



Contrasting impacts of Asian sulfate aerosols on regional summer extreme precipitation under different climate backgrounds

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Abstract. Asian sulfate aerosols substantially affect regional summer precipitation, yet whether and how their effects vary with the background climate state remains unclear. This study investigates these impacts under pre-industrial and pre-industrial +1 K climates, using the reduced-complexity climate model Fast Ocean Rapid Troposphere Experiment version 2 with the Systematic Regional Aerosol Perturbations simulations. Results show that increased Asian sulfate aerosols reduce the summer mean and extreme precipitation over East and South Asia in both climates, with stronger suppression over northern India in the +1 K climate. The atmospheric energy budget analysis reveals that this is primarily due to enhanced dynamic effects in the warmer climate. When aerosols are added to the pre-industrial climate, the increased horizontal dry static energy (DSE) gradient partially offsets the aerosol-induced dynamic suppression over northern India. Under the +1 K climate, higher atmospheric static stability weakens the local meridional circulation induced by aerosol forcing, thereby reducing the meridional temperature gradient and diminishing the offsetting effect, making the dynamic suppression more dominant. Further analysis indicates that this difference in precipitation responses results from the nonlinear interaction between the aerosol-radiation and aerosol-cloud interactions under the +1 K climate, whereas the two effects combine approximately linearly under the pre-industrial climate. This study suggests that the reduction in precipitation, including extremes, over northern India caused by Asian sulfate aerosols is amplified under a warmer climate background. This implies that future aerosol emissions reductions may unmask or amplify extreme precipitation increases in this region.

1 Introduction

Extreme precipitation and its associated hydrometeorological and geological disasters, such as flooding, landslides, and debris flows, pose a serious threat to natural ecosystems and the safety of people's lives and property. This threat is exacerbated by global warming, which has increased the intensity and frequency of extreme precipitation on the global scale (IPCC, 2021). Anthropogenic aerosols, as a key driver of climate change, significantly influence extreme precipitation events, with effects comparable to, or even stronger than, those of greenhouse gases and internal variability in certain regions, including Asia (Lin et al., 2016; Samset et al., 2018; Guo et al., 2023; Iles et al., 2024).

Since the 1970s, anthropogenic aerosol emissions have increased substantially over East and South Asia due to rapid economic development, significantly impacting the spatiotemporal changes in Asian summer monsoon rainfall through aerosol-radiation interactions (ARI) and aerosol-cloud interactions (ACI), as well as through associated large-scale circulation changes (e.g., Bollasina et al., 2011; Li et al., 2016; Tian et al., 2018; Luo et al., 2019; Dong et al., 2019; Wilcox et al., 2020; Monerie et al., 2022; Lang et al., 2025; Yang et al., 2026). Further, the aerosol emissions contributed to a reduction in heavy precipitation over China, partially offsetting the greenhouse gas-induced increase resulting from enhanced atmospheric water vapor holding capacity (Ma et al., 2017; Bai et al., 2024). However, aerosol impacts exhibit marked regional differences and uncertainties. Lin et al. (2018) attributed the reduced extreme precipitation over North China and India mainly to ACI effect, while Guo et al. (2023) shown that aerosol forcing dominates the increase in summer extreme precipitation over Northwest China, primarily through the dynamic enhancement of moisture flux convergence. More recently, the sharp reduction in aerosol emissions over China has markedly accelerated the increase in extreme precipitation, primarily by increasing cloud droplet size and promoting more efficient coalescence (Zou et al., 2025), and further reductions are expected to intensify extreme precipitation over the Asian monsoon region in the future (Zhao et al., 2019; Wang et al., 2023).

Among anthropogenic aerosol species, sulfate is of foremost importance in Asian summer monsoon rainfall, where it constitutes the dominant fraction of the regional aerosol burden and exerts strong cooling effects through both ARI and ACI (Liu et al., 2009; Guo et al., 2013; Westervelt et al., 2020; Xie et al., 2022; Fang et al., 2023). Given that sulfate dominates the aerosol loading and the ACI effects, the aforementioned aerosol effects on extreme precipitation are likely largely attributable to sulfate. While its role in mean precipitation is well documented (Guo et al., 2013, 2015; Li et al., 2016; Liu et al., 2018; Westervelt et al., 2020), its impacts on extreme precipitation over Asia have rarely been quantified. Moreover, global warming is expected to alter atmospheric water vapour, static stability, and cloud properties,

all of which may influence the efficiency of sulfate-climate interactions. Hence, the sulfate effect on extreme precipitation may differ across climate backgrounds. Yet, whether and how this effect varies under different global warming levels remains unclear, hindering our ability to project future regional climate risks associated with sulfate emission changes.

In this study, we address this question by comparing idealized simulations of the same Asian anthropogenic sulfate aerosol perturbations under two distinct climate states using the coupled climate model FORTE2 (Fast Ocean Rapid Troposphere Experiment version 2). This model is of reduced complexity and well-suited for aerosol-climate studies, as it incorporates all the key mechanisms of aerosol-climate interactions and can efficiently run long simulations at low computational cost (Herbert et al., 2022; Stjern et al., 2024; Luo et al., 2025).

The rest of the paper is organized as follows. Section 2 describes the models and simulations, datasets, extreme precipitation indices, and analysis methods. Section 3 first evaluates the model skill in simulating precipitation and large-scale circulations, then examines the precipitation responses to Asian sulfate aerosol perturbations and the underlying mechanisms, and finally compares the differences between the two climate states and investigates the potential reasons. Sections 4 and 5 provide a discussion and conclusion.

2 Models, simulations and analysis methods

2.1 The FORTE2 model and simulations

FORTE2 was developed as an intermediate-complexity coupled atmosphere-ocean general circulation model (Blaker et al., 2021). Its atmospheric module, the Intermediate General Circulation Model 4, operates at a T42 spectral resolution corresponding to roughly 2.8° horizontally, with 35σ vertical levels extending up to 0.1 hPa (Joshi et al., 2015). This atmospheric component integrates full physical parameterizations for radiation, land-surface properties, convection, precipitation, and clouds schemes (Zhong and Haigh, 1995; Betts and Miller, 1993). For the oceanic component, the Modular Ocean Model-Array is adopted (Webb, 1996), featuring a $2^\circ \times 2^\circ$ horizontal grid with 15 vertical z -levels whose thickness increases with depth, ranging from 30 m at the sea surface to 800 m at the model bottom, with a total ocean depth of 5000 m (Stjern et al., 2024). Within the model system, sea ice functions as a thermal barrier restricting heat exchange between the ocean and atmosphere, and the coupled system runs without any flux adjustment terms.

Building on the FORTE2 platform, Stjern et al. (2024) designed and implemented a suite of Systematic Regional Aerosol Perturbations experiments. For brevity, hereafter we refer to these simulations collectively as FORTE2. This experimental framework supports systematic investigation of climate impacts driven by aerosols from distinct geographic

regions and of different chemical compositions, across various background climate scenarios. It also enables quantitative comparison between ARI and ACI effects, facilitating assessment of their respective contributions and potential interactive mechanisms. Instead of using aerosol emission or concentration fields as forcing inputs, a standard practice in most CMIP6 models including those participating in the Precipitation Driver and Response Model Intercomparison Project (PDRMIP) (Myhre et al., 2017), the FORTE2 simulations are forced by global gridded monthly aerosol optical depth (AOD) products with explicit vertical profiles, derived from the Copernicus Atmosphere Monitoring Service Reanalysis (CAMSRA) dataset (Inness et al., 2019).

Within the CAMSRA dataset, anthropogenic emissions for BC, organic carbon, and sulfur dioxide are sourced from the MACCity emission inventory for the 2003–2010 period, and switch to the Representative Concentration Pathway 8.5 emission scenarios from 2010 onward (Granier et al., 2011; Riahi et al., 2011). In the model setup, aerosols are assigned a vertically uniform distribution spanning from the second-lowest model layer, where σ (the ratio of grid pressure to surface pressure) equals approximately 0.88, corresponding to an altitude of around 950 m above the surface, upward to a defined upper pressure boundary referred to as $p_{\min}$. For each individual grid cell, the value of $p_{\min}$ is calculated from CAMSRA data as the lower of two thresholds: 850 hPa, or the lowest pressure level at which the 2003–2021 average mixing ratio of the combined BC, OC, and SO_4 mixture drops below $5 \times 10^{-9} \text{ kg kg}^{-1}$. In areas with complex terrain, additional constraints are enforced to avoid unrealistic aerosol vertical distributions, with $\sigma_{\min}$ constrained to below 0.75 and $p_{\min}$ to above 300 hPa (Stjern et al., 2024). To generate the regional AOD perturbation fields, monthly speciated AOD and three-dimensional mass mixing ratio data from CAMSRA (2003–2021) are first interpolated to match the T42 model resolution. Monthly climatologies are then computed for three AOD categories at each grid point: total anthropogenic aerosols (BC, OC, and SO_4), absorbing aerosols (BC and OC), and scattering aerosols (SO_4). These constructed idealized aerosol vertical profiles are subsequently input into FORTE2's radiation calculation scheme. Notably, FORTE2 does not include aerosol transport processes in its simulation configuration. A more detailed description of the aerosol implementation methodology in FORTE2 simulations is available in Stjern et al. (2024).

The FORTE2 simulations used in this study are summarized in Table 1. They include two baseline simulations without aerosol forcing: one with CO_2 concentrations at pre-industrial levels (piC, 280 ppmv), and one with elevated CO_2 (p1K, 500 ppmv). In this model, the p1K simulation yields a global-mean warming of approximately 1 K relative to piC. In addition, six perturbation simulations were performed with SO_4 AOD forcing added over Asia (Fig. 1a). These comprise combined ARI and ACI effects (ARI + ACI), ARI-only and ACI-only effects, each run under both the piC

and p1K background climate states. All simulations were carried out over a total 200-year period, with the first 50 years discarded as spin-up, and the remaining 150 years (model years 51–200) used for the analysis. For the climate response, subtracting each baseline from its corresponding perturbation (e.g., $\text{SO}_4\text{p1K-p1K}$ or $\text{SO}_4\text{piC-piC}$) isolates the climate effects of sulfate aerosol relative to a no-aerosol state, including the total (ARI + ACI) effect as well as the separate contributions from ARI and ACI. The impact of the background climate is then estimated by comparing these effects between the p1K and piC backgrounds, i.e., $(\text{SO}_4\text{p1K-p1K}) - (\text{SO}_4\text{piC-piC})$, which reveals how a warmer, higher- CO_2 climate modulates the sulfate-aerosol-induced responses examined here.

For ARI, the prescribed SO_4 AOD and vertical profiles are input into the FORTE2 radiation scheme. The ACI parameterization for sulfate perturbations is applied exclusively within the Asian study domain, which spans 60–140° E and 0–53° N (marked by the white box in Fig. 1a). The ACI effect is triggered once the local AOD value surpasses a threshold of 0.07. This threshold was selected based on observed relationships between AOD variations and cloud top effective radius changes reported in Dong et al. (2019). To represent the magnitude of ACI effects, the effective radius of cloud droplets is reduced from 15 to 10 μm across low-level clouds, mid-level clouds, and shallow convective clouds. The 5 μm reduction in droplet radius falls within the range of values simulated by the majority of CMIP5 models for this cloud property (Wilcox et al., 2015).

In this experimental design, both the sulfate AOD magnitude and its vertical profile are prescribed as fixed monthly climatologies, meaning they do not evolve or adjust in response to simulated climate variations. This idealized approach means that no feedbacks exist between the climate response and aerosol distribution (e.g., enhanced precipitation does not lead to increased aerosol removal), and also excludes any interactive atmospheric chemistry changes. As a result, any observed differences in sulfate-induced climate response between the p1K and piC backgrounds can be attributed entirely to differences in the background climate state (such as warmer temperatures, higher atmospheric water vapor content, and altered large-scale circulation patterns), rather than to variations in the strength or distribution of the aerosol forcing itself.

2.2 PDRMIP simulations

We also qualitatively compare the FORTE2 results with simulations from the PDRMIP (Myhre et al., 2017). The PDRMIP models are fully coupled earth system models and are substantially more comprehensive than the FORTE2 framework. Specifically, we use experiments from five global climate models (CESM1-CAM5, GISS-E2-R, HadGEM3, MIROC-SPRINTARS, and NorESM1; Table 2). In the perturbation simulations, Asian SO_4 emissions/concentrations

Table 1. Summary of FORTE2 simulations used in the study.

Experiment	Name	Aerosol (aerosol effects included)	GHG
Baseline	piC	No aerosol	Pre-industrial climate conditions (280 ppmv, piC)
Perturbation ^a	SO ₄ _piC	Asian ^b SO ₄ AOD (ACI + ARI) ^c	
	ARI_piC	Asian SO ₄ AOD (ARI-only)	
	ACI_piC	Asian SO ₄ AOD (ACI-only)	
Baseline	p1K	No aerosol	Pre-industrial +1 K climate conditions (500 ppmv, p1K)
Perturbation	SO ₄ _p1K	Asian SO ₄ AOD (ACI + ARI)	
	ARI_p1K	Asian SO ₄ AOD (ARI-only)	
	ACI_p1K	Asian SO ₄ AOD (ACI-only)	

^a All of the perturbation simulations are forced by observationally constrained (CAMSRA) repeating monthly sulfate AOD climatologies from 2003–2021, ^b 60–140° E, 0–53° N, ^c ACI: aerosol-cloud interactions; ARI: aerosol-radiation interactions.

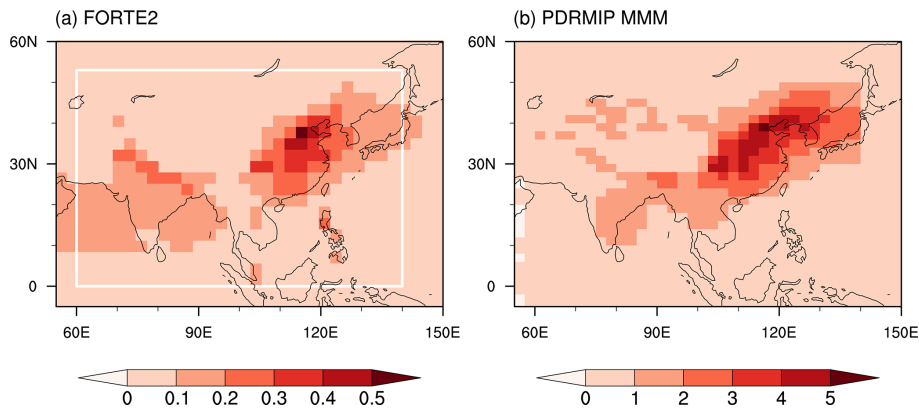


Figure 1. Summer (June–August) sulfate AOD spatial patterns in (a) FORTE2 and (b) PDRMIP MMM. The white box marks the Asian region (60–140° E, 0–53° N), over which ACI is parameterized for sulfate perturbations in FORTE2.

are set to ten times their year-2000 levels, while greenhouse gases are fixed at year-2000 levels. Each is compared against the corresponding model’s baseline simulation with year-2000 aerosols and greenhouse gases. The climate response to sulfate aerosols is quantified as the difference between the perturbation and baseline simulations. It should be noted that the PDRMIP simulations prescribe a much stronger Asian SO₄ perturbation than FORTE2, with a regional summer multi-model mean (MMM) AOD of ~ 2.5 over East Asia and South Asia, compared to ~ 0.23 in FORTE2 (Fig. 1). Despite this difference in magnitude, the spatial pattern of the prescribed perturbation is similar between the two experiments (Fig. 1). Therefore, the comparison between PDRMIP and FORTE2 focuses on the sign and spatial pattern of the responses, rather than their magnitudes, in the subsequent analysis. In addition, the PDRMIP experiments are conducted under a single background climate state and therefore cannot assess the influence of a warmer background climate, which is the central focus of the present study.

2.3 Reanalysis data and extreme precipitation index

To support observational comparison, daily precipitation records, monthly sea level pressure (SLP) fields, as well as monthly horizontal and vertical wind components were obtained from the fifth-generation ECMWF atmospheric reanalysis (ERA5). The dataset has a uniform horizontal grid spacing of $0.25^\circ \times 0.25^\circ$ and covers the period from 1981 through 2010 (Hersbach et al., 2023a, b). Following the standardized indicator framework put forward by the Expert Team on Climate Change Detection and Indices (ETCCDI), we derived four precipitation metrics for subsequent analysis. PRCPTOT (unit: mm) represents the cumulative precipitation sum across all wet days within the target season. R95p (unit: mm) denotes the total precipitation amount recorded exclusively on extremely wet days. R95d (unit: days) counts the total number of extremely wet days, and R95int (unit: mm d^{-1}) characterizes the average precipitation intensity of extreme events, calculated as the quotient of R95p divided by R95d. A wet day was defined as its daily precipitation reaches or exceeds 1 mm (Zhang et al., 2011). The 95th percentile of wet-day daily precip-

Table 2. Details of the five models in PDRMIP.

Model	Resolution (lon × lat)	Level	Aerosol setup
CESM1-CAM5	2.5° × 1.9°	30 levels	CMIP5 Emissions (year 2005)
GISS-E2-R	2.5° × 2°	40 levels	AeroCom Phase II concentrations
HadGEM3	1.875° × 1.25°	85 levels	AeroCom Phase II concentrations
MIROC-SPRINTARS	1.4° × 1.4°	40 levels	HTAP2 emissions (year 2010)
NorESM1	2.5° × 1.9°	26 levels	AeroCom Phase II concentrations

itation is adopted as the threshold for extremely wet days, with separate baseline references for different data sources: for FORTE2 and PDRMIP simulations, the percentile threshold is computed from their corresponding baseline simulations; for the ERA5 reanalysis, the 1981–2010 period is used as the reference baseline to derive the threshold. All analyses in this study focus on boreal summer (June–August, JJA).

2.4 Atmospheric energy budget

To uncover the physical mechanisms driving precipitation changes, we employ an atmospheric column energy budget framework, which partitions precipitation-related energy variations into a thermodynamic component (denoted Q) and a dynamic component (denoted H) (Muller and O’Gorman, 2011; Richardson et al., 2016; Liu et al., 2018). In this framework, the latent heat release associated with precipitation changes ($L_c\delta P$) is balanced by changes in net atmospheric diabatic cooling (δQ) and dry static energy (DSE) flux divergence (δH), as expressed in Eq. (1):

$$L_c\delta P = \delta Q + \delta H \quad (1)$$

where L_c is the latent heat of condensation, P stands for precipitation, and δ denotes the change relative to the reference baseline simulation. The term δQ is calculated by summing variations in three factors: atmospheric longwave cooling, atmospheric shortwave absorption, and surface sensible heat flux. Correspondingly, δH is derived as the residual value obtained by subtracting δQ from $L_c\delta P$.

The total DSE flux divergence anomaly δH is further divided into a time-mean component (δH_m) and a transient eddy component (δH_{trans}), as shown in Eq. (2):

$$\delta H = \delta H_m + \delta H_{trans} \quad (2)$$

δH_m can be broken down into four distinct terms, which correspond to the dynamic and thermodynamic effects on vertical and horizontal DSE advection respectively. The full decomposition is presented in Eq. (3):

$$\begin{aligned} \delta H_m = & \delta H_{Dy_v} + \delta H_{Th_v} + \delta H_{Dy_h} + \delta H_{Th_h} \\ = & \int \delta \bar{\omega} \frac{\partial \bar{s}}{\partial p} \frac{dp}{g} + \int \bar{\omega} \delta \left(\frac{\partial \bar{s}}{\partial p} \right) \frac{dp}{g} + \int \delta \bar{\mathbf{u}} \cdot \nabla \bar{s} \frac{dp}{g} \\ & + \int \bar{\mathbf{u}} \cdot \delta (\nabla \bar{s}) \frac{dp}{g} \end{aligned} \quad (3)$$

where ω is vertical velocity (Pa s^{-1}), s is DSE (J kg^{-1}), p is pressure (Pa), g is the gravitational acceleration (m s^{-2}), $\mathbf{u}$ is horizontal wind vector (m s^{-1}), ∇ is the horizontal gradient, and an overbar indicates climatological monthly means. Physically, δH_{Dy_v} reflects the dynamic effect arising from changes in vertical velocity; δH_{Th_v} corresponds to the thermodynamic effect induced by changes in vertical DSE gradients; δH_{Dy_h} represents the dynamic effect caused by changes in horizontal wind fields; δH_{Th_h} captures the thermodynamic effect related to changes in horizontal DSE gradients. Finally, δH_{trans} is calculated as a residual between δH and δH_m .

3 Results

3.1 Model evaluation

To understand whether the models produce reasonable precipitation patterns and physically plausible large-scale circulation, we compare the FORTE2 p1K baseline and the PDRMIP baseline simulations with ERA5 (1981–2010). It is important to note that the background forcing differs among these datasets: the FORTE2 p1K simulation has no aerosol forcing and the CO_2 concentration that is slightly higher than present-day levels, whereas the aerosol and greenhouse gas forcing in PDRMIP is representative of year-2000 conditions. Given these idealized and differing forcing configurations, the comparison is intended as a sanity check of whether the models produce reasonable background climate states, rather than as a validation of the models’ ability to reproduce the absolute observed climate. We therefore emphasize the spatial structures of precipitation and circulation over the exact magnitudes of the climatological fields.

In ERA5, R95p shows a spatial pattern similar to PRCP-TOT, with maxima over northern India, Southeast Asia and South China (Fig. 2a and b). R95d is generally higher in the tropics than at mid- to high-latitudes, with a local maximum over Northwest China (Fig. 2c). R95int shows its highest values over the Asian summer monsoon region (Fig. 2d). The PDRMIP MMM reasonably reproduces the observed spatial patterns of PRCP-TOT and extreme precipitation, with pattern correlation coefficients exceeding 0.85 (Fig. 2e–h). All individual PDRMIP models show pattern correlations above 0.6 for these indices, indicating reasonable agreement with the observed spatial patterns. FORTE2 also reasonably simulates

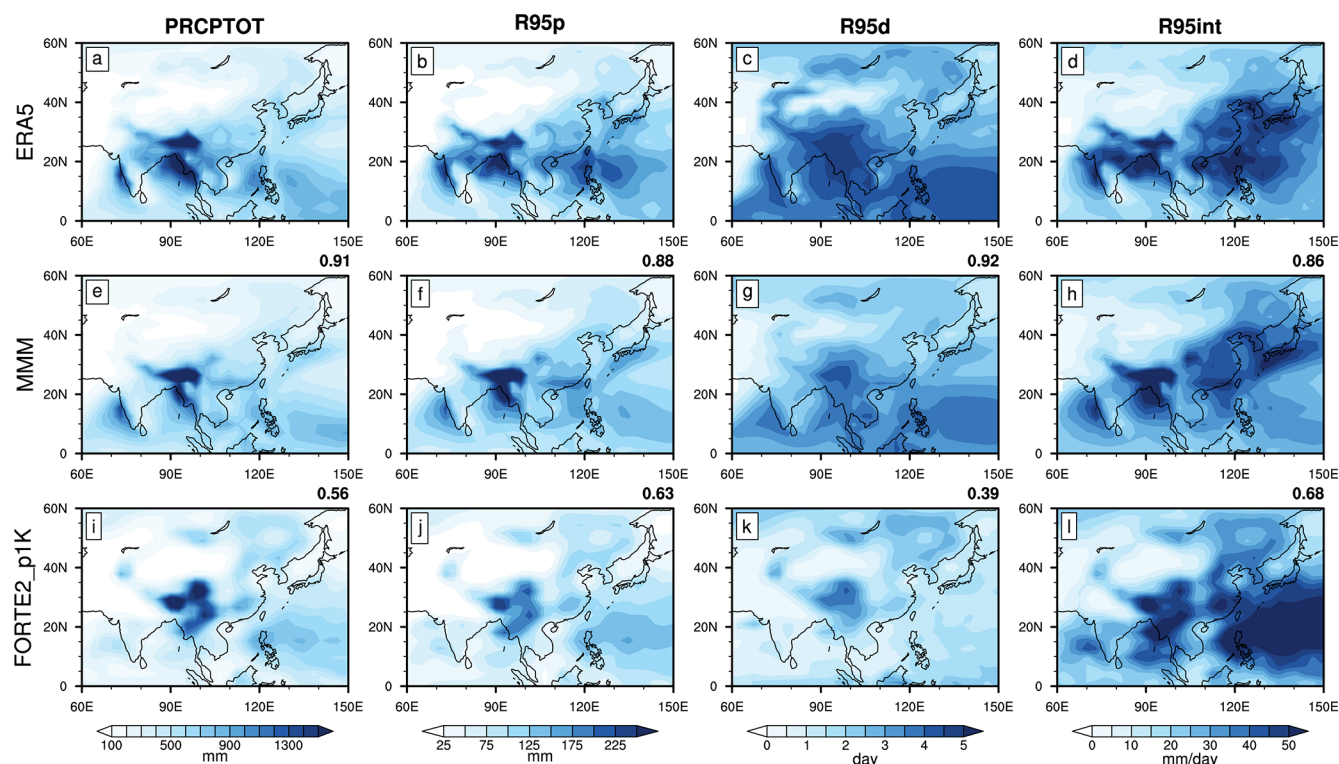


Figure 2. Comparison of climatological summer (June–August) PRCPTOT (mm), R95p (mm), R95d (day) and R95int (mm d^{-1}) from (a–d) ERA5 (1981–2010), (e–h) the PDRMIP MMM baseline simulation and (i–l) the FORTE2 p1K baseline simulation. The numbers in the upper right corner represent the spatial correlation coefficients between the models and ERA5.

these precipitation indices, although its pattern correlations are generally lower than those of the PDRMIP MMM, with values of 0.56 for PRCPTOT and 0.63 for R95p (Fig. 2i–j). Notable dry biases are also evident over India for PRCPTOT and R95p, a feature common among many CMIP5/6 models (Wilcox et al., 2020). The correlation is lower for R95d (0.39), largely associated with its relatively low values in the tropics, while R95int shows a comparatively higher correlation of 0.68 (Fig. 2k–l). These discrepancies may reflect both the differing prescribed external forcing and limitations in the model’s convective parameterization scheme.

The simulated precipitation structures are further supported by the representation of the associated large-scale summer circulation. Both the PDRMIP MMM and FORTE2 reasonably simulate the basic circulation features relevant to the Asian summer monsoon compared to ERA5, including the land–sea pressure gradient, the continental low, the western North Pacific Subtropical High, and the associated horizontal and vertical wind fields (Fig. 3). However, FORTE2 differs from both the PDRMIP MMM and ERA5 in the intensity and spatial extent of some circulation features, most notably a stronger continental low and a weaker western North Pacific Subtropical High (Fig. 3a–c). The horizontal and vertical wind fields also show regional differences, particularly

over the tropical Pacific, the Tibetan Plateau, and the tropical Indian Ocean (Fig. 3d–f).

Overall, the comparison suggests that, while the models differ from ERA5 in the magnitude and regional details of their climatological fields, they capture the key spatial structures of precipitation and large-scale circulation. Moreover, these precipitation and circulation characteristics in the FORTE2 p1K simulation mirror those found in its piC simulation (Fig. S1 in the Supplement), suggesting that their basic spatial structures remain robust across the two forcing conditions.

3.2 Responses to Asian sulfate aerosols and associated physical processes

The spatial patterns of precipitation indices in response to increased Asian sulfate aerosols are illustrated in Fig. 4 for the PDRMIP MMM and the $\text{SO}_4\text{p1K}$ and SO_4piC simulations in FORTE2. To intuitively reflect the magnitude of regional precipitation responses, relative changes in PRCPTOT, R95p and R95int with respect to the respective baseline simulations are shown in Figs. 4, 7–8, 11 and 13. It should be kept in mind that the sulfate perturbation in PDRMIP is roughly an order of magnitude stronger than the FORTE2 perturbation. Hence, the response magnitudes are expected to differ considerably between the two datasets. The PDR-

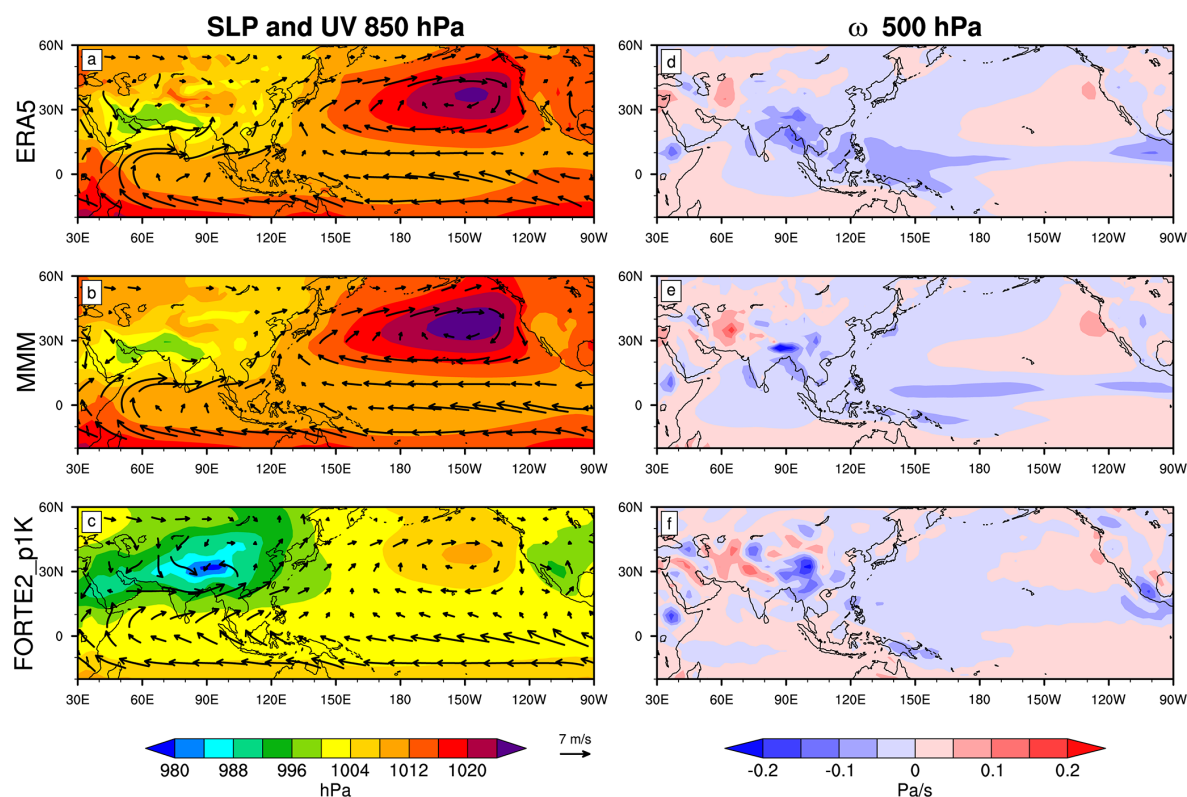


Figure 3. Comparison of climatological summer (a–c) SLP (hPa), 850 hPa horizontal winds (m s^{-1}) and (d–f) 500 hPa vertical winds (ω) (Pa s^{-1}) from ERA5 (1981–2010), the PDRMIP MMM baseline simulation and the FORTE2 p1K baseline simulation.

MIP MMM and the two FORTE2 simulations show significant reductions in PRCPTOT and R95p over East China and India, and enhancements over northwestern India (Fig. 4a–b, e–f, i–j), in response to increased sulphate, consistent with previous work (Liu et al., 2018). R95p exhibits a stronger response than PRCPTOT, suggesting that extreme precipitation is more sensitive to sulfate forcing than mean precipitation, consistent with Samset et al. (2018). The responses of R95d and R95int are similar to those of R95p, indicating that the reduction in R95p is characterized by a lower frequency and weaker intensity (Fig. 4c–d, g–h, k–l). While FORTE2 is a model of lower complexity, it broadly reproduces the key regional sign patterns of the five PDRMIP models, particularly drying over East Asia and South Asia and wetting over northwestern India.

In general, the changes in extreme precipitation are consistent with those in total precipitation, despite differences in magnitude, suggesting that the decreases in mean and extreme precipitation share some common drivers, such as large-scale circulation changes. To the extent that this holds, understanding the mechanisms behind mean precipitation changes can shed light on those driving extreme precipitation changes. Figure 5 shows the area-averaged atmospheric column energy budget terms (see Eqs. 1–3) for East Asia and South Asia (red and purple boxes in Fig. 4a, respectively). In

both regions, the responses of $L_c \delta P$ are nearly equal to the responses of δH in the PDRMIP MMM and FORTE2 simulations, a result that is consistent across the five PDRMIP models. δQ is relatively small compared to δH and remains close to zero in the PDRMIP MMM. Hence, the dynamic effects induced by Asian sulfate forcing play a dominant role in decreasing summer precipitation over East Asia and South Asia.

Further, δH can be decomposed into δH_m and δH_{trans} . δH_m comprises four terms: δH_{Dy_v} , δH_{Dy_h} , δH_{Th_v} , and δH_{Th_h} , which represent dynamic and thermodynamic contributions to vertical and horizontal DSE advection, respectively. For the PDRMIP MMM (gray bars in Fig. 5), δH_{Dy_v} shows relatively larger negative changes than the other terms over both regions, and thus serves as the primary contributor to δH . Over East Asia, δH_{Th_h} and δH_{trans} exhibit negative changes and contribute to δH , whereas δH_{Dy_h} provides a partial offset (Fig. 5a). Over South Asia, δH_{Th_v} and δH_{Dy_h} act as negative contributors to δH , while δH_{trans} partially counteracts this reduction (Fig. 4b). However, some differences exist among the PDRMIP models. For instance, the contribution of δH_{trans} in NorESM1 (green asterisk) exceeds that of δH_m over East China, which is opposite to the results in the other two models (purple triangle and blue cross) (Fig. 5a).

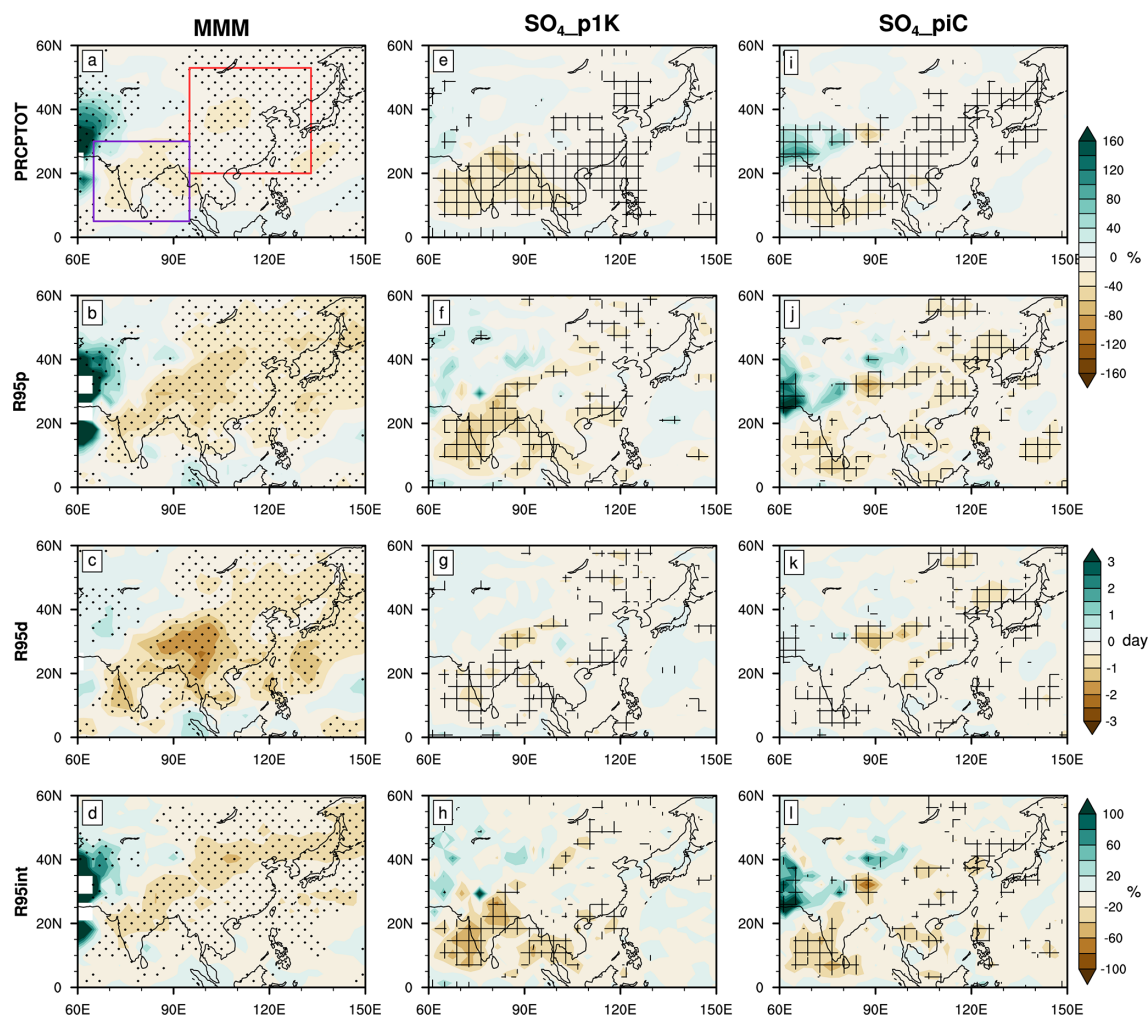


Figure 4. Spatial patterns of summer PRCPTOT (%), R95p (%), R95d (day) and R95int (%) responses to Asian SO_4 aerosol forcing, for (a–d) MMM, (e–h) SO_4_{p1K} , and (i–l) SO_4_{piC} . Black dots in MMM denote signals where at least three models agree. Black grid lines in (e)–(l) indicate regions where responses are statistically significant above the 90 % level based on a two-tailed Student's t test. The red and purple boxes in (a) delineate East Asia (EAS: 95–133° E, 20–53° N) and South Asia (SAS: 65–95° E, 5–30° N), respectively.

3D atmospheric outputs from FORTE2 were archived at three pressure levels (250, 500, and 850 hPa), allowing identification of the leading term within δH_{m} . In the FORTE2 simulations (blue and green bars in Fig. 5), the remaining three terms are consistently smaller in magnitude than δH_{Dy_v} in both simulations, a finding that aligns with the PDRMIP MMM results. Hence, the dynamic effect of vertical circulation (δH_{Dy_v}) is the dominant driver of the precipitation reduction over both East China and India.

Figure 6 shows the spatial patterns of summer responses for the relevant variables in the PDRMIP MMM and in the SO_4_{p1K} and SO_4_{piC} simulations of FORTE2. The decrease in δH_{Dy_v} is associated with anomalous descent (Fig. 6a–c), accompanied by high-pressure SLP anomalies (Fig. 6d–f). These SLP anomalies result from surface cooling induced by enhanced AOD forcing (Fig. 6g–i), which reduces incoming shortwave radiation (SW) (Fig. 6j–l). The

reduced SW partly results from direct scattering of SW through ARI, and partly from low cloud changes through ACI (Fig. 6m–n). The above analysis indicates that the responses to Asian sulfate forcing, along with the related physical processes simulated by FORTE2, agree with those of the PDRMIP models. The robustness of these responses confirms that FORTE2 provides a suitable tool for investigating precipitation responses under contrasting climate backgrounds.

3.3 Differences between the p1K and piC climate conditions and their potential causes

3.3.1 Both the ARI and ACI effects

Figure 7 presents the spatial patterns of the differences in summer precipitation responses to Asian sulfate forcing be-

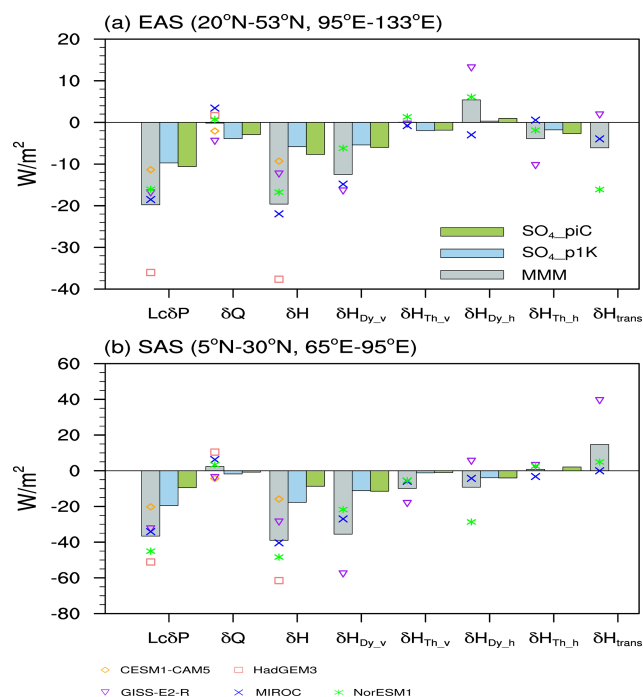


Figure 5. Summer area-averaged responses of the atmospheric energy budget terms over (a) East Asia (EAS) and (b) South Asia (SAS) for the MMM (gray bars), $\text{SO}_4\text{p1K}$ (blue bars), and SO_4piC (green bars). The symbols indicate the individual results from the five PDRMIP models. Note that only three of the five models are used for the decomposition analysis of δH (Eq. 2) due to data availability. Unit: W m^{-2} .

tween the p1K and piC climate states. Over East Asia, no significant difference in PRCPTOT is seen between the two climate conditions, whereas over northern India and northwestern China, sulfate forcing under p1K conditions produces a significantly stronger suppression of precipitation (Fig. 7a). The differences in R95p and R95int closely resemble those in PRCPTOT, but R95d exhibits no statistically significant change (Fig. 7b–d).

Figure 8 quantifies these differences over East Asia and South Asia. The response over East Asia is slightly weaker under the p1K climate than under the piC climate, though these differences do not attain 90 % statistical significance (Fig. 8a). Over South Asia, the increased Asian sulfate AOD forcing under the p1K conditions induces a substantially stronger fractional reduction than the equivalent forcing under the pre-industrial conditions, with differences of 14.5 % for PRCPTOT, 20 % for R95p, and 12.1 % for R95int (Fig. 8b). The differences in PRCPTOT, R95p, and R95int are statistically significant at the 95 % confidence level. For R95d, the reduction is 0.1 d greater under p1K than under piC, though this difference is not statistically significant. This suggests that the differences in total precipitation result primarily from changes in extreme precipitation over northern

India, manifesting as a pronounced reduction in intensity and a negligible reduction in frequency.

The precipitation responses to Asian sulfate forcing, in terms of both their spatial patterns and associated physical mechanisms, are consistent between the $\text{SO}_4\text{p1K}$ and SO_4piC simulations (Figs. 4–6). Nevertheless, the magnitude differences over northern India motivate a closer examination of the underlying mechanisms.

The atmospheric energy budget is diagnosed for the northern India region ($65\text{--}95^\circ\text{E}$, $20\text{--}30^\circ\text{N}$; black box in Fig. 9b). Figure 9a presents the decomposition of the energy budget terms. The results show that differences in the dynamic effect (δH) are the primary cause of the corresponding precipitation differences. Furthermore, the greater reduction of δH in $\text{SO}_4\text{p1K}$ relative to SO_4piC is largely attributable to an enhanced horizontal DSE gradient (δH_{Th_h}) in SO_4piC , which partially offsets the decreases in the other three terms. In contrast, $\text{SO}_4\text{p1K}$ exhibits a slight decrease in δH_{Th_h} , thereby contributing, albeit weakly, to the overall precipitation reduction. The other three terms show no significant differences between the two climate states. This contrast is further illustrated by the spatial distribution (Fig. 9b and c). In SO_4piC , an amplified increase in δH_{Th_h} over northern India and a marked decrease over northwestern India are observed (Fig. 9c), whereas these features are considerably weaker in $\text{SO}_4\text{p1K}$ (Fig. 9b), consistent with the significant precipitation differences over northern India between the two experiments (Fig. 7a).

Next, we examine the processes responsible for the contrasting behavior of δH_{Th_h} between the two climate states. In SO_4piC , the enhanced δH_{Th_h} over northern India is associated with the north–south surface temperature gradient, featuring warm anomalies over southern India and cold anomalies over northern India (Fig. 6h). Relative to the response in SO_4piC , the response in $\text{SO}_4\text{p1K}$ exhibits significant warm anomalies over northern India (Fig. 10a), corresponding to the weaker north–south surface temperature gradient and δH_{Th_h} in $\text{SO}_4\text{p1K}$ (Figs. 6h and 9b). These warm anomalies are driven by increased surface SW, which results from diminished convective cloud cover and stronger descent over northwestern India (Fig. 10b–d), indicating a dampened local meridional circulation in $\text{SO}_4\text{p1K}$ (Fig. 6b and c). This attenuation results from the increased lower troposphere stability in p1K compared to that in piC (Fig. 10e).

3.3.2 The respective roles of ARI and ACI effects and linearity

Figure 11 shows the spatial patterns of precipitation response to Asian sulfate AOD forcing in the ARI-only and ACI-only simulations under the two climate states, as well as their differences between these states. In the ARI-only simulations, no significant precipitation responses are evident over India for PRCPTOT and R95p, except for a localized enhancement over northwestern India (Fig. 11a–b and d–e). Differences

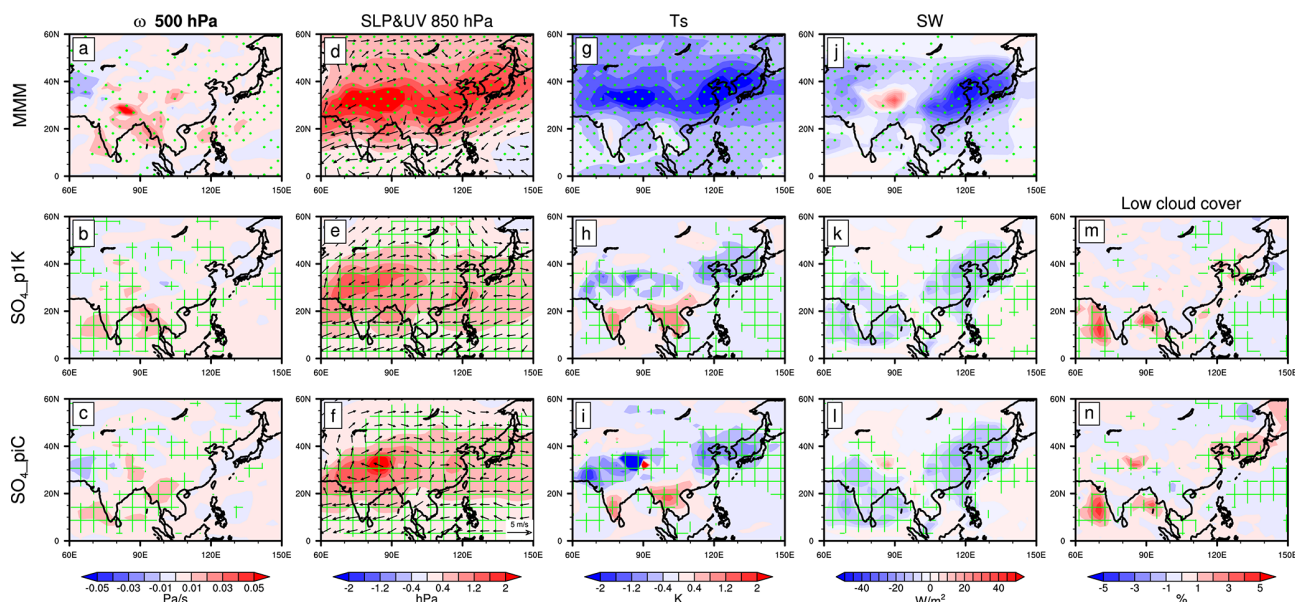


Figure 6. Summer spatial patterns of surface and atmospheric variable responses to Asian SO_4 aerosol forcing for the MMM, SO_4_{p1K} , and SO_4_{piC} : (a–c) ω at 500 hPa (Pa s^{-1}), (d–f) sea level pressure (SLP; hPa) and 850 hPa horizontal wind (m s^{-1}), (g–i) surface temperature (T_s ; K), (j–l) net surface shortwave radiation (W m^{-2}), and (m–n) low cloud cover (%) for SO_4_{p1K} and SO_4_{piC} only. Green dots in the MMM panels denote signals where at least three models agree. Green grid lines indicate regions where the responses are statistically significant above the 90 % confidence level based on a two-tailed Student's t -test.

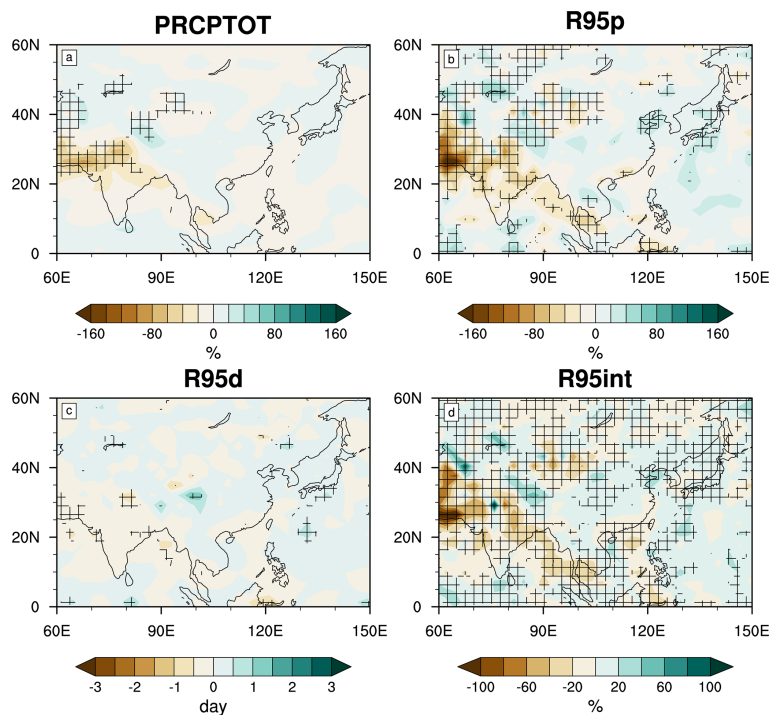


Figure 7. Spatial patterns of summer precipitation differences in responses to Asian SO_4 aerosol forcing between the p1K and piC climate states for (a) PRCPTOT (%), (b) R95p (%), (c) R95d (day), and (d) R95int (%). For PRCPTOT, R95p, and R95int, the difference is calculated as the relative response under p1K minus that under piC, i.e., $[(\text{SO}_4_{\text{p1K}} - \text{p1K}) / \text{p1K} - (\text{SO}_4_{\text{piC}} - \text{piC}) / \text{piC}]$; for R95d, the difference is the absolute response under p1K minus that under piC, i.e., $(\text{SO}_4_{\text{p1K}} - \text{p1K}) - (\text{SO}_4_{\text{piC}} - \text{piC})$. Black grid lines indicate regions where the differences are statistically significant above the 90 % confidence level based on a two-tailed Student's t -test.

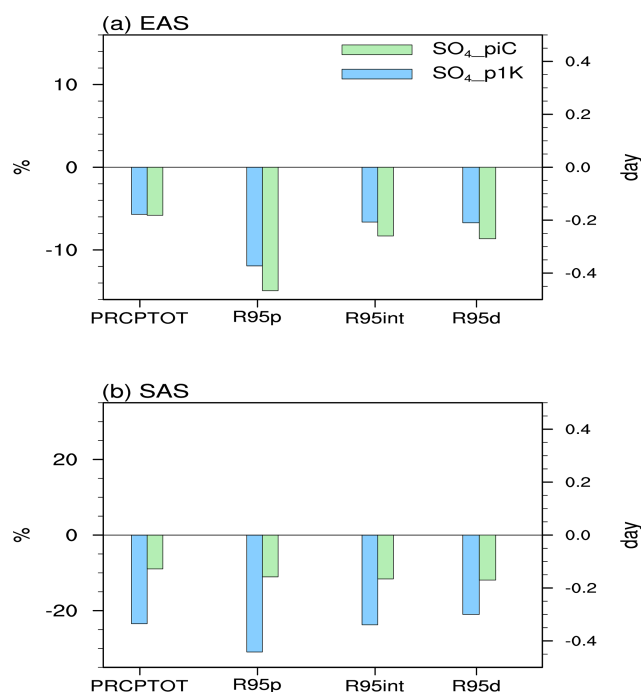


Figure 8. Summer area-averaged responses of PRCPTOT (%), R95p (%), R95d (day), and R95int (%) over (a) East Asia (EAS) and (b) South Asia (SAS) to Asian SO₄ aerosol forcing, shown for SO₄_p1K (blue bars) and SO₄_piC (green bars).

between the two climate states are also limited, except for a reduction in R95p over northern India in p1K relative to piC (Figs. 11c and f).

In both climate states, the ACI effect suppresses total and extreme precipitation over most of India (Fig. 11g–h and j–k), which is consistent with a previous study (Guo et al., 2015). The difference between the two climate states shows significantly more rainfall over northern India (Fig. 11i), indicating that this suppression caused by the ACI effect is significantly weaker over northern India in p1K compared to piC. This weakened suppression is also evident in extreme precipitation, where it exhibits an even stronger response than PRCPTOT (Fig. 11l). Hence, the precipitation response to ACI is significantly weakened over northern India under a warmer and wetter background climate in FORTE2.

Figure 12 provides insight into the possible causes of this weakened ACI-induced suppression. There are maximum centers of increased moisture and deep convection over northern India under the p1K state (Fig. 12a–b), which may enhance collision-coalescence efficiency or convective invigoration, promoting precipitation and offsetting the suppression (Rosenfeld et al., 2008; Chavez and Barros, 2023; Zhao et al., 2024). Besides, the surface SW response to Asian sulfate AOD does not differ significantly between the two climate states (Fig. 12c), indicating that the weakened precipitation suppression in p1K is not due to weaker radiative forc-

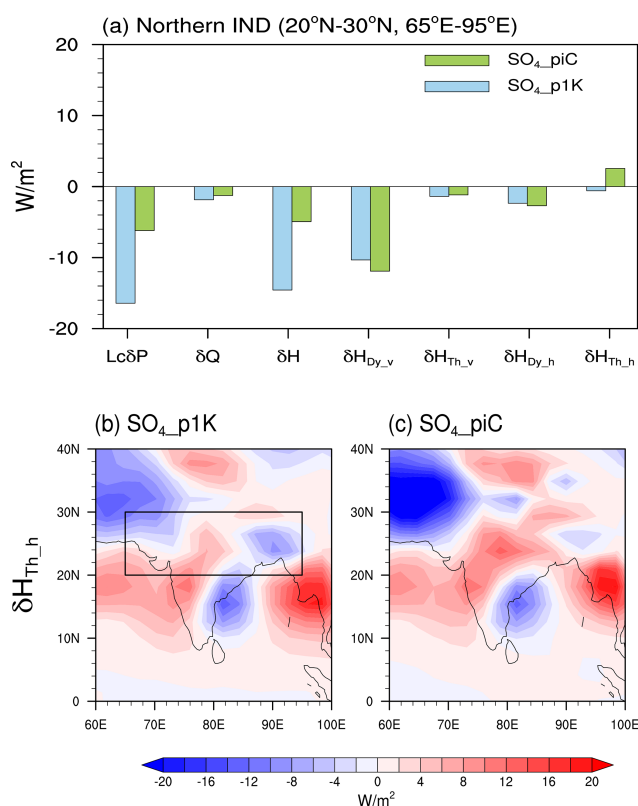


Figure 9. (a) Summer area-averaged responses of atmospheric energy budget terms over northern India for SO₄_p1K (blue bars) and SO₄_piC (green bars). (b–c) Summer spatial patterns of thermodynamic responses with changes in horizontal DSE gradients (δH_{Th_h}) for (b) SO₄_p1K and (c) SO₄_piC. The black box in (b) delineates northern India (65–95° E, 20–30° N). Units: W m⁻².

ing, but rather to the modulating effect of the warmer and wetter background climate.

To explore whether the ARI and ACI effects combine linearly, we compare their sum with the combined simulation under the two background states (Fig. 13). Under the piC state, this sum exhibits a decrease in precipitation over India and an increase over northwestern India (Fig. 13a). This spatial pattern resembles that of the combined simulation (Fig. 13b), and the differences between the sum and the combined simulation are insignificant (Fig. 13c), suggesting that the ARI and ACI effects combine approximately linearly in this case. In contrast, under the p1K state, the sum shows an increase over northern India and a decrease over central India (Fig. 13d). The combined simulation shows a decrease over India (Fig. 13e). Consequently, the differences reveal a significant decrease over northeastern India, indicating a notable nonlinear interaction between ARI and ACI under this background state (Fig. 13f). The nonlinearity may arise because the ARI effect induces surface cooling, which reduces water vapor through weakened evaporation, and reduces the Indian summer monsoon due to the weakened land–sea ther-

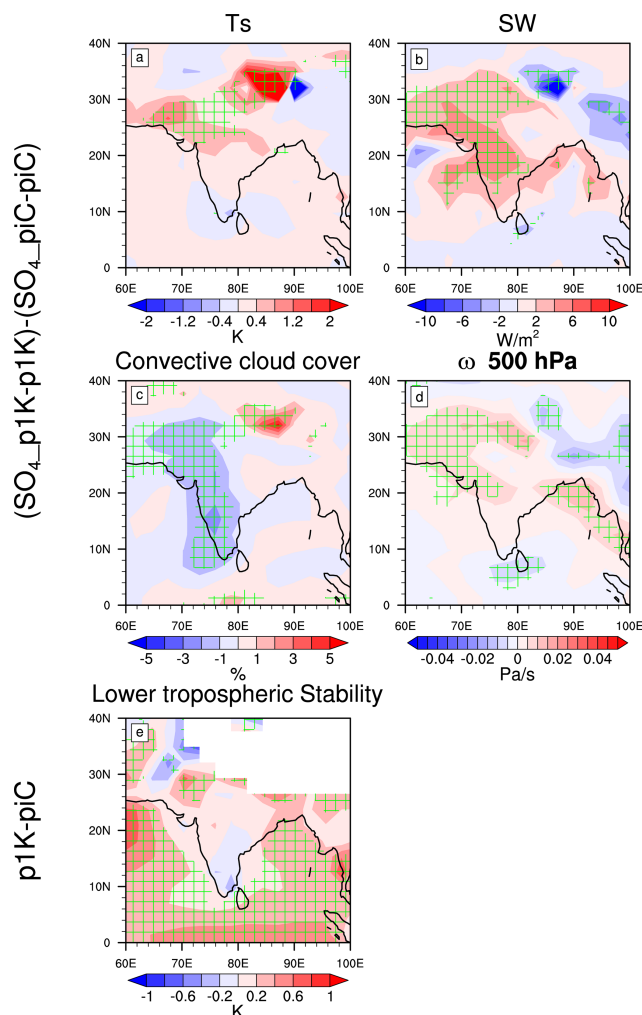


Figure 10. Summer spatial patterns of surface and atmospheric variable differences in the responses to Asian SO_4 aerosol forcing between the p1K and piC climate states, defined as $(\text{SO}_4_{\text{p1K}} - \text{p1K}) - (\text{SO}_4_{\text{piC}} - \text{piC})$: (a) T_s (K), (b) net surface SW (W m^{-2}), (c) convective cloud cover (%), and (d) ω at 500 hPa (Pa s^{-1}). (e) Summer lower tropospheric stability ($\theta_{850} - \theta_{\text{sfc}}$, where θ is potential temperature; K) differences between p1K and piC (p1K – piC). Green grid lines indicate regions where the responses are statistically significant above the 90 % confidence level based on a two-tailed Student's t -test.

mal contrast. These drier conditions may, in turn, favor the precipitation suppression by ACI. These mechanisms remain hypotheses that warrant further exploration.

Consequently, the precipitation difference between the two climate states derived from the sum of the individual effects (Fig. 13a and b) is of opposite sign to the difference seen in the combined simulation (Fig. 7b). This disparity indicates the critical role of the nonlinear interaction between the ARI and ACI effects under the p1K state in shaping the net precipitation differences between the two climate states.

4 Discussion

This study underscores the strong dependence of sulfate aerosol–precipitation relationships over northern India on the background climate state. Across the PDRMIP models and the FORTE2 simulations, the additional Asian sulfate aerosols generally suppress both summer mean and extreme precipitation over East and South Asia, consistent with previous studies (Liu et al., 2009; Guo et al., 2013; Westervelt et al., 2020). Furthermore, the FORTE2 experiments show that, under the same Asian sulfate AOD forcing, precipitation suppression over northern India is considerably stronger in the warmer p1K climate than in the piC climate. This finding extends the conventional view of aerosol–precipitation interactions, which has primarily emphasized the magnitude and characteristics of aerosol forcing, by demonstrating that the background climate can substantially modulate the precipitation response.

The stronger precipitation suppression under p1K can be understood from changes in the background thermodynamic and dynamical state. The warmer p1K climate is characterized by increased lower-tropospheric stability and a weakened north–south temperature gradient over northern India. These changes reduce the compensating contribution of horizontal thermal advection to the aerosol-induced precipitation response, allowing the dynamic vertical suppression to exert a stronger control on precipitation. Thus, the enhanced response under p1K does not simply reflect a stronger sensitivity to the same aerosol forcing, but rather results from the interaction between the aerosol-induced circulation response and the background thermodynamic state. This provides a physical explanation for why identical aerosol forcing can produce substantially different precipitation responses under contrasting climate states.

The dependence on the background climate state is further reflected in the interaction between ARI and ACI effects. ACI consistently contributes to precipitation suppression over India, but its contribution is weaker under the warmer and wetter p1K climate. More importantly, the combined ARI and ACI responses behave approximately linear under piC but become nonlinear under p1K. This indicates that the climate-state dependence cannot be explained simply by a change in the strength of an individual aerosol process. Instead, the warming alters the interaction between ARI and ACI, such that their combined effect is no longer adequately represented by the sum of their individual contributions. The transition from an approximately linear to a nonlinear ARI–ACI relationship therefore suggests that aerosol–climate interactions may change qualitatively as the background climate evolves, rather than simply scaling with aerosol forcing.

The comparison with PDRMIP places the mechanistic interpretation from FORTE2 in a broader multi-model context. Although the PDRMIP experiments cannot directly isolate the effect of background warming because they are conducted under a single climate state, their energy-budget re-

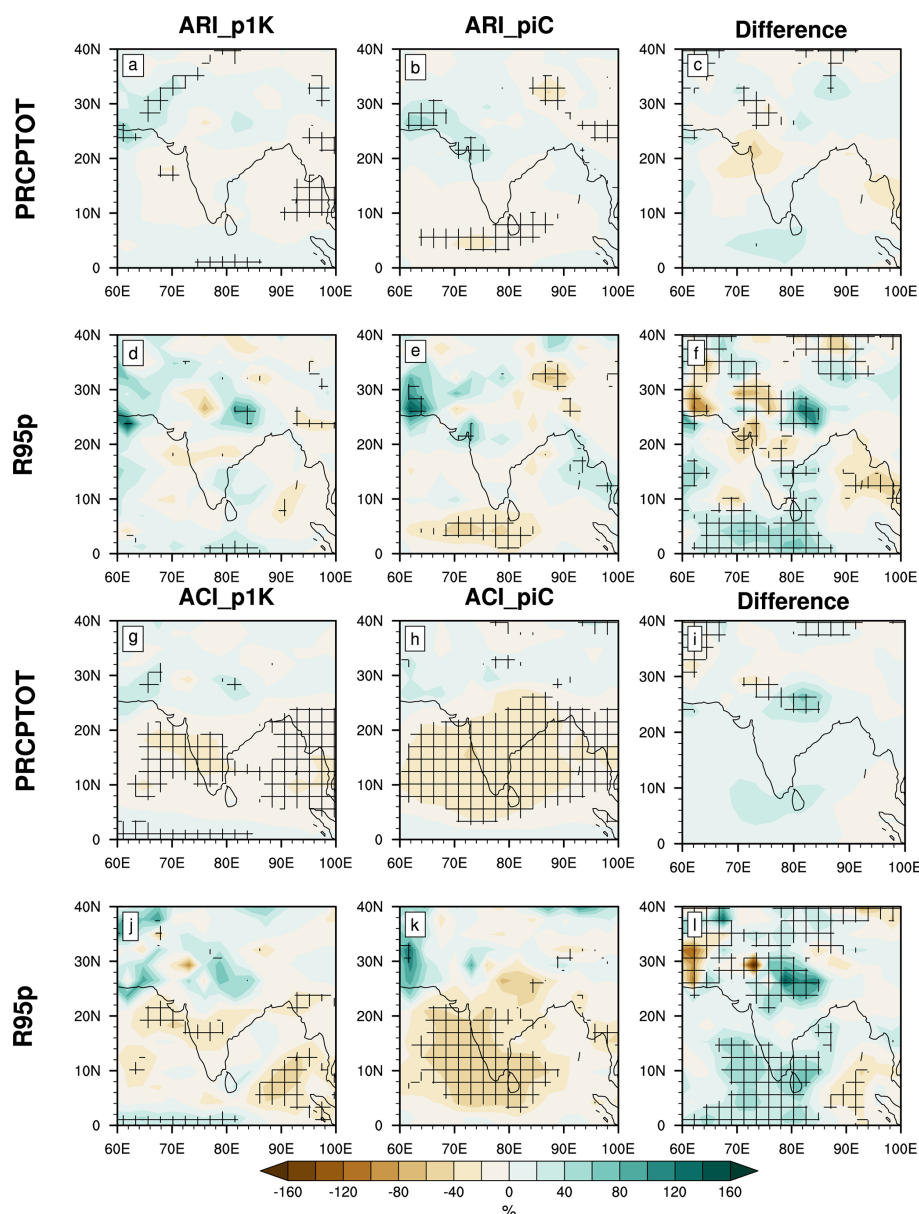


Figure 11. Spatial patterns of summer precipitation responses in (a, b, g, h) PRCPTOT and (d, e, j, k) R95p (%) to Asian SO_4 aerosol forcing (e.g., $(\text{ARI_p1K} - \text{p1K}) / \text{p1K}$, expressed as a percentage), and (c, f, i, l) precipitation response differences between the p1K and piC climate states (e.g., $(\text{ARI_p1K} - \text{p1K}) / \text{p1K} - (\text{ARI_piC} - \text{piC}) / \text{piC}$). (a, d) ARI_p1K; (b, e) ARI_piC; (c, f) precipitation response differences between $(\text{ARI_p1K} - \text{p1K}) / \text{p1K}$ and $(\text{ARI_piC} - \text{piC}) / \text{piC}$. (g, j) ACI_p1K; (h, k) ACI_piC; (i, l) precipitation response differences between $(\text{ACI_p1K} - \text{p1K}) / \text{p1K}$ and $(\text{ACI_piC} - \text{piC}) / \text{piC}$. Black grid lines indicate regions where the responses or their differences are statistically significant above the 90 % level based on a two-tailed Student's t -test.

sponses support the importance of dynamical vertical suppression identified in FORTE2. At the same time, differences among the PDRMIP models in the relative contributions of individual terms indicate that the detailed attribution of the precipitation response remains model dependent. Such differences may arise from variations in atmospheric resolution, circulation characteristics, physical parameterizations, and aerosol process representations.

Several limitations should be considered. FORTE2 does not include interactive wet deposition feedbacks, which may somewhat amplify the precipitation response to aerosols. In addition, the model exhibits a dry bias in climatological summer precipitation over India. Nevertheless, the consistency of the dominant response and dynamical mechanism with the PDRMIP models and previous sulfate aerosol perturbation studies supports the robustness of the major findings.

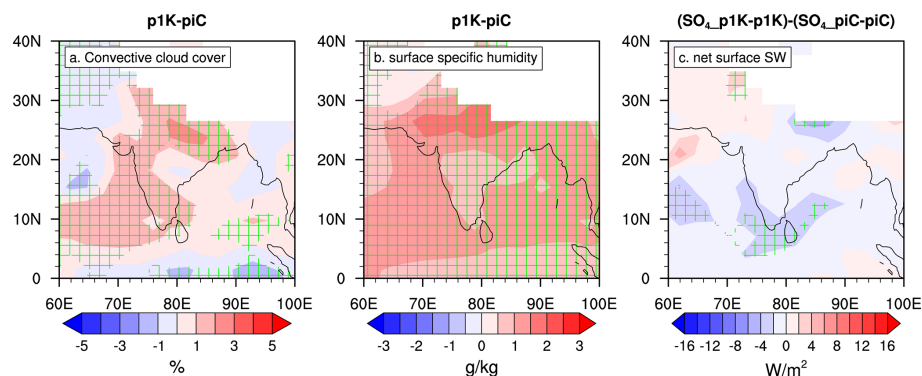


Figure 12. Spatial patterns of summer meteorological variable differences between p1K and piC ($p1K - piC$) for (a) convective cloud cover (%) and (b) surface specific humidity ($g\ kg^{-1}$). (c) Net surface shortwave radiation (SW) response differences to Asian SO_4 aerosol forcing between the two climate states ($SO_4_{p1K} - p1K - (SO_4_{piC} - piC)$) ($W\ m^{-2}$). Green grid lines indicate regions where the differences are statistically significant above the 90 % confidence level based on a two-tailed Student's *t*-test.

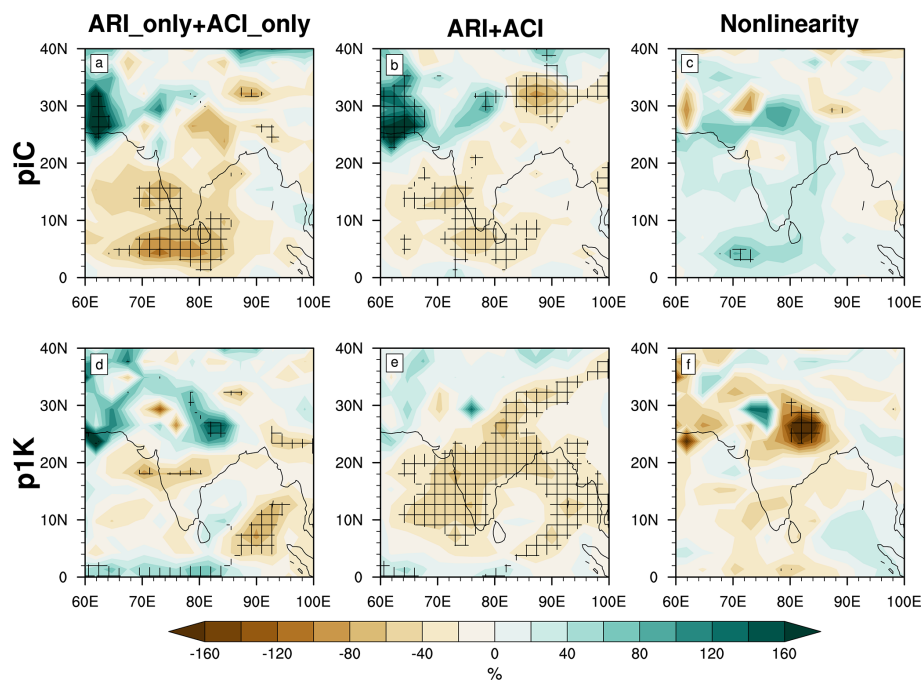


Figure 13. Spatial patterns of summer R95p responses to Asian SO_4 aerosol forcing for the piC (top) and p1K (bottom) climate states: (a, d) sum of R95p responses from the individual ARI_only and ACI_only simulations, (b, e) R95p responses from the combined ARI + ACI simulation, and (c, f) R95p response differences between the two (b and e minus a and d), quantifying the nonlinearity. Black grid lines indicate regions where the differences are statistically significant above the 90 % confidence level based on a two-tailed Student's *t*-test.

The FORTE2 experiments also provide a useful framework for isolating the influence of background climate state, which cannot be directly assessed from the single-background-state PDRMIP experiments.

The stronger aerosol-induced precipitation suppression under the warmer p1K climate may have implications for precipitation changes associated with the observed ongoing decline in sulfate aerosol emissions over East Asia (Samset et al., 2019). If the response to aerosol reduction is approximately symmetric with and opposite to the response

to aerosol addition, a warmer background climate could enhance the precipitation increase over northern India. However, this reversibility has not been directly tested in the present study, and this implication should therefore be regarded as a hypothesis rather than a direct projection. Further experiments with aerosol reduction and different background warming levels would be valuable for testing this hypothesis and determining whether the climate-state dependence identified here also applies to aerosol reductions.

5 Conclusion

In this study, we examined the responses of Asian summer mean and extreme precipitation to the additional Asian sulfate aerosols using both the FORTE2 simulations and PDRMIP multi-model simulations. Using the FORTE2 simulations, we further investigated how the precipitation responses differ between the pre-industrial +1 K (p1K) and pre-industrial (piC) climate conditions and explored the associated physical mechanisms.

The model evaluation indicates that both the PDRMIP models and FORTE2 reasonably reproduce the observed spatial patterns of precipitation and large-scale atmospheric circulation. Increased Asian sulfate forcing significantly reduces summer mean and extreme precipitation over East Asia and South Asia, with reductions in the frequency and intensity of extreme precipitation, and with extreme precipitation showing a stronger response than mean precipitation. These precipitation reductions are driven predominantly by the dynamic vertical suppression induced by aerosol-related surface cooling and the resulting circulation changes. FORTE2 is qualitatively consistent with the PDRMIP models in the major regional response characteristics and the dominant physical mechanism, supporting the robustness of the simulated aerosol-precipitation response.

Under the same Asian sulfate AOD forcing, the precipitation suppression over northern India is significantly stronger under p1K conditions than under piC. This difference stems from a weakened north–south temperature gradient due to increased lower-tropospheric stability in the p1K state, which reduces the counteracting effect of horizontal thermal advection on the vertical dynamical suppression, thereby allowing the latter to dominate more effectively. Additionally, the combined ARI and ACI responses are approximately linear under piC but become nonlinear under p1K, indicating that the interaction between these aerosol processes also depends on the background climate state.

These findings suggest that the precipitation response to sulfate aerosols is influenced not only by the magnitude of aerosol forcing but also by the background climate state in which the forcing occurs. Whether this climate-state dependence is reversible under aerosol reductions remains unresolved and warrants further investigation using aerosol reduction experiments under different background warming levels. Further studies using more comprehensive models would also be valuable for examining whether the climate-state dependence identified here is robust across different model frameworks.

Data availability. The ERA5 datasets are obtained from <https://doi.org/10.24381/cds.6860a573> (Hersbach et al., 2023a) and <https://doi.org/10.24381/cds.4991cf48> (Hersbach et al., 2023b). The PDRMIP data can be accessed through the World Data Center for Climate (WDCC) data server at

https://doi.org/10.26050/WDCC/PDRMIP_2012-2021 (Andrews et al., 2021). Data of the FORTE2 experiments reported in this paper are available without restriction on reasonable request from Camilla W. Stjern at CICERO Center for International Climate Research.

Supplement. The supplement related to this article is available online at <https://doi.org/10.5194/acp-26-15037-2026-supplement>.

Author contributions. FL, MJ, BHS and LJW designed the study. CWS, LJW, MJ ran the model simulations. FL carried out the analysis and visualized the results. All authors discussed the results and edited the paper.

Competing interests. At least one of the (co-)authors is a member of the editorial board of *Atmospheric Chemistry and Physics*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.

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