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INDCLIM: Bias Corrected Climate Projections from IITM-Earth System Model (IITM-ESM)

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Table of Contents

	Section	Page No.
	Abstract	1
1.	Introduction	2
2.	Data	3
3.	Methodology	5
4.	Results	10
5.	Dataset Visualization and Access	25
6.	Summary	26
7.	Acknowledgments	27
8.	Data availability	27
9.	References	28

Abstract

Climate model projections are essential for climate-impact assessments, but systematic biases in raw model outputs limit their regional applicability. Here, we develop a high-resolution ($0.25^\circ \times 0.25^\circ$) bias-corrected climate projection dataset (INDCLIM) for India using daily simulations from the IITM Earth System Model (IITM-ESM, CMIP6) for the historical period (1950–2014) and four future scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5; 2015–2099). Historical simulations were corrected using Empirical Quantile Mapping (EQM), while future projections employed Quantile Delta Mapping (QDM) to preserve model-projected climate change signals. Evaluation against IMD observations and ERA5 reanalysis shows substantial reductions in precipitation and temperature biases, with marked improvements in spatial patterns, seasonal cycles, and RMSE. The bias-corrected dataset reproduces observed climatology and historical variability while retaining long-term climate trends. Future projections indicate increasing monsoon precipitation and significant warming across India, reaching $\sim 3^\circ\text{C}$ for mean temperature and $\sim 4^\circ\text{C}$ for minimum temperature under SSP5-8.5 by the end of the century. The dataset provides a robust climate information resource for impact assessment and adaptation studies over India.

Introduction

Climate models are essential tools for understanding the Earth's climate system and projecting future climate variability and change under different warming scenarios. Although, Atmosphere Ocean General Circulation Models (AOGCMs) provide physically consistent simulations of large-scale atmospheric, oceanic and land-surface processes, their coarse spatial resolution limits their ability to accurately capture climate variability and changes at regional scale (Rampal et al., 2024). Consequently, raw climate model outputs often exhibit systematic biases in key variables such as precipitation and temperature, reducing their direct applicability for regional climate analysis, decision-making and impact assessment.

Among the various approaches developed to improve the usability of climate model projections at regional scales, bias correction methods have emerged as one of the most promising and widely adopted techniques. These methods aim to reduce discrepancies between model simulations and observed climatology by adjusting the statistical characteristics of climate variables, including their mean, variability, and probability distribution. Such adjustments enhance the reliability of climate projections and facilitate their application in impact assessment studies. Precipitation biases can significantly affect hydrological and agricultural assessments if left uncorrected. By aligning simulated climate data more closely with observations, bias-corrected datasets provide a scientifically robust basis for climate applications.

In addition to bias correction, spatial downscaling plays a crucial role in translating coarse-resolution climate information into finer-scale datasets suitable for regional and local studies. Downscaling techniques enhance the representation of spatial variability and extreme events, enabling climate information to better capture localized processes influenced by terrain, coastlines, and land-atmosphere interactions. Such high-resolution climate datasets are particularly important for impact assessment studies, where sector-specific analyses require climate information at scales relevant to human and natural systems.

Bias-corrected and downscaled climate projections are widely used in impact assessment studies related to hydrology, agriculture, urban planning, disaster risk management and renewable energy planning. These datasets support hydrological modeling, crop yield estimation, drought and flood assessment, heat stress analysis, and infrastructure vulnerability studies. Furthermore, they provide critical inputs for climate adaptation and mitigation planning by enabling policymakers and stakeholders to evaluate future risks and develop

region-specific resilience strategies. As climate extremes become more frequent and intense under global warming, the availability of reliable high-resolution climate projections becomes increasingly important for sustainable development and informed decision-making.

In this study, we developed a new set of bias-corrected climate projections (INDCLIM) from the Indian Institute of Tropical Meteorology Earth System Model (IITM-ESM) using two widely adopted statistical bias-correction techniques: Empirical Quantile Mapping (EQM) and Quantile Delta Mapping (QDM). These methods were applied to reduce systematic biases in the model simulations while preserving the statistical characteristics and long-term climate change signals in the projected datasets. The resulting high-quality bias-corrected projections offer improved regional climate data for the Indian region. They are highly effective for assessing climate variability, extremes, and impacts over Indian region.

2. DATA

2.1 IITM-ESM CMIP6 Simulations

The IITM-ESM is a coupled climate model developed at the Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), Pune (Swapna et al., 2018), and subsequently participated in Coupled Model Intercomparison Project Phase 6 (CMIP6). The daily output of the following variables from the realization r1i1p1f1 was retrieved from the CCCR-CDAS server for the experiments and time spans listed below:

Table 2.1. *IITM-ESM CMIP6 experiments and data spans used in this report.*

Experiment	experiment_id	Period used	Forcing description
Historical	historical	01-01-1950 to 31-12-2014	Observed GHG, aerosols, solar, land-use
SSP1-2.6	ssp126	01-01-2015 to 31-12-2099	Low forcing ($\sim 2.6 \text{ W m}^{-2}$)
SSP2-4.5	ssp245	01-01-2015 to 31-12-2099	Medium forcing ($\sim 4.5 \text{ W m}^{-2}$)

SSP3-7.0	ssp370	01-01-2015 to 31-12-2099	Medium-high forcing ($\sim 7.0 \text{ W m}^{-2}$)
SSP5-8.5	ssp585	01-01-2015 to 31-12-2099	High forcing ($\sim 8.5 \text{ W m}^{-2}$)

Table 2.2. CMIP6 variables used.

Variable	Standard_name	unit	Frequency
pr	precipitation_flux	$\text{kg m}^{-2} \text{ s}^{-1}$	day
tas	air_temperature (2 m)	K	day
Tmin	air_temperature (2 m, daily minimum)	K	day
Tmax	air_temperature (2 m, daily maximum)	K	day
hur	Near-Surface Relative Humidity	%	day
rsds	Surface Downwelling Shortwave Radiation	W m^{-2}	day
sfcWind	Near-Surface Wind Speed	m s^{-1}	day

2.2 Observational Dataset

The India Meteorological Department (IMD) provides gridded daily rainfall and temperature data over the Indian landmass. We have used IMD daily gridded rainfall (Pai et al., 2014) at $0.25^\circ \times 0.25^\circ$ spatial resolution, available from 1901 to present and IMD daily gridded temperature (Srivastava et al., 2009) at $0.5^\circ \times 0.5^\circ$ spatial resolution, available from 1951 to present, providing daily maximum and minimum temperature. The temperature is regridded to

the 0.25° grid using bilinear interpolation for compatibility with the rainfall grid. In addition to this, we have used the ERA5 u10 (zonal component of 10m wind), v10 (meridional component of 10m wind), Surface Downwelling Shortwave Radiation (ssrd), air temperature and dew point temperature dataset of the European Centre for Medium-Range Weather Forecasts (ECMWF; Hersbach et al., 2020). The relative humidity (RH) is calculated using ERA5 air temperature and dew point temperature (T and T_d, respectively, and both in °C) using:

$$RH = 100 \times \frac{\exp(17.625 T_d / 243.04 + T_d)}{\exp(17.625 T / 243.04 + T)}$$

3. Methodology

This section describes the bias-correction methodology applied. Daily simulations of precipitation (pr, mm/day), mean surface air temperature (T_{mean}, °C), minimum temperature (T_{min}, °C), maximum temperature (T_{max}, °C), surface downwelling shortwave radiation (rsds, W/m²), windspeed (m/s), and relative humidity (hur, %) from the realization r1i1p1f1 were utilized under the historical, ssp126, ssp245, ssp370, and ssp585 experiments.

3.1 Empirical Quantile Mapping

For the historical period, bias correction was carried out using the Empirical Quantile Mapping (EQM) technique. This method was chosen because it performs reliably for highly skewed distributions and effectively retains the characteristics of tail distributions. The correction was applied by aligning the model output distribution with the observed distribution via direct quantile-to-quantile matching. Since both datasets covered the same time span and had equal sample sizes, no interpolation was required.

3.2 Quantile Delta Mapping

Quantile Delta Mapping (QDM) is a widely used statistical bias-correction technique for climate model outputs and is recognized as a trend-preserving extension of EQM introduced by Cannon et al., (2015). In contrast to conventional Quantile Mapping (QM), QDM preserves the quantile-specific relative or absolute changes between historical and future climate states while simultaneously correcting systematic biases relative to observations. Consequently, this method maintains the integrity of the modeled climate change response across the entire probability distribution.

A major advantage of QDM lies in its ability to preserve long-term trends and changes in the climate extremes without artificially modifying the underlying model-projected signal.

By performing the correction in quantile space, QDM accounts for distribution-dependent biases while preserving the modeled climate change signal under non-stationary future climate conditions (Cannon et al., 2015; Maraun, 2016). Furthermore, QDM reduces issues associated with extrapolation beyond the historical cumulative distribution function (CDF), thereby providing a more physically consistent framework for correcting future climate projections (Cannon et al., 2015; Maraun, 2016; Switanek et al., 2017). Owing to these advantages, QDM was adopted as the primary bias-correction framework in the present study.

3.3 Notation and Variables

The following notation is used in the additive and multiplicative formulations of QDM:

- $X_{obs,h}(i)$ — observed (reference) value of the climate variable at time step i during the control (historical) period.
- $X_{sim,h}(i)$ — modeled (simulated) value at time step i during the control (historical) period.
- $X_{sim,p}(i)$ — modeled (simulated) value at time step i during the projection (scenario / future) period — i.e., the value to be bias-corrected.
- $F_{sim,p}$ — cumulative distribution function (CDF) of the modeled scenario-period data.
- $F_{sim,h}$ — CDF of the modeled control-period data.
- $F_{obs,h}$ — CDF of observed data during the historical (reference) period.
- F^{-1} — inverse cumulative distribution function (quantile function).
- $\varepsilon(i)$ — non-exceedance probability (quantile value) associated with $X_{sim,p}(i)$, where $\varepsilon(i) \in [0, 1]$.
- $\Delta(i)$ — quantile-dependent change (delta) between the modeled control and scenario periods at time step i .

3.4 Additive Quantile Delta Mapping

The additive formulation of QDM is typically applied to climate variables for which biases and climate change signals are well represented in absolute terms (e.g., temperature). It consists of four sequential steps.

Step 3.4.1 — Compute the quantile of the value to be adjusted

The non-exceedance probability $\varepsilon(i)$ of the modeled projection-period value $X_{sim,p}(i)$ is determined from the CDF of the modeled projection-period data:

$$\varepsilon(i) = F_{sim,p} [X_{sim,p}(i)], \quad \varepsilon(i) \in [0, 1]$$

This step locates the future modeled value within its own projection-period distribution and expresses it as a quantile rather than as an absolute magnitude.

Step 3.4.2 — Determine the bias-corrected baseline value

The same quantile $\varepsilon(i)$ is then projected onto the observed historical-period distribution by applying the inverse CDF (quantile function) of the observations:

$$X^{EQM(1)}_{sim,p}(i) = F^{-1}_{obs,h} [\varepsilon(i)]$$

This produces a bias-corrected baseline value corresponding to the observed climate distribution. However, the modeled climate change signal has not yet been incorporated.

Step 3.4.3 — Compute the absolute quantile change (delta)

The quantile-specific absolute climate change signal $\Delta(i)$ is computed as the difference between the modeled projection-period and modeled historical-period values at the same quantile. It is defined as:

$$\Delta(i) = F^{-1}_{sim,p} [\varepsilon(i)] - F^{-1}_{sim,h} [\varepsilon(i)]$$

which is equivalently expressed as:

$$\Delta(i) = X_{sim,p}(i) - F^{-1}_{sim,h} \{ F_{sim,p} [X_{sim,p}(i)] \}$$

The first form makes clear that $\Delta(i)$ is the absolute change between the model's scenario and control values at the same probability level $\varepsilon(i)$.

Step 3.4.4 — Apply the Quantile-Specific Change

Finally, the absolute change $\Delta(i)$ is added to the bias-corrected baseline value to obtain the final bias-corrected projection-period value:

$$X^{*QDM}_{sim,p}(i) = X^{EQM(1)}_{sim,p}(i) + \Delta(i)$$

This resulting value preserves the climate change signal of the model (through Δ) while correcting for the systematic bias against observations (through the use of $F^{-1}_{obs,h}$).

3.5 Multiplicative Quantile Delta Mapping

The multiplicative formulation of QDM is appropriate for variables that are non-negative and whose change signals are naturally expressed as ratios (e.g., precipitation, wind speed, radiation

and relative humidity). Steps 3.4.1 and 3.4.2 are identical to steps 3.3.1 and 3.3.2 of the additive variants. The change is then computed and applied multiplicatively.

Step 3.5.1 — Compute the quantile of the value to be adjusted

$$\varepsilon(i) = F_{sim,p} [X_{sim,p}(i)], \quad \varepsilon(i) \in [0, 1]$$

Step 3.5.2 — Determine the bias-corrected baseline value

$$X^{EQM(1)}_{sim,p}(i) = F^{-1}_{obs,h} [\varepsilon(i)]$$

Step 3.5.3 — Compute the relative quantile change (delta)

In this variant, the quantile-specific change is expressed as a ratio rather than a difference:

$$\Delta(i) = F^{-1}_{sim,p} [\varepsilon(i)] / F^{-1}_{sim,h} [\varepsilon(i)]$$

which is equivalently expressed as:

$$\Delta(i) = X_{sim,p}(i) / F^{-1}_{sim,h} \{ F_{sim,p} [X_{sim,p}(i)] \}$$

This ratio represents the modelled relative climate change signal at the same quantile.

Step 3.5.4 — Apply the relative change to the bias-corrected value

The bias-corrected scenario value is obtained by multiplying the bias-corrected baseline by the relative change factor (i.e., $\Delta(i)$):

$$X^{*QDM}_{sim,p}(i) = X^{EQM(1)}_{sim,p}(i) \times \Delta(i)$$

Thus, multiplicative QDM preserves the relative (percentage) change projected by the climate model at every quantile of the distribution.

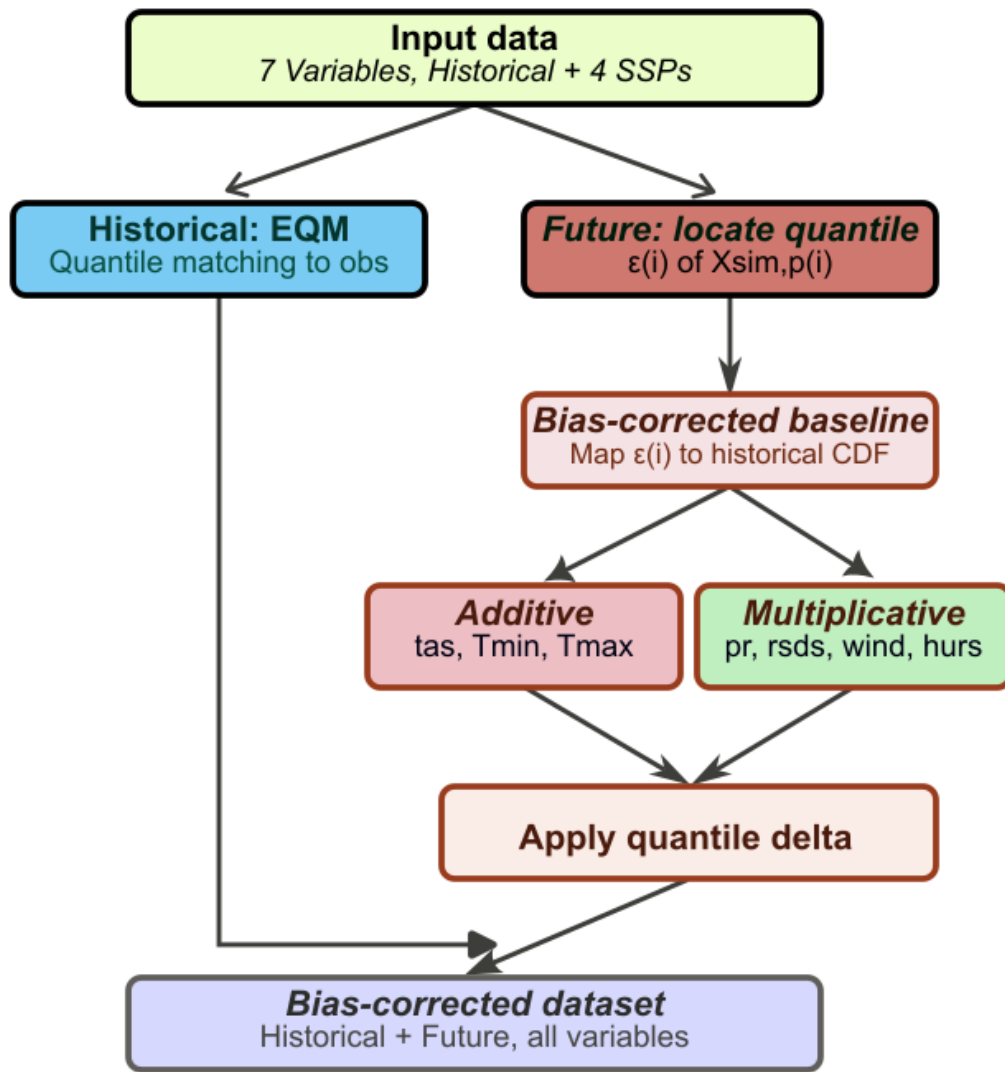


Figure 1: Schematic illustration of the bias-correction framework used for IITM-ESM climate projections. Historical simulations are bias-corrected using Empirical Quantile Mapping (EQM), while future projections are corrected using Quantile Delta Mapping (QDM).

Note that the QDM is a bias-correction method designed to adjust climate model projections while preserving the model-projected climate change signal at each quantile of the distribution. For future projections, QDM corrects model biases relative to observations and then applies the modeled quantile-specific climate change signal. The overall bias-correction workflow adopted in this study is illustrated in Figure 1.

3.5 Added-Value Assessment

The performance of the INDCLIM outputs relative to the raw IITM-ESM model output (RAW) is evaluated using an RMSE-based Added Value (AV) metric. Annual fields of Rx1day, R20mm, TXx, and TX90p were computed separately for observations (OBS), RAW, and INDCLIM. Rx1day is defined as the annual maximum 1-day precipitation amount, R20mm as the annual count of days with precipitation ≥ 20 mm, TXx as the annual maximum daily temperature, and TX90p as the annual percentage of days exceeding the calendar-day 90th-percentile temperature threshold.

For each grid cell, the root-mean-square error (RMSE) between observations and the simulated annual index values was calculated for both the RAW and BC datasets:

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

where N is the number of years and X_i represents either the RAW or INDCLIM outputs.

The Added Value was then computed as

$$AV = 100 \left(1 - \frac{RMSE_{BC}}{RMSE_{RAW}} \right)$$

Positive AV values indicate that bias correction reduced the error relative to the raw simulation, whereas negative values indicate a deterioration in performance. This formulation provides a dimensionless measure of the percentage reduction in RMSE and evaluates the bias correction's ability to improve the representation of observed interannual variability in climate extremes.

4. Results

4.1 Mean-State Biases in RAW IITM-ESM and INDCLIM Datasets

Figure 2 presents the climatological mean biases in annual precipitation (Fig. 2a–b), annual mean temperature (Tmean; Fig. 2c–d), annual maximum temperature (Tmax; Fig. 2e–f), and annual minimum temperature (Tmin; Fig. 2g–h) for the RAW historical simulations and the corresponding bias-corrected INDCLIM dataset. The comparison clearly demonstrates the ability of the bias-correction framework to substantially reduce the systematic errors present in the raw model while preserving the large-scale spatial structure of the observed climate.

The raw IITM-ESM outputs exhibit pronounced and spatially coherent precipitation biases over India (Fig. 2a). A widespread dry bias dominates the core monsoon rainfall regions,

including the Western Ghats, the west coast of peninsular India, central India, and parts of northeast India. Smaller but spatially organized wet and dry biases are also evident along the Himalayan foothills. These systematic errors reflect the challenges of coarse-resolution climate models in accurately representing the Indian summer monsoon and orographic precipitation. Following bias correction, these large-scale precipitation biases are substantially reduced (Fig. 2b). The widespread dry and wet anomalies observed in the raw simulation are largely eliminated, leaving only weak residual biases across most parts of the country, indicating a marked improvement in the representation of India's climatological rainfall.

The annual mean temperature (T_{mean}) in the raw simulation is characterized by widespread cold biases across much of India (Fig. 2c). The strongest cold anomalies, exceeding -6°C , occur over the Himalayan region, reflecting the difficulty of representing complex mountainous terrain at the relatively coarse spatial resolution of IITM-ESM. Moderate cold biases are also present over the Indo-Gangetic Plain, central India, and parts of peninsular India. After bias correction, these systematic errors are dramatically reduced (Fig. 2d), with residual biases generally confined within $\pm 0.5^{\circ}\text{C}$ over most of the country.

The climatological bias in annual maximum temperature (T_{max}) also displays considerable regional variability (Fig. 2e). Strong cold biases dominate the Himalayan region as well as large parts of central and eastern India, whereas warm biases are evident over portions of southern peninsular India. These contrasting errors indicate deficiencies in the simulation of daytime land-surface energy balance and near-surface temperature. The bias-corrected INDCLIM product substantially reduces these systematic errors (Fig. 2f), with residual T_{max} biases generally remaining within $\pm 0.5^{\circ}\text{C}$ throughout most of India.

The annual minimum temperature (T_{min}) exhibits a different spatial bias structure (Fig. 2g). Warm biases are evident over northwestern India and parts of southern peninsular India, while pronounced cold biases persist over the Himalayan region. The differing spatial distributions of T_{max} and T_{min} biases suggest that the raw model represents daytime and nighttime temperature variability with varying levels of accuracy. After bias correction, these systematic biases are largely removed (Fig. 2h), resulting in residual T_{min} errors that remain close to zero over most of the Indian landmass.

Overall, the INDCLIM dataset represents a significant improvement over the raw IITM-ESM historical simulations. Systematic biases in precipitation, annual mean temperature, maximum temperature, and minimum temperature are greatly reduced across India,

demonstrating that the adopted bias-correction framework effectively reproduces the observed climatological mean state with considerably higher fidelity. These improvements provide a robust foundation for subsequent analyses of historical climate variability and future climate projections over the Indian region.

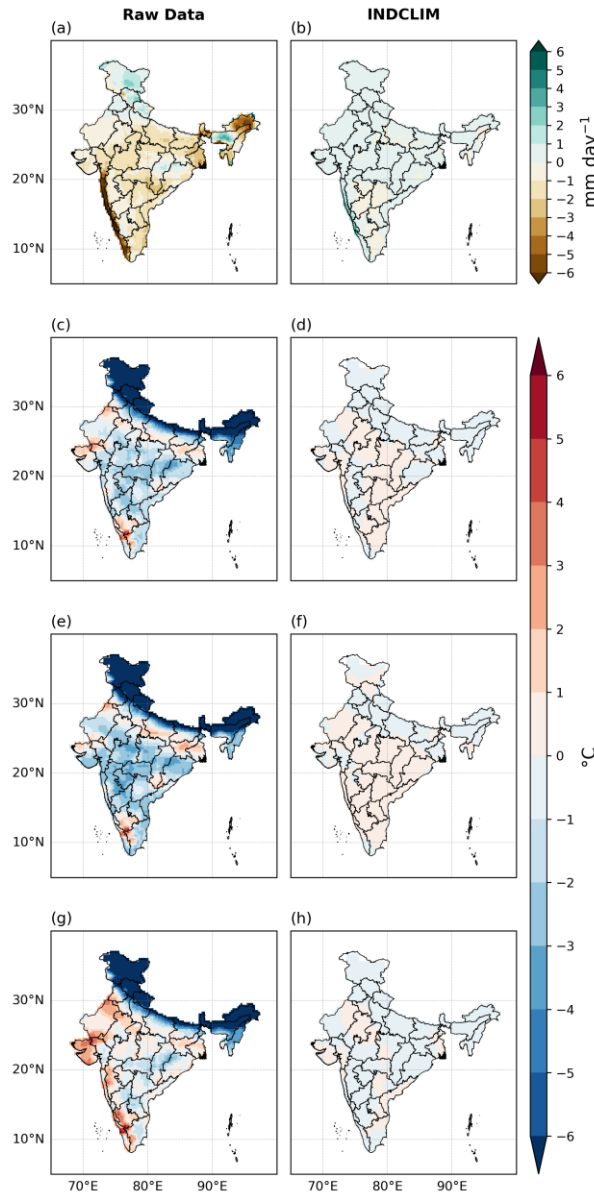


Figure 2: Mean bias (model minus IMD observation) over the Indian subcontinent for the historical period 1950–2014. The left column (a, c, e, g) shows raw IITM-ESM bias; the right column (b, d, f, h) shows residual bias after Bias correction. In (a-b), the precipitation bias corresponds to the annual mean (mm day^{-1}), in (c-d), the annual-mean temperature ($^{\circ}\text{C}$), in (e,

f) the annual-mean maximum temperature ($^{\circ}\text{C}$), and in (g-h) the annual-mean minimum temperature ($^{\circ}\text{C}$).

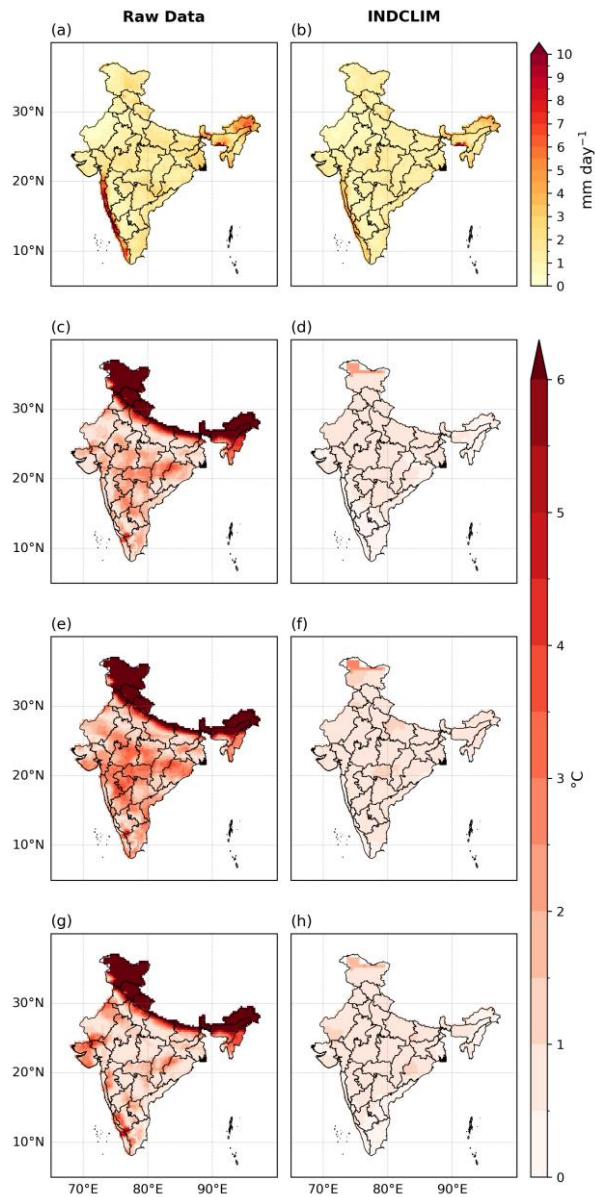


Figure 3: Same as Figure 2 but for the root-mean-square error (RMSE) between IITM-ESM and IMD observations for the historical period 1950–2014.

4.2 Assessment using RMSE

While the mean-bias maps (Fig. 2) quantify only the systematic error in the long-term climatological mean, the Root Mean Squared Error (RMSE) shown in Figure 3 provides a more comprehensive measure of model performance by accounting for both the systematic bias and the temporal variability of the climate fields. Consequently, RMSE represents a more rigorous metric for evaluating the effectiveness of the bias-correction procedure. Although quantile-

based bias correction substantially reduces the mean bias, it does not necessarily reproduce the exact timing and magnitude of day-to-day or interannual fluctuations, and therefore residual RMSE may remain even when the climatological bias approaches zero (Cannon et al., 2015).

The annual precipitation RMSE of the raw IITM-ESM simulation (Fig. 3a) exhibits a distinct spatial dependence on the climatological rainfall distribution. The largest errors ($>7\text{--}10\text{ mm day}^{-1}$) occur along the windward slopes of the Western Ghats and over the northeastern hill states, where intense orographic precipitation dominates the annual rainfall. Moderate RMSE values ($2\text{--}4\text{ mm day}^{-1}$) are found over central India and the Indo-Gangetic Plain, whereas the arid regions of northwestern India exhibit comparatively small errors ($<1\text{ mm day}^{-1}$) owing to their low climatological rainfall. This spatial correspondence indicates that precipitation errors scale with rainfall intensity, a behaviour commonly reported in CMIP-class climate models over India (e.g., Mishra et al., 2020).

Following bias correction, the precipitation RMSE decreases substantially across most of the country (Fig. 3b). Large portions of central India, the Indo-Gangetic Plain, and peninsular India exhibit RMSE values below approximately 2 mm day^{-1} , demonstrating a considerable improvement in rainfall simulation. Nevertheless, residual errors persist over the Western Ghats and northeastern India, where RMSE remains between $5\text{ and }10\text{ mm day}^{-1}$. These regions are characterized by steep topography, highly intermittent rainfall, and frequent extreme precipitation events. Since quantile mapping adjusts the statistical distribution of precipitation independently at each grid point without modifying the temporal sequence of rainfall events, it cannot fully correct errors associated with the timing and persistence of extreme orographically driven precipitation (Cannon et al., 2015).

The annual mean temperature (T_{mean}) RMSE in the raw simulation (Fig. 3c) is dominated by large errors exceeding $5\text{--}6\text{ }^{\circ}\text{C}$ over the Himalayan region. Elsewhere across India, RMSE values are generally between $1\text{ and }3\text{ }^{\circ}\text{C}$, consistent with the widespread cold bias identified in the climatological mean. Application of the bias-correction framework leads to a reduction in RMSE throughout the domain (Fig. 3d), with residual errors generally remaining below $0.5\text{ }^{\circ}\text{C}$ over most of India. Small residual errors are confined primarily to the northern Himalayan region.

Figure 3e and f reflect a similar result for T_{max} , with raw RMSE values of $2\text{--}4\text{ }^{\circ}\text{C}$ over the central India and southern peninsula India as further reduced to below $1\text{ }^{\circ}\text{C}$ after bias correction. Figure 3g and h show that the RMSE for T_{min} from raw model output is largest ($>$

4 °C) over the arid northwest, where the warm bias identified in Figure 2g was strongest. And with the application of QDM, it essentially eliminates this RMSE structure, reducing residual errors to within 0.5-1°C across the Indian domain.

In addition to annual bias and RMSE, we also assess the performance across various seasons (i.e., March to May, MAM, June to September, JJAS, Oct to November, OND and December to January, DJF). The residual seasonal bias after correction is small across the Indian domain in every season, generally within $\pm 1 \text{ mm day}^{-1}$ (Figure 4a, c, g). The one notable exception is in boreal summer season (JJAS) (Figure 4e), where a narrow but persistent positive bias band (up to $\sim 2\text{--}3 \text{ mm day}^{-1}$) remains along the Western Ghats. The Western Ghats is known for sharp spatial scale of orographic precipitation enhancement and hence limiting the ability of bias-corrected products, with a spatial resolution of 0.25° to fully capture these localized rainfall gradients. The RMSE is lowest in DJF and OND (Figure 4b, h) with below 1 mm day^{-1} across the domain. The RMSE rises substantially during the monsoon season (Figure 4f), with values of $3\text{--}6 \text{ mm day}^{-1}$ over central India, the Western Ghats, and the northeast - consistent with the much greater day-to-day variability of monsoon rainfall, again pointing out the inability of the present bias corrected product to completely resolve the inherent bias. MAM (Figure 4d) shows a similar pattern of minimal bias across the Indian landmass as that of DJF and OND, but there is an exception over the northeast. So, the absolute bias improves substantially across all seasons (68-92%), confirming that QDM successfully corrects the systematic wet/dry bias in the mean climatological state; however, the RMSE improvement is modest across the seasons.

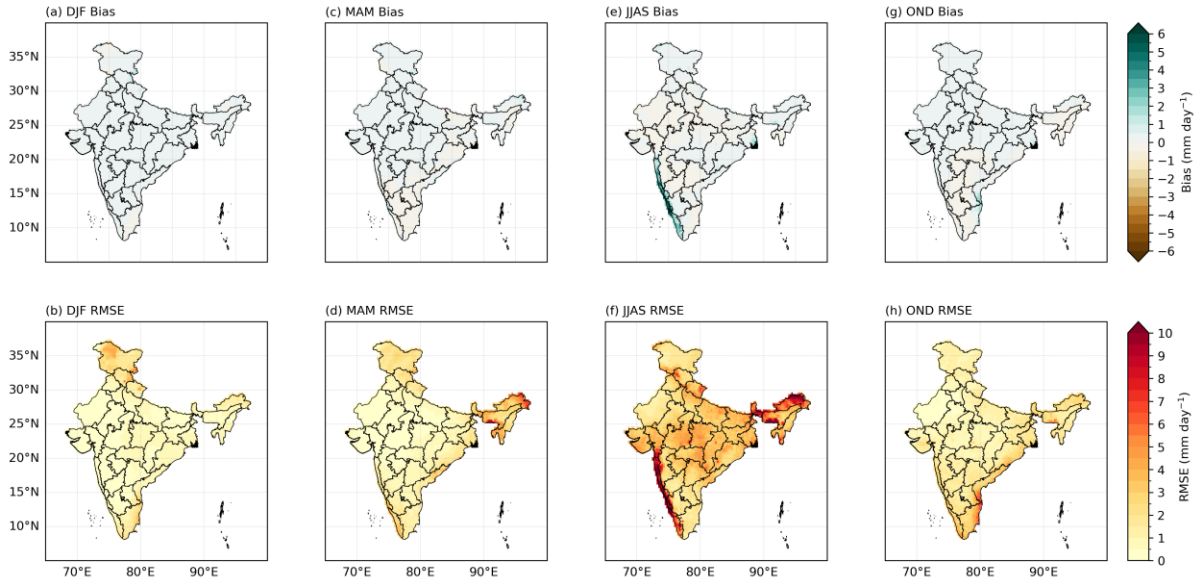


Figure 4: Seasonal bias (top row: a, c, e, g) and RMSE (bottom row: b, d, f, h) of the INDCLIM precipitation against IMD observations, for DJF, MAM, JJAS, and OND (1950–2014).

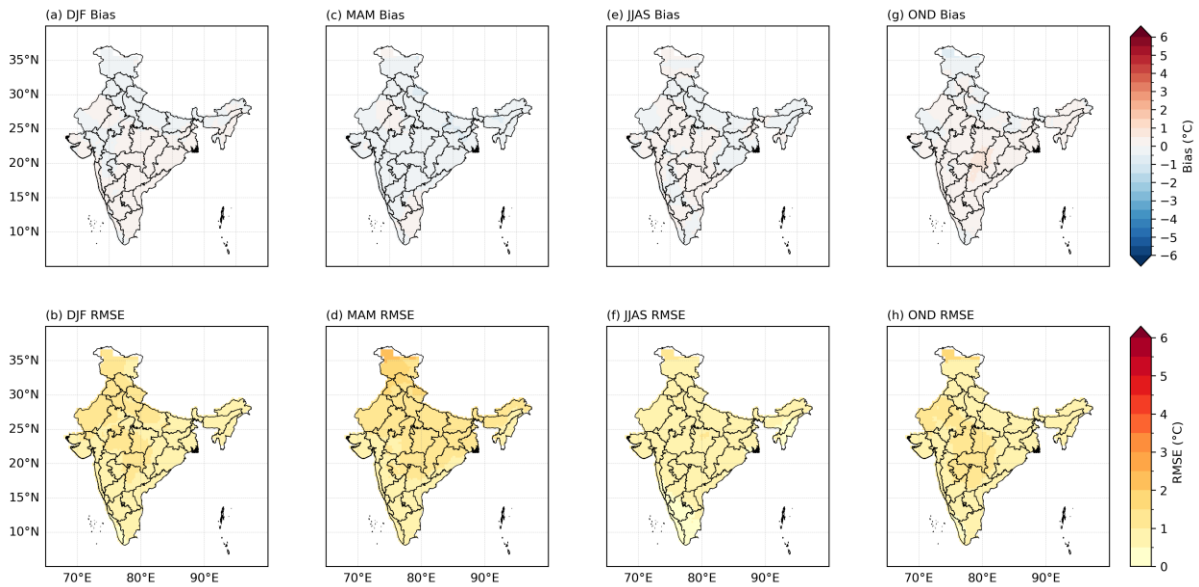


Figure 5: Same as Figure 4 but Mean Temperature (T_{mean}).

In contrast to precipitation, the bias-corrected mean temperature field shows almost no residual seasonal bias anywhere in the domain (Figure 5a, c, e, g are uniformly close to 0°C), with only a small negative value over central-western India in DJF-JJAS and a small positive value over the central-eastern India in OND – but both well within $\pm 1^{\circ}\text{C}$. RMSE (Figure 5b, d, f, h) is also correspondingly small and spatially uniform across all four seasons and is generally below 1°C over most of the entire domain. Overall, the absolute bias is reduced by 90–97%, and RMSE by 72–81%, with no strong seasonal dependence. Similarly, similar results are observed for T_{max} and T_{min} . In summary, the bias corrected product shows a clear

improvement in reproducing observed precipitation and temperature climatology compared to the raw model outputs as reflected by low bias and RMSE.

Mean	Bias corrected IITM-ESM (INDCLIM)	NASA-NEX GDDP	ISIMIP
Pr (JJAS) Central India	3.47	3.51	3.70
Tmean (Annual)	0.60	2.31	2.35

Table 3.1: Mean RMSE of JJAS precipitation (mm day^{-1}) and annual mean temperature ($^{\circ}\text{C}$) over India for bias-corrected IITM-ESM (INDCLIM), NASA-NEX GDDP, and ISIMIP datasets relative to observations.

To further evaluate the performance of the INDCLIM, regional RMSE statistics were compared against two widely used bias-corrected climate products, namely ISIMIP (Lange, 2019) and NASA-NEX GDDP (Thrasher et al., 2022; Table 3.1). For JJAS precipitation over Central India, the INDCLIM exhibits the lowest RMSE (3.47 mm day^{-1}), outperforming both NASA-NEX GDDP (3.51 mm day^{-1}) and ISIMIP (3.70 mm day^{-1}). Similarly, for annual mean temperature (Tmean), the bias-corrected IITM-ESM shows a substantially lower RMSE ($0.60 ^{\circ}\text{C}$) compared to NASA-NEX GDDP ($2.31 ^{\circ}\text{C}$) and ISIMIP ($2.35 ^{\circ}\text{C}$). These results indicate that the bias-correction framework not only reduces systematic errors relative to the raw model output but also produces a dataset whose regional-scale performance is comparable to, and in some cases superior to, widely used bias-corrected CMIP products. The particularly large improvement in temperature RMSE suggests that the applied correction methodology effectively captures the observed thermal climatology over India while retaining the underlying climate-change signal from the parent Earth System Model (Figure 6).

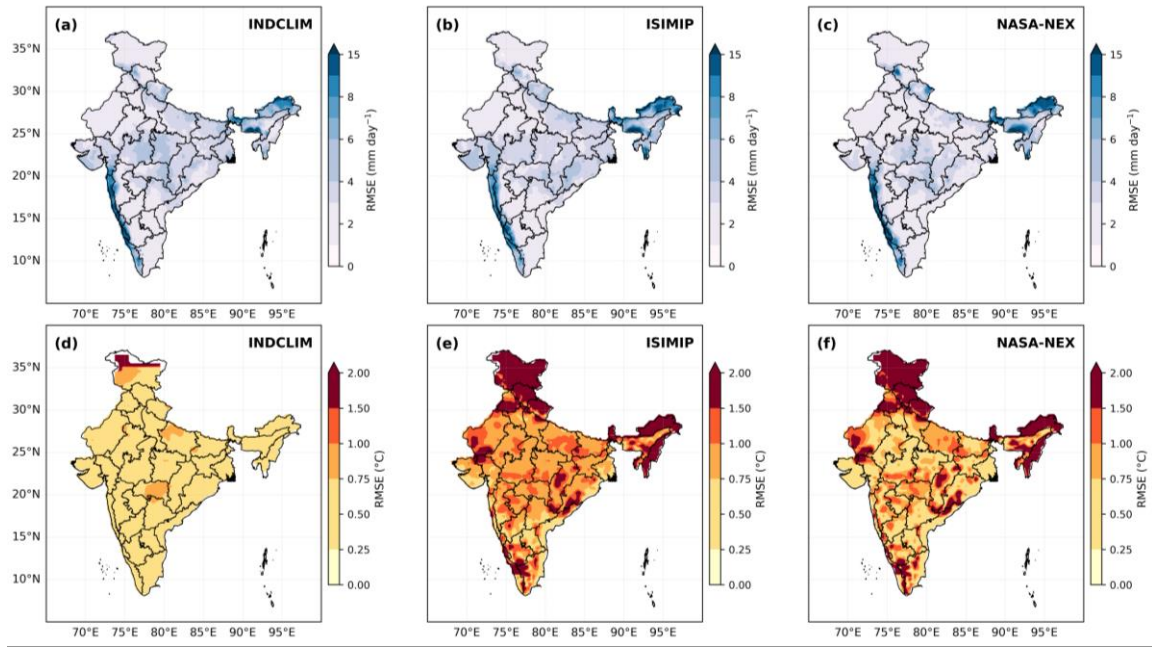


Figure 6: Spatial distribution of root-mean-square error (RMSE) between observations and historical simulations over India for precipitation (top row; mm day^{-1}) and near-surface air temperature (bottom row; $^{\circ}\text{C}$). Results are shown for INDCLIM (a, d), ISIMIP (b, e), and NASA-NEX (c, f) datasets (left to right). Precipitation RMSE is calculated from JJAS mean rainfall, and temperature RMSE from annual mean temperature over the common analysis period.

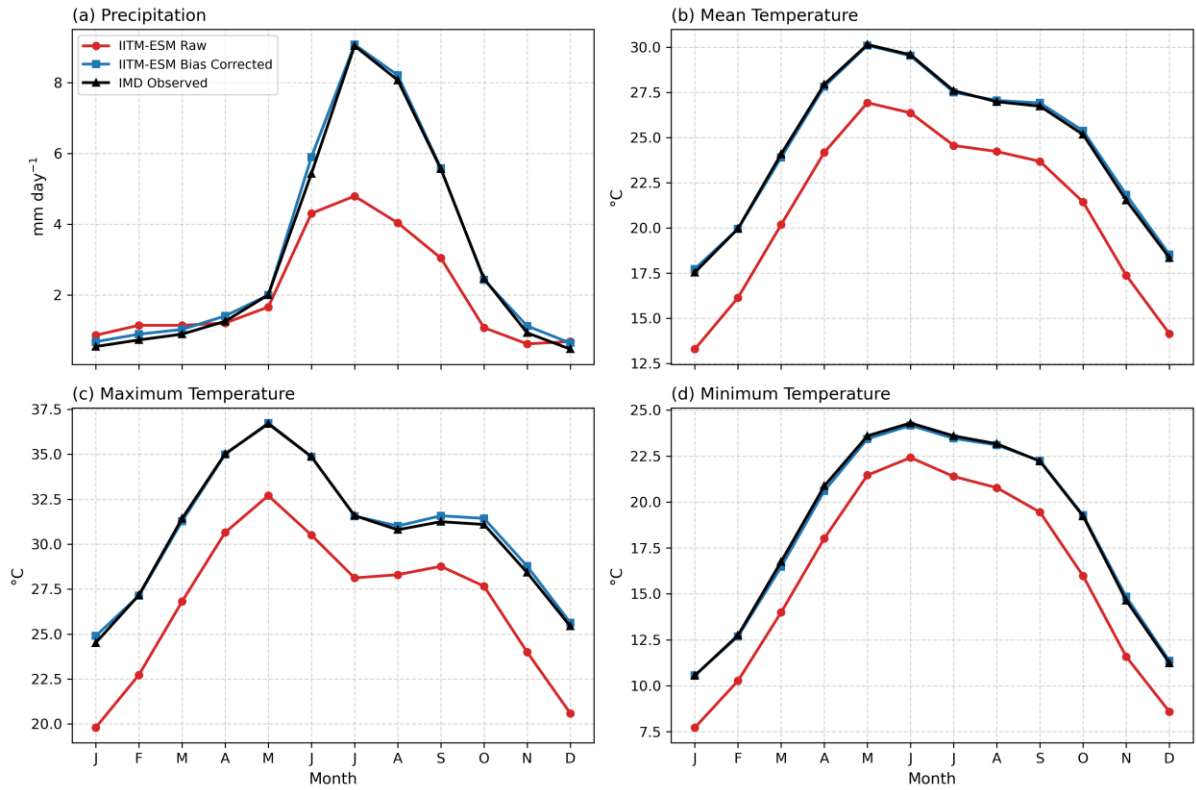


Figure 7: Area-averaged monthly climatology over the Indian landmass (8° to 38° N and 66° to 98° E) for the historical period 1950–2014. (a) precipitation (mm day⁻¹), (b) mean surface air temperature (°C), (c) maximum temperature (°C), and (d) minimum temperature (°C). Red lines with circles denote raw IITM-ESM, blue lines with squares denote INDCLIM, and black lines with triangles denote IMD observations.

4.3 Seasonal Cycle

Figure 7 compares the observed seasonal cycles of all-India precipitation, mean temperature (Tmean), maximum temperature (Tmax), and minimum temperature (Tmin) from IMD observations with those simulated by the raw IITM-ESM and the bias-corrected product (INDCLIM).

The observed precipitation climatology (Fig. 7a) exhibits the characteristic evolution of the Indian summer monsoon, with low rainfall during January–May, a rapid increase during June, a peak of approximately 9 mm day⁻¹ in July, sustained rainfall during August, and a gradual decline during September and October. The raw IITM-ESM successfully reproduces the timing of the seasonal cycle, including the onset, peak, and withdrawal phases of the monsoon. However, the magnitude of precipitation is substantially underestimated throughout the monsoon season. The simulated July peak reaches only about 4.8 mm day⁻¹, corresponding

to nearly half of the observed rainfall. This systematic underestimation is consistent with the widespread dry bias identified in the spatial climatology (Fig. 2a), indicating that the deficiency is present not only regionally but also in the all-India mean. Following bias correction, the precipitation seasonal cycle closely matches the observations, with marked improvements in both the monsoon peak and the transition seasons. INDCLIM successfully preserves the seasonal phase while substantially reducing amplitude errors.

The observed annual cycle of Tmean (Fig. 7b) is characterized by a pre-monsoon maximum of approximately 30 °C during May, followed by moderate cooling during the monsoon months and minimum temperatures during winter. The raw IITM-ESM reproduces the overall shape of the seasonal cycle but exhibits a persistent cold bias throughout the year. The bias is largest during winter and remains evident during all seasons, suggesting a systematic cold offset in the model climatology. This behavior is consistent with the widespread cold biases over the Indian landmass shown in Figure 2c. After bias correction, the simulated Tmean closely follows the observed seasonal evolution, with substantial reductions in monthly biases throughout the year.

The observed Tmax climatology (Fig. 7c) displays a pronounced pre-monsoon peak in May, followed by a sharp decline during the monsoon season and a gradual decrease toward winter. The raw IITM-ESM captures the temporal evolution of Tmax but substantially underestimates its magnitude, particularly during the pre-monsoon months when the bias exceeds 4 °C. The largest discrepancies occur during April–June, a period that strongly influences the representation of land-atmosphere coupling and thermal conditions preceding monsoon onset. The bias-corrected product (INDCLIM) reproduces both the magnitude and phase of the observed Tmax cycle with high accuracy, substantially reducing the large pre-monsoon cold bias present in the raw simulation.

The Tmin seasonal cycle (Fig. 7d) increases from winter to a summer maximum and remains elevated during the monsoon season before declining toward the end of the year. Similar to Tmean and Tmax, the raw IITM-ESM captures the seasonal evolution but exhibits a systematic cold bias across all months. Although the spatial analysis (Fig. 2g) revealed localized warm Tmin biases over northwestern India, the all-India average remains cold-biased, indicating that the extensive cold-biased regions dominate the national-scale mean. This highlights the importance of evaluating both spatial patterns and area-averaged statistics when

assessing model performance. The bias-corrected Tmin closely reproduces the observed seasonal cycle, with only minimal residual differences throughout the year.

Overall, the seasonal-cycle analysis demonstrates that the raw IITM-ESM realistically captures the timing and phase of the observed annual evolution of precipitation and temperature but exhibits substantial errors in magnitude. The consistency between the seasonal-cycle biases (Fig. 7) and the spatial climatological biases (Fig. 2) indicates that these errors are systematic features of the model climatology. The bias-correction framework effectively removes these systematic offsets while preserving the observed seasonal evolution, resulting in a substantially improved representation of the Indian hydroclimate and near-surface thermal conditions.

4.4 Evaluation of Daily Climate Extremes

Figure 8 shows that the bias-corrected dataset generally provides positive added value (AV) for all four extreme climate indices across most of India. For Rx1day, improvements are observed over northern, central, and northeastern India, with the largest gains over the Western Ghats and northeastern regions, though some localized negative AV remains over the eastern coast and leeward areas. R20mm exhibits widespread positive AV, indicating that the bias-correction method effectively improves the simulation of heavy rainfall occurrence across the country. The largest improvement is found for TXx, with positive AV over almost the entire Indian region, showing that annual maximum temperature is substantially better represented after bias correction. In contrast, TX90p shows relatively small changes, with AV close to zero over most regions, suggesting limited improvement in reproducing the frequency of warm extremes. Overall, the results demonstrate that the INDCLIM bias-corrected dataset is most effective for improving heavy rainfall occurrence and maximum temperature extremes, while improvements are comparatively smaller for the most localized rainfall and percentile-based temperature extremes.

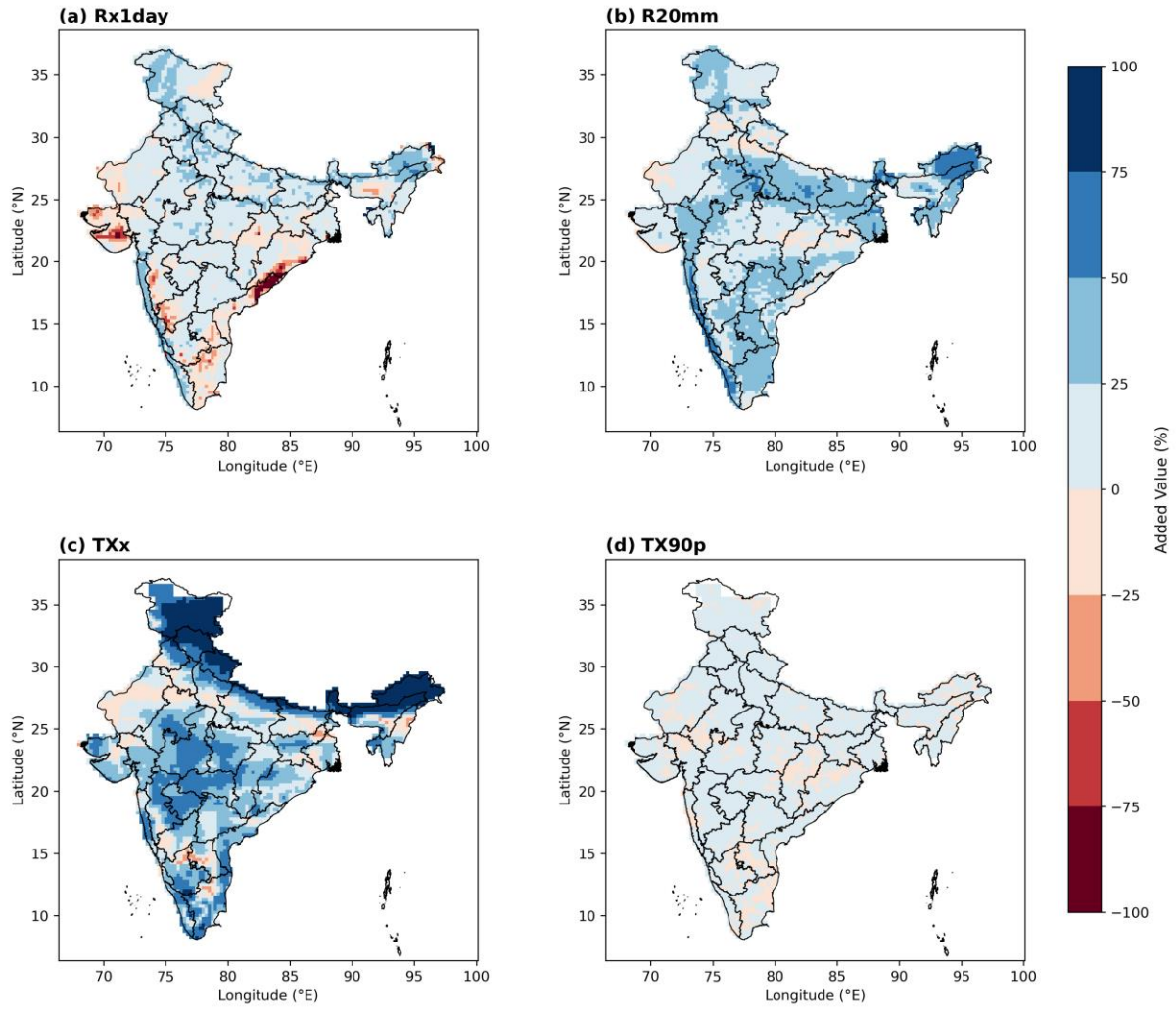


Figure 8: Spatial distribution of the added value (%) of the INDCLIM dataset relative to the raw IITM-ESM simulations for selected ETCCDI climate extreme indices during the historical period: (a) Rx1day (annual maximum 1-day precipitation), (b) R20mm (number of days with daily precipitation ≥ 20 mm), (c) TXx (annual maximum of daily maximum temperature), and (d) TX90p (percentage of days with daily maximum temperature above the 90th percentile).

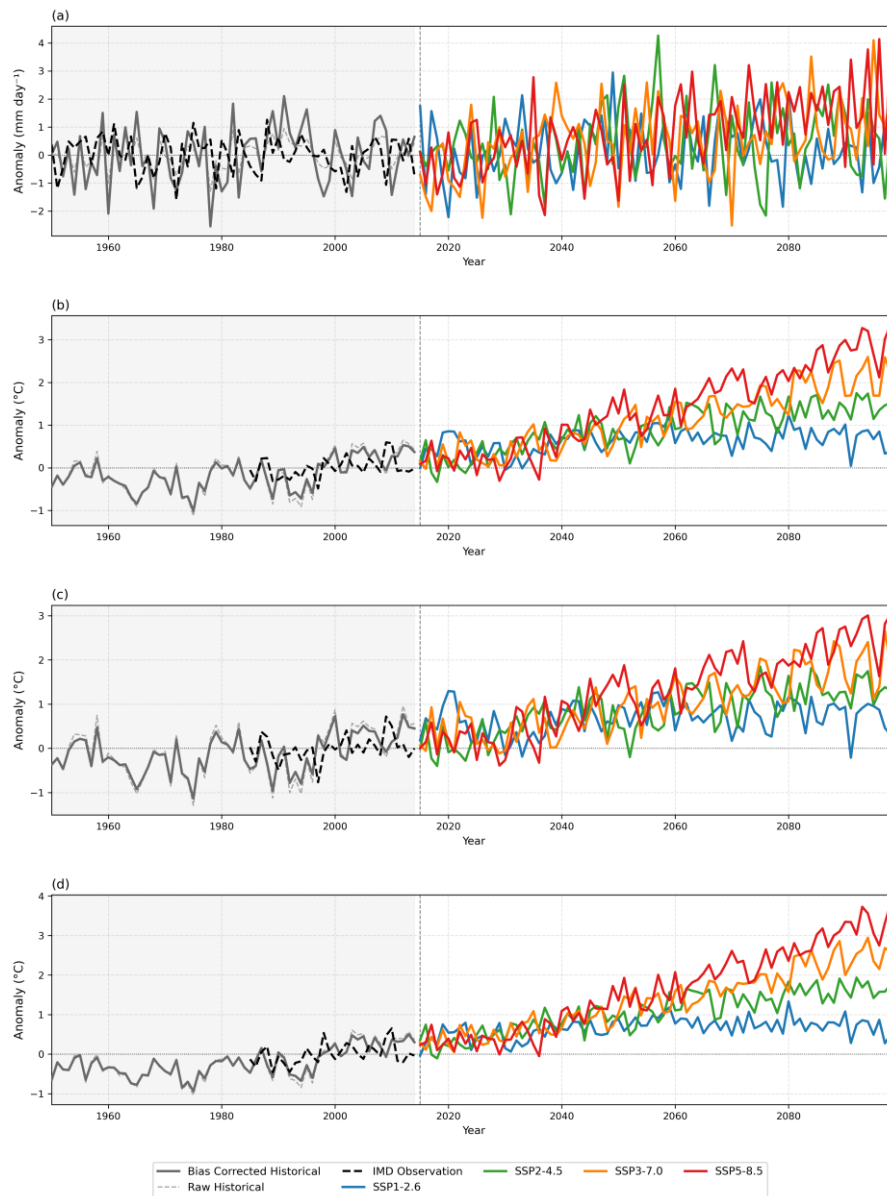


Figure 9: The time series of pr , T_{mean} , T_{max} and T_{min} over the Indian region under historical forcing and four SSP scenarios (1950–2099). (a) JJAS precipitation (pr , mm day^{-1}), (b) annual mean temperature (T_{mean} , $^{\circ}\text{C}$), (c) annual maximum temperature (T_{max} , $^{\circ}\text{C}$), and (d) annual minimum temperature (T_{min} , $^{\circ}\text{C}$). All anomalies are computed relative to a monthly climatology over the baseline period 1950–2014 for precipitation and 1985–2014 for temperature. The light grey shading marks the historical period (1950–2014); the dashed vertical line at 2015 separates the historical and projection periods. Bias-corrected historical IITM-ESM (dark grey solid), raw historical IITM-ESM (light grey dashed), and IMD observations (black dashed) are shown for the historical interval; bias-corrected projections under SSP1-2.6 (blue), SSP2-4.5 (green), SSP3-7.0 (orange), and SSP5-8.5 (red) extend through 2099.

4.5 Historical Variability and Future Climate Projections

Figure 9 presents the anomaly time series of all-India precipitation, mean temperature (Tmean), maximum temperature (Tmax), and minimum temperature (Tmin) for the historical period and future SSP scenarios. The anomaly series are referenced to the historical climatology, allowing a direct comparison of temporal variability and long-term trends.

A notable feature across all variables is the close agreement between the raw and bias-corrected historical simulations. Although substantial differences exist between the raw and corrected climatological means (Figs. 2–3 and Fig. 7), the anomaly time series remain nearly identical throughout the historical period. This indicates that the bias-correction procedure primarily adjusts the systematic mean-state bias while preserving the model's temporal variability and long-term evolution. The close correspondence between the corrected historical simulations and IMD observations further demonstrates the ability of the bias-corrected dataset to reproduce observed interannual variations while maintaining the underlying climate-change signal simulated by the model.

The precipitation anomaly series (Fig. 9a) exhibits pronounced interannual variability throughout the historical period, with fluctuations of approximately $\pm 2 \text{ mm day}^{-1}$ and no evident long-term monotonic trend. The bias-corrected historical simulation reproduces the observed variability reasonably well. Following 2015, all SSP scenarios project an increase in precipitation relative to the historical baseline, although the magnitude of change differs considerably among pathways. SSP1-2.6 remains within the range of historical variability for much of the century, whereas SSP2-4.5, SSP3-7.0, and SSP5-8.5 show progressively larger positive anomalies toward the end of the century. The strongest increase occurs under SSP5-8.5, where precipitation anomalies frequently exceed $+2 \text{ mm day}^{-1}$ during the late twenty-first century. Despite the overall increase, substantial year-to-year variability persists across all scenarios, indicating that internal climate variability remains an important component of future monsoon rainfall.

The Tmean anomaly series (Fig. 9b) displays a clear warming trend that strengthens during the late historical period and continues throughout the twenty-first century. The divergence among emission pathways becomes increasingly apparent after the middle of the century. Under SSP1-2.6, warming stabilizes during the latter half of the century, whereas SSP2-4.5, SSP3-7.0, and SSP5-8.5 exhibit progressively larger temperature increases. By the end of the century, Tmean anomalies approach approximately 1°C , 1.5°C , $2\text{--}2.5^\circ\text{C}$, and 3°C

under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, respectively. These projections are consistent with the expected dependence of regional warming on future greenhouse-gas emissions.

The Tmax projections (Fig. 9c) broadly follow the evolution of Tmean, with sustained warming under all future scenarios. While interannual variability remains evident, the long-term warming signal becomes increasingly dominant as the century progresses. End-of-century Tmax anomalies reach approximately 1 °C under SSP1-2.6 and approach 3 °C under SSP5-8.5. The similarity between the raw and bias-corrected historical anomaly series further confirms that the correction procedure preserves the temporal characteristics of daily maximum temperature variability.

The Tmin projections (Fig. 9d) reveal a stronger warming response than Tmax across all future scenarios. By the end of the century, Tmin anomalies exceed those of Tmax under each SSP pathway, with the largest increases occurring under SSP5-8.5. The projected Tmin anomaly approaches 3.5-4 °C by 2100, compared to approximately 3 °C for Tmax. This differential warming suggests a tendency toward a reduction in the diurnal temperature range (DTR) during the twenty-first century, particularly under higher-emission scenarios. The larger increase in nighttime temperatures is consistent with the broader climate-model literature, which identifies enhanced nocturnal warming as a characteristic response to increasing greenhouse-gas concentrations.

Overall, Figure 9 demonstrates that the bias-correction framework preserves historical climate variability and long-term trends while effectively correcting systematic biases in the mean state. The future projections indicate increasing precipitation and substantial warming across India, with the magnitude of change strongly dependent on the emissions pathway. Temperature changes are particularly pronounced under SSP3-7.0 and SSP5-8.5, while Tmin exhibits a stronger warming response than Tmax, implying a progressive reduction in the diurnal temperature range under future climate conditions.

5. Dataset Visualization and Access

To facilitate data exploration and enhance accessibility for researchers, policymakers, and stakeholders, the bias-corrected IITM-ESM (INDCLIM) climate projections have been integrated into a dedicated web-based visualization dashboard. The dashboard provides interactive access to historical and future climate projections for multiple variables, including precipitation, temperature (mean, minimum and maximum) under different SSP scenarios.

Users can visualize spatial patterns, temporal variations, and climate-change signals without requiring specialized data-processing tools. The platform serves as an effective interface for examining climate projections and supports a wide range of climate-impact and adaptation studies. The dashboard can be accessed at: <https://cccr.tropmet.res.in/esm/dashboard.php>.

Summary

Climate model projections are essential for assessing future climate risks; however, systematic biases in raw model simulations limit their direct applicability for regional-scale impact studies. In this study, a high-resolution bias-corrected climate projection (INDCLIM) dataset for India was developed using outputs from the IITM Earth System Model (IITM-ESM) participating in CMIP6. Daily simulations of precipitation, mean temperature, maximum temperature, minimum temperature, relative humidity, surface downwelling shortwave radiation, and near-surface wind speed from the historical and four future SSP scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) were bias-corrected using observational datasets from IMD and ERA5.

Empirical Quantile Mapping (EQM) was applied to the historical simulations, while Quantile Delta Mapping (QDM) was employed for future projections to preserve the model-projected climate change signal across the full probability distribution. Evaluation against observations revealed substantial improvements in the representation of Indian climate after bias correction. The widespread dry bias in monsoon precipitation and the systematic cold biases in near-surface temperatures present in the raw IITM-ESM simulations were significantly reduced across most regions of India. Root Mean Square Error (RMSE) analyses demonstrated large reductions in both precipitation and temperature errors, with the bias-corrected dataset exhibiting performance comparable to or better than widely used bias-corrected products such as NASA-NEX GDDP and ISIMIP, particularly over Central India. The RMSE-based added-value analysis confirmed that bias correction meaningfully improved the representation of climate extremes across India, with the strongest improvements for maximum temperature extremes (TXx) and heavy-rainfall occurrence (R20mm), moderate improvement for extreme one-day rainfall (Rx1day), and limited gains for warm-day frequency (TX90p). Localized negative added-value regions-mainly along orographic leeward zones and the eastern coastline-indicate areas where extreme-event behavior is harder to correct statistically, rather than an overall failure of the method.

The bias-corrected simulations accurately reproduced the observed seasonal cycles of precipitation, mean temperature, maximum temperature, and minimum temperature while preserving the timing and phase of the annual cycle. Analysis of historical anomaly time series further showed that the correction framework effectively retains interannual variability and long-term climate trends, indicating that the underlying climate-change signal from the parent Earth System Model remains intact.

Future projections indicate a robust warming signal across India under all SSP scenarios, with the magnitude of warming strongly dependent on future greenhouse-gas emissions. End-of-century warming reaches approximately 3 °C for mean and maximum temperature under SSP5-8.5, while minimum temperature increases by up to 4 °C, suggesting a progressive reduction in the diurnal temperature range. Monsoon precipitation is projected to increase under all scenarios, with the largest increases occurring under higher-emission pathways. Overall, the resulting bias-corrected IITM-ESM dataset provides a physically consistent and observation-constrained climate projection product for India, offering a valuable resource for climate impact assessments, adaptation planning, water-resource management, agriculture, and other sectoral applications requiring reliable future climate information.

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Data availability

All the observational datasets used in this document are publicly available, and the IITM-ESM model datasets used for this study are accessible through the ESGF repository <https://esgf-node.llnl.gov/search/cmip6/>. The analysis was carried out using open-source software tools, including Climate Data Operators (CDO) and Python (<https://www.python.org/>), for computations and visualizations.

References

- Cannon, A. J., Sobie, S. R., & Murdock, T. Q. (2015). Bias correction of GCM precipitation by quantile mapping: how well do methods preserve changes in quantiles and extremes? *Journal of Climate*, 28(17), 6938–6959.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., & Schepers, D. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049.
- Lange, S. (2019). Trend-preserving bias adjustment and statistical downscaling with ISIMIP3BASD (v1. 0). *Geoscientific Model Development*, 12(7), 3055–3070.
- Maraun, D. (2016). Bias correcting climate change simulations-a critical review. *Current Climate Change Reports*, 2(4), 211–220.
- Mishra, V., Bhatia, U., & Tiwari, A. D. (2020). Bias-corrected climate projections for South Asia from coupled model intercomparison project-6. *Scientific Data*, 7(1), 338.
- Pai, D. S., Rajeevan, M., Sreejith, O. P., Mukhopadhyay, B., & Satbha, N. S. (2014). Development of a new high spatial resolution (0.25×0.25) long period (1901-2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *Mausam*, 65(1), 1–18.
- Rampal, N., Hobeichi, S., Gibson, P. B., Baño-Medina, J., Abramowitz, G., Beucler, T., González-Abad, J., Chapman, W., Harder, P., & Gutiérrez, J. M. (2024). Enhancing regional climate downscaling through advances in machine learning. *Artificial Intelligence for the Earth Systems*, 3(2), 230066.
- Reji, M. J. K., Varikoden, H., & Vellore, R. K. (2026). Assessment of seasonal and extreme rainfall over Kerala using bias-corrected high-resolution climate models: historical and future changes. *Climate Dynamics*, 64(6), 290.
- Srivastava, A. K., Rajeevan, M., & Kshirsagar, S. R. (2009). Development of a high resolution daily gridded temperature data set (1969–2005) for the Indian region. *Atmospheric Science Letters*, 10(4), 249–254.
- Swapna, P., Krishnan, R., Sandeep, N., Prajeesh, A. G., Ayantika, D. C., Manmeet, S., & Vellore, R. (2018). Long-term climate simulations using the IITM Earth system model (IITM-

ESMv2) with focus on the South Asian Monsoon. *Journal of Advances in Modeling Earth Systems*, 10(5), 1127–1149.

Switanek, M. B., Troch, P. A., Castro, C. L., Leuprecht, A., Chang, H.-I., Mukherjee, R., & Demaria, E. M. C. (2017). Scaled distribution mapping: a bias correction method that preserves raw climate model projected changes. *Hydrology and Earth System Sciences*, 21(6), 2649–2666.

Thrasher, B., Wang, W., Michaelis, A., Melton, F., Lee, T., & Nemani, R. (2022). NASA global daily downscaled projections, CMIP6. *Scientific Data*, 9(1), 262.