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The Recent Decline and Recovery of Indian Summer Monsoon Rainfall: Relative Roles of External Forcing and Internal Variability

Xin HUANG[1,2], Tianjun ZHOU[1,2,3]*, Andrew TURNER[4], Aiguo DAI[5], Xiaolong CHEN[1], Robin CLARK[6], Jie JIANG[1,2], Wenmin MAN[1,3], James MURPHY[6], John ROSTRON[6], Bo WU[1,3], Lixia ZHANG[1,3], Wenxia ZHANG[1], Liwei ZOU[1,3]

1 LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 10029, China

2 University of Chinese Academy of Sciences, Beijing 100049, China

3 CAS Center for Excellence in Tibetan Plateau Earth Sciences, Chinese Academy of Sciences (CAS), Beijing 100101, China

4 National Centre for Atmospheric Science and Department of Meteorology, University of Reading, Reading RG6 6BB, United Kingdom

5 Department of Atmospheric and Environmental Sciences, University at Albany, State University of New York, Albany, NY, USA

6 Met Office Hadley Centre, Exeter, EX1 3PB, United Kingdom

Corresponding author:
Dr. Tianjun ZHOU
LASG, Institute of Atmospheric Physics
Chinese Academy of Sciences
Beijing 100029, China.
Phone: 86-10-8299-5279
Fax: 86-10-8299-5172
E-mail: zhoutj@lasg.iap.ac.cn
ORCID ID: https://orcid.org/0000-0002-5829-7279

Abstract

The Indian summer monsoon (ISM) rainfall affects a large population in South Asia. Observations show a decline in ISM rainfall from 1950-1999 and a recovery from 1999-2013. While the decline has been attributed to global warming, aerosol effects, deforestation, and a negative-to-positive phase transition of the Interdecadal Pacific Oscillation (IPO), the cause for the recovery remains largely unclear. Through analyses of a 57-member perturbed-parameter ensemble of model simulations, this study shows that the externally-forced rainfall trend is relatively weak and is overwhelmed by large internal variability during both 1950-1999 and 1999-2013. The IPO is identified as the internal mode that helps modulate the recent decline and recovery of the ISM rainfall. The IPO induces ISM rainfall changes through moisture convergence anomalies associated with an anomalous Walker circulation and meridional tropospheric temperature gradients and the resultant anomalous convection and zonal moisture advection. The negative-to-positive IPO phase transition from 1950-1999 reduces what would have been an externally-forced weak upward rainfall trend of 0.01 mm day^{-1} $decade^{-1}$ to –0.15 mm day^{-1} $decade^{-1}$ during that period, while the rainfall trend from 1999-2013 increases from the forced value of 0.42 to 0.68 mm day^{-1} $decade^{-1}$ associated with a positive-to-negative IPO phase transition. Such a significant modulation of the historical ISM rainfall trends by the IPO is confirmed by another 100-member ensemble of simulations using perturbed initial conditions. Our findings highlight that the interplay between the effects of external forcing and the IPO needs be considered for climate adaptation and mitigation strategies in South Asia.

1. Introduction

More than a fifth of the world's population lives on the Indian subcontinent and depends on the Indian summer monsoon (ISM) for their water supply (Singh et al. 2019). The ISM provides about 80% of the annual rainfall to South Asia and is the strongest component of the global monsoon system (Wang et al. 2017). Thus, understanding of ISM variability on different time scales is critical for effective risk management and adaptation planning in this densely populated and ecologically vulnerable region (Turner and Annamalai 2012).

The greatest ISM rainfall occurs over the Western Ghats, over the Himalayan foothills, in the core monsoon region over north-central India (NCI) and along the Burmese coast (Fig. 1a, c, e). Variations of summer rainfall over the core monsoon zone are widely used to measure the variability of the ISM (Gadgil 2003; Goswami et al. 2006; Bollasina et al. 2011; Jiang and Ting 2017). During the second half of the 20th century, summer rainfall decreased significantly over the NCI region, accompanied by a weakening of the large-scale ISM circulation (Bollasina et al. 2011; Salzmann et al. 2014; Roxy et al. 2015; Salzmann and Cherian 2015). Since the early 2000s however, the drying trend in NCI has ceased together with a revival of the ISM circulation (Jin and Wang 2017; Roxy 2017).

The observed long-term decline of rainfall over India in the latter half of the 20th century has been studied extensively. Several studies have attributed this to rapidly increasing anthropogenic aerosol loading, which slows down the monsoon meridional overturning circulation by reducing the land-ocean thermal contrast and inter-hemispheric energy imbalance (Bollasina et al. 2011; Salzmann et al. 2014; Guo et al. 2015; Li et al. 2015). Global warming from greenhouse gas (GHG) forcing increases atmospheric moisture holding capacity by virtue of the Clausius-Clapeyron relation. Combined with small changes in atmospheric relative humidity (Collins et al. 2013), this leads to

increased water vapour and thus increased moisture convergence and rainfall during the ISM (May 2010; Li et al. 2015). Different sea surface temperature (SST) warming patterns can also displace regions of convection and moisture transport, contributing to the regional precipitation response (Xie et al. 2010). For example, warming over the tropical Indo-Pacific warm pool displaces South Asian rainfall with an east-west rainfall shift by inducing anomalous northerlies, which advect drier and cooler air into South Asia (Annamalai et al. 2013). Changes in land use and land cover have also been proposed as another contributor: Local evapotranspiration, a source of atmospheric moisture, has decreased as a consequence of deforestation (Paul et al. 2016; Chou et al. 2018). In addition to the above anthropogenic forcings, a negative-to-positive phase transition from the 1950s to the 1990s of the Pacific Decadal Oscillation (PDO)/Interdecadal Pacific Oscillation (IPO), whose recent cycles result mainly from internal variability (Dong et al. 2014; Hua et al. 2018), also helps to explain the total drying trend over India during this period, as highlighted by Salzmann and Cherian (2015). Using the multi-model ensemble from the 5th Coupled Model Intercomparison Project (CMIP5), the NCI drying trend associated with the PDO/IPO was comparable to that caused by anthropogenic aerosols derived from the single-forcing experiments during the period 1950-1999 (Salzmann et al. 2014).

Compared with the extensive research focusing on the drying during 1950-1999, few studies have examined the subsequent recovery of the ISM rainfall after 2000; Jin and Wang (2017) is an exception. They found that ISM rainfall shows a positive trend after around 2000 with positive anomalies lasting for multiple years, a situation that has never been observed since 1950 (Jin and Wang 2017). Thus, the recent revival of the ISM in observations differs in character from the previous decadal variations. The accelerated warming seen over South Asia that exceeds the tropical Indian Ocean warming is considered as the main driver of the ISM revival (Jin and Wang 2017; Roxy 2017). Potential causes

for the recent warming over India include a reduction of low clouds due to decreased ocean evaporation in the Arabian Sea (Jin and Wang 2017), an increase of anthropogenic aerosols, particularly those from absorbing aerosols such as black carbon (Jin et al. 2016), changes in land-use and land cover (Paul et al. 2016), and the strengthening GHG warming effect and its dominance over other drivers (Kitoh et al. 2013). Although the observed revival of ISM rainfall appears to be underpinned by several factors, few CMIP5 models are able to reproduce the recent trend (Jin and Wang 2017). It is not entirely surprising considering the model performance in capturing the drying trend during 1950-1999 as suggested by Guo et al. (2015), Saha et al. (2014) and Salzmann and Cherian (2015). One of the explanations to the poor performance is that the externally-forced wetting trend after 2000 may be overshadowed by internal variability in individual model realizations. Since CMIP5 model historical simulations were not initialized from observed values, their output is not expected to match with observations, particularly of changes in phase associated with interannual and decadal variability. While the exact cause for the decline in ISM rainfall during 1950-1999 is still under debate, the relative contributions of external forcing and internal variability to its revival after 2000 remain unknown.

At a larger scale, the overall Northern Hemisphere summer monsoon rainfall, which also witnessed a recovery since the 1980s, has been partially attributed to internal variability in the Pacific (Wang et al. 2013). The PDO/IPO is the main internal mode in the Pacific on interdecadal time scales, which has been linked to decadal-to-multidecadal oscillations of the ISM (Krishnan and Sugi 2003; Krishnamurthy and Krishnamurthy 2013; Joshi and Pandey 2011; Joshi and Rai 2015; Joshi and Kucharski 2017). From the 1950s to the present, the PDO/IPO has experienced a negative-to-positive-to-negative phase transition (Mantua and Hare 2002; Dong and Dai 2015; Henley et al. 2015; Joshi and Rai 2015). The positive PDO/IPO phase appears to be related to decreased ISM rainfall through

weakened Walker and Hadley circulations induced by warm SST anomalies over the tropical central-eastern Pacific, and the opposite occurs for the IPO negative phase (Krishnan and Sugi 2003; Krishnamurthy and Krishnamurthy 2013; Dong and Dai 2015; Joshi and Kucharski 2017). The PDO/IPO can also influence the interannual variability of ISM rainfall by enhancing the El Niño-Southern Oscillation (ENSO)-ISM relationship when ENSO and PDO/IPO are in phase, while weakening the relationship when out of phase (Krishnan and Sugi 2003; Krishnamurthy and Krishnamurthy 2013; Dong et al. 2018). It is unclear whether the PDO/IPO is the dominant internal mode responsible for both the interdecadal decline and recovery of ISM rainfall since 1950.

Determining the role of internal variability requires the exclusion of the externally-forced signal. Previous studies rely heavily on the multi-model ensemble of CMIP5 with small numbers (<10) of realizations from individual models (Salzmann and Cherian 2015; Jin and Wang 2017). Different CMIP models may include different implementations of the forcings and also differ in their dynamical cores and physical parameterizations, which complicate the interpretation of the differences among individual simulations (Frankcombe et al. 2015; Dai and Bloecker 2019). Large differences exist in simulating the recent decline and recovery of ISM rainfall not only among different CMIP5 models but also among different realizations from individual models (Saha et al. 2014; Salzmann and Cherian 2015; Jin and Wang 2017). This hampers understanding of the relative role of internal variability and external forcing. To avoid these issues, a large ensemble from a single climate model is a more suitable tool for quantifying the internal variability and identifying the role of internal modes (Deser et al. 2012; Dai and Bloecker 2019). Here, we use a 57-member perturbed-parameter ensemble of simulations from the Earth system model HadCM3C (ESPPE) (Murphy et al. 2014). The relatively large ensemble size allows us to consider its ensemble mean as the externally-forced signal, whilst the deviation of an

individual member from the ensemble mean results primarily from internal variability and secondly from its own uncertain forced response (due to parameter uncertainty) (Murphy et al. 2004). To avoid model dependence, we also analyzed the output from a 100-member ensemble of simulations generated by the Max Planck Institute Earth System Model version 1.1 (MPI-ESM) with slightly different initial conditions (Maher et al. 2018; Maher et al. 2019). In this study, we therefore aim to answer the following questions: (1) what are the relative contributions of external forcing and internal variability to the recent interdecadal variations in ISM rainfall? And (2) what are the differences and similarities of the physical mechanisms responsible for the decline in ISM rainfall during 1950-1999 and its recovery during 1999-2013?

The remainder of the paper is organized as follows. In section 2, we describe the observational data, model data and analysis methods. In section 3, we investigate the influence of external forcing on the recent interdecadal variations of the ISM rainfall and its related physical processes. The influence of internal variability, the dominant contribution from the IPO and the underlying mechanisms are examined in section 4. In section 5, we quantify the contributions of external forcing and the observed IPO transitions to the interdecadal variations of ISM rainfall. Results derived from different large ensembles of model simulations are compared for robustness in section 6. A summary is given in section 7.

2. Data, methods, and models

a. Observational data

The following observational monthly gridded rainfall data are used in this study:

1) CRU version 4.02 from the Climatic Research Unit at the University of East Anglia, covering the

158 period of 1901-2017 with a horizontal resolution of 0.5°×0.5° (Harris et al. 2014).

159 2) GPCC monthly product version 2018 from the Global Rainfall Climatology Centre dataset,
160 covering the period of 1891-2016 with a horizontal resolution of 0.5°×0.5° (Schneider et al. 2014).

161 3) UDel version 5.01 from University of Delaware, covering the period of 1900-2017 with a
162 horizontal resolution of 0.5°×0.5° (Willmott and Matsuura 2001).

163 Here, we calculated the average of the three datasets over the period of 1901-2017 (except for
164 2017, since at the time of writing GPCC ends in 2016) as the observational rainfall data (referred to as
165 OBS) following previous studies (Huang et al. 2019; Jiang and Zhou 2019). The average OBS is
166 interpolated to the model's resolution to compare with the model results. Results for each dataset at
167 the raw resolutions are also shown in Fig. 1 and Fig. 3.

168 Observed monthly sea surface temperature (SST) data were taken from the Hadley Centre Global
169 Sea Ice and Sea Surface Temperature (HadISST1.1) dataset produced by the Met Office, starting from
170 1870 up to the present with a horizontal resolution of 1.0°×1.0° (Rayner et al. 2003). Monthly global
171 land-surface air temperature anomalies with respect to the 1961-90 average were taken from
172 CRUTEM4 produced by the Climatic Research Unit at the University of East Anglia, starting from
173 1850 to present at a resolution of 5.0°×5.0° (Jones et al. 2012).

174 Monthly atmospheric reanalysis data were obtained from the National Centers for Environmental
175 Prediction (NCEP)–National Center for Atmospheric Research (NCAR) reanalysis dataset
176 (NCEP/NCAR) (Kalnay et al. 1996).

177 To capture the interdecadal variability in the Pacific, we used two published indices in this study
178 for comparison. One is the PDO index from Mantua and Hare (2002; accessed at

179 http://www.jisao.washington.edu/pdo), and the other is the Tripole Index (TPI) from Henley et al (2015;
180 accessed at https://www.esrl.noaa.gov/psd/data/timeseries/IPOTPI).

181 ***b. Model Data***

182 ***(1) ESPPE***

183 We used output from a 57-member Earth system perturbed parameter ensemble (ESPPE) (Murphy
184 et al. 2014). The ESPPE simultaneously and selectively perturbs multiple parameters within expert-
185 specified limits in the atmosphere, ocean, sulphur cycle and terrestrial ecosystem components of the
186 Earth system model HadCM3C, which contains a fully interactive carbon cycle and an interactive
187 sulphur cycle scheme. The model includes the direct scattering and absorption effects along with the
188 cloud albedo effect of aerosols (first indirect effect), while the aerosol-rainfall efficiency effect (second
189 indirect effect) is excluded. The 57 members of the ESPPE are model variants of HadCM3C, with
190 regular latitude-longitude grids of 2.5°×3.75° and 1.25°×1.25° in the atmosphere and ocean, with 19
191 and 20 vertical levels respectively (Gordon et al. 2000). Each member is spun up from an identical
192 initial state taken from a standard HadCM3C run, providing starting conditions for the ESPPE
193 simulations of forced climate change (Lambert et al. 2013). The historical simulations of ESPPE are
194 integrated from 1860 to 2005 driven by observed historical changes in radiative forcing agents such as
195 emissions of CO_2 and aerosol precursors, ozone, solar variations and major volcanic eruptions
196 following CMIP5 protocol (Taylor et al. 2012). The RCP8.5 simulations, where the radiative forcing
197 increases and reaches around 8.5 W/m^2 near 2100 relative to 1750, are then performed from 2006 to
198 2099 continuously following each of the 57 members of the historical run. Details of the spin-up and
199 the perturbed parameters are provided in Lambert et al. (2013).

200 Compared to its contemporaries, ESPPE's parent model, HadCM3, is one of the best at simulating
201 the spatial pattern of ISM rainfall (Annamalai et al. 2007), the spatial structure of the IPO and the IPO-
202 ISM rainfall teleconnections (Joshi and Kucharski 2017). The ESPPE also reasonably simulates the
203 climatology of ISM rainfall (Fig. 1g). The climatological monsoon rainfall centers-of-action located
204 near the Western Ghats, over the foothills of the Himalayas and along the Burmese coast are well
205 simulated, aiding confidence in our further analysis based on this model. More detailed information
206 and a full evaluation of model performance for ESPPE is described in Murphy et al. (2014).

207 ***(2) MPI-ESM***

208 To verify the results derived from the ESPPE, we also analyzed the output from a 100-member
209 ensemble generated by the Max Planck Institute Earth System Model version 1.1 (MPI-ESM) with
210 slightly different initial conditions (Maher et al. 2018; Maher et al. 2019). It is an update of the coupled
211 ocean-atmosphere general circulation model submitted to CMIP5 in its low resolution configuration
212 (MPI-ESM-LR), which has a spectral horizontal resolution of T63 (~1.9°) and 47 vertical layers up to
213 0.01hPa in the atmosphere along with 1.5° horizontal resolution and 40 vertical levels in the ocean.
214 The 100 ensemble members started from different initial conditions in 1850, generated from different
215 years of the preindustrial control simulation (piControl). The historical simulations are then integrated
216 from 1850 to 2005 driven by observed historical changes in radiative forcing agents, including well-
217 mixed greenhouse gases, anthropogenic sulphate aerosols, man-made land use change, monthly zonal-
218 mean ozone concentrations and major volcanic eruptions following CMIP5 protocol (Taylor et al.
219 2012). The simulation was extended to 2099 following the RCP8.5 high emissions scenario. The MPI-
220 ESM reasonably reproduces the climatology of ISM rainfall (Fig. 1i), in addition to the IPO-related
221 SST patterns and the IPO-ISM rainfall relationship (Joshi and Kucharski 2017), providing further

222 confidence to the model.

223 ***c. Methods***

224 ***(1) Statistical analysis***

225 A 9-year-running mean was applied to observational and model data to isolate the interdecadal
226 signal. The Mann-Kendall (Mann 1945; Kendall 1975) non-parametric method was applied in this
227 study to test the significance of trends. The Monte Carlo non-parametric method was used to test the
228 significance of regression coefficients onto the filtered time series. A composite analysis was used to
229 calculate the average of the 10 members with the strongest positive (Pos10)/negative (Neg10) IPO
230 phase transitions. To test the significance of the trend differences between the Pos10 members and the
231 ensemble mean (and between Neg10 and the ensemble mean), the Student's t-test was used. Gridpoints
232 with at least 46 out of 57 ESPPE members or 80 out of 100 MPI-ESM members (80%) agreeing on
233 the sign of change are marked to indicate the consistency among ensemble members.

234 ***(2) Separating the externally forced signal and internal variability using the large ensemble***

235 Let $A(i)$ be a given variable of member i from the ESPPE or MPI-ESM ensemble. Generally,
236 time series of $A(i)$ at each grid point can be viewed as consisting of an externally-forced component
237 (due to GHGs, aerosols, land use, solar cycles, and other external forcing) and an internally-unforced
238 component (due to internal climate variability). In both ESPPE and MPI-ESM, the ensemble members
239 were driven by the same external forcing. The ensemble means (EM) of $A(i)$ in each model can be
240 taken as the model's response to external forcing, because the averaging over the ensemble members
241 largely smooths out uncertainties among them. The model's forced response is represented as

242 $$A_{forced} = (A(i))_{EM} \qquad (1).$$

243 The spread among the 100 MPI-ESM members is caused only by different realizations of the
244 internal variability. Thus, $A(i)$ of member i in MPI-ESM is separated as:

245 $$A(i) = A_{forced} + A_{internal}(i), \quad i = 1,2,3 \ldots 100 \qquad (2)$$

246 where $A_{internal}(i)$ is the internal component estimated as the residual of the original $A(i)$ minus the
247 forced response. $A_{internal}(i)$ varies among different ensemble members and shows the variability
248 associated with internal variability.

249 The spread of climate changes obtained from various ESPPE members contains both uncertainty
250 in their forced response and internal variability arising from random climate variations (Murphy et al.
251 2004). Thus, $A(i)$ of member i in ESPPE is separated as:

252 $$A(i) = A_{forced}(i) + A_{internal}(i), \quad i = 1,2,3 \ldots 57 \qquad (3)$$

253 where $A_{forced}(i)$ represents the response to external forcing within an individual member.
254 $A_{forced}(i)$ is different from the A_{forced} (the EM of the 57 members) in ESPPE due to uncertain
255 climate feedbacks caused by perturbed parameters. Several statistical methods have been suggested
256 for estimating the $A_{forced}(i)$, e.g., the linear trend, high-order polynomials approximation (Hawkins
257 and Sutton 2009, 2010) or using time series at each grid point linearly related to global-mean time
258 series of A (Dai et al. 2015). In this study, we calculated $A_{forced}(i)$ as a fourth-order polynomial of
259 time over the years 1860-2099 following Hawkins and Sutton (2009, 2010). We note that the estimated
260 $A_{forced}(i)$ may still contain some internal variability. However, since the polynomials were generated
261 over a long time period of 240 years, we consider $A_{forced}(i)$ as primarily consisting of the externally-
262 forced response.

263 ***(3) IPO definition***

264 Previous studies show many different ways to calculate the index representing the PDO/IPO, for
265 example the EOF method (Mantua and Hare 2002) and the difference of SST anomalies between
266 regions of the Pacific (Henley et al. 2015; Salzmann and Cherian 2015), showing an overall similarity
267 in featuring the decadal-to-multidecadal variability of Pacific SST in observations after 1920 (Hua et
268 al. 2018). Thus, for easier calculation and for direct comparison between observations and model
269 simulations and comparison between ensemble members, we use the latter method to define the IPO
270 index without applying EOF analysis, similar to Salzmann and Cherian (2015). We define the IPO
271 index as the JJA south minus north gradient of unforced SST. In the observations, we first remove the
272 linear trend and then calculate the SST anomalies averaged within the tropical central-eastern Pacific
273 (TCEP, 170°W–90°W, 10°S–10°N) and the northern Pacific (NP, 150°E–150°W, 25°N–45°N),
274 respectively. The observational IPO index (IPO_{OBS}) is defined as the 9-year running mean of the
275 difference of detrended SST between the TCEP and the NP. Here, we used the terminology of *IPO* as
276 we focus on wider Pacific-basin phenomena. We assess the IPO index derived from the HadISST1.1
277 dataset and find that it is highly consistent with published PDO and TPI indices in terms of both phase
278 evolution and spatial pattern during our research period (Fig. 2).

279 In the ESPPE, we first separate out the internal part of SST, $SST_{internal}(i)$, based on equation
280 (3). The IPO index for member (i) is calculated as the 9-year running mean area-averaged difference
281 of JJA $SST_{internal}(i)$ between TCEP and NP. The IPO indices in the 57 ensemble members are
282 continuous time series with various IPO phase evolutions in the period 1950-2013. Here, we calculate
283 the trends of IPO indices in 1950-1999 and 1999-2013 respectively. During each period, positive
284 values represent the IPO shifting from negative to positive phases, while negative values show the
285 opposite. To identify the internal IPO mode in ESPPE, we choose the 10 members with the strongest

positive (Pos10) and strongest negative (Neg10) IPO phase transitions for composition during 1950-1999 and 1999-2013, respectively (Fig. 2f).

(4) Adjustment of ISM rainfall trends based on IPO

On the multi-decadal time scale, the contribution of the IPO to ISM rainfall trends of member *i* in the selected time period τ, for example $\tau = 1950{\sim}1999, 1999{\sim}2013$, is calculated as

$$\partial_t pr_{IPO}(i) = r_{pr,IPO}(i) \cdot \partial_t IPO(i),\ i = 1,2,3 \ldots 57 \text{ or } 100 \quad (4)$$

$$r_{pr,IPO}(i) = {\partial pr(i)}\Big/{\partial IPO(i)}, \quad (5)$$

where $r_{pr,IPO}(i)$ is the regression coefficient of the 9-year running-mean rainfall with respect to the IPO time series of member *i* during the period of 1950-2013. Both ESPPE and MPI-ESM reasonably reproduce the negative correlation between the IPO and ISM rainfall found in observations and both have high consistency among ensemble members (Fig. 1). $\partial_t IPO(i)$ is the trend of the IPO(i) index over time period τ, representing the phase transition of IPO during the analysis period. $\partial_t pr_{IPO}(i)$ is the IPO-related rainfall trend of member *i* in period τ and varies among the ensemble members.

In order to achieve the rainfall trends influenced by both the external forcing and the observed IPO phase transition, we employ an adjustment method following Salzmann and Cherian (2015). We adjust the original rainfall trend based on Equation (4). After the adjustment, all ESPPE members are viewed as being influenced by the same observational IPO phase evolution during 1950-2013 instead of the random IPO transitions for the raw members. The adjusted rainfall trend of member *i* is the sum of the forced rainfall trend plus the internal component of the rainfall trend with an adjustment term depending on the difference between the simulated and observed IPO trends ($\partial_t IPO_{OBS}$), which is expressed as:

$$\partial_t pr_{adj}(i) = \partial_t pr_{forced} + \partial_t pr_{internal\_adj}(i),\ i = 1,2,3 \ldots 57 \text{ or } 100 \quad (6)$$

where

$$\partial_t pr_{internal\_adj}(i) = \partial_t pr_{internal}(i) + \alpha_{internal}(i), \quad (7)$$

where

$$\alpha_{internal}(i) = -r_{pr,IPO}(i) \cdot (\partial_t IPO(i) - \partial_t IPO_{OBS}), \quad (8)$$

where $\partial_t pr_{internal\_adj}(i)$ is the adjusted internal rainfall trend calculated by adding the original internal trend to an adjustment term, $\alpha_{internal}(i)$. As shown in equation (8), the adjustment term takes the observational IPO phase transition into consideration. $\partial_t pr_{internal\_adj}(i)$ can be viewed as the internal rainfall trends after replacing the raw IPO phase transitions with the observational one. Thus, the EM of the $\partial_t pr_{internal\_adj}(i)$ represents the observed IPO's contribution to the rainfall trend. The IPO-adjusted total rainfall trend, $\partial_t pr_{adj}(i)$, is the sum of the simulated externally forced signal ($\partial_t pr_{forced}$) and the adjusted internal trend. After the above adjustment, the rainfall trend uncertainty among the 57 ESPPE members (or 100 MPI-ESM members) related to their random IPO phase transition is narrowed but the other internal uncertainty remains. The EM of $\partial_t pr_{adj}(i)$ represents the rainfall changes in response to external forcing and the observed IPO phase transition.

(5) Moisture budget analysis

The moisture-budget analysis method has been used in many studies (Chou and Neelin 2004; Chou et al. 2009; Seager et al. 2010). Here we apply it to understand the physical mechanisms governing historical changes in ISM rainfall. Using pressure-level coordinates, the moisture budget equation is expressed as:

$$\partial_t q = -P + E - < \nabla \cdot (\boldsymbol{V} q) > + res \quad (9)$$

where $\partial_t q$ is the time derivative of vertically integrated moisture in the atmosphere, which is small and can be neglected. P and E are rainfall and evaporation, $\boldsymbol{V}$ and q are horizontal winds and specific humidity; res is the residual term including the moisture transport by surface processes due to topography and transient eddies (Li et al. 2013). For long-term trends, equation (9) is mainly balanced by $P - E$ and $-<\nabla \cdot (\boldsymbol{V}q)>$. Triangle parentheses indicate a vertical integration from the surface to the tropopause. $-<\nabla \cdot (\boldsymbol{V}q)>$ refers to the vertically integrated moisture flux convergence. We separate $\boldsymbol{V} = \overline{\boldsymbol{V}} + \boldsymbol{V}'$ and $q = \overline{q} + q'$, where the overbars and primes indicate long-term means and departures, respectively, as is the convention. Equation (9) can be transformed to:

$$P' - E' = -<\nabla \cdot (\overline{\boldsymbol{V}}q')> -<\nabla \cdot (\boldsymbol{V}'\overline{q})> -<\nabla \cdot (\boldsymbol{V}'q')> + res \qquad (10)$$

where the first, second and third terms on the right-hand side of equation (10) denote thermodynamic, dynamic and nonlinear components of moisture convergence terms, separated from the total vertically integrated moisture flux convergence. They are contributed by changes of moisture only, circulation only and both moisture and circulation, respectively.

Considering the continuity equation, the dynamic components of moisture convergence can be further decomposed into three terms as:

$$-<\nabla \cdot (\boldsymbol{V}'\overline{q})> = -<u'\partial_x \overline{q}> -<v'\partial_y \overline{q}> -<\omega'\partial_p \overline{q}> \qquad (11)$$

where u', v' and ω' are the zonal wind, meridional wind and vertical pressure-velocity anomalies, respectively. The three terms on the right-hand side of equation (11) denote zonal, meridional and vertical dynamic components of the moisture convergence term, respectively.

3. Impact of external forcing

3.1 Influence of external forcing on ISM rainfall trends

From 1950 to 1999, a decreasing rainfall trend was seen over north-central India (NCI) in the observations (Fig. 3a, b, c, m; significant in all datasets, except GPCC), consistent with previous studies (Bollasina et al. 2011; Salzmann et al. 2014; Salzmann and Cherian 2015). The multi-dataset average (referred to as OBS) trend is -0.11 mm day^{-1} decade^{-1} for this period (Fig. 3g). To determine the role of external forcing in this drying trend, we examined the ESPPE's ensemble mean (EM). The EM can be considered as the response to external forcing. In the EM, a dipole pattern between a drying trend close to the Himalayan foothills and a wetting trend further south was seen (Fig. 3h). The bipolar rainfall change gave an overall insignificant trend of 0.01 mm day^{-1} decade^{-1} (p value is 0.55) over the NCI, indicating little role of external forcing in the observed drying (Fig. 3n).

Following the decreasing trend, the observed NCI rainfall reversed to a significant increasing trend during 1999-2013 (Fig. 3d, e, f), with a multi-dataset average of 0.66 mm day^{-1} decade^{-1} (Fig. 3j, m). Unlike the drying trend, this recovery of monsoon rainfall was partially reproduced by the ensemble mean of ESPPE. The EM shows a homogenous increasing trend over the NCI region of 0.42 mm day^{-1} decade^{-1} (Fig. 3k, 3n), indicating a role for external forcing in the observed revival during this period.

3.2 Physical mechanisms

To explore why external forcing induces different rainfall trends during 1950-1999 and 1999-2013, we compared the moisture budget terms of the two periods (Equations (9-10)). Figure 4a shows quantitative results of the moisture budget analysis on the NCI rainfall trends. Rainfall change is balanced by the changes of evaporation, dynamic and thermodynamic components and a nonlinear

370 term. The dynamic component is further separated into vertical, zonal and meridional dynamic
371 components of moisture convergence. During 1950-1999, opposing trends of dynamic and
372 thermodynamic moisture convergence lead to the weak NCI rainfall trend (Fig. 4a). Their spatial
373 patterns show that the thermodynamic component increases the NCI rainfall homogenously (Fig. 4d),
374 while the dynamic component results in the bipolar rainfall trend (Fig. 4b). Further decomposition of
375 the dynamic component shows that the dominant contribution comes from the vertical dynamic
376 moisture convergence (Fig. 4a, f), while the role of horizontal dynamic components is small (Fig. 4a,
377 h). In contrast to the pre-1999 period, the accumulative influence of the dynamic and thermodynamic
378 components results in the increasing rainfall trend after 1999 (Fig. 4a, c, e). Furthermore, the vertical
379 and zonal dynamic components comparably contribute to the increasing rainfall over southern and
380 northern India, respectively (Fig. 4a, g, i). These calculations reveal that while the thermodynamic
381 component related to changes in specific humidity is consistently increasing during the two periods,
382 the dynamic component indicating monsoon circulation changes caused by external forcing are
383 different.

384 We further investigated the interdecadal variations of specific humidity and monsoon circulation
385 caused by external forcing. During 1950-1999, atmospheric moisture content increased with GHG-
386 induced global warming (Fig. 5a, e, g), which explains the positive trend of the thermodynamic
387 component in this period. Meanwhile, a positive Indian Ocean (IO) dipole warming pattern was seen
388 with increased external forcing (Fig. 5e). The relatively larger warming trend in the western IO SST
389 helps maintain the anomalous easterly winds along the equator (Dong and Zhou 2014; Roxy et al.
390 2015). The divergent circulation induces anomalous descent and decreased rainfall from the Maritime
391 Continent to tropical southern IO (Fig. 5c). The rainfall is then increased over the western and southern

Indian subcontinent and adjacent seas due to anomalous moisture convergence associated with changes in local Hadley-type circulation (Fig. 5c, 5g). Furthermore, the increased anthropogenic aerosols subdue the warming over the Indian subcontinent as indicated in previous studies (Bollasina et al. 2011; Guo et al. 2015; Jin and Wang 2017). The regional surface cooling near the Himalayan foothills decreases local rainfall via the vertical dynamic term (Figs. 4f, 5e).Thus, the forced zonally nonuniform warming over the tropical IO and local surface cooling together explain the bipolar trend pattern of dynamic moisture convergence (Fig. 4b). Compared to the pre-1999 period, atmospheric moisture content increased faster after 1999 due to enhanced global warming (Fig. 5b), resulting in a larger positive trend in the thermodynamic component (Fig. 4e). Moreover, the most noticeable difference in monsoon circulation changes between pre- and post-1999 period is the anomalous south-easterly winds over the Bay of Bengal (Fig. 5c, 5d). After 1999, the stronger land-sea thermal contrast between the East Asia and the western north Pacific Ocean intensifies the low-level subtropical anticyclone and decreases rainfall over the western Pacific (Liu et al. 2012; Fig. 5d, 5f), which then incites a Rossby wave to its west (Annamalai et al. 2013). The resultant anomalous south-easterly winds over the Bay of Bengal dynamically increase rainfall over India by through inducing anomalous ascent and moisture advection (Figs. 4g, 4i, 5d, 5h).

The above results suggest that external forcing has partially played a role in modulating the interdecadal variations of ISM rainfall during 1950-2013. However, the insignificant rainfall trend caused by external forcing from 1950-1999 is different from that observed. Also, the forced positive trend after 1999 is relatively weaker than the OBS. These indicate the non-negligible contributions of internal variability during both periods that shall be examined next.

4. Impact of internal variability

4.1 Influence of internal variability on ISM rainfall trends

The spread of rainfall trends is large among the 57 members during both periods, as demonstrated by the large standard deviations of rainfall trends across the ensemble members (Fig. 3i, l). Histograms demonstrating spread in quantitative rainfall trends among the 57 members are show in Figure 6a and 6b. During 1950-1999, 27 of the 57 simulations show negative trends for NCI rainfall (Fig. 6a). The NCI rainfall trends from the ensemble members range from -0.25 to 0.54 mm day^{-1} decade^{-1} during this period. On the other hand, the spread among ensemble members ranges from -0.82 to 2.00 mm day^{-1} decade^{-1} during 1999-2013 (Fig. 6b). Despite being forced by increasing GHG, there are still 14 out of the 57 ESPPE realizations that show negative NCI rainfall trends during this period. The spread of ensemble members includes the influence of both the response uncertainty (due to uncertainties in model parameters; $pr_{uncertain}(i)$) and internal variability ($pr_{internal}(i)$; Equation (3)). These two different sources of uncertainty are partitioned with a fourth-order polynomial following previous studies (Hawkins and Sutton 2009, 2010). After dividing the NCI rainfall trends into the above two parts, the trend uncertainty caused by internal variability is larger than that caused by the uncertain forced response (Fig. 6a, b). Furthermore, the correlation coefficients between the original rainfall trends ($pr(i)$) and the trends of the internal part ($pr_{internal}(i)$) are 0.78 and 0.99, respectively, for the period of 1950-1999 and 1999-2013 (Fig. 6c, d). The significant correlation coefficients imply that at the regional scale the total spread of rainfall trend is dominated by the uncertainties arising from internal variability during both historical periods. Thus, internal variability can greatly modulate both the decline during 1950-1999 and the recovery during 1999-2013 of ISM rainfall.

4.2 IPO helps modulate ISM rainfall trends

435 The PDO/IPO has been shown to have an influence on decadal rainfall variations over India in
436 previous studies (Krishnan and Sugi 2003; Krishnamurthy and Krishnamurthy 2013; Joshi and Pandey
437 2011; Dong and Dai 2015; Joshi and Rai 2015). The observed PDO/IPO experienced a negative-to-
438 positive-to-negative phase evolution during 1950-2013 (Dong and Dai 2015; Joshi and Rai 2015; Dong
439 et al. 2018), as also indicated by an IPO index defined in terms of SST gradients between the tropical
440 central-eastern Pacific (TCEP) and the Northern Pacific (NP) (see Methods; Fig. 2). The switch points
441 are seen around the late 1970s and around 2000 (Fig. 2e). Due to the combined influence of external
442 forcing and internal variability in the observations, the negative correlation between temporal
443 variations of the IPO and NCI rainfall during 1950-2013 is only weak. However, the observed IPO
444 index still shows an increasing trend of 0.66 K decade^{-1} ($p < 0.01$) during 1950-1999 and a decreasing
445 trend of -0.37 K decade^{-1} (p value is 0.11 due to the small number of years) during 1999-2013. Since
446 the negative-to-positive IPO phase transition has been suggested to help explain the 1950-1999 ISM
447 drying trend (Salzmann and Cherian 2015), the positive-to-negative IPO transition afterwards may
448 have a link with the recent wetting trend.

449 To determine whether the IPO evolution helps modulate ISM changes, we used the ESPPE to
450 quantify the principal internal mode responsible for the spread in the rainfall trends. The 57 SST trend
451 patterns derived from ESPPE members are regressed onto the 57 values of internal NCI rainfall trends
452 through the member index during both periods (Fig. 6e, f). This regression method helps identify the
453 dominant internal variability in the ocean related to the trend spread of monsoon rainfall. The results
454 of both periods feature a negative correlation in TCEP and a positive correlation in NP (Fig. 6e, f),
455 which is similar to the observed IPO-like pattern and the internal IPO mode of ESPPE (Fig. 2). To
456 directly confirm the influence of the IPO, we chose the 10 members with the strongest positive IPO

457 phase transitions (Pos10) during 1950-1999 and the 10 members with the strongest negative phase
458 transitions (Neg10) during 1999-2013, respectively (Fig. 2f). The composites of Pos10 and Neg10
459 indeed reproduce a decreasing trend of NCI rainfall over 1950-1999 and an increasing trend afterwards,
460 respectively (Fig. 3n). The differences between the chosen members and the ensemble mean (Pos10-
461 EM or Neg10-EM) suggest that the IPO helps modulate both the ISM decline during 1950-1999 and
462 its recovery over 1999-2013.

463 ***4.3 Physical mechanisms of IPO modulating the decline and recovery of ISM rainfall***

464 Our large ESPPE also offers the opportunity to re-examine how IPO phase transitions help
465 modulate the interdecadal decline and recovery of ISM rainfall in 1950-2013. Through a moisture
466 budget analysis on the rainfall trend difference between the Pos10-EM during 1950-1999 and Neg10-
467 EM during 1999-2013, the dynamic component of moisture convergence appears to play a dominant
468 role in modulating the NCI rainfall (Fig. 7a), which is also shown in its spatial patterns (Fig. 7b-e).
469 Further decomposition of the dynamic component shows that the dominant contributions come from
470 the vertical and zonal moisture convergence (Fig. 7a, f-i). The anomalous vertical moisture
471 convergence covers a wide spatial scale including the Indian subcontinent and adjacent seas (Fig. 7f,
472 g), similar to the anomaly rainfall pattern (Fig. 7b, c), while the zonal moisture convergence shows a
473 bipolar pattern that leading to the rainfall anomalies over northern India (Fig. 7h, i). These results
474 suggest a consistently key role of anomalous vertical motion and zonal moisture advection in
475 modulating both the decline and the recovery of ISM rainfall by the IPO.

476 To investigate the anomalous circulation associated with the IPO phase transitions, we further
477 calculated the composite differences of Pos10-EM in 1950-1999 and Neg10-EM in 1999-2013 (Fig.

478 8). During 1950-1999, warm SST anomalies over the TCEP weaken the Walker circulation (Fig. 8a).
479 The 200hPa velocity potential trend differences of Pos10-EM exhibit a decrease (divergence) over the
480 central-eastern Pacific and an increase (convergence) across 40°E–140°E, especially over the tropical
481 Indian Ocean and Indian subcontinent (Fig. 8a). The upper-level convergence over India and the
482 adjacent seas corresponds to the anomalous descending motion, which suppresses ISM convection and
483 rainfall (Fig. 7f). Meanwhile, the depressed convection over India establishes two anomalous
484 anticyclones to its northwest and southwest asymmetrically (Fig. 8c, e) according to the Matsuno–Gill
485 theory (Matsuno 1966; Gill 1980). The anomalous circulation opposes the climatological monsoon
486 flow over India and weakens the cross-equatorial monsoon circulation (Fig. 8e). The westerlies on the
487 northern flank of the northwest anticyclonic anomalies advect relatively drier air from the Eurasian
488 landmass (Parker et al. 2016) (i.e. Pakistan, Afghanistan) to the west of NCI (Fig. 8e). The dry
489 advection decreases rainfall over northern India via zonal moisture convergence (Fig. 7h). The
490 anomalous low-level westerlies over the tropical central western Pacific and South China Sea (Fig. 8e)
491 associated with the weakened Walker circulation also help to maintain the zonal dry advection from
492 the west (Chen and Zhou 2015).

493 Accompanying the IPO phase shift from positive to negative during 1999-2013, the anomalous
494 circulation shows opposite patterns associated with cold SST anomalies over the TCEP. The Walker
495 circulation is enhanced as indicated by the 200hPa velocity potential trend difference of Neg10-EM
496 (Fig. 8b). The upper-level divergence represents the anomalous ascent over India and the adjacent seas,
497 which enhances ISM convection and rainfall (Fig. 7g). Similarly, the enhanced convection over India
498 establishes two anomalous asymmetric cyclones to its west, leading to the strengthened monsoon
499 circulation (Fig. 8d, f). Easterlies over the northern Indian subcontinent advect relatively wetter air

500 from the Bay of Bengal and Indochina peninsula into the east of NCI (Fig. 8f). The moisture
501 convergence increases rainfall over northern India via positive zonal moisture convergence (Fig. 7i).
502 Furthermore, the anomalous low-level easterlies over the tropical central western Pacific and South
503 China Sea are also evident (Fig. 8f). Our results suggest consistent atmospheric processes related to
504 the IPO appear to work in both directions during the two periods of decline and revival of ISM rainfall.

505 Previous studies have also suggested that the interdecadal variations of ISM rainfall during 1950-
506 2013 are closely related to changes in the meridional thermal contrast extending from the surface to
507 the mid-upper troposphere (Jin and Wang 2017; Roxy 2017). Thus, in addition to the above changes
508 in large-scale circulation, we further show that another mechanism of the IPO helps modulate the
509 interdecadal variations of ISM via influencing the related meridional thermal contrast (Figs. 9-10).

510 Accompanying the positive IPO phase transition during 1950-1999, the trend differences of
511 Pos10-EM exhibit warming SST anomalies over the tropical Indian Ocean (40°E–100°W, 10°S–25°N)
512 and cooling surface temperature over the landmass to the north of India (65°E–90°E, 30°N–45°N) (Fig.
513 9a). The strong surface warming of the Indian subcontinent is consistent with the decreased ISM
514 rainfall in this period (Fig. 8c). From 1999 to 2013, the trend of Neg10-EM shows opposite land-sea
515 surface temperature changes accompanying the IPO phase shift from positive to negative (Fig. 9b). As
516 shown in previous studies (Dong et al. 2016), the IPO has a footprint on decadal SST variations in the
517 Indian Ocean via atmospheric adjustments caused by changing surface heat fluxes, sea surface height
518 and thermocline depth. Meanwhile, the IPO also has a negative correlation with surface temperature
519 in a band across the Mediterranean-Middle East-northern India through anomalous atmospheric
520 circulation (Dong and Dai 2015). The composite surface thermal contrast between the tropical Indian
521 Ocean and the landmass north of India shows a strengthening tendency during 1950-1999, followed

522 by a weakening tendency during 1999-2013, similar to the time variations derived from observations
523 (Fig. 9c). However, the surface temperature over land and the SST of Indian Ocean are at different
524 pressure levels because of local topography. The role of the tropospheric temperature gradients at the
525 same pressure level on ISM variations should be considered (Dai et al. 2013).

526 The vertical wind shear over South Asia has been widely used to define the strength of ISM
527 (Webster and Yang 1992). Considering the thermal wind relationship, similar temperature gradients in
528 the mid-upper layers play a larger role on the vertical wind shear over the ISM region than gradients
529 in the lower troposphere (Dai et al. 2013). Thus, the IPO can affect the ISM more effectively through
530 its influence on the meridional thermal contrast in the mid-upper troposphere (Fig. 10). During 1950-
531 1999, the 500-200hPa tropospheric thickness trend of Pos10-EM increases over the tropical Indian
532 Ocean (60°E–100°E, 10°S–10°N) and decreases over Eurasia (60°E–100°E, 25°N–45°N), while an
533 opposite trend pattern occurs in 1999-2013 for Neg10-EM (Fig. 10a, b). The composite variations of
534 meridional thermal contrast in the troposphere based on Pos10-EM in 1950-1999 and Neg10-EM in
535 1999-2013 feature an increasing trend in the former period and a decreasing trend afterwards (Fig.
536 10c). In response to the SST anomalies over TCEP, the local convective latent heating changes, which
537 then affects the tropical tropospheric temperature and thus the meridional tropospheric temperature
538 gradient over the Indian sector (Chiang and Sobel 2002). Previous studies (Goswami and Xavier 2005;
539 Xavier et al. 2007) have discussed how ENSO-related tropical SST anomalies influence ISM via
540 changes in tropospheric temperatures. Here, we show that IPO-related tropical Pacific SST anomalies
541 can also modulate the ISM on decadal-to-multidecadal time scales through similar processes, thus
542 extending the ENSO-related tropospheric temperature mechanism to a longer time scale. With the
543 detailed investigation of the IPO's dynamical mechanisms showed above, our study helps reconcile

different explanations for the recent interdecadal variations in ISM rainfall proposed by previous studies (Krishnamurthy and Krishnamurthy 2013; Roxy et al. 2015; Salzmann and Cherian 2015; Jin and Wang 2017).

5. Adjustments to simulated ISM rainfall trends considering both external forcing and observed IPO evolution

Both external forcing and internal variability (with a non-negligible contribution from the IPO) contribute to the recent decline and recovery of ISM rainfall. To further quantify the relative contributions of external forcing and the IPO to the rainfall trends, we applied an 'adjustment' method to the 57 ESPPE members to take the observational IPO phase transition into account with the externally-forced change, following Salzmann and Cherian (2015). The raw ESPPE members have different IPO phases due to its random realizations in the freely-run coupled model. The 'adjustment' method first removes the raw IPO-related rainfall trends and then adds the influence of the observed IPO phase transition through regression within each member (see Methods; Equation (6)-(8)). Compared to the EM without the adjustment (Fig. 3h, k), which represents the response to external forcing only, the EM of the adjusted ESPPE members (Fig. 11b, e) is the combination of the response to external forcing and the influence of the observed IPO phase transition (Fig. 11a, d). Here, the adjustment to the ISM rainfall trend during 1950-1999 also provides a comparison with the results of Salzmann and Cherian (2015), which were derived from the CMIP5 multi-model ensemble.

After considering the influence of the observed IPO evolutions, the EM of the adjusted internal part of rainfall derived from ESPPE, representing the rainfall changes caused by the observed IPO transition, shows a strong drying trend over the ISM region during 1950-1999 (Fig. 11a). Meanwhile,

565 it shows an additional wetting trend over India during 1999-2013 (Fig. 11d). In both time periods, the
566 EMs of the adjusted rainfall trends (see Methods; $\partial_t pr_{adj}(i)$), which represent the combined
567 influences of external forcing and the observational IPO phase transition, are close to the observed
568 ISM rainfall trends (Fig. 11b, e).

569 Quantitatively, during 1950-1999, the adjustment considering the observed negative-to-positive
570 IPO transition decreases the NCI rainfall trend from 0.01±0.14 to -0.15±0.13 mm day^{-1} decade^{-1} in
571 ESPPE (Fig. 11c), which is comparable to the adjustment from -0.02±0.06 to -0.11±0.08 mm day^{-1}
572 decade^{-1} derived from the CMIP5 multi-model ensemble by Salzmann and Cherian (2015). The IPO-
573 induced NCI rainfall trend is -0.16 mm day^{-1} decade^{-1} in ESPPE during this period. During the revival
574 in 1999-2013, the adjustment increases the simulated NCI rainfall trend from 0.42±0.61 to 0.68±0.54
575 mm day^{-1} decade^{-1} (Fig. 11f). Taking the IPO shift from a positive to a negative phase into
576 consideration together with the external forcing, the adjusted NCI rainfall trend is close to the observed
577 wetting trend of 0.66 mm day^{-1} decade^{-1}, with the IPO-induced trend of 0.26 mm day^{-1} decade^{-1}.
578 Moreover, the signal-to-noise ratio of rainfall trends among ESPPE members increases from 0.07 to
579 1.15 in 1950-1999 and from 0.69 to 1.26 in 1999-2013; thus, it becomes much higher after the
580 adjustment than before in both time periods. It indicates that the uncertainties in ISM rainfall trends
581 among the 57 members can be narrowed through the adjustments which allow them to have the same
582 observed IPO phase transitions. These results suggest that the adjusted ISM rainfall trends, taking the
583 observed IPO evolution into account as well as the external forcing, becomes close to those observed
584 with a narrowed range of uncertainty. Thus, for effective near-future climate adaptation and mitigation
585 efforts, the IPO's phase transitions must be considered in addition to anthropogenic climate change in
586 South Asia.

6. Comparison of different large ensembles of model simulations

Our results derived from the ESPPE provide a comparison with those from the CMIP5 multi-model ensemble of Salzmann and Cherian (2015) and Jin and Wang (2017). We further confirmed the results with another 100-member ensemble of simulations based on the MPI-ESM which has been recently completed and made available (Maher et al. 2019). As the largest perturbed-initialization ensemble using a comprehensive climate model, it allows us to directly consider the differences between the individual members as arising from internal variability, without the need for any complicated statistical separation method. The EM of the MPI-ESM also indicates that external forcing partly explains the interdecadal variations of ISM rainfall (Fig. 12a, b), though the forced rainfall trends are quantitatively different from that of the ESPPE (Fig. 3g, k), as expected. The large spread of ISM rainfall trends among ensemble members caused by internal variability is also evident during both periods (Fig. 12c, d). The regression patterns of SST trends with respect to the NCI rainfall trends across the 100 MPI-ESM members confirm that the IPO helps modulate the interdecadal variability of ISM rainfall (Fig. 13a, b). The composites of Pos10 members from 1950-1999 and Neg10 members from 1999-2013 in MPI-ESM ensemble, respectively, also reproduce the recent decline and recovery of ISM rainfall (Fig. 12e-g). Moreover, the adjusted ISM rainfall taking into account the influence of the observed IPO evolution with external forcing shows a decreasing trend during 1950-1999 and an increasing trend during 1999-2013, close to the observations (Fig. 13c-f). This strongly supports our earlier results derived from the ESPPE.

7. Summary and concluding remarks

In this study, we investigated the influence of historical external forcing and internal variability

608 on interdecadal variability of ISM rainfall during 1950-2013 using a 57-member ensemble of ESPPE
609 and a 100-member ensemble of MPI-ESM. We also explored possible physical mechanisms related to
610 the recent drying and subsequent recovery. The main results are summarized in Fig. 14 and given
611 below:

612 (1) **Role of external forcing:** In ESPPE's ensemble mean, an insignificant externally-forced ISM
613 rainfall trend was seen from 1950-1999 followed by a significant increasing trend from 1999-2013.
614 During 1950-1999, atmospheric moisture content increased due to global warming, which
615 enhances ISM rainfall thermodynamically. Dynamically, the zonally nonuniform warming over the
616 tropical Indian Ocean induces anomalous ascent over southern and western India associated with
617 increase local rainfall. Meanwhile, a cooling trend of surface temperature close to the foothills of
618 the Himalayas induces anomalous descent reducing rainfall over northern India. Overall, the
619 competing dynamic and thermodynamic processes appear to result in the overall insignificant
620 rainfall trend. During 1999-2013, atmospheric moisture content continued to increase associated
621 with enhanced global warming. At the same time, dynamic moisture convergence has also
622 strengthened related to enhanced land-sea thermal contrast between East Asia and the western
623 north Pacific Ocean. The accumulative impact of the dynamic and thermodynamic processes
624 results in the increasing ISM trend during this period. As a result, external forcing partly
625 contributes to the observed interdecadal variability of ISM rainfall.

626 (2) **Role of internal variability:** From our analysis, it appeared that neither of the trends of ISM
627 rainfall pre- and post-2000 can be solely explained as a response to external forcing. Internal
628 variability also had a significant role, mainly arising from the IPO. The negative-to-positive-to-
629 negative IPO evolution during 1950-2013 modulates the ISM by inducing anomalous vertical

motion and zonal moisture convergence related to an anomalous Walker circulation. The IPO can also influence ISM variability through modulating the meridional thermal contrasts over South Asia. The underlying mechanisms of the IPO in modulating the recent ISM rainfall variability appear to be valid in both directions during the two periods.

(3) **Relative contributions of external forcing & internal variability:** Quantitatively, the observed negative-to-positive IPO phase transition during 1950-1999 induced a negative NCI rainfall of -0.16 mm day^{-1} decade^{-1}, which decreased the externally-forced rainfall trend from 0.01 to -0.15 mm day^{-1} decade^{-1}. During 1999-2013, the positive-to-negative IPO transition caused a positive NCI rainfall trend of 0.26 mm day^{-1} decade^{-1}, which increased the forced trend of 0.42 to 0.68 mm day^{-1} decade^{-1}. The ensemble mean of the adjusted rainfall trends ($\partial_t pr_{adj}(i)$), which represent the combined influences of external forcing and the observational IPO phase transition, are close to the observed rainfall trends of -0.11 and 0.68 mm day^{-1} decade^{-1} pre- and post-2000, respectively. Moreover, the signal-to-noise ratios have also become greater after the adjustment, indicating that the uncertainties in ISM rainfall trends among the ensemble members are reduced after modifying their IPO phase transitions to match those of observations.

(4) **Comparison of different ensembles:** We also verified the results with a second ensemble of 100 simulations based on the MPI-ESM. Differences were found in the quantitative rainfall trends caused by external forcing between the two ensembles. However, the MPI-ESM ensemble supports the main results given by the ESPPE that the IPO helps modulate the recent decline and recovery of ISM rainfall. By adjusting the simulated rainfall trends, according to the observed IPO phase transition, both ensembles successfully reproduced the observed decline in 1950-1999 and the recovery afterwards.

In summary, our study implies the roles of both external forcing and internal variability in the observed variability of ISM rainfall, with the IPO identified as a contributing internal mode. We also analysed the physical processes through which external forcing and the IPO modulate the ISM, respectively. Our results reveal, for the first time, the linkage between and consistency among different explanations of the decadal-to-multidecadal variations in ISM rainfall proposed in the literature (Goswami and Xavier 2005; Xavier et al. 2007; Krishnamurthy and Krishnamurthy 2013; Salzmann and Cherian 2015; Jin and Wang 2017). Our findings also pose a new perspective for future projections of ISM, that the phase transitions of the IPO must be considered in addition to the response to external forcing.

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679 ge/. Detailed information of the data and references can be found from the website:
680 https://www.mpimet.mpg.de/en/grand-ensemble/. The observational rainfall and surface temperature
681 datasets are available on the Climate Data Guide website (*https://climatedataguide.ucar.edu*). The
682 NCEP/NCAR reanalysis dataset can be obtained from *https://www.esrl.noaa.gov/psd*. The published
683 PDO index of Mantua and Hare (2002) is available from the University of Washington, USA

(*http://www.jisao.washington.edu/pdo*). The published TPI index of Henley et al. (2015) was accessed at *https://www.esrl.noaa.gov/psd/data/timeseries/IPOTPI*. We also acknowledge the support from Jiangsu Collaborative Innovation Center for Climate Change.

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Figures Caption List

Fig. 1. Evaluation of the ESPPE and MPI-ESM in simulating climatological June-July-August (JJA) Indian summer monsoon (ISM) rainfall and its relation to IPO. (a) CRU, (c) GPCC, (e) UDel, (g) ESPPE ensemble mean and (i) MPI-ESM ensemble mean (EM) climatological JJA mean rainfall over ISM region in 1950-2013. Regressed 9-year running mean JJA rainfall with respect to the observed IPO index during 1950-2013: (b) CRU, (d) GPCC and (f) UDel. (d) ESPPE and (f) MPI-ESM EM of the regressed internal component of JJA 9-year running mean rainfall onto the IPO index within each ensemble member during 1950-2013. Stippling denotes 4 of 5 ensemble members agreeing on the sign of change. Units: mm day^{-1}.

Fig. 2. Regressed 9-year running-mean JJA SST anomalies from HadISST (units: K) with respect to standardized 9-year running-mean (a) PDO index, (b) TPI index and (c) IPO index during the period of 1920-2013. (d) ESPPE EM of regressed 9-year running mean JJA SST with respect to standardized IPO index within each member during the period of 1920-2013. Slant hatching denotes regional signals significant at the 95% confidence level. Stippling denotes 4 of the 5 ensemble members in agreement on the sign of change. (e) Standardized time series of observed IPO index (defined as 9-year running-mean SST gradients between TCEP and NP, positive in red and negative in blue), standardized 9-year running-mean PDO (orange) and TPI (grey) index. The correlation coefficients between the IPO and PDO or TPI indexes are 0.93 and 0.89 ($p < 0.01$), respectively, during the historical period of 1920-2013. (f) Time series of IPO index from different ESPPE members. Black, brown and blue lines denote the IPO indices derived from HadISST observations and the 10 members with the strongest positive (Pos10) and the strongest negative (Neg10) transitions, respectively. The 10 members are chosen separately for both periods of 1950-1999 and 1999-2013. Light brown and blue shadings show the spread among the 10 members.

Fig. 3. Spatial patterns of 9-year running-mean JJA rainfall trends during the period of 1950-1999 derived from the (a) CRU, (b) GPCC, (c) UDel, (g) the average OBS and (h) the ESPPE EM. (i) The standard deviation (STD) of the rainfall trends among the 57 ESPPE members for 1950-1999. (d, e, f, j, k, l) are same as (a, b, c, g, h, i) but for 1999-2013. Units: mm day^{-1} $decade^{-1}$. Slant hatching denotes rainfall trends significant at the 95% confidence level. (m-n)

927 Time series of the 9-year running-mean JJA rainfall anomalies relative to 1950-2013 mean average over north-central
928 India (NCI; 20°N–28°N, 76°E–87°E) outlined by the rectangle in (a-l). Units: mm day^{-1}. In (m), colours of orange,
929 purple, green and black represent the CRU, GPCC, UDel datasets and their average (referred to as OBS), respectively.
930 The coloured numbers in (m) denote the NCI rainfall trends of corresponding datasets during both periods. In (n),
931 black is for the OBS. Red line and shading denote the EM and 5th and 95th percentile of the 57 members. Brown and
932 blue solid lines represent the mean of 10 members with strongest positive (Pos10) and the strongest negative (Neg10)
933 IPO transitions during 1950-1999 and 1999-2013, respectively. Brown and blue dashed lines represent the mean
934 difference of the Pos10 minus EM during 1950-1999 and the Neg10 minus EM during 1999-2013.

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937 **Fig. 4.** Moisture budget analysis of the external forced rainfall trend derived from the ESPPE EM. (a). Moisture
938 budget analysis on EM NCI rainfall trend (dots denote trend differences significant at 95% confidence level) during
939 1950-1999 (dark color bars) and 1999-2013 (light color bars). Rainfall change is balanced by the changes of
940 evaporation, dynamic and thermodynamic components and a nonlinear term (blue and light blue bars). The dynamic
941 component is further separated into vertical, zonal and meridional dynamic components of moisture convergence
942 (red and pink bars). (b, d, f, h) are spatial patterns of EM trend during 1950-1999 of dynamic component,
943 thermodynamic component, vertical dynamic component and zonal dynamic component of moisture advection,
944 respectively. (c, e, g, i) are same as (b, d, f, h) but for 1999-2013. Units: mm day^{-1} decade^{-1}. Slant hatching denotes
945 regions significant at 95% confidence level.

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948 **Fig. 5.** (a) Trend of EM JJA 850hPa specific humidity (shading, units: g kg^{-1} decade^{-1}) and EM climatological 850hPa
949 winds (vectors, units: m s^{-1}) from 1950-1999. (c) EM climatological JJA 850hPa specific humidity (shading, units: g
950 kg^{-1}) and trend of EM rainfall (contours, positive in solid blue lines and negative in dashed brown lines; units: mm
951 day^{-1} decade^{-1}) and 850hPa winds (vectors, units: m s^{-1} decade^{-1}) from 1950-1999. (e) Trend of EM JJA near surface
952 temperature and SST (shading, units: K decade^{-1}) and sea level pressure (contours, positive in solid purple lines and
953 negative in dashed cyan lines; units: Pa decade^{-1}). (g) Cross section of zonally-averaged (65°E–95°E) trend of EM
954 air temperature (shading, units: K decade^{-1}) and winds (vectors, meridional and vertical components; units: m s^{-1}
955 decade^{-1}). The vertical component is calculated with a scale factor of -100 to allow the vertical pressure-velocity to

be comparable with the meridional component. (b, d, f, h) are same as (a, c, e, g) but for 1999-2013. Slant hatching denotes regions significant at 95% confidence level.

Fig. 6. Histograms of spread in NCI rainfall trends among 57 members during (a) 1950-1999 and (b) 1999-2013 (grey, yellow and blue bars denote the trends of the original rainfall, the internal component and the uncertain-forced component of rainfall). Correlation between trends of the original rainfall (x-bar, units: mm day^{-1} $decade^{-1}$) and the internal component of the rainfall (y-bar, units: mm day^{-1} $decade^{-1}$) over the NCI region derived from ESPPE members (number indicated in the circle) during the period (c) 1950-1999 and (d) 1999-2013. (The outlined member "37" in c. is caused by the combination of a positive internal rainfall trend and an evidently positive forced trend.) Brown circles in (c) denote the 10 members with the strongest positive IPO phase transition during 1950-1999. Blue circles in (d) denote the 10 members with the strongest negative IPO phase transition during 1999-2013. The regression pattern of the internal SST trends with respect to the NCI rainfall trends across 57 members through the member index: (e) 1950-1999 and (f) 1999-2013 (units: K $(decade)^{-1}$). Slant hatching denotes regions significant at the 95% confidence level. The rectangles in (e-f) outline the tropical central-eastern Pacific (TCEP, 170°W–90°W, 10°S–10°N) and the North Pacific (NP, 150°E–150°W, 25°N–45°N).

Fig. 7. Moisture budget analysis of the rainfall trend related to IPO phase transitions. (a). Moisture budget analysis on NCI rainfall trend difference between the 10 members with the strongest positive IPO phase transition and ensemble mean during 1950-1999 (Pos10-EM; dark colour bars). Light colour bars are for Neg10-EM during 1999-2013. Dots denote trend differences significant at 95% confidence level. Rainfall change is balanced by the changes of evaporation, dynamic and thermodynamic components and a nonlinear term (blue and light blue bars). The dynamic component is further separated into vertical, zonal and meridional dynamic components of moisture advection (red and pink bars). (b, d, f, h) are spatial patterns of Pos10-EM trend during 1950-1999 of rainfall, dynamic component, vertical dynamic component and zonal dynamic component of moisture advection, respectively. (c, e, g, i) are same as (b, d, f, h) but for Neg10-EM during 1999-2013. Units: mm day^{-1} $decade^{-1}$. Slant hatching denotes regions significant at 95% confidence level.

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986 **Fig. 8.** Mechanisms of IPO's modulation of ISM rainfall reduction and revival. JJA trend differences between the 10
987 members with the strongest positive IPO phase transition and ensemble mean (Pos10-EM) from 1950-1999 for: (a)
988 velocity potential (shading, units: $m^2\ s^{-1}\ decade^{-1}$) and divergent winds (vectors, units: $m\ s^{-1}\ decade^{-1}$) at 200hPa; (c)
989 rainfall (shading, units: $mm\ day^{-1}\ decade^{-1}$) and 850hPa stream function anomalies (contours, units: $10^6\ m^2\ s^{-1}\ decade^{-1}$);
990 (e) 850hPa winds (vectors, units: $m\ s^{-1}\ decade^{-1}$) and climatological specific humidity (shading, units: g/kg). (b),
991 (d) and (f) are the same as (a), (c) and (e) but for Neg10-EM trend differences in 1999-2013. Slant hatching denotes
992 regions significant at 95% confidence level.

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995 **Fig. 9.** JJA surface temperature trend related to IPO phase transitions. (a) Spatial patterns of the trend differences of
996 the JJA surface temperature between the 10 members with the strongest positive IPO phase transition and ensemble
997 mean (Pos10-EM) during 1950-1999. (b) is the same as (a) but for trend differences of Neg10-EM during 1999-2013.
998 (c) Composite 9-year running mean anomalies (relative to 1950-2013 mean) derived from the Pos10-EM composite
999 difference for 1950-1999 and the Neg10-EM composite difference for 1999-2013 for surface air temperature over
1000 the landmass north of India (red, land area in 30°N–45°N, 65°E–90°E), SST over the tropical Indian Ocean (blue,
1001 ocean area over the 10°S–25°N, 40°E–100°E) and the land-sea thermal contrast (black, i.e., the difference between
1002 the red and blue lines). The purple line denotes the observed land-sea surface thermal contrast derived from the
1003 CRUTEM4 and HadISST datasets.

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1006 **Fig. 10.** JJA mid-upper tropospheric thickness trend related to IPO phase transitions. (a) Spatial patterns of the trend
1007 differences of the JJA 500-200hPa tropospheric thickness between the 10 members with the strongest positive and
1008 the ensemble mean (Pos10-EM) during 1950-1999. (b) is the same as (a) but for trend differences of Neg10-EM
1009 during 1999-2013. (c) Composite 9-year running mean anomalies (relative to 1950-2013 mean) derived from the
1010 Pos10-EM composite difference for 1950-1999 and the Neg10-EM composite difference for 1999-2013 for 500-
1011 200hPa tropospheric thickness over Eurasia (brown, the northern box over 25°N–45°N, 60°E–100°E in a-b), the

tropical Indian Ocean (green, the southern box over 10°S–10°N, 60°E–100°E in a-b) and the meridional thermal gradient over India (black, i.e., the difference between the brown and green lines). The purple line denotes the meridional 500-200hPa tropospheric thickness gradient derived from the NCEP/NCAR reanalysis.

Fig. 11. Adjustments of the ISM rainfall trends according to the IPO phase transition. (a) EM of the IPO-adjusted internal JJA rainfall trends ($\partial_t pr_{internal\_adj}$) in ESPPE during 1950-1999, representing the rainfall trend caused by the observed IPO phase transition. (b) EM of the IPO-adjusted total JJA rainfall trends ($\partial_t pr_{adj}$) in ESPPE during 1950-1999, representing the rainfall trend caused by both the external forcing and the observed IPO. (c) Histograms (bars) and fitted distribution with 100 bins (lines) of the area-averaged rainfall trends over the NCI region during 1950-1999 derived from the 57 ESPPE members. The blue bars and the fitted blue curves show the frequency of occurrence of the original rainfall trends, with the blue dot and horizontal blue line denote the EM and STD of 0.01 ± 0.14. The red bars and the fitted red curves show the frequency of occurrence of the rainfall trends with adjustments accounting for the influence of the observational IPO phase transition (red dot and horizontal red line denote the EM and STD of -0.15 ± 0.13. (d-f) are same as (a-c) but for 1999-2013. The EM and STD for the blue and red bars in (f) are 0.42 ± 0.61 and 0.68 ± 0.54, respectively. The black dashed lines in (c) and (f) denote the observed NCI rainfall trends of -0.11 and 0.66, respectively. Units: mm day^{-1} decade^{-1}.

Fig. 12. Spatial patterns of 9-year running-mean JJA rainfall trends during the period of (a) 1950-1999 and (b) 1999-2013 derived from the EM of the 100-member MPI-ESM ensemble. The STD of the rainfall trends among the 100 MPI-ESM members for (c) 1950-1999 and (d) 1999-2013. Rainfall trends derived from (e) the 10 members with the strongest positive IPO phase transition (Pos10) during 1950-1999, (f) the 10 members with the strongest negative IPO phase transition (Neg10) during 1999-2013. Units: mm day^{-1} decade^{-1}. Slant hatching denotes trends significant at the 95% confidence level. (g) Time series of the 9-year running-mean of JJA rainfall anomalies averaged over NCI. Units: mm day^{-1}. Black is for the OBS. Red line and shading denote the EM and 5th and 95th percentile of the 100 members. Brown and blue solid lines represent the mean of Pos10 and Neg10 members during 1950-1999 and 1999-2013, respectively. Brown and blue dashed lines represent the mean difference of the Pos10 minus EM during 1950-

1040 1999 and the Neg10 minus EM during 1999-2013.

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1043 **Fig. 13.** The regression pattern of the internal SST trends with respect to the NCI rainfall trends across 100 members
1044 through the member index: (a) 1950-1999 and (b) 1999-2013 (units: K (decade)$^{-1}$). Slant hatching denotes regions
1045 significant at the 95% confidence level. (c) EM of the IPO-adjusted internal JJA rainfall trends ($\partial_t pr_{internal\_adj}$) in
1046 MPI-ESM during 1950-1999, representing the rainfall trend caused by the observed IPO phase transition. (d) EM of
1047 the IPO-adjusted total JJA rainfall trends ($\partial_t pr_{adj}$) in MPI-ESM during 1950-1999, representing the rainfall trend
1048 caused by both the external forcing and the observed IPO. (e-f) are same as (c-d) but for 1999-2013. Units: mm day^{-1} decade^{-1}.

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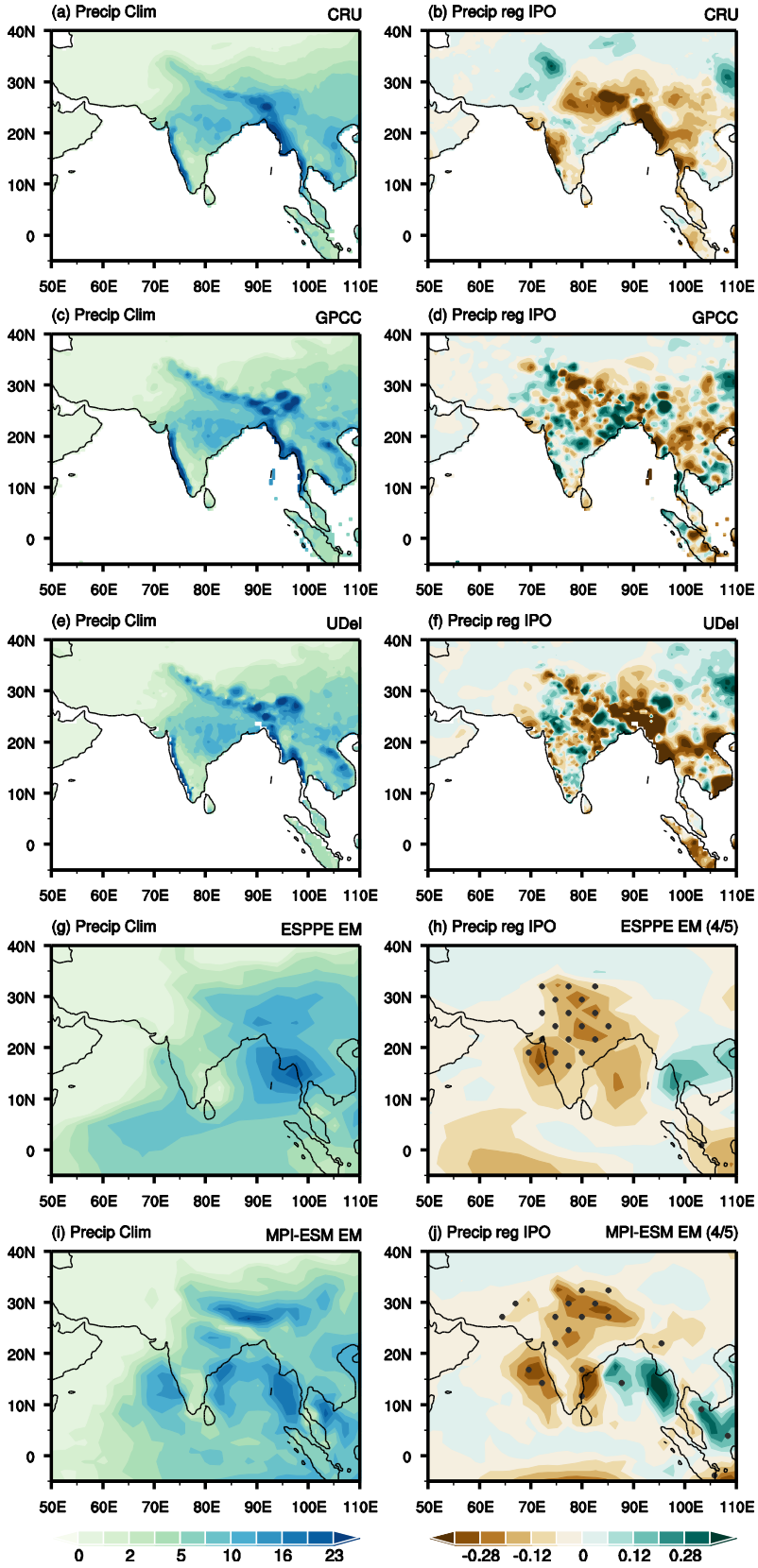
1052 **Fig. 14.** Schematic diagrams showing how external forcing and internal variability affect the recent decline and
1053 recovery of ISM rainfall, respectively.

1054

1055

Figures


(a) Precip Clim
CRU
(b) Precip reg IPO
CRU
(c) Precip Clim
GPCC
(d) Precip reg IPO
GPCC
(e) Precip Clim
UDel
(f) Precip reg IPO
UDel
(g) Precip Clim
ESPPE EM
(h) Precip reg IPO
ESPPE EM (4/5)
(i) Precip Clim
MPI-ESM EM
(j) Precip reg IPO
MPI-ESM EM (4/5)
40N
30N
20N
10N
0
50E
60E
70E
80E
90E
100E
110E
0
2
5
10
16
23
-0.28
-0.12
0
0.12
0.28

1058 **Fig. 1.** Evaluation of the ESPPE and MPI-ESM in simulating climatological June-July-August (JJA) Indian summer
1059 monsoon (ISM) rainfall and its relation to IPO. (a) CRU, (c) GPCC, (e) UDel, (g) ESPPE ensemble mean and (i)
1060 MPI-ESM ensemble mean (EM) climatological JJA mean rainfall over ISM region in 1950-2013. Regressed 9-year
1061 running mean JJA rainfall with respect to the observed IPO index during 1950-2013: (b) CRU, (d) GPCC and
1062 (f) UDel. (d) ESPPE and (f) MPI-ESM EM of the regressed internal component of JJA 9-year running mean
1063 rainfall onto the IPO index within each ensemble member during 1950-2013. Stippling denotes 4 of 5 ensemble
1064 members agreeing on the sign of change. Units: mm day^{-1}.
1065

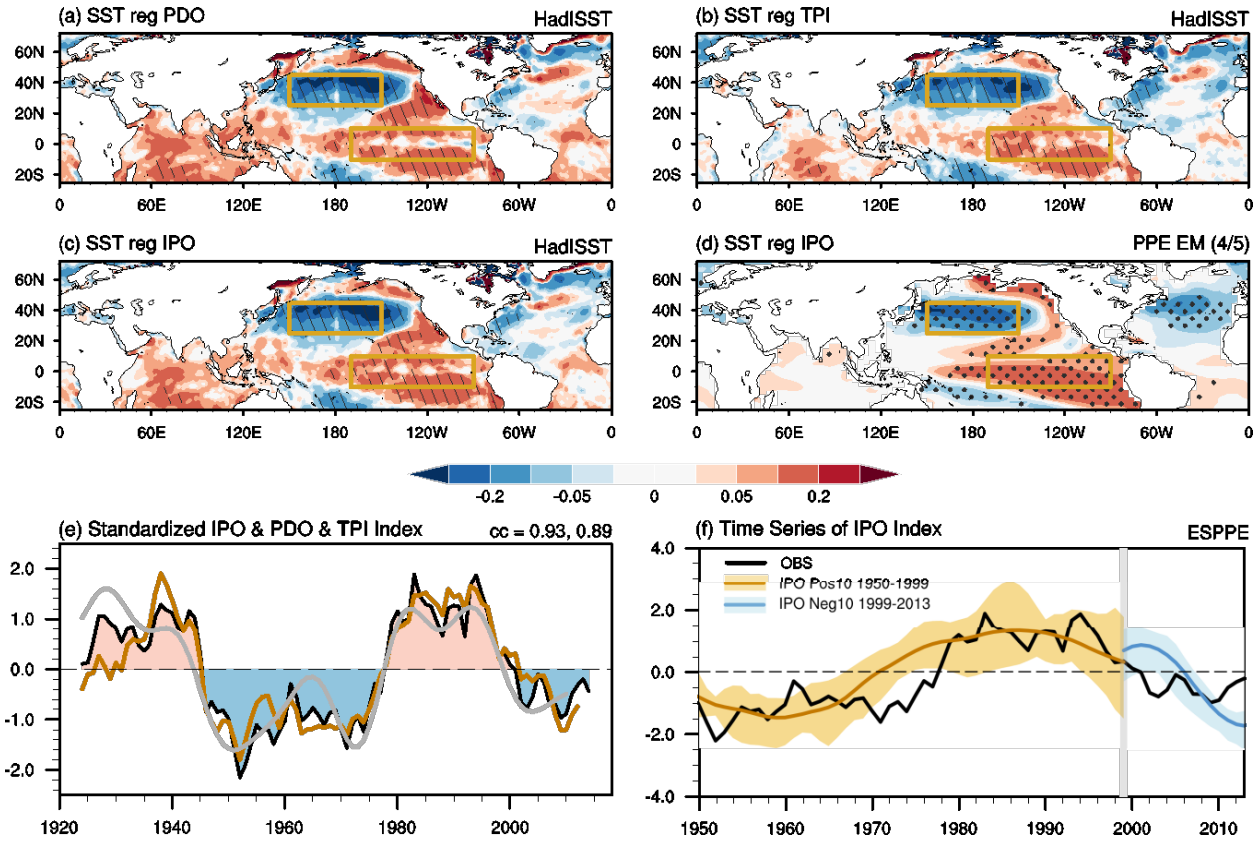


Fig. 2. Regressed 9-year running-mean JJA SST anomalies from HadISST (units: K) with respect to standardized 9-year running-mean (a) PDO index, (b) TPI index and (c) IPO index during the period of 1920-2013. (d) ESPPE EM of regressed 9-year running mean JJA SST with respect to standardized IPO index within each member during the period of 1920-2013. Slant hatching denotes regional signals significant at the 95% confidence level. Stippling denotes 4 of the 5 ensemble members in agreement on the sign of change. (e) Standardized time series of observed IPO index (defined as 9-year running-mean SST gradients between TCEP and NP, positive in red and negative in blue), standardized 9-year running-mean PDO (orange) and TPI (grey) index. The correlation coefficients between the IPO and PDO or TPI indexes are 0.93 and 0.89 ($p < 0.01$), respectively, during the historical period of 1920-2013. (f) Time series of IPO index from different ESPPE members. Black, brown and blue lines denote the IPO indices derived from HadISST observations and the 10 members with the strongest positive (Pos10) and the strongest negative (Neg10) transitions, respectively. The 10 members are chosen separately for both periods of 1950-1999 and 1999-2013. Light brown and blue shadings show the spread among the 10 members.

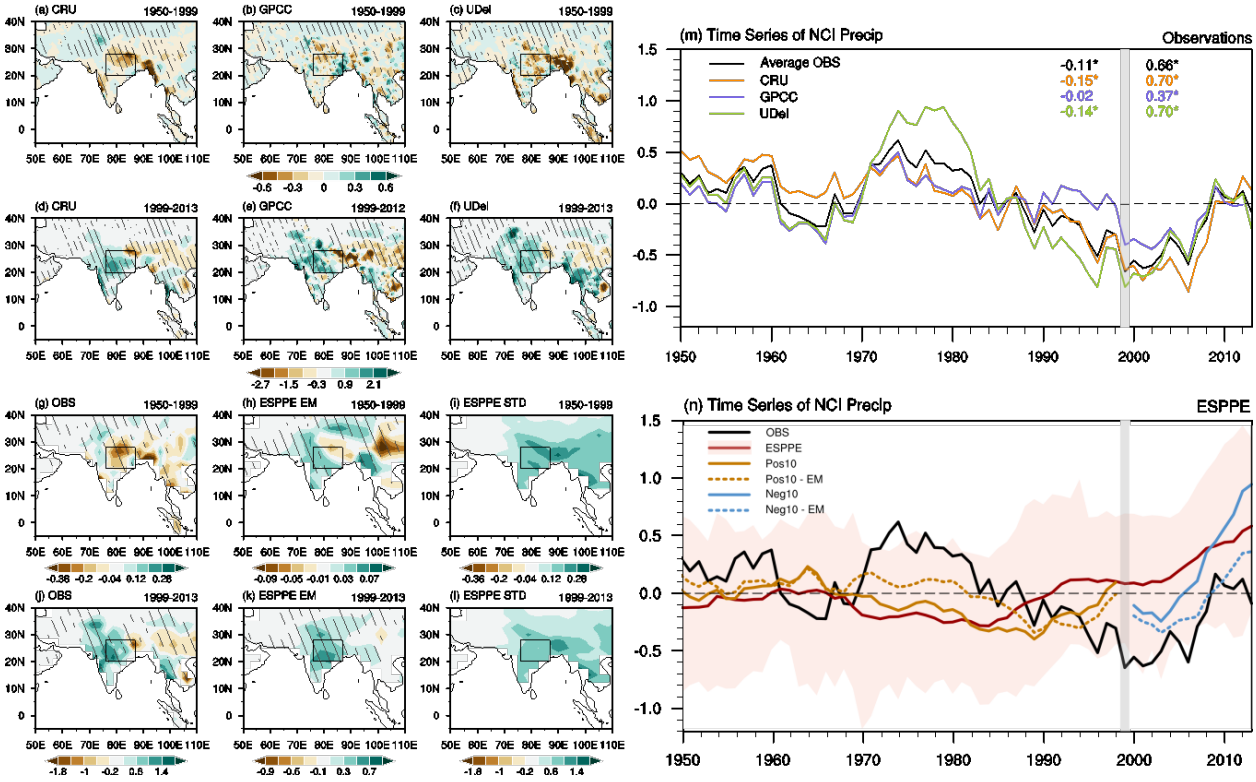
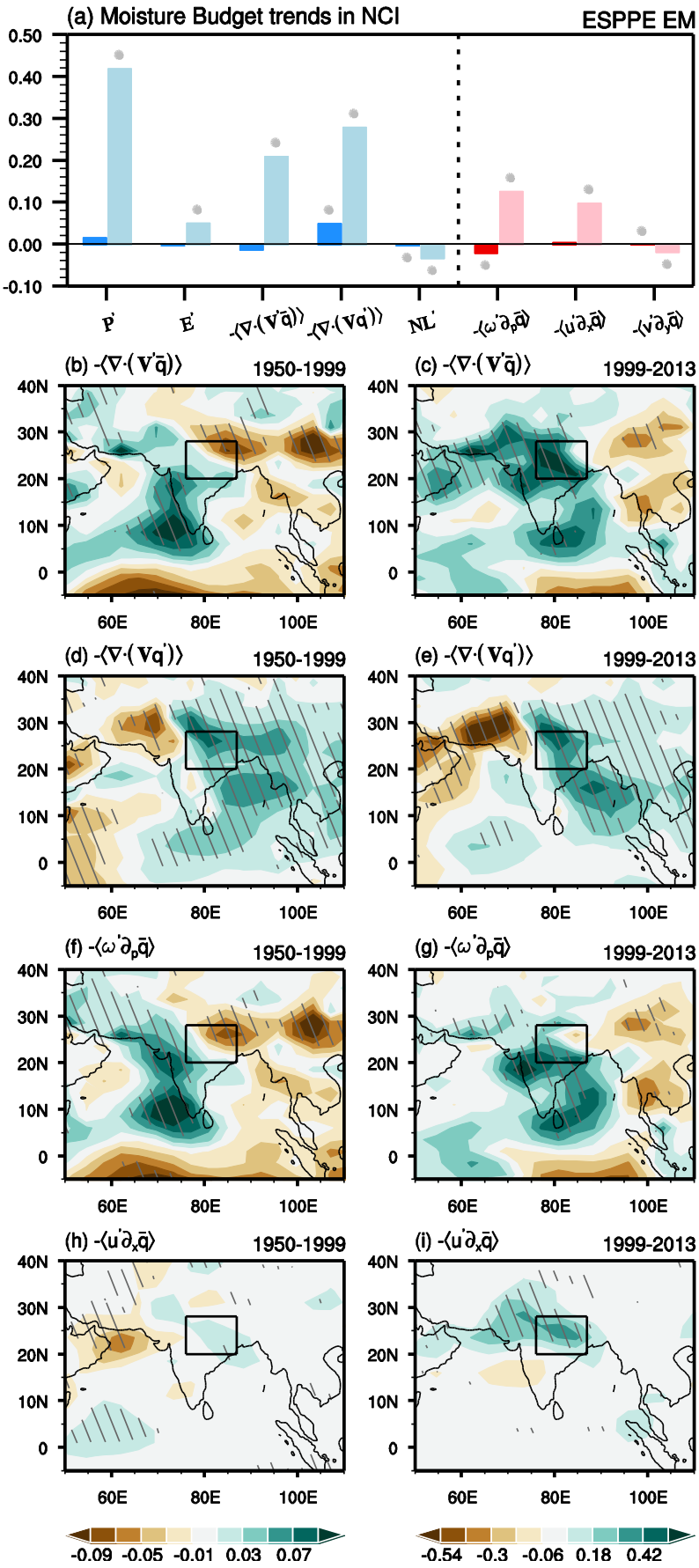


Fig. 3. Spatial patterns of 9-year running-mean JJA rainfall trends during the period of 1950-1999 derived from the (a) CRU, (b) GPCC, (c) UDel, (g) the average OBS and (h) the ESPPE EM. (i) The standard deviation (STD) of the rainfall trends among the 57 ESPPE members for 1950-1999. (d, e, f, j, k, l) are same as (a, b, c, g, h, i) but for 1999-2013. Units: mm day^{-1} decade^{-1}. Slant hatching denotes rainfall trends significant at the 95% confidence level. (m-n) Time series of the 9-year running-mean JJA rainfall anomalies relative to 1950-2013 mean average over north-central India (NCI; 20°N–28°N, 76°E–87°E) outlined by the rectangle in (a-l). Units: mm day^{-1}. In (m), colours of orange, purple, green and black represent the CRU, GPCC, UDel datasets and their average (referred to as OBS), respectively. The coloured numbers in (m) denote the NCI rainfall trends of corresponding datasets during both periods. In (n), black is for the OBS. Red line and shading denote the EM and 5th and 95th percentile of the 57 members. Brown and blue solid lines represent the mean of 10 members with strongest positive (Pos10) and the strongest negative (Neg10) IPO transitions during 1950-1999 and 1999-2013, respectively. Brown and blue dashed lines represent the mean difference of the Pos10 minus EM during 1950-1999 and the Neg10 minus EM during 1999-2013.


(a) Moisture Budget trends in NCI
ESPPE EM
0.50
0.40
0.30
0.20
0.10
0.00
-0.10
P'
E'
-⟨∇·(V'q̄)⟩
-⟨∇·(Vq')⟩
NL'
-⟨ω'∂pq̄⟩
-⟨u'∂xq̄⟩
-⟨v'∂yq̄⟩
(b) -⟨∇·(V'q̄)⟩ 1950-1999
(c) -⟨∇·(V'q̄)⟩ 1999-2013
(d) -⟨∇·(Vq')⟩ 1950-1999
(e) -⟨∇·(Vq')⟩ 1999-2013
(f) -⟨ω'∂pq̄⟩ 1950-1999
(g) -⟨ω'∂pq̄⟩ 1999-2013
(h) -⟨u'∂xq̄⟩ 1950-1999
(i) -⟨u'∂xq̄⟩ 1999-2013
40N
30N
20N
10N
0
60E
80E
100E
-0.09 -0.05 -0.01 0.03 0.07
-0.54 -0.3 -0.06 0.18 0.42

1095

Fig. 4. Moisture budget analysis of the external forced rainfall trend derived from the ESPPE EM. (a). Moisture budget analysis on EM NCI rainfall trend (dots denote trend differences significant at 95% confidence level) during 1950-1999 (dark color bars) and 1999-2013 (light color bars). Rainfall change is balanced by the changes of evaporation, dynamic and thermodynamic components and a nonlinear term (blue and light blue bars). The dynamic component is further separated into vertical, zonal and meridional dynamic components of moisture convergence (red and pink bars). (b, d, f, h) are spatial patterns of EM trend during 1950-1999 of dynamic component, thermodynamic component, vertical dynamic component and zonal dynamic component of moisture advection, respectively. (c, e, g, i) are same as (b, d, f, h) but for 1999-2013. Units: mm day^{-1} $decade^{-1}$. Slant hatching denotes regions significant at 95% confidence level.

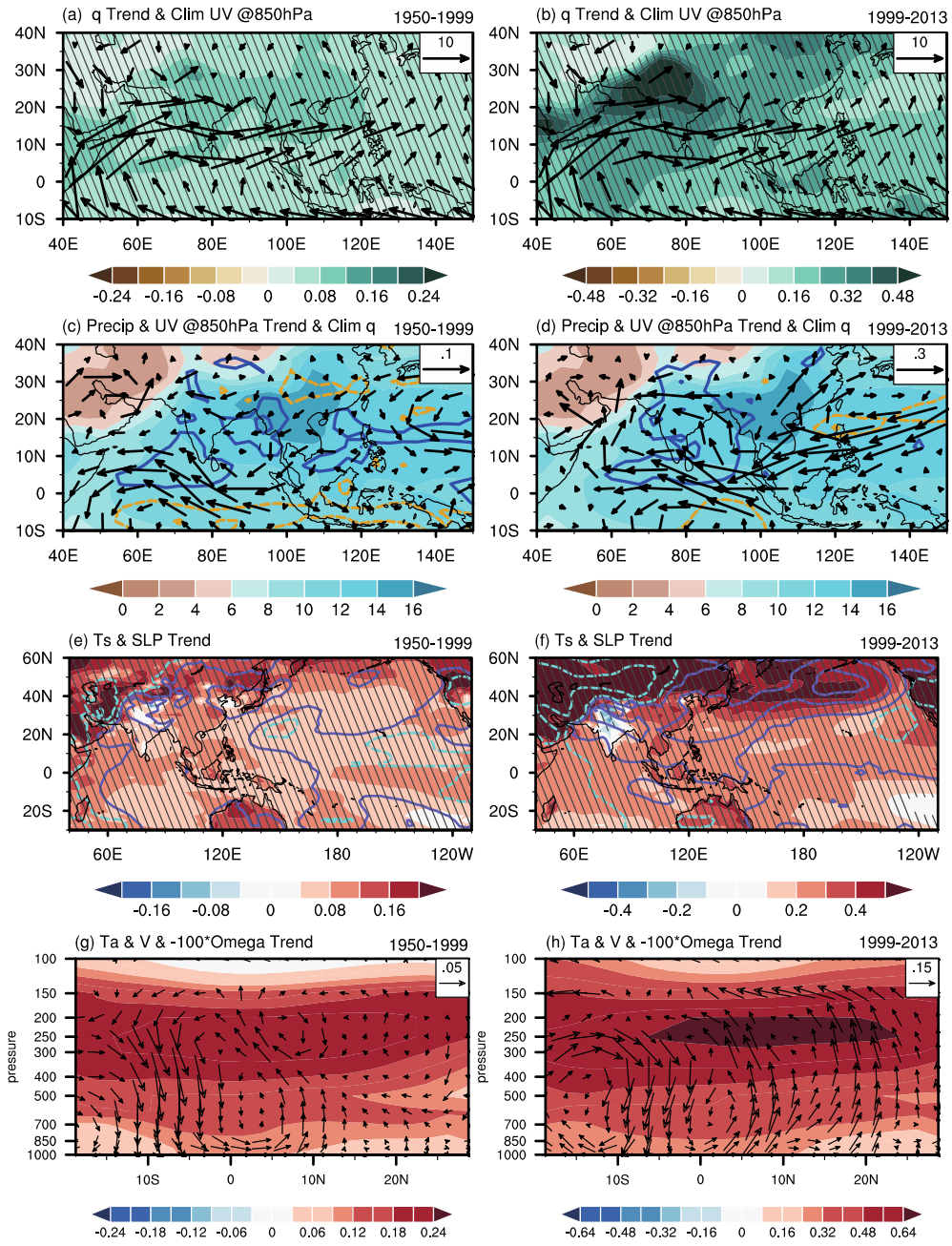
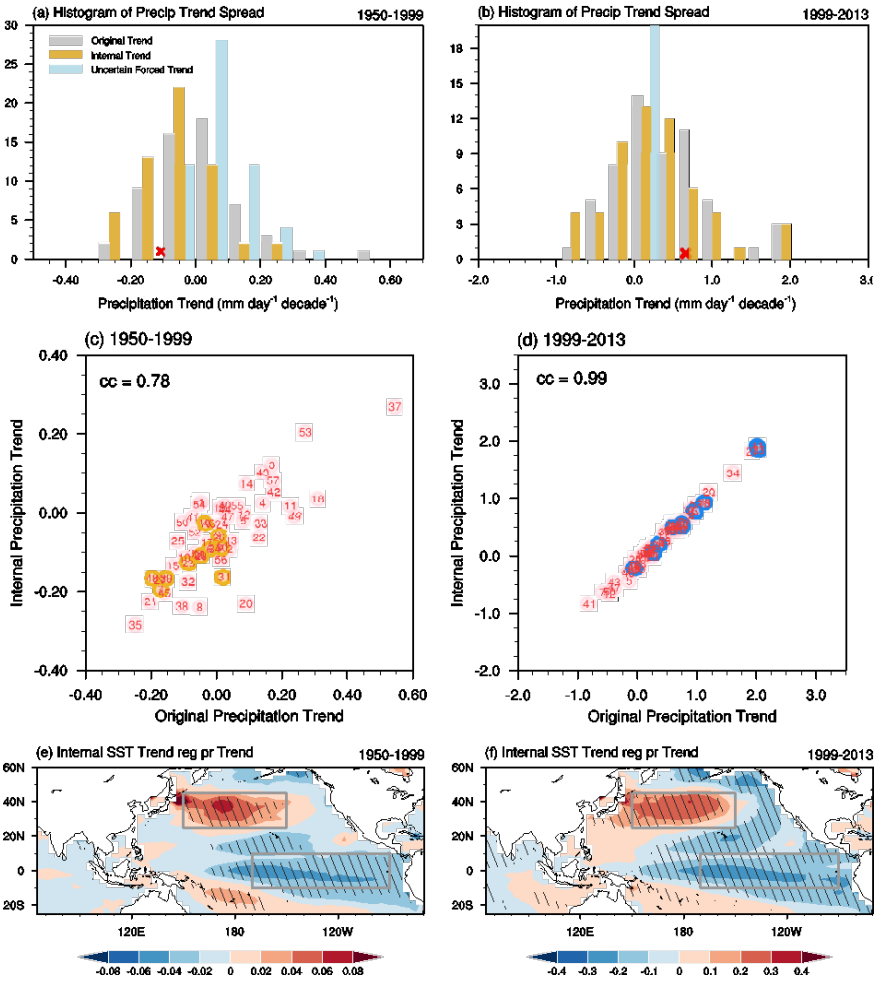


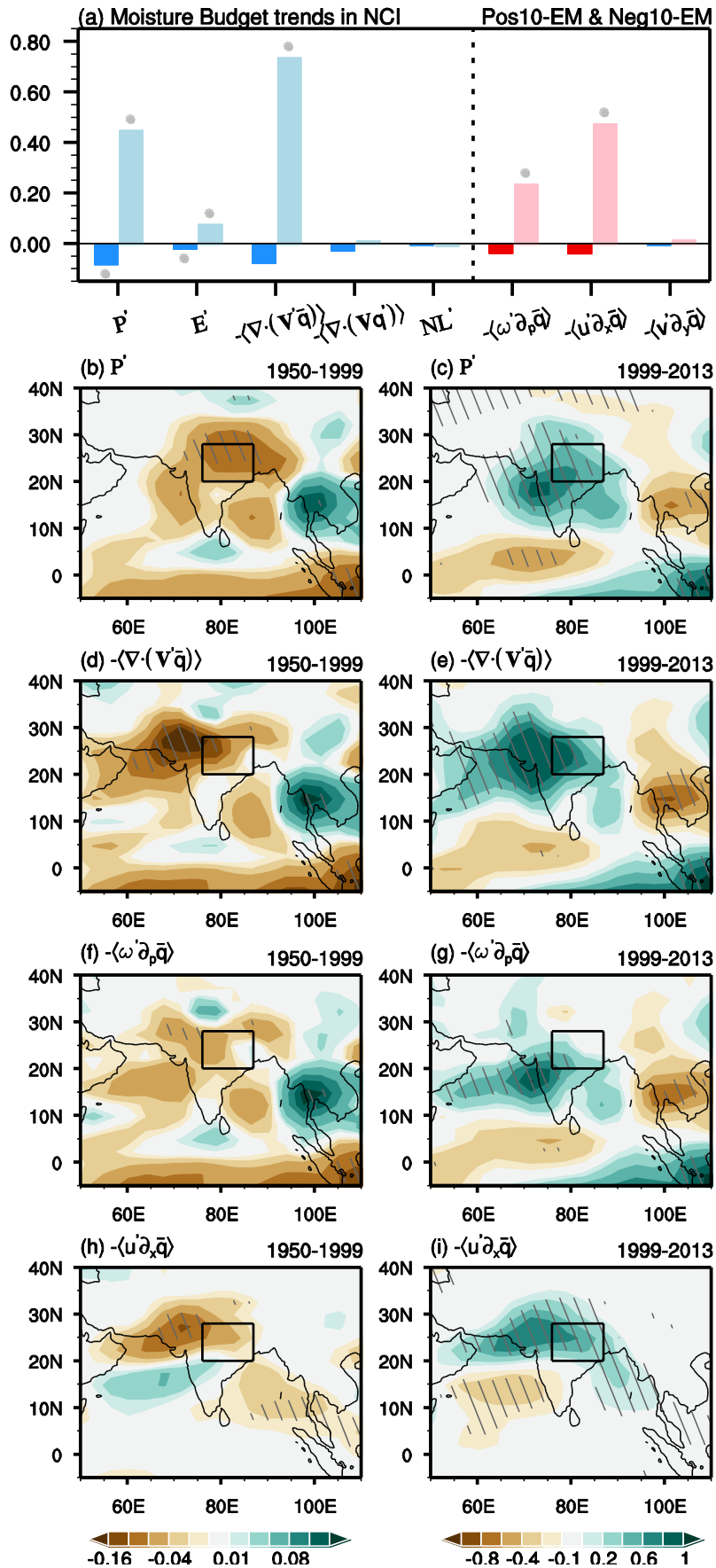
Fig. 5. (a) Trend of EM JJA 850hPa specific humidity (shading, units: g kg^{-1} decade^{-1}) and EM climatological 850hPa winds (vectors, units: m s^{-1}) from 1950-1999. (c) EM climatological JJA 850hPa specific humidity (shading, units: g kg^{-1}) and trend of EM rainfall (contours, positive in solid blue lines and negative in dashed brown lines; units: mm day^{-1} decade^{-1}) and 850hPa winds (vectors, units: m s^{-1} decade^{-1}) from 1950-1999. (e) Trend of EM JJA near surface temperature and SST (shading, units: K decade^{-1}) and sea level pressure (contours, positive in solid purple lines and negative in dashed cyan lines; units: Pa decade^{-1}). (g) Cross section of zonally-averaged (65°E–95°E) trend of EM air temperature (shading, units: K decade^{-1}) and winds (vectors, meridional and vertical components; units: m s^{-1} decade^{-1}). The vertical component is calculated with a scale factor of -100 to allow the vertical pressure-velocity to

be comparable with the meridional component. (b, d, f, h) are same as (a, c, e, g) but for 1999-2013. Slant hatching denotes regions significant at 95% confidence level.



1118

1119 **Fig. 6.** Histograms of spread in NCI rainfall trends among 57 members during (a) 1950-1999 and (b) 1999-2013
1120 (grey, yellow and blue bars denote the trends of the original rainfall, the internal component and the uncertain-forced
1121 component of rainfall). Correlation between trends of the original rainfall (x-bar, units: mm day^{-1} decade^{-1}) and the
1122 internal component of the rainfall (y-bar, units: mm day^{-1} decade^{-1}) over the NCI region derived from ESPPE
1123 members (number indicated in the circle) during the period (c) 1950-1999 and (d) 1999-2013. (The outlined member
1124 "37" in c. is caused by the combination of a positive internal rainfall trend and an evidently positive forced trend.)
1125 Brown circles in (c) denote the 10 members with the strongest positive IPO phase transition during 1950-1999. Blue
1126 circles in (d) denote the 10 members with the strongest negative IPO phase transition during 1999-2013. The
1127 regression pattern of the internal SST trends with respect to the NCI rainfall trends across 57 members through the
1128 member index: (e) 1950-1999 and (f) 1999-2013 (units: K (decade)$^{-1}$). Slant hatching denotes regions significant at
1129 the 95% confidence level. The rectangles in (e-f) outline the tropical central-eastern Pacific (TCEP, 170°W–90°W,
1130 10°S–10°N) and the North Pacific (NP, 150°E–150°W, 25°N–45°N).
1131


(a) Moisture Budget trends in NCI
Pos10-EM & Neg10-EM
0.80
0.60
0.40
0.20
0.00
P'
E'
-⟨∇·(V'q̄)⟩
-⟨∇·(Vq')⟩
NL'
-⟨ω'∂pq̄⟩
-⟨u'∂xq̄⟩
-⟨v'∂yq̄⟩
(b) P'
1950-1999
(c) P'
1999-2013
(d) -⟨∇·(V'q̄)⟩
1950-1999
(e) -⟨∇·(V'q̄)⟩
1999-2013
(f) -⟨ω'∂pq̄⟩
1950-1999
(g) -⟨ω'∂pq̄⟩
1999-2013
(h) -⟨u'∂xq̄⟩
1950-1999
(i) -⟨u'∂xq̄⟩
1999-2013
40N
30N
20N
10N
0
60E
80E
100E
-0.16 -0.04 0.01 0.08
-0.8 -0.4 -0.1 0.2 0.6 1

1132

Fig. 7. Moisture budget analysis of the rainfall trend related to IPO phase transitions. (a). Moisture budget analysis on NCI rainfall trend difference between the 10 members with the strongest positive IPO phase transition and ensemble mean during 1950-1999 (Pos10-EM; dark colour bars). Light colour bars are for Neg10-EM during 1999-2013. Dots denote trend differences significant at 95% confidence level. Rainfall change is balanced by the changes of evaporation, dynamic and thermodynamic components and a nonlinear term (blue and light blue bars). The dynamic component is further separated into vertical, zonal and meridional dynamic components of moisture advection (red and pink bars). (b, d, f, h) are spatial patterns of Pos10-EM trend during 1950-1999 of rainfall, dynamic component, vertical dynamic component and zonal dynamic component of moisture advection, respectively. (c, e, g, i) are same as (b, d, f, h) but for Neg10-EM during 1999-2013. Units: mm day^{-1} $decade^{-1}$. Slant hatching denotes regions significant at 95% confidence level.

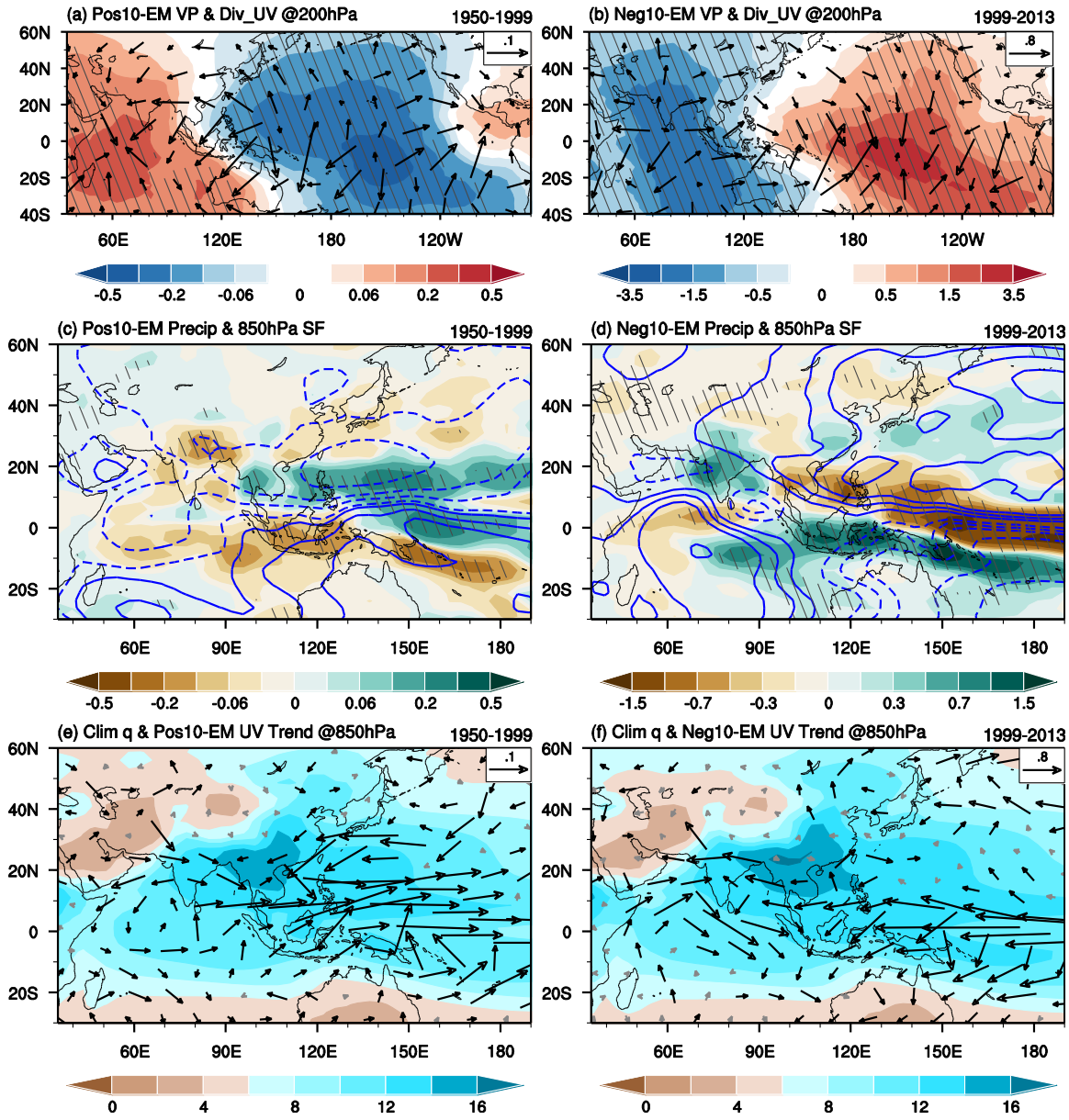


Fig. 8. Mechanisms of IPO's modulation of ISM rainfall reduction and revival. JJA trend differences between the 10 members with the strongest positive IPO phase transition and ensemble mean (Pos10-EM) from 1950-1999 for: (a) velocity potential (shading, units: $m^2\ s^{-1}\ decade^{-1}$) and divergent winds (vectors, units: $m\ s^{-1}\ decade^{-1}$) at 200hPa; (c) rainfall (shading, units: $mm\ day^{-1}\ decade^{-1}$) and 850hPa stream function anomalies (contours, units: $10^6\ m^2\ s^{-1}\ decade^{-1}$); (e) 850hPa winds (vectors, units: $m\ s^{-1}\ decade^{-1}$) and climatological specific humidity (shading, units: g/kg). (b), (d) and (f) are the same as (a), (c) and (e) but for Neg10-EM trend differences in 1999-2013. Slant hatching denotes regions significant at 95% confidence level.

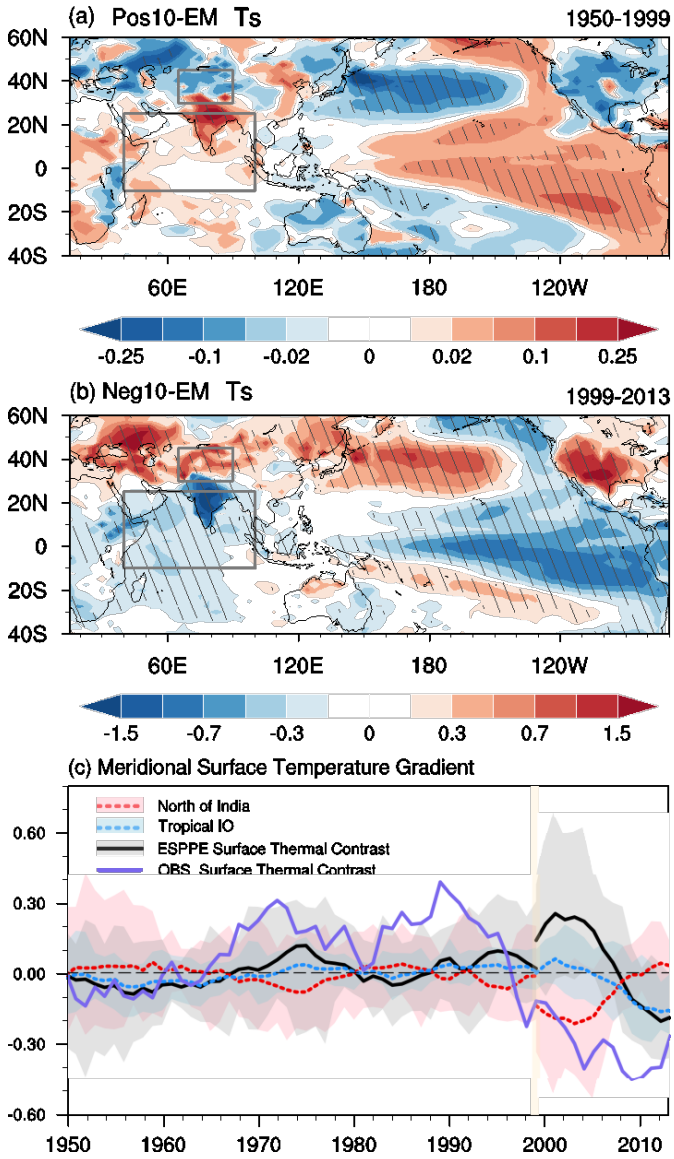


Fig. 9. JJA surface temperature trend related to IPO phase transitions. (a) Spatial patterns of the trend differences of the JJA surface temperature between the 10 members with the strongest positive IPO phase transition and ensemble mean (Pos10-EM) during 1950-1999. (b) is the same as (a) but for trend differences of Neg10-EM during 1999-2013. (c) Composite 9-year running mean anomalies (relative to 1950-2013 mean) derived from the Pos10-EM composite difference for 1950-1999 and the Neg10-EM composite difference for 1999-2013 for surface air temperature over the landmass north of India (red, land area in 30°N–45°N, 65°E–90°E), SST over the tropical Indian Ocean (blue, ocean area over the 10°S–25°N, 40°E–100°E) and the land-sea thermal contrast (black, i.e., the difference between the red and blue lines). The purple line denotes the observed land-sea surface thermal contrast derived from the CRUTEM4 and HadISST datasets.

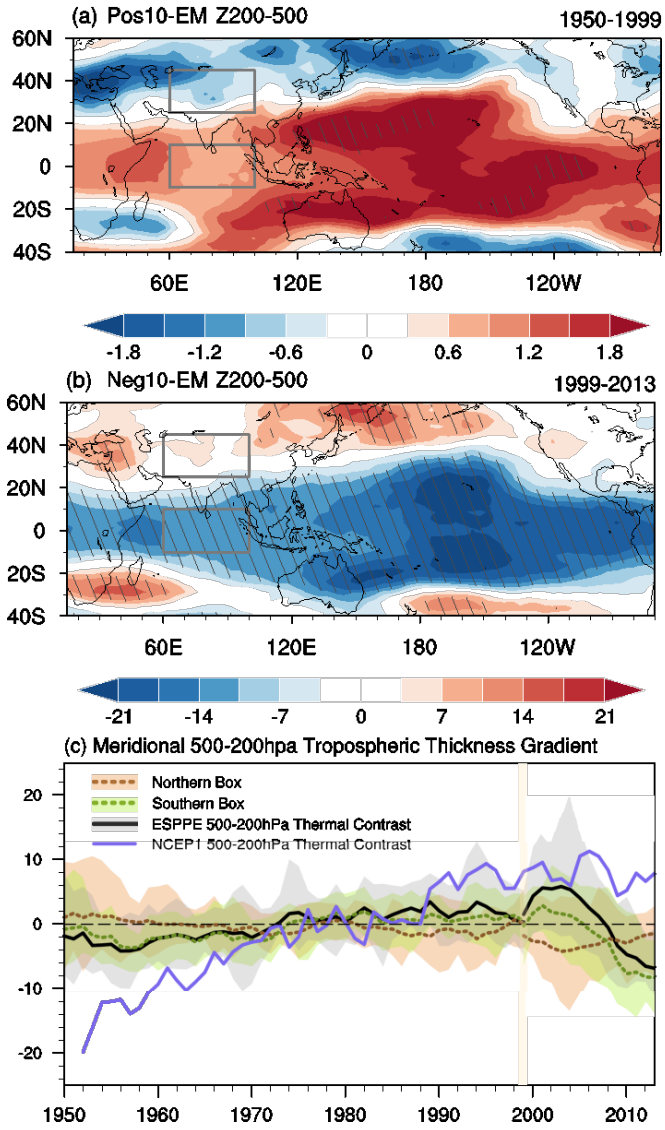


Fig. 10. JJA mid-upper tropospheric thickness trend related to IPO phase transitions. (a) Spatial patterns of the trend differences of the JJA 500-200hPa tropospheric thickness between the 10 members with the strongest positive and the ensemble mean (Pos10-EM) during 1950-1999. (b) is the same as (a) but for trend differences of Neg10-EM during 1999-2013. (c) Composite 9-year running mean anomalies (relative to 1950-2013 mean) derived from the Pos10-EM composite difference for 1950-1999 and the Neg10-EM composite difference for 1999-2013 for 500-200hPa tropospheric thickness over Eurasia (brown, the northern box over 25°N–45°N, 60°E–100°E in a-b), the tropical Indian Ocean (green, the southern box over 10°S–10°N, 60°E–100°E in a-b) and the meridional thermal gradient over India (black, i.e., the difference between the brown and green lines). The purple line denotes the meridional 500-200hPa tropospheric thickness gradient derived from the NCEP/NCAR reanalysis.

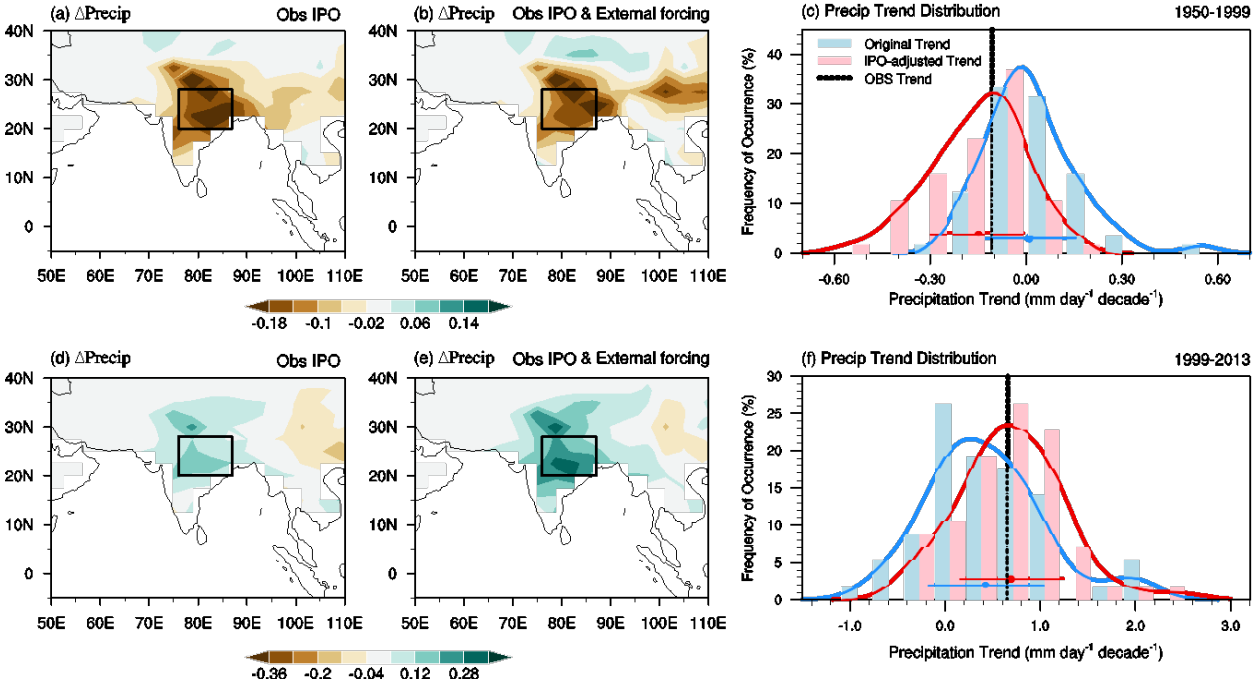


Fig. 11. Adjustments of the ISM rainfall trends according to the IPO phase transition. (a) EM of the IPO-adjusted internal JJA rainfall trends ($\partial_t pr_{internal\_adj}$) in ESPPE during 1950-1999, representing the rainfall trend caused by the observed IPO phase transition. (b) EM of the IPO-adjusted total JJA rainfall trends ($\partial_t pr_{adj}$) in ESPPE during 1950-1999, representing the rainfall trend caused by both the external forcing and the observed IPO. (c) Histograms (bars) and fitted distribution with 100 bins (lines) of the area-averaged rainfall trends over the NCI region during 1950-1999 derived from the 57 ESPPE members. The blue bars and the fitted blue curves show the frequency of occurrence of the original rainfall trends, with the blue dot and horizontal blue line denote the EM and STD of 0.01 ± 0.14. The red bars and the fitted red curves show the frequency of occurrence of the rainfall trends with adjustments accounting for the influence of the observational IPO phase transition (red dot and horizontal red line denote the EM and STD of -0.15 ± 0.13. (d-f) are same as (a-c) but for 1999-2013. The EM and STD for the blue and red bars in (f) are 0.42 ± 0.61 and 0.68 ± 0.54, respectively. The black dashed lines in (c) and (f) denote the observed NCI rainfall trends of -0.11 and 0.66, respectively. Units: mm day^{-1} decade^{-1}.

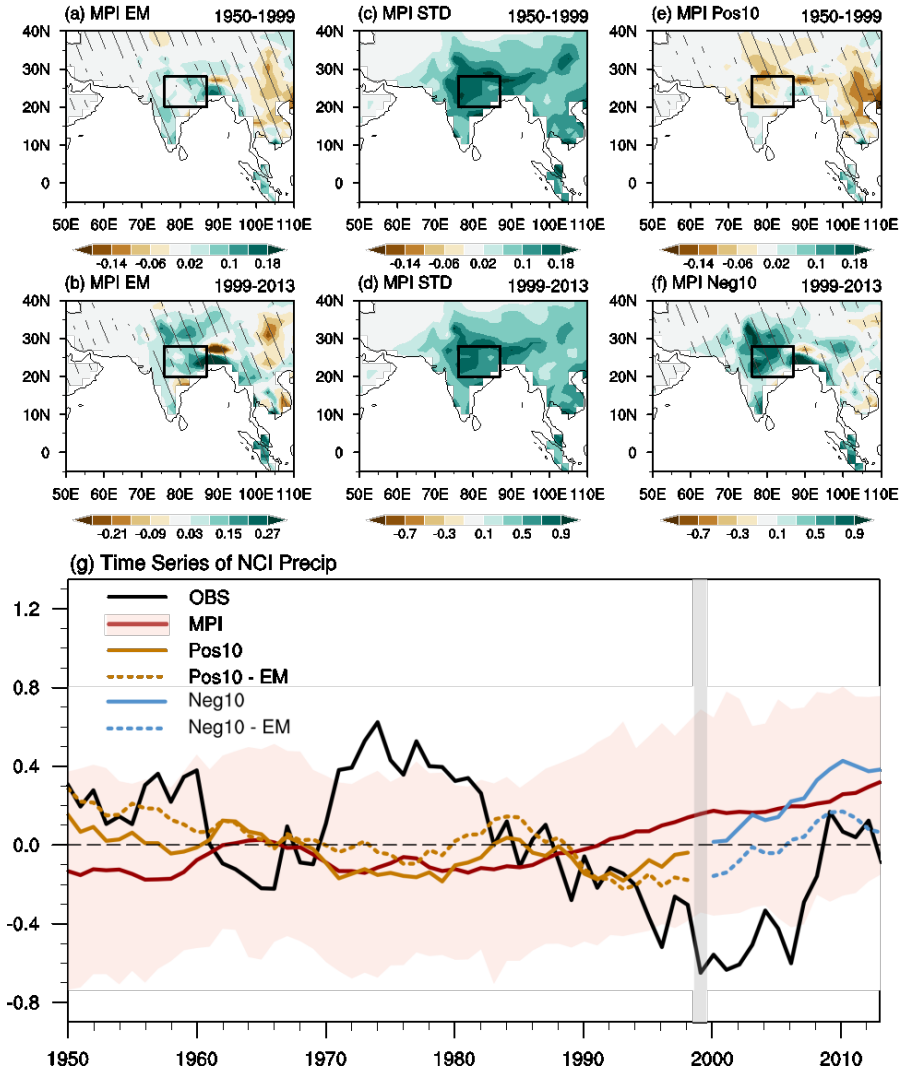


Fig. 12. Spatial patterns of 9-year running-mean JJA rainfall trends during the period of (a) 1950-1999 and (b) 1999-2013 derived from the EM of the 100-member MPI-ESM ensemble. The STD of the rainfall trends among the 100 MPI-ESM members for (c) 1950-1999 and (d) 1999-2013. Rainfall trends derived from (e) the 10 members with the strongest positive IPO phase transition (Pos10) during 1950-1999, (f) the 10 members with the strongest negative IPO phase transition (Neg10) during 1999-2013. Units: mm day^{-1} decade^{-1}. Slant hatching denotes trends significant at the 95% confidence level. (g) Time series of the 9-year running-mean of JJA rainfall anomalies averaged over NCI. Units: mm day^{-1}. Black is for the OBS. Red line and shading denote the EM and 5th and 95th percentile of the 100 members. Brown and blue solid lines represent the mean of Pos10 and Neg10 members during 1950-1999 and 1999-2013, respectively. Brown and blue dashed lines represent the mean difference of the Pos10 minus EM during 1950-1999 and the Neg10 minus EM during 1999-2013.

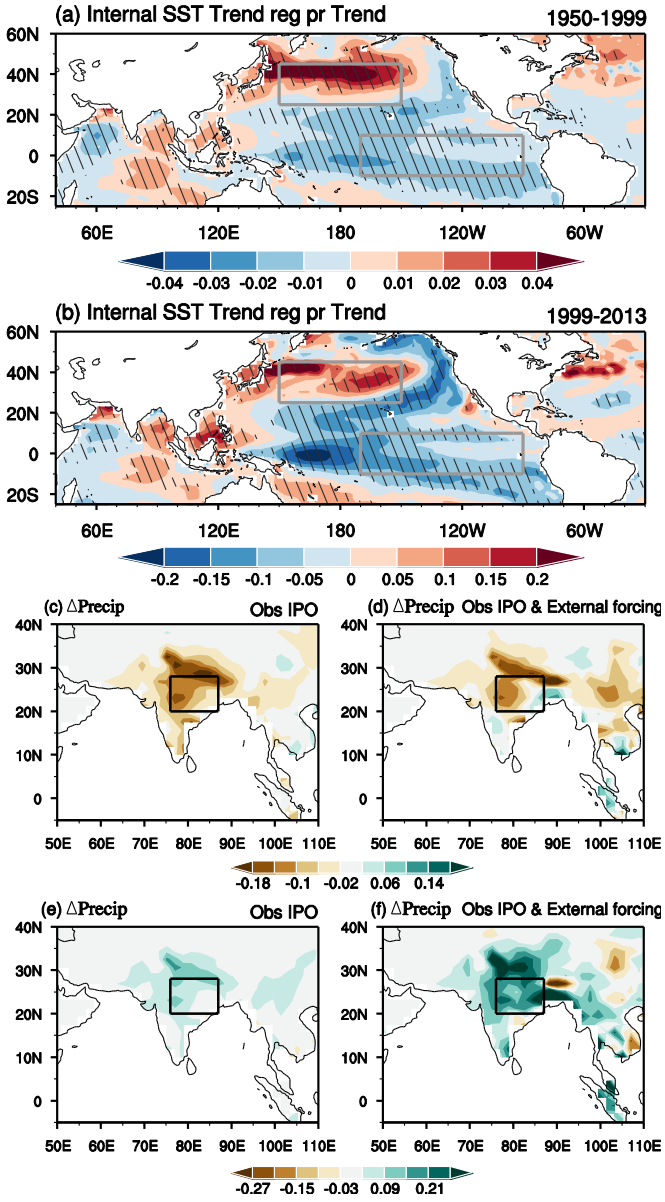


Fig. 13. The regression pattern of the internal SST trends with respect to the NCI rainfall trends across 100 members through the member index: (a) 1950-1999 and (b) 1999-2013 (units: K (decade)$^{-1}$). Slant hatching denotes regions significant at the 95% confidence level. (c) EM of the IPO-adjusted internal JJA rainfall trends ($\partial_t pr_{internal\_adj}$) in MPI-ESM during 1950-1999, representing the rainfall trend caused by the observed IPO phase transition. (d) EM of the IPO-adjusted total JJA rainfall trends ($\partial_t pr_{adj}$) in MPI-ESM during 1950-1999, representing the rainfall trend caused by both the external forcing and the observed IPO. (e-f) are same as (c-d) but for 1999-2013. Units: mm day^{-1} decade^{-1}.

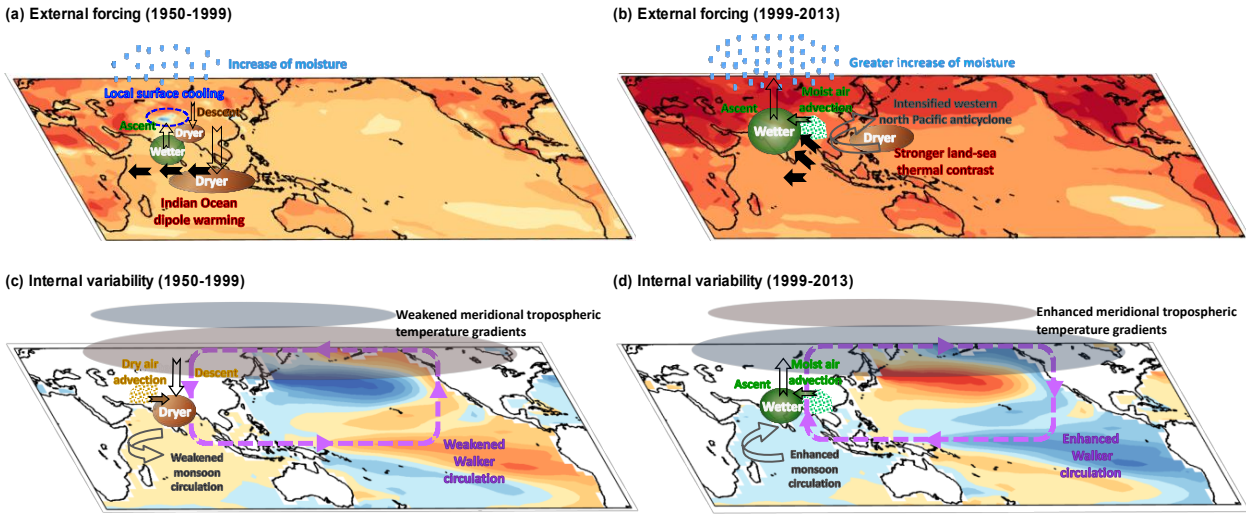


Fig. 14. Schematic diagrams showing how external forcing and internal variability affect the recent decline and recovery of ISM rainfall, respectively.