Nigerian Journal of Theoretical and Environmental Physics (NJTEP)
ISSN Print: 3026-9601
ISSN Online: 1597-9849
DOI: https://doi.org/10.62292/njtep.v4i1.2026.108
Volume 4(1), March 2026

Evaluating the Accuracy of MERRA-2 Reanalysis Data Against In-Situ Observations Under Varying Weather Conditions

†[1]Gbadebo I. Olatona, *[1]Shuaib A. Adisa, ⁑[2]Muyideen O. Lawal, ‡[1]Saheed A. Adewinbi and §[1]Sheriffdeen M. Oyedokun

[1]Department of Physics, Faculty of Basic and Applied Sciences, Osun State University, Osogbo, Nigeria
[2]Department of Electrical and Electronics Engineering, Faculty of Engineering, Osun State University, Osogbo, Nigeria.

*Corresponding author's email: adisashuayb98@gmail.com Phone: +2347065199968
ORCID iD: †https://orcid.org/0000-0001-9415-6265 *https://orcid.org/0000-0001-9389-1874
⁑https://orcid.org/0000-0001-8705-0569 ‡https://orcid.org/0000-0002-1057-2462
§https://orcid.org/0000-0001-9013-5512

ABSTRACT
Accurate estimation of surface atmospheric parameters is essential for climate and environmental studies, especially in regions with limited ground-based observations. This study addressed a key gap by evaluating Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) reanalysis data against in-situ measurements of solar radiation, temperature, and wind speed under varying weather conditions. In-situ data were collected in Osogbo, Osun State, Nigeria, using a Professional Weather Station and a Solar Meter (SM205), while MERRA-2 data were obtained from the NASA GIOVANNI platform, covering January 1 to March 31, 2025. Data were synchronized to hourly resolution and categorized by weather type. Statistical analysis applied linear, quadratic, and logarithmic regression models, with performance evaluated using Root Mean Square Error (RMSE) and Coefficient of Determination (R^2). Results showed strong agreement between MERRA-2 and in-situ temperature across most conditions, with the quadratic model performing best. Under sunny conditions, R^2 reached 0.994 and 0.948, with RMSEs of 0.27 °C and 0.62 °C. Overcast days also showed good reliability (R^2 = 0.860 and 0.767), though accuracy declined during rainfall (R^2 = 0.377; RMSE = 2.61 °C). For solar irradiance, performance varied by condition: the quadratic model performed best on sunny Day 1 (R^2 = 0.759), while the logarithmic model gave the lowest RMSE on Day 2 (114.78 W/m²). Overcast and rainy Day 2 favored the quadratic model (R^2 = 0.925 and 0.881). Wind speed showed poor agreement across all conditions, with best R^2 = 0.289 and RMSE up to 8.97 m/s.

Keywords:
MERRA-2,
In-situ observations,
Atmospheric parameters,
Weather conditions,
Reanalysis validation,
Southern Nigeria.

INTRODUCTION
Solar radiation, wind speed and air temperature are important atmospheric parameters whose concepts form the foundation for having deep knowledge about Earth's climate and weather systems. Solar radiation, wind speed and air temperature play critical roles in shaping the Earth's climate and weather systems. Solar irradiance is the primary source of energy for the Earth (Kren et al., 2017; Penza et al., 2022) and serves as a factor in the analysis and interpretation of many atmospheric and environmental processes. Air temperature is an important climatic parameter that contributes to understanding the impacts of climate change (Ahmadi et al., 2018; Hekmatzadah et al., 2020). It addresses societal challenges, especially those related to human health and environmental sustainability. Also, air temperature is a key factor for accurate weather forecasting and climate modeling (Astsatryan et al., 2020). On the other hand, wind speed is used as a renewable energy source for developed wind turbine systems at the local level. There parameters are crucial to understanding atmospheric behaviors, modeling climate variability, and designing renewable energy systems (Malik et al., 2022).

Many studies have compared reanalysis data with in-situ measurements of solar radiation, wind speed and air temperature to evaluate the accuracy of re-analysis measurements. (Boyo and Adeyemi, 2012) conducted a comparison of global horizontal solar radiation data obtained from a Gun-Bellani pyranometer at the Meteorological Agency, Oshodi, Lagos, and satellite-derived data from National Aeronautics and Space Administration (NASA). Their analysis used the Kolmogorov-Smirnov test, Mean Bias Error (MBE), and Root Mean Square Error (RMSE), and showed the usefulness of combining these statistical tools to assess the agreement between the two measurements. Also, (Malvern and Maurice, 2018) carried out a comparative analysis of satellite and ground-based data of rainfall and temperature using measurements obtained from an automated weather station and a satellite earth station. Their study focused on differences in spatial representation, point based for ground stations and areal for satellite data, also influencing the local topography, which ground observations were capture better. They concluded that both data sources exhibited similar trends, their discrepancies limited their use to trend validation rather than exact calibration. Recently, (Katsekpor et al., 2024) evaluated the accuracy of satellite and reanalysis measurements for rainfall, temperature, and soil moisture against in-situ observations in Nothern Ghana. Their findings showed the reliability of selected satellite products, especially Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) and ERA5, as alternatives for hydrological applications in data-scarce regions. The study highlighted the value of satellite measurements in supporting prediction of flood, drought monitoring, and streamflow modeling, especially where conventional ground networks are limited or unavailable.
While these studies have demonstrated the potential of satellite-derived datasets for complementing or replacing in-situ observations, they have often focused on individual atmospheric variables such as rainfall or temperature, or were conducted in regions with different climatic and geographic conditions. Most studies do not account for variation under different weather conditions, which are important for understanding the behavior and accuracy of satellite estimates across variable atmospheric states.
This study seeks to fill the gap by conducting an evaluation of Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) and in-situ measurements of solar radiation, temperature, and wind speed under different weather conditions. The findings aim to provide insight into reliability of satellite data for local-scale environmental monitoring and climate analysis in Southern Nigeria.

MATERIALS AND METHODS

Study Area

Osogbo urban rural is the capital of Osun state, Made up of two local government areas (LGAs), namely Osogbo local government area and Olorunda local government area. The town covers a total of about 47km^2. The area is within the tropical rain forest like other parts of the south western Nigeria (Alabi et al., 2016). The mean annual temperature in the state ranges from 24.0 °C to 28.35 °C, with approximately 127.75 millimeters of annual rainfall and has about 237.62 rainy days 9 (Adeleke et al., 2025). In situ measurements were collected from an observation station located on the rooftop of the Faculty of Basic and Applied Sciences (FBAS) building, Osun state University, Osogbo, Osun State, Nigeria situated at approximately 7°45′41.68″N and 4°36′7.48″ E. The study area is a viable location for the research and it can serve as a model for other major town in the south western part of Nigeria and other zones with the same climatic conditions in Nigeria at large.

Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2)

MERRA-2 is generated using version 5.12.4 of the Golden Earth Observing System (GEOS) atmospheric data assimilation system. This system consists of the GEOS atmospheric model (Molod et al., 2015; Gelaro et al., 2017) and the Gridpoint Statistical Interpolation (GSI) analysis technique (Wu et al., 2002; Gelaro et al., 2017).
MERRA-2 data used were obtained from the NASA GIOVANNI website, which provides global coverage at spatial resolution 0.5° × 0.5° and temporal resolution of hourly. The datasets collected for this study include surface windspeed instantaneous, surface incoming shortwave flux, and surface air temperature over land instantaneous. These measurements were collected between the period from January 1, 2025, to March 31, 2025.

In-situ Data

The Professional Weather Station used for in situ measurements displays real-time measurements on a digital panel, it does not support automatic data logging. Therefore, data were manually recorded instantaneously at hourly intervals during daylight hours.
Solar irradiance was measured using the SM205 solar meter equipped with a silicon photodiode sensor. It displays Global Horizontal Irradiance (GHI) in Wm^{-2} and is suitable for field measurements. Also, readings were recorded instantaneously at hourly intervals. The SM205 have a manufacturer-stated measurement accuracy of approximately ±10% under standard operating conditions. The device was factory-calibrated prior to use. The Professional Weather Station used for temperature, wind speed, and rainfall measurements

operates within standard meteorological tolerances as specified by the manufacturer. However, as the station does not support automatic data logging, measurements were manually recorded at hourly intervals. Care was taken to ensure accurate transcription during data collection, although minor human recording errors cannot be completely excluded. These procedural limitations are acknowledged as potential sources of uncertainty in the in-situ dataset.

The weather condition of each measurement was recorded and the data covered the same period the MERRA-2 reanalysis measurements. Figure 1 shows both Professional Weather Station and SM205 Solar Meter respectively.

Figure 1: Solar Meter (SM205) sensor (Left) and Professional weather station (Right)

Data Preprocessing

MERRA-2 and in-situ measurements were synchronized to ensure temporal consistency, aligning all variables at an hourly resolution. This synchronization is important for accurate comparisons. Nighttime solar irradiance values were excluded using a physical threshold approach, whereby only observations with irradiance values greater than 0 W/m² were retained for analysis. This method ensures that only actual daylight periods were considered, independent of fixed clock-time assumptions. This filtering ensures that the analysis focus on daylight periods, which are relevant for solar irradiance modeling (Schurman and Meyer; 2025).

To understand the agreement between MERRA-2 and in-situ measurements under different weather conditions, the dataset was categorized into three weather conditions: sunny, overcast, and rainy days. For each weather conditions, two days were randomly selected, and their corresponding data were extracted for detailed comparison and validation.

Weather conditions were objectively classified using daily rainfall totals and solar irradiance characteristics recorded at the in-situ observation station. A day was classified as sunny when no rainfall (0 mm) was recorded and solar irradiance values remained consistently high with minimal short-term fluctuations during daylight hours. A day was considered overcast when no rainfall was recorded but solar irradiance intensity was significantly reduced and exhibited attenuation patterns associated with persistent cloud cover. A rainy day was defined as any day with measurable rainfall (> 0 mm) within the 24-hour period. This approach ensured consistent, transparent, and reproducible categorization of atmospheric conditions throughout the study period.

Although the study period covered three months (January-March 2025), rainfall events within this period were limited and unevenly distributed. To ensure balanced representation across the three defined weather categories (sunny, overcast, and rainy), an equal number of days (two per category) were selected for detailed comparative analysis. This approach prevented over-representation of dominant weather conditions, particularly sunny days, and allowed controlled evaluation of MERRA-2 performance under distinct atmospheric states. The selected days were randomly chosen within each category to minimize selection bias.

For each weather condition, two representative days were randomly selected within the study period (1 January–31 March 2025) following prior classification of all days based on the predefined weather criteria. The selected dates were as follows: Sunny days – (27/1/2025) and (3/3/2025); Overcast days – (19/2/2025) and (20/3/2025); Rainy days – (24/2/2025) and (21/3/2025). Random selection within each category was conducted to minimize selection bias while ensuring balanced representation across the three atmospheric conditions. This procedure enhances the transparency and reproducibility of the dataset selection process.

Statistical Analysis

In order to evaluate the accuracy of MERRA-2 solar irradiance, windspeed and temperature measurements, statistical techniques were used to compare these values against in-situ observations. The analysis was carried using Python (with NumPy, Pandas, and Scikit-learn libraries).

Also, in order to estimate the relationship between MERRA-2 and in situ measurements of solar irradiance and temperature, a parametric approach was adopted by evaluating three commonly used functional forms: linear ($y = ax + b$), quadratic ($y = ax^2 + bx + c$) and logarithmic ($y = a + b\ln x$). These forms have been widely used in previous studies for modeling linear and nonlinear relationships (Criqui, 1999; Ellerman and Decaux, 1998; Morris et al., 2012; Nordhaus 2010; Zhou et al., 2013). Each regression model was fitted to the paired datasets, and their performances were compared to determine the most suitable functional form for capturing the relationship between the reanalysis and in situ observations.

Error Metrics

To evaluate the agreement between MERRA-2 and in situ measurements of solar irradiance, windspeed and temperature, two statistical metrics were used: Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2).

RMSE measures the average magnitude of the difference between the predicted (MERRA-2) and observed in situ) values, providing insight into the accuracy of the model. It is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(X_i - Y_i)^2} \qquad (1)$$

X_i represents the MERRA-2 value, Y_i is the corresponding in situ measurements, and n is the number of paired data points. A lower RMSE indicates stronger agreement between the datasets (Willmott and Matsuura, 2006; Halimi et al., 2024) **R²** quantifies the proportion of variability in the in-situ measurements that is explained by the MERRA-2 data. It is computed as:

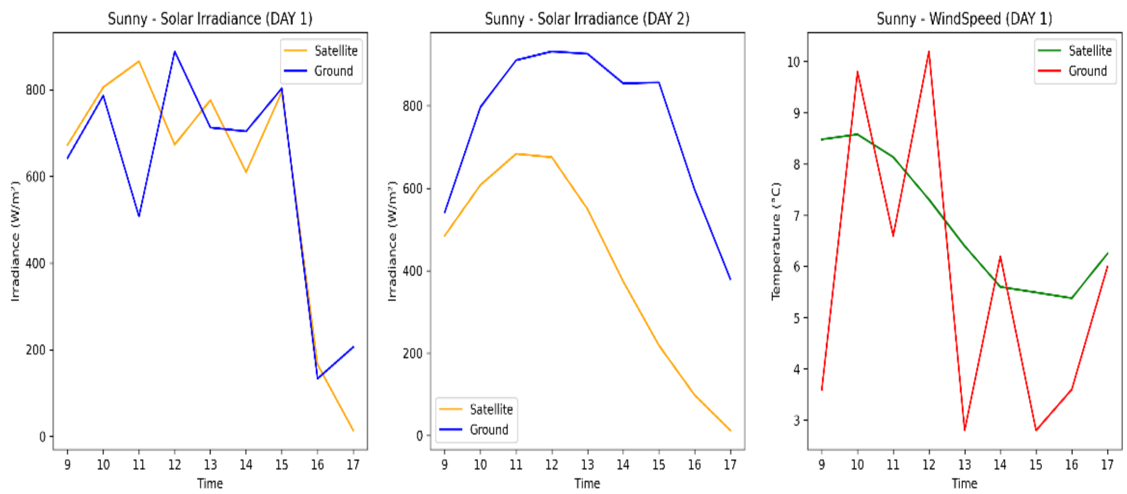
$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad (2)$$

In this equation, x_i represents the MERRA-2 value, y_i is the in-situ measurement, $\bar{x}$ is the mean of the MERRA-2 values, and n is the number of data points. R^2 values range from 0 to 1, where higher values indicate that a greater portion of the observed variance is captured by the model. An R^2 of 1 suggests perfect agreement, while a value near 0 indicates that the model explains little to none of the variation (Esposito et al., 2024).

RESULTS AND DISCUSSION

Distribution Plot

Figure 2 shows the distributions for sunny weather. Here, solar irradiance from MERRA-2 data followed the same pattern as in-situ data, but peak values were underestimated. Temperature from MERRA-2 data was in close agreement with an in-situ values, especially during the midday period, while there was little variation occurred early in the day. Wind speed in the other hand showed differences between both sources, with MERRA-2 data failing to capture variations that is observed in in-situ measurements.



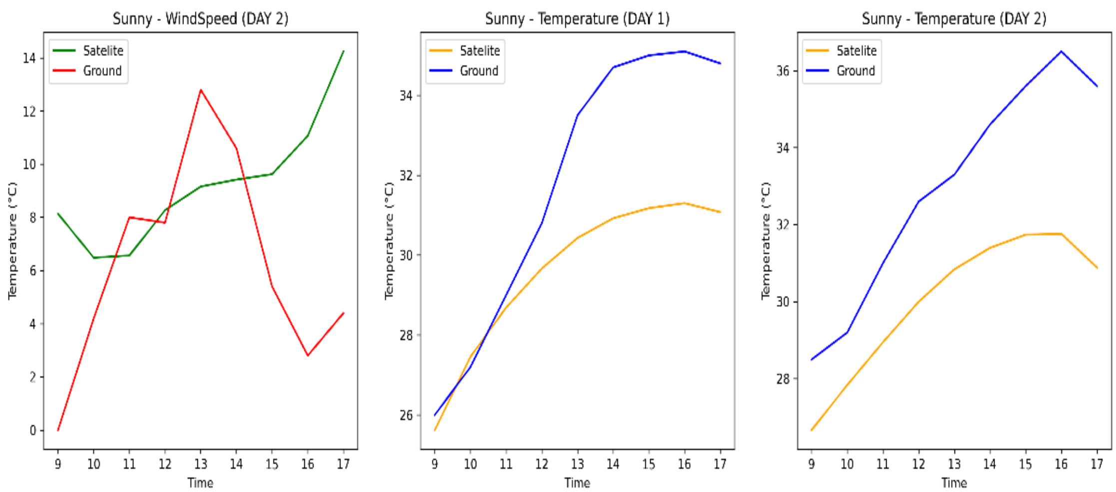


Figure 2: Comparison of Satellite and In Situ Measurements for Solar Irradiance, Wind Speed, and Temperature on Sunny Days

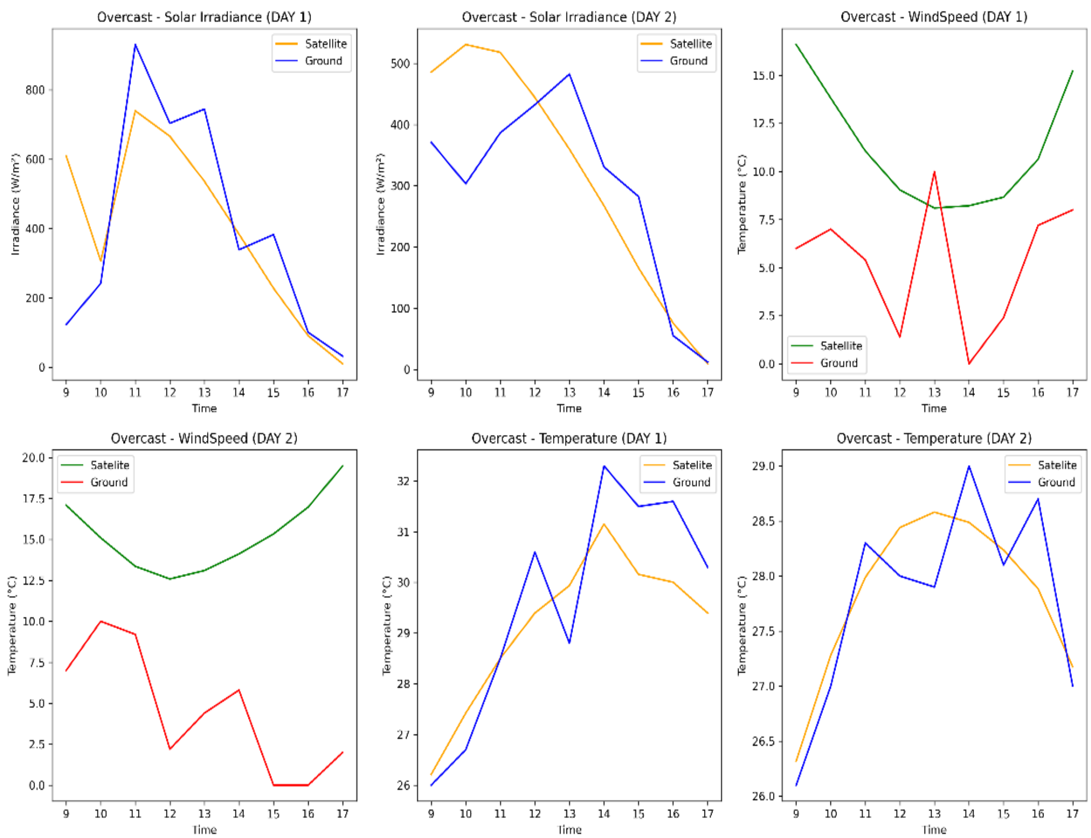


Figure 3: Comparison of Satellite and In Situ Measurements for Solar Irradiance, Wind Speed, and Temperature on Overcast Days

Figure 3 shows distributions for overcast weather. Here, solar irradiance from MERRA-2 maintained agreement with in-situ measurements, though with more obvious differences in intensity throughout the day compared to sunny conditions. Temperature measurements showed consistent alignment between MERRA-2 and in-situ sources during both day and night periods. Wind speed measurements revealed greater differences between datasets, with MERRA-2 measurements revealed greater differences between datasets, with MERRA-2 observations displaying less sensitivity to the different conditions captured by in-situ instruments.

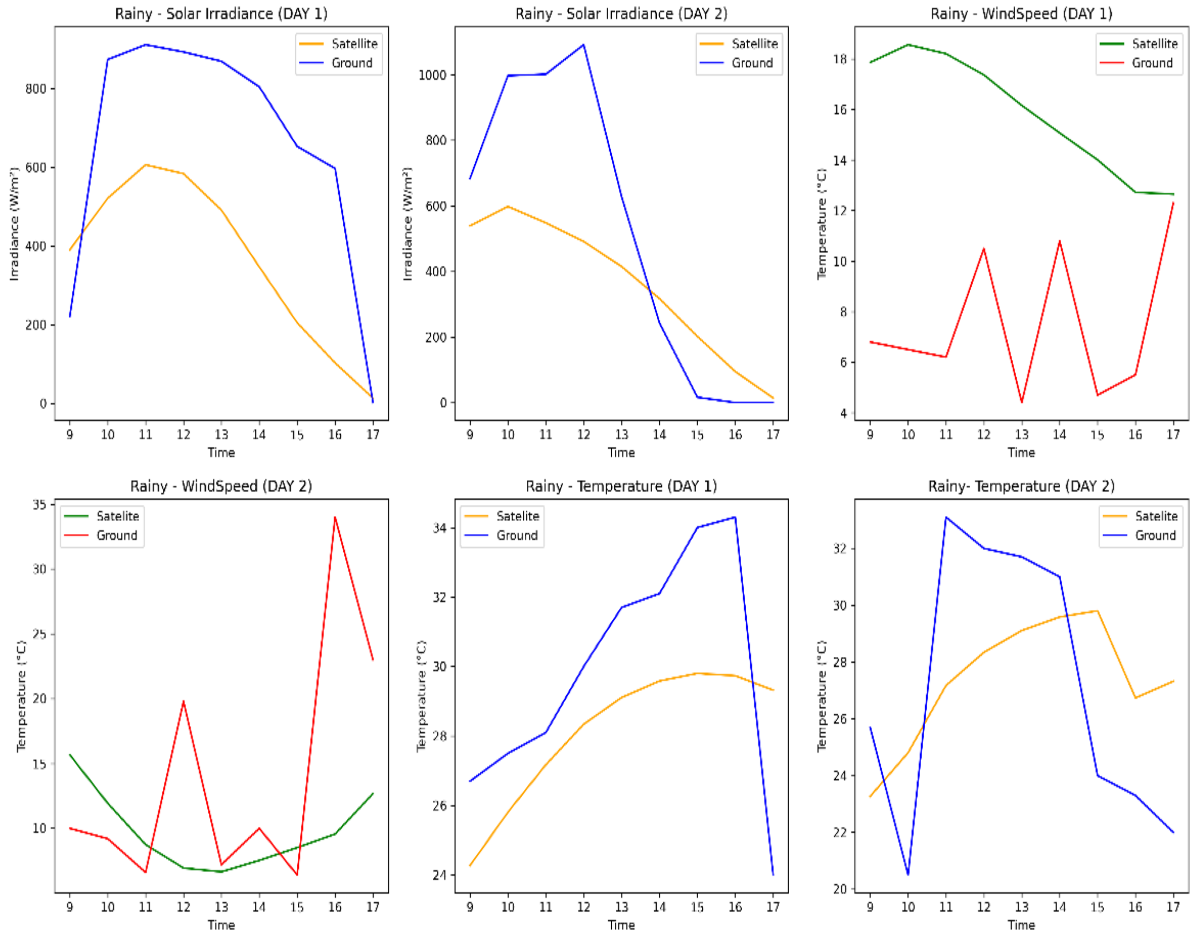


Figure 4: Comparison of Satellite and In-Situ Measurements for Solar Irradiance, Wind Speed, and Temperature on Rainy Day.

Figure 4 displays distributions for rainy weather. Here, solar irradiance from MERRA-2 showed agreement with in-situ measurements, though with more frequent deviations throughout the day. Temperature observations maintained reasonable agreement between MERRA-2 and in-situ sources across most time periods. Wind speed measurements showed the most disparities, with MERRA-2 data struggling to match the variable conditions recorded by in-situ stations during precipitation events.

Performance Metrics

This section presents the correlations performance between satellite and in-situ measurements for solar irradiance, wind speed, and temperature under sunny, overcast and rainy conditions.

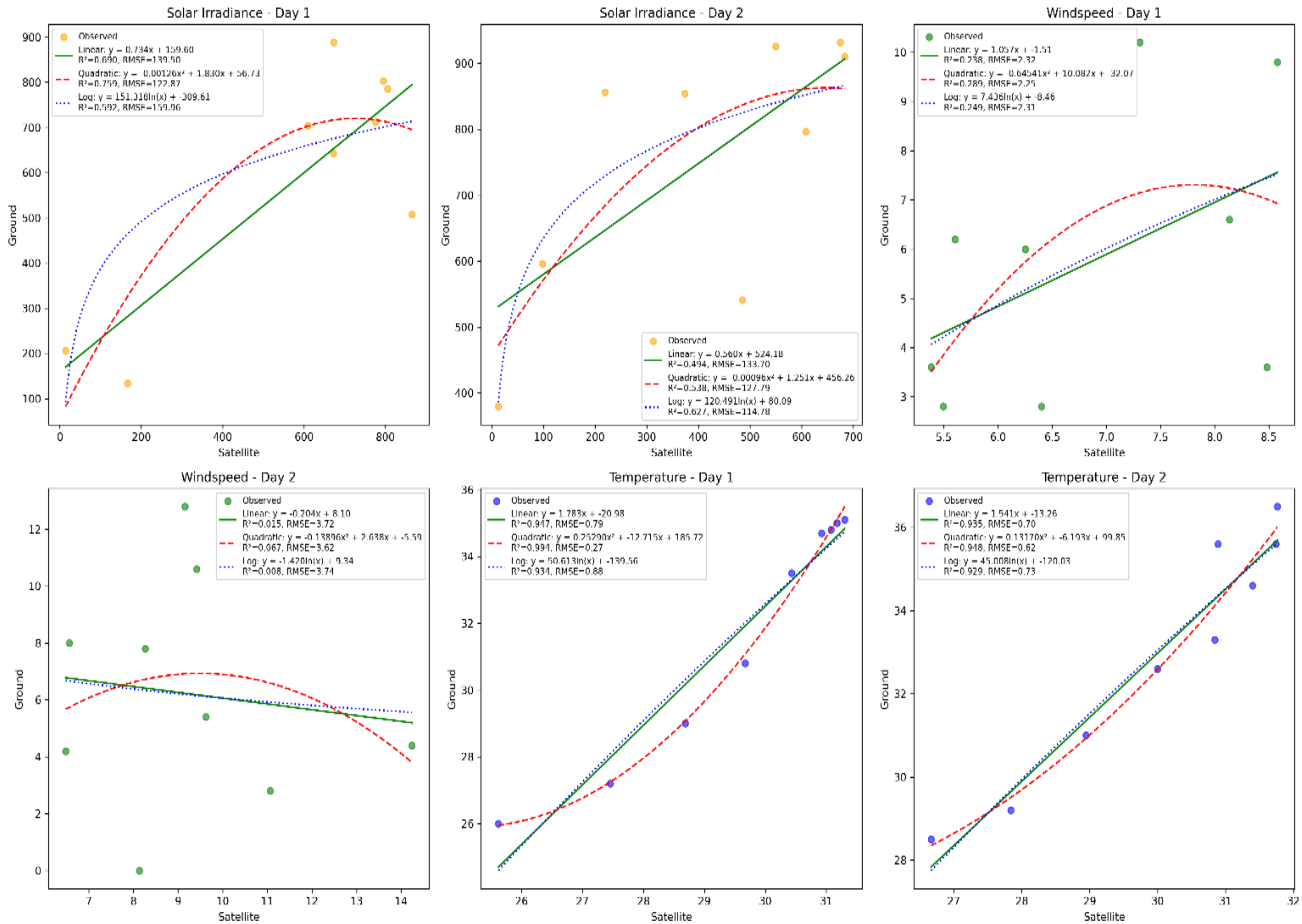


Figure 5: Correlation Between Satellite and In-Situ Measurements for Solar Irradiance, Wind Speed, and Temperature for Sunny Days

Table 1: Statistical Performance for sunny days

Parameter	Day	Regression Type	Equation	R^2	RMSE
Solar Irradiance	Day 1	Linear	y = 0.734x + 159.60	0.69	139.5
Solar Irradiance	Day 1	Quadratic	$y = -0.00126x^2 + 1.830x + 56.73$	0.759	122.87
Solar Irradiance	Day 1	Logarithmic	y = 151.318ln(x) + -309.61	0.592	159.96
Solar Irradiance	Day 2	Linear	y = 0.560x + 524.18	0.494	133.7
Solar Irradiance	Day 2	Quadratic	$y = -0.00096x^2 + 1.251x + 456.26$	0.538	127.79
Solar Irradiance	Day 2	Logarithmic	y = 120.491ln(x) + 80.09	0.627	114.78
Windspeed	Day 1	Linear	y = 1.057x + -1.51	0.238	2.32
Windspeed	Day 1	Quadratic	$y = -0.64541x^2 + 10.082x + -32.07$	0.289	2.25
Windspeed	Day 1	Logarithmic	y = 7.436ln(x) + -8.46	0.249	2.31
Windspeed	Day 2	Linear	y = -0.204x + 8.10	0.015	3.72
Windspeed	Day 2	Quadratic	$y = -0.13896x^2 + 2.638x + -5.59$	0.067	3.62
Windspeed	Day 2	Logarithmic	y = -1.420ln(x) + 9.34	0.008	3.74
Temperature	Day 1	Linear	y = 1.783x + -20.98	0.947	0.79
Temperature	Day 1	Quadratic	$y = 0.25290x^2 + -12.715x + 185.72$	0.994	0.27
Temperature	Day 1	Logarithmic	y = 50.613ln(x) + -139.56	0.934	0.88
Temperature	Day 2	Linear	y = 1.541x + -13.26	0.935	0.7
Temperature	Day 2	Quadratic	$y = 0.13170x^2 + -6.193x + 99.85$	0.948	0.62
Temperature	Day 2	Logarithmic	y = 45.008ln(x) + -120.03	0.929	0.73

Figure 5 and Table 1 show the correlation performance between satellite and in-situ measurements for solar irradiance, wind speed, and temperature under sunny conditions, MERRA-2 satellite-derived data showed varied agreement with in-situ measurements across solar irradiance, temperature, and windspeed. For solar irradiance, a moderate to strong correlation was observed. On Day 1, the quadratic model provided the best fit (R^2 = 0.759, RMSE = 122.87 W/m²), outperforming the linear (R^2 = 0.690) and logarithmic (R^2 = 0.592) models. On Day 2, the logarithmic model achieved the lowest RMSE (114.78 W/m²), though the quadratic model retained a slightly better R^2 (0.538), reflecting moderate nonlinearity. These findings are consistent with the evaluation conducted by Khadka et al. (2022), who reported that reanalysis radiation products such as ERA5-Land can exhibit reasonable agreement with ground-based observations, although performance is influenced by site-specific factors such as elevation differences and local atmospheric conditions. Similarly, Boyo and Adeyemi (2012) demonstrated that statistical metrics such as RMSE and MBE are effective tools for assessing agreement between satellite-derived and in-situ solar radiation measurements.

For temperature, strong consistency was observed. The quadratic model gave near-perfect fits on both days (R^2 = 0.994 and 0.948; RMSE = 0.27 °C and 0.62 °C), indicating excellent agreement. This supports findings from (Katsekpor et al., 2024), who reported high reliability of reanalysis temperature data in West Africa. The high accuracy under sunny skies highlights the suitability of satellite temperature data for monitoring applications in clear weather.

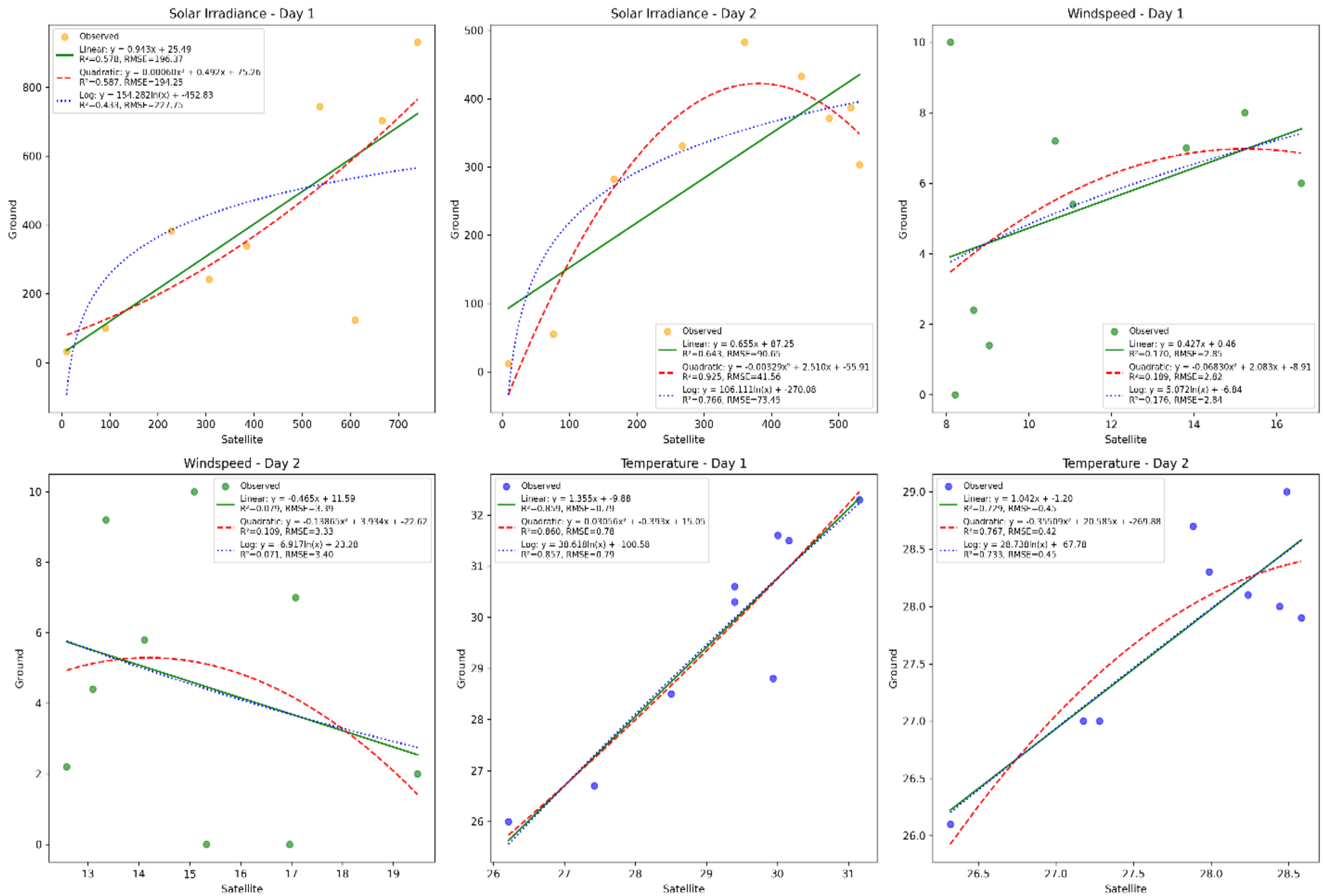


Figure 6: Correlation Between MERRA 2 and In-Situ Measurements for Solar Irradiance, Wind Speed, and Temperature for Overcast Day

Windspeed, however, exhibited poor agreement. The best model (quadratic) yielded only $R^2 = 0.289$ (RMSE = 2.25 m/s) on Day 1, and all models had $R^2 < 0.07$ on Day 2. This is consistent with (Potisomporn et al., 2023) and (Alkhalidi et al., 2025), who noted that satellite products often underestimate wind variability and fail to capture localized patterns.

Table 2: Statistical Performance for Overcast days

Parameter	Day	Regression Type	Equation	R^2	RMSE
Solar Irradiance	Day 1	Linear	$y = 0.943x + 25.49$	0.578	196.37
Solar Irradiance	Day 1	Quadratic	$y = 0.00060x^2 + 0.492x + 75.26$	0.587	194.25
Solar Irradiance	Day 1	Logarithmic	$y = 154.282\ln(x) + -452.83$	0.433	227.75
Solar Irradiance	Day 2	Linear	$y = 0.655x + 87.25$	0.643	90.65
Solar Irradiance	Day 2	Quadratic	$y = -0.00329x^2 + 2.510x + -55.91$	0.925	41.56
Solar Irradiance	Day 2	Logarithmic	$y = 106.111\ln(x) + -270.08$	0.766	73.45
Windspeed	Day 1	Linear	$y = 0.427x + 0.46$	0.17	2.85
Windspeed	Day 1	Quadratic	$y = -0.06830x^2 + 2.083x + -8.91$	0.189	2.82
Windspeed	Day 1	Logarithmic	$y = 5.072\ln(x) + -6.84$	0.176	2.84
Windspeed	Day 2	Linear	$y = -0.465x + 11.59$	0.079	3.39
Windspeed	Day 2	Quadratic	$y = -0.13865x^2 + 3.934x + -22.62$	0.109	3.33
Windspeed	Day 2	Logarithmic	$y = -6.917\ln(x) + 23.28$	0.071	3.4
Temperature	Day 1	Linear	$y = 1.355x + -9.88$	0.859	0.79
Temperature	Day 1	Quadratic	$y = 0.03056x^2 + -0.393x + 15.05$	0.86	0.78
Temperature	Day 1	Logarithmic	$y = 38.618\ln(x) + -100.58$	0.857	0.79
Temperature	Day 2	Linear	$y = 1.042x + -1.20$	0.729	0.45
Temperature	Day 2	Quadratic	$y = -0.35509x^2 + 20.585x + -269.88$	0.767	0.42
Temperature	Day 2	Logarithmic	$y = 28.738\ln(x) + -67.78$	0.733	0.45

Figure 6 and Table 2 show the correlation performance between satellite and in-situ measurements for solar irradiance, wind speed, and temperature under overcast conditions, the relationship between MERRA 2 reanalysis and in-situ data varied by parameter. For solar irradiance, Day 1 showed moderate correlation, with the quadratic model performing best ($R^2 = 0.587$, RMSE = 194.25 W/m²), closely followed by the linear ($R^2 = 0.578$) and logarithmic ($R^2 = 0.433$) models. On Day 2, performance improved markedly, with the quadratic model achieving a strong fit ($R^2 = 0.925$, RMSE = 41.56 W/m²), suggesting more stable satellite estimates despite cloud cover.

Temperature maintained high reliability, with the quadratic model again yielding the best fits $R^2 = 0.860$ (RMSE = 0.78 °C) on Day 1 and $R^2 = 0.767$ (RMSE = 0.42 °C) on Day 2 demonstrating that satellite-derived temperature remains robust even under limited solar exposure. This aligns with (Katsekpor, 2024), who found temperature to be one of the most dependable reanalysis parameters across varying weather scenarios.

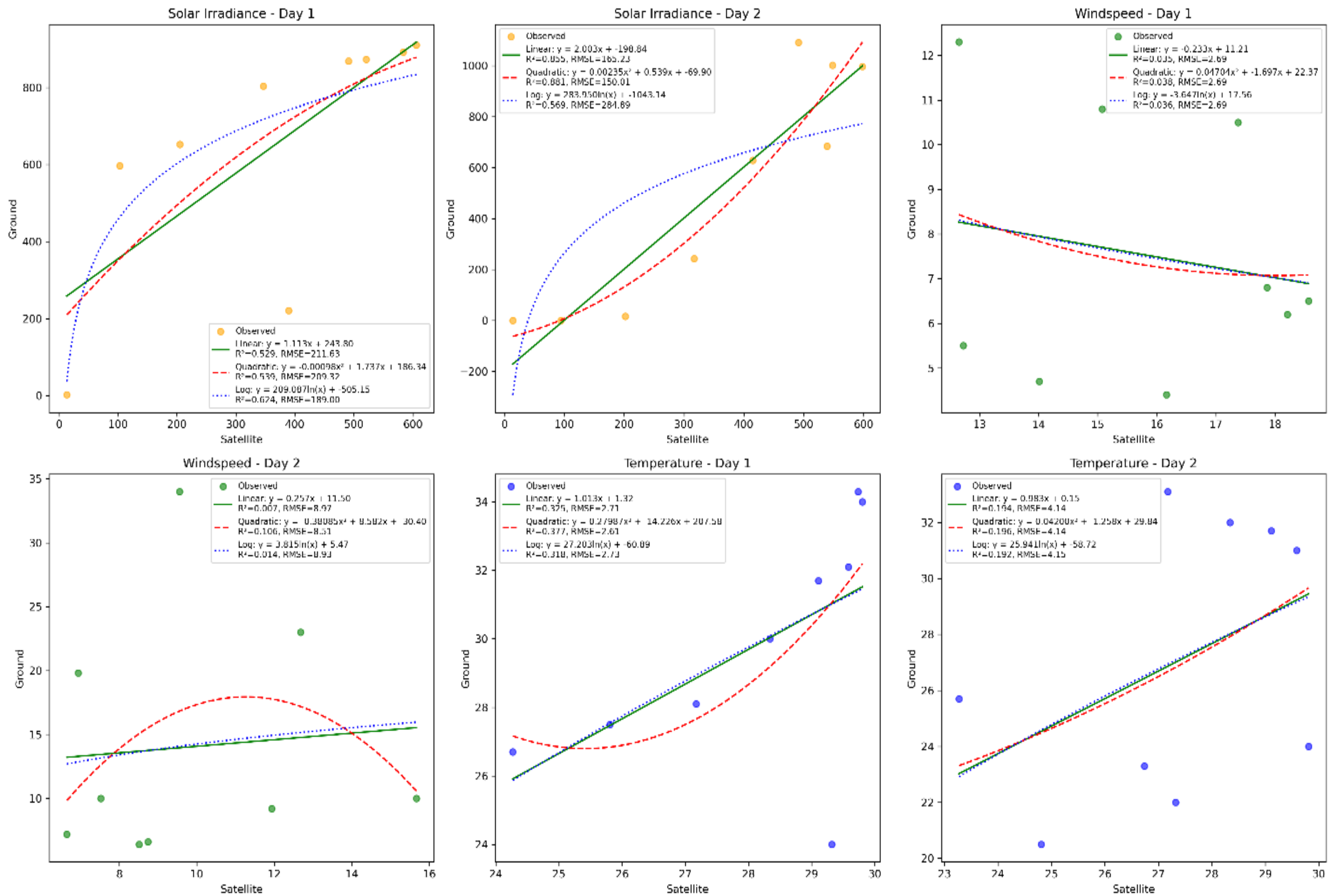


Figure 7: Correlation Between Satellite and In-Situ Measurements for Solar Irradiance, Wind Speed, and Temperature for Rainy Days

Table 3: Statistical Performance for Rainy days

Parameter	Day	Regression Type	Equation	R^2	RMSE
Solar Irradiance	Day 1	Linear	$y = 1.113x + 243.80$	0.529	211.63
Solar Irradiance	Day 1	Quadratic	$y = -0.00098x^2 + 1.737x + 186.34$	0.539	209.32
Solar Irradiance	Day 1	Logarithmic	$y = 209.087\ln(x) + -505.15$	0.624	189
Solar Irradiance	Day 2	Linear	$y = 2.003x + -198.84$	0.855	165.23
Solar Irradiance	Day 2	Quadratic	$y = 0.00235x^2 + 0.539x + -69.90$	0.881	150.01
Solar Irradiance	Day 2	Logarithmic	$y = 283.950\ln(x) + -1043.14$	0.569	284.89
Windspeed	Day 1	Linear	$y = -0.233x + 11.21$	0.035	2.69
Windspeed	Day 1	Quadratic	$y = 0.04704x^2 + -1.697x + 22.37$	0.038	2.69
Windspeed	Day 1	Logarithmic	$y = -3.647\ln(x) + 17.56$	0.036	2.69
Windspeed	Day 2	Linear	$y = 0.257x + 11.50$	0.007	8.97
Windspeed	Day 2	Quadratic	$y = -0.38085x^2 + 8.582x + -30.40$	0.106	8.51
Windspeed	Day 2	Logarithmic	$y = 3.815\ln(x) + 5.47$	0.014	8.93
Temperature	Day 1	Linear	$y = 1.013x + 1.32$	0.325	2.71
Temperature	Day 1	Quadratic	$y = 0.27987x^2 + -14.226x + 207.58$	0.377	2.61
Temperature	Day 1	Logarithmic	$y = 27.203\ln(x) + -60.89$	0.318	2.73
Temperature	Day 2	Linear	$y = 0.983x + 0.15$	0.194	4.14
Temperature	Day 2	Quadratic	$y = 0.04200x^2 + -1.258x + 29.84$	0.196	4.14
Temperature	Day 2	Logarithmic	$y = 25.941\ln(x) + -58.72$	0.192	4.15

In contrast, windspeed correlations remained poor. On Day 1, the best model (quadratic) showed low accuracy (R^2 = 0.189, RMSE = 2.82 m/s), while all models produced R^2 values below 0.1 on Day 2. These results reflect the limitations identified by Alkhalidi et al. (2025) and Potisomporn et al. (2023), who reported that satellite datasets often fail to capture localized wind behavior, especially under variable atmospheric conditions.

Figure 7 and Table 3 show the correlation performance between satellite and in-situ measurements for solar irradiance, wind speed, and temperature during rainy conditions, satellite-derived estimates, showed varying performance across parameters. For solar irradiance, Day 1 showed moderate correlation, with the logarithmic model performing slightly better (R^2 = 0.624, RMSE = 189 W/m²) than the quadratic (R^2 = 0.539) and linear (R^2 = 0.529) models. On Day 2, performance improved with the quadratic model achieving a strong fit (R^2 = 0.881, RMSE = 150.01 W/m²), indicating its ability to better capture irradiance dynamics under rainfall. This agrees with Khadka et al. (2022), who observed that reanalysis irradiance data can still provide meaningful results under cloud-heavy conditions when using appropriate models. The findings also complement Boyo and Adeyemi. (2012), who demonstrated the usefulness of RMSE and other statistical tools in evaluating satellite-ground agreement during variable weather.

Windspeed estimates remained poor throughout, with R^2 values consistently below 0.11 and RMSEs reaching up to 8.97 m/s which is likely due to MERRA-2's grid smoothing, which dampens local gusts and terrain-driven wind variations, causing large differences compared to high-resolution ground measurements. This reflects the known limitations of satellite products under precipitation, as supported by Alkhalidi et al. (2025) and Potisomporn et al. (2023), who found that reanalysis datasets often underestimate wind variability and fail to represent localized gusts during storms.

Temperature performance declined significantly compared to sunny and overcast conditions. Day 1 showed low-to-moderate agreement (quadratic: R^2 = 0.377, RMSE = 2.61 °C), while Day 2 exhibited poor correlation across all models. This declination under rain may be attributed to cloud cover, which modifies surface radiation and dampens the diurnal temperature cycle, making satellite and reanalysis estimates less accurate (Mueller et al., 2011; Martens et al., 2020).

This study recommend the use of MERRA-2 for temperature and solar studies in southern Nigeria with site-specific bias correction, but caution against its use for wind-resource assessment without dense ground-based validation

Study Limitations

This study focused on a limited number of representative days per weather category to ensure balanced comparison across atmospheric conditions. While this controlled design enables detailed event-based evaluation, it may restrict broader seasonal generalization. Future studies incorporating full seasonal or multi-year datasets would further strengthen statistical robustness and general applicability of the findings.

CONCLUSION

This study successfully conducted a comprehensive evaluation of MERRA-2 reanalysis data against in-situ observations of solar radiation, temperature, and wind speed, specifically accounting for variations under sunny, overcast, and rainy weather conditions in Southern Nigeria. The comparative analysis revealed distinct patterns in the reliability of MERRA-2 data across the atmospheric parameters.

For temperature, MERRA-2 consistently demonstrated strong agreement with in-situ measurements, maintaining high reliability even under limited solar exposure or during precipitation events. This consistent accuracy, often reflected by high R^2 values and low RMSE, supports the suitability of satellite-derived temperature data for monitoring applications across diverse weather scenarios.

Also, in solar irradiance the study found moderate to strong correlations between MERRA-2 and in-situ observations. While peak values were sometimes underestimated on sunny days, and more obvious intensity differences appeared on overcast days, specific regression models, particularly quadratic and logarithmic forms, were able to capture these dynamics effectively, providing meaningful results even under cloud-heavy or rainy conditions.

Wind speed measurements from MERRA-2 consistently exhibited poor agreement with in-situ observations across all assessed weather conditions. The satellite data struggled to capture variations and localized patterns observed by ground instruments, particularly during precipitation events, yielding very low R^2 values. This aligns with known limitations of satellite products in accurately representing localized wind behavior.

In conclusion, the findings provide crucial insights into the reliability of satellite data for local-scale environmental monitoring, renewable energy planning, and climate analysis in Southern Nigeria. While MERRA-2 temperature data is highly dependable and solar irradiance data shows potential with appropriate model selection, its utility for wind speed assessment is severely limited. These results emphasize the continued necessity of robust in-situ observation networks, especially for parameters like wind speed, to complement satellite-derived datasets and ensure accurate environmental and climatic assessments.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the use of data products from NASA's Giovanni online data system, developed and maintained by the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC).

REFERENCES

Penza, V., Berrilli, F., Bertello, L., Cantoresi, M., Criscuoli, S., & Giobbi, P. (2022). Total Solar Irradiance during the Last Five Centuries. *The Astrophysical Journal*, *937*(2), 84. https://doi.org/10.3847/1538-4357/ac8a4b

Kren, A. C., Pilewskie, P., & Coddington, O. (2017). Where does Earth's atmosphere get its energy? *Journal of Space Weather and Space Climate*, *7*, A10. https://doi.org/10.1051/swsc/2017007

Hekmatzadeh, A. A., Kaboli, S., & Haghighi, A. T. (2020). New indices for assessing changes in seasons and in timing characteristics of air temperature. *Theoretical and Applied Climatology*, *140*(3–4), 1247–1261. https://doi.org/10.1007/s00704-020-03156-w

Ahmadi F, Nazeri Tahroudi M, Mirabbasi R, Khalili K, Jhajharia D (2018) Spatiotemporal trend and abrupt change analysis of temperature in Iran. Meteorol Appl 25:314–321

Astsatryan, H., Grigoryan, H., Poghosyan, A., Abrahamyan, R., Asmaryan, S., Muradyan, V., Tepanosyan, G., Guigoz, Y., & Giuliani, G. (2021). Air temperature forecasting using artificial neural network for Ararat valley. *Earth Science Informatics*, *14*(2), 711–722. https://doi.org/10.1007/s12145-021-00583-9

Malik, P., Gehlot, A., Singh, R., Gupta, L. R., & Thakur, A. K. (2022). A Review on ANN Based Model for Solar Radiation and Wind Speed Prediction with Real-Time Data. *Archives of Computational Methods in Engineering*, *29*(5), 3183–3201. https://doi.org/10.1007/s11831-021-09687-3

Boyo, A. O., & Adeyemi, K. (2012). Analysis of Solar Radiation data From Satellite and Nigeria Meteorolocical Station. *International Journal of Renewable Energy Research*, *1*(4), 314–322. https://doi.org/10.20508/ijrer.29218

Malvern, S. F., & Maurice, C. (2018b). Comparison of satellite data and ground-based weather data in Masvingo, Zimbabwe. *International Journal of Environmental Sciences & Natural Resources*, *8*(3). https://doi.org/10.19080/ijesnr.2018.08.555739

Katsekpor, J. T., Greve, K., Yamba, E. I., & Amoah, E. G. (2024b). Comparative analysis of satellite and reanalysis data with ground-based observations in Northern Ghana. *Meteorological Applications*, *31*(4). https://doi.org/10.1002/met.2226

Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., Randles, C. A., Darmenov, A., Bosilovich, M. G., Reichle, R., Wargan, K., Coy, L., Cullather, R., Draper, C., Akella, S., Buchard, V., Conaty, A., Da Silva, A. M., Gu, W., . . . Zhao, B. (2017). The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). *Journal of Climate*, *30*(14), 5419–5454. https://doi.org/10.1175/jcli-d-16-0758.1

Molod, A., L. Takacs, M. Suárez, and J. Bacmeister, (2015). Development of the GEOS-5 atmospheric general circulation model: Evolution from MERRA to MERRA2. Geosci. Model Dev., 8, 1339–1356, https://doi.org/10.5194/gmd-8-1339-2015.

Wu, W. S., R. J. Purser, and D. F. Parrish, (2002). Three-dimensional variational analysis with spatially inhomogeneous covariances. Mon. Wea. Rev., 130, 2905–2916, https://doi.org/10.1175/1520-0493(2002)130,2905:TDVAWS.2.0.CO;2.

Schuurman, K. R., & Meyer, A. (2025). Surface solar radiation: AI satellite retrieval can outperform Heliosat and generalizes to other climate zones. *International Journal of Remote Sensing*, 1–32. https://doi.org/10.1080/01431161.2025.2471596

Criqui, P., Mima, S., & Viguier, L. (1999). Marginal abatement costs of CO2 emission reductions, geographical flexibility and concrete ceilings: an assessment using the POLES model. *Energy Policy*, *27*(10), 585–601. https://doi.org/10.1016/s0301-4215(99)00051-8

Ellerman, A. D., & Decaux, A. (1998). Analysis of post-Kyoto CO_2 emissions trading using marginal abatement curves. *MIT Working Paper*. http://dspace.mit.edu/bitstream/handle/1721.1/3608/MITJPSPGC_Rpt40.pdf?sequence=1

Morris J, Paltsev S, Reilly J. Marginal abatement costs and marginal welfare costs for greenhouse gas emissions reductions: results from the EPPA model. Environmental Modeling & Assessment 2012;17; 325-336.

Nordhaus WD. The cost of slowing climate change: a survey. The Energy journal 1991;12; 37-66. Oh D-h. A metafrontier approach for measuring an environmentally sensitive productivity growth index.Energy Economics 2010;32; 146-157.

Zhou P, Zhang L, Zhou DQ, Xia WJ. Modeling economic performance of interprovincial CO_2 emission reduction quota trading in China. Applied Energy 2013;112; 1518-1528.

HaliMi, A. H., Karaca, C., & Büyüktaş, D. (2023). Evaluation of NASA POWER Climatic Data against Ground-Based Observations in The Mediterranean and Continental Regions of Turkey. *Tekirdağ Ziraat Fakültesi Dergisi*, *20*(1), 104–114. https://doi.org/10.33462/jotaf.1073903

Willmott, C.J., Matsuura, K. (2006). On the use of dimensioned measures of error to evaluate the performance of spatial interpolators. International Journal of Geographical Information Science, 20: 89-102

Esposito, E., Leanza, G., & Di Francia, G. (2024). Comparative analysis of Ground-Based solar irradiance measurements and Copernicus satellite observations. *Energies*, *17*(7), 1579. https://doi.org/10.3390/en17071579

Khadka, A., Wagnon, P., Brun, F., Shrestha, D., Lejeune, Y., & Arnaud, Y. (2022). Evaluation of ERA5-Land and HARV2 reanalysis data at high elevation in the Upper Dudh Koshi Basin (Everest Region, Nepal). *Journal of Applied Meteorology and Climatology*, *61*(8), 931–954. https://doi.org/10.1175/jamc-d-21-0091.1

Katsekpor, J. T., Greve, K., Yamba, E. I., & Amoah, E. G. (2024b). Comparative analysis of satellite and reanalysis data with ground-based observations in Northern Ghana. *Meteorological Applications*, *31*(4). https://doi.org/10.1002/met.2226

Alkhalidi, M., Al-Dabbous, A., Al-Dabbous, S., & Alzaid, D. (2025). Evaluating the accuracy of the ERA5 model in predicting wind speeds across coastal and offshore regions. *Journal of Marine Science and Engineering*, *13*(1), 149. https://doi.org/10.3390/jmse13010149

Potisomporn, P., Adcock, T. A., & Vogel, C. R. (2023). Evaluating ERA5 reanalysis predictions of low wind speed events around the UK. *Energy Reports*, *10*, 4781–4790. https://doi.org/10.1016/j.egyr.2023.11.035