Assessing the Suitability of NASA POWER Temperature Products for Filling Climatic Data Gaps in Sri Lanka

J K H Madushan, K P S C Jayaratne, and A L K Wijemannage

Astronomy and Space Science Unit, Department of Physics, University of Colombo, Colombo - 03, Sri Lanka

chandanajayaratne@gmail.com

1. ABSTRACT

The NASA Prediction of Worldwide Energy Resources (NASA POWER) project provides accessible, satellite-derived daily meteorological datasets at a 0.5° × 0.625° spatial resolution, serving as a vital resource for environmental and agricultural modeling in regions with sparse ground observations. This study investigates the precision of NASA POWER's daily temperature estimates by comparing them with calculated and observed ground temperatures from 11 stations across Sri Lanka over a 30-year span. Five statistical assessments were conducted across four parameters: Daily Maximum Temperature (T_{Max}), Daily Minimum Temperature (T_{Min}), Daily Mean Temperature (T_{Mean}), and Daily Temperature Range (DTR). The statistical metrics used were the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), and Willmott Index of Agreement (d). Validation revealed a relative performance hierarchy, determined by a combined assessment of correlation, absolute errors, and systematic biases. While T_{Max} showing the highest correlation (mean R^2 = 0.447), though the average RMSE was substantial at 2.72 °C. In contrast, T_{Min} exhibited a weaker correlation (mean R^2 = 0.393) with an average RMSE of 2.12 °C. Furthermore, the Mean Bias Error revealed significant regional systematic biases: while T_{Max} showed the highest random error (mean RMSE =2.72 °C), DTR showed the largest systematic bias (mean MBE = -1.79 °C) alongside a large RMSE (2.68 °C). T_{Mean} showed moderate correlation (mean R^2 = 0.444) with a smaller positive bias (MBE = +0.37 °C). Overall, the results suggest that NASA POWER data contain significant random errors across all parameters and exhibit systematic biases, particularly struggling with T_{Min} and DTR in high-elevation stations (e.g., Nuwara Eliya and Badulla). NASA POWER temperature data require parameter- and location-specific bias correction before use in applications demanding high accuracy in Sri Lanka.

Keywords: NASA POWER, Temperature, Remote Sensing, Satellite Reanalysis

2. INTRODUCTION

Accurate near-surface air temperature (≈2 m) data are fundamental for climate analysis, agriculture, hydrology, and environmental assessment[1–3]. Daily maximum temperature (T_{Max}) is critical for estimating evapotranspiration and heat stress, minimum temperature (T_{Min}) for cold stress and dew formation, and the Daily Temperature Range (DTR) for evaluating surface energy balance and boundary-layer processes[4,5]. In Sri Lanka, strong monsoon influences, coastal effects, and complex topography produce pronounced spatial variability, increasing the need for reliable temperature datasets[6–9].

Although ground-based observations provide direct measurements, sparse station networks, data gaps, and operational limitations restrict their spatial and temporal representativeness[10]. As a result, satellite-based and reanalysis products such as NASA Prediction of Worldwide Energy Resources (NASA POWER) are widely used, offering daily T_{Max} and T_{Min} at 0.5° × 0.625° resolution and enabling derivation of T_{Mean} and DTR in data-scarce regions[11].

Previous validation studies reported generally strong agreement between NASA POWER temperature estimates and observations, though systematic biases persist, often with higher accuracy for T_{Max} than T_{Min} and errors influenced by elevation, seasonality, and coastal proximity[12–15]. In Sri Lanka, limited evaluations suggest that NASA POWER temperatures are suitable for gap-filling despite identifiable biases[16], but assessments remain spatially and temporally constrained and largely exclude T_{Mean} and DTR.

This study addresses these gaps by evaluating NASA POWER daily T_{Max}, T_{Min}, T_{Mean}, and DTR against observations from 11 meteorological stations across Sri Lanka's major climatic zones, using standard statistical metrics (R^2, RMSE, MAE, MBE, and Willmott's d) to assess performance and applicability.

3. METHODOLOGY

3.1 Study Area

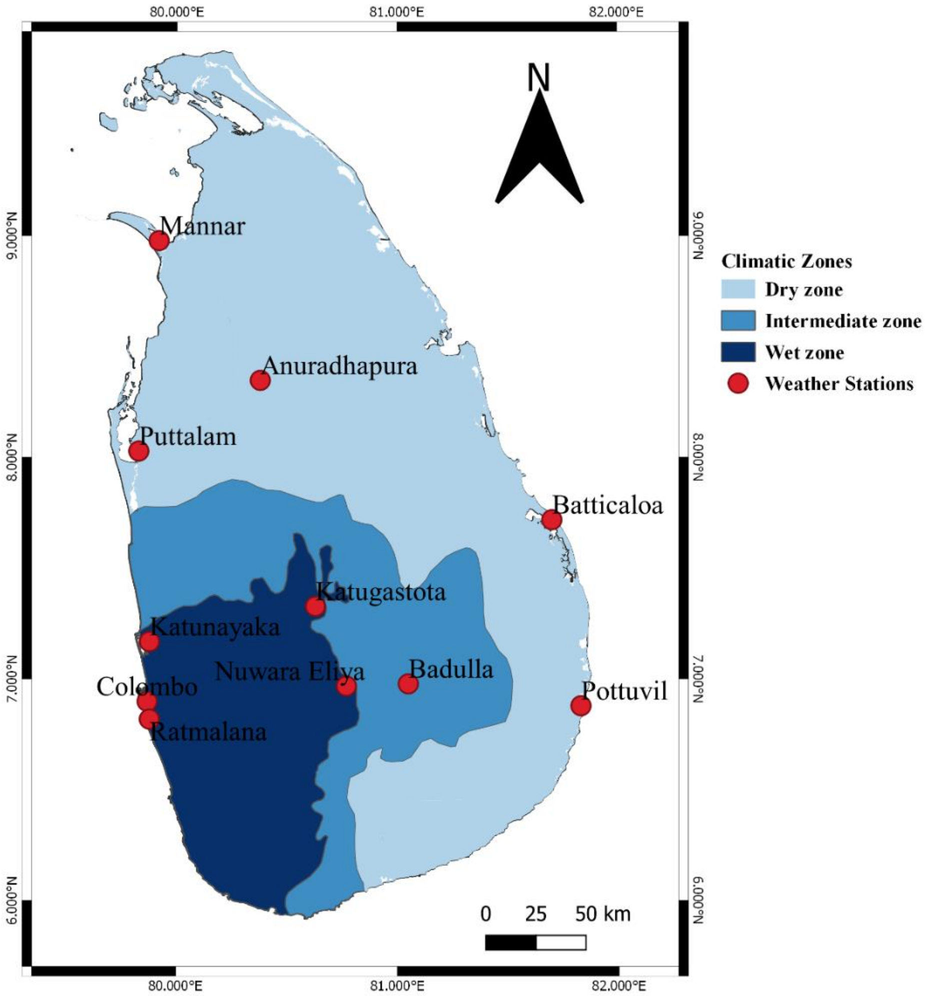
Sri Lanka is an island nation situated in the Indian Ocean, approximately between latitudes 5°55' N and 9°51' N and longitudes 79°42' E and 81°53' E. The country features a tropical monsoon climate characterized by distinct climatic zones influenced by two main monsoon periods (Southwest : May-September, Northeast : December-February) and two inter-monsoonal periods [17]. Sri Lanka is classified into three principal climatic zones based primarily on annual average rainfall: the Wet Zone (>2500 mm), the Intermediate Zone (1750 mm - 2500 mm), and the Dry Zone (<1750 mm)[9].

Table 1: Weather stations used in this study, climatic zone, elevation, latitude, and longitude

Climate Zone	Weather Station	Elevation (m)	Latitude (°N)	Longitude (°E)
Wet Zone	Colombo	7	6.90	79.87
	Katugastota	417	7.33	80.63
	Katunayaka	8	7.17	79.88
	Nuwara Eliya	1894	6.97	80.77
	Ratmalana	5	6.82	79.88
Intermediate Zone	Badulla	670	6.98	81.05
Dry Zone	Anuradhapura	92	8.35	80.38
	Batticaloa	8	7.72	81.70
	Mannar	4	8.98	79.92
	Pottuvil	4	6.88	81.83
	Puttalam	2	8.03	79.83

3.2 Data

Daily temperature data (1988–2018) were analyzed from 11 meteorological stations representing diverse elevations and geographical settings across three climatic zones (Figure



1; Table 1). Ground-based daily T_{Max} and T_{Min} provided by the Department of Meteorology, Sri Lanka, were compared with corresponding 2 m air temperatures retrieved from the NASA POWER data access viewer (v2.5.22; single-point method).

Figure 1: Spatial distribution of ground weather stations used in this study along with climatic zones

All datasets were processed to ensure temporal consistency. This involved merging the NASA and ground datasets based on a common 'Date' index and excluding all days with missing data in either the ground or POWER records. Subsequently, a rigorous quality control step was applied using the Interquartile Range (IQR) method to mitigate the influence of outliers on statistical metrics[18,19]. Data points that fell outside the range of $Q_1 - 1.5 \times IQR$ and $Q_3 + 1.5 \times IQR$ for both the predicted and observed temperature series were excluded from the final correlation analysis for each parameter.

To evaluate the statistical agreement between the NASA POWER estimates and the ground observations for the temperature parameters, five statistical metrics were employed. These metrics provide a comprehensive assessment of correlation, overall error magnitude, and systematic bias. The statistical tests and their standard formulas are listed in table 2.

Table 2: Statistical tests, formulas and their ideal conditions

Statistical Test	Formula	Ideal Conditions	Reference(s)
Coefficient of Determination (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$ (1)	Close to 1 (Range: 0 – 1)	[20]
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}}$ (2)	Close to 0 (Range: 0 – ∞)	[21,22]
Mean Bias Error (MBE)	$MBE = \frac{\sum_{i=1}^{n}(P_i - O_i)}{n}$ (3)	0 indicates no bias (Range: −∞ – +∞)	[23]
Willmott Index of Agreement (d)	$d = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(\lvert P_i - \bar{O}\rvert + \lvert O_i - \bar{O}\rvert)^2}$ (4)	Close to 1 (Range: 0 – 1)	[24,25]
Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert P_i - O_i\rvert$ (5)	Close to 0 (Range: 0 – ∞)	[26]

Note: O_i denotes the observed (ground), $\bar{O}$ denotes the average of observed, and P_i denotes the estimated/predicted (POWER) values.

4. RESULTS

The accuracy of the NASA POWER products was assessed against ground station observations across four parameters: T_{Max} , T_{Min}, T_{Mean} and DTR. The overall mean values for the five statistical metrics (R^2, MAE, MBE, RMSE, and d) across the 11 stations are summarized in Table 3.Because the correlation metrics ($R^2$and d) exhibited a narrow range of variation, the relative performance of each parameter was determined by evaluating the combined magnitude of absolute errors (RMSE, MAE) and systematic biases (MBE). Based on this combined assessment, T_{Max} and T_{Mean} exhibited the strongest performance ($R^2 \approx$ 0.447 and 0.444) with moderate errors (RMSE 2.72°C and 1.97°C), despite a negative bias in T_{Max} (MBE = −0.59°C) and slight positive bias in T_{Mean} (+0.37°C). Conversely, T_{Min} and DTR performed poorly. T_{Min} showed the lowest correlation (R^2 = 0.393) and systematic overestimation (MBE = +1.25°C), while DTR reflected compounded errors (MAE = 2.26°C) and strong underestimation (MBE = −1.79°C). As shown in Figures 6–10, T_{Mean} generally had the lowest error magnitudes, while DTR had the largest.

As shown in figures 2,3,4,5 and 6 spatially, NASA POWER performed best at low-elevation Dry Zone stations (e.g., Batticaloa, Mannar, Anuradhapura) but struggled significantly at coastal (Colombo, Ratmalana) and high-elevation sites. Nuwara Eliya emerged as an extreme outlier with minimal predictive reliability, recording RMSE > 6.9°C across all variables (except DTR), and massive overestimation of T_{Min}. While the dataset captures lowland variability reasonably well, it fails to accurately represent nocturnal cooling and diurnal amplitude in complex terrains.

Table 3: Summary of statistical test results for daily temperature parameters (overall)

Parameter	R^2 (Mean)	MAE (Mean) (°C)	RMSE (Mean) (°C)	MBE (Mean) (°C)	d (Mean)	Performance Assessment
T_{Max}	0.447	2.40	2.72	-0.59	0.63	Highest relative correlation; moderate absolute errors with a negative bias.
T_{Mean}	0.444	1.75	1.97	0.38	0.68	Lowest absolute errors; slight positive bias.
T_{Min}	0.393	1.87	2.12	1.25	0.66	Lowest correlation; strong systematic overestimation.
DTR	0.423	2.26	2.68	-1.79	0.68	Highest absolute errors; severe systematic underestimation.

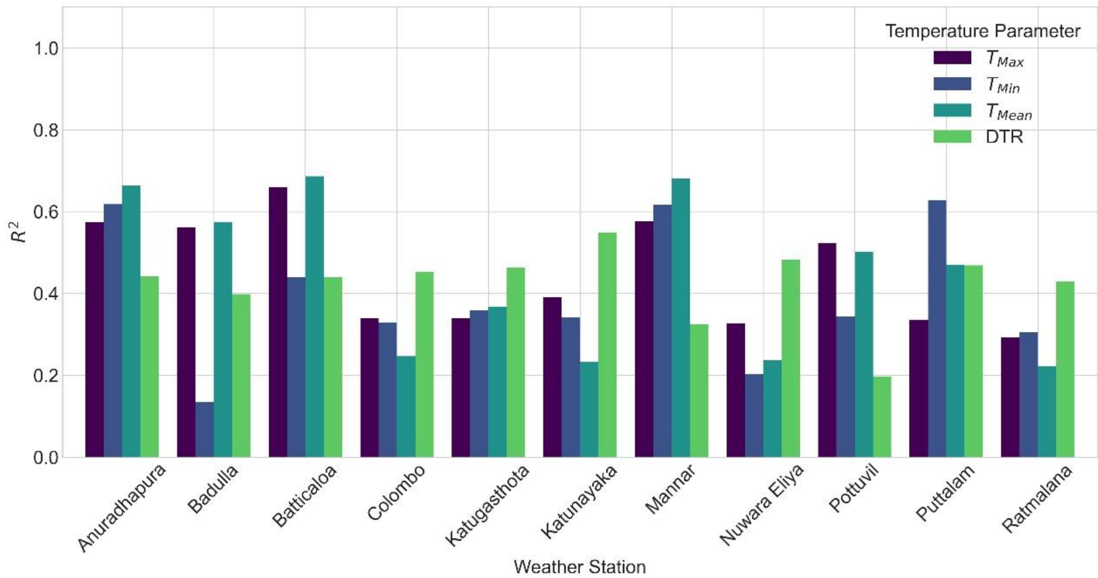


Figure 2: R^2 comparison by temperature parameter across all 11 weather stations

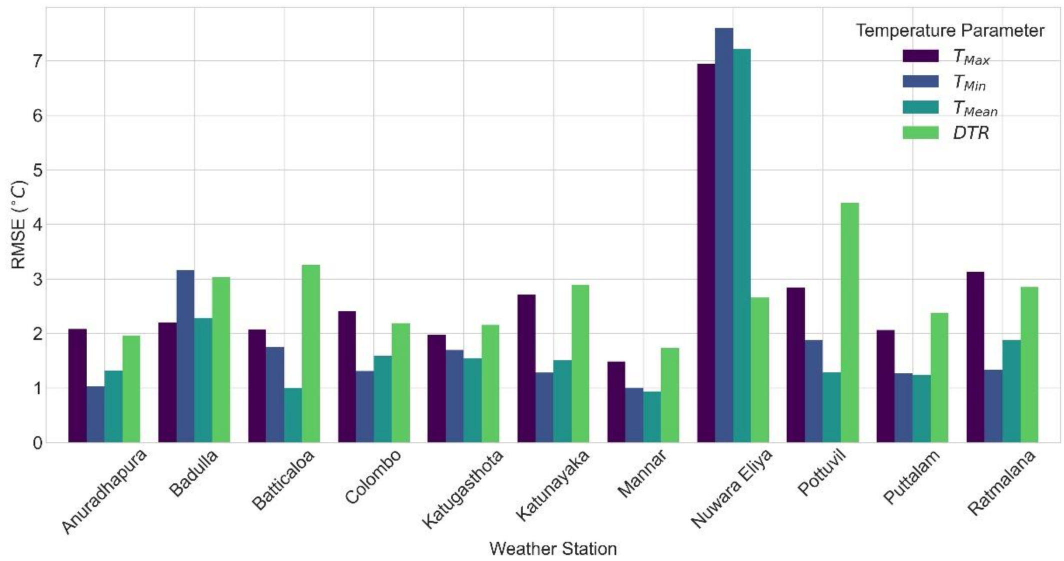


Figure: **3** RMSE comparison by temperature parameter across all 11 weather stations

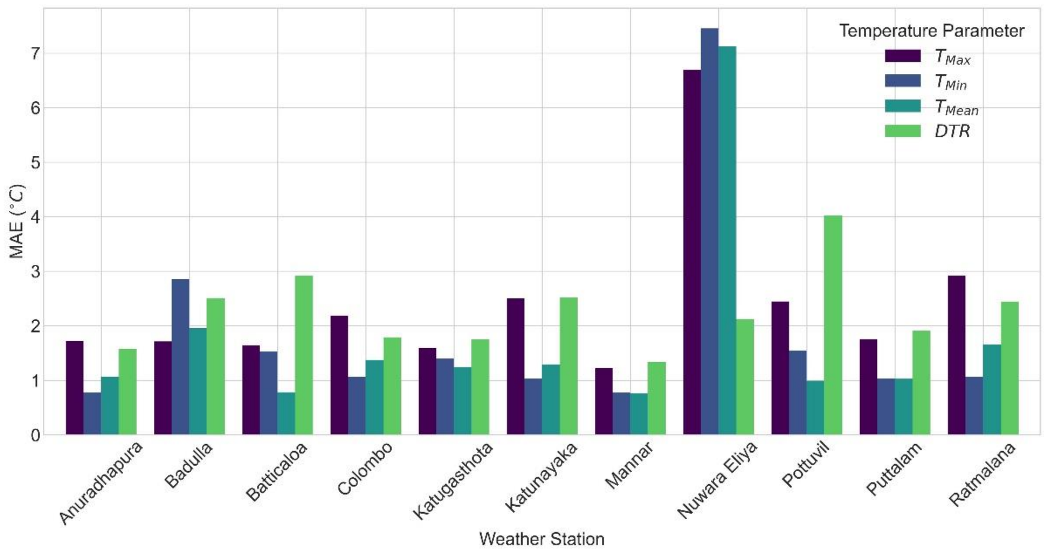


Figure 4: MAE comparison by temperature parameter across all 11 weather stations

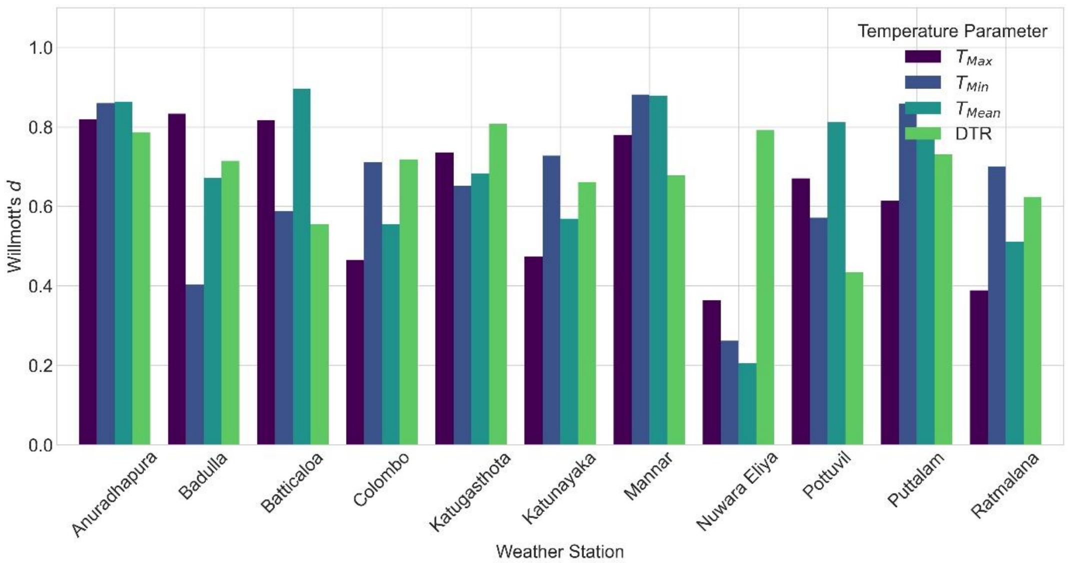


Figure 5: Willmott's d comparison by temperature parameter across all 11 weather stations

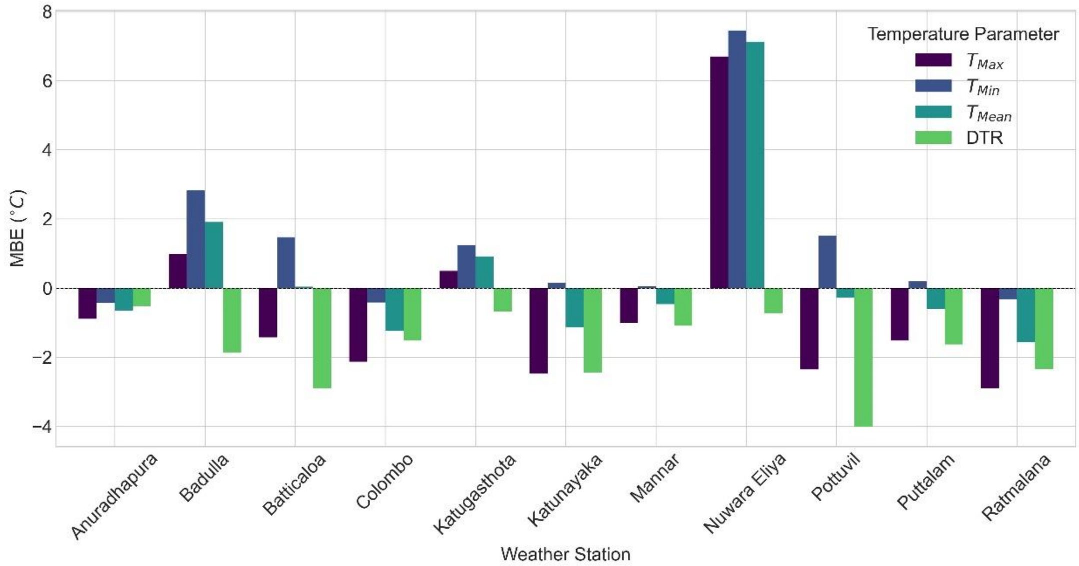


Figure 6: MBE comparison by temperature parameter across all 11 weather stations

5. DISCUSSION

The analysis confirmed that the accuracy of satellite-derived temperature estimates is highly variable, driven by parameter type and local geography. Comparing raw NASA POWER data against ground observations revealed larger errors and stronger systematic biases which cannot be neglected. Because correlation metrics (R^2 and d) were narrowly clustered across all parameters, the hierarchy was defined primarily by error magnitudes and systematic biases. While T_{Max} and T_{Mean} led slightly in correlation, the error magnitudes (RMSE, MAE) favored T_{Mean}, followed by T_{Max} and T_{Min}, with the DTR exhibiting the highest overall error and largest systematic bias.

T_{Max} showed the highest mean correlation ($R^2 \approx 0.447$), likely due to the dominance of solar radiation during daytime, which satellite sensors capture effectively. However, substantial random errors (RMSE ≈ 2.72 °C) and a negative bias (MBE ≈ -0.59°C) indicate a tendency to underestimate peak temperatures, particularly at coastal sites. In contrast, T_{Min} presented the greatest modeling challenges. It recorded the lowest correlation ($R^2 = 0.393$) and a systematic positive bias (MBE ≈ +1.25 °C), reflecting the limitations of reanalysis models in capturing nocturnal boundary-layer processes and terrestrial cooling.

These opposing biases—underestimation of T_{Max} and overestimation of T_{Min}—resulted in a severe compression of the DTR. DTR recorded the highest systematic error (MBE ≈ -1.79 °C) and substantial random error (RMSE ≈ 2.68 °C), confirming that the dataset fails to capture the full diurnal amplitude of Sri Lanka's climate. When compared to international literature, where R^2 values typically exceed 0.80 for continental regions, the correlations in this study are notably lower, and RMSE values are significantly higher.

Geographically, performance was markedly lower in complex terrain. High-elevation stations like Nuwara Eliya were outliers, with RMSE exceeding 7 °C for extreme variables and massive overestimation of T_{Min}. Conversely, flat Dry Zone regions (e.g., Mannar, Anuradhapura) showed superior agreement. While NASA POWER captures broad seasonal patterns, the prevalence of large random errors and systematic biases limits its daily reliability. For applications requiring high precision, such as agricultural modeling, station-specific bias correction is essential.

6. CONCLUSIONS

In this study, the accuracy of NASA POWER daily temperature products, T_{Max}, T_{Min}, T_{Mean}, and DTR was evaluated against daily ground-based observations from 11 meteorological stations across Sri Lanka using statistical indicators, including R^2, RMSE, MAE, MBE, and Willmott's d. The analysis provided key insights into the model's performance and limitations after correcting the validation methodology to compare raw datasets directly. The results revealed a clear performance hierarchy among temperature parameters, determined by a combined evaluation of correlation, absolute error, and systematic bias. While T_{Max} and T_{Mean} showed the highest correlations ($R^2 \approx 0.45$),their relative superiority is largely due to having lower bias and error magnitudes than the other parameters, though substantial absolute errors persisted across all variables, with mean RMSE values exceeding 1.90 °C for every parameter ($T_{Max} \approx 2.72\,^{\circ}\mathrm{C}$, $T_{Min} \approx 2.12\,^{\circ}\mathrm{C}$, $T_{Mean} \approx 1.97\,^{\circ}\mathrm{C}$, and DTR $\approx 2.68\,^{\circ}\mathrm{C}$). Significant systematic biases were also identified. T_{Min} exhibited a strong positive bias (overestimation) of approximately $+1.25\,^{\circ}\mathrm{C}$. Conversely, DTR showed a pronounced negative bias (underestimation) of approximately $-1.79\,^{\circ}\mathrm{C}$, primarily resulting from the combined effects of underestimating T_{Max}(mean MBE $\approx -0.59\,^{\circ}\mathrm{C}$) and overestimating T_{Min}. T_{Mean} displayed a smaller overall positive bias (mean MBE $\approx +0.37\,^{\circ}\mathrm{C}$). Geographical influences were also found to be critical. Stations located in high-elevation terrain, such as Badulla and Nuwara Eliya, showed the poorest agreement and largest errors. In contrast, flat, Dry Zone stations such as Mannar and Anuradhapura displayed relatively better correlations, though errors remained significant.

The magnitude of these biases is notably larger than suggested by traditional regression-based validation approaches. Despite the easy accessibility of the data, for applications demanding high temporal and spatial precision, such as precision agriculture, hydrological forecasting, and local climate impact assessments, parameter-specific and location-specific bias correction is strongly recommended rather than using the data directly. Future work should extend validation to humidity and radiation parameters, assess temporal stability across monsoonal transitions, and explore machine learning-based correction frameworks to enhance the reliability of NASA POWER products for tropical island environments.

7. REFERENCES

[1] Jones PD, New M, Parker DE, Martin S, Rigor IG. Surface air temperature and its changes over the past 150 years. Rev Geophys 1999;37:173–99. https://doi.org/10.1029/1999RG900002.

[2] Z Ustrnul, A Wypych DC. Air Temperature Change. Springer Clim., 2021, p. 45–68. https://doi.org/10.1007/978-3-030-70328-8_4.

[3] Aweda FO, Samson TK. Relationship between Air Temperature and Rainfall Variability of Selected Stations in Sub-Sahara Africa. Iran J Energy Environ 2022;13:248–57. https://doi.org/10.5829/IJEE.2022.13.03.05.

[4] Stone DA, Weaver AJ. Daily maximum and minimum temperature trends in a climate model. Geophys Res Lett 2002;29:70-1-70–4. https://doi.org/10.1029/2001GL014556.

[5] Caesar J, Alexander L, Vose R. Large-scale changes in observed daily maximum and minimum temperatures: Creation and analysis of a new gridded data set. J Geophys Res Atmos 2006;111. https://doi.org/10.1029/2005JD006280.

[6] Chandrasekara S, Prasanna V, Kwon H-H. Monitoring Water Resources over the Kotmale Reservoir in Sri Lanka Using ENSO Phases. Adv Meteorol 2017;2017:1–9. https://doi.org/10.1155/2017/4025964.

[7] Naveendrakumar G, Vithanage M, Kwon H-H, Iqbal MCM, Pathmarajah S, Obeysekera J. Five Decadal Trends in Averages and Extremes of Rainfall and Temperature in Sri Lanka. Adv Meteorol 2018;2018:1–13. https://doi.org/10.1155/2018/4217917.

[8] Shelton S, Pushpawela B, Liyanage G. The long-term trend in the diurnal temperature range over Sri Lanka from 1985 to 2017 and its association with total cloud cover and rainfall. J Atmos Solar-Terrestrial Phys 2022;227:105810. https://doi.org/10.1016/j.jastp.2021.105810.

[9] Madushan H, Jayaratne C, Wijemannage A. Evaluation of NASA POWER Daily Rainfall Products Against Ground Observations in Sri Lanka. Remote Sens Earth Syst

Sci 2025;8:264–72. https://doi.org/10.1007/s41976-024-00173-5.

[10] Sun Y-J, Wang J-F, Zhang R-H, Gillies RR, Xue Y, Bo Y-C. Air temperature retrieval from remote sensing data based on thermodynamics. Theor Appl Climatol 2005;80:37–48. https://doi.org/10.1007/s00704-004-0079-y.

[11] Paul W, Stackhouse, Jr.,Bradley Macpherson, Madison Broddle, Chequel McNeil, A. Jason Barnett, Colleen Mikovitz TZ. Introduction to the POWER Project Prediction Of Worldwide Energy Resource (POWER) 2021:21.

[12] Halimi AH, Karaca C, Büyüktaş D. Evaluation of NASA POWER Climatic Data against Ground-Based Observations in the Mediterranean and Continental Regions of Turkey. J Tekirdag Agric Fac 2023;20:104–14. https://doi.org/10.33462/jotaf.1073903.

[13] Kheyruri Y, Sharafati A, Ahmadi Lavin J. Performance assessment of NASA POWER temperature product with different time scales in Iran. Acta Geophys 2023;72:1175–89. https://doi.org/10.1007/s11600-023-01186-2.

[14] Kadhim Tayyeh H, Mohammed R. Analysis of NASA POWER reanalysis products to predict temperature and precipitation in Euphrates River basin. J Hydrol 2023;619:129327. https://doi.org/10.1016/j.jhydrol.2023.129327.

[15] White JW, Hoogenboom G, Stackhouse PW, Hoell JM. Evaluation of NASA satellite- and assimilation model-derived long-term daily temperature data over the continental US. Agric For Meteorol 2008;148:1574–84. https://doi.org/10.1016/j.agrformet.2008.05.017.

[16] Gunaratne M.D.N, De Silva S.H.N.P AR. Can NASA Power Climatic Data Fill the Gap of Climatic Data Required for Agriculture and Forest Ecosystems Modeling? Proc 26th Int For Environ Symp 2022:21.

[17] Burt TP, Weerasinghe KDN. Rainfall distributions in Sri Lanka in time and space: An analysis based on daily rainfall data. Climate 2014;2:242–63. https://doi.org/10.3390/cli2040242.

[18] Vinutha HP, Poornima B, Sagar BM. Detection of Outliers Using Interquartile Range Technique from Intrusion Dataset. Theor. Popul. Biol., vol. 701, Springer Singapore; 2018, p. 511–8. https://doi.org/10.1007/978-981-10-7563-6_53.

[19] Tukey JW. Exploratory data analysis. 1977.

[20] Di Bucchianico A. Coefficient of Determination (R 2). Encycl. Stat. Qual. Reliab., Wiley; 2007, p. 2. https://doi.org/10.1002/9780470061572.eqr173.

[21] Wang W, Lu Y. Analysis of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) in Assessing Rounding Model. IOP Conf Ser Mater Sci Eng 2018;324:012049. https://doi.org/10.1088/1757-899X/324/1/012049.

[22] Rodrigues GC, Braga RP. Evaluation of nasa power reanalysis products to estimate daily weather variables in a hot summer mediterranean climate. Agronomy 2021;11:1–17. https://doi.org/10.3390/agronomy11061207.

[23] Jacovides CP, Kontoyiannis H. Statistical procedures for the evaluation of evapotranspiration computing models. Agric Water Manag 1995;27:365–71. https://doi.org/10.1016/0378-3774(95)01152-9.

[24] Willmott CJ. ON THE VALIDATION OF MODELS. Phys Geogr 1981;2:184–94. https://doi.org/10.1080/02723646.1981.10642213.

[25] Willmott CJ, Robeson SM, Matsuura K. A refined index of model performance. Int J

Climatol 2012;32:2088–94. https://doi.org/10.1002/joc.2419.

[26] Hodson TO. Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not. Geosci Model Dev 2022;15:5481–7. https://doi.org/10.5194/gmd-15-5481-2022.

8. ACKNOWLEDGEMENTS

The data was obtained from the NASA POWER Project's Data Access Viewer (DAV) (POWER single point daily) version v2.5.22 on 2025/10/25. This work is financially supported by the National Research Council (NRC) of Sri Lanka. Grant No 20–119.