

Larger increase in future global terrestrial water availability than projected by CMIP6 models

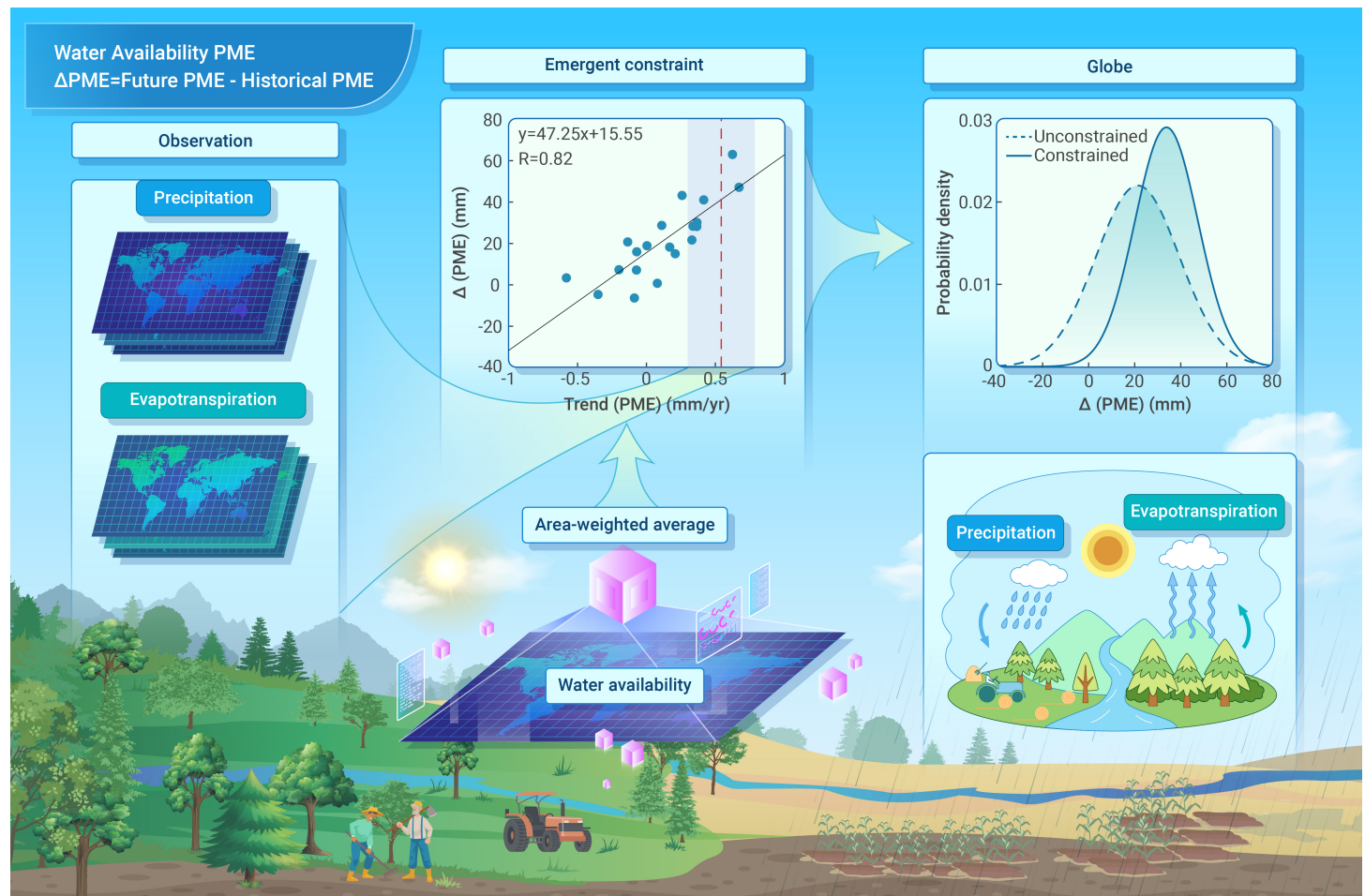
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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Most models have underestimated the increase in water availability (PME) from 1982 to 2011.
- Under SSP5-8.5, the emergent-constrained water availability shows a significant increase of $13\% \pm 5\%$.
- Implementing the emergent constraint reduces the uncertainty range in projections of water availability.
- Accurate model representation of precipitation is crucial for producing reliable projections of PME.



Larger increase in future global terrestrial water availability than projected by CMIP6 models

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Climate change and increasing water use associated with socio-economic growth have exacerbated the water crisis in most of the world. However, terrestrial water availability (precipitation minus evapotranspiration, PME) is inadequately represented within Earth System Models, directly affecting the reliability and consistency of future projections. To address this issue, we employ twenty Coupled Model Intercomparison Project Phase 6 (CMIP6) models and multiple observational PME datasets to produce more robust future projections. Most models underestimate the increase in PME over 1982–2011, while over 80% of the models project a continued rise in future PME. We thus constrain future changes in global mean PME (Δ PME) under medium and high greenhouse gas emission scenarios (SSP2-4.5 and SSP5-8.5) using the hierarchical emergent constraint (HEC) approach. The constrained PME shows a significant increase by 33.81 ± 13.72 mm, or $13\% \pm 5\%$, during the period 2070–2099 relative to 1982–2011 under SSP5-8.5. Implementation of the HEC method reduces the uncertainty range by 24% and shows the Δ PME of the raw CMIP6 was underestimated by 37%. The PME change trends are most evident in low-latitude regions, with constrained PME increasing by 75.69 ± 24.35 mm, or $28\% \pm 9\%$, in the Northern Hemisphere's low latitudes and by 34.56 ± 38.91 mm, or $8\% \pm 10\%$ in the Southern Hemisphere's low latitudes by 2070–2099 under SSP5-8.5. Our findings highlight the importance of accurate model representation of precipitation to produce reliable projections of global terrestrial water availability. The observationally-constrained Δ PME is valuable for sustainable management of water resources.

INTRODUCTION

The terrestrial hydrological cycle is essential for the functioning of land ecosystems and the sustainability of the Earth system. Global climate change has intensified the terrestrial water cycle in recent decades by directly influencing evapotranspiration (ET), precipitation (P), runoff, and terrestrial water storage with resulting shifts in terrestrial water availability (precipitation minus evapotranspiration, PME).^{1–2} Almost 5 billion people are estimated to live in areas with severe water security threats — a situation worsened by climate change, population growth and human activities.³ Therefore, one key environmental challenge of the 21st century is the sustainable management of water resources. PME characterizes the flux of water between the atmosphere and the earth's surface, representing the maximum available renewable freshwater.⁴ PME has important implications and widespread social and ecological consequences for food security, residents' livelihoods, and ecosystem functioning.⁵ In addition, PME may become a key limiting factor for the agricultural and industrial sectors, especially in drylands where water supply already represents a severe constraint.

Numerous studies have investigated the patterns, mechanisms, and ecological effects of terrestrial drying and wetting under climate change, considering various meteorological and hydrological factors such as precipitation, runoff, vegetation, and their interrelationships. For extreme wet and dry events, climate change may be increasing the severity and frequency of droughts,^{6,7} posing challenges for water management, agriculture, and natural ecosystems. Moreover, it was forecasted that flood areas and the severity of its risks would increase.^{8,9} For average wet and dry state, studies indicate conflicting findings based on different indicators. Some studies have identified locations where terrestrial water storage (TWS) appears to be trending below previous ranges, notably where ice sheets or glaciers are diminishing in

response to climate change.¹⁰ Other studies suggest that global land surface drought changes little over the same period due to combined trends in precipitation and evapotranspiration.^{11,12} More than 70% of global permanent net water loss occurs in the Middle East and Central Asia, linked to drought and human activities such as reservoir regulation and unregulated water withdrawals.¹³ A recent study found that global terrestrial water availability showed a declining trend from 2001 to 2020, and the Southern Hemisphere dominates this change.¹⁴ Overall, drying and wetting trends remain controversial due to differences across study periods or seasons, regional heterogeneity of the surface, and the diversity of indicators employed. It is still unclear how water availability may change in the future and whether the drying trend may worsen.

Therefore, understanding changes in future PME (Δ PME) and their underlying mechanisms is fundamental for predicting the response of terrestrial ecosystems to environmental change. Earth system models (ESMs) offer an effective way to derive PME estimates across temporal and spatial scales.¹⁵ ESMs are routinely used to assess evaporation and water resource changes in response to rising atmospheric greenhouse gas concentrations,^{16–18} as well as feedbacks between the hydrological cycle and climate systems.¹⁹ However, different ESMs project divergent patterns of future PME (hereafter referred to as uncertainty). Although the current ESMs are developed based on the latest understanding of physical processes, various factors such as insufficient understanding of certain water cycle processes and inaccurate parameterizations in the models are likely to affect the projections of changes in global or regional water availability.

The question of how to reduce uncertainty among models has been an important research topic in recent years. A promising way to reduce persistent uncertainties among climate change projections is the Emergent constraint (EC) approach.²⁰ The EC technique defines emergent relationships between observable current climate and future change across ESMs,²⁰ and then uses observations to constrain the range of future climate projections from the model-defined relationships.²¹ The EC approach has been widely used to reduce the uncertainty of model spread in future climate projections, including primary production in the tropical oceans,²² Indian summer monsoon rainfall,²³ the ratio of transpiration to ET (that is, T/ET),²⁴ climate sensitivity,²⁵ and the frequency of global precipitation extremes.²⁶

Here we employ outputs from 20 state-of-the-art ESMs (Methods and Table S1) from the Coupled Model Intercomparison Project Phase 6 (CMIP6), together with multiple remote sensing and ground-based precipitation (Table S2) and ET datasets (Tables S3 & S4) to derive new projections of Δ PME under shared socioeconomic pathway 2-4.5 and 5-8.5 (SSP2-4.5 and SSP5-8.5) scenarios using the EC approach.¹⁵

MATERIALS AND METHODS

CMIP6 model simulations

We selected 20 state-of-the-art ESMs from CMIP6 (Table S1).¹⁵ We used monthly precipitation and evapotranspiration (calculated by surface upward latent heat flux) from the historical (1850–2014), SSP2-4.5 (a medium-emissions scenario) and SSP5-8.5 (a high-emission scenario, 2015–2099) simulations. We selected only the first ensemble member “r1i1p1f1” for each model under each scenario. All model outputs were re-gridded to a common $1^\circ \times 1^\circ$ grid using bilinear interpolation because the spatial resolution of different models varies greatly.

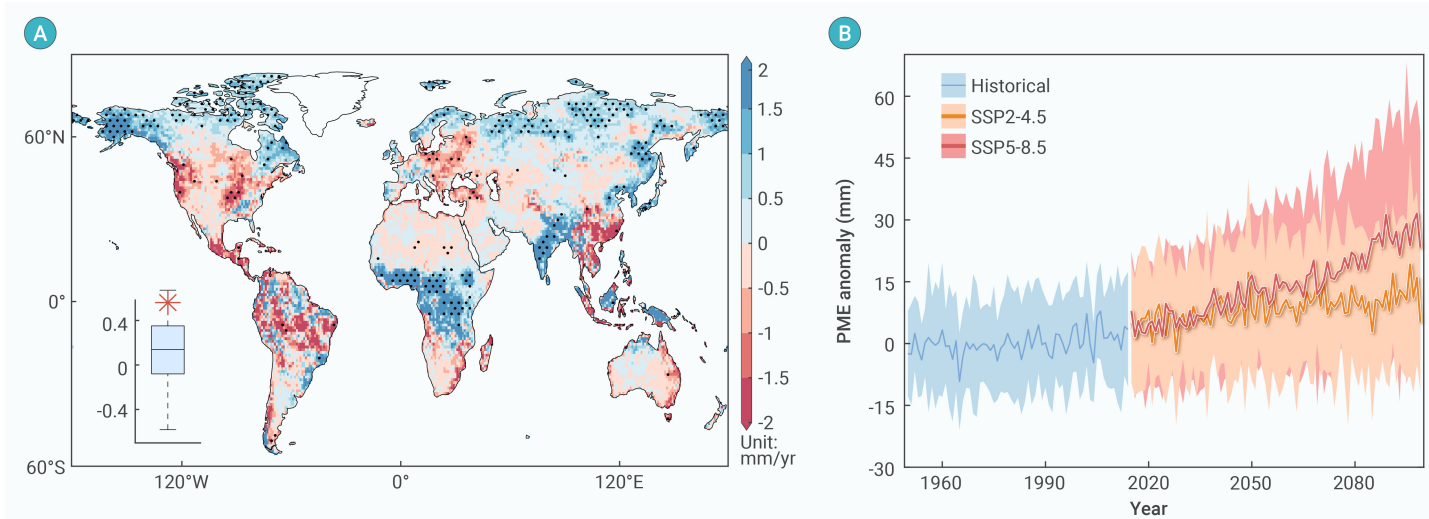


Figure 1. Historical and future trends in global PME in CMIP6 (A) Trend of PME over the global land surface from 1982 to 2011 based on the CMIP6 multi-model ensemble median (unit: mm yr^{-1}). Stippling indicates that the trend is statistically significant ($P < 0.05$). In the left panel, the box plot shows the CMIP6-based global area-weighted mean PME trend (1982–2011) across all grid cells, while the red star represents the median PME trend from the nine observational datasets (based on the Three-Cornered Hat approach (TCH, see method), the top three ET datasets (Table S4) and three precipitation datasets were combined in pairs to form the final nine PME sets (Table S5)). The central line in the box plot represents the median, and the bottom and top edges represent the 25th and 75th percentiles, respectively. (B) CMIP6 annual PME anomaly time series over the global land surface (except Antarctica and Greenland) for 1950–2099 (unit: mm). The historical simulations (1950–2014) are shown in gray and the raw future projections (2015–2099) in orange (SSP2-4.5) and red (SSP5-8.5). The solid curves and shadings denote the multi-model ensemble global mean and uncertainty (one standard deviation across the multi-model ensemble), respectively.

Observational and reanalysis datasets

Precipitation products. This study used three gauge-based precipitation products (Table S2): the Climatic Research Unit gridded Time Series (CRU),²⁷ the Global Precipitation Climatology Centre (GPCC),²⁸ and the NOAA's Precipitation Reconstruction over Land (PRECL).²⁹ The CRU dataset provides a monthly precipitation record covering global land areas, excluding Antarctica. The GPCC dataset, available from 1891 to present, is derived from quality-controlled data from 67,200 stations worldwide with record durations of 10 years or longer. The PRECL dataset is generated based on gauge observations from over 17,000 stations collected in the Global Historical Climatology Network (GHCN), version 2, and the Climate Anomaly Monitoring System (CAMS) datasets.

Evapotranspiration products. In this study, ten actual evapotranspiration (ET) products were employed (Table S3). These products encompass the Penman–Monteith–Leuning Evapotranspiration (PML),³⁰ Global Land Evaporation Amsterdam Model dataset (GLEAM),³¹ Global Land Surface Satellite Evapotranspiration (GLASS),³² monthly climate and climatic water balance for global terrestrial surfaces (TerraClimate),³³ NASA Global Land Data Assimilation System Version 2 (GLDAS) Noah Land Surface Model Evapotranspiration (GLDAS-Noah),³⁴ GLDAS Catchment Land Surface Model (GLDAS-CLSM),³⁵ GLDAS VIC Land Surface Model (GLDAS-VIC),³⁴ Model Tree Ensemble Evapotranspiration (MTE),³⁶ Modern Era Retrospective-Analysis for Research and Application (MERRA)-Land Evapotranspiration (MERRA-Land),³⁷ and ECMWF Reanalysis v5 (ERA5)-Land Evapotranspiration (ERA5-Land).³⁸

Data preprocessing

All observational and reanalysis datasets of precipitation and evapotranspiration mentioned above were resampled to $1^\circ \times 1^\circ$ spatial resolution. Considering that grid cells have different area extents depending on their latitude, we computed the annual time series for global mean precipitation and evapotranspiration using the area-weighted method based on the grid-cell area. The same methodology is applied consistently for global-scale aggregated metrics described in this study. Given the variable time span of different datasets, we selected 1982–2011 as the common historical base period. Three sets of precipitation products (Table S2) and ten sets of evapotranspiration products (Table S3) were then combined to form 30 PME datasets. We evaluated the interannual changes of ten sets of evapotranspiration products (Table S3) from 1982 to 2011 based on the three-cornered hat method (TCH) (Table S4, see Supplemental Information).

This study takes 2040–2069 as the mid-term future and 2070–2099 as the long-term future periods.

The research scope of this article is the global land except Antarctica and Greenland. This study also conducts research at the regional scale. Among the regions with much larger PME trends (Figure 1A), the low latitudes of the Northern Hemisphere (0° – 30°N) are densely populated areas and relatively vulnerable to climate change. The low latitudes of the Southern hemisphere (0° – 30°S) include several important tropical rainforests such as the American Rainforest, African Rainforest and Asia-Australia Rainforest, and they play an important role in mitigating global climate change and regulating the global water cycle. Therefore, these two regions serve as hotspots for this study.

RESULTS

Simulation of global PME changes by the ESMs

The historical trend in PME exhibits substantial spatial heterogeneity (Figure 1A). Areas with much larger (positive and negative) PME trends are mainly located in the low latitudes near the equator, such as the Amazon rainforest, African rainforest, India, southeastern China, and the Southeast Asian archipelago (Figure 1A). The magnitude of the present-day mean global PME trend varies considerably across ESMs (Figure S1). Inter-model discrepancies span a large range (from -0.58 mm yr^{-1} in CESM2-WACCM to 0.67 mm yr^{-1} in UKESM1-0-LL). Critically, the CMIP6 multi-model ensemble median of the PME trend (0.14 mm yr^{-1}) is considerably lower than the median of the nine observational datasets (0.56 mm yr^{-1}) (Figure 1A). Almost all models underestimate the trend in PME from 1982 to 2011, and some models even show the opposite trend (Figures 1A & S1). To further assess this underestimation, we also compared model simulations with observations on a grid-by-grid scale (Figures S2 & S3). As noted at the global scale, although the proportion of areas with underestimated trends in PME is similar to the proportion of areas with overestimated trends (50% vs. 50%, Figure S3), the extent of underestimation significantly surpasses the extent of overestimation observed in the corresponding regions, especially in the 30°N – 30°S zone (referred to as hotspot areas, see Methods). The uncertainties of simulated PME among models increase over time and with higher emission scenarios, with the uncertainty magnitude rising from 12.24 mm during 1950–2014 to 18.84 mm (SSP2-4.5) and 25.72 mm (SSP5-8.5) during 2070–2099 (Figure 1B).

Averaged globally, there are large differences among the models for future ΔPME , with some models even showing opposite changes (Figure S4). Nonetheless, over 80% of the models project an increase in future ΔPME

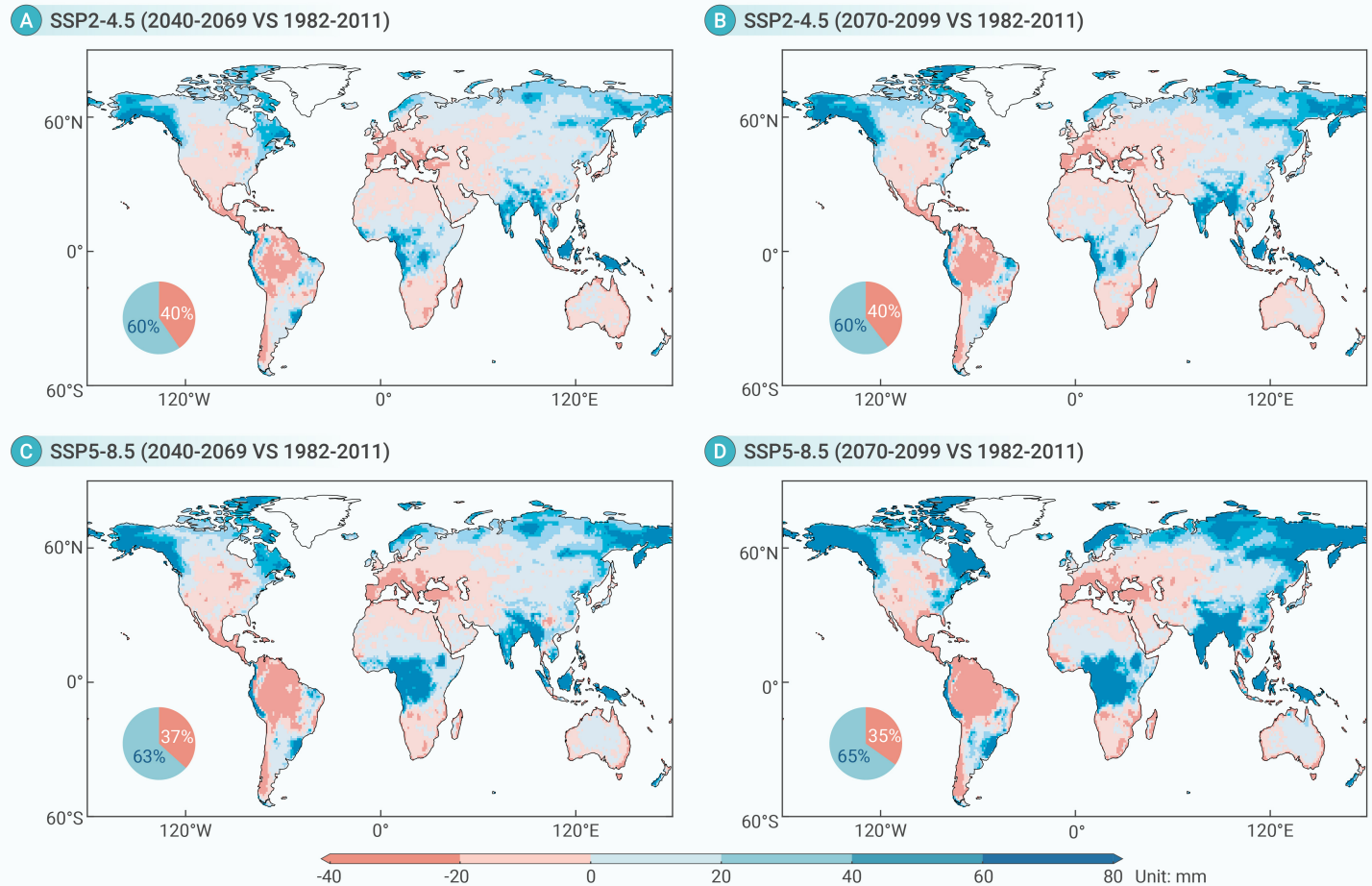


Figure 2. Raw CMIP6 multi-model median projections of Δ PME over the global land surface, except Antarctica and Greenland, relative to 1982–2011 (Unit: mm) (A) mid-term Δ PME under SSP2-4.5, (B) long-term Δ PME under SSP2-4.5, (C) mid-term Δ PME under SSP5-8.5, (D) long-term Δ PME under SSP5-8.5. Mid-term projections are for 2040–2069 minus 1982–2011; long-term projections are for 2070–2099 minus 1982–2011. The pie chart in the lower-left corner of each panel uses blue for the proportion of positive change (labeled in blue) and orange for the proportion of negative change (labeled in orange).

(Figure S4). Notably, the overall spatial pattern of future Δ PME closely resembles that of the historical simulated trend of PME (Figures 1A & 2). Consistent hotspot areas for Δ PME and historical PME trends are predominantly found in the low latitudes. From the medium- to high-emission scenarios, the magnitude of future Δ PME is projected to strengthen (Figure 2), indicating increased global water availability by CMIP6 in the future. This consistency in spatial patterns (Figures 1A & 2) leads us to believe that there is a strong link between historical PME trends and future PME changes. Furthermore, given similarities between the recent and future ensemble median changes, it is worth exploring whether recent changes in individual models are predictive of those models' future changes.

Observation-constrained estimates of future PME change

To improve the robustness of ESM-based global estimates of Δ PME, we made use of the hierarchical emergent constraint approach (see Supplemental Information). Applying this approach here, a tight linear relationship across ESMs ($R = 0.82$, $P < 0.05$ (Figure 3A)) was found between the modelled global mean Δ PME under SSP5-8.5 for the long-term (2070–2099) and the modelled trend of global mean PME for the contemporary period (1982–2011). This relationship suggests that ESMs with larger PME trends in the recent past tend to project greater Δ PME in the future. We also find significant emergent relationships between historical PME trends and future Δ PME in the long-term under SSP5-8.5 in the 0–30N area ($R = 0.78$, $P < 0.05$ (Figure 3B)) and the 0–30S area ($R = 0.62$, $P < 0.05$ (Figure 3C)).

Our results show that the constrained global PME increase by 33.81 ± 13.72 mm, which corresponds to a $13\% \pm 5\%$ increase, in the long-term under SSP5-8.5 relative to 1982–2011 (Figure 3D), by applying the historical PME observation from nine datasets (Table S5) into the relationship (Figure 3A)

constructed in this study. Additionally, the Δ PME of the raw CMIP6 ensemble mean (21.32 ± 18.13 mm) is underestimated by 37%, and the corresponding uncertainty range is reduced by 24% (Figure 3D). This strong linear relationship also exists in the SSP2-4.5 scenarios ($R = 0.78$, $P < 0.05$, Figure S5). The constrained Δ PME exceeds the raw CMIP6 Δ PME ensemble mean for long-term projections under SSP5-8.5 in both the 0–30N (75.69 ± 24.35 mm vs. 26.84 ± 32.51 mm) and 0–30S (34.56 ± 38.91 mm vs. 8.14 ± 44.76 mm) areas, with reductions in the uncertainty range of 25% and 13%, respectively (Figures 3E & F). This corresponds to constrained PME increases of $28\% \pm 9\%$ in the 0–30N and $8\% \pm 10\%$ in the 0–30S areas relative to 1982–2011. These emergent relationships persist for future mid-term and medium-emission scenarios (Figures S6–S7). As the emission scenario increases, water availability increases more (Figure 4).

Robustness verification of emergent relationships

Additional statistical and sensitivity analyses were performed that confirm the robustness of the constrained future Δ PME estimates relative to the raw CMIP6 model outputs. We selected the base period as 1982–2011 (the period when ten ET datasets are available; Table S3) to verify whether the emergent relationship is also found in different future periods. Correlation coefficients of the emergent relationship between the trend in CMIP6 PME during 1982–2011 and the future Δ PME are around 0.8, even under different future periods (Figure S8). The global terrestrial Δ PME of the raw CMIP6 ensemble mean, i.e. $8.14\text{mm} \pm 9.11\text{mm}$ for SSP2-4.5 ($11.76\text{mm} \pm 11.27\text{mm}$ for SSP5-8.5), is underestimated by 40% (38%) in the mid-term (2040–2069), with a constrained Δ PME of $13.75\text{mm} \pm 7.39\text{mm}$ ($18.84\text{mm} \pm 9.05\text{mm}$), and a reduction in the uncertainty range of 19% (20%) (Figures S6–S7, Table S6). In the same way, we also verified the impact of choosing different reference

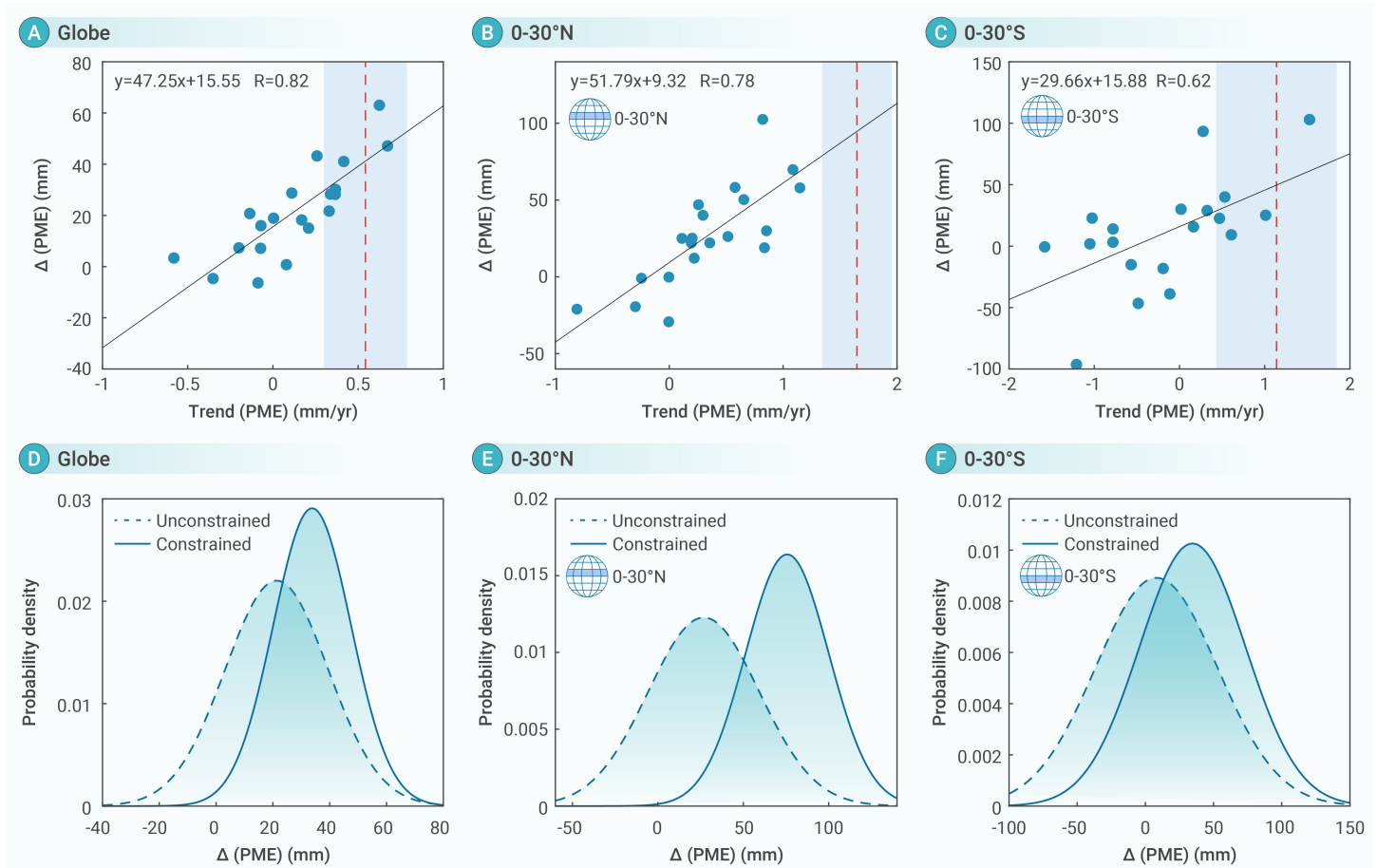


Figure 3. Emergent constraints on future projections of Δ PME (A) The emergent relationship of the historical PME trend (1982–2011) and future Δ PME (long-term 2070–2099 minus 1982–2011) under SSP5-8.5 over the globe. Each black circle represents a CMIP6 model. The black line indicates the best-fit regression line across the models. The observed estimates of the global mean PME trend are indicated as a vertical red dashed line (mean trend) and rectangle (uncertainty range, namely one standard deviation (1 Std)). (B) Same as (A), but for 0–30°N. (C) Same as (A), but for 0–30°S. (D) Probability density distributions for the raw ESM global mean Δ PME (dashed line), and the constrained global mean Δ PME (solid line) after applying the observation to the emergent relationship (A). (E) Same as (D), but for 0–30°N. (F) Same as (D), but for 0–30°S.

periods on the above-mentioned emergent relationships (Figure S9). Correlation coefficients between the historical trend in PME and the future Δ PME are above 0.7 for most reference periods (Figure S9), which supports the robustness of the results.

The reliability of observations significantly influences the range of uncertainty in the final constraint outcomes. The precipitation datasets used in this study sourced from ground-based observations exhibit high agreement.³⁹ Conversely, the agreement among the ET data examined was relatively poor. Therefore, we conducted an ET screening test, that is, either the first or the top two ET datasets (the relative uncertainty ranking of ET data is available in Table S4) were selected and combined individually with the three precipitation datasets (Figure S10). Upon repeated application of the HEC process, it was observed that the outcomes remained largely consistent with those resulting from using top three ET datasets (Table S7). When only the first three groups are considered, there is little difference in the mean (0.45–0.55 mm yr⁻¹) and uncertainty range (0.16–0.21 mm yr⁻¹) of the observation datasets (Table S7). Based on group 1 to group 3, the constrained future Δ PME is robust, from 13.07 mm to 13.97 mm under SSP2-4.5 (from 17.98 mm to 19.11 mm under SSP5-8.5) in the medium-term (Table S7). The range of uncertainty in future Δ PME is also small, namely 7.04–7.39 mm yr⁻¹ under SSP2-4.5 (8.60–9.05 mm yr⁻¹ under SSP5-8.5). The constrained Δ PME in the long-term is also robust. Since we lack observational data for the future period, we employed a model-based cross-validation method (See Supplementary Information) to assess the reliability of our constrained projections for Δ PME. Our findings demonstrate that the EC method effectively mitigates bias in Δ PME projections across more than 75% of models during the future periods (mid- and long-term) under medium and high emission scenarios (Figure 5).

Discussion and implications

Our findings suggest that the underestimation of future Δ PME is mainly due to the underestimation of historical PME trends by the CMIP6 models (Figures 1A & 3). To assess this, we conducted two sets of control experiments – we calculated the trend in PME with precipitation or evapotranspiration replaced by the corresponding observations or climate reanalysis for all models (Figure 6). The results show that the PME trends of each model after using the precipitation observations (rather than evapotranspiration) are closer to the observed values of PME. This suggests that the precipitation bias between the CMIP6 simulations and observations is the main cause of the simulation bias in the PME trend, compared to evapotranspiration. At the same time, we also conducted a sensitivity analysis (see Supplementary information) of the uncertainty of PME to the uncertainty of precipitation and ET.⁴⁰ The results show that the sensitivity coefficient of PME uncertainty to precipitation uncertainty is positive at 99% of the global land during 2015–2099, while the sensitivity coefficient of PME uncertainty to ET uncertainty is negative at more than 85% of the global land, and most of the global land passed the significance test (Figure 7). The precipitation sensitivity is still positive, while ET sensitivity is negative under different emission scenarios (Figure S11). The relative contributions of precipitation uncertainty and ET uncertainty to PME uncertainty are similar, but the relative contribution of precipitation is larger. Previous research found that precipitation dominates the variability and trends in water availability, particularly the El Niño–Southern Oscillation.⁴¹ Therefore, it is reasonable to find that the simulation bias of PME is mainly attributed to the biases in precipitation.⁴² Reliable precipitation simulations are essential for prospective assessments of water availability. Model simulations can be highly uncertain, and understanding the underlying errors and biases is crucial for accurate interpretation of the results. Charac

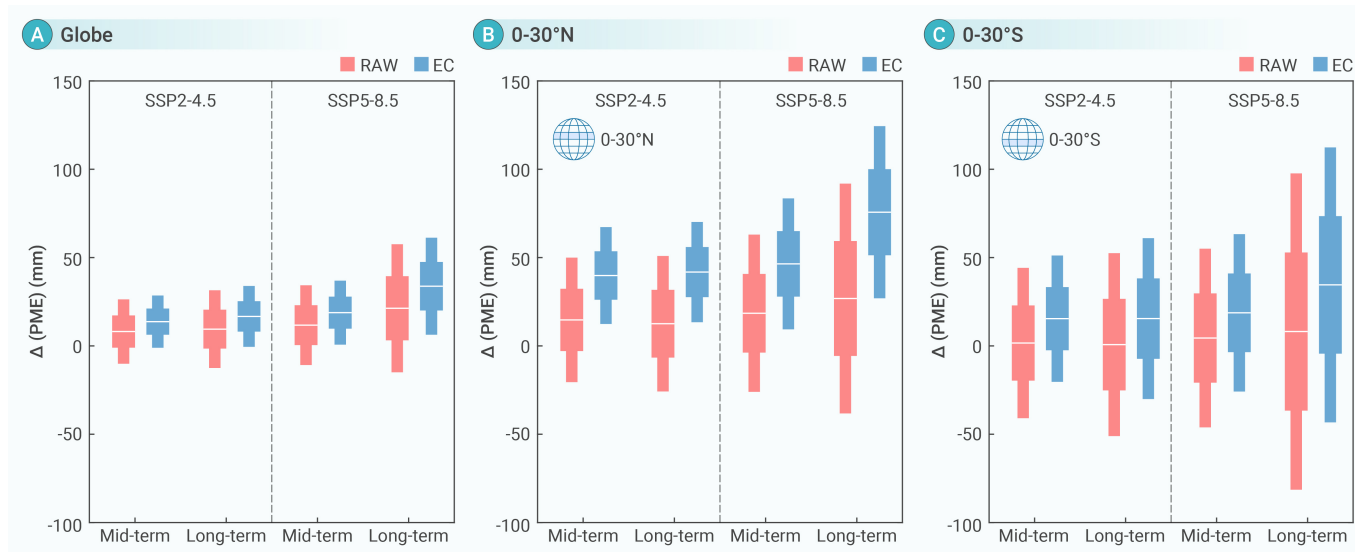


Figure 4. Future Δ PME relative to 1982–2011 before and after application of the emergent constraints (EC) “RAW” (red) denotes the unconstrained values before application of the EC, and “EC” (blue) denotes constrained values after application of the EC. For each bar, the white line represents the mean value, the body and tail of the boxplots represent the 66% and 95% confidence interval, respectively.

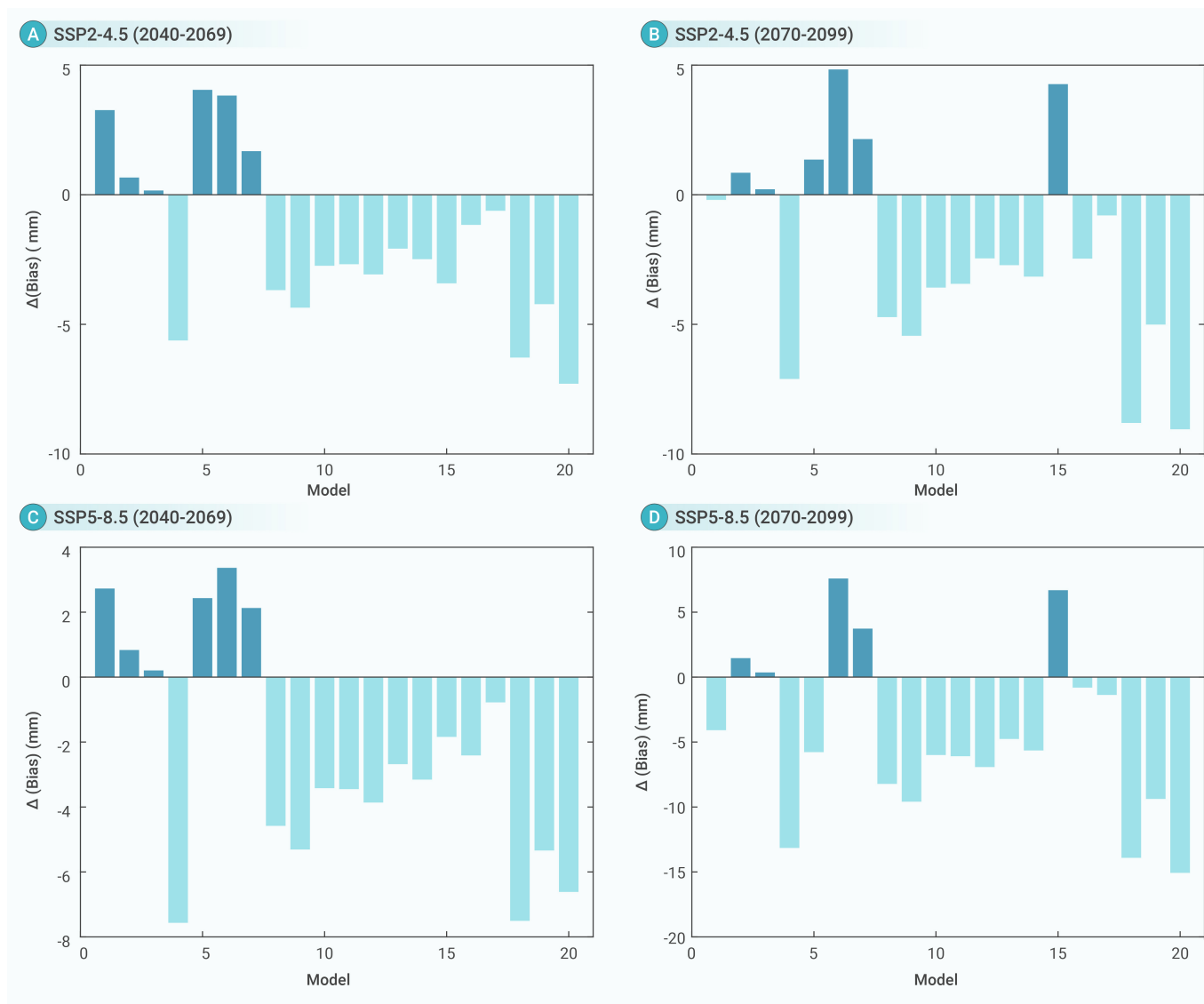


Figure 5. Model-based cross-validation of hierarchical emergent constraint on Δ PME Δ (Bias) is constrained bias minus raw bias. The horizontal axis of each panel represents the model ID as the “true value”. (A) mid-term (2040–2069) under SSP2-4.5, (B) long-term (2070–2099) under SSP2-4.5, (C) mid-term (2040–2069) under SSP5-8.5, (D) long-term (2070–2099) under SSP5-8.5.

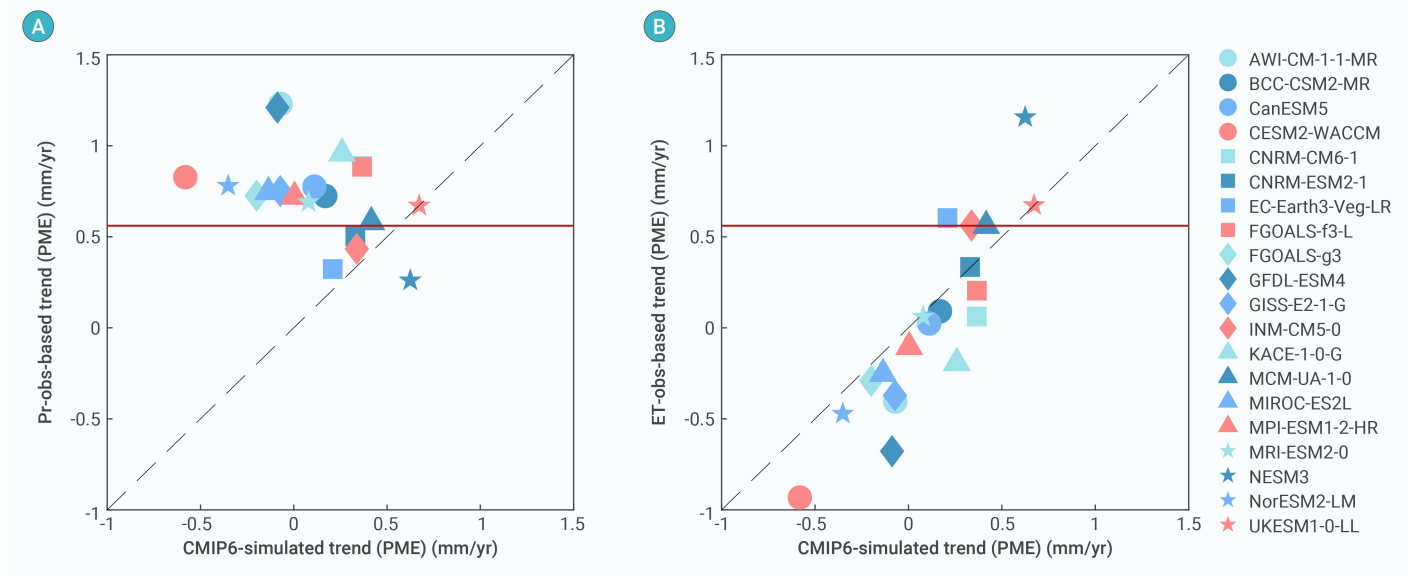


Figure 6. CMIP6-modelled PME trend versus CMIP6-modelled PME trend with (A) precipitation or (B) evapotranspiration replaced by observations or climate reanalysis. Red horizontal line represents the median observed PME trend among nine datasets (see Table S5). Diverse symbols in the figure depict the respective outputs from various models.

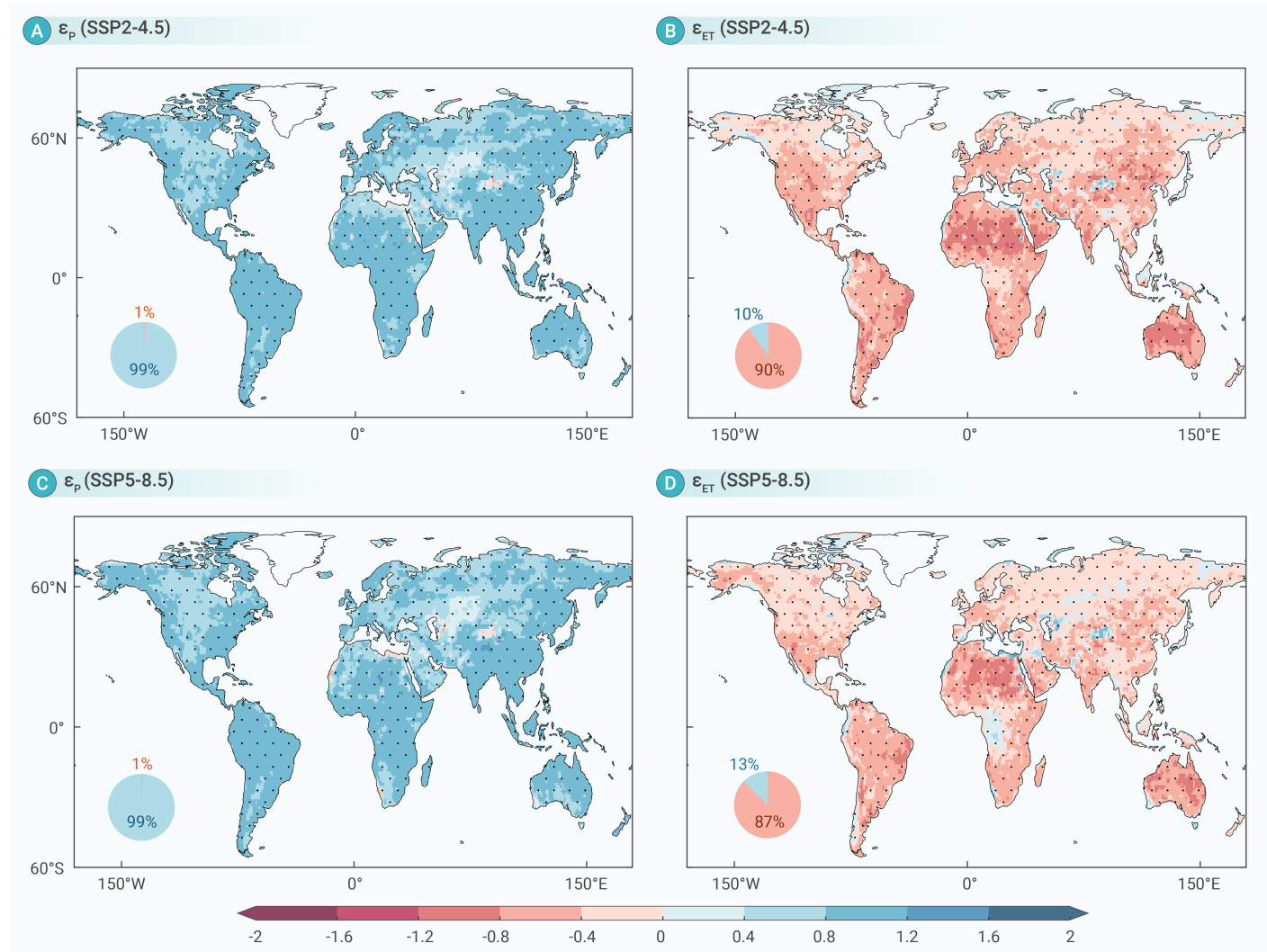


Figure 7. Sensitivity coefficients of U_{PME} to U_P (ε_P) and U_{ET} (ε_{ET}) for CMIP6 at annual scale during 2015–2019 (A) ε_P under SSP2-4.5, (B) ε_{ET} under SSP2-4.5, (C) ε_P under SSP5-8.5, (D) ε_{ET} under SSP5-8.5. The pie chart in the lower-left corner of each panel uses blue for the proportion of areas with a positive sensitivity coefficient and orange for the proportion of areas with a negative sensitivity coefficient. The black dots on the maps represent sensitivity coefficients with significance levels of at least $P < 0.05$.

terization of biases in climate model simulations is hence a critical step in advancing the development of future models. In the Tropics, the mechanism of cloud formation and its spread are the dominant sources of uncertainty in precipitation model outputs.⁴³ Various factors such as convective processes,⁴⁴ atmospheric humidity,⁴⁵ and local topography can contribute to the complexity of cloud formation and the subsequent changes in precipitation.⁴⁶ The inconsistency in the climate models' representation of precipitation sensitivity to local warming in the Tropics is a significant concern in climate science.⁴⁷ Thus, more efforts are needed in the future to improve the precipitation simulation capabilities of these models. First, enhancing current global climate models to accurately represent physical processes such as local temperature changes, sea-ice changes, and the physics of orographic regions remains a significant challenge. These complex processes require further refinement to improve their accuracy and reliability. Second, high-resolution models offer the potential to capture the spatial variability of precipitation more effectively, particularly in regions affected by monsoons. By using high-resolution models, future projections may benefit from improved accuracy in representing complex dynamics.⁴⁸

Our findings suggest that global land surface's water availability is projected to increase in the future by a greater extent than raw projection by the models. It should be noted that our results are limited to the global land surface mean and regional mean in low latitudes; constraints established in other regions failed to pass the significance test, preventing their analysis in this study.

Global mean water availability is projected to increase, seemingly alleviating future water stress. However, the question of how to efficiently utilize the increased water availability is likely to be a sizeable challenge. Efficient water use involves many aspects such as domestic water use, agricultural irrigation, and water conservancy projects. The concerning aspect is that the projected rise in water availability is primarily due to extreme precipitation events. Previous research has suggested that global precipitation extremes are expected to occur roughly $32 \pm 8\%$ more often than at present by 2100 under a medium-emissions pathway (and $55 \pm 13\%$ more often under high emissions).²⁶ Future extreme precipitation intensity increases in most models across the majority of the global land surface.⁴⁹ However, many regions are projected to experience increasing extreme precipitation (Figure S12 & Table S8) and declining water availability (Figure 2). These areas are mainly distributed in the Amazon rainforest, United States of America and Western Asia. Therefore, the question of how to make good use of limited water resources and improve water use efficiency will be a key issue in future water resources research.

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AUTHOR CONTRIBUTIONS

Y.W. and C.Y.Miao conceived the study. Y.W. and X.W.Fan completed the pre-processing the data. Y.W. and Y.F.Chai conducted the analysis of the hierarchical emergent constraint. L.S. and Q.Y.Duan contributed to the robustness verification of emergent relationships. Y.W. and C.Y.Miao wrote the manuscript. All authors discussed, commented and edited the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

The model outputs from CMIP6 used in this study are available at <https://esgf-node.llnl.gov/search/cmip6/>. The CRU precipitation is provided at https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.06/cruts.2205201912.v4.06/. The GPCC precipitation is provided by <https://psl.noaa.gov/data/gridded/data.gpcc.html>. The PRECL precipitation can be accessed at <https://psl.noaa.gov/data/gridded/data.precl.html>. The PML evapotranspiration is provided at https://data.csiro.au/collection/csiro:17375?_st=browse&_str=6&_si=5&browseType=kw&browseValue=evapotranspiration. The GLEAM evapotranspiration is available at <https://www.gleam.eu/>. The GLASS evapotranspiration can be found at <http://www.glass.umd.edu/>. The TerraClimate evapotranspiration is provided by <https://www.climatologylab.org/terraclimate.html>. The GLDAS-Noah evapotranspiration is provided at https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH10_M_2.0/summary?keywords=GLDAS. The GLDAS-CLSM evapotranspiration can be accessed at <https://disc.gsfc.nasa.gov/datasets?keywords=GLDAS&page=1&source=Models%20Catchment-LSM>. The GLDAS-VIC evapotranspiration is provided at <https://disc.gsfc.nasa.gov/datasets?keywords=GLDAS&page=1&source=Models%20VIC-LSM>. The MTE evapotranspiration is available at <https://www.bgc-jena.mpg.de/geodb/projects/DataDnld.php>. The MERRA-Land evapotranspiration is provided by https://disc.gsfc.nasa.gov/datasets/MSTMNXMLD_5.2.0/summary?keywords=MERRA%20land. The ERA5-Land evapotranspiration is available at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means?tab=overview>. All computer codes used in the current study are available upon reasonable request.

SUPPLEMENTAL INFORMATION

It can be found online at <https://doi.org/10.59717/j.xinn-geo.2024.100097>

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