

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

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To be submitted to Atmospheric Chemistry and Physics

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 ~~the impact of Asian sulfate aerosols on regional summer extreme precipitation~~these impacts under ~~both~~ pre-industrial and pre-industrial +1K climate ~~states~~, using the reduced-complexity climate model Fast Ocean Rapid Troposphere Experiment version 2 (~~FORTE2~~) with the Systematic Regional Aerosol Perturbations simulations. Results show that increased Asian sulfate aerosols reduce ~~extreme precipitation, characterized by lower the summer mean and frequency and weaker intensity~~extreme precipitation over East and South Asia in both climates, ~~but with the stronger~~ suppression ~~is more pronounced~~ over northern India in the +1K climate. ~~The a~~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 ~~state~~, ~~an~~ the increased horizontal dry static energy (DSE) gradient partially offsets the aerosol-induced dynamic suppression over northern India. Under the +1K climate, higher atmospheric static stability weakens the local meridional circulation induced by aerosol forcing, thereby reducing the meridional temperature gradient and ~~thus~~ diminishing the offsetting effect, making the dynamic suppression more dominant. Further analysis indicates that this difference in precipitation responses ~~between the two climates~~ results from the nonlinear interaction~~effect~~ between the aerosol-radiation and aerosol-cloud interactions under the +1K climate, whereas the two effects combine approximately linearly under the pre-industrial climate. This study suggests that the reduction in continued global warming alone will exacerbate Asian sulfate aerosols' weakening of precipitation, including extremes, over northern India caused by Asian sulfate aerosols is amplified under a warmer climate background. This implies that future ~~reductions in~~ 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. ~~These emissions have significantly impacted—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., 2018; Dong et al., 2019; Wilcox et al., 2020; Monerie et al., 2022; Lang et al., 2025; Yang et al., 2026). ~~During the rapid industrialization period~~ 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). However, the impacts of aerosols exhibit marked regional differences and uncertainties. For instance, Lin et al. (2018) have found that anthropogenic aerosols are a primary cause of reduced extreme precipitation over North China and India, mainly through ACI, which decreases cloud droplet effective radius and increases cloud droplet number concentration, thereby enhancing cloud albedo and cloud lifetime. This subsequently reduces surface solar radiation and temperature, weakening the land-sea thermal contrast and moisture transport. Guo et al. (2023) have shown that anthropogenic aerosol forcing is the dominant driver of increased summer extreme precipitation intensity and frequency in Northwest China, primarily through the dynamic enhancement of moisture flux convergence.

In recent decades, 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 droplet coalescence and precipitation (Zou et al., 2025). Under future scenarios, further aerosol emission reductions are expected to increase the extreme precipitation over the Asian monsoon region (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, 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 aerosol-sulfate-climate interactions. Hence, the sulfate effect on extreme precipitation may differ across climate backgrounds. Yet, however,

whether and how ~~the this effect influence of anthropogenic aerosols on Asian extreme precipitation~~ varies under different global warming levels with different climate backgrounds remains unclear, hindering our ability to project future regional climate risks associated with sulfate emission changes. Understanding this question is helpful for more accurately projecting the future impact of anthropogenic aerosols on climate.

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 ~~extreme 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 provides a ~~summary and~~ discussion and conclusion.

2. ~~Models~~Models, Simulations-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 35 sigma 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°×2° 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 ~~(Webb, 1996), 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 adjustments terms.

Building on the FORTE2 platform, Stjern et al. (2024) designed and implemented a suite of Systematic Regional Aerosol Perturbations experiments. For brevity, hereafter hereafter we refer to these simulations collectively as FORTE2, referred to as SyRAP-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 ~~SyRAP-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 SO₄ mixture drops below 5×10^{-9} kg kg⁻¹. In areas with complex terrain, additional constraints are enforced to avoid unrealistic aerosol vertical distributions, with-ensure $\sigma_{\min}$ constrained to remains below 0.75 and $p_{\min}$ to stays 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 SO₄), absorbing aerosols (BC and OC), and scattering aerosols (SO₄). 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 SyRAP-FORTE2 simulations is available in Stjern et al. (2024).

The SyRAP-FORTE2 experiments-simulations used in this study are summarized in include (Table 1). They include (1) two baseline simulations without aerosol forcing: one with CO₂ concentrations at pre-industrial levels (piC, 280 ppmv), and one with elevated CO₂ at a level (p1K, 500 ppmv). In this model, the p1K simulation at yields a global-mean warming of approximately 1K relative to pre-industrial conditions in this model piC. In addition, (2) six perturbation simulations were performed with SO₄ AOD forcing added over Asia (Fig. 1a), encompassing These comprise combined (ARI and ACI effects (ARI+ACI)), ARI-only and ACI-only effects, all each conducted 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–through 200) used for the analysis. For the climate response, Subtracting-subtracting each baseline from its corresponding perturbation (e.g., SO₄ p1K-p1K or SO₄ 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.,

(SO₄_p1K-p1K) -(SO₄_piC-piC), which reveals how a warmer, higher-CO₂ climate modulates the sulfate-aerosol-induced responses examined here.

For ARI, the prescribed SO₄ 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 μm 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, ~~10× present-day~~ Asian SO₄ emissions/concentrations are set to ten times their year-2000 levels, while greenhouse gases are fixed at year-2000 levels. ~~experiments from five global climate models (CESM1-CAM5, GISS-E2-R, HadGEM3, MIROC-SPRINTARS, and NorESM1; Table 2), each~~ Each is compared against the corresponding model's ~~its own year-2000 baseline experiment simulation~~ with year-2000 ~~present-day~~ aerosols and greenhouse gases. The climate response to sulfate aerosols is quantified as the difference between the perturbation and baseline simulations. ~~The PDRMIP models are fully coupled earth system models and are substantially more comprehensive than the FORTE2 framework. Two important caveats~~ It should be noted ~~that~~. First, the PDRMIP simulations prescribe a much ~~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 ~~SO₄ perturbation, with a regional summer multi-model mean (MMM) AOD value 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 only focuses on the sign and spatial pattern of the responses, rather than ~~not their~~ magnitudes, ~~in the subsequent analysis, of the responses should be compared, which would support the robustness of the FORTE2 results. Second~~ 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° × 0.25° 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/day) 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 precipitation 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): $\delta H = \delta H_m + \delta H_{trans}$ (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):

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

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}), 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~~ the ability of the models to simulate precipitation patterns and physically plausible large-scale circulation, we compare the FORTE2 p1K baseline and the PDRMIP ~~year-2000~~ 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 CO₂ 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 PRCPTOT, with maxima over northern India, Southeast Asia and South China (Fig. 2a and 2b). R95d is generally higher characterized by approximately five extremely wet days in the tropics thanal regions at, and three in mid- to high-latitudes, with a local maximum over Northwest China (Fig. 2c). ~~The highest R95int shows its highest values values are concentrated~~ over the Asian summer monsoon region (Fig. 2d). The PDRMIP MMM reasonably reproduces the observed spatial patterns of PRCPTOT and extreme precipitation, with pattern correlation coefficients exceeding 0.85 (Fig. 2e–h). ~~All~~The individual PDRMIP models show pattern correlations above 0.6 for these indices, with indicating reasonable agreement with the observed spatial patterns values ranging from 0.70 (GISS-E2-R) to 0.85 (HadGEM3) for PRCPTOT, 0.69 to 0.82 for R95p, 0.69 to 0.89 for R95d, and 0.64 to 0.80 for R95int, all of which are, as expected, lower than the MMM skill. FORTE2 also reasonably simulates these precipitation indices, although its pattern correlations are generally exhibits relatively 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 pattern correlation coefficients for PRCPTOT (0.56) and R95p (0.63), with notable dry biases over India (Fig. 2i and 2j). ~~FORTE2 also shows a low pattern correlation coefficient of 0.39 for R95d (0.39), largely associated with its relatively low values in the tropics, while, particularly in tropical regions (Fig. 2k). For R95int shows a comparatively higher correlation of 0.68, FORTE2 achieves a pattern correlation coefficient of 0.68 (Fig. 2k–l), indicating a reasonable representation of the spatial structure. These systematic discrepancies in FORTE2, particularly the dry biases and low spatial correlation for extreme wet days in the tropics, are likely due to the convective parameterization scheme employed in the model. However, it should be noted that Tsome of these~~ discrepancies may reflect bothstem from the differing prescribed external forcingbackground climate states among the three datasets and limitations in the model’s convective parameterization scheme. ~~The p1K simulation in FORTE2 has no aerosol and the CO₂ concentration~~

slightly higher than present-day levels, whereas the aerosol and greenhouse gas forcing in PDRMIP is close to observation.

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 summer atmospheric circulation features relevant to the Asian summer monsoon patterns compared to ERA5, including capturing the land-sea pressure gradient, the continental low, the western North Pacific Subtropical High, and the associated distributions of 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 much stronger continental low and a weaker western North Pacific Subtropical High relative to both the PDRMIP MMM and ERA5 (Fig. 3a-c). This difference likely reflects the strength of the trade winds, Hadley and Walker circulations in the model, which are closely tied to the untuned convective parameterizations and their coupling with SST. The simulated horizontal winds and vertical wind fields also show regional differences, particularly over the tropical Pacific, the Tibetan Plateau, and the tropical Indian Ocean (Fig. 3d-f). In FORTE2, there is an excessive eastward extension of the westerlies over the western tropical Pacific and weakened easterlies over the tropical Pacific. Compared to ERA5, both the PDRMIP MMM and FORTE2 underestimate upward motion over the western tropical Pacific. Unlike ERA5 and the PDRMIP MMM, FORTE2 overestimates upward motion over the eastern Tibetan Plateau, corresponding to its wet precipitation biases in the region (Fig. 3d-f). Additionally, FORTE2 fails to simulate the upward motion over the tropical Indian Ocean seen in ERA5 and the PDRMIP MMM.

These biases in the FORTE2 p1K simulation mirror those found in its piC simulation (Luo et al., 2025). 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), 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 figure 4 for the PDRMIP MMM and the SO₄_p1K and SO₄_piC 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~~here~~. 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 PDRMIP 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, its broadly reproduces the key regional sign patterns of results show high agreement with 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 Eq. 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).

3D atmospheric outputs from FORTE2 were archived at three pressure levels (250 hPa, 500 hPa, 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 between 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 precipitation responses to Asian sulfate forcing, in terms of both their spatial patterns and associated physical mechanisms, are consistent between the SO₄-p1K and SO₄-piC simulations (Fig. 4-6). Nevertheless, some differences in the magnitude of the response can be found between the two climate states. Specifically, no significant difference in PRCPTOT is seen between the response to sulfate in p1K and piC climate conditions over East Asia, whereas a significantly stronger suppression of precipitation is evident over northern India and northwestern China under the p1K conditions (Fig. 7a). The differences in R95p and R95int closely resemble those in PRCPTOT, but R95d exhibits no statistically significant change (Fig. 7b-d). Quantitatively, 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 day 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 SO₄_p1K and SO₄_piC simulations (Fig. 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 ~~used to investigate the potential mechanisms underlying the differing precipitation responses over northern India~~ region (65°-95°E, 20°-30°N; black box in Fig. 9b). Figure 9a presents the decomposition of the energy budget terms. ~~As shown in figure 9a~~ 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 SO₄_p1K relative to SO₄_piC is largely attributable to an enhanced ~~the~~ horizontal DSE gradient ($\delta H_{Th,h}$) in SO₄_piC, which partially offsets the decreases in the other three terms. In contrast, SO₄_p1K exhibits a slight decrease in $\delta H_{Th,h}$, 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 SO₄_piC, an amplified increase in $\delta H_{Th,h}$ over northern India and a marked decrease over northwestern India are observed (Fig. 9c), whereas these features are considerably weaker in SO₄_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_4_piC , 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. 6i~~10ha~~). ~~The warm anomalies over southern India are induced by decreased precipitation and subsidence (Fig. 10b), while the cold anomalies over northern India result from reduced surface SW caused by the increased sulfate AOD forcing and enhanced convective cloud cover over northwestern India (Fig. 10c–d). The increased convection is linked to ascent triggered by the subsidence over southern India (Fig. 10c–d).~~ Relative to the response in SO_4_piC , the response in SO_4_p1K exhibits significant weaker cold/warm anomalies over northern India (Fig. 10a), corresponding to the weaker north–south surface temperature gradient (Fig. 10e) and δH_{Th_h} in SO_4_p1K (Fig. 6h and 9b). These weaker cold/warm anomalies are consistent with driven by reduced/increased surface SW dimming, which results from weaker ascent, and diminished convective cloud cover and stronger descent over northwestern India (Fig. 10f–h~~b–d~~), indicating a dampened local meridional circulation in SO_4_p1K (Fig. 6b and 6c). This attenuation results from the increased lower troposphere stability in $p1K$ compared to that in piC (Fig. 10i~~10ei~~).

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 11d–e). Differences between the two climate states are also limited, except for a reduction ~~Although the ARI effect exerts a negligible influence on the Indian summer precipitation, it nonetheless induces a discernible difference in the response between the two climate states, marked~~

513 ~~by a reduction, especially~~ in R95p over northern India in p1K relative to piC (Fig. 11c
514 and 11f).

515 In both climate states, the ACI effect suppresses total and extreme precipitation
516 over most of India ~~by increasing cloud albedo and lifetime~~ (Fig. 11g-h and 11j-k), which
517 is consistent with a previous study (Guo et al., 2015). The difference between the two
518 climate states shows significantly more rainfall over northern India (Fig. 11i),
519 indicating that tThis suppression caused by the ACI effect is significantly weaker over
520 northern India in p1K compared to piC ~~(Fig. 11i)~~. This weakened suppression is also
521 evident in extreme precipitation, where it exhibits an even stronger response than
522 PRCPTOT (Fig. 11l). Hence, the precipitation response to ACI is significantly
523 weakened over northern India under a warmer and wetter background climate in
524 FORTE2.—

525 Figure 12 provides insight into the possible causes of this weakened ACI-induced
526 suppression. There are maximum centers of~~This may be because abundant increased~~
527 moisture ~~and~~ deep convection over northern India under the p1K state (Fig. 12a-b),
528 which may enhances collision-coalescence efficiency or convective invigoration,
529 promoting precipitation and offsetting the suppression (Rosenfeld et al., 2008; Chavez
530 and Barros, 2023; Zhao et al., 2025). Besides, the surface SW response to Asian sulfate
531 AOD does not differ significantly between the two climate states (Fig. 12c), indicating
532 that the weakened precipitation suppression in p1K is not due to ~~a~~-weaker radiative
533 forcing, but rather to the modulating effect of the warmer and wetter background
534 climate.

535 To explore whether the ARI and ACI effects combine linearly, we compare their
536 sum with the combined simulation under the two background states (Fig. 13). Under
537 the piC state, this sum exhibits a decrease in precipitation over India and an increase
538 over northwestern India (Fig. 13a). This spatial pattern resembles that of the combined
539 simulation (Fig. 13b), and the differences between the sum and the combined
540 simulation are insignificant (Fig. 13c), suggesting that the ARI and ACI effects combine
541 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, there, the differences relative to the combined simulation reveal a significant decrease over northeastern India (Fig. 13e), 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 moisture–water vapor through weakened evaporation, and reduces the Indian summer monsoon due to the weakened land–sea thermal contrast. These drier conditions may, in turn, favor the precipitation suppression by ACI. These mechanisms ~~remains~~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 13b) is of opposite sign to the difference seen in the combined simulation (Fig. 7ba). 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

571 temperature gradient over northern India. These changes reduce the compensating
572 contribution of horizontal thermal advection to the aerosol-induced precipitation
573 response, allowing the dynamic vertical suppression to exert a stronger control on
574 precipitation. Thus, the enhanced response under p1K does not simply reflect a stronger
575 sensitivity to the same aerosol forcing, but rather results from the interaction between
576 the aerosol-induced circulation response and the background thermodynamic state. This
577 provides a physical explanation for why identical aerosol forcing can produce
578 substantially different precipitation responses under contrasting climate states.

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

591 The comparison with PDRMIP places the mechanistic interpretation from
592 FORTE2 in a broader multi-model context. Although the PDRMIP experiments cannot
593 directly isolate the effect of background warming because they are conducted under a
594 single climate state, their energy-budget responses support the importance of dynamical
595 vertical suppression identified in FORTE2. At the same time, differences among the
596 PDRMIP models in the relative contributions of individual terms indicate that the
597 detailed attribution of the precipitation response remains model dependent. Such
598 differences may arise from variations in atmospheric resolution, circulation
599 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. 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.

4.5. Conclusion

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

The model evaluation indicates that both the PDRMIP models and FORTE2 reasonably reproduce the observed spatial patterns of precipitation and large-scale atmospheric circulation. Our main findings are summarized as follows.

A comparison with the PDRMIP multi-model simulations demonstrates that FORTE2 reasonably reproduces the response of summer mean and extreme precipitation over Asia to regional sulfate forcing and its underlying physical processes. Increased Asian sulfate forcing significantly reduces summer mean and extreme precipitation – the frequency and intensity of summer extreme precipitation over East Asia and South Asia, with reductions in the frequency and intensity of. While the spatial patterns of these changes are consistent with those of mean precipitation, the magnitude of the response in extreme precipitation, and with extreme precipitation showing a stronger response than mean precipitation. R95p is considerably larger, suggesting that extreme precipitation exhibits heightened sensitivity to sulfate forcing relative to mean precipitation. Energy budget analysis reveals that precipitation these precipitation reductions over East Asia and South Asia are driven predominantly by changes in DSE flux divergence (δH), with the dynamic vertical suppression advection induced by aerosol-related surface cooling and the resulting circulation changes term (δH_{Dy-v}) identified as the leading contributor in both the PDRMIP MMM and FORTE2 simulations. Physically, this reflects anomalous descent associated with surface high-pressure anomalies induced by surface cooling via ARI and ACI effects. 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. Although there is high agreement across the models, some differences exist, especially for changes in horizontal winds (δH_{Dy-h}) and the transient term (δH_{trans}). These differences may be related to the horizontal and vertical resolutions in the PDRMIP models.

Under the same Asian sulfate AOD forcing, The the precipitation responses to same Asian sulfate AOD forcing exhibit consistent spatial patterns but divergent magnitudes between p1K and piC climates, with significantly stronger suppression over

northern India is significantly stronger under p1K conditions than under piC (14.5% for PRCPTOT, 20% for R95p). The difference manifests as a pronounced reduction in intensity (12.1% for R95int) but a negligible reduction in frequency. This enhanced response over northern India difference stems from a weakened differences in the dynamic response, specifically the horizontal DSE gradient term (δH_{T-H}). In SO_4 piC, a stronger north-south temperature gradient due to increased lower-tropospheric stability in the p1K state amplifies δH_{T-H} over northern India, which reduces the counteracting effect of horizontal thermal advection on the vertical dynamical suppression, thereby allowing the latter to dominate more effectively, thereby partially offsetting the precipitation reduction. Additionally, the combined – However, under SO_4 p1K, increased lower-tropospheric stability weakens the local meridional circulation and diminishes this offset, yielding a larger net reduction in precipitation.

The findings further reveal distinct roles of ARI and ACI under the two climate states. The ARI-only effect negligibly influences Indian summer precipitation, whereas the ACI-only effect consistently suppresses it. Notably, this ACI-induced suppression weakens significantly over northern India under the warmer, wetter p1K state relative to the cooler piC state, likely due to the more abundant moisture or stronger deep convection in the p1K state. Critically, 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 two effects combine linearly under piC but nonlinearly under p1K, suggesting a change in the ARI-ACI interaction under the background climate. Consequently, the precipitation difference between the two climate states derived from summing the individual ARI and ACI effects is of opposite sign to that obtained from the combined ARI and ACI simulation.

5.—Discussion

These results findings suggest indicate 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. ~~under global warming, the background climate amplifies suppression of precipitation, including extreme events, by Asian sulfate aerosols over northern India through its influence on atmospheric stability and circulation strength. This amplification is independent of changes in the aerosol burden itself. If this modulating effect also holds for sulfate aerosol reductions and is approximately linear, northern India is likely to experience more severe extreme heavy precipitation events in the future. This is because ongoing reductions in sulfate aerosol emissions from air quality measures, particularly in East Asia, directly enhance precipitation, and continued global warming both intensifies precipitation directly and amplifies the precipitation increase driven by aerosol reductions.~~

~~This study underscores the strong dependence of aerosol-precipitation relationships on the background climate. However, FORTE2 is a simplified climate model, while it includes most of the key processes, certain limitations remain, such as the lack of wet deposition feedbacks, and biases in simulating the Indian summer precipitation. The findings reported here should therefore be tested with more comprehensive models to establish their robustness.~~

Acknowledgements. Some of the research presented in this paper was carried out on the High Performance Computing Cluster supported by the Research and Specialist Computing Support service at the University of East Anglia. We acknowledge the Center for Advanced Study in Oslo, Norway that funded and hosted our HETCLIF centre during the academic year of 2023/24. F. L. is supported by the National Natural Science Foundation of China (Grant 42305049). B. H. S., C. W. S., L. J. W., M. J. and R. J. A were supported by the Research Council of Norway [Grant 324182 (CA3THY)]. The authors acknowledge the editor, Dr. N'Datchoh Evelyne Touré, and the two anonymous reviewers for their valuable comments that improved the paper.

Data availability. The ERA5 datasets are obtained from <https://cds.climate.copernicus.eu/datasets>. 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. Data of the ~~SyRAP~~-FORTE2 experiments reported in this paper are available without restriction on reasonable request from Camilla W. Stjern at CICERO Center for International Climate Research.

Author contribution. F. L., M. J., B. H. S. and L. J. W. designed the study. C. W. S., L. J. W., M. J. ran the model simulations. F. L. carried out the analysis and visualized the results. All authors discussed the results and edited the paper.

Competing interests. L. J. W. is a member of the editorial board of *Atmospheric Chemistry and Physics*.

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Table 1. Summary of ~~SyRAP~~-FORTE2 simulations used in the study

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

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

902 **Table 2.** Details of the five models in PDRMIP

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

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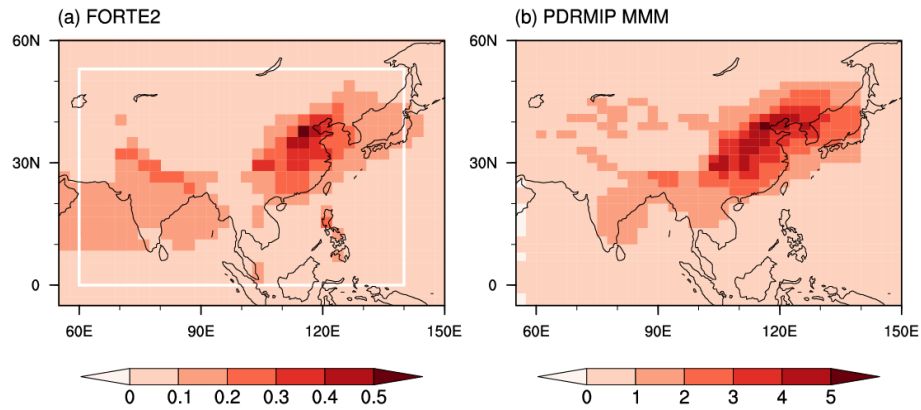


Figure 1. Summer (June-August) sulfate AOD spatial patterns in (a) FORTE2 and (b) PDRMIP MMM. The white box marks the Asian region (60°-140°E, 0°-53°N), over which ACI is parameterized for sulfate perturbations in FORTE2.

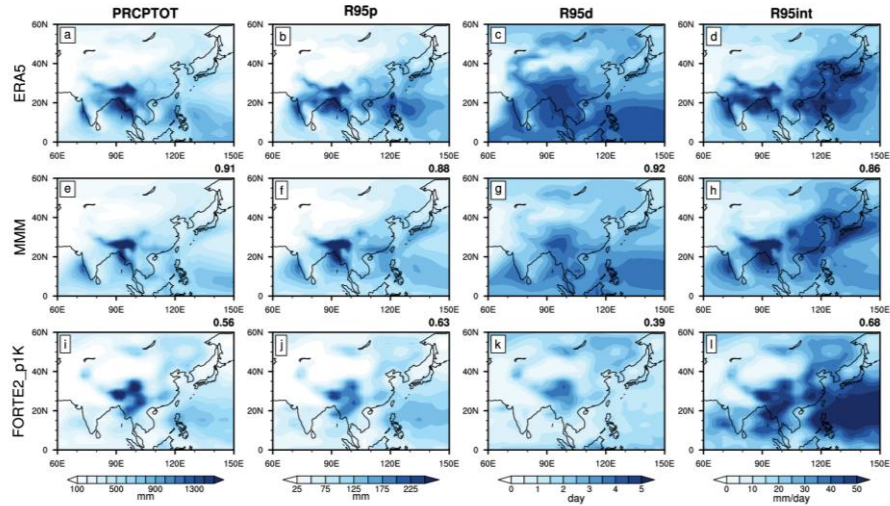


Figure 2. Comparison of climatological summer (June-August) PRCPTOT (mm), R95p (mm), R95d (day) and R95int (mm/day) from (a-d) ERA5 (1981–2010), (e-h) the PDRMIP MMM baseline simulation and (i-l) the FORTE2 p1K baseline simulation. The numbers in the upper right corner represent the spatial correlation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

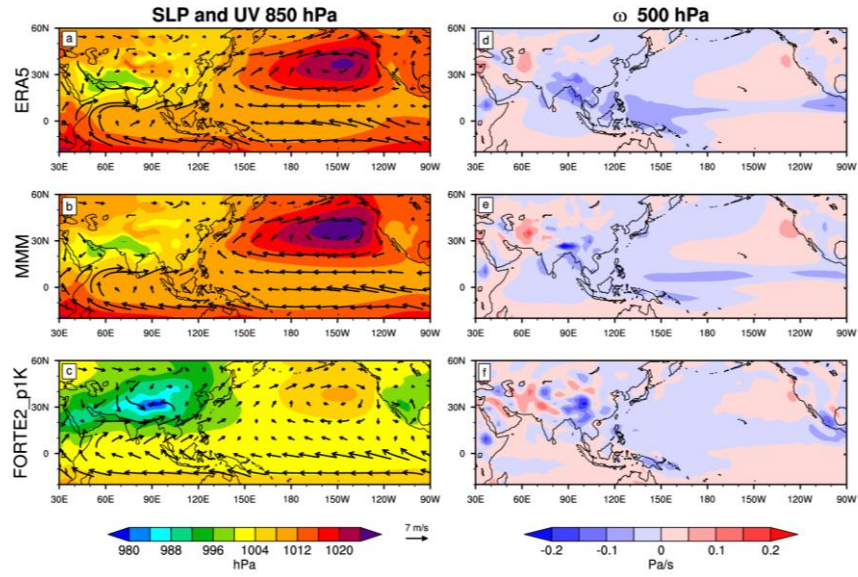
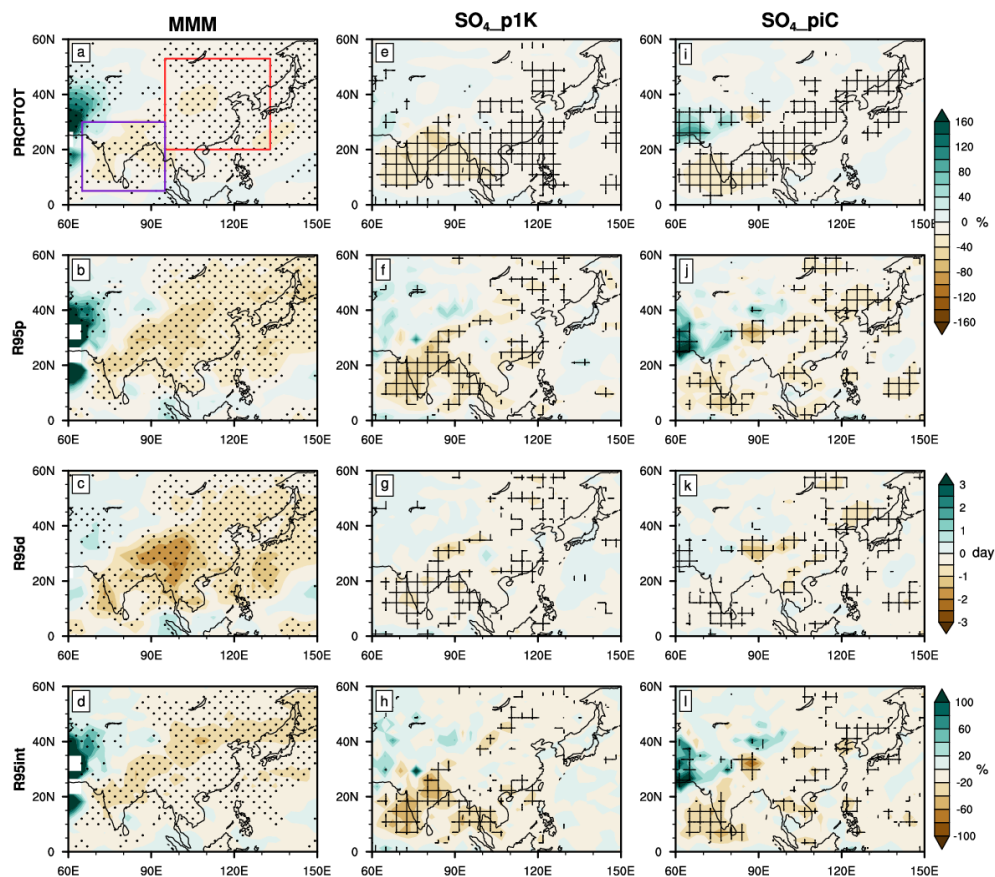


Figure 3. Comparison of climatological summer (a-c) SLP (hPa), 850 hPa horizontal winds (m s^{-1}) and (d-f) 500 hPa vertical winds (ω) (Pa s^{-1}) from ERA5 (1981–2010), the PDRMIP MMM baseline simulation and the FORTE2 p1K baseline simulation.



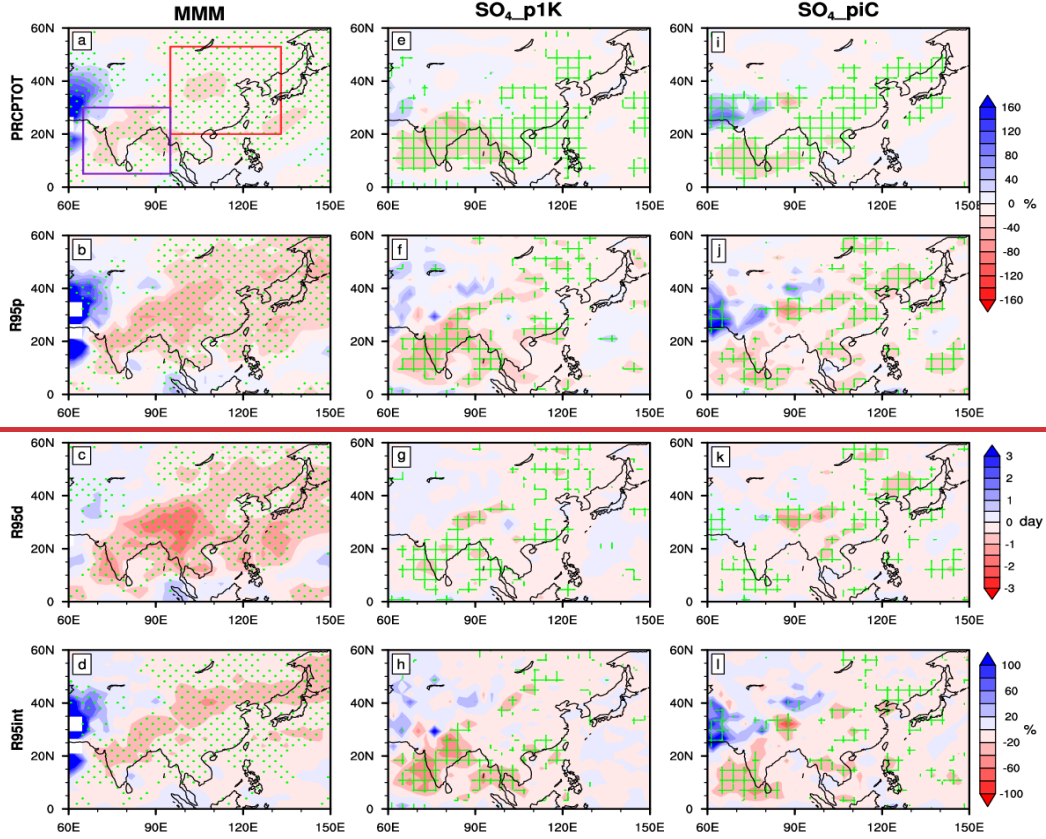


Figure 4. Spatial patterns of summer PRCPTOT (%), R95p (%), R95d (day) and R95int (%) responses to Asian SO₄ aerosol forcing, for (a-d) MMM, (e-h) SO₄_p1K, and (i-l) SO₄_piC. Green-Black dots in MMM denote signals where at least three models agree. Green-Black grid lines in (e-l) indicate regions where 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°E–133°E, 20°N–53°N) and South Asia (SAS: 65°E–95°E, 5°N–30°N), respectively.

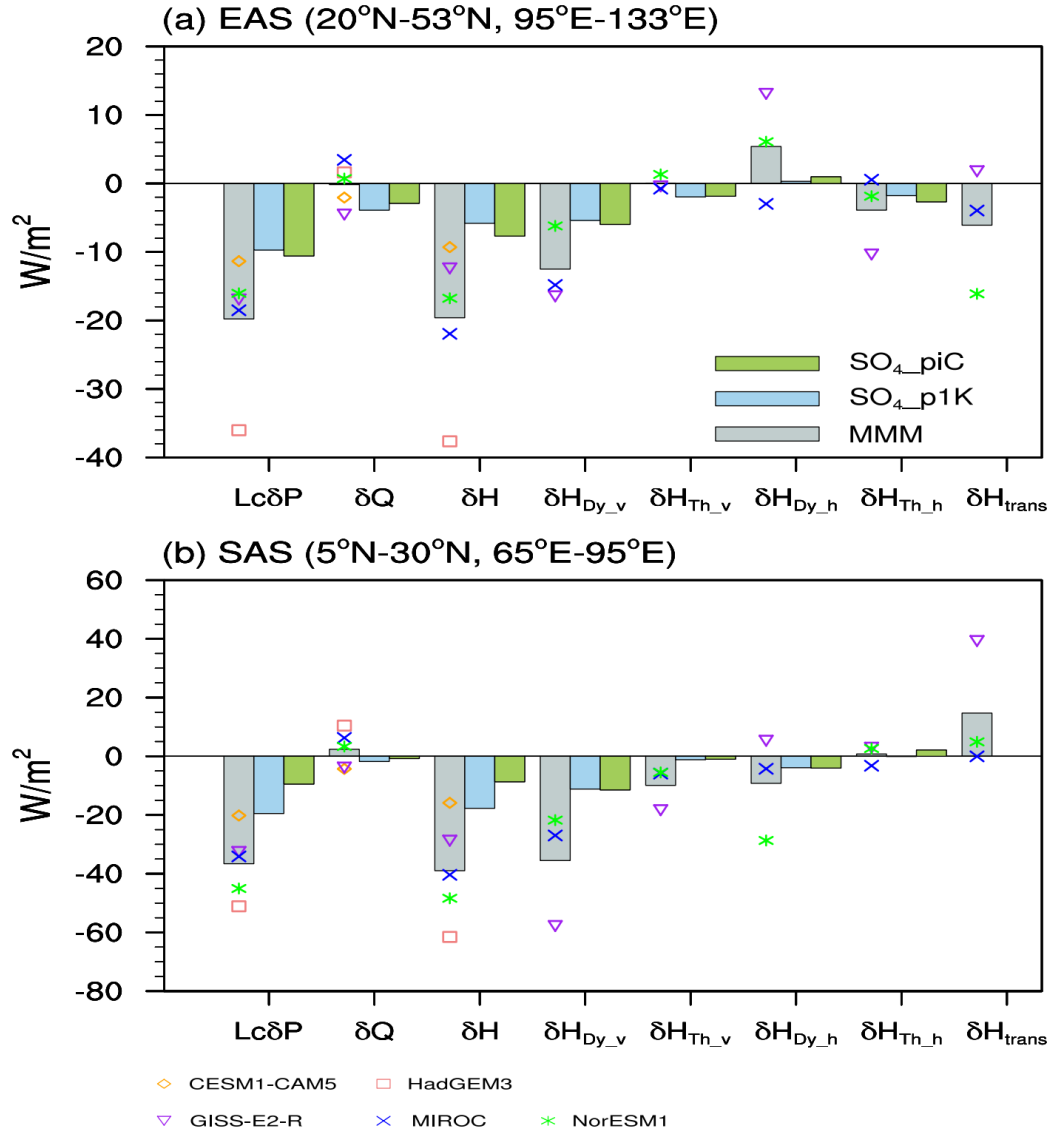


Figure 5. Summer area-averaged responses of the atmospheric energy budget terms over (a) East Asia (EAS) and (b) South Asia (SAS) for the MMM (gray bars), SO_4_p1K (blue bars), and SO_4_piC (green bars). The symbols indicate the individual results from the five PDRMIP models. Note that only three of the five models are used for the decomposition analysis of δH (Eq. 2) due to data availability. Unit: $W\ m^{-2}$

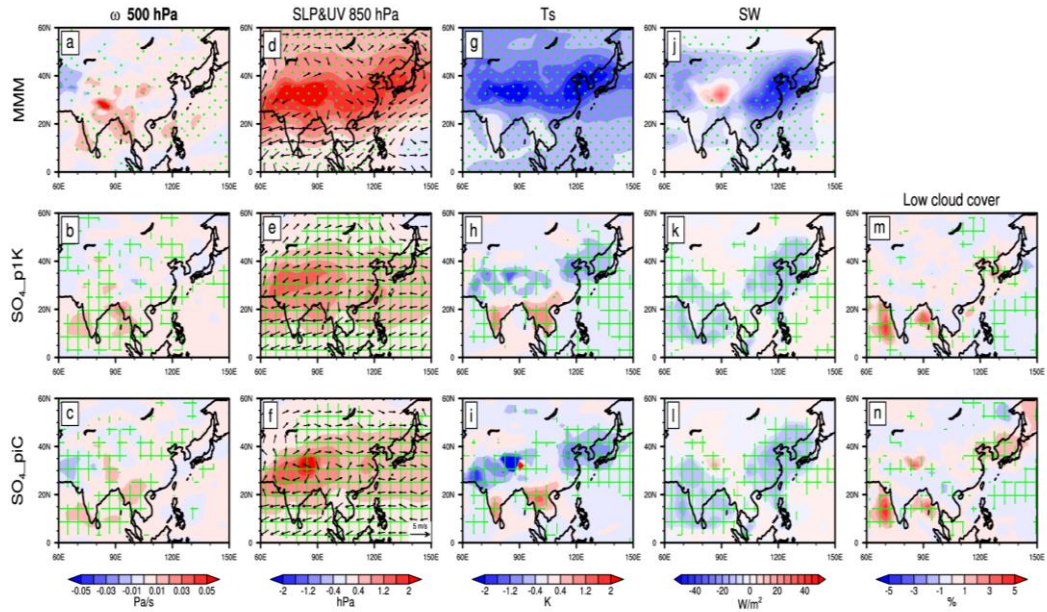


Figure 6. Summer spatial patterns of responses to Asian SO_4 aerosol forcing for the MMM, SO_4_p1K , and SO_4_piC : (a–c) ω at 500 hPa (Pa s^{-1}), (d–f) sea level pressure (SLP; hPa) and 850-hPa horizontal wind (m s^{-1}), (g–i) surface temperature (T_s ; K), (j–l) net surface shortwave radiation (W 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.

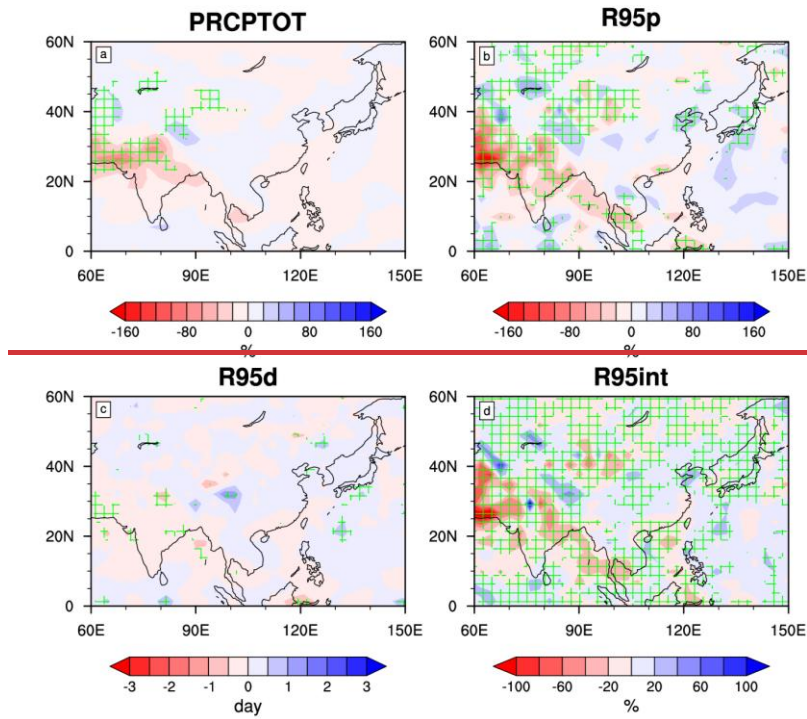
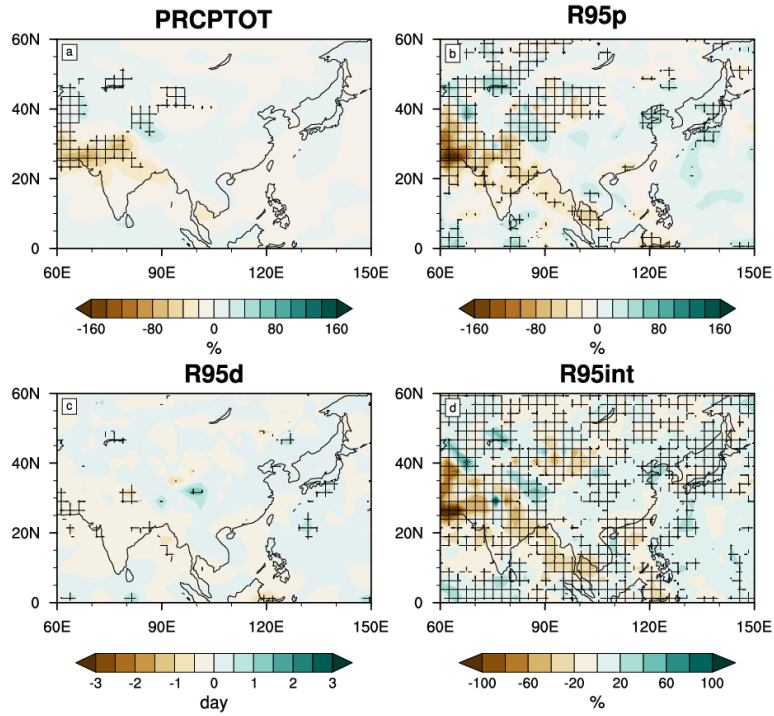


Figure 7. Spatial patterns of summer differences in responses to Asian SO₄ aerosol forcing between the p1K and piC climate states for (a) PRCPTOT (%), (b) R95p (%), (c) R95d (day), and (d) R95int (%). For PRCPTOT, R95p, and R95int, the difference is calculated as the relative response under p1K minus that under piC, i.e., $[(SO_4_p1K - p1K)/p1K - (SO_4_piC - piC)/piC]$; for R95d, the difference is the absolute response

956 under p1K minus that under piC, i.e., $(\text{SO}_4\text{p1K} - \text{p1K}) - (\text{SO}_4\text{piC} - \text{piC})$. ~~Green~~
957 Black grid lines indicate regions where the differences are statistically significant above
958 the 90% confidence level based on a two-tailed Student's t-test.

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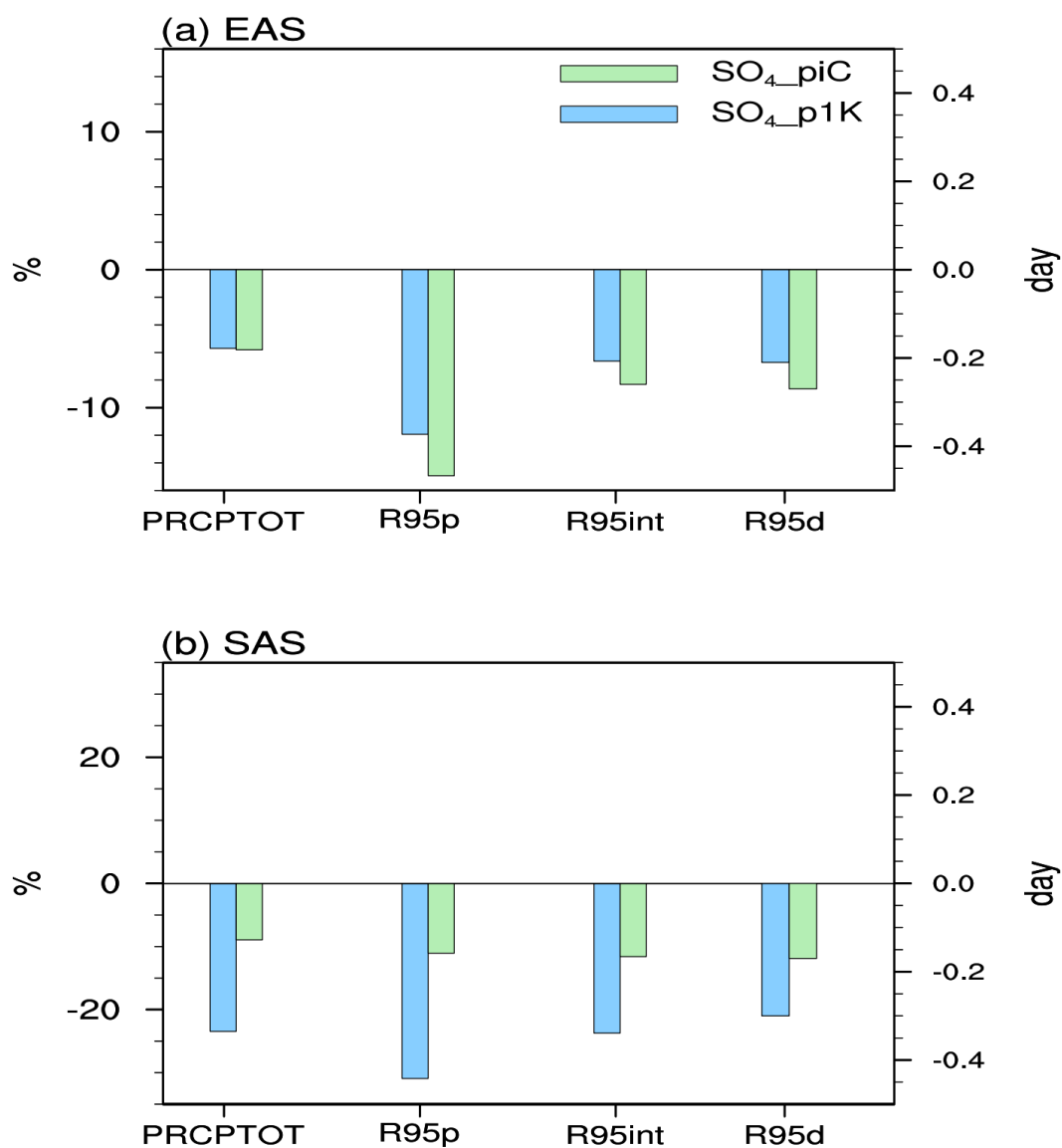


Figure 8. Summer area-averaged responses of PRCPTOT (%), R95p (%), R95d (day), and R95int (%) over (a) East Asia (EAS) and (b) South Asia (SAS) to Asian SO₄ aerosol forcing, shown for SO₄_p1K (blue bars) and SO₄_piC (green bars).

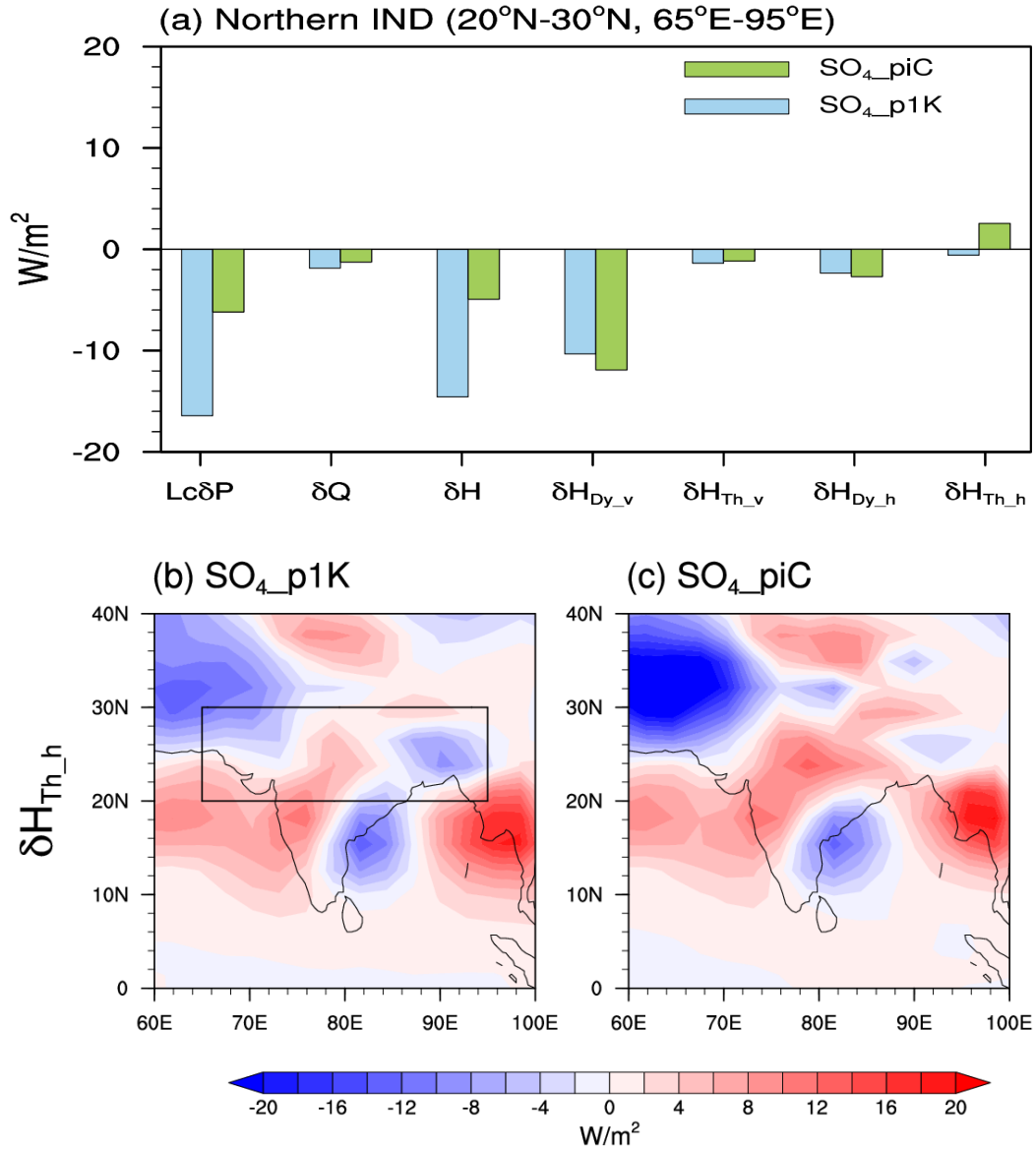
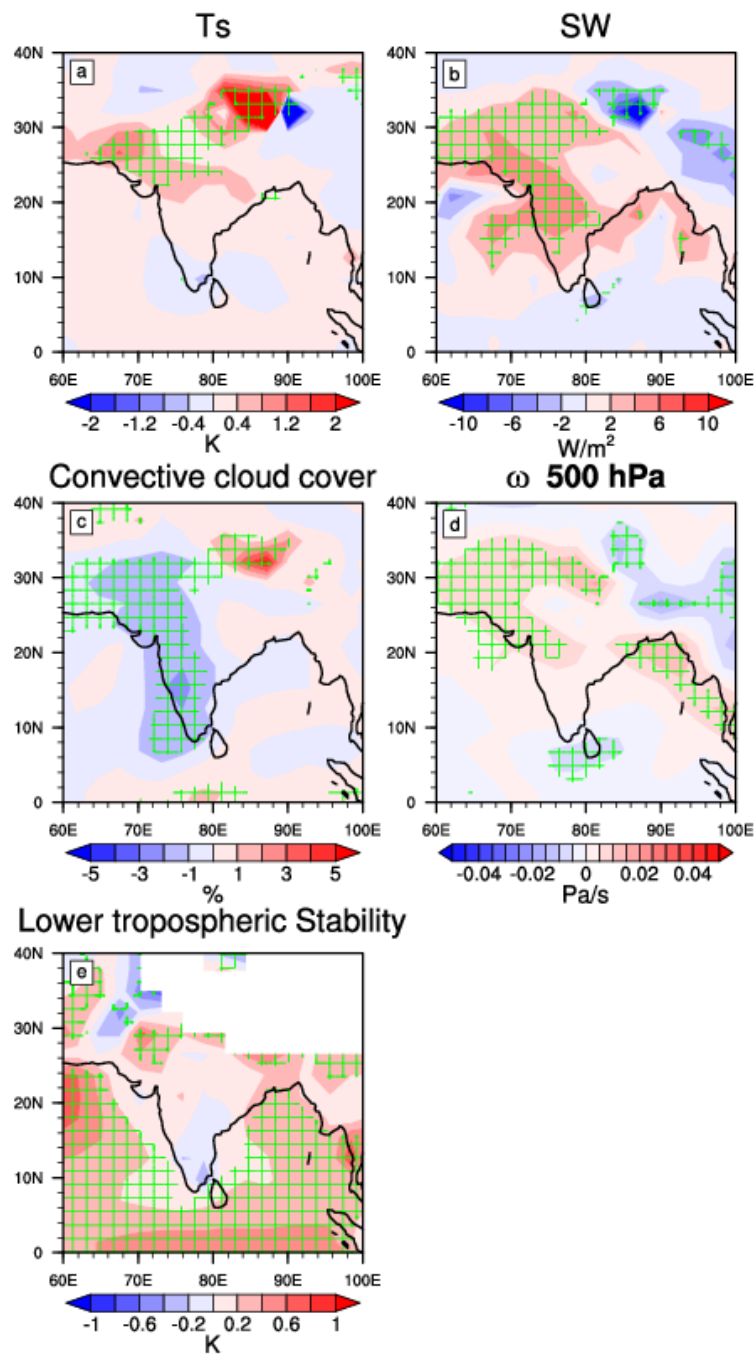


Figure 9. (a) Summer area-averaged responses of the atmospheric energy budget terms over northern India for SO_4_p1K (blue bars) and SO_4_piC (green bars). (b-c) Summer spatial patterns of responses in thermodynamic components with changes in horizontal DSE gradients (δH_{Th_h}) for (b) SO_4_p1K and (c) SO_4_piC . The black box in (b) delineate northern India (65°E–95°E, 20°N–30°N). Units: $W\ m^{-2}$

$(SO_4_p1K-p1K)-(SO_4_piC-piC)$

p1K-piC



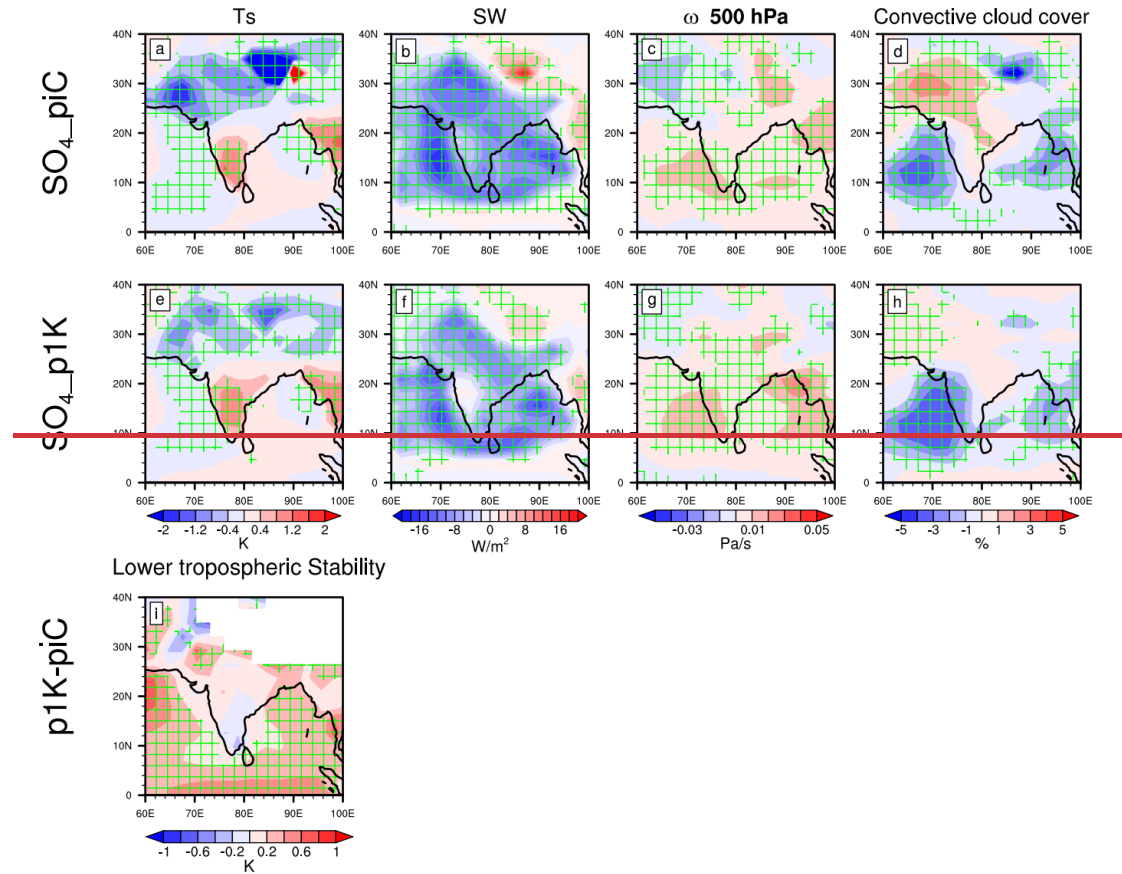
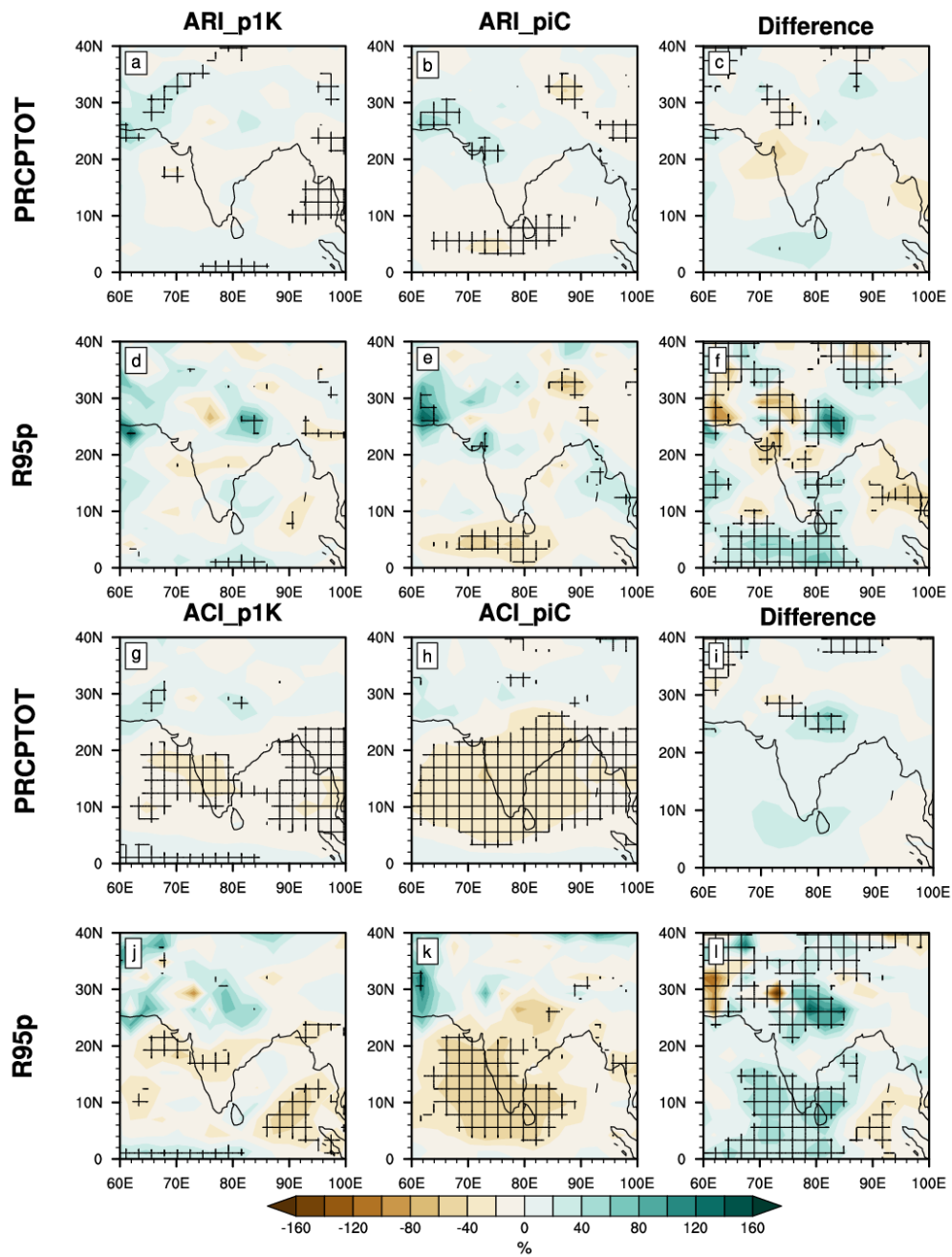


Figure 10. Summer spatial patterns of the difference in the responses to Asian SO_4 aerosol forcing between the p1K and piC climate states, defined as $(\text{SO}_4_{\text{p1K}} - \text{SO}_4_{\text{piC}})$ responses to Asian SO_4 aerosol forcing for SO_4_{p1K} , and SO_4_{piC} : (a, e) Ts (K), (b, f) net surface SW (W m^{-2}), (c, g) convective cloud cover (%), (d, h) ω at 500 hPa (Pa s^{-1}), and (i) Differences in lower tropospheric stability ($\theta_{850} - \theta_{\text{sfc}}$, where θ is potential temperature; K) 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.



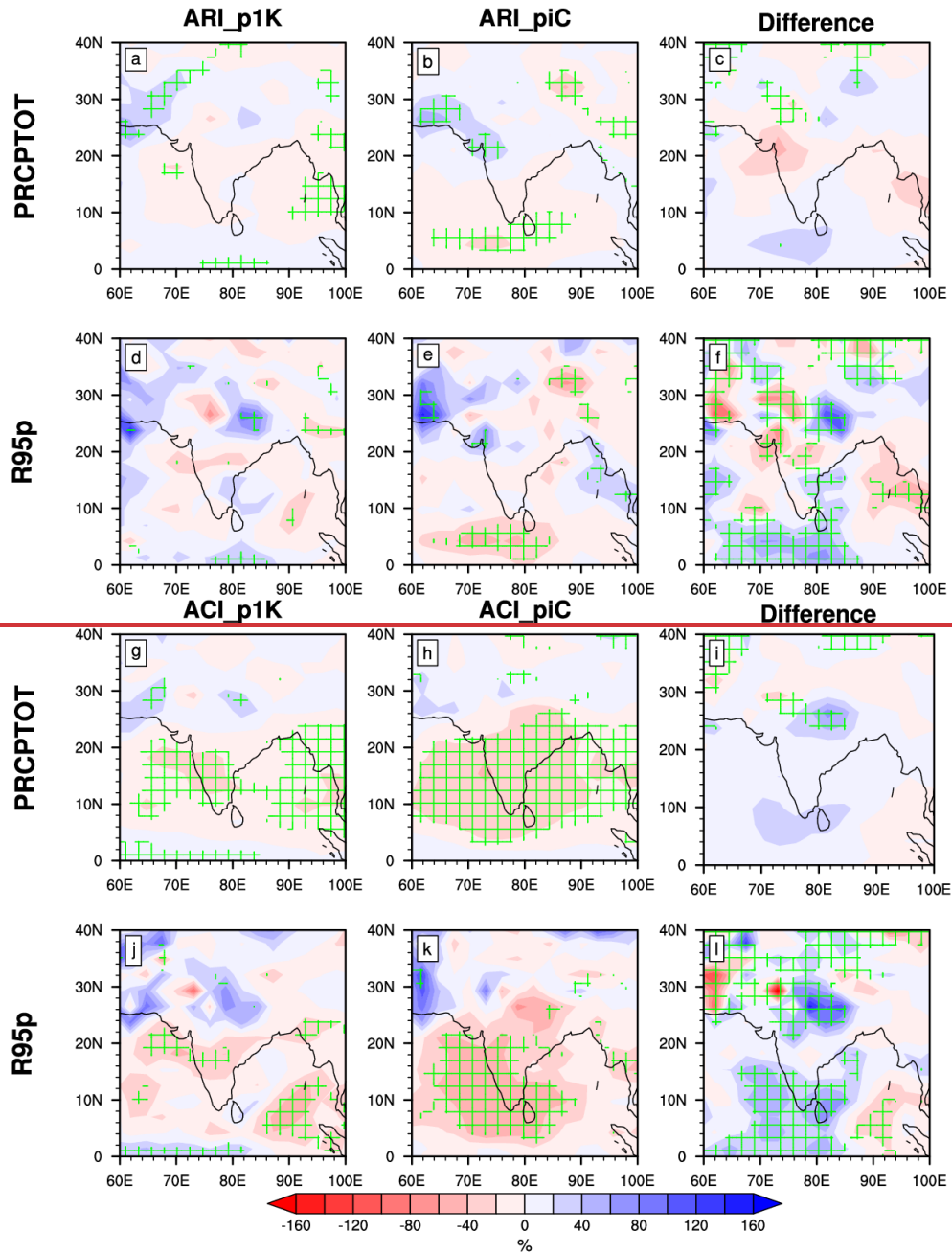


Figure 11. Spatial patterns of summer responses in (a, b, g, h) PRCPTOT and (d, e, j, k) R95p (%) to Asian SO₄ aerosol forcing [e.g., (ARI_p1K – p1K)/p1K, expressed as a percentage], and (c, f, i, l) the difference in these responses between the p1K and piC climate states. Spatial patterns of summer responses of (a–e) PRCPTOT and (d–f) R95p (%) for ARI_p1K (a, d), ARI_piC (b, e), and the difference in responses between the p1K and piC climate states [e.g., (ARI_p1K–p1K)/p1K–(ARI_piC–piC)/piC] (c, f); (a, d) ARI p1K; (b, e) ARI piC; (c, f) difference between (ARI_p1K–p1K)/p1K and (ARI_piC–piC)/piC. (g, j) ACI_p1K; (h, k) ACI_piC; (i, l) difference between (ACI_p1K–p1K)/p1K and (ACI_piC–piC)/piC. and for ACI_p1K (g, j), ACI_piC (h, k);

998 ~~and the difference in responses between the present day and pre-industrial climate~~
999 ~~$[(ARI_{p1K} - p1K)/p1K - (ARI_{piC} - piC)/piC]$ (i, l). ~~Green~~ Black grid lines indicate~~
1000 regions where ~~the~~ responses or their differences are statistically significant above the
1001 90% level based on a two-tailed Student's t test.

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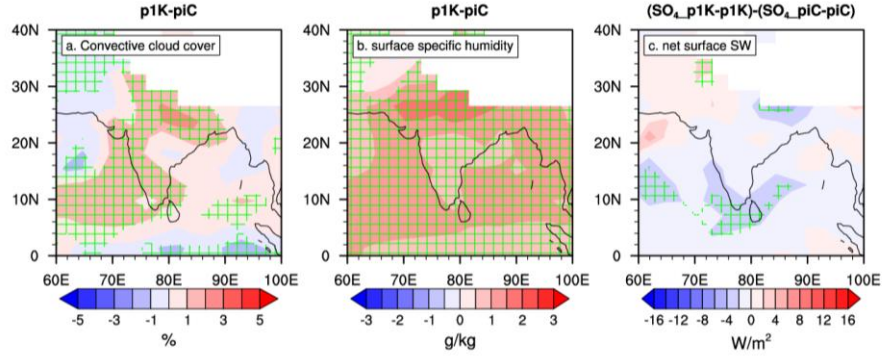


Figure 12. Spatial patterns of summer differences between p1K and piC (p1K- piC) for (a) Convective cloud cover (%) and (b) surface specific humidity (g/kg). (c) Difference in the net surface shortwave radiation (SW) response to Asian SO₄ aerosol forcing between the two climate states (SO₄_p1K – p1K) – (SO₄_piC – piC) (W/m²). 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.

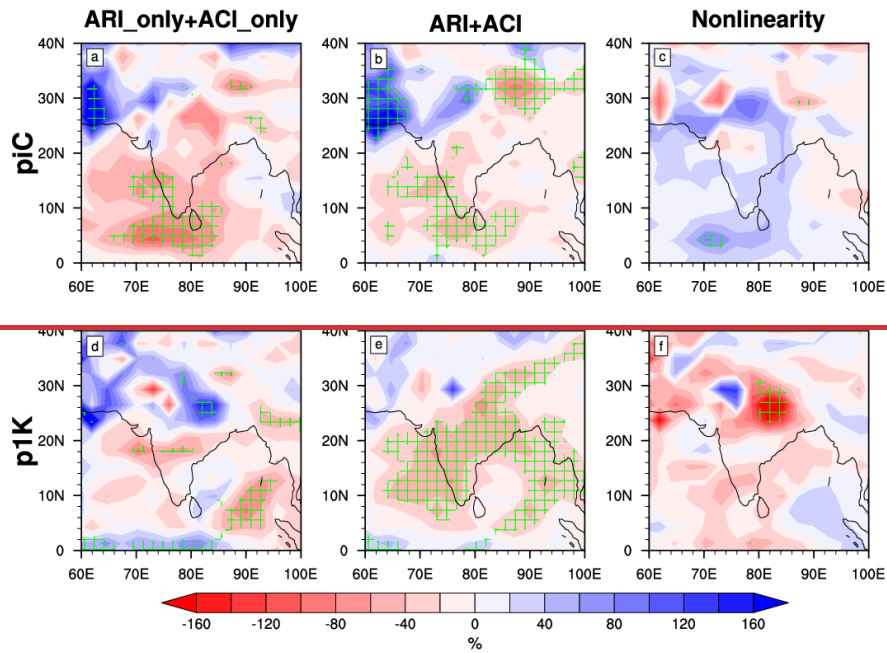
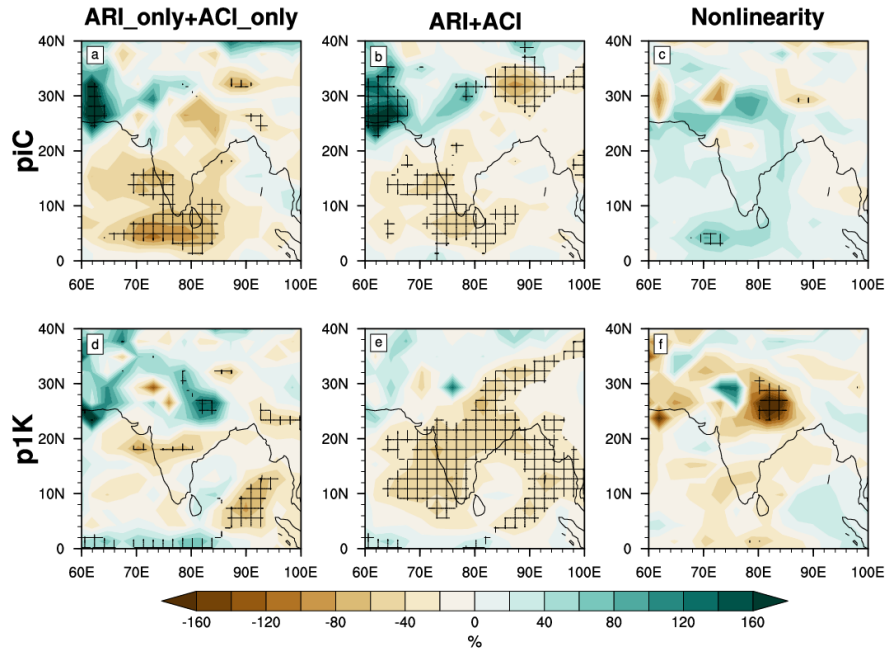


Figure 13. Spatial patterns of summer R95p responses to Asian SO₄ aerosol forcing for the piC (top) and p1K (bottom) climate states: (a, d) sum of the responses from the individual ARI_only and ACI_only simulations, (b, e) response from the combined ARI+ACI simulation, and (c, f) difference between the two [(b, e) minus (a, d)], quantifying the nonlinearity. ~~Green-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.