

Benchmarking Regional Climate Variability in CMIP6 over India in the Recent Accelerated Global Warming Epoch

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Abstract

This study evaluated 30 CMIP6 models and their Multi-Model Mean (M3) with observations in capturing India's regional climate variability and extremes during 2015–2024, a period when global temperatures reached approximately 1.5°C above pre-industrial levels. The mean state of the climate and Expert Team on Climate Change Detection and Indices (ETCCDI)-based extremes in models are compared against observations from the Indian Meteorological Department (IMD). The M3 showed notable skill-pattern correlations of up to 0.96 for rainfall and greater than 0.9 for temperature; Kling-Gupta Efficiency (KGE) scores also typically exceeded 0.8 for temperature and 0.6 for rainfall, especially over central and eastern India. However, substantial uncertainties remain; dry spells were underestimated by up to 8 spells/year in arid and southern India, and warm, wet days by as much as 16 days/year in key regions. Individual models struggled with daily extremes and with matching observed precipitation trends. Persistent regional errors, particularly in orographic and coastal zones, limit direct use of projections for adaptation in the coming decades. Future work should prioritise improved simulation of extremes, robust bias correction/downscaling, and advanced representation of monsoon dynamics and teleconnections. This study highlights that benchmarking climate models against high-resolution regional observational data is essential for meaningful regional risk management.

Introduction

Between 2015 and 2024, Earth experienced its most pronounced warming since the beginning of reliable measurements, with every year in this period ranking among the ten hottest on record (Berkeley Earth, 2025; NASA, 2025; WMO, 2025). During this epoch, global mean temperatures increased by approximately 1.3–1.5°C above pre-industrial levels, touching/exceeding the critical 1.5°C threshold targeted by international climate agreements (WMO, 2025; Bevacqua et al., 2025; Hansen et al., 2025). This accelerated warming has driven pervasive increases in the frequency and severity of extreme events worldwide, lethal heatwaves, severe droughts, catastrophic floods, wildfires, and accelerated loss of glaciers and sea ice (WMO, 2025; Copernicus, 2025; Germanwatch, 2025).

Rising ocean heat content and record-high atmospheric greenhouse gas concentrations have introduced new long-term stressors to global systems (Cheng et al., 2021, 2022). The resulting impacts are now observed across numerous sectors, including diminished food security, strained water supplies, public health threats, and mounting challenges to economic stability and societal resilience (IPCC, 2023; Abdul-Nabi et al., 2024). These pressures and risks fall especially hard on vulnerable regions, such as developing nations, coastal zones, and much of South Asia, thereby heightening the urgency of effective climate adaptation and mitigation (Germanwatch, 2025; UN, 2021).

Within this evolving global context, India emerges as one of the world's most climate-sensitive regions. Over the past decade, the country has experienced a dramatic rise in the frequency and magnitude of climate extremes-most notably severe floods, deadly heatwaves, and far-reaching droughts (Gupta et al., 2024). These changes threaten the lives and livelihoods of millions, making robust, high-resolution

regional climate projections an increasingly urgent priority for planning and resilience (Chupal et al., 2025; Krishnan et al., 2025; Archana et al., 2024).

Recent advances in climate modelling, led by the Coupled Model Intercomparison Project Phase 6 (CMIP6), have provided the scientific community with powerful tools for diagnosing and anticipating such regional risks (Eyring et al., 2016; Kodna et al., 2023). High-fidelity projections of both mean climate and extremes are crucial for disaster risk reduction, agricultural management, water resource management, and infrastructure safeguarding (CEEW, 2024; DNI, 2030; Sandeep et al., 2025). Improvements in model skill are now closely linked to better predictions of hazards such as monsoon variability and heat extremes, which CEEW2024).

Hence, multiple studies have benchmarked CMIP6 outputs against high-resolution records from the Indian Meteorological Department (IMD) in the historical context. While notable advances have been made relative to previous generations, significant biases and uncertainties persist in CMIP6, particularly in regional climate details and extreme-event representation (Vinodhkumar et al., 2025; Kushwaha et al., 2024; Saha & Sateesh, 2022; Suthinkumar et al., 2023; Kaagita et al., 2024, 2025; Thandlam et al., 2024).

On the other hand, multi-model mean/ensembles (M3) and advanced bias-corrected datasets generally capture the major patterns and climatology of Indian monsoon rainfall and mean temperatures (Kaagita et al., 2024). These models often achieve high pattern correlations with mean rainfall and some standard extreme indices, providing confidence in their representation of average climate features (Vinodhkumar et al., 2025; Kushwaha et al., 2024; Saha & Sateesh, 2022; Yaduvanshi et al., 2021). However, individual models, and even their ensembles, may markedly underestimate or overestimate extremes, particularly for event characteristics at sub-daily scales and in orographic or coastal regions (Kushwaha et al., 2024; Chatterjee et al., 2023; Konda et al., 2023; Saikranthi et al., 2024; Kaagita et al., 2024).

Among the best-performing models, there is growing agreement that the frequencies of extreme precipitation and heat events will intensify under high-emission scenarios, pointing primarily to central and western India as future hotspots (Reddy & Saravanan, 2023; Shahi et al., 2022; Suthinkumar et al., 2023; Varikoden et al., 2025; Saha & Sateesh, 2022; Varghese et al., 2025). However, the ability of CMIP6 simulations to provide actionable projections for adaptation is still constrained by biases, the underestimation of compound and daily-scale events, and the incomplete capture of the teleconnections and internal climate variability that shape monsoon extremes (Kushwaha et al., 2024; Chowdary et al., 2022; Saikranthi et al., 2024; Choudhury et al., 2021).

Upon closer examination, CMIP6 models, particularly when employed as bias-corrected multi-model means, perform well in simulating the broad spatial and seasonal patterns of mean monsoon rainfall over India. Correlations with IMD data for mean rainfall can reach 0.96 (Vinodhkumar et al., 2025; Kushwaha et al., 2024; Saha & Sateesh, 2022). However, the performance of extreme precipitation indices (such as RX1DAY, RX5DAY, consecutive dry days, and wet days) is highly variable, with substantial inter-model uncertainty and notable under- or overestimation in the Western Ghats and Northeastern regions (Chatterjee et al., 2023; Suthinkumar et al., 2023). Models such as EC-Earth3, MRI-

ESM2-0, and GFDL-ESM4 have been highlighted for their ability to reproduce several extremes (Vinodhkumar et al., 2025; Kushwaha et al., 2024; Vinod & Agilan, 2024).

Similarly, CMIP6 models consistently project strong warming trends across India, most ensemble means indicating a 1.2–2.4°C rise by 2040 under high-emission pathways (Sabarinath et al., 2024; Norgate et al., 2024; Das and Umamahesh, 2021). While spatial patterns for both mean and maximum temperatures are broadly credible, simulating temporal variability and heatwave events remains a challenge, and some models (HadGEM3-GC31, UKESM1-0-LL) show greater skill than others at event scales (Sabarinath et al., 2024; Norgate et al., 2024; Das and Umamahesh, 2021). Future projections from CMIP6 consistently suggest that the frequency and intensity of climate extremes-especially heavy rainfall and heatwaves-will escalate, particularly in central India, the Western Ghats, and the Northeastern states under the highest emission scenarios (Shahi et al., 2022; Suthinkumar et al., 2023; Khardekar et al., 2023; Varikoden et al., 2025; Kaagita et al., 2025). More wet days and increasing rainfall intensity are anticipated across large parts of the country, although intermodel spread and persistent biases require cautious interpretation (Norgate et al., 2024; Yaduvanshi et al., 2021; Saha & Sateesh, 2022; Varghese et al., 2025).

Despite these advances, systematic limitations remain, including biases in regional rainfall estimation, difficulties with short-duration and compound events, and imperfect simulation of monsoon onset, withdrawal, and key teleconnection patterns such as El Niño and the Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) (Choudhury et al., 2021; Konda et al., 2023; Saikranthi et al., 2024). Bias correction and emerging machine learning approaches improve agreement with observations but do not fully resolve errors for high-impact, short-duration, or compound events (Kesavavarthini et al., 2023; Velpuri et al., 2024; Saikranthi et al., 2024; Varghese et al., 2025).

In this context, the central scientific questions that the present work would address are:

1. How well do state-of-the-art CMIP6 models capture the Indian regional climate, particularly precipitation and temperature extremes, during an era of exceptional global warming (2015–2024)?
2. Does the benchmarking of the first decade of CMIP6 (2015–2024) predictions help to gain confidence and choose the best models for future predictions/projections?
3. Does a multi-model mean (M3) perform better than individual models in representing the observed regional climate, both for the mean state and climate extremes?
4. By choosing M3, could we transform probabilistic CMIP6 climate prediction into a deterministic one for future decades?

To address these scientific and policy challenges, this study rigorously evaluates the skill of CMIP6 models in simulating observed climate variability and extremes over India during the unprecedented warming epoch of 2015–2024, which also coincides with their first decade of projections. By systematically comparing CMIP6 outputs against high-resolution IMD observations, this analysis clarifies both the strengths and enduring limitations of current-generation simulations, informing future improvements in event-scale modelling, bias correction, and scenario assessment. Ultimately, these

insights will support more robust climate risk management and adaptation planning in one of the world's most vulnerable regions.

Data and Methods

Daily temperature and rainfall data from 30 CMIP6 models, available at various spatial resolutions for 1981–2024, and IMD observations for 1951–2024 were used. Daily minimum and maximum temperature data from the IMD ($1^\circ \times 1^\circ$) were used to compute the daily mean temperature. While IMD rainfall observations are available at $0.25^\circ \times 0.25^\circ$ (Pai et al., 2014), all CMIP6 and IMD datasets are interpolated onto a standard grid of 1° resolution. Historical reference values were established using the baseline period 1981–2010, in accordance with WMO and IMD standards (IMD, 2022). Global surface temperature data from the European Centre for Medium-Range Weather Forecasts Reanalysis v5 (ERA5) during 1951–2024 at a $0.25^\circ \times 0.25^\circ$ resolution are also used. Model performance was assessed across 30 CMIP6 models (details in Supplementary Table S1), and figures comparing anomalies, biases, and trends were generated to visualise ensemble and individual model results. Mean rainfall and temperature anomalies for major seasons (JJAS, OND, MAM) were computed for each model and compared to IMD records and the M3.

Skill metrics, including root mean square error (RMSE), mean absolute error (MAE), standard deviation (SD), Pearson correlation coefficient, and Kling-Gupta Efficiency (KGE), were calculated to quantify the fidelity with which the observed mean climate was captured. Extreme indices such as consecutive dry days (CDD), consecutive wet days (CWD), annual total days with heavy rainfall (90th percentile), and warm days (90th percentile) were analysed at daily resolution, following the Expert Team on Climate Change Detection and Indices (ETCCDI) metrics. Spatial and temporal differences between model outputs and IMD records were mapped across India to illustrate the extent to which CMIP6 models accurately simulate event intensity and distribution. A single moderate scenario, SSP2-4.5, was selected from the CMIP6 models and the computed ensemble for this study, as it closely aligns with observed warming trends (1.5°C) during 2015–2024. By focusing on SSP2-4.5, the analysis ensures that model simulations are directly comparable with observed IMD and reanalysis records of temperature and rainfall anomalies, thereby maintaining a realistic assessment of model fidelity for both mean climate and extremes over the recent warmest decade.

The study did not use the higher-resolution NEX-GDDP-CMIP6 data; instead, it used CMIP6 individual models and M3. The main disadvantages of the NEX-GDDP-CMIP6 dataset, relative to raw CMIP6 output, are closely linked to the statistical downscaling and bias-correction methods employed. Although these approaches effectively correct systematic biases and enhance spatial resolution to 25 km, they can suppress or smooth estimates of climate extremes, thereby underrepresenting the actual intensity of high-impact events such as heatwaves and intense precipitation. Furthermore, because statistical downscaling relies on historical observational data, any biases or errors in the reference dataset are inevitably inherited by the final projections. This process can also fail to preserve the physically consistent relationships and covariances among climate variables inherent in the original global climate

model output. As a result, for studies requiring the most accurate representation of underlying physical processes, complete variable sets, or the internal dynamics of extreme events, raw CMIP6 data remains preferable for reliability, even with its coarser resolution (Vinodhkumar et al., 2025; Gupta et al., 2024; Saha & Sateesh, 2022). Thus, the bias-corrected, downscaled datasets are advantageous for simulating the mean climate. However, they may not fully capture daily or compound extremes, especially in complex topography or rapidly changing event characteristics in India (Maraun et al., 2017; Kesavavarthini et al., 2023; Velpuri et al., 2024).

$$KGE = 1 - \sqrt{\left((r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2\right)} \text{-----} (1)$$

Where r = Pearson correlation coefficient

$$\beta = \frac{\mu_s}{\mu_o} \text{ (bias ratio)}$$

$$\gamma = \left(\frac{\sigma_s}{\mu_s}\right) / \left(\frac{\sigma_o}{\mu_o}\right) \text{ (relative variability ratio)}$$

μ_s, σ_s = mean and standard deviation of simulated values

μ_o, σ_o = mean and standard deviation of observed values

Scatter Index (SI)

$$SI = \frac{\sqrt{\left[\left(\frac{1}{N}\right) \sum_{i=1}^N (S_i - O_i)^2\right]}}{\mu_o} \text{-----} (2)$$

where S_i = model value

O_i = observed value

μ_o = mean of the observed values

N = number of observations

Willmott's Index

$$d = 1 - \frac{\sum_{i=1}^N (S_i - O_i)^2}{\left\{ \sum_{i=1}^N (|S_i - \mu_o| + |O_i - \mu_o|)^2 \right\}} \text{-----} (3)$$

where: S_i = model value

O_i = observed value

μ = mean of observed values

N = number of observations

Range: $0 \leq d \leq 1$ $d = 1 \rightarrow$ perfect agreement $d = 0 \rightarrow$ no agreement

Results and discussions

Temperature anomalies for the global and Indian domains from 2015 to 2024 exhibit significant changes relative to the 1981–2010 period (Fig. 1). Global mean temperature anomalies have risen by 1.3–1.4°C over the last decade, with the Arctic, northern Eurasia, and Asia witnessing some of the highest regional increases, exceeding +2°C (Forster et al., 2022). A record-low planetary albedo and reduced low-cloud cover are key factors contributing to the recent temperature surge (Goessling et al., 2025). In India, IMD observations indicate that mean annual temperature anomalies peaked at +0.65°C in 2024 (relative to the 1991–2020 baseline), with an average of +0.31°C above this baseline for the period 2015–2024. Notably, each year since 2010 has ranked among the warmest on record. Regionally, areas such as Himachal Pradesh and Kerala have experienced anomalies exceeding +1°C. In contrast, some parts of Uttar Pradesh and East Madhya Pradesh have reported localised cooling of up to -1°C in certain years.

The IMD and ERA5 (IMD-ERA5) comparison (Fig. 1c) reveals predominantly strong spatial agreement but persistent regional biases of up to $\pm 1^\circ\text{C}$, most notably a systematic offset in northern, coastal, and northeastern India. The annual mean temperature series (Fig. 1d) for 1951–2024 exhibits a significant upward trend: India's linear trend is +0.68°C per century for annual means and +0.89°C per century for annual maximums, with 2024 surpassing previous records by +0.65°C. Both ERA5 and IMD show accelerated warming from 2015 onwards, mirroring the trends observed in global datasets. Recent CMIP6 ensemble studies also capture these trends and spatial gradients across India, although individual models can differ by $\pm 0.5^\circ\text{C}$ regionally and still struggle with extremes and decadal variability. The potential of reanalyses to reproduce precipitation and temperature patterns is considered excellent at the global scale. However, it varies significantly across regions, particularly in areas with considerable spatial and temporal variability, such as India (Ghodichore et al., 2025). Given these biases-annual, spatial, and in trends- this study relies on IMD for analysis in India, supporting adaptation strategies with robust, high-resolution data and consistent methodologies.

The interannual variability of rainfall and temperature anomalies across seasons in India is illustrated in Fig. 2. The black line in each panel represents IMD observations, while the M3 (thick, coloured red line) aggregates outputs from 30 CMIP6 models. Notably, the M3 closely tracks the IMD record for both rainfall and temperature, in contrast to the broad scatter of individual models. Averaging across structurally distinct models cancels out random and model-specific biases, leaving more robust forced signals in rainfall and temperature (Varghese et al., 2025; Kim et al., 2020; Lei et al., 2023). CMIP6 also

shows reduced inter-model spread compared with CMIP5 in several regions, further tightening ensemble agreement with observations (Gulakhmadov et al., 2025; Hamed et al., 2021).

IMD rainfall anomalies fluctuate within ± 1 mm/day, and the M3 remains within ~ 0.3 mm/day of the IMD for most years during the summer monsoon (JJAS, Fig. 2a). This high agreement is also evident in the post-monsoon (OND, Fig. 2b), where the M3 rarely deviates by more than ± 0.4 mm/day from the IMD. In contrast, individual model runs can deviate by $\pm 2\text{--}3$ mm/day during the summer monsoon and ± 1 mm/day during the winter monsoon. Similarly, for temperature anomalies (Figs. 2c and 2d), the M3 remains within approximately $\pm 0.25^\circ\text{C}$ of the IMD, whereas individual models occasionally exceed ± 1 to $\pm 2^\circ\text{C}$. These results emphasise that, despite uncertainties in regional climate drivers during the warmest epoch, the M3 approach significantly reduces random errors and aligns much more closely with observed interannual variations than nearly any single CMIP6 model.

These findings align with recent research showing M3 superior skill at capturing mean and seasonal climate patterns across India, with correlation coefficients with the IMD often exceeding 0.9 for temperature and 0.7–0.85 for rainfall (Kaagita et al., 2024; Vennapu et al., 2025). Still, considerable spread among individual members demonstrates persistent model uncertainty for extremes and event-scale anomalies, a limitation highlighted in numerous evaluations of CMIP6 projections (Vinodhkumar et al., 2025; Suthinkumar et al., 2023). Thus, Figs. 1 and 2 together illustrate the value of M3 for high-confidence seasonal projections, reinforcing the need for robust benchmarking against high-quality observational data such as IMD for India.

Fidelity in simulating the mean climate

The temperature and rainfall anomalies derived from 30 individual CMIP6 models over India for the period 2015–2024 reveal notable spatial biases relative to IMD observations when M3 is not employed (Figs. 3 and 4). Notably, specific models, such as CanESM5 and FGOALS-g3, display significant warm biases of up to $+2^\circ\text{C}$ over northern India, whereas others, such as CMCC-CM2, exhibit cold biases of up to -2°C over central and coastal regions. Figure 4 (rainfall anomaly bias) exposes distinct model performance issues: wet biases ($> +1$ mm/day) are frequent in the northeast, coastal Gujarat, and Odisha, while dry biases (< -1 mm/day) cluster in the Western Ghats and southern peninsula-locations where local monsoon, convective events, and topographic rainfall are typically underrepresented or misrepresented by individual models. Models such as ACCESS-CM2 and CanESM5-CanOE consistently exhibit significant positive or negative deviations, depending on their ability to accurately resolve local monsoon circulations and terrain.

Despite the spatial biases in individual CMIP6 models highlighted in Figs. 3 and 4, many models still achieve relatively high agreement with IMD when evaluated using the Willmott index (WI) for monthly temperature and precipitation over India during 2015–2024 (Figs. 5 and 6). In other words, Figs. 5 and 6 translate the bias patterns from Figs. 3 and 4 into quantitative skill scores, enabling a more objective ranking (Supplementary Tables S1) of models that appear noisy or strongly biased in the anomaly maps.

Figures 3 and 5 together show that several models with notable warm or cold regional biases can still reproduce the observed spatial-temporal structure of monthly temperature reasonably well. For example, models such as KACE-1-0-G, MIROC6, NorESM2-MM, ACCESS-CM2, and UKESM1-0-LL rank at the top for temperature with WI values typically above 0.94–0.97, despite having regional biases of up to about $\pm 2^{\circ}\text{C}$ in Fig. 3.

At the other end, models with strong cold biases (INM-CM4-8, INM-CM5-0, CNRM-CM6-1, CNRM-CM6-1-HR, IPSL-CM6A-LR) show both large spatial biases in Fig. 3 and relatively low WI and KGE scores in Fig. 5, confirming that their apparent visual errors translate into weaker overall temperature skill. This comparison emphasises that the sign and magnitude of bias in Fig. 3 are closely linked to the WI and KGE rankings in Fig. 5 (Supplementary Table S1), and that models with modest mean biases and high correlations tend to cluster at the top of the temperature ranking.

For precipitation, models with large wet- or dry-anomaly patches in Fig. 4 generally obtain lower WI and KGE, whereas models with more moderate spatial biases perform best in Fig. 6 (Supplementary Table S2). FIO-ESM-2-0, AWI-CM-1-1-MR, INM-CM5-0, MIROC6, and MIROC-ES2L, which show relatively restrained wet/dry anomalies over central and eastern India (Fig. 4), achieve the highest rainfall KGE (around 0.87–0.91) and WI (≈ 0.94 –0.97), and the smallest scatter indices (Supplementary Table S2).

In contrast, models that severely overestimate or underestimate rainfall in climatically sensitive regions—such as CanESM5-CanOE and FGOALS-g3, which show strong wet biases in the northeast and coastal belts, and ACCESS-CM2, which exhibits pronounced dry biases over parts of the monsoon core zone—fall to the bottom of the rainfall skill ranking, with KGE often below 0.4–0.5 and WI below about 0.89 (Supplementary Table S2). This confirms that the spatial bias structures in Fig. 4 directly degrade integrated monthly performance metrics (Fig. 6), especially in regions dominated by monsoon convection and orographic rainfall.

Comparing Figs. 5 and 6 with 3 and 4 also highlights that some models with non-negligible local biases can still be helpful for monthly-scale applications because they capture variability and patterns well, as reflected in high correlation and WI despite a systematic offset. For instance, models such as NorESM2-MM, CMCC-ESM2, and CMCC-CM2-SR5 exhibit clear warm- or wet-bias patterns (Figs. 3 and 4) yet maintain strong temperature and rainfall WI and KGE (Figs. 5 and 6), indicating that they may be amenable to bias correction rather than rejection. Overall, the analysis shows that spatial anomaly maps diagnose where and how models misrepresent the Indian regional climate in the warmest epoch. At the same time, the WI (Figs. 5 and 6) summarises how these errors translate into overall model skill and enables a robust ranking of temperature and rainfall over 2015–2024.

Overall, these results emphasise that although the multi-model approach helps quantify uncertainty, each CMIP6 model still exhibits considerable regional errors and spread for both temperature and rainfall. These discrepancies are primarily attributed to limitations in the models' ability to accurately represent regional land-atmosphere feedback, orographic processes, and cloud-aerosol interactions (Ch  r  y et al., 2020; Lee & Hohenegger, 2024; Findell et al., 2024). These findings reinforce prior calls for

continuous model improvement, systematic bias correction, and benchmarking against reliable, high-resolution datasets, such as the IMD, in Indian climate research.

Spatial evaluation of temperature and rainfall skill and error statistics for the M3 of CMIP6 models, compared with IMD observations over India, is shown in Fig. 6. This directly connects to the model evaluation and bias patterns illustrated in Figs. 1–4. For temperature (top row), the subplots detail M3's performance across key metrics: KGE (a1), RMSE (a2), scatter index (a3), Pearson correlation (a4), SD difference (a5), and coefficient of variation (CV) difference (a6). The rainfall diagnostics (bottom row, b1–b6) use the same statistical suite.

For temperature, high KGE values (> 0.8) and strong correlations (> 0.9) across most of India (a1, a4) confirm that the CMIP6 M3 reproduces the observed spatial and temporal variability, consistent with the warming consistency shown in Fig. 1 and the time-series agreement with IMD in Fig. 2. However, RMSE (up to $4\text{--}5^\circ\text{C}$; a2) and scatter index (> 1.2 ; a3) are elevated in the northern regions, paralleling warm biases highlighted in Fig. 3. The SD and CV differences (a5, a6) indicate that the models slightly overestimate variability in the Indo-Gangetic Plain but better match variability in the central and southern regions. This pattern is linked to persistent difficulties in simulating cold winter extremes and regional land-climate feedback (Chakraborty et al., 2018; Jha et al., 2022; Shahi, 2022; Tiwari & Sarthi, 2025).

For rainfall, M3 skill (KGE > 0.6 and correlation > 0.7 in b1 and b4) remains robust across central and eastern India. However, it is lower over the northwest and peninsular regions, echoing the spatial mismatch, wet/dry biases, and high RMSE (up to 12 mm/day , b2) previously outlined for individual models in Fig. 4. The scatter index and differences in SD/CV (b3, b5, b6) indicate prominent overdispersion and underestimation of rainfall variability in the north/northwest, and overestimation farther south and east, consistent with M3's difficulty in capturing the full spectrum of Indian monsoon and temperature variability in the warming epoch (Konda et al., 2023; Rajendran et al., 2021; Stella et al., 2025).

Fidelity in simulating extreme events

The spatial distribution of the annual number of CWD (> 3 days) spells over India, based on IMD observations for 2015–2024, is compared with M3 and a wide range of individual CMIP6 models (Fig. 8). The IMD panel shows the highest CWD spells, extending to 15 per year, in the Western Ghats, northeastern India, and the Himalayan foothills, reflecting regions of prolonged monsoon rainfall (Venugopal et al., 2018; Ali et al., 2015; Thandlam et al., 2023). The M3 (a2) and most CMIP6 models failed to replicate the spatial pattern of larger wet spells along the west coast but reproduced it over the northeast and the Himalayan foothills. However, systematic biases remain: several models (CanESM5, FGOALS-g3, CNRM-CM6-1) overestimate CWD by 2–5 spells in these wetter regions, while others (CMCC-ESM2, KACE-1-0-G) significantly underestimate persistent rainfall spells in central and southern India. These errors are consistent with the rainfall RMSE and spatial spread identified (Fig. 7), as well as the rainfall bias patterns (Fig. 4), reflecting ongoing difficulties in simulating local monsoon dynamics

and topographic rainfall enhancement, along with the persistent biases in zonal flow in the models (Qin et al., 2021; Vibhute et al., 2025).

The contiguous wet spell structure seen in the IMD is moderately captured in M3. However, the extremes and spatial gradients are less well represented by most individual models, mirroring the seasonal rainfall anomaly spread shown in Fig. 2 and confirming previous studies on the use of ensemble and bias-corrected approaches for wet spell projections (Kaagita et al., 2025). Annual CDD spells over India for the 2015–2024 period, contrasting IMD observations (9a1), the M3 (9a2), and individual CMIP6 model outputs (9a3-f3). In IMD, the northwest (Rajasthan, western Gujarat, parts of Punjab) experiences the driest spells—often exceeding 18 per year—reflecting the region’s arid to semi-arid climate and supporting the rainfall minima observed in previous figures (Fig. 4 and Fig. 9).

The M3 (a2) captures the broad geographic gradient well, showing long dry spells in the northwest and shorter spells (as low as 3–5 days) in the Western Ghats and northeast regions, which are dominated by frequent rainfall. However, individual models differ substantially: some (FGOALS-g3, CESM2, CanESM5) overestimate dry spells in the Indo-Gangetic Plain and central peninsula by up to 4 spells, while others (ACCESS-CM2, CMCC-CM2-SR5) underestimate duration in the northwest by up to 6 spells. These spatial differences and biases are consistent with the spread shown for RMSE, scatter index, and SD/CV differences (Fig. 7) and are driven by persistent model challenges in simulating low rainfall regimes, monsoon breaks, and land-atmosphere feedback (Chakraborty et al., 2018; Jha et al., 2022).

Notably, dry-spell errors also mirror biases observed for CWD: regions that overestimate wet-spell duration (e.g., Ghats, NE India) often underestimate dry-spell duration, demonstrating the coupled nature of rainfall-event persistence in climate models. These findings reinforce the sensitivity of dry and wet spells to model physics, convective parameterisation, and seasonal rainfall variability (Mishra et al 2021, Pieri et al 2015).

Figure 10 provides a comprehensive annual and inter-model evaluation of heavy rainfall days (10a), warm days (10b), consecutive wet days (10c), and consecutive dry days (10d) over India for 2015–2024. These metrics are crucial for understanding weather extremes, persistence, and variability, and they directly connect to the spatial patterns and model biases. These results reveal that IMD and the M3 both typically register 33–39 heavy rainfall days annually (Fig. 8a), with outliers in certain years (e.g., 47 in 2019) and some models (e.g., CanESM5, EC-Earth3-Veg-LR, UKESM1-0-LL) consistently producing more frequent events (50–58 per year). Similar model overestimation of extremes was observed in biases in rainfall intensity and spell length (Figs. 4 and 10), reflecting challenges with convective parameterisation and overactive monsoon simulations in some CMIP6 models (Shahi, 2022; Tiwari & Sarthi, 2025). Meanwhile, IMD and the M3 centre around 5–7 CWD spells per year, but some models (BCC-CSM2-MR, CanESM5) extend up to 12 spells (Fig. 10c), mirroring their positive bias in CWD identified (Fig. 8). The persistence of wet spells in model outputs underscores the ongoing challenge of accurately reproducing event duration and variability in Indian monsoon rainfall, which can significantly influence hydrological extremes.

Warm days vary from the observed IMD baseline of around 39–57 per year (Fig. 10b), with specific models and years (BCC-CSM2-MR, IPSL-CM6A-LR) showing notably higher counts (exceeding 60). This temporal and spatial overproduction aligns with regional temperature biases identified in Fig. 3, highlighting the need for bias correction and improved simulation of heat extremes (Kaagita et al., 2025). This led to the most frequent and most extended CDD spells in IMD (up to 15). However, many models underestimate extremes, typically staying in the 10–13 range (Fig. 10d). This tendency to smooth over observed dry extremes is consistent with the regional CDD under/overestimation (Fig. 9), as well as the RMSE and correlation patterns of rainfall (Fig. 7). It highlights the risk that current CMIP6 models (and ensembles) may underplay drought hazard (Vinodhkumar et al., 2025; Rao et al., 2025).

The spatial differences between the M3 and IMD observations for four key climate extremes in India were examined, with a focus on major metropolitan cities (Fig. 11). These maps enable direct comparison with previous results, highlighting regions in which the M3 over- or underestimates observed extremes. The M3 tends to underestimate CDD spells (Fig. 11a) throughout much of northwest and southern India (cool blue shading, up to -8 spells/year), mirroring the persistent model underestimation (Fig. 9). Conversely, slight overestimations (red shading) are observed in some central and eastern regions, indicating the model's limitations in capturing drought persistence in arid zones.

The ensemble mean shows significant negative differences in CWD (up to -8 spells/year) in the northeast and parts of the southern/coastal regions, reflecting the M3's tendency, as shown in Figs. 8 and 10c, to underpredict persistent rainfall events in monsoon-heavy areas (Fig. 11b). M3 overestimates heavy rainfall days notably across the Himalayan foothills, Western Ghats, and coastal regions (red shading, up to + 16 days/year) (Fig. 11c), highlighting the M3's challenges with convective rainfall extremes and orographic enhancement. In warm days (11d), positive differences (up to + 16 days/year) are concentrated over north, central, and parts of south India, where the M3 tends to simulate more extreme heat events than what IMD records show, echoing the warm biases and model spread described previously (Figs. 3 and 10b).

Uncertainty in spatial trends

The spatial regression analysis of temperature trends across India, using Sen's slope estimator for IMD, M3, and each CMIP6 model, is further examined (Fig. 12). Sen's slope robustly quantifies monotonic change at each grid point, is highly resilient to noise and outliers, and is widely recommended for trend analysis in climate extremes (Sen, 1968; Rao et al., 2025). The IMD shows widespread warming trends (0.2–0.4°C/year) in central, western, and northern India. Most CMIP6 models and the M3 broadly reproduce this pattern; however, some overestimate local trends in parts of northwest and central India (up to 0.6°C/year), whereas others (models with blue shading) underestimate or simulate minor cooling in isolated coastal or northeastern regions. This inter-model spread and spatial structure closely match biased temperature anomalies, spells, and warm days (Figs. 3, 7, and 10b).

Hatched dots mark areas with statistically significant (90%) warming, emphasising model agreement and observed change. In contrast, regions with lower agreement exhibit greater variability, underscoring the value of ensemble approaches while also highlighting remaining uncertainty (Kaagita et al., 2025; Vinodhkumar et al., 2025). These trend diagnostics validate and extend earlier findings of persistent warming, particularly in regions most sensitive to monsoon variability and heat extremes.

A similar analysis of precipitation is shown in Fig. 13. The IMD panel (a1) reveals heterogeneous but mostly weak and statistically insignificant rainfall trends, with localised increases in parts of central and northeast India and declines in the northwest consistent with the observed variability and spatial contrasts highlighted in Figs. 4, 7, and 10a. The M3 generally reflects this weak signal, showing minimal trends on average, but individual models (a3-f2) reveal considerable diversity. Some models (ACCESS-CM2, CNRM-CM6-1) simulate widespread drying, particularly in northwest and central India, whereas others (BCC-CSM2-MR, FGOALS-g3, MIROC6) show broad areas of wetting (red shading), mainly across the peninsular and northeastern regions. The stippling denotes regions with statistically significant trends (90%), which are mostly absent except in a few models and small, localised zones. This spread in projected rainfall trends closely matches the spatial bias in rainfall extremes (Figs. 4, 10a) and spell statistics (Figs. 8, 10c-d), underlining persistent model uncertainty in Indian monsoon modelling.

Summary and Conclusions

During the decade of accelerated global warming (2015–2024), CMIP6 models in M3 mode have substantially improved simulations of mean temperature and rainfall over India. The M3's ability to reproduce IMD-observed warming trends and interannual variability, with high KGE and correlation scores for both temperature (> 0.8 , > 0.9) and rainfall (up to 0.7–0.85 centrally/eastern), marks a clear step forward compared to previous generations. CMIP6 M3 successfully captures the broad decadal signals of warming and the overall monsoon structure; its aggregated statistics are consistently improved relative to most individual CMIP6 models.

Nevertheless, significant challenges persist in simulating extremes and regional event-scale variability. Dry spell duration (CDD) is still underestimated by up to 8 spells/year in India's arid northwest and transitional south. In contrast, the persistence and frequency of wet spells and heavy rainfall remain over- or underestimated in climatically critical zones, such as the Western Ghats, the northeastern hills, and the Himalayan foothills (often by + 16 days/year). Similarly, the frequency of warm days is overestimated across north-central India, indicating structural issues in the model's representation of heat and compound events.

A key theme emerging from these results is broad model agreement for mean gradients (CWD/CDD “hotspots”), but persistent regional and event-scale biases, particularly for daily extremes, which are essential for climate risk management. Notably, a large intermodel spread persists in the spatial patterns of monsoon precipitation trends: no single model or M3 consistently agrees with the IMD for India's

diverse hydroclimate. Overall, local benchmarking, model spread, and spatial mismatch reinforce the urgency for next-generation improvements. The key findings from these results are:

1. CMIP6 models capture the mean Indian climate well (correlations up to 0.96 for rainfall and > 0.9 for temperature) but underestimate dry spells by 8/year and overestimate warm/wet days by 16/year in key regions.
2. Benchmarking identifies top models (e.g., KACE-1-0-G, MIROC6 for temperature; FIO-ESM-2-0 for rainfall) to build confidence for future projections.
3. The M3 outperforms individuals for mean state (closer to IMD variability) and reduces errors in extremes, though biases persist.
4. The M3 improves mean fidelity, but lingering extremes/trends uncertainties prevent fully deterministic predictions.

These findings lead to three priorities in climate modelling:

1. Enhanced simulation of daily, severe, and compound extremes.
2. More effective bias correction and high-resolution downscaling bridge the persistent gap between regional projections and local climate realities.
3. Advances in simulating teleconnections and monsoon process dynamics enable credible projections of future risk.

Current CMIP6 ensemble outputs, although an improvement over previous generations, remain constrained by these limitations, which limit actionable reliability for local adaptation or sectoral planning, particularly for extremes and regional detail. The synthesis spanning mean state to extremes and timescales indicates the most straightforward way forward: intensified efforts in model refinement, targeted bias correction, and continuous, high-resolution comparison against robust observational datasets, such as IMD, which are essential for transforming climate projections into confident adaptation on the ground in India.

This study, while providing a comprehensive evaluation of CMIP6 model skill and biases over India during an era of unprecedented warming, still faces several limitations that present avenues for future research. First, the analysis is constrained by the spatial and temporal resolution of both observational data and model outputs, thereby limiting the ability to resolve event-scale features and sub-daily extremes that are crucial for risk management. Many models continue to struggle to replicate the full spectrum of observed daily and compound extreme events, particularly in arid, mountainous, and monsoon transition zones, where persistent biases persist even after bias correction and ensemble averaging. The methodology also cannot fully address teleconnection impacts or the non-stationarity of monsoon onset and withdrawal, both of which are critical for seasonal forecasting and decadal projections.

Additionally, while bias correction and M3 approaches mitigate some systematic errors, they do not eliminate regional-scale uncertainties or adequately address the inter-model spread observed in both temperature and precipitation trends. Also, they do not guarantee robust projections under non-analogue future climate states. The absence of dynamic downscaling or the incorporation of emerging machine-learning tools limits the capacity to address local adaptation needs, particularly for infrastructure resilience and disaster risk reduction.

Future research should focus on evaluating and improving sub-daily, seasonal, sub-seasonal, and compound-event simulations; developing optimal bias-correction and downscaling frameworks suited to a rapidly warming and highly variable Indian climate; and enhancing the representation of monsoon-teleconnection dynamics in new model generations. Expanding model evaluation frameworks to include process-based diagnostics, multiple observational references, and climate impacts/sectoral risk analyses will help transform raw projections into actionable climate information. Continuous benchmarking against high-resolution IMD data and the integration of new observational datasets remain critical pathways to refine the reliability and usability for stakeholders in India's evolving climate landscape.

Declarations

Data availability

All the data used in the present work are freely available online. Data from the ERA5 and CMIP6 models can be downloaded from <https://cds.climate.copernicus.eu/datasets/projections-cmip6?tab=download>. The rainfall and temperature data can be downloaded from <https://www.imdpune.gov.in/cmpg/Griddata>. The ETCCDI indices can be obtained from https://etccdi.pacificclimate.org/list_27_indices.shtml.

Code availability

The data and code used to generate the results in this paper are available at <https://github.com/kvrmtechsvu2020/paper4.git>.

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Contributions

VT formulated the research idea. VT and VK contributed equally to data processing, analysis, figure generation, and preparation of the first draft. All other authors contributed to improving the draft and shaping the final version of the present work.

Competing interests

The authors declare no competing interests.

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Figures

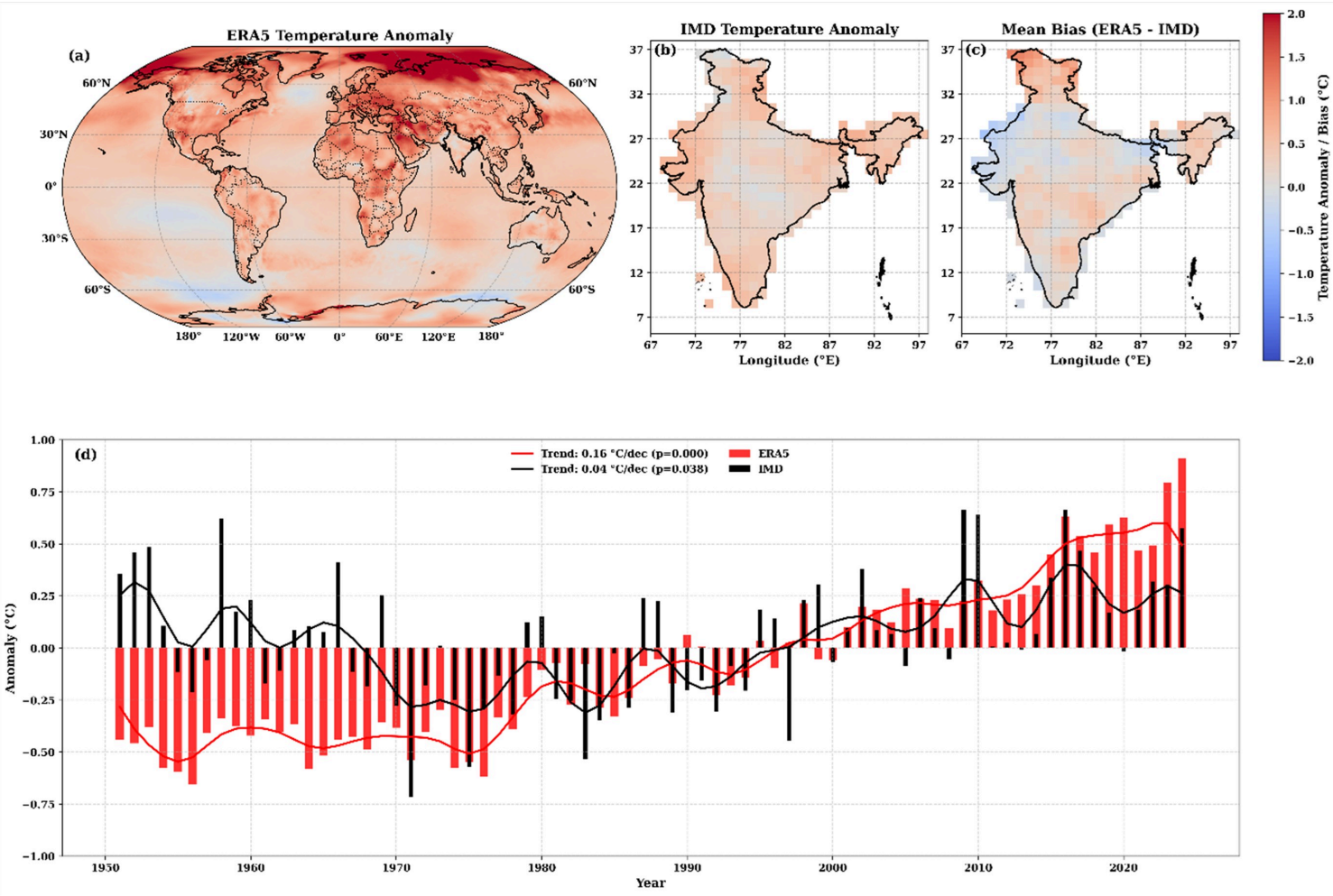


Figure 1

Observed and reanalysis temperature anomalies. (a) Global temperature anomalies, (b) India temperature anomalies, (c) ERA5-IMD bias for 2015-2024 and (d) annual temperature anomalies of ERA5 and IMD over India with respect to 1981-2010 for the period 1951-2024.

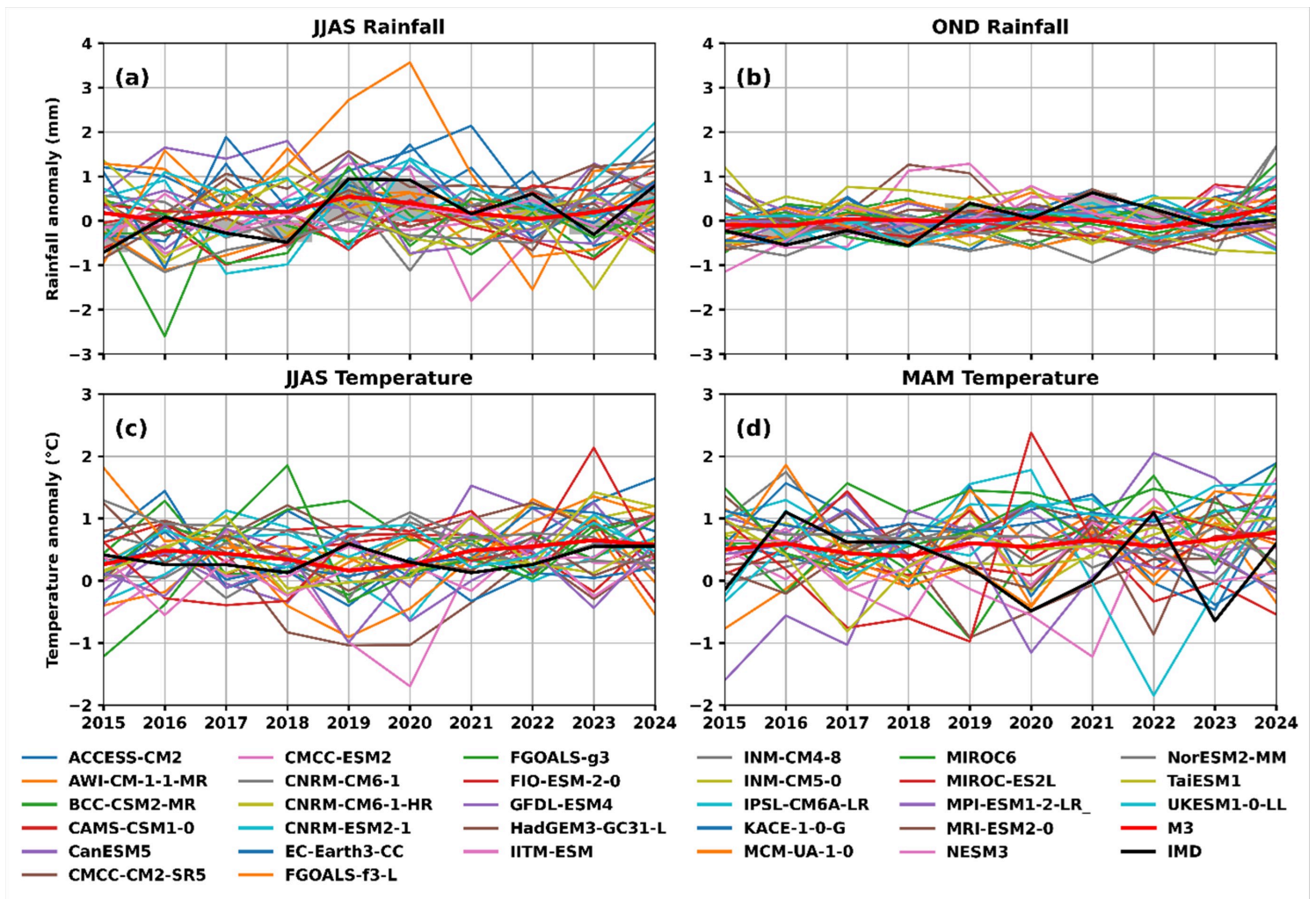


Figure 2

Seasonal rainfall and temperature anomalies in India: CMIP6 vs IMD observations (2015-2024).

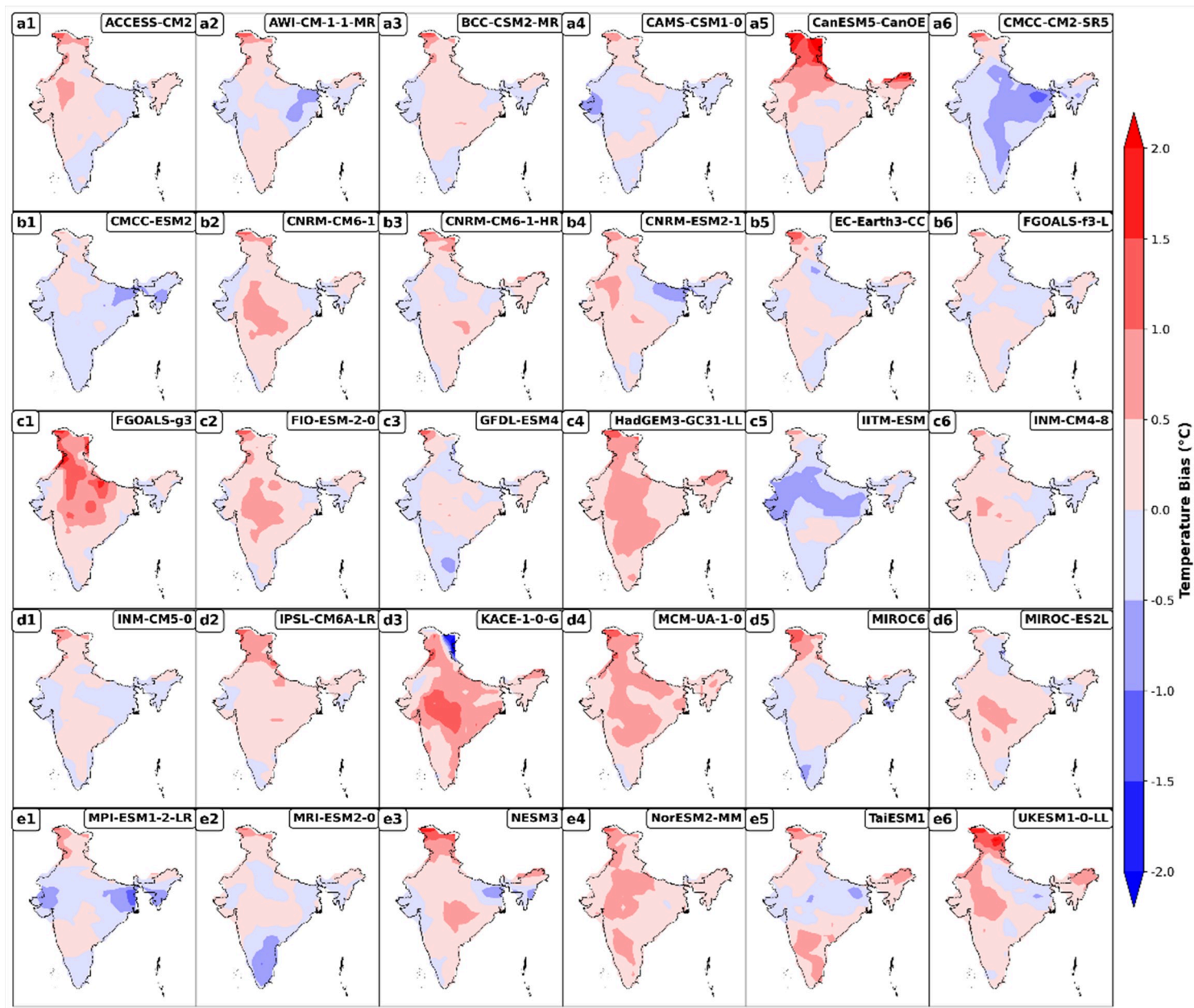


Figure 3

Spatial biases in temperature anomalies from individual CMIP6 models over India (2015-2024 vs. 1981-2010, relative to IMD observations)

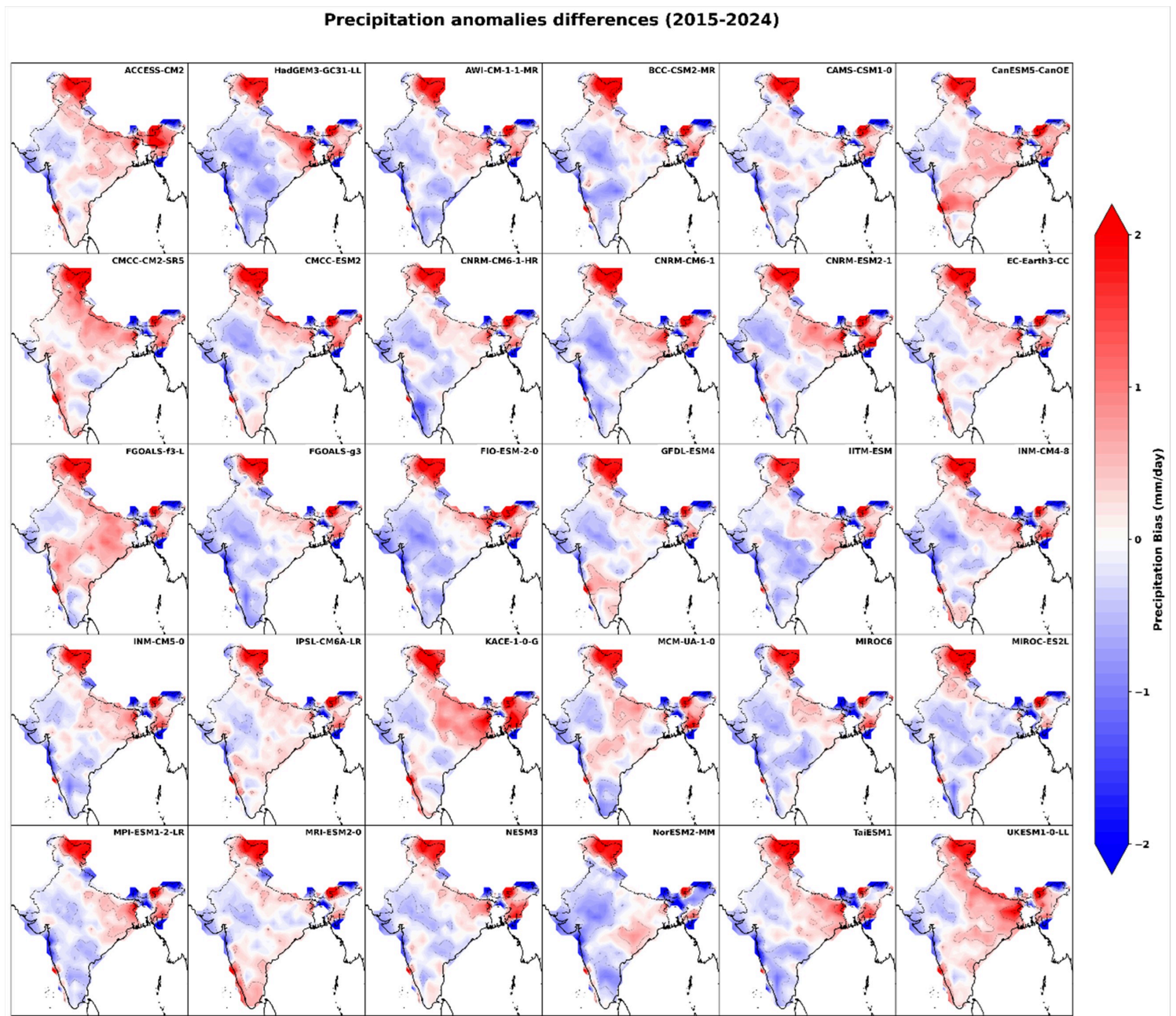


Figure 4

Spatial biases in rainfall anomalies from individual CMIP6 models over India (2015-2024 vs. 1981-2010, relative to IMD observations)

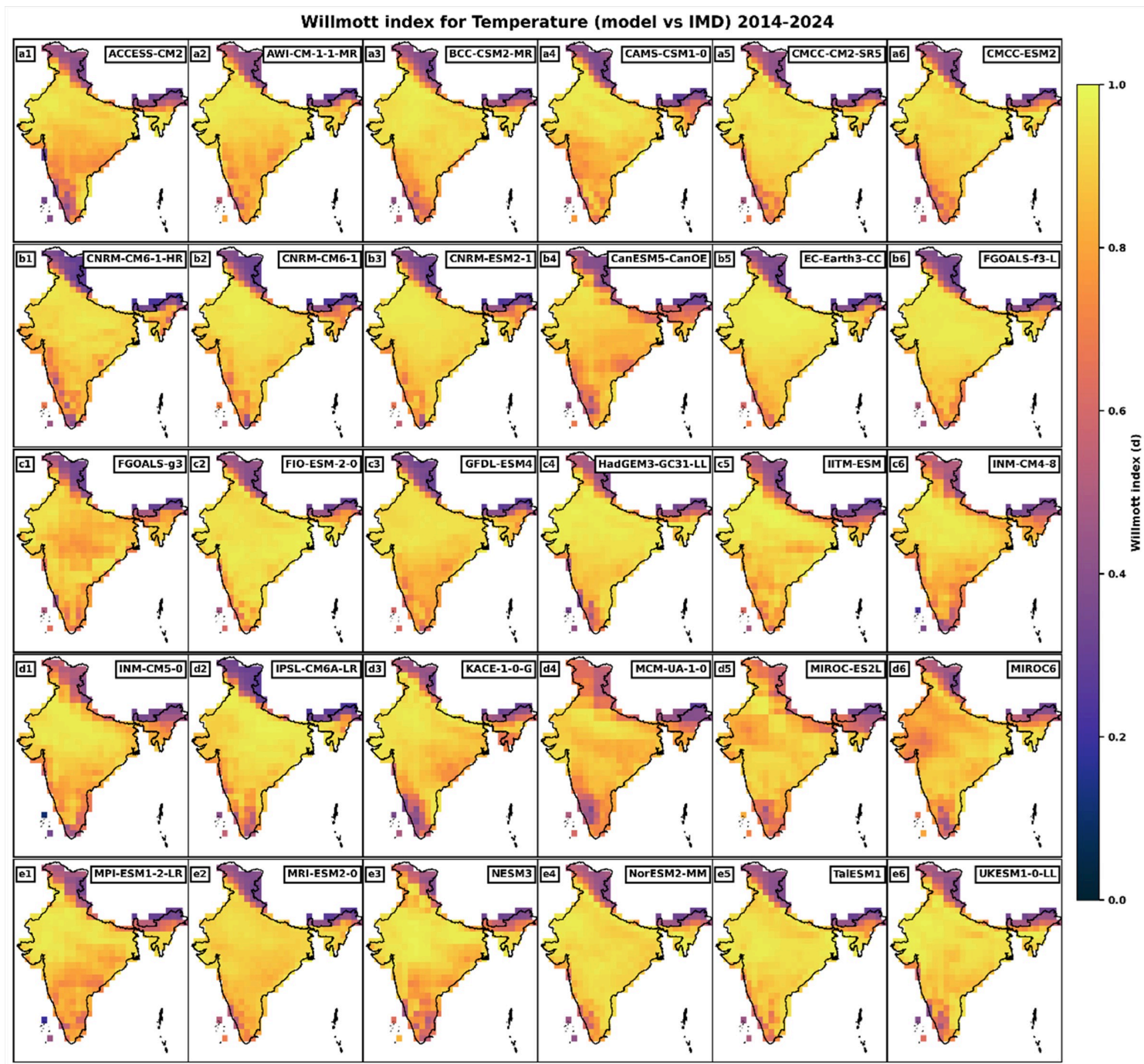


Figure 5

Willmott index for monthly temperature from individual CMIP6 models over India during 2015-2024

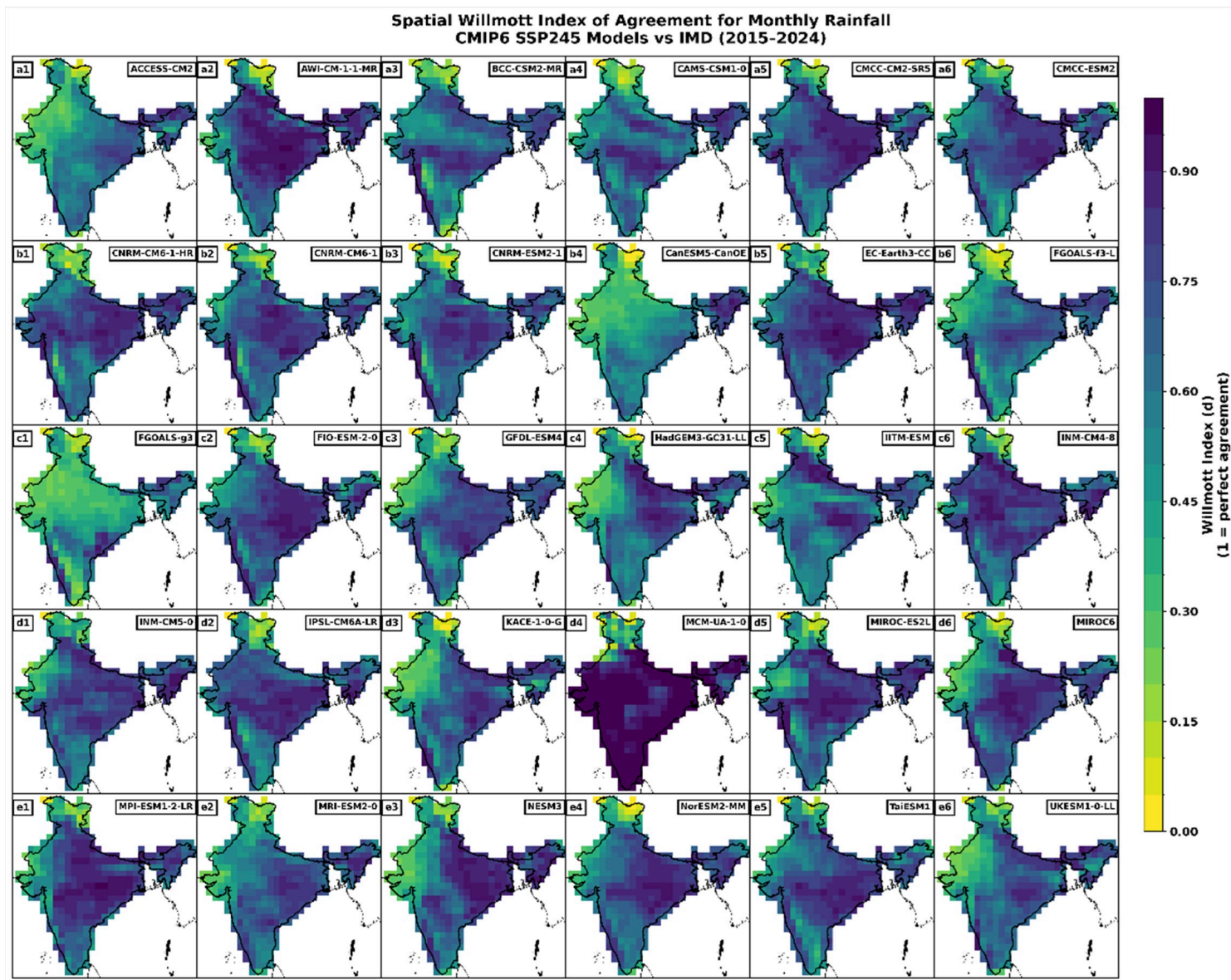


Figure 6

Willmott index for monthly precipitation from individual CMIP6 models over India during 2015-2024

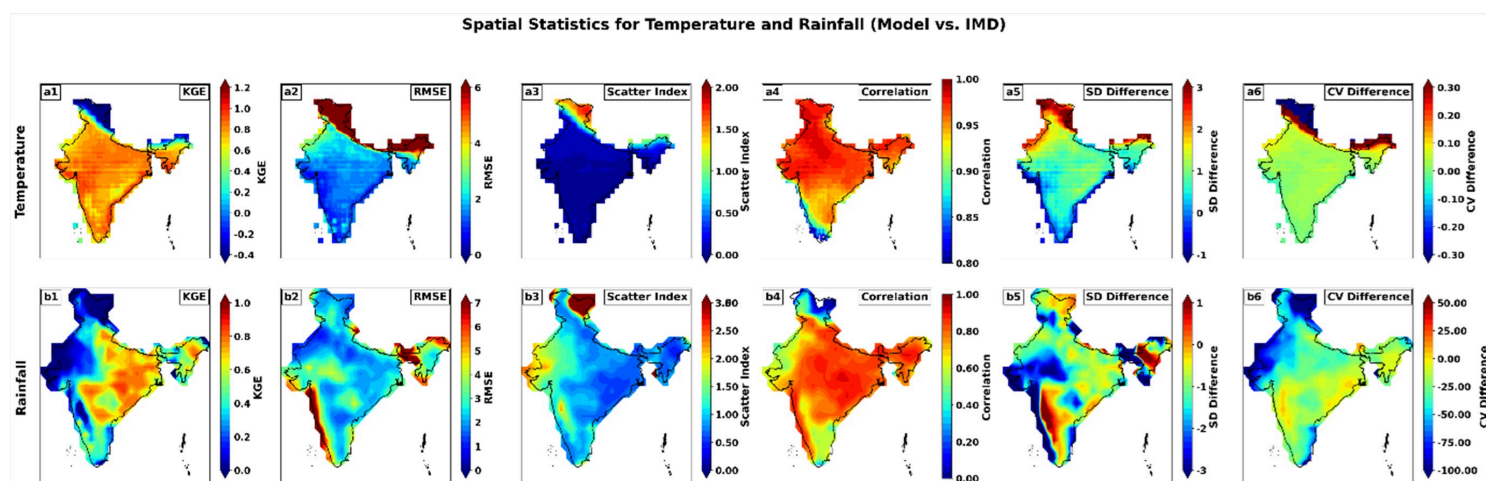


Figure 7

Spatial skill and error metrics for CMIP6 M3 of temperature and rainfall over India (2015-2024 vs. IMD).

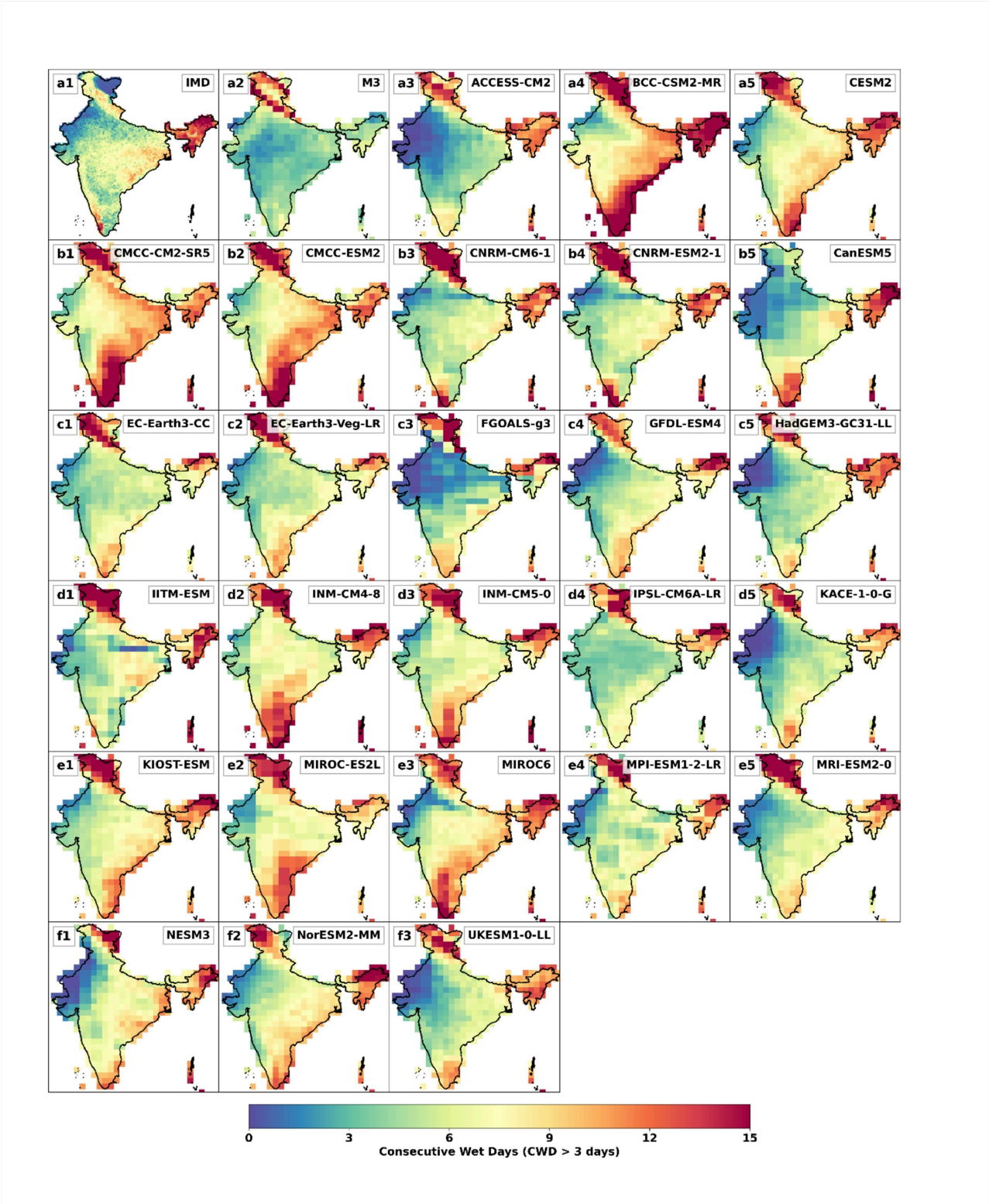


Figure 8

Annual mean CWD over India: IMD, M3, and individual CMIP6 Models during 2015-2024.

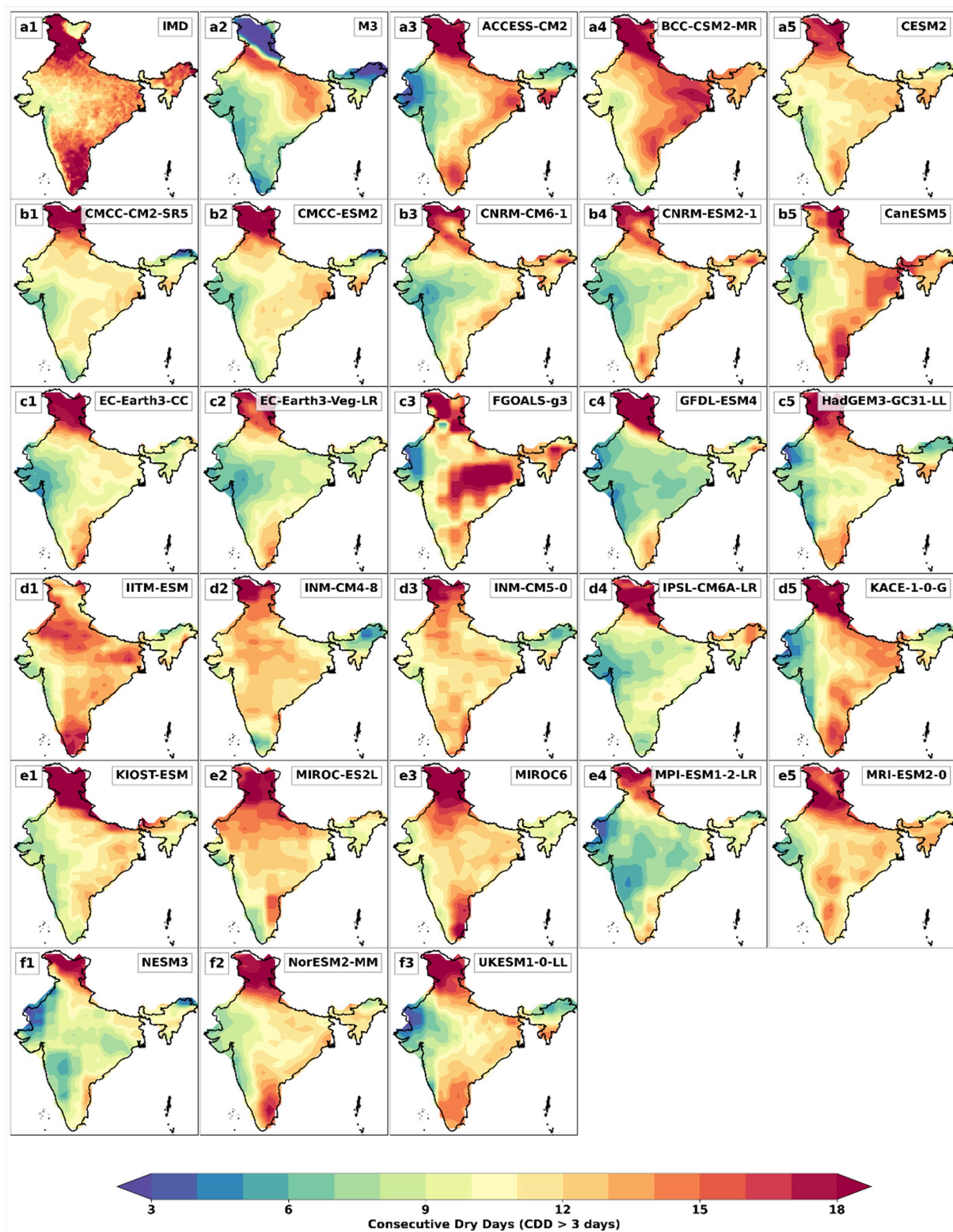


Figure 9

Annual mean CDD spells over India: IMD, M3, and CMIP6 Models (2015-2024).

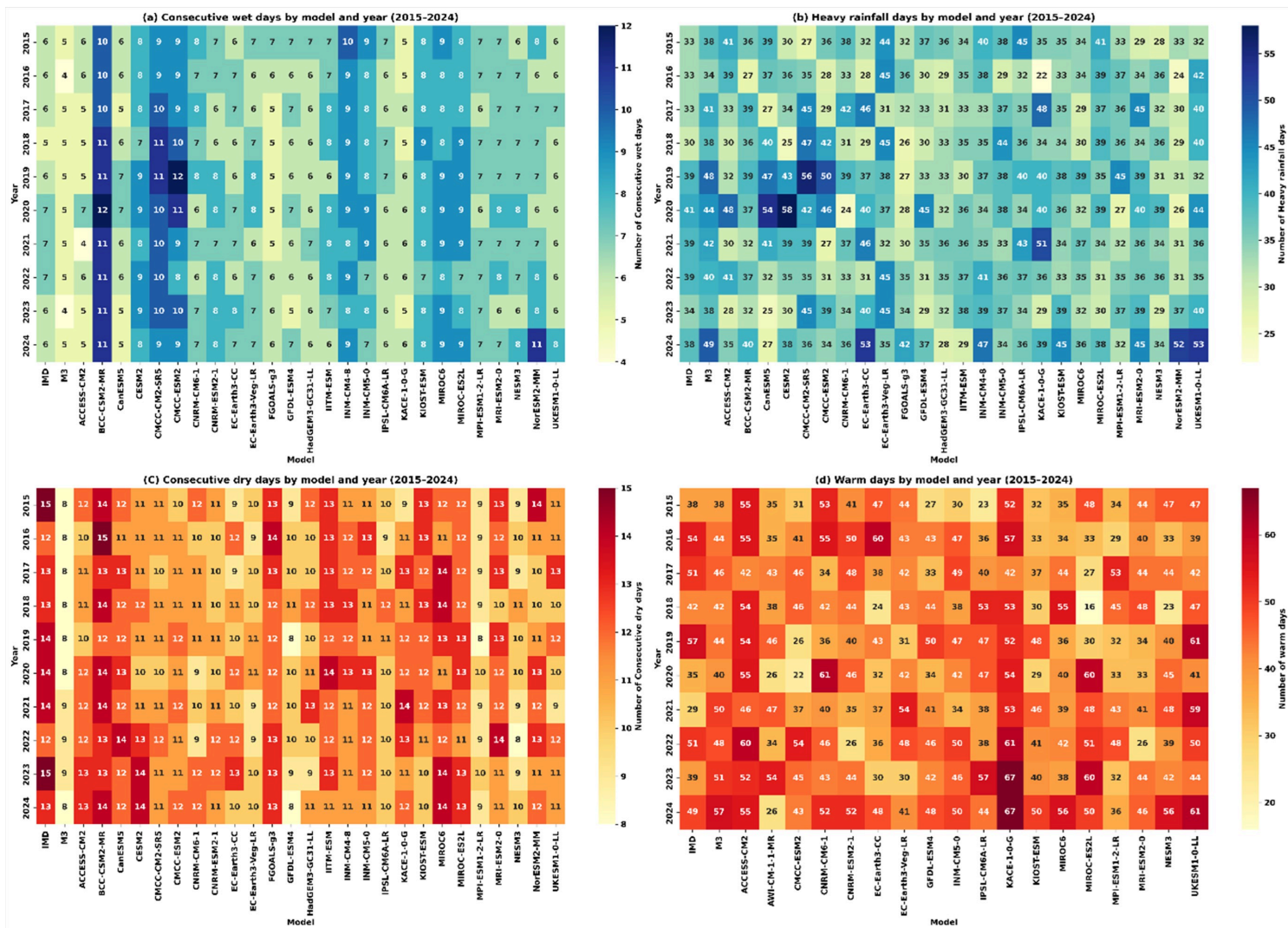


Figure 10

Annual extremes and spell statistics (2015-2024): Comparison of IMD, M3, and CMIP6 models for India.

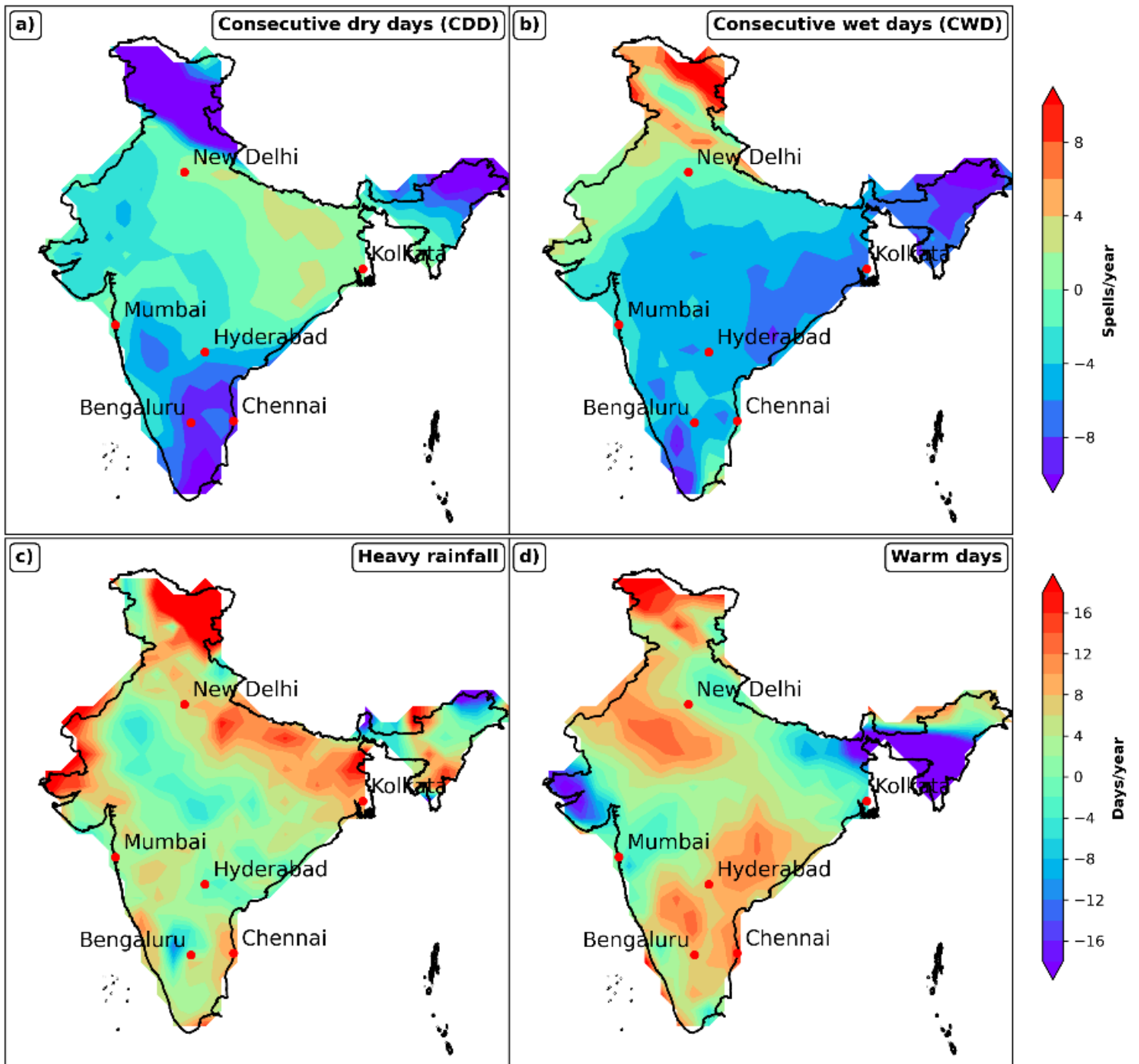


Figure 11

Spatial differences in extreme climate indices between CMIP6 M3 and IMD (2015-2024).

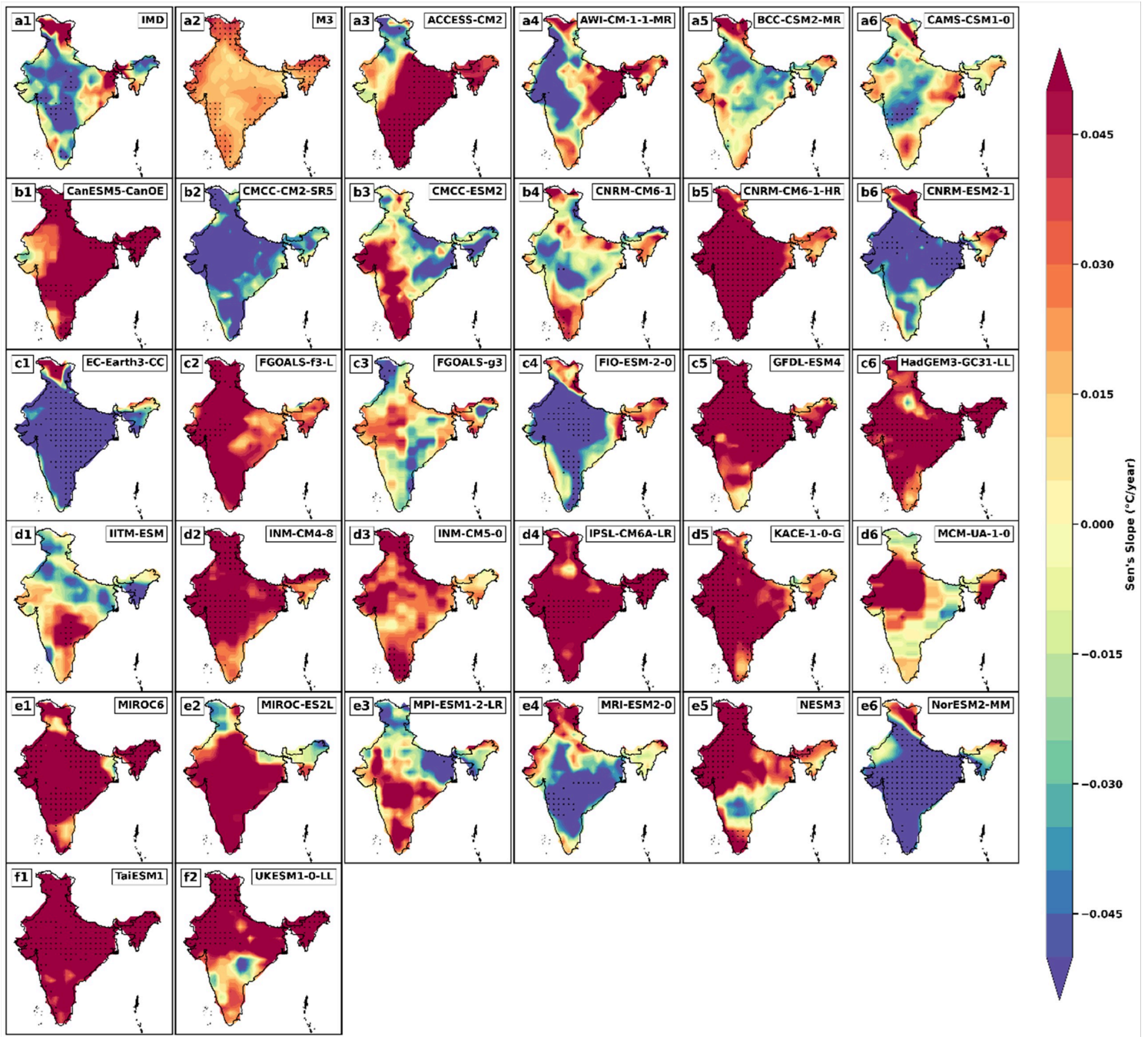


Figure 12

Spatial trends in temperature over India (2015-2024) from Sen's slope regression of IMD, M3, and CMIP6 Models. Areas with 90% statistical significance are marked with hatched dots.

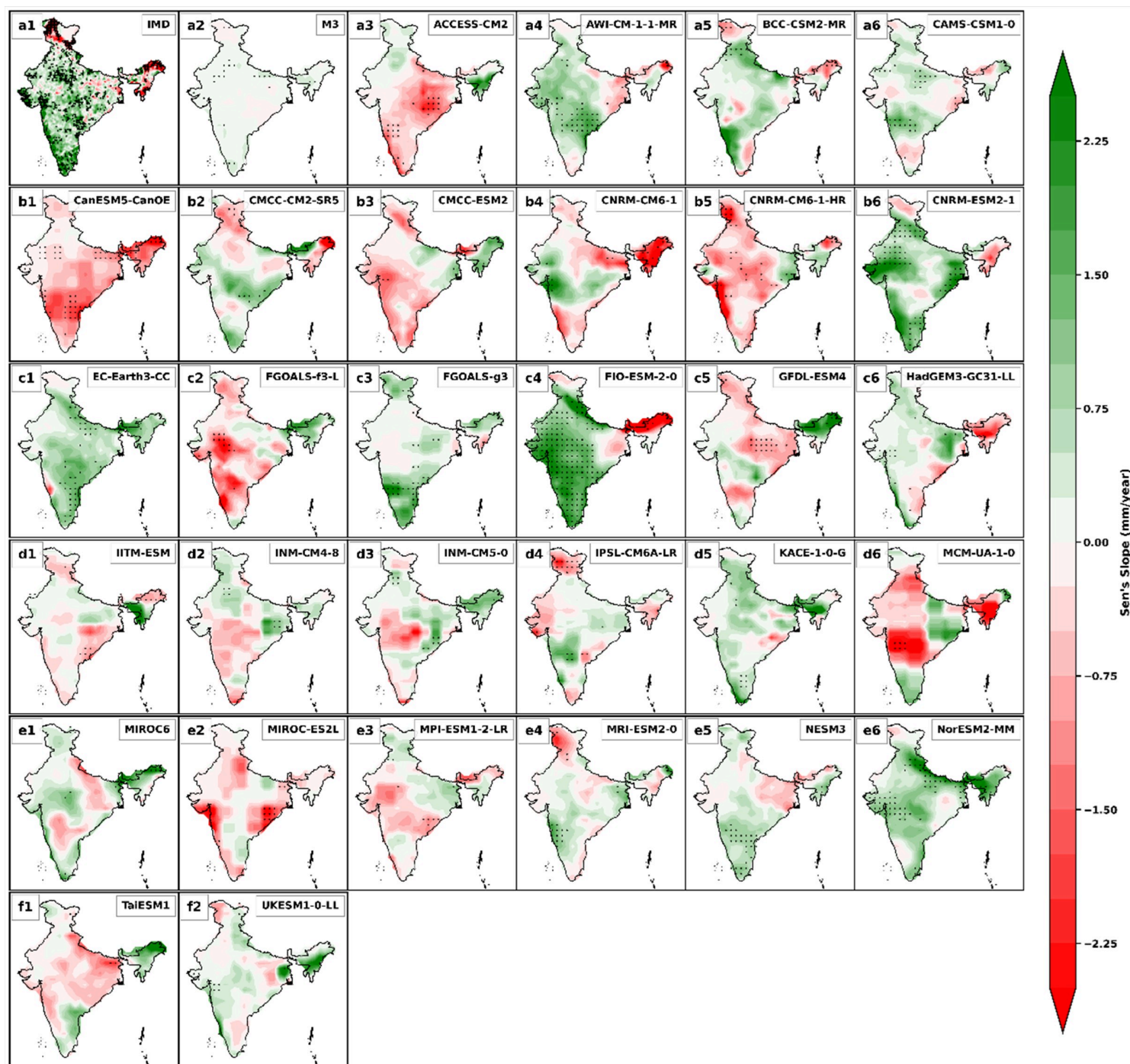


Figure 13

Spatial trends in rainfall over India (2015-2024) from Sen's slope regression of IMD, M3, and CMIP6 Models.

Supplementary Files

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- [supplementaryinformation.odt](#)