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Validation of ERA5 and ERA5-Land Reanalysis Data for Daily Air Temperature and Extreme Temperature Indices over Bangladesh

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Abstract

Reanalysis datasets are often used as an ideal alternative to weather station observations because they provide temporally and spatially consistent data coverage. However, these reanalysis products need validation against weather station readings, as their performance varies regionally. In this study, we compared daily maximum (T_{max}) and minimum air temperature (T_{min}) from the ERA5 and ERA5-Land reanalysis datasets with 31 ground meteorological station observations of Bangladesh from 1989 to 2019. Both products reproduced observed temperatures well, with overall correlations exceeding 0.89 for T_{max} and 0.95 for T_{min} . Wilcoxon signed-rank tests revealed that ERA5 significantly ($p < 0.05$) outperformed ERA5-Land for T_{max} across multiple performance metrics, with large effect sizes (> 0.90), whereas the two datasets exhibited comparable performance for T_{min} . Both products showed a cold bias in T_{max} and a warm bias in T_{min} . Seasonal analyses revealed the lowest T_{min} correlations during the monsoon season (ERA5 = 0.648; ERA5-Land = 0.531), despite relatively low RMSE and MAE values, suggesting difficulties in reproducing day-to-day variability under relatively uniform monsoon conditions. For absolute extreme temperature indices, ERA5 generally exhibited significantly ($p < 0.05$) lower values, whereas ERA5-Land more accurately reproduced observed trends in percentile-based extreme indices. These findings indicate that both ERA5 and ERA5-Land provide reliable temperature data for Bangladesh, with ERA5 performing better for daily temperatures and absolute extremes. At the same time, ERA5-Land showed greater agreement with observed long-term changes in percentile-based extremes.

Keywords: ERA5, ERA5-Land, air temperature, temperature extremes, Bangladesh.

1 Introduction

Earth’s climate is changing substantially. A recent Intergovernmental Panel on Climate Change (IPCC), 2022 report states that human-induced warming increased by 0.2°C every ten years, reaching about 1°C above pre-industrial levels in 2017. Global warming has affected around 85% of the world’s population (Callaghan et al., 2021) and is expected to rise (Karl & Trenberth, 2003). Understanding historical climate variability, projecting future climate change, and evaluating its impact are crucial. Therefore, the use of consistent meteorological data as a reference dataset is critical.

Some studies use ground-based station observations as a reference dataset. Even though these observations are regarded as the most accurate data sources, they are often inconsistent both temporally and spatially (Colston et al., 2018). These limitations can reduce their suitability for studies requiring spatially and temporally continuous datasets, such as climate modeling. Therefore, reanalysis products are often considered an ideal alternative to ground observations.

Climate reanalyses are developed by combining historical observational data (like weather stations, satellites, and balloons) with a numerical Earth system model through a process called data assimilation (Buontempo et al., 2025). This creates a comprehensive, physically consistent, and gridded time series of past weather and climate. Among the reanalysis products, ERA5 produced by the Copernicus Climate Change Service (C3S) is the most widely used dataset. It is the fifth-generation atmospheric reanalysis product developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), providing global climate data from January 1950 to the present at a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$, with hourly temporal coverage that is also available in aggregated monthly form (Hersbach et al., 2020).

Additionally, ERA5-Land, which was released in July 2019, is an enhanced version of ERA5 that was produced by forcing the terrestrial component of ERA5 reanalysis, covering the same period but with a spatial resolution of $0.1^{\circ} \times 0.1^{\circ}$ and without data available for the oceans (Muñoz-Sabater et al., 2021). Given their increasing use in climate monitoring, impact assessment, and climate modeling, understanding the reliability of these datasets is essential.

Previous studies have generally reported strong agreement between ERA5 and ERA5-Land temperature data and ground observations across different climatic regions (Araújo et al., 2022;

Clelland et al., 2024; Zhao et al., 2023). Both semiarid and cold-region environmental studies have found high correlations and consistent seasonal patterns, suggesting the overall reliability of these reanalysis products. However, the magnitude of errors and performance vary across regions. For example, a study conducted in Siberia reported higher RMSE values compared to semiarid regions of Brazil, whereas ERA5 often showed comparatively better performance than ERA5-Land for maximum temperature estimation (Clelland et al., 2024; dos Santos Ferreira et al., 2026). These regional differences indicate that the accuracy of reanalysis products may depend on local climatic and geographic conditions, highlighting the importance of region-specific validation studies.

Despite the importance of region-specific validation of reanalysis datasets, a comprehensive assessment of ERA5 and ERA5-Land for daily air temperature over Bangladesh remains limited. In particular, their performance in representing both daily temperature characteristics and extreme temperature indices has received comparatively less attention. Therefore, this chapter evaluates ERA5 and ERA5-Land against Bangladesh Meteorological Department (BMD) station observations for daily maximum and minimum temperature across Bangladesh. In addition to assessing their agreement with station observations, the analysis examines selected extreme temperature indices to evaluate their ability to represent the magnitude and variability of temperature extremes. The rest of the paper is organized as follows: the methodology section describes the study area, data sources, data preprocessing, and validation procedures, followed by the results and discussion. The paper concludes by discussing the study's limitations and main conclusions.

2 Methodology

2.1 Study Area

Bangladesh is situated between 20.34°–26.38° N latitude and 88.01°–92.41° E longitude. The Bay of Bengal borders it to the south, Myanmar to the southeast, and India to the west, north, and northeast. According to the Intergovernmental Panel on Climate Change (IPCC, 2007), Bangladesh is one of the most vulnerable countries due to climate change. Its geographical location creates several seasons, as categorized by the Bangladesh Meteorological Department (BMD): pre-monsoon, monsoon, post-monsoon, and winter. Pre-monsoon months, especially March, April, and

May, are marked by intense heat and little precipitation, with occasional thunderstorms (Rashid, 2019). The monsoon season, from June to September, brings the most precipitation, with roughly 80% of the yearly rainfall occurring during this time. The post-monsoon months of October and November see a drop in temperature. The winter months, December to February, are chilly and dry, with January being the coldest.

2.2 Data Sources

In this study, observational daily maximum (T_{max}) and minimum (T_{min}) air temperatures were obtained from the Bangladesh Meteorological Department (BMD) for the available time period from 1989 to 2019. These datasets were used to validate the ERA5 and ERA5-Land reanalysis datasets for bias correction. Before validation, these datasets were pre-processed to ensure strict quality control, reducing the final number of stations to 31. Information on the locations and spatial distribution of the meteorological stations is provided in Fig. 1 and Table 1.

ERA5 represents the fifth-generation global atmospheric reanalysis developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). It spans the period from January 1940 to the present and delivers hourly data for a wide range of atmospheric, terrestrial, and oceanic climate variables. This data, which has a horizontal resolution of $0.25^\circ \times 0.25^\circ$ (~31 km), was created by combining observations from multiple sources with a numerical weather prediction model through advanced four-dimensional data assimilation in ECMWF's Integrated Forecast System (Hersbach et al., 2020).

ERA5-Land has been generated by replaying the land component of the ECMWF ERA5 climate reanalysis. A key benefit of ERA5-Land is its finer spatial resolution, which is improved globally to approximately 9 km. The dataset provides hourly data and covers the period from 1950 to the present (Muñoz-Sabater et al., 2021).

Daily maximum and minimum temperature data for ERA5 and ERA5-Land were downloaded from Copernicus Data Store using an automated Python script (<https://cds.climate.copernicus.eu/>). The time zone was selected to be UTC+6 in order to ensure alignment with Bangladesh's time zone.

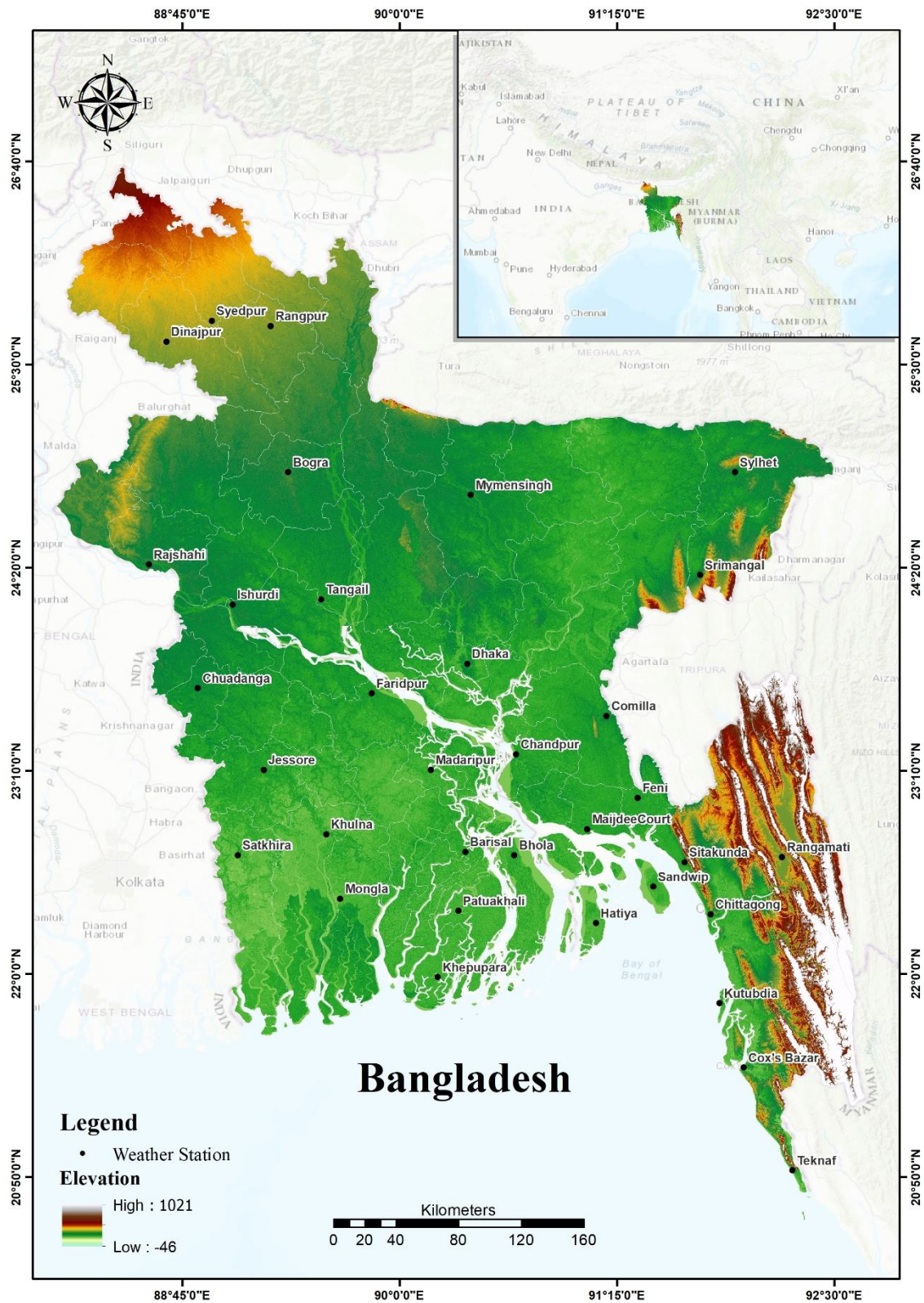


Fig. 1 Elevation map of Bangladesh along with locations of BMD stations

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Table 1 List of BMD stations with their name, station ID, location (latitude, and longitude), and altitude

Serial	Station Name	Station ID	Latitude	Longitude	Altitude
1	Barisal	11704	22.7	90.38	4
2	Bhola	11706	22.68	90.66	5
3	Bogra	10408	24.88	89.36	20
4	Chandpur	11316	23.26	90.67	7
5	Chuadanga	41926	23.64	88.84	17.4
6	Comilla	11313	23.48	91.19	10
7	Cox's Bazar	11927	21.46	91.98	4
8	Dhaka	11111	23.78	90.39	9
9	Dinajpur	10120	25.63	88.66	37
10	Faridpur	11505	23.61	89.84	9
11	Feni	11805	23.01	91.37	8
12	Ishurdi	10910	24.12	89.04	14
13	Jessore	11407	23.17	89.22	7
14	Khepupara	12110	21.98	90.22	3
15	Khulna	11604	22.8	89.58	4
16	Kutubdia	11925	21.83	91.84	6
17	Madaripur	11513	23.17	90.18	5
18	MaijdeeCourt	11809	22.83	91.08	6
19	Mongla	41958	22.43	89.66	4
20	Mymensingh	10609	24.75	90.41	19
21	Patuakhali	12103	22.36	90.34	3
22	Rajshahi	10320	24.35	88.56	20
23	Rangamati	12007	22.67	92.2	63
24	Rangpur	10208	25.72	89.26	34
25	Satkhira	11610	22.68	89.07	6
26	Sitakunda	11912	22.64	91.64	4
27	Srimangal	10724	24.29	91.73	23
28	Syedpur	41858	25.75	88.92	39.6
29	Sylhet	10705	24.88	91.93	35
30	Tangail	41909	24.15	89.55	10
31	Teknaf	11929	20.87	92.26	4

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2.3 Data Preprocessing

BMD stations with more than 10% missing observations were excluded from the analysis. The missing observations were primarily associated with recently established stations and prolonged technical failures, resulting in extended gaps in the records. The remaining data were further inspected for physical inconsistencies ($T_{max} < T_{min}$) and implausible ranges, including extremely high or unusually low values that were considered potential data errors. Such inconsistencies were extremely rare and treated as missing, as they had negligible impact on the outcome. No imputation was performed for the remaining missing observations to avoid introducing potential bias. For consistency in the comparison, dates with missing observations were excluded from both the BMD and corresponding reanalysis time series.

To spatially match the reanalysis data with the BMD station locations, bilinear interpolation was applied to estimate the reanalysis temperature at each station from the values of the four surrounding grid cells. This method assigns greater weights to grid cells located closer to the target station (Accadia et al., 2003). Bilinear interpolation was applied to both ERA5 and ERA5-Land datasets. However, while interpolating ERA5-Land data for six coastal stations, this technique failed as it was picking null ocean grid cells. To address this issue, nearest-neighbor interpolation was applied for those six stations.

2.4 Extreme Indices

To evaluate the ability of the reanalysis datasets in reproducing temperature extremes, eight extreme temperature indices (Table 2) were calculated from daily maximum (T_{max}) and minimum (T_{min}) temperatures following the guidelines of the Expert Team on Climate Change Detection and Indices (ETCCDI) (Alexander et al., 2006). These indices capture key aspects of temperature extremes, including intensity, frequency, and variability, providing a comprehensive characterization of both hot and cold events.

To ensure precise calculation of temperature percentiles, data quality control was implemented before calculating the percentile-based indices. In particular, to avoid biased percentile computation, years with more than 10% missing daily records were excluded from the analysis. By taking this step, the resulting extreme indices are ensured to be based on annual records that are sufficiently comprehensive.

Table 2 List of daily and extreme temperature indices used in this study

Index	Definition	Unit
T_{max}	Daily maximum air temperature	°C
T_{min}	Daily minimum air temperature	°C
TXx	Yearly maximum of maximum daily temperatures	°C
TXn	Yearly minimum of maximum daily temperatures	°C
TNx	Yearly maximum of minimum daily temperature	°C
TNn	Yearly minimum of minimum daily temperature	°C
TX90p	Percentage of days when $T_{max} > 90$ th percentile	% of days
TN90p	Percentage of days when $T_{min} > 90$ th percentile	% of days
TX10p	Percentage of days when $T_{max} < 10$ th percentile	% of days
TN10p	Percentage of days when $T_{min} < 10$ th percentile	% of days

167

168 2.5 Evaluation Metrics

169 The effectiveness of the reanalysis datasets in replicating observed daily maximum (T_{max}) and
 170 minimum (T_{min}) air temperatures was assessed using four statistical criteria. These consist of the
 171 Pearson correlation coefficient (r), Root Mean Squared Error (RMSE), Mean Absolute Error
 172 (MAE), and Mean Bias.

173 The Pearson correlation coefficient measures the strength and direction of the linear relationship
 174 between the reanalysis data and the BMD observations. It ranges from -1 to 1 , where values closer
 175 to 1 indicate stronger agreement between the two datasets. The correlation coefficient is calculated
 176 as follows:

$$177 \quad r = \frac{\sum_{i=1}^n (R_i - \bar{R})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^n (R_i - \bar{R})^2} \sqrt{\sum_{i=1}^n (O_i - \bar{O})^2}}$$

178 where R_i represents the temperature obtained from the reanalysis dataset (ERA5 or ERA5-Land),
 179 O_i represents the observed temperature from BMD stations, and n denotes the total number of
 180 observations.

181 RMSE and MAE were used to quantify the magnitude of errors between the reanalysis datasets
 182 and the observed temperature values. Both metrics measure the deviation between modeled and

observed data in degrees Celsius (°C). Lower values indicate better agreement with observations. RMSE gives larger weight to higher degrees of error, whereas MAE represents the average absolute deviation. The formulas for RMSE and MAE are given below:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (R_i - O_i)^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |R_i - O_i|$$

Mean Bias is represented by the mean difference between the reanalysis estimates and the observed values. It was used to identify overestimation or underestimation in the reanalysis datasets. Overestimation is indicated by positive bias, whereas negative bias indicates underestimation of observed temperatures.

$$Bias = \frac{1}{n} \sum_{i=1}^n (R_i - O_i)$$

The Wilcoxon signed-rank test is a non-parametric method suitable for paired samples without assuming normality (Wilcoxon, 1945). It was applied to determine whether the differences in station-wise performance metrics between ERA5 and ERA5-Land were statistically significant. For each station (i), the paired difference was calculated as,

$$d_i = X_{i,ERA5} - X_{i,ERA5-Land}, \quad i = 1, 2, \dots, n$$

where (X_i) denotes the corresponding performance metric at station (i), and n is the number of stations included in the analysis.

Differences equal to zero were omitted, and the absolute values of the remaining differences were ranked from smallest to largest. If R_i denotes the rank of $|d_i|$, the sums of the positive and negative ranks were calculated as,

$$W^+ = \sum_{d_i > 0} R_i \text{ and } W^- = \sum_{d_i < 0} R_i$$

The Wilcoxon signed-rank test statistic was then defined as,

205
$$W = \min(W^+, W^-).$$

206 The corresponding p-value was used to assess the statistical significance of the difference between
207 the two reanalysis datasets. Statistical significance was evaluated at the 5% level ($\alpha = 0.05$), with
208 $p < 0.05$ indicating a statistically significant difference.

209 The sign of the median paired difference was used to indicate the direction of the difference. For
210 error metrics such as RMSE, MAE, and mean absolute bias, a positive median difference indicates
211 that ERA5-Land has lower errors than ERA5, whereas a negative median difference indicates
212 lower errors for ERA5.

213 To quantify the magnitude of the difference independently of statistical significance, the effect size
214 was calculated as,

215
$$r = \frac{|Z|}{\sqrt{N}}$$

216 where Z is the standardized Wilcoxon test statistic, and N is the number of non-zero paired
217 differences. Larger values of r indicate a greater magnitude of difference between the two paired
218 datasets.

219

220 **3 Results and Discussion**

221 **3.1 Daily Maximum Air Temperature**

222 In general, both reanalysis products show good agreement with BMD observed T_{max} data, as most
223 data points are clustered near the 1:1 line (Fig. 2). However, as T_{max} increases, both reanalysis
224 datasets tend to underestimate the observed values, indicating the presence of a cold bias. The
225 underestimation is slightly larger for ERA5-Land than ERA5, as reflected by the slopes of the
226 fitted regression lines, which are 0.82 and 0.86, respectively.

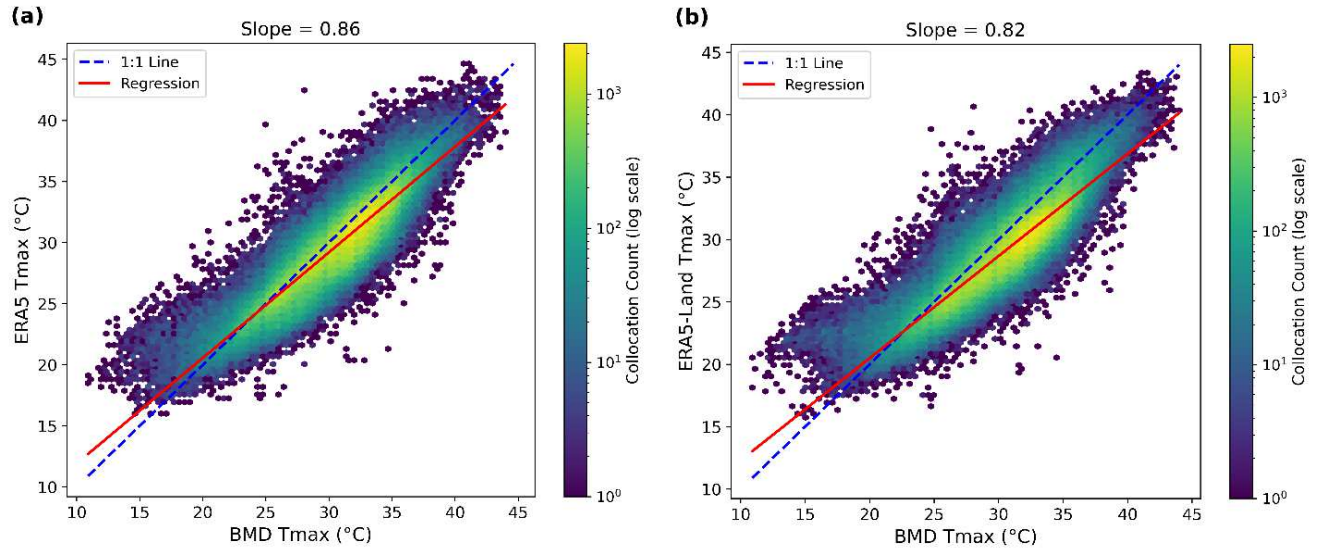


Fig. 2 Scatter density plot comparing T_{max} from ERA5 (a) and ERA5-Land (b) with BMD observations. The dashed blue line represents perfect agreement, and color intensity shows observation density on a logarithmic scale.

Overall, both datasets exhibit a strong correlation (above 0.8) with observations throughout the year, although slightly reduced agreement is observed during the monsoon season (Table 3). Furthermore, the geographical variability of correlation is almost the same for both products, as seen in Fig. 3. However, during the pre-monsoon season, ERA5-Land demonstrates considerably higher variability in correlation across stations, ranging from 0.70 to 0.89. The relatively lower correlation during the monsoon may be associated with seasonal differences in temperature variability and land–atmosphere interactions. During the monsoon, frequent cloud cover and rainfall can alter surface energy exchange and contribute to short-term variations in daily maximum temperature, which may be more difficult for reanalysis products to reproduce at the station scale.

The strong correlations in this study broadly align with previous evaluations. In the Brazilian semi-arid region, dos Santos Ferreira et al. (2026) reported correlations generally above 0.85 across stations, with values reaching 0.90 or higher at many locations; ERA5 also showed slightly better performance than ERA5-Land. In contrast, Clelland et al. (2024) reported correlations above 0.98 in Siberia and found little difference between ERA5 and ERA5-Land. The higher correlations reported for Siberia may partly reflect differences in the climatic conditions, spatial characteristics, station network, and evaluation period, and therefore should not be interpreted as directly comparable with the present results.

Table 3 Seasonal and overall performance of ERA5 and ERA5-Land for T_{max} against station observations over Bangladesh, evaluated using the correlation coefficient (r), root mean squared error (RMSE), mean absolute error (MAE), and mean bias

Season	ERA5				ERA5-Land			
	r	RMSE (°C)	MAE (°C)	Bias (°C)	r	RMSE (°C)	MAE (°C)	Bias (°C)
Winter (DJF)	0.834	1.75	1.29	-0.69	0.835	1.87	1.48	-0.96
Pre-monsoon (MAM)	0.823	1.9	1.51	-0.82	0.813	2.02	1.63	-1.05
Monsoon (JJAS)	0.779	1.7	1.37	-0.99	0.759	2.31	2.02	-1.83
Post-monsoon (ON)	0.841	1.69	1.36	-1.15	0.845	2.4	2.17	-2.07
Overall	0.907	1.76	1.38	-0.9	0.897	2.15	1.81	-1.46

The seasonal RMSE values for ERA5 range between 1.69°C and 1.9°C. When examined spatially, the variability in RMSE remains similar across all seasons except pre-monsoon, with most stations exhibiting errors below 2°C (Fig. 3). Despite having a slightly higher average RMSE during winter and pre-monsoon, ERA5-Land shows lower spatial variation in these seasons. However, during the monsoon and post-monsoon seasons, both the average error and station-wise variability increase substantially, with ERA5-Land showing errors above 2°C for most stations. In addition, for both datasets, a small number of stations show RMSE values that are greater than 3°C during all seasons, making them outliers in the distribution.

ERA5 shows relatively consistent MAE values across all seasons, with comparable levels of spatial variability. This consistency further supports the reliability of ERA5 in representing daily maximum temperature patterns across Bangladesh. On the other hand, ERA5-Land exhibits MAE values that follow a seasonal pattern similar to the previously discussed error metric, RMSE, indicating that the magnitude and distribution of errors remain generally consistent across different evaluation metrics.

The results are broadly comparable with those reported for the Brazilian semi-arid region, where RMSE and MAE were mostly between 1°C and 2°C, and ERA5 consistently performed better than

268 ERA5-Land (dos Santos Ferreira et al., 2026). In Siberia, Clelland et al. (2024) reported
269 substantially larger errors, with seasonal RMSE values generally ranging from approximately 2°C
270 to 6°C across stations. Their largest RMSE occurred during winter (3.94°C), while the smallest
271 occurred during spring (3.10°C). The substantially different error magnitudes between Siberia and
272 Bangladesh likely reflect differences in climate, surface characteristics, temperature variability,
273 and the spatial representativeness of the reanalysis data.

274

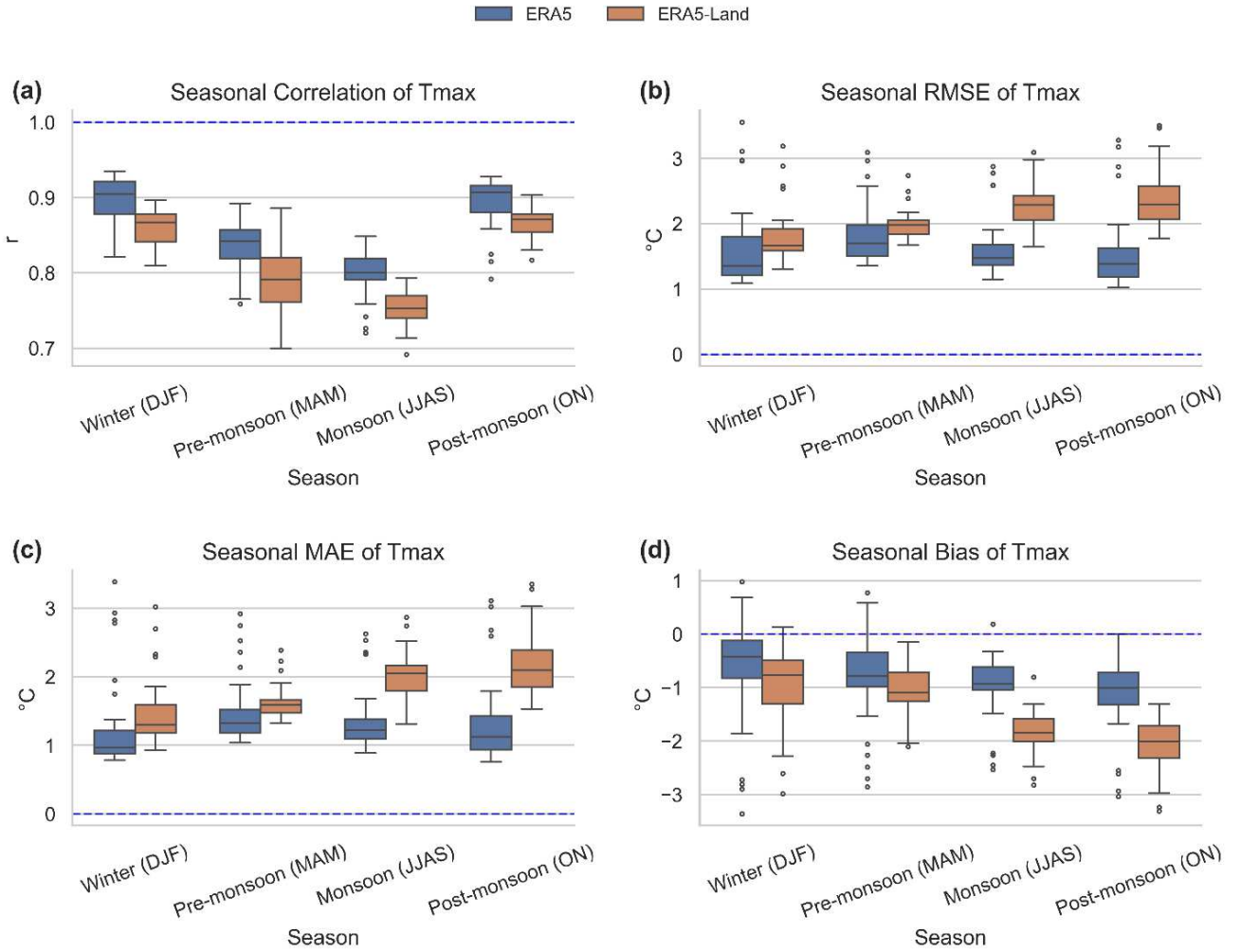


Fig. 3 Seasonal box plots showing the distribution of performance metrics (correlation coefficient, RMSE, MAE, and mean bias) across stations for ERA5 and ERA5-Land T_{max} . The dashed blue horizontal line denotes the ideal value for each metric.

In both reanalysis datasets, a cold bias is observed throughout the year, with only a few stations showing a warm bias. ERA5-Land's seasonal mean bias extends up to -2°C , while ERA5's typically stays above -1°C . The presence of such systematic cold bias suggests that both reanalysis products tend to underestimate daily maximum temperature over Bangladesh. The degree of station-wise bias variations over seasons is comparable in both datasets. But during the monsoon and post-monsoon seasons, the bias of ERA5-Land increases, showing a much larger cold bias than ERA5. The predominance of cold bias is consistent with findings from the Brazilian semi-arid region, where negative biases were also reported for both reanalysis products (dos Santos Ferreira et al., 2026). Moreover, the bias was lower for ERA5 than ERA5-Land. In contrast, Clelland et al. (2024)

found broadly similar bias variability among ERA5-Interim, ERA5, and ERA5-Land across Siberian stations, with the largest seasonal bias occurring during summer (-2.45°C). The differences between the studies suggest that the magnitude and seasonal behavior of T_{max} bias are strongly dependent on regional climatic and surface characteristics.

The superior performance of ERA5 is further confirmed by the Wilcoxon signed-rank test (Table 4). Across all error metrics, ERA5 exhibits significantly lower errors than ERA5-Land ($p < 0.01$), with consistently large effect sizes (≥ 0.92), indicating that the observed differences are both statistically robust and practically meaningful across stations.

Table 4 Wilcoxon signed-rank test of ERA5 and ERA5-Land T_{max} performance metrics. Negative and positive median differences indicate better performance of ERA5 and ERA5-Land, respectively.

Metric	Median Difference	P Value	Effect Size
RMSE ($^{\circ}\text{C}$)	-0.54	1.57e-07	0.94
MAE ($^{\circ}\text{C}$)	-0.52	2.86e-07	0.92
Mean Bias ($^{\circ}\text{C}$)	-0.61	1.57e-07	0.94

3.2 Daily Minimum Air Temperature

For T_{min} , both reanalysis products showed proper alignment with observed data, with ERA5 and ERA5-Land having slopes of 0.90 and 0.86, respectively (Fig. 4). A gentle warm bias is observed for values below 25°C for both products, whereas ERA5-Land exhibits a slight cold bias when T_{min} exceeds 25°C .

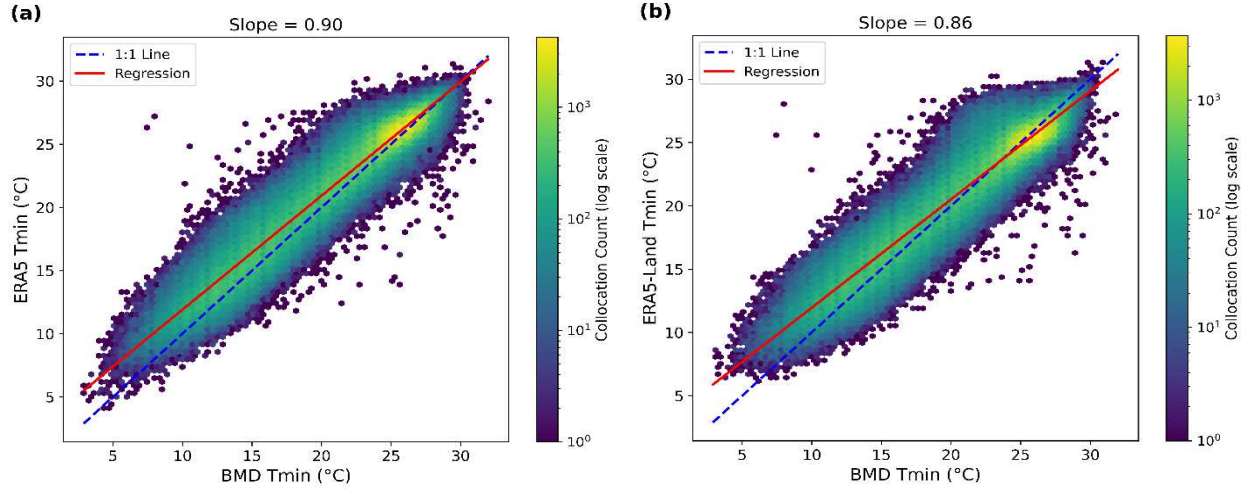


Fig. 4 Scatter density plot comparing T_{min} from ERA5 (a) and ERA5-Land (b) with BMD observations. The dashed blue line represents perfect agreement, and color intensity shows observation density on a logarithmic scale.

Overall, the seasonal evaluation of T_{min} closely resembles that of T_{max} . However, during the monsoon, the correlation is considerably lower for T_{min} compared to T_{max} , with correlation coefficients of 0.648 and 0.531 for ERA5 and ERA5-Land, respectively (Table 5). Fig. 5 also illustrates this tendency, with monsoon showing relatively lower correlation and greater station-wise variability than the other seasons. This decline in correlation during monsoon is similar to patterns found in Siberia, where inadequate simulated cooling caused summer T_{min} correlations to fall below 0.60, reaching as low as 0.40 for some stations (Clelland et al., 2024). Similarly, performance drops were noted during summer on the Greenland Ice Sheet, where correlations fell to 0.85 (Delhasse et al., 2020).

Table 5 Seasonal and overall performance of ERA5 and ERA5-Land for daily minimum air temperature (T_{min}) against station observations over Bangladesh, evaluated using the correlation coefficient (r), root mean squared error (RMSE), mean absolute error (MAE), and mean bias.

	ERA5				ERA5-Land			
Season	r	RMSE (°C)	MAE (°C)	Bias (°C)	r	RMSE (°C)	MAE (°C)	Bias (°C)
Winter (DJF)	0.855	2.11	1.67	1.29	0.837	2.05	1.63	1.11
Pre-monsoon (MAM)	0.895	1.75	1.34	0.89	0.864	1.83	1.37	0.65
Monsoon (JJAS)	0.648	1.01	0.76	0.42	0.531	1.09	0.83	-0.29
Post-monsoon (ON)	0.928	1.42	1.08	0.63	0.915	1.39	1.08	-0.16
Overall	0.966	1.6	1.18	0.79	0.958	1.61	1.21	0.32

The differences between the average seasonal and overall RMSE values of the two reanalysis products are minimal ($\leq 0.08^\circ\text{C}$), indicating comparable performance. Spatial variability across stations remains small and broadly consistent throughout the seasons, although ERA5-Land exhibits noticeably lower geographical variability during the post-monsoon period. On the other hand, during winter both models exhibit far greater spatial variability than other seasons, with an interquartile range of roughly 1°C to 3°C . A similar spatial pattern is observed for MAE, where the average values of both datasets are also nearly identical, supporting the consistency of their performance across metrics.

For both models, the monsoon exhibited the lowest correlation with observations, indicating weaker agreement in temporal temperature variability. In contrast, winter showed larger errors and greater station-to-station variability. These discrepancies suggest that the lower monsoon correlations may reflect regional cloud cover and convective activity, whereas the larger winter errors may reflect differences in how near-surface atmospheric and land–surface processes are represented. However, this differs from findings in the Qilian Mountains and Siberia, where spring showed the largest error magnitude (Clelland et al., 2024; Zhao et al., 2023).

Generally, ERA5-Land shows significantly lower mean bias than ERA5 throughout the season. For ERA5, the mean bias is lowest during the monsoon season (0.42°C), while for ERA5-Land, it is the lowest during the post-monsoon season (-0.16°C). Moreover, in contrast to the cold bias in T_{max} , T_{min} generally shows a minor warm bias throughout most seasons and is generally less biased than T_{max} . Furthermore, as shown in Fig. 5, winter displays greater variability in bias across stations, consistent with the patterns observed in RMSE and MAE. These findings are mostly similar to the literature. For instance, studies in the Canadian Prairies reported a $+0.74^{\circ}\text{C}$ bias for T_{min} under clear skies (Betts et al., 2019), and Clelland et al. (2024) attributed such errors to the models' inability to simulate sufficient nighttime cooling. In extreme cases like the Brazilian semiarid, this warm bias peaked at over 8°C (dos Santos Ferreira et al., 2026), highlighting the universal difficulty reanalyses face in accurately capturing nocturnal surface-atmosphere interactions. Despite the similarity of our study with previous literature, a study validating ERA5-Land for extreme temperatures of the Qilian Mountains in China found that the model underestimates both maximum and minimum temperature, though the magnitude of underestimation by T_{min} was lower compared to T_{max} . This might be due to the distinct geographic and weather patterns, notably the average temperature of that region was around 5°C (Zhao et al., 2023).

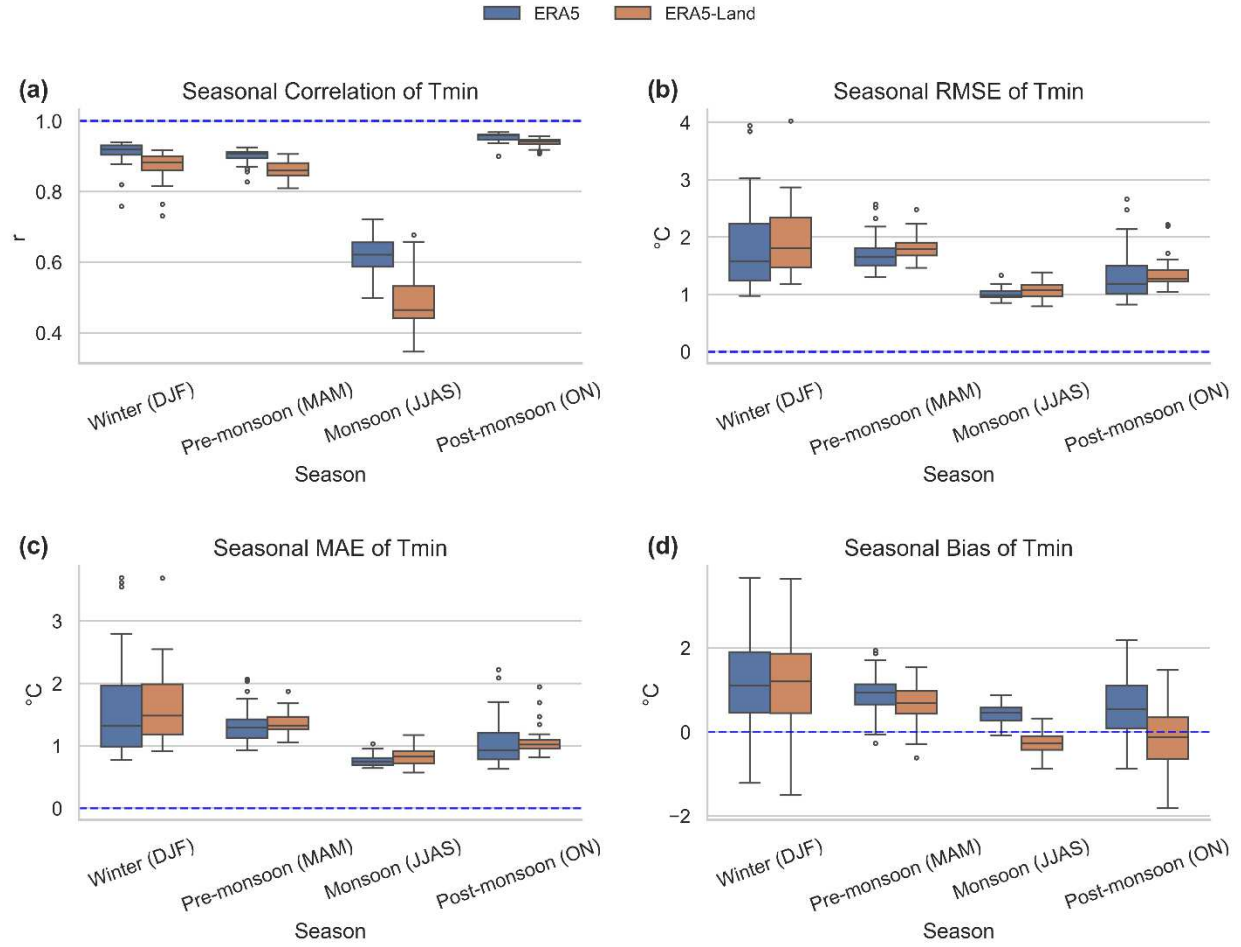


Fig. 5 Seasonal box plots showing the distribution of performance metrics (correlation coefficient, RMSE, MAE, and mean bias) across stations for ERA5 and ERA5-Land T_{min} . The dashed blue horizontal line denotes the ideal value for each metric.

When tested for statistical significance, both ERA5 and ERA5-Land showed comparable performance. ERA5-Land showed significantly lower bias ($p < 0.01$, effect size = 0.58) than ERA5, whereas the opposite was true for RMSE, although the median difference and effect size were much smaller (Table 6). In contrast, for MAE, both datasets showed non-separable performance ($p > 0.05$).

Table 6 Wilcoxon signed-rank test of ERA5 and ERA5-Land T_{min} performance metrics. Negative and positive median differences indicate better performance of ERA5 and ERA5-Land, respectively.

Metric	Median Difference	P Value	Effect Size
RMSE (°C)	-0.11	0.026	0.46
MAE (°C)	-0.11	0.209	0.26
Mean Bias (°C)	0.41	0.004	0.58

3.3 Evaluation of Extreme Temperature Indices

For replicating the magnitude of the hottest and coldest days and nights (TXx, TNx, TXn, and TNn), ERA5 shows slightly better agreement with observed data than ERA5-Land (Table 7). This implies that ERA5 is somewhat more effective in capturing the absolute extremes of daily temperature. The Wilcoxon signed-rank test further supported this, showing significantly lower bias for ERA5 ($p < 0.01$) for all indices except TXx (Table 8). In contrast, both reanalysis products perform comparably for percentile-based indices (TX90p, TN90p, TX10p, and TN10p), suggesting a similar capacity to depict the frequency of warm and cold extremes.

Table 7 Mean bias of extreme temperature indices derived from ERA5 and ERA5-Land relative to observations over Bangladesh. Negative values indicate underestimation, whereas positive values indicate overestimation

	TXx	TXn	TNx	TNn	TX90p	TN90p	TX10p	TN10p
ERA5	-0.87	1.3	-0.19	1.97	2.25	1.7	1.93	1.6
ERA5-Land	-1.16	1.71	-0.64	2.07	2.25	1.71	1.93	1.59

Examining temporal trends, ERA5-Land often shows better agreement with observed extreme-index trends (Fig. 6). Both reanalysis datasets show comparable ability to capture the observed trend patterns for TXx, TXn, TNx, and TNn. However, a noticeable discrepancy is observed for TXn, where both products fail to reproduce the substantial cooling trend in the -observed data. For the percentile-based indices, both datasets capture the overall trend direction, although ERA5-Land shows closer agreement with the observed trend slopes. Despite this general agreement in variability and trend direction, a consistent discrepancy remains between the reanalysis results and

the observations. Specifically, the reanalysis datasets tend to somewhat overestimate the magnitude of most extreme indices. The spatial matching process used to match the gridded reanalysis data with station observations may be partially accountable for this mismatch, as bilinear interpolation may introduce minor biases in extreme values and smooth out local variability.

Table 8 Wilcoxon signed-rank test comparing ERA5 and ERA5-Land biases for eight extreme temperature indices. Positive and negative median differences indicate lower bias for ERA5-Land and ERA5, respectively.

Indices	Median Difference	P Value	Effect Size
TXx	-0.30	0.595	0.11
TXn	-0.42	0	0.90
TNx	-0.29	0	0.86
TNn	-0.32	0.007	0.55
TX90p	0.00	0.789	0.11
TN90p	-0.02	0.681	0.08
TX10p	-0.01	0.918	0.08
TN10p	0.04	0.313	0.21

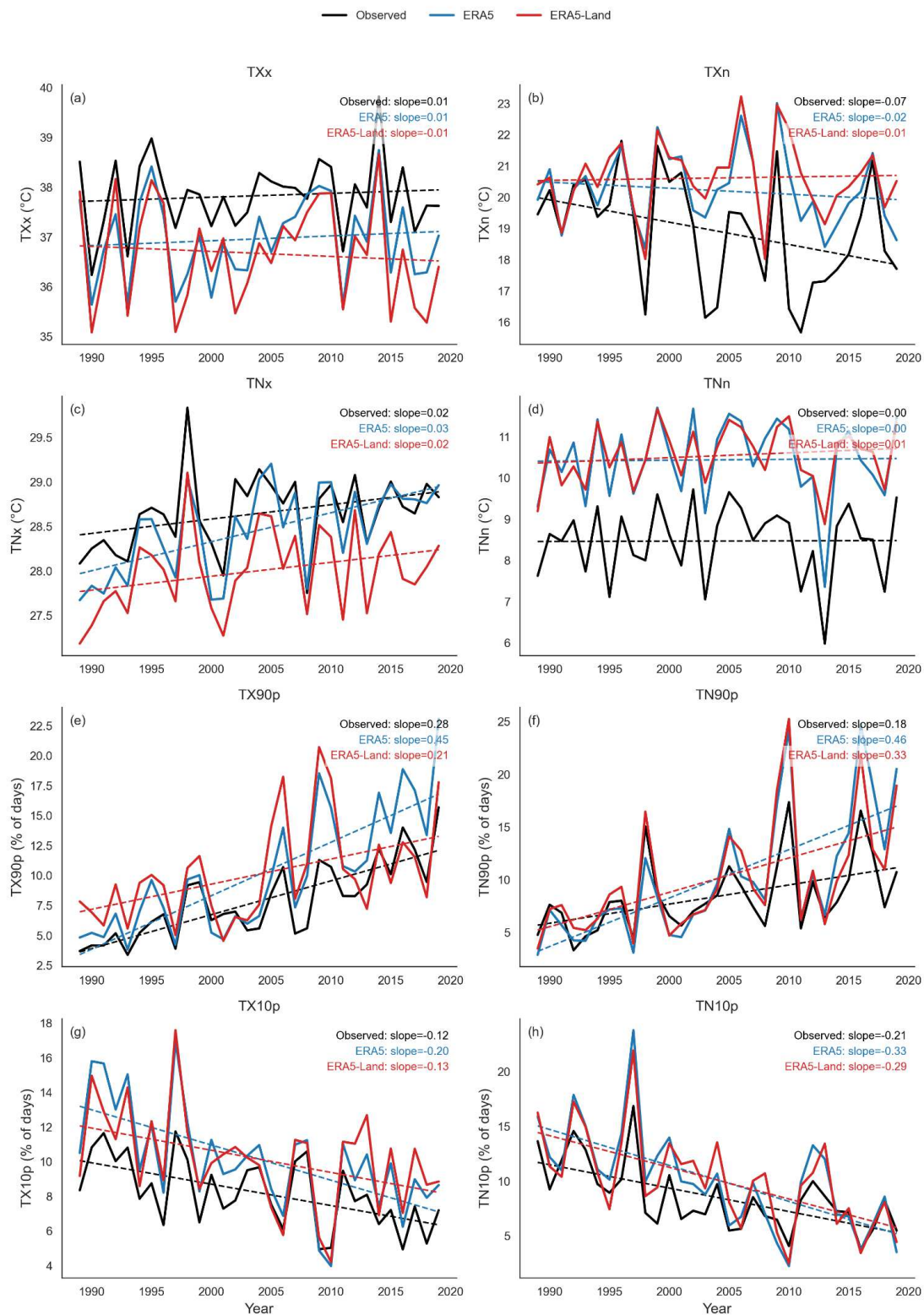


Fig. 6 Temporal trends of eight extreme temperature indices derived from observations, ERA5, and ERA5-Land over Bangladesh.

397

398 Studies in Siberia and Turkey report that ERA5 is often marginally superior to ERA5-Land in
399 capturing temporal variability and long-term trend signals (Clelland et al., 2024; Yilmaz, 2023).
400 However, despite ERA5's marginal superiority, ERA5-Land showed better agreement with
401 observed temporal trends in Bangladesh for percentile-based indices (*TX90p*, *TN90p*, *TX10p* and
402 *TN10p*). This aligns with evaluations in the Qilian Mountains, where ERA5-Land was considered
403 reliable for identifying trends in nearly all extreme temperature indices. Regardless, researchers
404 there also noted that reanalyses typically capture intensity indices (magnitudes) more accurately
405 than frequency indices (day counts) (Zhao et al., 2023). Despite this general proficiency in trend
406 detection, a consistent discrepancy remains, as reanalyses in Bangladesh tend to overestimate the
407 magnitude of most extreme indices. Finally, both models fail to reproduce the substantial cooling
408 trend in *TXn* in Bangladesh, highlighting a potential limitation in capturing specific regional
409 cooling signals, even though they remain "adept" at simulating broader spatially varying warming
410 trends.

411

412 **4 Limitations**

413 The hybrid spatial interpolation technique used in this work may introduce some degree of
414 artificial bias. However, this can be considered negligible, as this procedure is the most widely
415 accepted way to spatially match gridded datasets. Elevation differences might be another source
416 of bias that needs to be considered. Future studies should consider multiple variables such as
417 precipitation, wind speed, and humidity to better understand the capability of these products for
418 regional climate implications in Bangladesh.

419

420 **5 Conclusion**

421 This study provides the first comprehensive evaluation of the ERA5 and ERA5-Land reanalysis
422 datasets for daily temperature over Bangladesh, and is among the few to assess their performance
423 for extreme temperature indices in the region. The results show that both datasets reliably
424 reproduce observed temperature variability, with consistently high correlations. For regional-scale

research in Bangladesh, ERA5 is a reliable substitute for station observations since it performs marginally better overall in capturing the daily maximum temperature and the severity of extreme occurrences. However, ERA5-Land exhibits advantages in reducing bias in minimum temperature and capturing temporal trends in percentile-based extreme indices, likely due to its finer spatial resolution. The results indicate that ERA5 should be the preferred for general applications, while ERA5-Land can be useful in applications where high spatial resolution and trend analysis are important. Therefore, the selection of one of the two datasets should depend on the research aims and the advantages and disadvantages of each of the datasets.

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501 **Statements & Declarations**

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505 **Competing Interests**

506 The authors have no relevant financial or non-financial interests to disclose.

507 **Author Contributions**

508 Anwoy Barua: Conceptualization, methodology, data curation, formal analysis, investigation,
509 visualization, and writing–original draft. Sanjib Ghosh: Supervision and writing–review and
510 editing. Shaymal Karmakar: Writing–review and editing.

511 **Data Availability**

512 The publicly available ERA5 and ERA5-Land reanalysis datasets used in this study can be
513 downloaded from the Copernicus datastore (<https://cds.climate.copernicus.eu/>). Moreover, the
514 BMD stations dataset for daily maximum and minimum temperatures can be purchased from their
515 official website (<https://dataportal.bmd.gov.bd/web/>).