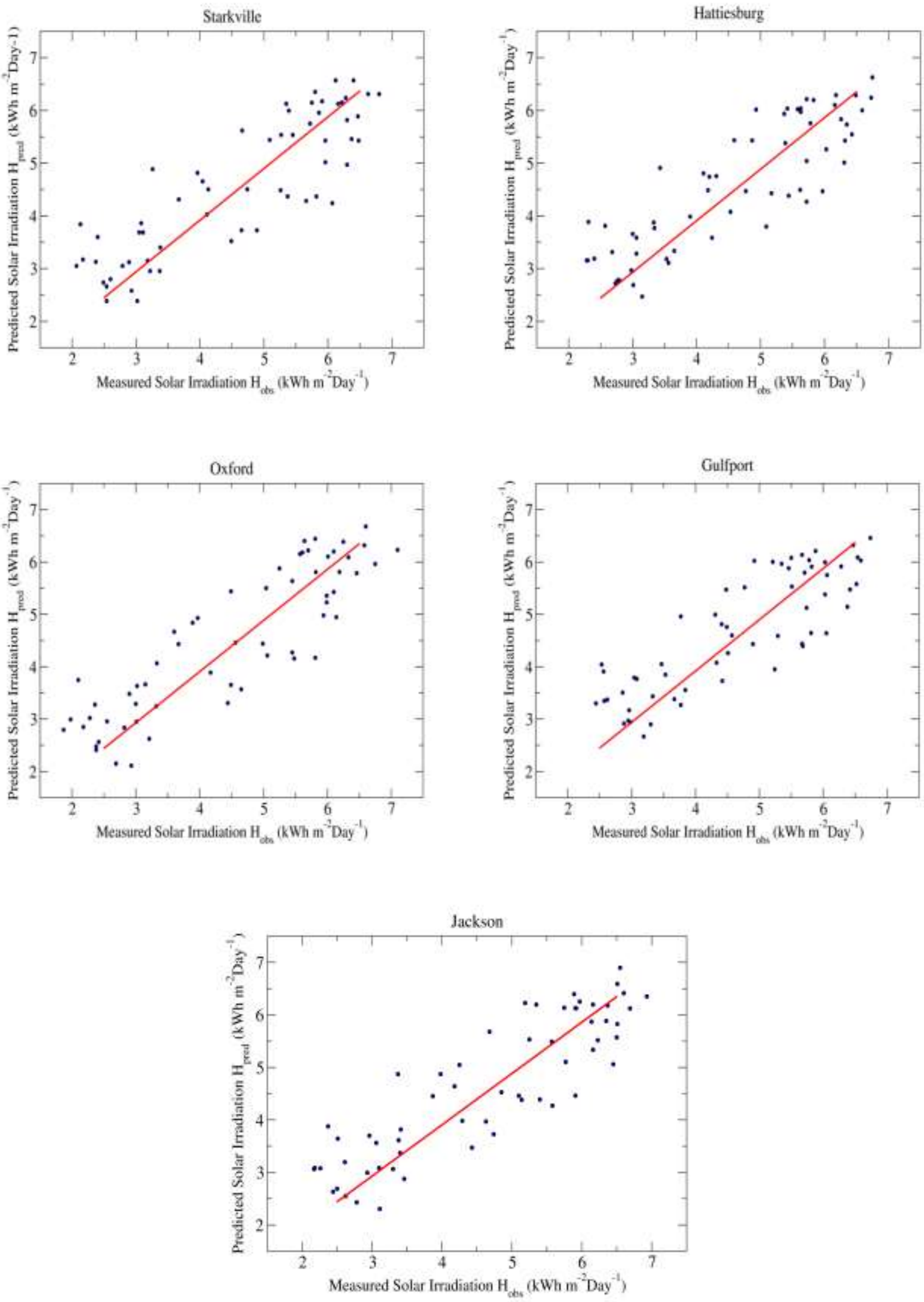

Figure 8. Predicted (H_{pred}) monthly versus Measured (H_{obs}) solar irradiation for all sites.

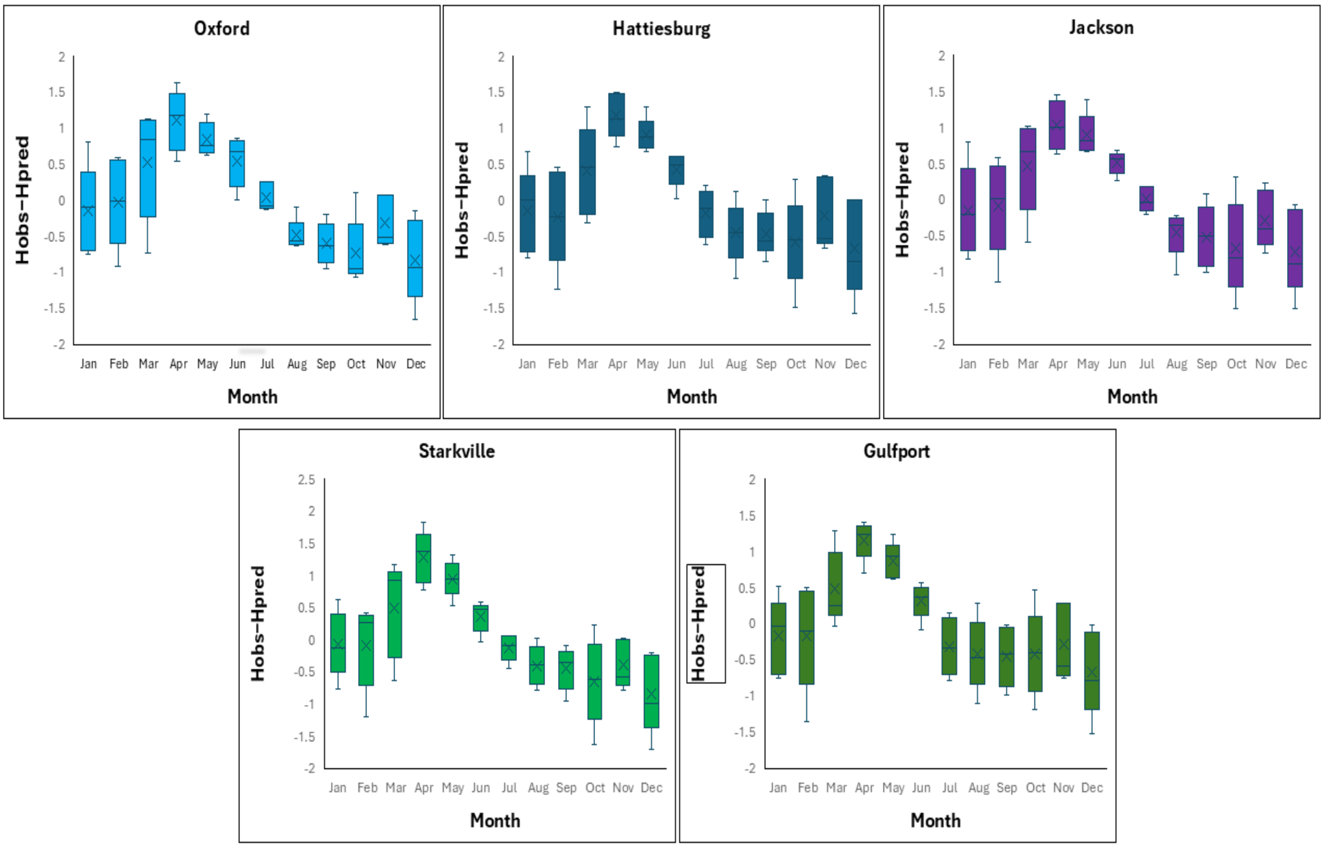

Figure 9. Monthly residuals (H_{obs} - H_{pred}) for the linear model across the five sites: box-and-whisker summary of seasonal bias and dispersion.

Conclusion

This study investigated the applicability of a simple temperature-based linear model for estimating monthly average daily global solar irradiation across five representative sites in Mississippi, USA. Using observational data from 2019 to 2023, the model H= a + b T was calibrated and evaluated using robust statistical indicators, including R^2, RMSE, regression slope analysis, and residual diagnostics.

Overall, the findings reaffirm the usefulness of the temperature-based linear model as a quick and reliable approach for solar irradiation estimation. Such models, when calibrated with local data, can serve as practical tools for preliminary solar resource assessment, supporting energy planning and policy.

The results demonstrated that the model performed consistently well across all sites, with R^2 values exceeding **0.75** and RMSE values remaining within acceptable limits. The 1:1 comparison plots indicated a strong correlation between observed and predicted values, with minimal underestimation during peak irradiation months. Residual diagnostics further confirmed the adequacy of the model, showing no significant seasonal bias and random dispersion of residuals.

These findings confirm the reliability of the linear temperature-based model as a practical and low-data-demanding approach for solar resource assessment in Mississippi and similar climatic regions. The model's simplicity, combined with its satisfactory performance, makes it suitable for preliminary site assessments, solar project feasibility studies, and energy planning, particularly in rural and data-scarce environments.

Acknowledgement: *These data were obtained from the NASA Langley Research Center (LaRC) POWER Project funded through the NASA Earth Science/Applied Science Program.*
Disclosure statement: *Conflict of Interest:* The author declares that there are no conflicts of interest.
Compliance with Ethical Standards: This article does not contain any studies involving human or animal subjects.

References

Ahmed S. abd askar (2025) Emerging photocatalytic nanomaterials for industrial wastewater treatment and removal using solar energy, *J. Mater. Environ. Sci.*, 16(7), 1210-1228

AlFaraj J., Popovici E., Leahy P. (2024). Solar Irradiance Database Comparison for PV System Design: A Case Study. *Sustainability.* 16(15), 6436. https://doi.org/10.3390/su16156436

Almorox, J., Quej, V. H., & Benito, M. (2015). Evaluation of monthly solar radiation models under different weather conditions. *Energy Conversion and Management*, 105, 66-73.

Atsbeha, A.K., Gebremariam, G.G., Gebru, K.G. et al. Assessment of solar resource potential and estimation of direct and diffuse solar irradiation from sunshine hours data for Eastern Zone of Tigray, Northern Ethiopia. *Sustainable Energy res.* 12, 16 (2025). https://doi.org/10.1186/s40807-025-00162-2

Behar, O., Sbarbaro, D., Marzo, A., & Moran, L. (2019). A simplified methodology to estimate solar irradiance and atmospheric turbidity from ambient temperature and relative humidity. *Renewable and Sustainable Energy Reviews, 116*, 109310. https://doi.org/10.1016/j.rser.2019.109310

Beven, K. (2012). Front Matter. In Rainfall-Runoff Modelling, K. Beven (Ed.). https://doi.org/10.1002/9781119951001.fmatter

Boughamrane, L., Boulaid, M., Tihane, A., Sdaq, A., Bouabid, K., & Ihlal, A. (2016). Comparative analysis of measured and simulated performance of the Moroccan first MV grid-connected photovoltaic power plant of Assa, southern Morocco. J. Mater. Environ. Sci., *7*(12), 4682–4691.

Byiringiro, J., Chaanaoui, M. & Hammouti, B. (2025). Thermal performance enhancement of a novel receiver for parabolic trough solar collector. *Interactions*, 246, 13 https://doi.org/10.1007/s10751-024-02230-3

Byiringiro, J., Chaanaoui, M., Hammouti, B. (2025) Enhancement of thermal performance in parabolic trough solar Collectors: Investigation of three novel receiver configurations using advanced heat transfer fluids, *Solar Energy Materials and Solar Cell*, 293, 113833, https://doi.org/10.1016/j.solmat.2025.113833

Carrara, E. R., Lopes, P. S., Reis, A. C. Z., et al. (2023). NASA POWER satellite meteorological system is a good tool for obtaining estimates of the temperature-humidity index under Brazilian conditions compared to INMET weather stations data. *International Journal of Biometeorology, 67*, 1273–1277. https://doi.org/10.1007/s00484-023-02493-5

Chakir H., Aichouch I., Kachbou Y. (2023). Corrosion inhibition of mild steel by benzimidazole-based organic compounds in a 1M HCl environment: a review, Journal of Applied Science and Environmental Studies 6 (1), 61-82

Chuvieco, E., Riaño, D., Aguado, I., & Cocero, D. (2002). Estimation of fuel moisture content from multitemporal analysis of Landsat Thematic Mapper reflectance data: Applications in fire danger assessment. *International Journal of Remote Sensing, 23*(11), 2145–2162. https://doi.org/10.1080/01431160110069818

Ertekin, C., & Evrendilek, F. (2007). Spatio-temporal modeling of global solar radiation dynamics as a function of sunshine duration for Turkey. *Agricultural and Forest Meteorology, 145*(1–2), 36–47. https://doi.org/10.1016/j.agrformet.2007.04.004

El-Sebaii, A. A., & Trabea, A. A. (2005). Estimation of global solar radiation on horizontal surfaces over Egypt. *Egyptian Journal of Solids, 28*(1), 163–175. https://doi.org/10.21608/ejs.2005.149357

Fan, J., Chen, B., Wu, L., Zhang, F., Lu, X., & Xiang, Y. (2018). Evaluation and development of temperature-based empirical models for estimating daily global solar radiation in humid regions. *Energy, 144*, 903–914. https://doi.org/10.1016/j.energy.2017.12.091

Gandoman, F. H., Abdel Aleem, S. H. E., Omar, N., Ahmadi, A., & Alenezi, F. Q. (2018). Short-term solar power forecasting considering cloud coverage and ambient temperature variation effects. *Renewable Energy, 123*, 793–805. https://doi.org/10.1016/j.renene.2018.02.102

Gourdo, L., Bazgaou, A., Ezzaeri, K., Tiskatine, R., Wifaya, A., Demrati, H., Aharoune, A., & Bouirden, L. (2018). Heating of an agricultural greenhouse by a reservoir filled with rocks. J. Mater. Environ. Sci., *9*(4), 1193–1199. https://doi.org/10.26872/jmes.2017.9.4.131

Güney, T. (2021). Solar energy and sustainable development: Evidence from 35 countries. *International Journal of Sustainable Development & World Ecology, 29*(2), 187–194. https://doi.org/10.1080/13504509.2021.1986749

Hargreaves, G. H., & Samani, Z. A. (1982). Estimating potential evapotranspiration. *Journal of Irrigation and Drainage Engineering*, 108(3), 225–230.

Jamil, A., Ahmad, F., & Jeon, G. (2016). Application of empirical models for estimating solar radiation in Pakistan. *Renewable and Sustainable Energy Reviews*, 65, 635–646.

Jensen, A. R., Sifnaios, I., Anderson, K. S., & Gueymard, C. A. (2025). SolarStations.org—A global catalog of solar irradiance monitoring stations. *Solar Energy*, *295*, 113457. https://doi.org/10.1016/j.solener.2025.113457

Kafka, J. L., & Miller, M. A. (2019). A climatology of solar irradiance and its controls across the United States: Implications for solar panel orientation. *Renewable Energy, 135*, 897–907.

Karzazi, Y., & Arbouch, I. (2014). Inorganic photovoltaic cells: Operating principles, technologies and efficiencies—Review. *J. Mater. Environ. Sci., 5*(5), 1505–1515.

Kómar, L., & Kocifaj, M. (2016). Statistical cloud coverage as determined from sunshine duration: A model applicable in daylighting and solar energy forecasting. *Journal of Atmospheric and Solar-Terrestrial Physics*, *150–151*, 1–8. https://doi.org/10.1016/j.jastp.2016.10.011.

Laita M., Sabbahi R., Elbouzidi A., Hammouti B., Messaoudi Z., Benkirane R., Aithaddou H. (2024) Effects of Sustained Deficit Irrigation on Vegetative Growth and Yield of Plum Trees Under the Semi-Arid Conditions: Experiments and Review with Bibliometric Analysis, *ASEAN Journal of Science and Engineering*, 4(2), 167-190

Lrhoul H., Turki H., Hammouti B. (2023), Benammar O., Internationalization of the Moroccan Journal of Chemistry: A bibliometric study, *Heliyon*, 9(5), e15857, ISSN 2405-8440, https://doi.org/10.1016/j.heliyon.2023.e15857

Maka, A. O. M., & Alabid, J. M. (2022). Solar energy technology and its roles in sustainable development. *Clean Energy*, *6*(3), 476–483. https://doi.org/10.1093/ce/zkac023

Nalina, U., Prema, V., Smitha, K., & Rao, K. U. (2014). Multivariate regression for prediction of solar irradiance. In *Proceedings of the 2014 International Conference on Data Science & Engineering (ICDSE)* (pp. 177–181). IEEE. https://doi.org/10.1109/ICDSE.2014.6974633

N'diaye A.D., Hammouti B., Nandiyanto A. B. D., Al Husaeni D. F. (2022), A review of biomaterial as an adsorbent: From the bibliometric literature review, the definition of dyes and adsorbent, the adsorption phenomena and isotherm models, factors affecting the adsorption process, to the use of Typha species waste as a low-cost adsorbent, *Communications in Science and Technology*, 7 No.1, 140-153

Novas, N., Garcia, R. M., Camacho, J. M., & Alcayde, A. (2021). Advances in solar energy towards efficient and sustainable energy. *Sustainability*, *13*(11), 6295. https://doi.org/10.3390/su13116295

Obaideen, K., Olabi, A. G., Al Swailmeen, Y., Shehata, N., Abdelkareem, M. A., Alami, A. H., Rodriguez, C., & Sayed, E. T. (2023). Solar energy: Applications, trends analysis, bibliometric analysis and research contribution to Sustainable Development Goals (SDGs). *Sustainability*, *15*(2), 1418. https://doi.org/10.3390/su15021418

Oyewole, O. J., Sirola, C., Pandit, A., & Ayo, S. (2025). The Study of Altitudinal Refractivity and Refractivity Gradient Variations by Weather Parameters in Some Selected Locations in Nigeria. *Physical Science International Journal*, 29(3), Article 882. https://doi.org/10.9734/psij/2025/v29i3882

Pranckutė R. (2021). Web of Science (WoS) and Scopus: The Titans of Bibliographic Information in Today's Academic World. *Publications*. 9(1), 12. https://doi.org/10.3390/publications9010012

Sabbagh, A. A., Khair, A. M., & Hegazy, A. S. (2023). Temperature-based estimation of global solar radiation using empirical and statistical techniques. *Renewable Energy*, 206, 159–172.

Salim R., Loukili, E.H., Ech-chihbi E., Merimi C. (2022). Insight on the scientific production of USMBA until 2022: bibliometric analyses, *Journal of Applied Science and Environmental Studies*, 5 (4), 219-230

Winslow, J. C., Hunt, E. R., & Piper, S. C. (2001). A globally applicable model of daily solar irradiance estimated from air temperature and precipitation data. *Ecological Modelling, 143*(3), 227–243. https://doi.org/10.1016/S0304-3800(01)00341-6

You, C., Awang, S.R., Wu, Y. (2024). Bibliometric analysis of global research trends on higher education leadership development using Scopus database from 2013–2023. *Discov Sustain.*, 5, 246, https://doi.org/10.1007/s43621-024-00432-x

Zhang, T., Chandler, W. S., Hoell, J. M., Westberg, D., Whitlock, C. H., & Stackhouse, P. W. (2008). A global perspective on renewable energy resources: NASA's Prediction of Worldwide Energy Resources (POWER) project. In D. Y. Goswami & Y. Zhao (Eds.), *Proceedings of ISES World Congress 2007 (Vol. I–V)*. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-75997-3_532

(2025) ; http://www.jmaterenvironsci.com