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Research Article

Keywords: Indian Summer Monsoon Rainfall(ISMR), CMIP5, CMIP6, Model Evaluation, SST, Teleconnections, EOF Analysis

Posted Date: August 4th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10468674/v1>

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Improvements of CMIP6 over CMIP5 for Simulating Indian Summer Monsoon Rainfall and Indian Ocean Teleconnections

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Abstract:

This study evaluates the capability of CMIP5 and CMIP6 models in simulating Indian Summer Monsoon Rainfall (ISMR) during 1975 to 2005 and examines their representation of sea surface temperature (SST) teleconnections over the Indian and Pacific Ocean. Multiple observational datasets are used to benchmark model performance through correlation coefficients (CC), Taylor statistics, skill scores, and rainfall distribution analysis. CMIP6 models show substantial improvements over CMIP5 in reproducing the spatial structure of ISMR, especially over the Western Ghats, Northeast, and Central India. The CMIP6 multi-model ensemble (MME) attains a higher correlation with observations (0.86) compared to CMIP5 (0.68). Empirical Orthogonal Function (EOF) analysis indicates that CMIP6 (CMIP5) captures dominant monsoon variability more realistically, with EOF1 explaining ~61.7% (58.2%) of variance and PC1 aligning more closely with observed anomalous years. Better representation of SST rainfall teleconnections is noted across the Arabian Sea (AS), Bay of Bengal (BoB), South China Sea (SCS), and Southern Indian Ocean(SIO) and matching well with the large-scale circulation features such as the low-level jet (LLJ) and tropical easterly jet (TEJ) by CMIP6. Overall, CMIP6 provides better advances in simulating monsoon dynamics and air sea interactions, though regional-scale variability and observational uncertainties still pose challenges.

Keywords: Indian Summer Monsoon Rainfall(ISMR), CMIP5, CMIP6, Model Evaluation, SST, Teleconnections, EOF Analysis

27 **1. Introduction**

28 The Indian Summer Monsoon Rainfall (ISMR), which contributes about ~70-80% of the annual
29 rainfall over the Indian subcontinent during June-September, is a lifeline for more than one-sixth of
30 the world's population. This seasonal rainfall activity governs a vital role in the socio-economic
31 development of country, regulating for planning, budgeting, monitoring in Indian agriculture and
32 shapes many sectors and industries related to agriculture, human health (Gadgil 2003; Singh et al.
33 2014; Maurya and Singh 2016; Shukla and Huang 2016). Globally, about two-thirds of the population
34 lives in monsoon-dominated regions (Wang 2018), highlighting the importance of understanding its
35 variability and predictability. ISMR is inherently complex, governed by coupled land-ocean-
36 atmosphere interactions and modulated by global and regional forcing (Ashfaq et al. 2009; Rajeevan
37 et al. 2012). The previous literature records since 1871, highlights the significant variability of Indian
38 monsoon systems in multidimensional temporal and spatial (Goswami et al. 2006; Kodra et al. 2012;
39 Singh 2013a, 2013b). The variability in the climate system is robustly linked to anthropogenic drivers
40 like greenhouse gases and aerosol emissions in global warming world, contributes to regulating
41 increment and declination of monsoon. (Roxy et al. 2015; Lau et al. 2015; Rai et al. 2023).
42 Observations indicate a declining trend in mean ISMR since the mid-20th century, alongside a rise in
43 extreme rainfall events, particularly over the central India (Goswami et al. 2006; Roxy et al. 2017;
44 Shekhar et al. 2017; Tomar et al. 2024). A large change in the intensity and quantity of monsoon
45 rainfall were detected across different parts of Indian landmass, leads to an increase in the frequency
46 of compound extremes such as heavy rain, droughts and floods (Guhathakurta et al. 2011 Mohapatra
47 et al. 2021). It is well known that monsoon variability is strongly influenced by large-scale circulation
48 features like cross-equatorial low-level jet(LLJ) at ~850 hPa plays a critical role in transporting
49 moisture from the Indian Ocean into the Indian subcontinent (Sijikumar et al. 2003). It's interannual
50 fluctuations may be linked to droughts (2009) and near-normal rainfall years (2010) (Bisht et al.
51 2019). Similarly, the tropical easterly jet (TEJ) and monsoon trough are also key dynamical
52 components, modulating rainfall distribution during the ISMR (Krishnan et al. 2009; Roja Raman et
53 al. 2009; Naidu et al. 2017).

54 Sea surface temperature (SST) variability, particularly across the tropical Indian Ocean (TIO), is
55 another dominant driver of ISMR variability (Charney and Shukla 1981; Singh and Oh 2007).
56 Anomalous SST patterns modify atmospheric thermodynamics and convection, influencing rainfall
57 intensity and distribution (Trenberth et al. 2011). Teleconnections with the El-Niño – Southern
58 Oscillation (ENSO), Indian Ocean Dipole (IOD), and Pacific Decadal Oscillation (PDO) are well
59 established (Shukla et al. 1983; Wang 2018; Sohn et al. 2019; Dunstone et al. 2020). In recent
60 decades, the Indo-Pacific warm pool expansion and rapid Indian Ocean warming have further

61 intensified the regional hydrological cycle and rainfall extremes (Cai et al. 2014; Roxy et al. 2015).
62 Global climate model (GCMs) are essential tools to simulate and project ISMR variability under past
63 and future climate scenarios.

64 The Coupled Model Intercomparison Project (CMIP) provides a coordinated framework for
65 evaluating GCM performance (Taylor et al. 2012; Eyring et al. 2016; Shafeeque et al. 2021). The
66 CMIP framework developments are now constitutes key component of both national and
67 international assessments of climate change for understanding climate processes (Eyring et al. 2016;
68 Rivera and Arnould 2020, Saha and Singh 2024), have played a crucial role in informing both
69 scientific discourse and climate governance policy (Forster et al. 2013; Knutti and Sedláček 2013;
70 Sillmann et al. 2013; Miao et al. 2014; Aloysius et al. 2016; Singh et al. 2017a; Singh et al. 2017b;
71 Singh et al. 2018). CMIP5 models have been extensively evaluated for their skill in simulating ISMR
72 climatology, variability, and teleconnections, but notable biases persist, including dry rainfall biases
73 over the Western Ghats and Northeast, and misrepresentation of monsoon-ENSO relationships
74 (Sperber et al. 2013; Hagos et al. 2019). CMIP6 represents a significant advancement, with improved
75 physical parameterizations, higher spatial resolution, and updated forcing datasets (Eyring et al. 2016;
76 Matthes et al. 2017; Meehl et al. 2020). Several recent studies suggest that CMIP6 models capture
77 ISMR seasonal mean, variability, and extremes slightly better as compared to CMIP5 (Eyring et al.
78 2016; Matthes et al. 2017; Meinshausen et al. 2017; Konda et al. 2023; Saha et al. 2024). However,
79 uncertainties are remaining present regarding the fidelity of teleconnections with Indian Ocean SSTs,
80 which are crucial for monsoon predictability (Zhao et al. 2019; Holland et al. 2024; Singh and
81 Sandeep 2024). Despite progress, systematic evaluation of both rainfall patterns and oceanic
82 teleconnections in CMIP5 vs CMIP6 remain limited. Past studies have mainly emphasized mean
83 climatology or ENSO-monsoon links, with fewer focusing on Indian Ocean SST variability and its
84 influence on monsoon dynamics. Moreover, EOF based assessments of dominant ISMR modes, along
85 with circulations features such as LLJ and TEJ are compared using both CMIP models.

86 The present study addresses these gaps by systematically comparing CMIP5 and CMIP6 models in
87 representing the Indian Summer Monsoon (ISM), ensuring a consistent framework for evaluation.
88 Model performance is assessed in terms of rainfall climatology, variability, and long-term trends us-
89 ing multiple observational datasets. In addition, SST–rainfall teleconnections are examined across
90 key oceanic regions, including the AS, BoB, SCS, and SIO, along with major circulation features
91 such as the LLJ and TEJ. Understanding these biases is crucial for improving model skill and enhanc-
92 ing the reliability of interannual monsoon variability predictions. The primary objective is to assess
93 whether CMIP6 models exhibit improved skill over CMIP5 in reproducing observed monsoon rainfall
94 characteristics and their underlying dynamical mechanisms, thereby strengthening confidence in fu-
95 ture monsoon projections under climate change.

The remainder of the paper is structured as follows. Section 1 shows introduction, Section 2 describes the models, observational datasets, and methodology. Section 3 presents and compares the results from CMIP5 and CMIP6. Finally, Section 4 provides the conclusions.

2. Materials and Methods

2.1. Detail of Model and Observed Datasets:

The sixth phase of the Coupled Model Intercomparison Project (CMIP6) advances beyond CMIP5 by incorporating more sophisticated Earth System Models (ESM) and a wider range of experiments. While CMIP5 products are well reported in the IPCC Fifth Assessment Report (AR5, 2013), CMIP6 provides the foundation for the IPCC Sixth Assessment Report (AR6, 2021). This study uses 13 models (Tables S1, S2) from CMIP5 (Taylor et al. 2012) and CMIP6 (Eyring et al. 2016) covering categories, institutions, origins, and resolutions. Only the first realization (variant label r1i1p1 for CMIP5, r1i1p1f1 for CMIP6) was used. Monthly precipitation, SST and wind data, were obtained from the Earth System Grid Federation (ESGF). The multi models ensembles is calculated by mean of the variables across all CMIP5 and CMIP6 models, by equal weight of each models.

For validation, high-resolution Indian Meteorological Department (IMD) rainfall data ($0.25^\circ \times 0.25^\circ$, 1975-2005; Pai et al., 2015) was used. The IMD record spans 1901–2022, based on ~6995 gauges, with 900 additional stations compared to earlier $0.5^\circ \times 0.5^\circ$ datasets (Rajeevan and Bhate 2009). Other datasets include GPCP ($2.5^\circ \times 2.5^\circ$; Adler et al. 2003), CRU TS v4.05 ($0.5^\circ \times 0.5^\circ$; Harris et al., 2020) and the European Centre for Medium-Range Weather Forecasts ERA5 reanalysis ($0.25^\circ \times 0.25^\circ$; Hersbach et al. 2020). SST validation employed HadISST ($1^\circ \times 1^\circ$; Rayner et al. 2003). Models were selected for continuous precipitation records (1975–2005) and established use in Indian summer monsoon studies. Four oceanic SST regions were analysed; the Arabian Sea (58°E – 73°E , 0° – 20°N), Bay of Bengal (86°E – 94°E , 0° – 20°N), South Indian Ocean (100°E – 120°E , 20°S – 0°) (Dey et al. 2015), and South China Sea (105°E – 120°E , 5° – 20°N ; Liu et al. 2023). Four SST regions were selected based on their established roles in modulating ISM variability reported in previous observational and modelling studies. These include the Arabian Sea representing the primary moisture source and low-level jet pathway; the Bay of Bengal strongly influences monsoon depressions and synoptic disturbances; the South China Sea affects large-scale atmospheric circulation through western Pacific teleconnections; and the Southern Indian Ocean modulates cross-equatorial moisture transport and Walker circulation. These domains follow previous studies investigating Indian Ocean SST–monsoon teleconnections (Saji et al., 1999; Wang et al., 2000; Dash et al., 2002; Roxy et al., 2015; Ratna et al., 2016; Khan et al. 2021).

128 2.2. Methodology

129 The study period (1975 to 2005) was chosen to incorporate recent updates in global communication
130 infrastructure and revised CMIP5/CMIP6 datasets. The study also structured with an initial model
131 evaluation using Taylor diagrams, Taylor skill scores(TSS), cumulative distribution functions(CDF),
132 and correlation coefficients (CCs) to assess model performance against observations. Subsequent
133 sections detail data sources and methods, then compare CMIP5 and CMIP6 rainfall climatology and
134 skill to identify best-performing models. To identify skilful models for subsequent SST–monsoon
135 teleconnection analyses, individual GCMs were evaluated using a combination of performance
136 metrics, including (i) spatial correlation coefficient, (ii) normalized standard deviation, (iii) Taylor
137 Skill Score. Models that consistently achieved high correlation ($CC \geq 0.80$), Taylor Skill Scores close
138 to unity, normalized standard deviation near one, and realistic rainfall distributions were classified as
139 best-performing models. Finally, monsoon–ocean interactions were presented through ensemble
140 means, correlation, and EOF analyses focusing on the influence of the key oceanic regions mentioned.
141 This analysis was conducted over the core monsoon region, approximately spanning 18.0° to 28.0°
142 N latitude and 65.0° to 88.0° E longitude within the ISMR area, following the methodology detailed
143 by Rajeevan et al. (2010). These analyses enhance the understanding of monsoon variability, which
144 can improve monsoon prediction and support early warning systems for extreme rainfall events over
145 the Indian subcontinent. Seasonal changes were further tested using a Student’s t-test at the 95%
146 significance level.

147 A Taylor diagram (Taylor 2001) was used to evaluate model performance over study domain,
148 supported by the TSC (Equation 1). The skill score (S) incorporates correlation (R), simulated
149 standard deviation (σ), theoretical maximum correlation ($R_0=1$), and the standard deviation ratio
150 (SDR) between model and observations (Chen et al., 2010; Xin et al., 2020).

$$151 \quad Skill\ Score(S) = \frac{(1+R)^2}{\left(SDR + \left[\frac{1}{SDR}\right]\right)^2} \text{ -----} 1$$

152 TSC ranges from 0 to 1, and values closer to 1 indicate better performance in simulating precipitation
153 (Du et al. 2022).

154 3. RESULTS AND DISCUSSION:

155 3.1. Comparisons of CMIP5 and CMIP6 Rainfall climatology:

156 We compared the simulated rainfall from CMIP5 and CMIP6 MME with observation for the periods
157 1975 to 2005. Both CMIP5 and CMIP6 reasonably reproduce the observed monsoon rainfall over the

158 Western Ghats and Northeast India, along with the east-to-west decreasing gradient. However, a per-
159 sistent underestimation of rainfall along the west coast and central India is evident in both generations,
160 largely due to limitations in representing orographic convection and mesoscale moisture transport.
161 CMIP6 partly reduces these biases through improvements in boundary-layer processes, convective
162 parameterizations, and cloud microphysics (Morrison et al. 2020; Zelinka et al. 2020). In addition,
163 the generally higher horizontal resolution of CMIP6 models provides a more realistic representation
164 of the Western Ghats and associated orographic lifting, which enhances moisture transport and oro-
165 graphic precipitation along the west coast of India. These improvements collectively contribute to the
166 enhanced spatial coherence of simulated monsoon rainfall, particularly over the Western Ghats and
167 Northeast India (Rajendran et al. 2013; Varikoden et al. 2018; He et al. 2023).

168 The reduced dry bias in CMIP6 relative to CMIP5 highlights progress in simulating monsoon dynam-
169 ics and air-sea interactions that govern regional precipitation (Fig. 1a-c). Additionally, the spatial
170 distribution of mean JJAS precipitation from individual 13 CMIP6 and CMIP5 models compared to
171 observations is shown in Supplementary Fig. S1 and S2. The models generally capture overestimate
172 rainfall bias over Northeast but underestimate rainfall bias significantly along the west coast and
173 central India. This bias is common to both the CMIP5 and CMIP6 MME with observation, where
174 simulated fairly realistic rainfall pattern over the parts of Northeast India, Western Ghats, and some
175 part of North India, they consistently but deficiency in rainfall over central and Southern India (Fig.
176 1d, e). Sreenath et al. (2022) also reported persistent central India dry biases in both MME and noted
177 CMIP6 as better capturing west coast. These discrepancies points to a key area where climate models
178 performance differ significantly. In particular, the CMIP6 exhibits a positive rainfall bias over North-
179 east India compared to CMIP5 (Fig. 1f), indicating a deterioration in model performance over this
180 region.

181 To provide a mechanistic understanding of the rainfall biases, we examined the vertical velocity (ω)
182 structure (Fig. 2). The ERA5 reanalysis (Fig. 2a) shows strong and vertically coherent upward motion
183 (negative ω) eastern India, extending from the lower to mid-troposphere, consistent with active
184 monsoon convection and enhanced rainfall. In contrast, CMIP5 MME (Fig. 2c) exhibits weaker and
185 less coherent ascent along with enhanced subsidence over central India, which explains the persistent
186 dry bias in this region. CMIP6 MME (Fig. 2b) shows a partial improvement with stronger and more
187 organized upward motion compared to CMIP5, indicating improved representation of large-scale
188 monsoon circulation. However, the magnitude of ascent remains weaker than ERA5, leading to
189 residual dry biases. Over the Western Ghats, both CMIP5 and CMIP6 underestimate rainfall, which
190 is consistent with weak low-level ascent and insufficient orographic lifting in the vertical velocity
191 fields. Conversely, over Northeast India, CMIP6 shows stronger upward motion compared to CMIP5,
192 resulting in a positive rainfall bias due to enhanced convective activity. This suggest that the regional

193 rainfall biases are closely linked to deficiencies in simulating vertical motion and associated moisture
194 transport. The improvement in CMIP6 can therefore be attributed to better representation of boundary
195 layer processes and convective parameterization, which enhance vertical moisture transport and
196 ascent, although significant biases still persist.

197 However, the most prominent enhancement is observed along the western coast of India in CMIP6
198 simulations relative to CMIP5, suggesting improved model performance in capturing regional rainfall
199 characteristics. Overall, the CMIP6 MME does not demonstrate substantial or statistically significant
200 improvement over most parts of India compared to CMIP5, although localized enhancements are
201 evident in regions such as the western coast and central India.

202 Relative bias analysis indicates that both CMIP5 and CMIP6 models exhibit systematic errors in
203 simulating JJAS rainfall with widespread underestimation over central and peninsular India and
204 localized wet biases over northern and north-eastern regions (Supplementary Figs. S3–S4). To better
205 understand the physical origin of these biases, we examined the vertical velocity (ω) structure from
206 individual models (Supplementary Figs. S5–S6). The results show that regions with pronounced dry
207 bias, particularly over central India and the western coast, correspond to weaker and less vertically
208 coherent upward motion, along with intermittent mid-tropospheric subsidence. This indicates a
209 deficiency in simulating large-scale monsoon ascent and associated moisture convergence.

210 In contrast, regions exhibiting wet bias, such as Northeast India in some CMIP6 models are associated
211 with stronger and deeper upward motion, suggesting overactive convection. Compared to CMIP5,
212 CMIP6 models show relatively improved vertical structure of ascent, with enhanced low- to mid-
213 tropospheric upward motion, which contributes to partial reduction of dry bias. Comparison of
214 Supplementary Figures S3–S6 indicates that models with relatively smaller precipitation biases
215 generally reproduce more realistic large-scale monsoon ascent (negative ω_{500}), whereas models with
216 larger precipitation biases exhibit weaker or displaced ascent. This relationship is further supported
217 (Supplementary Fig. S7) by the positive correlation between rainfall RMSE and ω_{500} RMSE for both
218 CMIP5 ($r = 0.84$, $p = 0.004$) and CMIP6 ($r = 0.75$, $p = 0.002$), suggesting that improved simulation
219 of large-scale circulation contributes to improved precipitation simulation. However,
220 the weak correlation suggests that other processes, such as convective parameterization, cloud
221 microphysics, boundary-layer processes, and model resolution, also influence precipitation biases.

222 In Fig. 3, the annual cycle examined the key characteristics and seasonal patterns of precipitation,
223 analysed monthly rainfall data over an extended period. An effective GCM should be capable of
224 accurately reproducing the annual cycle of climate variables (Turner et al. 2011). CMIP6 slightly
225 underestimates peak rainfall during July–August but performs closer to observations compared to
226 CMIP5. In contrast, CMIP5 shows a larger underestimation during the peak monsoon months and a

227 smoother, weaker seasonal cycle. The shaded regions indicate inter-model spread, which is
228 particularly large during the monsoon season (June–September), highlighting substantial uncertainty
229 among individual models. This spread is larger in CMIP5 than CMIP6, suggesting some improvement
230 in model consistency in CMIP6. Both model generations capture the general seasonal evolution of
231 rainfall, CMIP6 demonstrates better agreement with observations in terms of magnitude and reduced
232 spread, although biases during peak monsoon months persist.

233 **3.2. Comparative Assessments of Models Fidelity and skill:**

234 Figure 4, shows the Taylor diagram of rainfall over Indian region, comparing the simulations from
235 CMIP6 and CMIP5 models, including MME, with reference to IMD data sets. Specifically, models
236 with a correlation coefficient (CC) ≥ 0.8 demonstrate strong agreement respect to observed summer
237 rainfall. Notably, the majority of CMIP6 models such as ACCESS-CM2, CanESM5, MPI-ESM1-2-
238 LR, CNRM-CM6-1, MIROC6, GFDL-CM4, IPSL-CM6-LR and MRI-ESM2-0 simulated models
239 show normalized standard deviation (SD) closed to 1 and higher correlation value (i.e. equal or more
240 than 0.80). Similarly, CMIP5 models such as ACCESS1-0, MPI-ESM-LR, MRI-ESM-LR, IPSL-
241 CM5A-LR show correlations equal or above 0.8 and normalized SD close to 1. In particularly, the
242 CMIP6 MME results show a normalized SD close to observation, indicates high performance models,
243 whereas the CMIP5 MME tends to more underestimation of rainfall. Over all, the skill of all CMIP6
244 models illustrate improved compared to CMIP5. The CMIP6 MME achieves a CC of 0.86, which is
245 higher as compared to CMIP5 MME models such as 0.68. Remarkably, MIROC6 achieve 0.99
246 correlations with observations.

247 Taylor skill scores (TSC) are calculated for all individual CMIP6 and CMIP5 models, along with their
248 respective MME, as demonstrated in Fig. 5. The skill scores of CMIP6 and CMIP5 models values
249 closer to 1 indicate better performance in simulating precipitation including ACCESS-CM2,
250 ACCESS-ESM1-5, CNRM-CM6-1, MIROC6, NorESM2-LR, GISS-E2-1-H, whereas the CMIP5
251 models such as ACCESS1-0, ACCESS-ESM1-5, CNRM-CM5, MPI-ESM-LR, MRI-ESM1 show
252 high skill scores, illustrating a relatively high fidelity in simulating rainfall patterns. Furthermore, the
253 skill score of CMIP6 MME found approximately 0.80, which is higher than CMIP5 MME skill score
254 0.68. These results indicate, the collective predictive capability of CMIP6 have substantial better than
255 individual model. However, the most of CMIP6 models improved skill score of the rainfall over
256 CMIP5 simulated models.

257 **3.3. Cumulative Probability Distribution Function (CPDF):**

258 The summer rainfall distribution of anomalous rainfall frequency is represented through CPDF (Fig.
259 6a and 6b), which offer insights into how well models simulate the likelihood of moderate to extreme
260 rainfall (6 to 9 mm/day). The observed data show high rainfall probability reaching up to 9 mm/day.

CMIP6 models including MIROC6, GISS-E2-1-H, and CNRM-CM6-1 effectively captured high rainfall probabilities in range from 6 to 9 mm/day. However, the models like CanESM5 tend to underestimate the frequency of heavy rainfall, particularly under the 5 mm/day. The CMIP6 MME captures rainfall probability in the range of 6–7 mm day⁻¹ but shows noticeable clustering effects and slight underestimation when compared with observations. In case of CMIP5, models including as MIROC5, CNRM-CM5, and CanESM2 demonstrate relatively good performance, with probability close to the observed 8 to 9 mm/day. Conversely, IPSL-CM5A-LR and MRI-ESM1 consistently underestimate by capturing probability below 5 mm/day. The CMIP5 MME captures around 5 to 6 mm/day. However, CMIP5 models shows underestimation of high rainfall events and experience more model spread than CMIP6. Notably, MIROC6(CMIP6) and MIROC5, CanESM2 (CMIP5) show the closest agreement with observed CPDFs for high rainfall intensities, indicating better skill in representing extreme rainfall events. Additionally, models such as GISS-E2-H(CMIP6) and GISS-E2-R(CMIP5) simulate moderate rainfall range in 5 to 7 mm/day with reasonable accuracy. In general, CMIP6 models showing improved representation of extremes over CMIP5.

3.4. Distribution of Long-term Trends:

Figures 7a and 7b illustrate the linear trends in ISMR simulated by CMIP5 and CMIP6 models. Both ensembles exhibit substantial inter-model variability, with individual models showing contrasting trends ranging from weak negative to positive values. The CMIP5 MME indicates a weak negative trend (−0.46), whereas the CMIP6 MME shows a weak positive trend (0.42), highlighting inconsistencies in the sign of the forced response across model generations. The inter-model spread, representing internal variability and structural differences, is considerably larger than the ensemble means in both cases resulting in low signal-to-noise ratios are low. This indicates that internal variability dominates over the externally forced signal. Such behaviour is well documented in climate projections, where large ensemble spread and internal variability often obscure forced responses (Deser et al., 2012).

The spatial patterns of JJAS rainfall trends are shown in Supplementary Figs. S8 and S9 for CMIP5 and CMIP6 models. Observational datasets indicate a noticeable decreasing trends in rainfall over India (0 to −2.00 mm day⁻¹ per 100 years). The CMIP5 models exhibit some agreement in indicating a drying tendency over central India and wetting over parts of Northeast India (positive trends) like ACCESS1-3, CNRM-CM5, GFDL-CM3, MIROC5, MRI-ESM1-LR. The CMIP6 models exhibit spatial rainfall trends that qualitatively resemble the observed dry over northern and central India and localized wet over northeast India. However, the agreement varies considerably among individual models, and no consistent improvement over CMIP5 is evident across all regions (Supplementary Figs. S8–S9). The CMIP6 MME reproduces some of the large-scale spatial characteristics but

smooths regional details because of ensemble averaging. Overall, both CMIP5 and CMIP6 exhibit substantial uncertainty in simulating long-term rainfall trends rather than the ability of the models to reproduce interannual monsoon variability. Model performance regarding variability is evaluated separately using EOF and principal component analyses in Section 4.3.

4. Selection of Skilful GCMs in Application in Monsoon-Ocean Interaction:

Based on the multi-metric evaluation presented in Figures 4–6, the best-performing CMIP6 models include ACCESS-CM2, ACCESS-ESM1-5, CNRM-CM6-1, GISS-E2-1-H, MIROC6, NorESM2-LR, whereas ACCESS1-0, ACCESS1-3, CNRM-CM5, MPI-ESM-LR, MRI-ESM1 represent the best-performing CMIP5 models. These models consistently exhibited high spatial correlation ($CC \geq 0.80$), Taylor Skill Scores close to unity, realistic normalized standard deviations. Using MME of these two model groups, the skilful models provide the basis for interpreting SST–monsoon teleconnections presented in Figures 8–14.

4.1. Relationship between Indian Summer Monsoon Rainfall and SST in Key Ocean Basins:

CMIP6 models consistently show stronger and spatially coherent positive correlations, particularly over regions influenced by AS, BOB, SCS, and SIO SST variability (Fig. 8a1-a4 and Fig. 9). These relationships suggest that CMIP6 models better represent the underlying ocean-atmospheric coupling process that regulate monsoon rainfall (Eyring et al. 2016). However, this improvement is not uniform across all regions and datasets, indicating persistent model uncertainties in simulating regional monsoon dynamics. The AS warming seems to be associated with reduced rainfall over western and parts of central India (Fig. 8), and a broader weakening of rainfall over India (Fig. 9). AS weakens the large-scale monsoon circulation, contributing to a decline in rainfall over the Western Ghats and central India, while promoting increased rainfall over Northeast India (Ratna et al. 2014). Such these changes are also linked to a weakening of the land–ocean thermal gradient and large-scale circulation adjustments associated with Indian Ocean warming (Roxy et al. 2015, 2017). However, the relationship remains spatially heterogeneous, suggesting that Arabian Sea forcing does not uniformly suppress rainfall across India.

The Bay of Bengal (BOB) exhibits relatively stronger and more consistent positive correlations, particularly over eastern and northeastern India. This reflects its dominant role in modulating monsoon depressions, synoptic-scale systems, and regional convection, which are key drivers of rainfall variability over these regions (Goswami et al. 2006; Krishnan et al. 2016).

The SCS exhibiting weaker correlations, still shows potential remote influence through upper-level wave propagation, as captured by both models and observations but southern India get positive

327 correlation for all models and observation. The Southern Indian Ocean (SIO) demonstrates basin-
328 scale influences, with correlations indicating its role in modulating large-scale circulation and
329 atmospheric stability. Variability in this region is often linked to changes in cross-equatorial flow and
330 Walker circulation, which can influence monsoon strength and spatial rainfall distribution (Brierley
331 et al. 2023).

332 In Figure 9, however, a different picture emerges. The CMIP5 MME shows closer agreement with
333 observational datasets in reproducing the spatial pattern of SST–rainfall relationships, particularly
334 over central and northern India. This suggests that, despite advancements in CMIP6, certain large-
335 scale teleconnections and regional feedback processes are still better captured in CMIP5 models, as
336 also noted in comparative model evaluation studies (Sperber et al. 2013). Among observational da-
337 taset, IMD data show predominantly negative correlations across much of India, especially with AS
338 and SCS SSTs, indicating an inverse relationship between SST anomalies and rainfall variability.
339 This is consistent with studies showing a decline in rainfall associated with warming oceans and
340 weakened monsoon circulation (Rajeevan et al. 2005; Goswami et al. 2006). In contrast, GPCP and
341 CRU datasets exhibit more spatially heterogeneous patterns, reflecting differences in observational
342 methodologies and sensitivity to interannual variability. Such discrepancies among datasets are well
343 documented and highlight uncertainties in rainfall estimation and model validation.

344 The discrepancy between CRU, GPCP, and IMD datasets in SST–rainfall teleconnections arises pri-
345 marily from differences in rainfall variability and dataset construction. Variance analysis (Fig. 10 a,
346 b, c) indicates that IMD exhibits higher variability compared to CRU and GPCP, while mean rainfall
347 remains comparable across datasets. Reduced variability in CRU leads to smoother spatial fields,
348 which tend to weaken correlation strength and obscure teleconnection signals. Such discrepancies are
349 consistent with previous studies, which highlight that gridded datasets like CRU may be affected by
350 sparse station coverage and interpolation uncertainties, influencing rainfall variability and telecon-
351 nection strength (Tarek et al. 2021; Degefu et al. 2017; Aneesh and Bodai 2024). Overall, these results
352 emphasize the role of observational uncertainty in modulating SST–rainfall relationships and under-
353 score the importance of multi-dataset evaluation. CMIP6 models demonstrate improved spatial co-
354 herence and stronger coupling signals in some regions, CMIP5 models show better consistency with
355 observed SST–rainfall relationships in Fig. 9. This indicates that improvements in newer model gen-
356 erations are region-dependent, and emphasizes the importance of multi-dataset evaluation for robust
357 assessment of monsoon variability and its response to oceanic forcing (Gleckler et al. 2008).

358 4.2. Composite wind vectors and wind speed anomalies in Key Ocean Basins:

359 Figure 11 represents the 850 hPa and 200 hPa composite wind patterns during the monsoon season
360 (JJAS), which reflecting a dynamics perspective on the monsoon flow structure at 850 hPa, the ob-
361 servational dataset shows the south-westerly low-level jet (LLJ) originating over the equatorial Indian
362 Ocean, intensifying over the Arabian Sea and extending toward the Indian subcontinent and BoB
363 (Fig. 11c). This LLJ plays a crucial role in transporting moisture and sustaining monsoon rainfall over
364 India, consistent with earlier studies (Joseph and Sijikumar, 2004). In comparison, both model en-
365 sembles reproduce the large-scale structure of the LLJ, but with notable biases. CMIP6 models (Fig.
366 11a) exhibit stronger wind speed anomalies and enhanced jet intensity, particularly over the Arabian
367 Sea and adjoining regions, indicating an underestimation of LLJ strength relative to observations.
368 This leads to higher biases in low-level wind speeds, especially over key moisture source regions. In
369 contrast, CMIP5 models (Fig. 11b) show comparatively weaker wind speeds and reduced biases, alt-
370 hough they still display spatial inconsistencies, including slight displacement of the jet core and
371 weaker extension into the BOB.

372 At the 200 hPa level, observations depict the TEJ, characterized by strong easterly winds extending
373 across the Indian subcontinent with peak intensity over peninsular and central India (Fig. 11f). This
374 upper-level jet is essential for maintaining divergence aloft and supporting deep convection during
375 the monsoon season. CMIP6 models (Fig. 11d) capture the broad zonal structure and spatial extent
376 of the TEJ but tend to overestimate wind speeds in certain regions, reflecting biases in upper-level
377 circulation strength. Meanwhile, CMIP5 models (Fig. 11e) simulate a relatively weaker and some-
378 what displaced TEJ, consistent with previously reported deficiencies in representing upper-tropo-
379 spheric monsoon dynamics (Rajendran and Kitoh 2008; Kong et al. 2022). Both CMIP5 and CMIP6
380 models are able to reproduce the fundamental structure of monsoon circulation at lower and upper
381 levels. However, CMIP6 models exhibit larger biases in low-level jet (LLJ) strength, particularly
382 through underestimation of wind speeds over the Arabian Sea, whereas CMIP5 models, despite
383 weaker circulation, show relatively smaller magnitude biases. At upper levels, CMIP6 better captures
384 the spatial extent of the TEJ, while CMIP5 tends to underestimate its intensity and misplace its core.
385 These results suggest that improvements in CMIP6 are more evident in the representation of large-
386 scale structure rather than in reducing magnitude biases.

387 To further investigate the dynamical coupling between circulation and rainfall variability, we ana-
388 lysed the lead-lag correlation between principal components (PC1 and PC2) of rainfall and zonal
389 winds at 850 hPa and 200 hPa (Fig. 12). The results show a strong and coherent correlation between
390 rainfall variability and atmospheric circulation. At 850 hPa, PC1 exhibits a significant positive cor-
391 relation near zero lag in both observations and models, indicating that enhanced rainfall is closely

392 associated with strengthening of the low-level south-westerly flow (LLJ). In contrast, at 200 hPa,
393 PC1 shows a pronounced negative correlation, reflecting the inverse relationship between upper-level
394 winds and deep convection, consistent with the role of upper-level divergence in supporting monsoon
395 activity. Furthermore, the lead–lag correlations derived from individual models (Supplementary Figs.
396 S10) show considerable inter-model variability, highlighting differences in the representation of mon-
397 soon dynamics across models. These results emphasize that, while CMIP6 shows improved skill in
398 capturing circulation–rainfall coupling, uncertainties remain in simulating the temporal evolution and
399 feedback mechanisms of the monsoon system. CMIP6 models capture this lead–lag relationship more
400 realistically compared to CMIP5, particularly in representing the timing and strength of low-level and
401 upper-level circulation responses. However, some discrepancies in lag structure and magnitude per-
402 sist, indicating residual limitations in simulating the phase relationship between convection and cir-
403 culation.

404 **4.3. Principal Modes of Monsoon Rainfall Variability**

405 The First EOF mode, which captures the dominant, large-scale variability patterns, show a strong
406 monopole structure in both CMIP6 and CMIP5 MME with CMIP6 showing 61.7% of total variance
407 higher than CMIP5 showing 58.2% (Fig. 13). This spatial coherence across India suggests that both
408 generations of models, particularly CMIP6, effectively capture the broad-scale monsoon signal linked
409 to interannual drivers such as ENSO and IOD. The observational data GPCP and CRU capture
410 moderate monopole feature in EOF1 explaining about 45.7% and 40.8% of the total variance (Fig.
411 13 d1 and e1), where the IMD data shows the weakest dominance (22.6%) (Fig. 13 c1). This reduction
412 is the explained variance and coherence in observations likely reflects the influence of regional
413 topography, localized convective activity and mesoscale dynamics that are not fully captured in
414 coarse-resolution climate models. It underscores a gap between idealized model representations and
415 the spatial complexity of real-world monsoon behaviour.

416 The second mode EOF provides further insight into sub-regional and intra-seasonal variability.
417 CMIP6 models show a north-south dipole pattern in EOF2, and explaining 8.6% of the variance (Fig.
418 13 a2). This mode of EOF indicates alternating rainfall anomalies between northern and southern
419 India. This structure likely represents the spatial redistribution of rainfall due to monsoon breaks and
420 shifts in convergence zones. CMIP5 models show a more spatially complex EOF2 with a pattern
421 explaining 13.7% of the variance (Fig. 13 b2), highlighting their stronger sensitivity to regional-scale
422 dynamics though perhaps at the cost of spatial coherence. In (Fig. 13 c2, d2 and e2), the observational
423 EOF2 patterns (7.7%, 11.6%, 11.4%) of GPCP data reflects localized dipoles particularly between
424 the southern peninsula and northeast-central India and consistent with CMIP5, while IMD and CRU
425 capture structures consistent with CMIP6 model outputs and regional monsoon mechanisms. These

include influences from the Western Ghats, monsoon trough variations, and northward-propagating convective systems. The EOF2 mode in observations typically explains less variance than models, suggesting that regional variability in observed rainfall is more episodic and less structured. The PC1 and PC2 corresponding to these EOFs confirm the temporal behaviour of the dominant modes. PC1 time series of CMIP6 and CMIP5 reflect the anomalies pattern during monsoon, indicating that models accurately reproduce the timing and structure of interannual variability and PC2 in CMIP5 shows larger amplitude fluctuations, consistent with the greater spatial complexity seen in EOF2 (Fig. 14 a, b). Observational PCs components especially from IMD data (Fig. 14 c) display more irregular and weaker signals showing localized drivers of rainfall anomalies. The lower explained variance in EOF1 (22.6%) is consistent with the more chaotic PC1 structure and PC2 shows substantial fluctuation in certain years (like 1988, 1990, 1996), highlighting the role of regional-scale variability and sub-seasonal processes in observed rainfall patterns. PCs components of GPCP (Fig. 14d) demonstrate clear structure and somewhat higher amplitude than IMD. PC1 captures major anomalous years (like 1983, 1987, 1994, 2002), aligning well with CMIP5 & CMIP6 PC1, indicating that satellite based data better captures large scale rainfall variability. PC2 shows moderate variability and is consistent with the EOF2 dipole structures seen in GPCP and model datasets. The PCs of CRU (Fig. 14e) reflect intermediate behaviour between IMD and GPCP. PC1 shows discernible peaks in years (like 1978, 1987 and 2003) while PC2 captures contrasting fluctuations (like 1983 1987, 1988, 2002). The amplitude is lower than models but higher than IMD, supporting the view that gridded global datasets retain more large-scale signals than station-based observations. The spatial patterns and variance contributions of the Indian Ocean EOF identified in this study show strong agreement with the results presented by Saji et al. (1999). Overall, the EOF-PC analysis confirms the improved realism of CMIP6 models, particularly in simulating broad-scale monsoon patterns. However, it also emphasizes the need for further refinement in capturing regional structures and sub-seasonal variability, especially in orographically complex and convectively active zones.

4.4. Relationship Between Principal Components and Sea Surface Temperature

In figure 15 shows the correlation patterns between the leading PC1 and PC2 of rainfall variability and SST anomalies, insight into the oceanic drivers of dominant monsoon modes across models and observation. In Fig. 15a1, CMIP6 PC1 show a robust positive correlation with SST anomalies over the central-eastern equatorial Indian Ocean and, to a lesser extent over the western pacific indicating PC1 is modulated by warm SST anomalies with consistent with the IOD and ENSO. PC2 (Fig. 15a2) shows broader warm anomalies across the western Indian Ocean (WIO). This pattern suggests that the dominant rainfall mode EOF1 is significantly influenced by large-scale warm SST anomalies

460 associated with ENSO and IOD teleconnection. Figs. 15 a2, PC2 displays broader SST warming over
461 the WIO and northern Arabian Sea, implying a regional modulation of north-south rainfall dipoles,
462 likely reflecting basin-scale SST gradients linked to regional monsoon variability (Cherchi and
463 Navarra 2013). In fig. 13b1, CMIP5 PC1-SST correlations reveal warming over the south-eastern AS
464 and WIO, accompanied by cooling south of the equator indicates a stronger IOD-like structure. In
465 fig. 15 b2, captures warm anomalies spanning over the AS and south-eastern IO, reinforcing the role
466 of zonal SST gradients in shaping secondary rainfall patterns.

467 In fig. 15 c1, IMD data show weak and spatially inconsistent SST correlations with PC1, with only
468 marginal warming near Sumatra and cooling over the WIO. This dispersion suggests that observed
469 rainfall variability in EOF1 may be driven by non-linear dynamics beyond large-scale SST control.
470 For PC2, significant negative correlations emerge over the SIO, suggesting an inverse link between
471 SST warming and rainfall anomalies (Fig. 15c2). GPCP based PC1-SST (Fig. 15d1) correlations
472 indicate warming signals in the central Indian Ocean and the western Pacific, link a weak connection
473 to ENSO-IOD variability. In contrast, PC2 (Fig. 15d2) highlights stronger regional coupling, with
474 pronounced positive SST correlations over the Bay of Bengal and south-eastern AS, aligning with
475 known influences along the monsoon trough (Roxy et al. 2014).

476 In the CRU dataset (Fig. 15e1-e2), PC1 again shows weak correlation over the central IO, while PC2
477 exhibits warm SST anomalies over the eastern AS and near the Maritime Continent, suggesting
478 localized thermal influence on rainfall. Overall, the results reveal that CMIP6 models demonstrate
479 stronger and more spatially coherent SST-rainfall relationships for both PC1 and PC2, especially over
480 ENSO and IOD-sensitive regions. CMIP5 models show similar patterns but often with stronger IOD-
481 like signatures in PC1. Observational datasets exhibit weaker coupling, particularly for PC1. These
482 findings suggest the improved fidelity of CMIP6 in capturing the large-scale ocean-atmosphere
483 interactions underlying Indian monsoon variability (Eyring et al. 2016; Gusain et al. 2020).

484 **5. Conclusions:**

485 This study evaluated the performance of thirteen CMIP5 and CMIP6 models in simulating
486 precipitation over India during the historical periods from 1975-2005. The results reveal substantial
487 inter-model variability, reflecting differences in model structure and parameterization when compared
488 with multiple observational datasets. MME consistently outperformed single models in replicating
489 observed climatic patterns, confirming the advantage of ensemble-based approaches in reducing
490 random and systematic errors. CMIP6 models show notable improvements over CMIP5 in
491 representing ISMR, particularly in terms of spatial climatology, statistical skill, and SST–rainfall
492 teleconnections.

CMIP6 and CMIP5 models reproduce the broad spatial pattern of ISMR but exhibit persistent regional biases, particularly dry conditions over central India and wet biases over the northeast. CMIP6 shows modest improvements over CMIP5, particularly in enhancing spatial coherence, vertical structure and stronger ascent compared to CMIP5, significant biases remain. Both CMIP models generations capture the seasonal cycle with peak rainfall during JJAS, but systematic biases remain, including underestimation in July and overestimation in June.

CMIP6 models show clear improvement over CMIP5, with higher correlations (≥ 0.8) and better agreement with observed variability. The MME further enhances performance, with CMIP6 MME (0.80) outperforming CMIP5 (0.68), demonstrating improved reliability in representing monsoon rainfall characteristics. TSC analysis confirms these findings, with several CMIP6 models (e.g., ACCESS-CM2, ACCESS-ESM1-5, CNRM-CM6-1, MIROC6, NorESM2-LR, GISS-E2-1-H) demonstrating higher skill in simulating precipitation patterns, while CMIP5 models show comparatively lower performance. The CMIP6 MME exhibits the highest overall skill (~ 0.80), indicating a significant improvement in collective predictive capability. However, persistent biases in rainfall magnitude and distribution remain, indicating limitations in simulating key monsoon processes.

Trend analysis reveals large inter-model variability in both CMIP5 and CMIP6, with inconsistent signals in the direction and magnitude of ISMR trends. While CMIP6 shows a weak positive trend and CMIP5 a weak negative trend, the ensemble spread exceeds the mean signal, indicating a low signal-to-noise ratio. This suggests that internal variability dominates over the forced response, limiting confidence in long-term projections.

CMIP6 models exhibit stronger and more spatially coherent correlations, indicating improved representation of coupling processes. However, this improvement is not uniform, and CMIP5 models often show closer agreement with observed spatial patterns, particularly over central and northern India (Menon. 2013). Observations consistently indicate that AS warming is associated with reduced rainfall over western and central India, reflecting weakening monsoon circulation, while the BoB shows a stronger positive influence on rainfall variability. The SCS and SIO exert secondary but regionally important influences. Previous studies have highlighted significant uncertainties in CMIP simulations of the Indian monsoon, particularly related to convection and inter-model spread (Sperber et al. 2013; Menon et al. 2013).

CMIP5 and CMIP6 models reproduce the key monsoon circulation features, including the LLJ (850 hPa) and TEJ (200 hPa), but with notable biases. CMIP6 shows improved spatial structure and better representation of circulation–rainfall coupling, though it tends to overestimate wind magnitude, especially at low levels. CMIP5, while weaker, exhibits relatively smaller magnitude biases but poorer spatial accuracy. Lead–lag analysis confirms strong coupling between rainfall and circulation with

enhanced rainfall linked to stronger low-level winds and weaker upper-level flow. CMIP6 captures this relationship more realistically than CMIP5, although uncertainties in timing and inter-model variability persist.

CMIP5 and CMIP6 models successfully capture the dominant large-scale monsoon variability where CMIP6 showing modest improvements in spatial coherence. However, models overemphasize large-scale uniformity, while observations exhibit stronger regional and sub-seasonal complexity. Although CMIP6 generally exhibits improved representation of rainfall climatology and SST–monsoon teleconnections, substantial uncertainty remains in simulating long-term rainfall trends because internal climate variability and structural model differences continue to dominate the forced signal. These uncertainties should be considered when interpreting future monsoon projections.

AUTHOR CONTRIBUTIONS

Anmol Yadav: Conceptualization; investigation; methodology; writing – original draft; visualization; data collection and Software. **G.P. Singh:** Supervision; investigation; review and editing. **Pra-deep Kumar Rai:** writing; review; editing; visualization and Software. All authors have reviewed and approved the manuscript.

Acknowledgement:

The authors sincerely acknowledge the **Institute of Eminence (IoE), Banaras Hindu University (BHU), Varanasi** for providing support for this research. The authors also express gratitude to the India Meteorological Department (IMD) for providing the high-resolution gridded rainfall data, Global Precipitation Climatology Project (GPCP) dataset, Climate Research Unit Time-Series (CRU TS v4.05) datasets, European Centre for Medium-Range Weather Forecasts (ERA5 reanalysis) dataset, HadISST and dataset available and the authors would also like to express their gratitude to the World Climate Research Programme (WCRP) for providing open access to the CMIP5 and CMIP6 model datasets.

CONFLICT OF INTEREST STATEMENTS

The authors declare no conflicts of interest.

DATA AVAILABILITY

The rainfall data used in this study were obtained from the **IMD** (<https://www.imdpune.gov.in>), while the atmospheric circulation data, were sourced from the **Climate Research Unit Time-Series (CRU TS v4.05)** datasets (<https://crudata.uea.ac.uk/cru/data/hrg/>) and **Global Precipitation Climatology Project (GPCP)** dataset (<https://psl.noaa.gov/data/gridded/data.gpcp.html>). Additionally the **SST data** were sourced from the **Hadley Centre Sea Ice and Sea Surface Temperature dataset (HadISST)** (<https://www.metoffice.gov.uk/hadobs/hadisst/data/download.html>). **ERA5 reanalysis**

561 data were obtained from the European Centre for Medium-Range Weather Forecasts ERA5 reanalysis
562 dataset and are publicly available via the Copernicus Climate Data Store
563 (<https://cds.climate.copernicus.eu/>). These datasets are publicly available and can be accessed through
564 their respective portals.

565 **CONSENT FOR PUBLICATION**

566 All authors give consent for the publication of all details in the manuscript.

567 **Funding**

568 The authors declare that no funding was received for this study.

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853 **FIGURES CAPTION:**

854 **Fig. 1** Climatological summer rainfall (mm/day) over India during 1975 to 2005 from (a)
855 observations, (b) CMIP6 MME, and (c) CMIP5 MME. Panels d to f show differences: (d) CMIP6

856 minus OBS, (e) CMIP5 minus OBS, and (f) CMIP6 minus CMIP5. CMIP5/6 refer to Phases 5/6 of
857 the Coupled Model Intercomparison Project; MME = multi-model ensemble. Dot indicate statistically
858 significant correlations at the 95% confidence level.

859 **Fig. 2** Vertical Velocity (pa/s) averaged over 5°–30°N across the study for (a) observations (ERA5),
860 (b) CMIP6 and (c) CMIP5 multi-model ensemble means (MME). The plots illustrate their ensemble
861 means capture the observed seasonal rainfall pattern during 1975 to 2005.

Fig. 3 Annual cycle of rainfall (mm/day) over the study region for observations (black line), individual CMIP5 and CMIP6 models, as well as the multi-model ensemble means (MME) of CMIP5 and CMIP6 (red line). Shaded area shows different models. The plots illustrate how well the models and their ensemble means capture the observed seasonal rainfall pattern across the annual cycle during 1975 to 2005.

862 **Fig. 4** Taylor diagram comparing CMIP5 (blue), CMIP6 (red), and their MMEs against observed
863 summer rainfall (black star, IMD) over India during 1975 to 2005. CMIP5/6 denote Phases 5/6 of the
864 Coupled Model Intercomparison Project.

865 **Fig. 5** Skill scores of individual models and multi-model ensembles (MMEs) from CMIP5 and
866 CMIP6 in simulating the climatological summer rainfall over India during 1975 to 2005. Higher skill
867 indicates better agreement with the observed IMD dataset. CMIP5 and CMIP6 refer to Phases 5 and
868 6 of the Coupled Model Intercomparison Project.

869 **Fig. 6 (a, b)** Cumulative distribution functions (CDFs) of summer precipitation over India for
870 observations, individual CMIP6 and CMIP5 models, and their respective MME during 1975 to 2005.
871 Observed data is based on IMD; MME denotes Multi-Model Ensemble.

872 **Fig. 7 (a, b)** Linear trends of Indian Summer Monsoon (ISM) indices (per 100 years) simulated by
873 CMIP5 (a) and CMIP6 (b) models during 1975–2005. Individual bars represent trends from each
874 model, while the red marker indicates the multi-model ensemble (MME) mean trend, and the red
875 error bar represents the inter-model spread (± 1 standard deviation). The black bar labelled OBS
876 denotes the observed trend.

877 **Fig. 8** Spatial correlation maps of JJAS (June to September) rainfall with area-averaged SST
878 anomalies over four key oceanic Regions-Arabian Sea (AS), Bay of Bengal (BOB), South China Sea
879 (SCS), and Southern Indian Ocean (SIO). The analysis compares the multi-model ensembles of the
880 best-performing models from CMIP6 (MME) and CMIP5 (MME) with observational datasets (IMD,
881 GPCP, and CRU) during 1975 to 2005. Black dot indicates statistically significant correlations at the
882 95% confidence level based on linear regression.

883 **Fig. 9** Spatial correlation maps between averaged SST anomalies (from HadISST) and JJAS rainfall
884 over India from observations (IMD, GPCP, CRU) and the multi-model ensemble means of best-

885 performing CMIP6 and CMIP5 models (MMEs) during 1975 to 2005. Correlations are shown for key
886 oceanic regions: The Arabian Sea (AS), Bay of Bengal (BOB), South China Sea (SCS), and Southern
887 Indian Ocean (SIO). Black dot indicates statistically significant correlations at the 95% confidence
888 level, based on linear regression.

889 **Fig. 10** Variance analysis of different observation dataset (a) CRU, (b) IMD, and (c) GPCP

890 **Fig. 11** Composite wind vectors (arrows) and wind speed anomalies (shading, m s^{-1}) during the JJAS
891 season at 850 hPa (left panels) and 200 hPa (right panels) for (a, d) CMIP6 MME, (b, e) CMIP5
892 MME, and (c, f) observations (NCEP) during 1975–2005. Wind anomalies are computed relative to
893 the climatological mean. The boxes indicate key oceanic regions: Arabian Sea (AS), Bay of Bengal
894 (BOB), South China Sea (SCS), and Southern Indian Ocean (SIO). Reference vectors (top right of
895 each panel) denote wind speeds of $9\text{--}10 \text{ m s}^{-1}$ at 850 hPa and $26\text{--}31 \text{ m s}^{-1}$ at 200 hPa.

896 **Fig. 12** Lead and Lag correlation between Principal Components(PCs) and Zonal Wind: (a)
897 Observations (b) CMIP6 and (c) CMIP5 MME at 850hPa and (d) Observations (e) CMIP6 and (e)
898 CMIP5 MME at 200hPa

899 **Fig. 13** Empirical Orthogonal Function (EOF) analysis of JJAS seasonal rainfall anomalies over the
900 Indian subcontinent. The first two leading EOF modes are shown along with their explained variances
901 for CMIP6 MME, CMIP5 MME, and three observational datasets (IMD, GPCP, and CRU) during
902 1975 to 2005.

903 **Fig. 14** Time series of the first two principal components (PC1 and PC2) corresponding to the leading
904 EOF modes of JJAS precipitation over India for CMIP6 MME, CMIP5 MME, and observational
905 datasets (IMD, GPCP, and CRU).

906 **Fig. 15** Spatial correlation patterns between the leading principal components (PC1 and PC2) of JJAS
907 precipitation and sea surface temperature (SST) anomalies over oceanic regions, derived from CMIP6
908 MME, CMIP5 MME, and observational datasets (IMD, GPCP, and CRU). These patterns highlight
909 the dominant oceanic drivers influencing rainfall variability over India during 1975 to 2005.

910 **SUPPLEMENTARY CAPTION:**

911 **Fig. S1** Mean monthly precipitation (mm/day) for the period 1975 to 2005 from observations,
912 individual CMIP5 models, and the CMIP5 multi-model ensemble mean (MME).

913 **Fig. S2** Mean monthly precipitation (mm/day) for the period 1975 to 2005 from observations,
914 individual CMIP6 models, and the CMIP6 multi-model ensemble mean (MME).

915 **Fig. S3** Monthly mean precipitation bias (mm/day) patterns over India, showing the relative bias
916 between each individual GCM (including the CMIP5 MME) and observations from the IMD dataset.
917 Dot indicate statistically significant correlations at the 95% confidence level.

918 **Fig. S4** Monthly mean precipitation bias (mm/day) patterns over India, showing the relative bias
919 between each individual GCM (including the CMIP6 MME) and observations from the IMD dataset.
920 Dot indicate statistically significant correlations at the 95% confidence level.

921 **Fig. S5** Vertical Velocity(ω) averaged over 5°–30°N across the India, showing x axis Longitude and
922 y axis is Pressure from 1000 hPa to 10hPa for different CMIP6 models from (a to m).

923 **Fig. S6** Vertical Velocity(ω) averaged over 5°–30°N across the India, showing x axis Longitude and
924 y axis is Pressure from 1000 hPa to 10hPa for different CMIP5 models from (a to m).

925 **Fig. S7** Relationship between rainfall RMSE and vertical velocity (ω_{500}) RMSE across individual (a)
926 CMIP5 and (b) CMIP6 models during the JJAS season over India.

927 **Fig. S8** Spatial linear trends of annual rainfall (mm/year/100 year) over India during 1975 to 2005
928 for individual CMIP5 models, the CMIP5 multi-model ensemble, and the observational dataset
929 (IMD). Trends are calculated using linear regression, and *black dot* indicate statistically significant
930 trends at the 95% confidence level.

931 **Fig. S9** Spatial linear trends of annual rainfall (mm/year/100 years) over India during 1975 to 2005
932 for individual CMIP6 models, the CMIP6 multi-model ensemble mean, and the observational dataset
933 (IMD). Trends are calculated using linear regression, and *black dot* indicate statistically significant
934 trends at the 95% confidence level.

935 **Fig. S10** Lead and Lag correlation between Principal Components(PCs) and Zonal Wind (850hPa)
936 for different CMIP6 and CMIP5 Models form (a to k).

937 **Tables:**

938 **Table S1** List of 13 CMIP6 models used in this study, including their modelling centres, atmospheric
939 resolution, and availability of historical simulations for the period 1975 to 2005.

940 **Table S2** List of 13 CMIP5 models used in this study, including their modelling centres, atmospheric
941 resolution, and availability of historical simulations for the period 1975 to 2005.

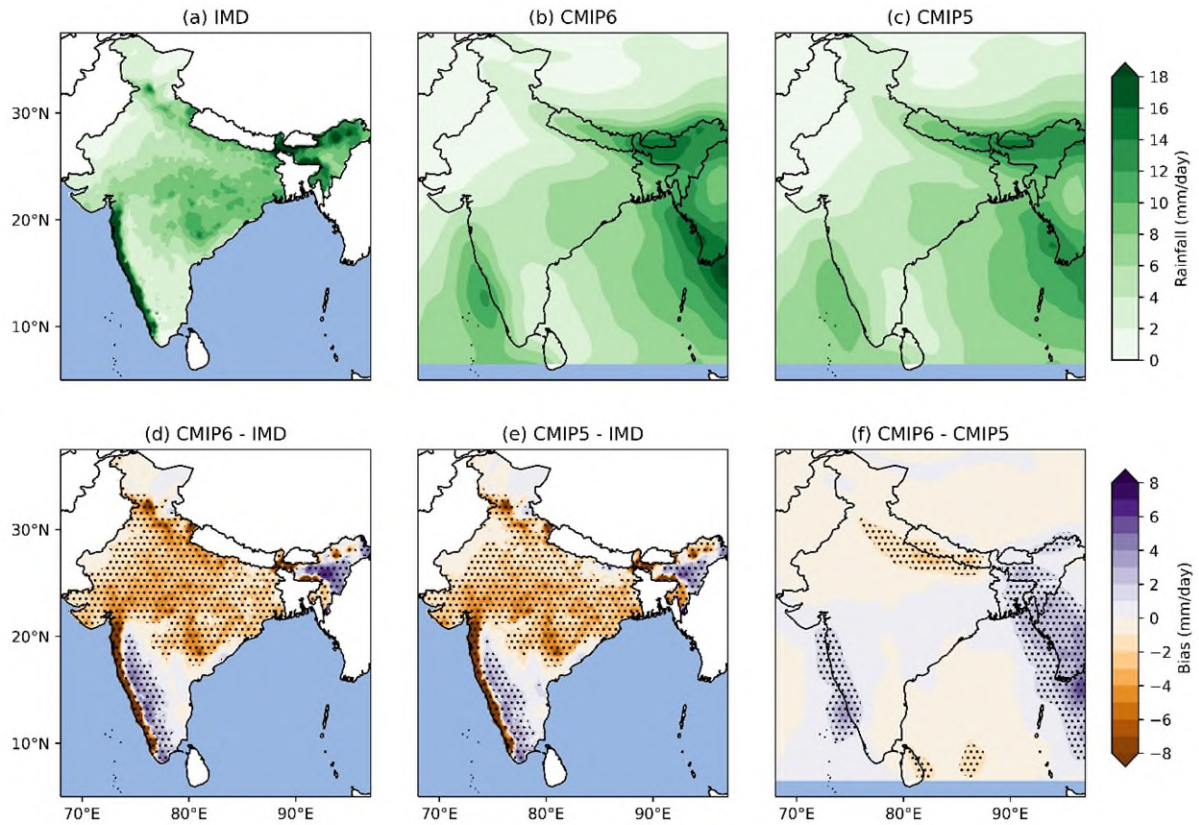


Fig. 1 Climatological summer rainfall (mm/day) over India during 1975 to 2005 from (a) observations, (b) CMIP6 MME, and (c) CMIP5 MME. Panels d to f show differences: (d) CMIP6 minus OBS, (e) CMIP5 minus OBS, and (f) CMIP6 minus CMIP5. CMIP5/6 refer to Phases 5/6 of the Coupled Model Intercomparison Project; MME = multi-model ensemble. dot indicate statistically significant correlations at the 95% confidence level.

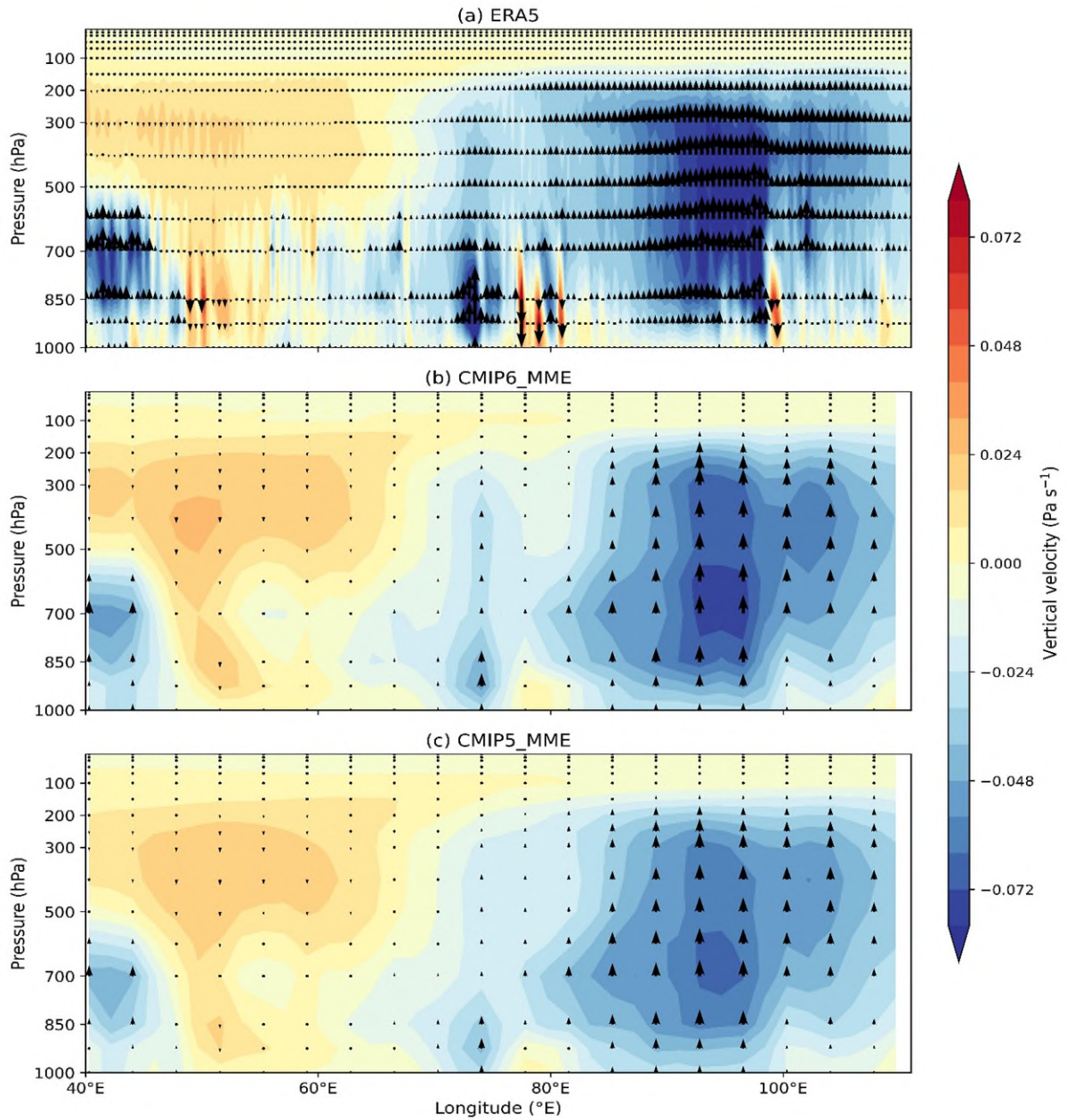


Fig. 2 Vertical Velocity (Pa/s) averaged over 5° – 30°N across the study for (a) observations (ERA5), (b) CMIP6 and (c) CMIP5 multi-model ensemble means (MME). The plots illustrate their ensemble means capture the observed seasonal rainfall pattern during 1975 to 2005.

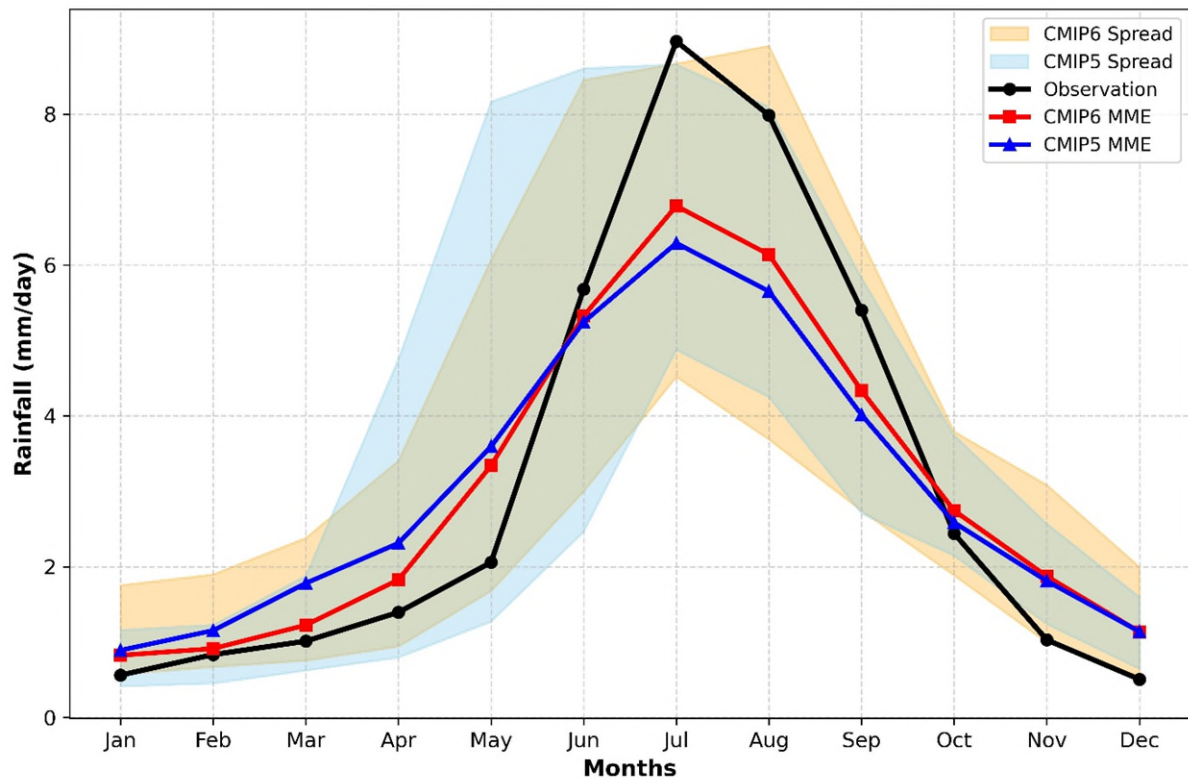


Fig. 3 Annual cycle of rainfall (mm/day) over the study region for observations (black line), individual CMIP5 and CMIP6 models, as well as the multi-model ensemble means (MME) of CMIP5 and CMIP6 (red line). Shaded area shows different models. The plots illustrate how well the models and their ensemble means capture the observed seasonal rainfall pattern across the annual cycle during 1975 to 2005.

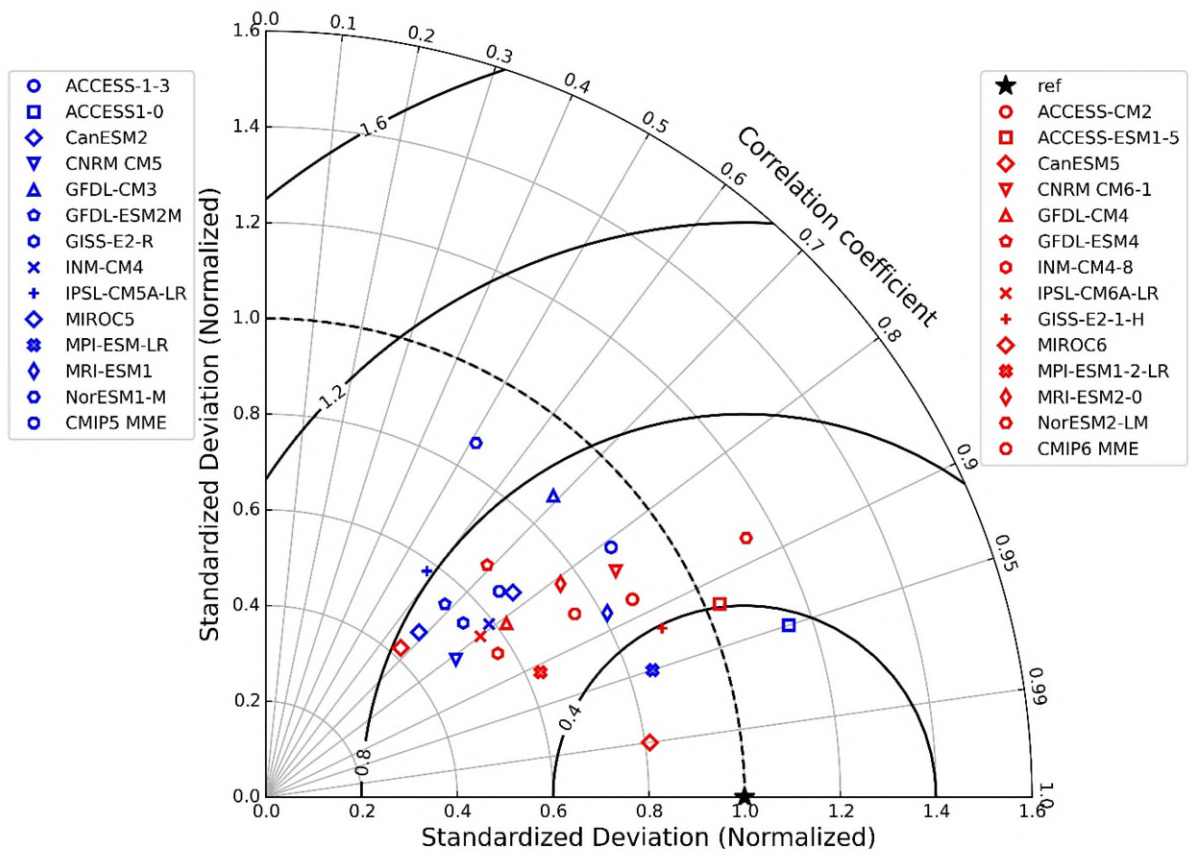


Fig. 4 Taylor diagram comparing CMIP5 (blue), CMIP6 (red), and their MMEs against observed summer rainfall (black star, IMD) over India during 1975 to 2005. CMIP5/6 denote Phases 5/6 of the Coupled Model Intercomparison Project.

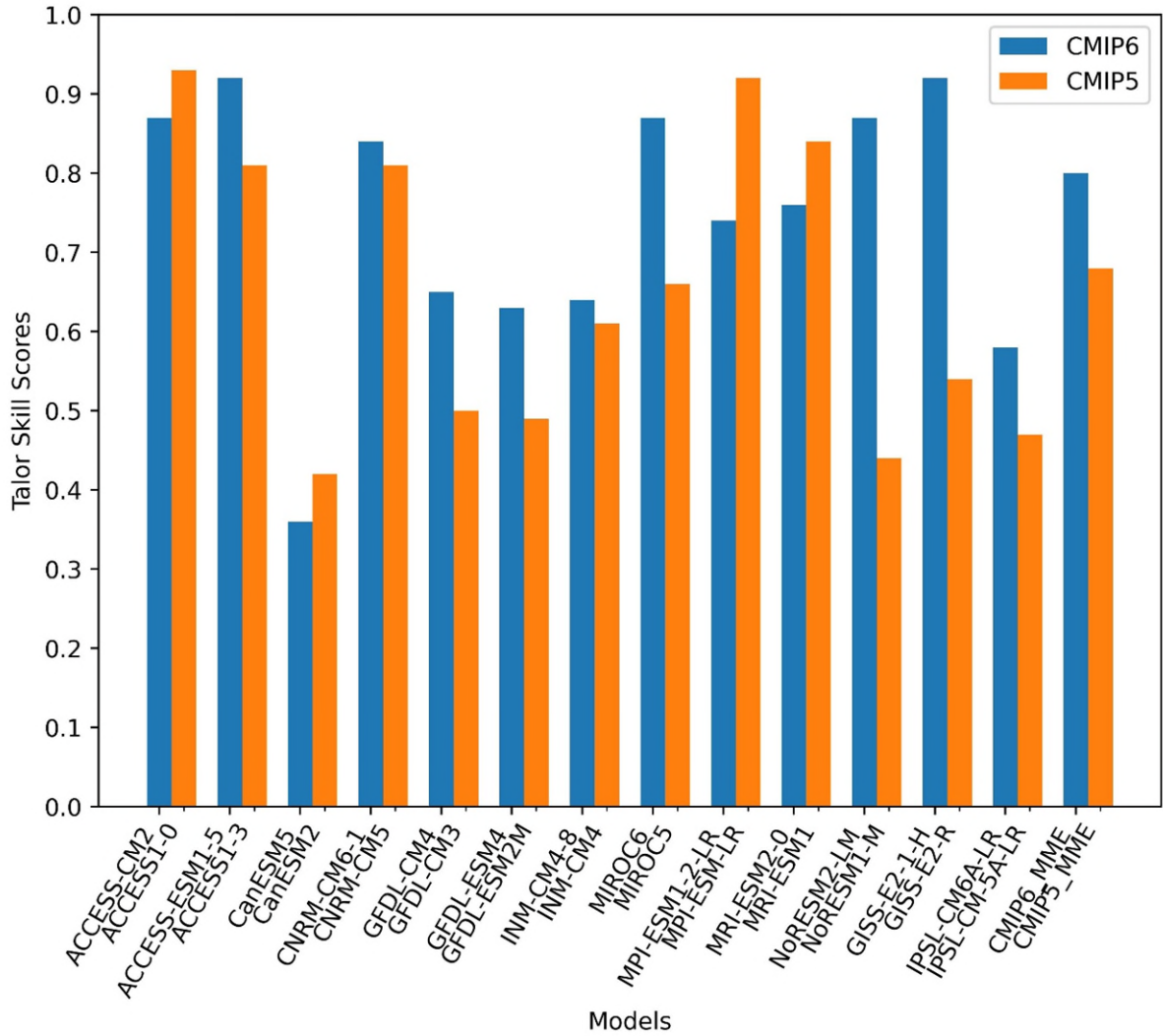


Fig. 5 Skill scores of individual models and multi-model ensembles (MMEs) from CMIP5 and CMIP6 in simulating the climatological summer rainfall over India during 1975 to 2005. Higher skill indicates better agreement with the observed IMD dataset. CMIP5 and CMIP6 refer to Phases 5 and 6 of the Coupled Model Intercomparison Project.

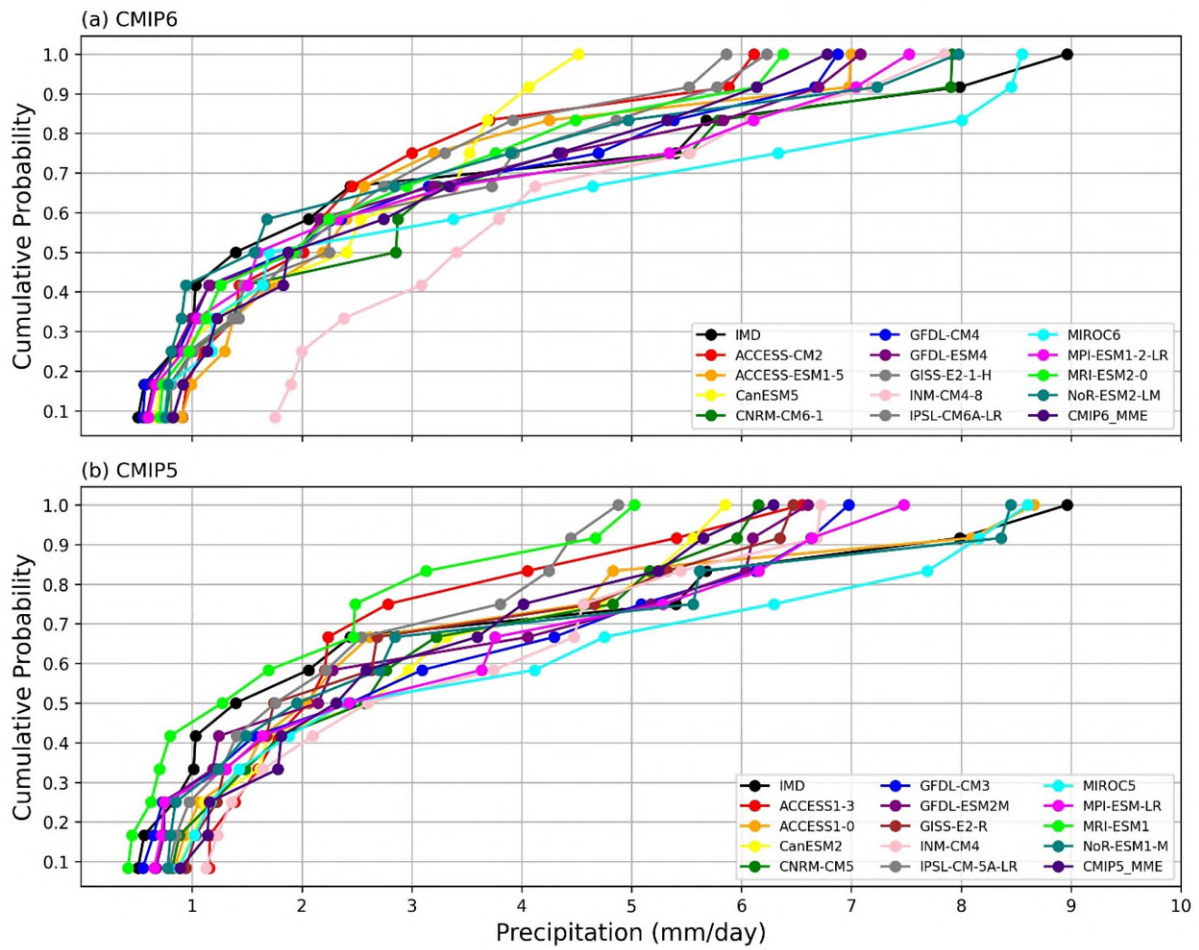


Fig. 6 (a, b) Cumulative distribution functions (CDFs) of summer precipitation over India for observations, individual CMIP6 and CMIP5 models, and their respective MME during 1975 to 2005. Observed data is based on IMD; MME denotes Multi-Model Ensemble.

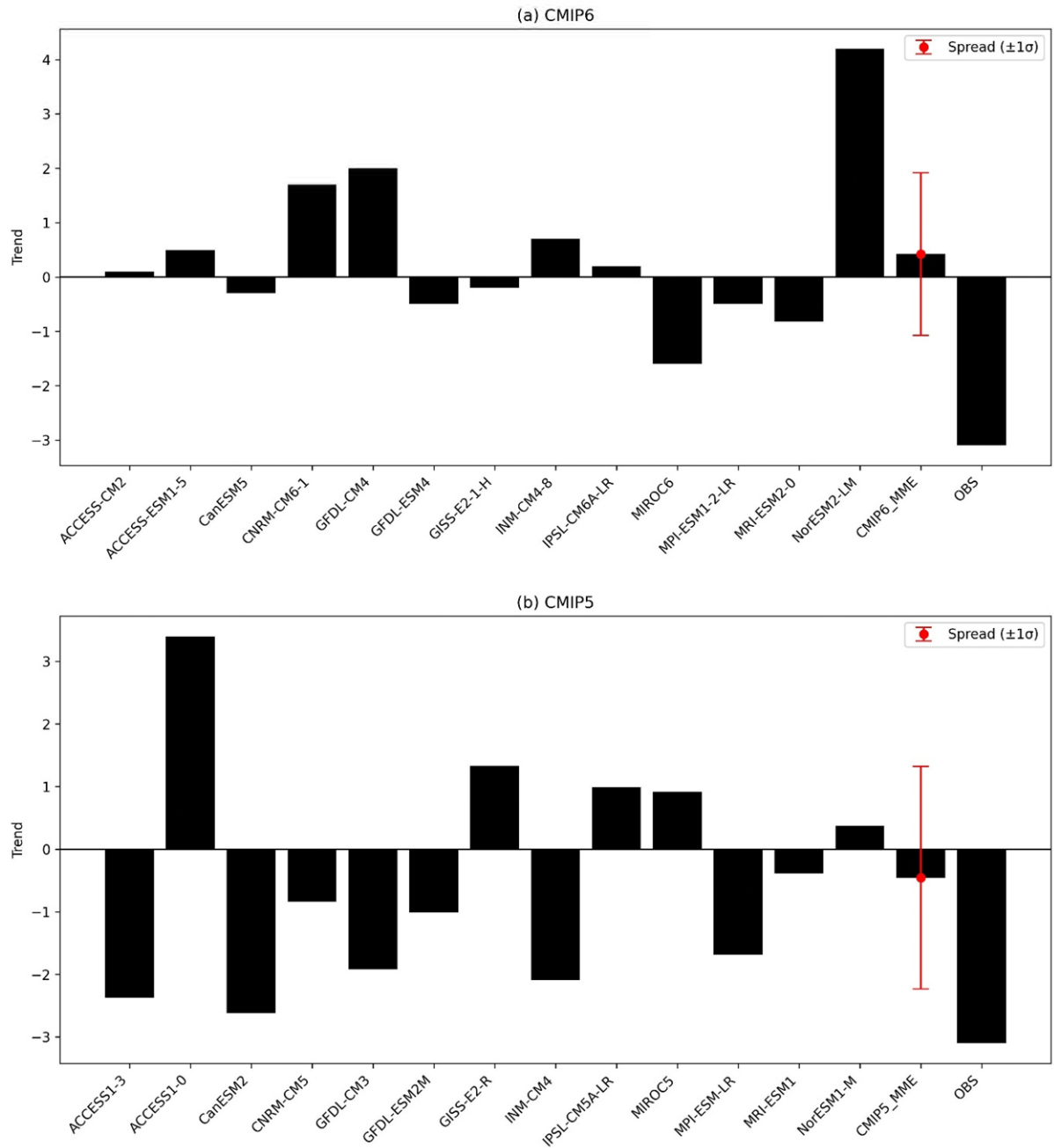


Fig. 7 (a, b) Linear trends of Indian Summer Monsoon (ISM) indices (per 100 years) simulated by CMIP5 (a) and CMIP6 (b) models during 1975–2005. Individual bars represent trends from each model, while the red marker indicates the multi-model ensemble (MME) mean trend, and the red error bar represents the inter-model spread ($\pm 1\sigma$). The black bar labelled OBS denotes the observed trend.

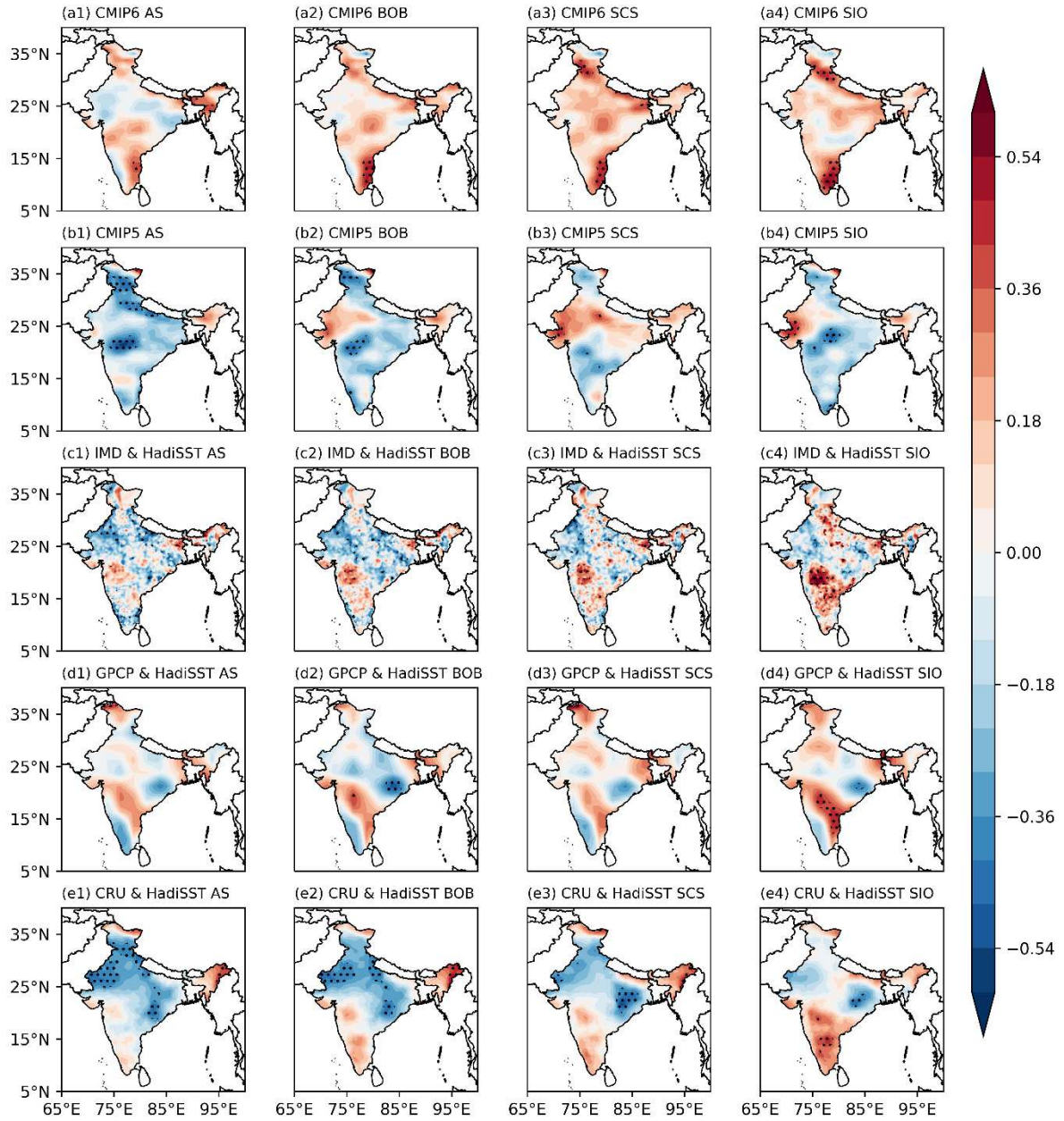


Fig. 8 Spatial correlation maps of JJAS (June to September) rainfall with area-averaged SST anomalies over four key oceanic Regions-Arabian Sea (AS), Bay of Bengal (BOB), South China Sea (SCS), and Southern Indian Ocean (SIO). The analysis compares the multi-model ensembles of the best-performing models from CMIP6 (MME) and CMIP5 (MME) with observational datasets (IMD, GPCP, and CRU) during 1975 to 2005. Black dot indicates statistically significant correlations at the 95% confidence level based on linear regression.

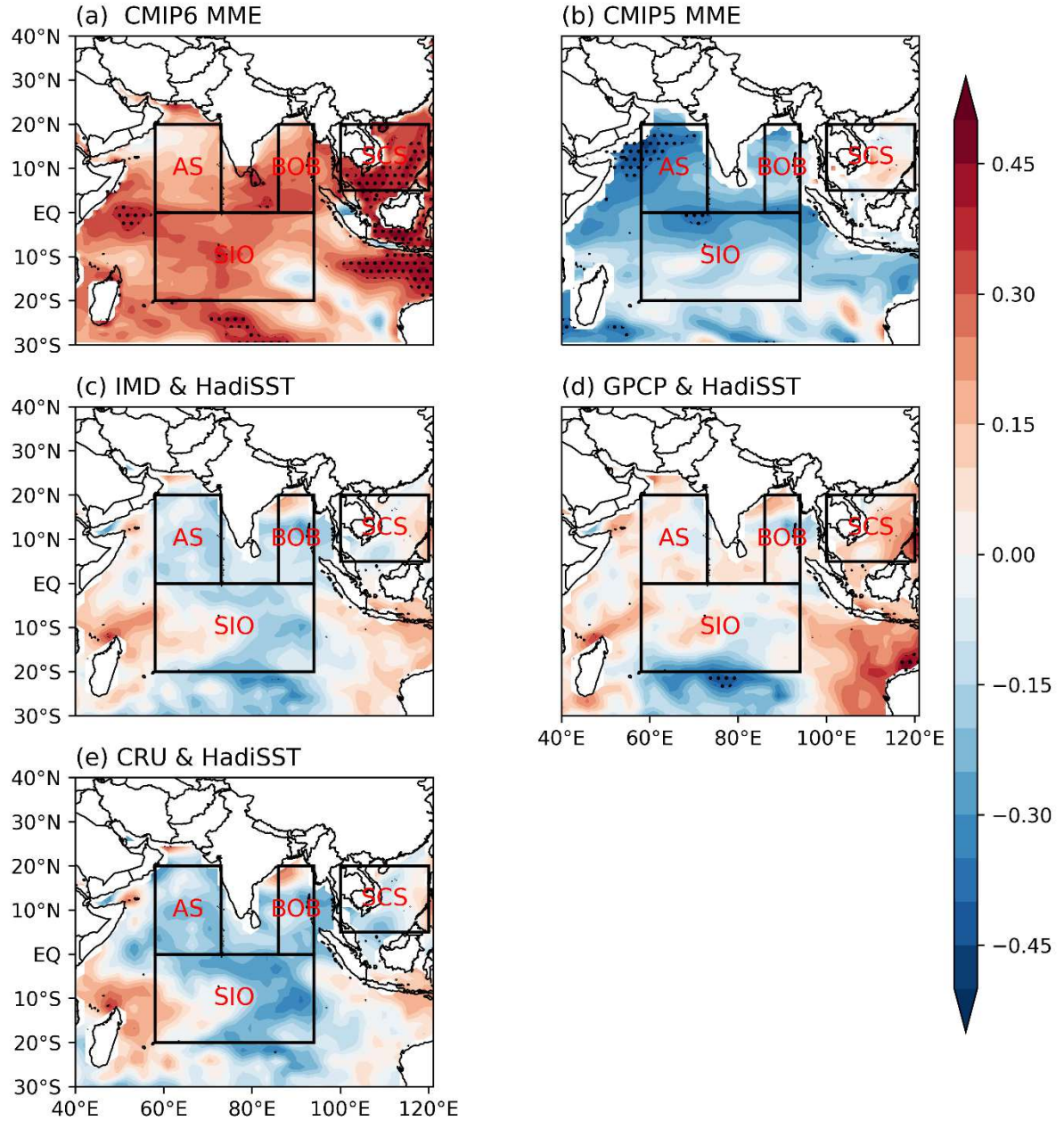


Fig. 9 Spatial correlation maps between averaged SST anomalies (from HadISST) and JJAS rainfall over India from observations (IMD, GPCP, CRU) and the multi-model ensemble means of best-performing CMIP6 and CMIP5 models (MMEs) during 1975 to 2005. Correlations are shown for key oceanic regions: The Arabian Sea (AS), Bay of Bengal (BOB), South China Sea (SCS), and Southern Indian Ocean (SIO). Black dot indicates statistically significant correlations at the 95% confidence level, based on linear regression.

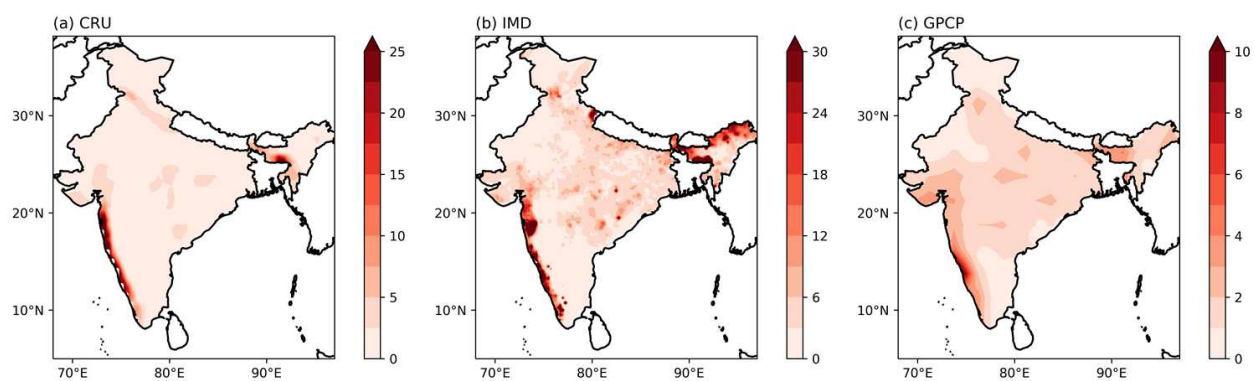


Fig. 10 Variance analysis of different observation dataset (a) CRU, (b) IMD, and (c) GPCP

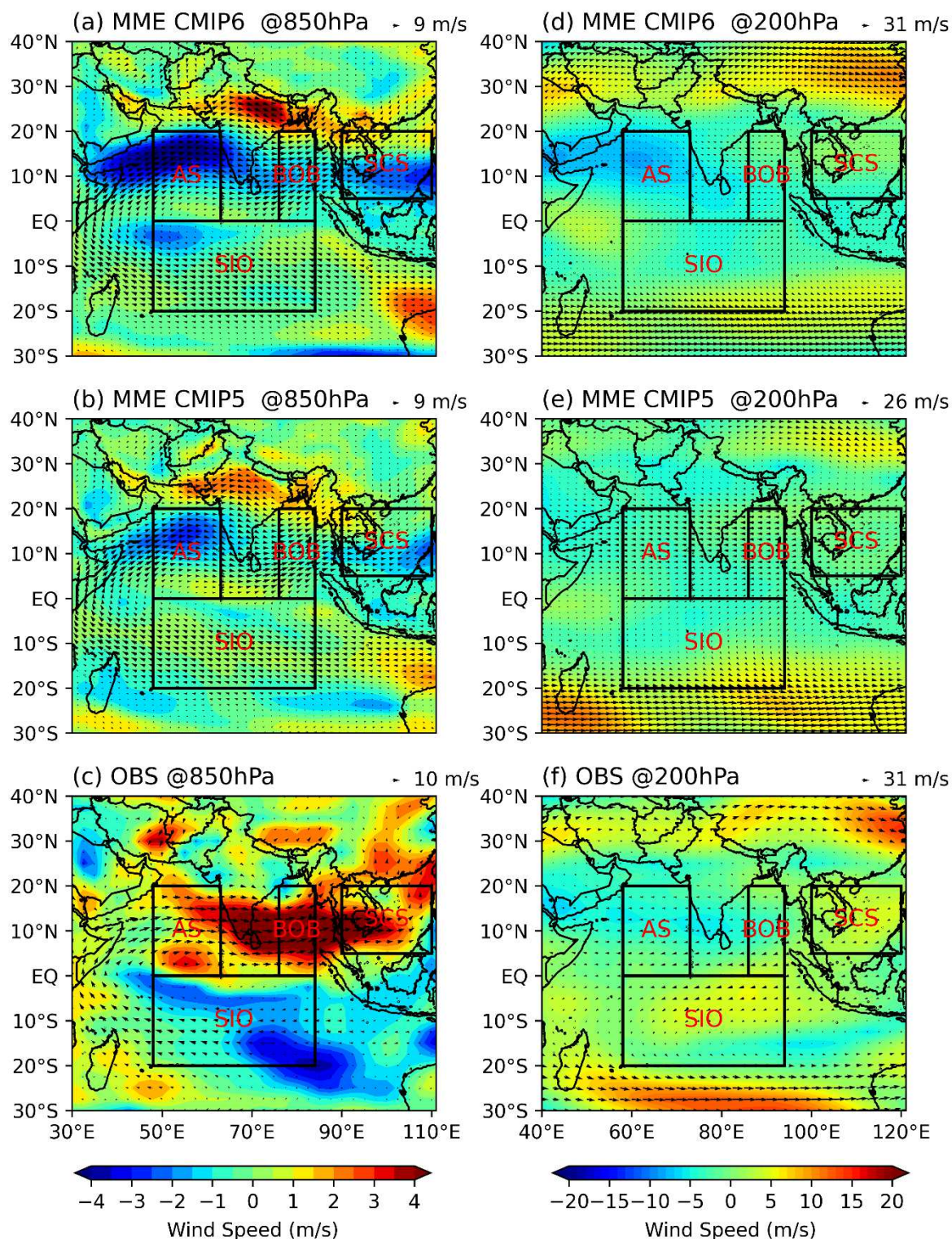


Fig. 11 Composite wind vectors (arrows) and wind speed anomalies (shading, m s^{-1}) during the JJAS season at 850 hPa (left panels) and 200 hPa (right panels) for (a, d) CMIP6 MME, (b, e) CMIP5 MME, and (c, f) observations (NCEP) during 1975–2005. Wind anomalies are computed relative to the climatological mean. The boxes indicate key oceanic regions: Arabian Sea (AS), Bay of Bengal (BOB), South China Sea (SCS), and Southern Indian Ocean (SIO).

Reference vectors (top right of each panel) denote wind speeds of 9–10 m s⁻¹ at 850 hPa and 26–31 m s⁻¹ at 200 hPa.

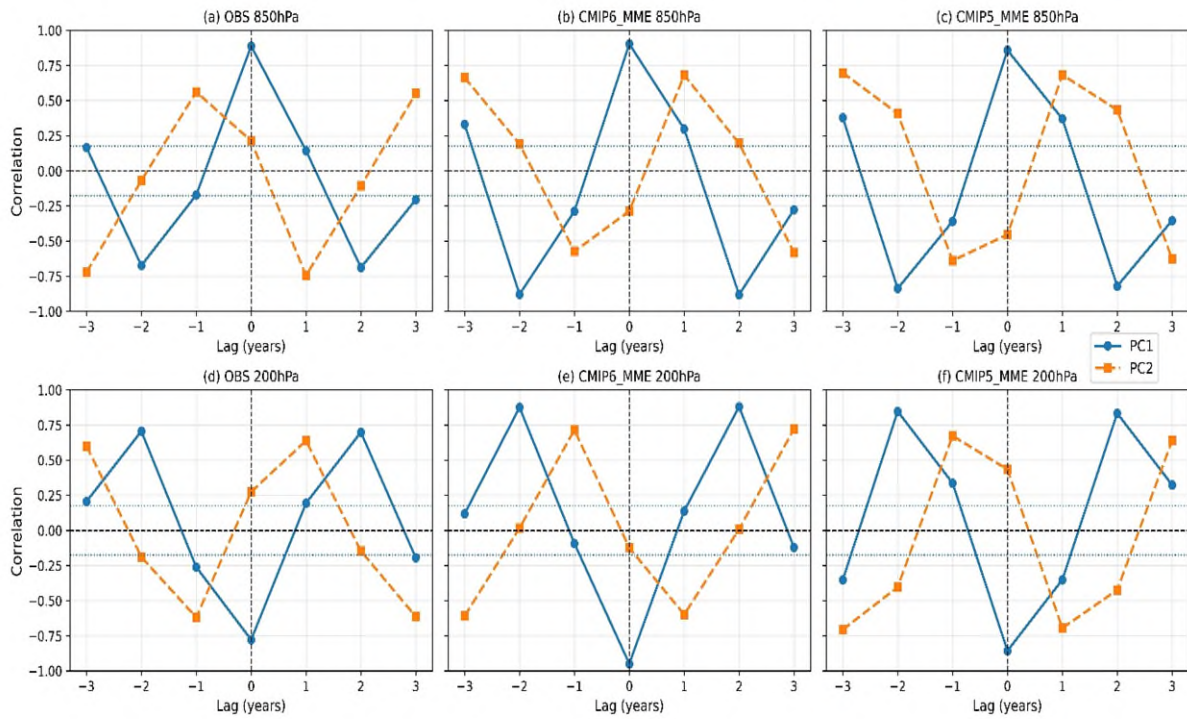


Fig. 12 Lead and Lag correlation between Principal Components(PCs) and Zonal Wind: (a) Observations (b) CMIP6 and (c) CMIP5 MME at 850hPa and (d) Observations (e) CMIP6 and (f) CMIP5 MME at 200hPa

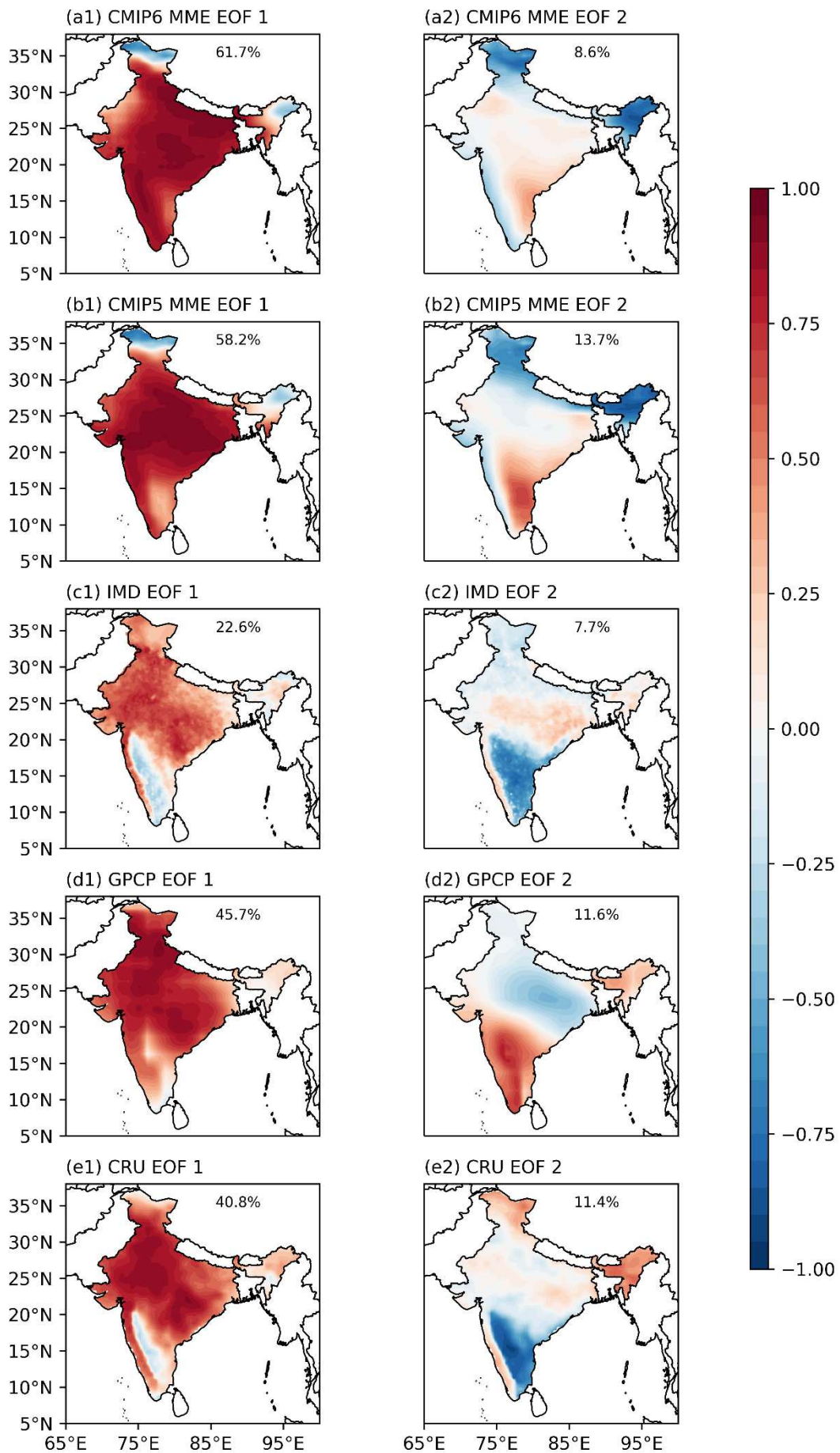


Fig. 13 Empirical Orthogonal Function (EOF) analysis of JJAS seasonal rainfall anomalies over the Indian subcontinent. The first two leading EOF modes are shown along with their explained variances for CMIP6 MME, CMIP5 MME, and three observational datasets (IMD, GPCP, and CRU) during 1975 to 2005.

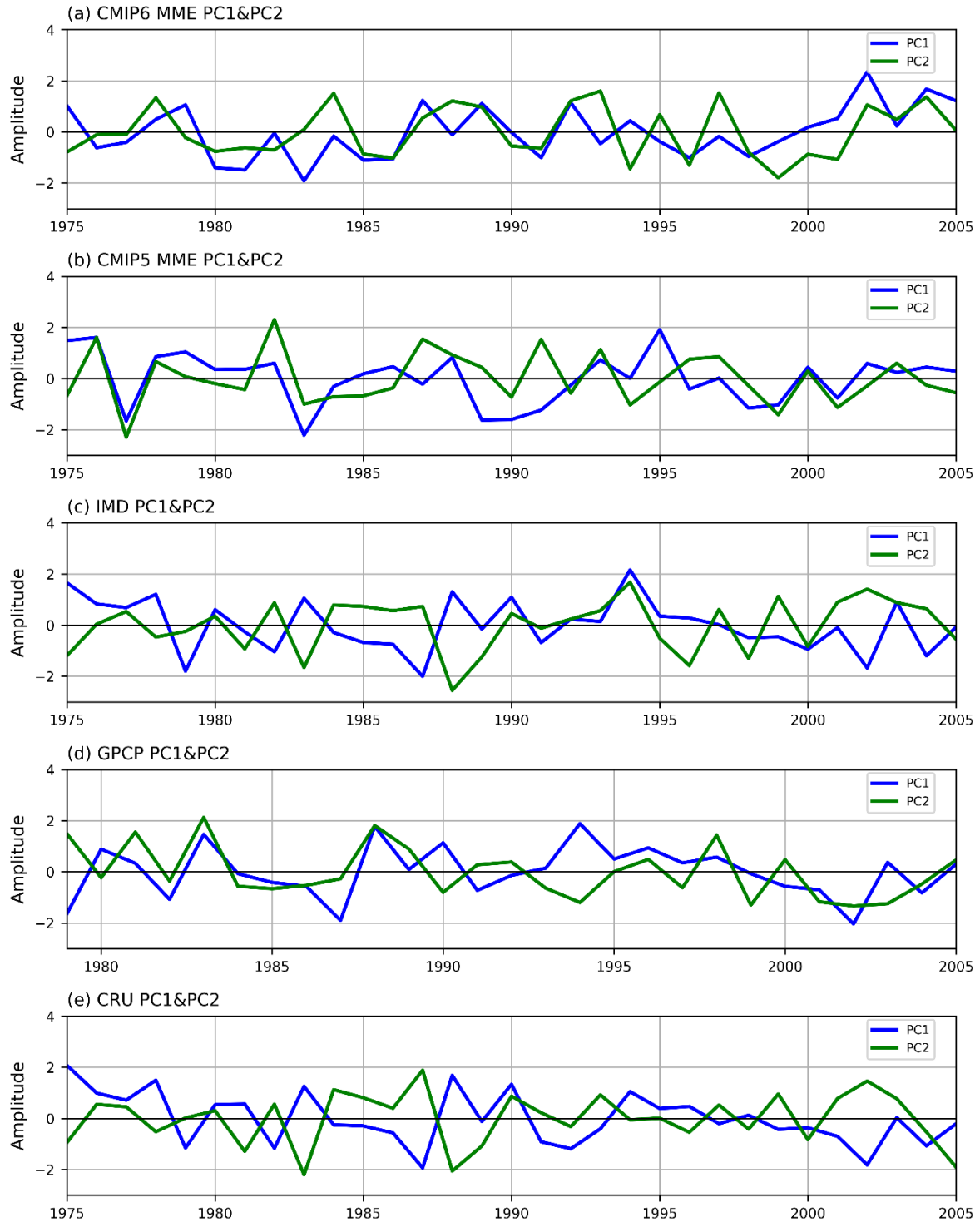


Fig. 14 Time series of the first two principal components (PC1 and PC2) corresponding to the leading EOF modes of JJAS precipitation over India for CMIP6 MME, CMIP5 MME, and observational datasets (IMD, GPCP, and CRU).

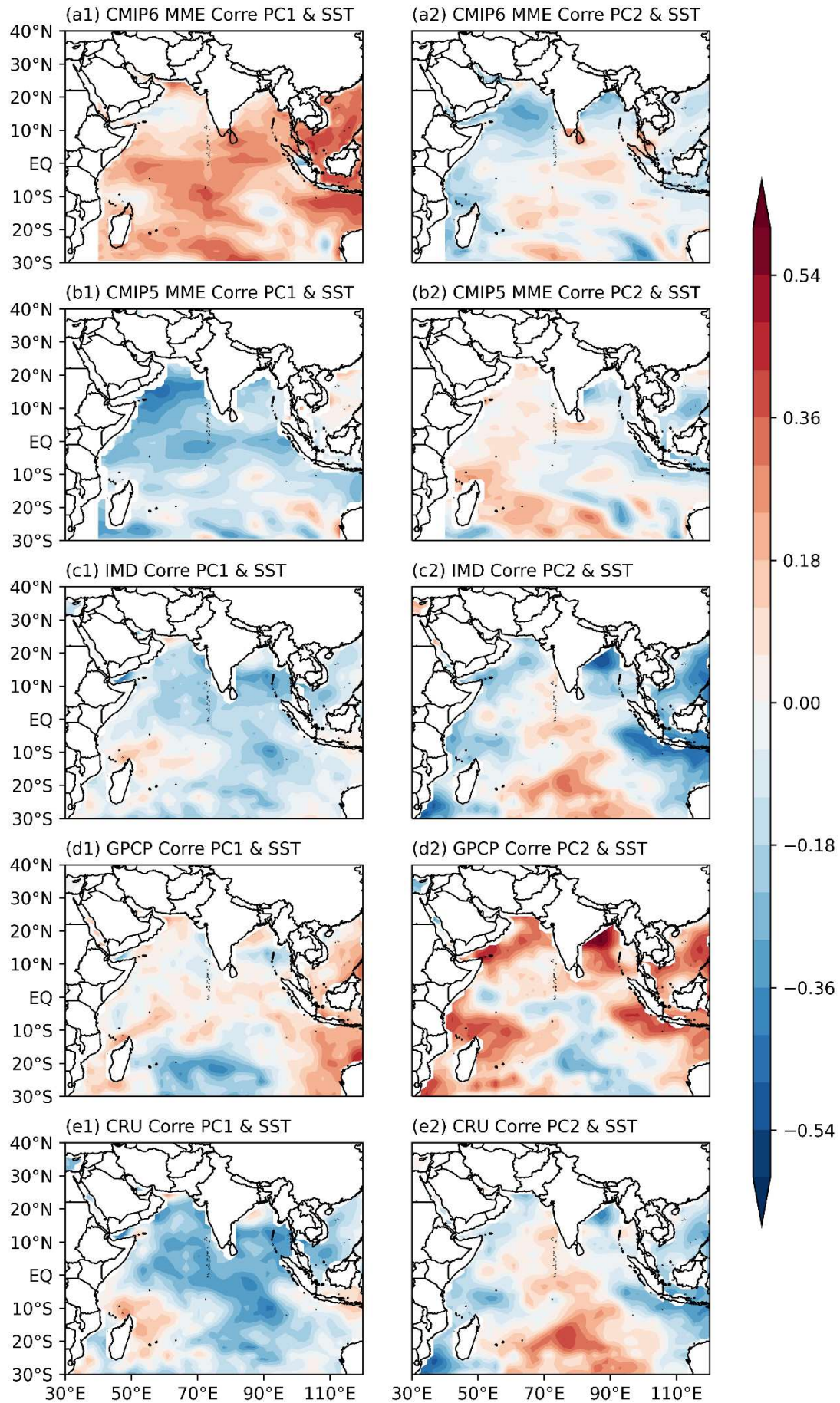


Fig. 15 Spatial correlation patterns between the leading principal components (PC1 and PC2) of JJAS precipitation and sea surface temperature (SST) anomalies over oceanic regions, derived from CMIP6 MME, CMIP5 MME, and observational datasets (IMD, GPCP, and CRU). These patterns highlight the dominant oceanic drivers influencing rainfall variability over India during 1975 to 2005.

Supplementary Files

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