

# Observed Variability and Trends in Global Precipitation During 1979-2020

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## Research Article

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# Abstract

How global precipitation might have changed on the interdecadal-to-trend time scales during the satellite (post-1979) era is examined by means of the satellite-based GPCP V2.3 monthly precipitation analysis. Comparisons with the results from CMIP6 and AMIP6 are further made in terms of global mean precipitation change and regional features of precipitation change, aiming to provide not only an improved understanding of the effects of major physical mechanisms on precipitation change, but also an assessment of the skills of current climate models and likely some clues for diagnosing possible limitations in observed precipitation.

Long-term change/trend in global mean precipitation is generally weak in GPCP. Although the GPCP trend is statistically significant at the 90% confidence level over global land + ocean during 1979–2020, it is not significant over either global land or ocean separately. For the shorter, overlap period with the CMIP6 historical experiments (1979–2014), GPCP positive trends can't reach the 90% confidence level, while significant and more intense precipitation trends appear in CMIP6 ensemble-means. However, a roughly similar global sensitivity to surface temperature change can be derived in GPCP, CMIP6, and AMIP6, providing confidence in both observed and simulated global mean precipitation change. Large regional trends with positive and negative values can readily be seen across the world in GPCP. AMIP6 can generally reproduce these large-scale spatial features. Comparisons with CMIP6 confirm the combined effects from anthropogenic greenhouse-gases (GHG) forcing and internal modes of climate variability such as the Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation (AMO). Limiting the PDO/AMO effect makes the trend patterns in GPCP residuals more similar to those in CMIP6, implying that the GHG effect would become more readily detectable in observed precipitation in the near future with regards to both global mean and regional precipitation changes. Furthermore, similar changes in precipitation seasonal range, especially over global lands, occur in GPCP, CMIP6, and AMIP6, suggesting that the GHG effect might already be discernible in certain aspects of precipitation change.

## 1. Introduction

During the satellite (post-1979) era, surface temperature has been increasing on the global scale due to the increase of anthropogenic greenhouse-gases (GHG). However, this warming trend was not always steady, but often deviated substantially by various natural and anthropogenic factors (e.g., Hegerl et al. 2019). The two volcanic eruptions (El Chichon, March 1982 and Pinatubo, June 1991) significantly cooled the global temperature, decelerated the hydrological cycle by suppressing surface evaporation and precipitation, and also modulated spatial distribution of precipitation (e.g., Gu et al. 2007; Trenberth and Dai 2007). Decadal-scale (internal) modes of climate variability including the Pacific Decadal Oscillation (PDO) or the Interdecadal Pacific Oscillation (IPO) and Atlantic Multidecadal Oscillation (AMO) had exerted impact on the global climate and hydrological cycle as well during the period (e.g., Gu and Adler 2013; Dong and Dai 2015; Gu et al. 2016), so did a variety of anthropogenic aerosols especially over the Northern Hemisphere (e.g., Polson et al. 2014).

Efforts have been made to explore how the global hydrological cycle including precipitation would have responded to various external/internal forcings and mechanisms and furthermore whether the anthropogenic GHG effect could be identified globally and/or regionally during the satellite era in which the precipitation analyses with global (land + ocean) coverage are available (e.g., Gu et al. 2007, 2016; Gu and Adler 2013; John et al. 2009; Liu and Allan 2013). Global mean precipitation has been increasing based on the satellite-based product from the Global Precipitation Climatology Project (GPCP; e.g., Gu et al. 2007; John et al. 2009). General consistency can be found with the results from climate model outputs including CMIP historical and AMIP runs, especially in terms of the signs of long-term changes/trends in global mean precipitation over land + ocean and over land and ocean separately (e.g., Liu and Allan 2013; Allan et al. 2019). However, the increase in global mean precipitation is generally weak ( $\sim 1-2\%/K$ ) under surface warming because of the atmospheric and surface energy constraints, unlike a more intense tropospheric water vapor increase ( $\sim 6-7\%/K$ ) (e.g., Held and Soden 2006; Liu and Allan 2013; Adler et al. 2018; Allan et al. 2019). Compared to climate model (ensemble-mean) results, the global mean precipitation trend in GPCP is even smaller (e.g., Liu and Allan 2013; Adler et al. 2018). Because GPCP can be considered just as one realization with various internal modes on the interannual-interdecadal time scales, discrepancies are generally expected against model ensemble-means. However, these discrepancies might also be related to model deficiencies and possible observational data quality issues especially associated with temporal inhomogeneity (e.g., Liu and Allan 2013; Adler et al. 2018). Hence there is no doubt that we need a more detailed exploration and understanding of these discrepancies, which is highly relevant to quantifying the long-term changes/trends in global mean precipitation during the satellite era and furthermore to assessing the possible contributions of anthropogenic-related global warming signals.

Although the global mean trend in GPCP and climate model outputs is weak during the satellite era, large regional trends with rich spatial structures do appear across the world especially in the tropical region (e.g., Gu et al. 2016). Exploring the possible reasons for these spatial features and more specifically regional precipitation changes/trends has great scientific and societal significance. Past studies suggest that under global surface warming, precipitation varies roughly following “wet-get-wetter, dry-get-drier”, especially over tropical ocean (e.g., Held and Soden 2006). Observational studies are qualitatively in agreement with this notion (e.g., Zhou et al. 2011). Based on the stratification of distinct tropical zones, long-term precipitation increase (reduction) can be found in tropical wet (dry) zone and/or ascending (descending) region (e.g., Allan and Soden 2007; Polson et al. 2013; Liu and Allan 2013; Gu and Adler 2018; Schurer et al. 2020). However, this simple thermodynamic notion does not certainly hold over global land areas (e.g., Greve et al. 2014; Byrne and O’Gorman 2015), and also does not exactly hold even over ocean (e.g., Chadwick et al. 2013). The likely circulation changes and related changes or shifts in location of distinct (tropical) wet and dry zones following surface warming were claimed to be the major reason (e.g. Chadwick et al. 2013; Byrne and O’Gorman 2015), though limited soil moisture holding capacity over land is important too. Internal modes of climate variability including the PDO and AMO can induce large-scale circulation changes as well, specifically on the interannual-interdecadal time scales (e.g., Gu et al. 2016), so that the observed patterns of GPCP precipitation trends tend to be sensitive to the

length of data record (e.g., Gu and Adler 2013; Gu et al. 2016). The effects of the PDO and AMO have been emphasized in past studies (e.g., Gu and Adler 2013; Gu et al. 2016), including their possible role in the occurrence of the so-called “hiatus” period during the period of 1998–2014 (e.g., Trenberth and Fasullo 2013). However, how these internal modes would have influenced or shaped the global precipitation trend patterns during the satellite era and how they can be accounted for are far from clear.

Precipitation changes may have also manifested in another important aspect: changes in seasonal cycle. Relevant evidence has been reported for many regions (e.g., Chou et al. 2013; Marvel et al. 2017), including changes in seasonal precipitation range, starting date and duration of wet season, etc. These changes have tremendous impact on local ecological system, agriculture, and economy, even if annual total precipitation does not change much. Seasonality changes in other hydrological-cycle components during the past decades have also been investigated (e.g., Liang et al. 2020; Chandanpurkar et al. 2020). Nevertheless, a detailed global survey of changes in precipitation seasonal cycle based on both observations and models is still lacking. Obviously, this survey should be focused on whether any consistency could be derived from current satellite-based precipitation analyses and climate model outputs given issues likely existing in both of them.

Therefore, by harnessing the satellite-based precipitation analysis with global coverage, specifically the GPCP and the precipitation outputs from the CMIP6 archives, this study has four primary objectives: (i) exploring whether any significant long-term changes in precipitation both globally and regionally could be identified in current satellite/ground based precipitation; (ii) investigating whether and how various (anthropogenic and natural) physical factors would have affected global precipitation given that the observational data record is still relatively short; (iii) exploring whether the anthropogenic-related global warming signals could be identified in the current satellite-based precipitation or to what extent these signals had contributed to the observed global precipitation changes during the satellite era; and finally (iv) assessing the skills of current climate models in reproducing observed precipitation changes, and also diagnosing limitations, if possible, in the satellite-based precipitation analysis.

The data sets used in this study are described in section 2, including the GPCP monthly precipitation analysis, the NASA GISS surface temperature anomaly analysis, and several distinct precipitation outputs from the CMIP6 archives. Section 3 focuses on the global mean precipitation changes/trends during the satellite era including both global mean precipitation trends and precipitation sensitivities to surface temperature changes. Regional features of precipitation changes are primarily discussed in section 4, which also covers an exploration of the PDO and AMO effect on precipitation change, and an examination of changes in precipitation annual cycle during the satellite era. Summary and concluding remarks are given in section 5.

## 2. Data Sets

The monthly precipitation analysis from Global Precipitation Climatology Project (GPCP) (Version 2.3), archived on a global  $2.5^\circ \times 2.5^\circ$  grid, is applied. The product is merged from a variety of input data

sources: passive microwave rainfall estimates from the Special Sensor Microwave/Imager (SSM/I) and the Special Sensor Microwave Imager Sounder (SSMIS), infrared (IR) rainfall estimates from geostationary and polar-orbiting satellites, and surface rain gauges over land. Certain procedures have been applied to reduce data bias by taking advantage of particular strengths of the individual input data (Adler et al. 2003, 2018; Huffman et al. 2009). The monthly product lasts from January 1979 to the present. GPCP has been widely applied in various fields of global precipitation change and variations (e.g., Adler et al. 2018), despite its still relatively short record and likely, remaining quality issues. To apply it to investigate global precipitation changes and trends, the challenge is how to disentangle and assess the impact of various factors including anthropogenic-related global surface warming in precipitation changes. For comparing with and assessing the performance of current climate model outputs, constructing any useful metrics from the GPCP is also a challenge, partly due to the relative short model/observation overlap.

The NASA-GISS surface temperature anomaly analysis (GISTEMP V4) is used to estimate global temperature trends for its global coverage (Hansen et al. 1999). Archived on a global  $2^{\circ} \times 2^{\circ}$  grid, the data with the 1200-km smoothing level are applied.

The climate model outputs, specifically monthly precipitation and surface temperature used in this study, include (1) the historical full radiative forcing runs (CMIP6-hist) from 28 CMIP6 models driven by natural (solar variation, volcanic eruptions, etc.) and anthropogenic (GHG and aerosols) radiative forcings, and (2) the atmosphere-only (AMIP6) simulations from 28 CMIP6 models forced by observed SST and sea ice extent, in addition to the radiative forcings used in the CMIP6 historical full forcing experiments (Table 1; Eyring et al. 2016). One realization from each model is chosen for both types of simulations. The monthly precipitation and surface temperature outputs from the CMIP6 historical GHG-only simulations (CMIP6-histGHG) are applied as well and one or two realizations from each model totaling 17 ensemble members are used to compute the ensemble means (Table 1).

Table 1

CMIP6 models and ensemble variants including the historical full radiative forcing (CMIP6-hist; 1979–2014), GHG-only (CMIP6-histGHG; 1979–2020), and atmosphere-only (AMIP6; 1979–2014) runs.

| Model Name      | CMIP6-hist | AMIP6    | CMIP6-histGHG      |
|-----------------|------------|----------|--------------------|
| ACCESS-CM2      | r1i1p1f1   | r1i1p1f1 |                    |
| ACCESS-ESM1-5   | r1i1p1f1   | r1i1p1f1 |                    |
| BCC-CSM2-MR     | r1i1p1f1   | r1i1p1f1 | r1i1p1f1, r2i1p1f1 |
| BCC-ESM1        | r1i1p1f1   | r1i1p1f1 |                    |
| CAMS-CSM1-0     |            | r1i1p1f1 |                    |
| CAMS-ESM1-0     | r1i1p1f1   |          |                    |
| CanESM5         | r1i1p1f1   | r1i1p1f1 | r1i1p1f1, r2i1p1f1 |
| CESM2           | r1i1p1f1   | r1i1p1f1 |                    |
| CESM2-WACCM     | r1i1p1f1   | r1i1p1f1 |                    |
| CNRM-CM6-1      | r1i1p1f2   | r1i1p1f2 | r1i1p1f2, r2i1p1f2 |
| CNRM-ESM2-1     | r1i1p1f2   | r1i1p1f2 |                    |
| E3SM-1-0        | r1i1p1f1   | r1i1p1f1 |                    |
| EC-Earth3       |            | r1i1p1f1 |                    |
| FGOALS-f3-L     |            | r1i1p1f1 |                    |
| GFDL-ESM4       | r1i1p1f1   | r1i1p1f1 | r1i1p1f1           |
| GISS-E2-1-G     | r1i1p1f1   | r1i1p1f1 |                    |
| GISS-E2-1-H     | r1i1p1f1   |          |                    |
| HadGEM3-GC31-LL |            | r1i1p1f3 | r1i1p1f3, r2i1p1f3 |
| INM-CM4-8       | r1i1p1f1   | r1i1p1f1 |                    |
| INM-CM5-0       | r1i1p1f1   | r1i1p1f1 |                    |
| IPSL-CM6A-LR    | r1i1p1f1   | r1i1p1f1 | r1i1p1f1, r2i1p1f1 |
| KACE-1-0-G      | r1i1p1f1   | r1i1p1f1 |                    |
| MCM-UA-1-0      | r1i1p1f1   |          |                    |
| MIROC6          | r1i1p1f1   | r1i1p1f1 | r1i1p1f1, r2i1p1f1 |
| MPI-ESM-1-2-HAM | r1i1p1f1   |          |                    |
| MPI-ESM1-2-HR   | r1i1p1f1   | r1i1p1f1 |                    |

| Model Name  | CMIP6-hist | AMIP6    | CMIP6-histGHG      |
|-------------|------------|----------|--------------------|
| MRI-ESM2-0  | r1i1p1f1   | r1i1p1f1 | r1i1p1f1, r3i1p1f1 |
| NESM3       | r1i1p1f1   |          |                    |
| NorCPM1     | r1i1p1f1   | r1i1p1f1 |                    |
| NorESM2-LM  | r1i1p1f1   | r1i1p1f1 | r1i1p1f1, r2i1p1f1 |
| SAM0-UNICON | r1i1p1f1   | r1i1p1f1 |                    |
| TaiESM1     |            | r1i1p1f1 |                    |
| UKESM1-0-LL | r1i1p1f1   | r1i1p1f2 |                    |

Two types of pacemaker simulations from the CMIP6 archive are also applied (Zhou et al. 2016), i.e., hist-resIPO and hist-resAMO, to estimate the possible impact of the PDO and AMO, respectively, on global precipitation during the satellite era, though the PDO is more localized compared to the IPO (Folland et al. 2002). In addition to the full radiative forcings used in the CMIP6 historical full forcing experiments, the hist-resIPO runs are forced by observed SST over the tropical Pacific Ocean domain of 20°S-20°N, 175°E-75°W, while the hist-resAMO runs are driven by observed SST over the Atlantic Ocean domain of 0-70°N, 0-70°W (Zhou et al. 2016). Eight ensemble members from 4 models are applied for hist-resIPO: BCC-CSM2-MR (r1i1p1f1), FGOALS-f3-L (r1i1p1f1, r2i1p1f1, r5i1p1f1), FIO-ESM-2-0 (r1i1p1f1), and MRI-ESM2-0 (r1i1p1f1, r2i1p1f1, r3i1p1f1); and 5 ensembles from 3 models for hist-resAMO: BCC-CSM2-MR (r1i1p1f1), FIO-ESM-2-0 (r1i1p1f1), and MRI-ESM2-0 (r1i1p1f1, r2i1p1f1, r3i1p1f1).

Finally, for fair comparisons, all model outputs have been interpolated to the GPCP 2.5° x 2.5° grid.

### 3. Global Mean Precipitation Variability And Trends

Long-term changes in global mean precipitation during the post-1979 period are the focus of this section. Precipitation trends and precipitation sensitivities to global surface temperature change or specifically the apparent hydrological sensitivity ( $\eta_a$ ; e.g., Fläschner et al. 2016) are primarily examined. In particular, we intend to investigate whether any consistency can be found with regards to global mean precipitation changes between GPCP and climate model outputs given various anthropogenic and natural physical factors having played a role during the period (e.g., Gu et al. 2007, 2016; Trenberth and Dai 2007; Trenberth and Fasullo 2013; Polson et al. 2014; Hegerl et al. 2019; Allan et al. 2020).

#### 3.1 Trends in global mean annual precipitation and during two contrasting seasons

Annual-mean anomalies of global precipitation are depicted in Fig. 1. The trend magnitudes and corresponding 95% confidence intervals are estimated for GPCP and model outputs, and so are the model ensemble spreads in parentheses for AMIP6 and CMIP6-hist represented by one standard deviation of

multi-model results (Table 2). Positive trends appear in GPCP precipitation over global land + ocean, and also over global land and ocean separately. However, because of intense interannual fluctuations, even though the global (land + ocean) mean trend can reach the 90% confidence level for the longer GPCP period (1979–2020), the observed precipitation trend is not significant over either land or ocean. The larger relative inter-annual variations over land and ocean separately, as compared to the global total, is due to ENSO and its affect in shifting major precipitation features from ocean to land and back again. These variations indicate the difficulties and possible uncertainties with regards to quantifying a global mean precipitation trend for the satellite era using the observations in that the signal-to-noise ratios are still very low. The GPCP results are roughly confirmed by the AMIP6 simulations, though the AMIP6 global trend (land + ocean) can reach the 95% confidence level likely because of reduced interannual variations in the multi-model ensemble means. In contrast, CMIP6-hist and GHG-only show more intense global mean trends than either GPCP or AMIP, and these trends are statistically significant. It is noted that model outputs generally have larger global mean precipitation values than GPCP. The global mean (land + ocean) precipitation numbers are 2.69, 2.94, and 2.97 mm day<sup>-1</sup> for GPCP, CMIP6-hist, and AMIP6, respectively. However, these climatological differences seem not the primary reason for the differences in precipitation trends given the almost same global mean precipitation in CMIP6-hist and AMIP6. Therefore, internal modes of climate variability (e.g., the PDO phase shift during the period in about 1998) are the major factor that can significantly influence the precipitation trend magnitudes or even help obscure the precipitation trend in GPCP and AMIP6 during the period. This factor could be sensitive to the length of the data record as evidenced by the differences in GPCP trends between the two periods: 1979–2014 and 1979–2020. It appears that in both the GPCP and AMIP, the effect of the inter-decadal variations is to reduce the observed or calculated trends therein. However, both the GPCP and AMIP plots also show greater inter-annual variations as expected since the real and AMIP atmospheres are driven primarily by the surface temperature variations.

Table 2

Trends (mm day<sup>-1</sup> per decade) in global annual-mean precipitation from GPCP, CMIP6-hist, and AMIP6. Also included are the 95% confidence interval. Statistically significant values at the 95% confidence level are marked bold. Statistically significant values at the 90% confidence level are underlined and marked italics. Values in parentheses are the spreads of multi-model ensembles represented by one standard deviation.

|              | GPCP<br>(1979–2020) | GPCP<br>(1979–2014) | CMIP6-hist (1979–2014)             | AMIP6<br>(1979–2014)               |
|--------------|---------------------|---------------------|------------------------------------|------------------------------------|
| Land + ocean | 0.0074 ± 0.0060     | 0.0062 ± 0.0075     | <b>0.0106 ± 0.0021</b><br>(0.0046) | <b>0.0049 ± 0.0034</b><br>(0.0022) |
| Land         | 0.0060 ± 0.0116     | 0.0082 ± 0.0143     | <b>0.0149 ± 0.0036</b><br>(0.0083) | 0.0086 ± 0.0147<br>(0.0102)        |
| Ocean        | 0.0080 ± 0.0096     | 0.0053 ± 0.0114     | <b>0.0086 ± 0.0026</b><br>(0.0063) | 0.0032 ± 0.0076<br>(0.0038)        |

Possible differences in precipitation trends during distinct seasons are important as well and have been shown in past studies (e.g., Noake et al. 2012; Polson et al. 2013). Here, two contrasting seasons (June-July-August (JJA) and December-January-February (DJF)) are examined. GPCP has significant positive global (land + ocean) trend in DJF despite intense interannual variability, while the trend in JJA is very weak (Fig. 2 and Table 3). Seasonal differences in precipitation trend can also be found over global ocean and land separately (not shown). This seasonal difference is generally in agreement with past studies based on gauge-based land precipitation which showed that external forcing signals could not generally be detected during boreal summer (Noake et al. 2012; Polson et al. 2013). In contrast, global precipitation trends in AMIP6 and CMIP6 (both CMIP6-hist and CMIP6-histGHG) do not show any significant seasonal difference, though the AMIP6 trend in DJF can only reach the 90% confidence level. For mean precipitation over global land and ocean separately, models do not have any seasonal difference in trends too (not shown). The discrepancy between satellite-based GPCP and model outputs might be due to possible observational data issues or model deficiencies or both. Further comparisons between GPCP and models with regards to spatial patterns of seasonal precipitation trends will be made in the next section.

Table 3

Trends ( $\text{mm day}^{-1}$  per decade) in global (land + ocean) mean precipitation anomalies from GPCP, CMIP6-hist, and AMIP6 during JJA and DJF. Also included are the 95% confidence interval. Statistically significant values at the 95% confidence level are marked bold. Statistically significant values at the 90% confidence level are underlined and marked italics.

|     | GPCP<br>(1979–2020)                   | GPCP<br>(1979–2014)                   | CMIP6-hist (1979–2014)                | AMIP6<br>(1979–2014)                  |
|-----|---------------------------------------|---------------------------------------|---------------------------------------|---------------------------------------|
| JJA | $0.0026 \pm 0.0067$                   | $0.0007 \pm 0.0084$                   | <b><math>0.0108 \pm 0.0022</math></b> | <b><math>0.0057 \pm 0.0041</math></b> |
| DJF | <b><math>0.0139 \pm 0.0101</math></b> | <b><math>0.0156 \pm 0.0115</math></b> | <b><math>0.0116 \pm 0.0025</math></b> | $0.0052 \pm 0.0052$                   |

## 3.2 Sensitivities of global mean precipitation to surface temperature change

To further examine and compare global mean precipitation changes in GPCP and model outputs, corresponding sensitivities to surface temperature changes are estimated (Table 4). The hydrological sensitivity ( $\eta$ ) has been found to be  $\sim 2\text{--}3\%/^{\circ}\text{C}$ , generally consistent among different forcing agents based on climate model simulations (e.g., Fläschner et al. 2016; Samset et al. 2018). However,  $\eta$  can't be estimated directly from observations and historical transient simulations (e.g., Fläschner et al. 2016). Hence, the apparent hydrological sensitivity ( $\eta_a$ ) is the focus here, though it is sensitive to various forcing mechanisms and generally less than  $\eta$ , primarily due to rapid atmospheric adjustment in response to various forcings including anthropogenic GHG and aerosols (e.g., Fläschner et al. 2016; Kramer and Soden 2016; Samset et al. 2018; Allan et al. 2020; Yeh et al. 2021). Here,  $\eta_a$  is estimated by calculating the ratios between global mean precipitation trend and surface temperature trend during the same time period (Table 4). For GPCP, GISS ts is applied to estimate global mean surface temperature trend, while for CMIP6-hist and AMIP6, temperature trends are estimated from respective (ensemble-mean) surface

temperature outputs. The observed global mean temperature trend and that used in AMIP6 are roughly the same during 1979–2014 (0.16°C per decade for GISS ts vs 0.15°C per decade for AMIP6), while a much stronger ensemble-mean temperature trend (0.23°C per decade) is found in CMIP6-hist. The more intense warming trend in CMIP6-hist could provide further evidence for the impact of internal modes, specifically the PDO phase shift, despite possible model deficiencies.

Table 4

Percentage changes with surface temperature (%/C) in global annual-mean precipitation from GPCP, CMIP6-hist, and AMIP6. One standard deviation is used to represent the ensemble spread for model outputs.

|              | <b>GPCP<br/>(1979–2020)</b> | <b>GPCP<br/>(1979–2014)</b> | <b>CMIP6-hist (1979–2014)</b> | <b>AMIP6<br/>(1979–2014)</b> |
|--------------|-----------------------------|-----------------------------|-------------------------------|------------------------------|
| Land + ocean | 1.42                        | 1.41                        | 1.52 (0.55)                   | 1.10 (0.50)                  |
| Land         | 1.39                        | 2.23                        | 2.87 (1.65)                   | 2.50 (2.88)                  |
| Ocean        | 1.43                        | 1.12                        | 1.08 (0.78)                   | 0.63 (0.78)                  |

Hence, even though CMIP6-hist shows larger trend in global mean precipitation (Fig. 1 and Table 2), it has a similar  $\eta_a$  as GPCP because of both a larger global mean precipitation value and a stronger temperature trend. Thus, for global mean precipitation (land + ocean), GPCP, CMIP6-hist, and AMIP6 have a similar  $\eta_a$ , ranging from 1.1 to 1.52 %/C (Table 4), roughly consistent with past studies (e.g., Fläschner et al. 2016; Kramer and Soden 2016). This similarity and consistency provide confidence in current understanding of global precipitation change based on both observation and model simulations, despite the short data record (1979–2014) in use here, likely resulting in low signal-to-noise ratios especially in GPCP and AMIP6. Differences in  $\eta_a$  between over land and ocean can also be seen in GPCP, AMIP6, and CMIP6-hist for their overlap period (1979–2014).  $\eta_a$  is generally larger over land than over ocean (Yeh et al. 2021), as is its ensemble spread for model outputs. However, for a longer period (1979–2020),  $\eta_a$  for GPCP is comparable between over land and ocean, suggesting the necessity of a further examination in the future, when observed and modeled precipitation with a longer common data record are available.

Because of the impact of volcanic eruptions and internal modes of climate variability during the satellite era (e.g., Gu and Adler 2013; Gu et al. 2016; Allan et al. 2020),  $\eta_a$  can be sensitive to the length of data record and thus vary with time. It is hence interesting to further examine whether any consistency in  $\eta_a$  can be reached between GPCP and model outputs given the impact from these factors.  $\eta_a$  is then estimated and compared by varying the starting/ending years of the data record (Figs. 3 and 4).

Figure 3 depicts  $\eta_a$  for GPCP and model outputs during the time periods from 1979 to various ending years since 2002. For GPCP, large variations are seen when the ending year is roughly prior to 2011, probably due to the impact from two volcanic eruptions and decadal-scale internal modes. However, it is noted that  $\eta_a$  gradually stabilizes and approaches a value of around 1.5%/C. As shown in Table 4, GPCP  $\eta_a$  is 1.4 and 1.33%/C for 1979–2014 and 1979–2020, respectively. CMIP6-hist  $\eta_a$  approaches and

stabilizes around 1.5%/C when the ending year is roughly later than 2006, much earlier than GPCP. AMIP6  $\eta_a$  is approximately within the same range as those for GPCP and CMIP6-hist, however it tends to become smaller as the ending year becomes more recent. AMIP6  $\eta_a$  is 1.1%/C for the period of 1979–2014. As indicated in Table 4, this smaller value might be due to weaker precipitation responses in AMIP6 over global land compared to both GPCP and CMIP6-hist. It is also noted that for CMIP6-histGHG,  $\eta_a$  has already approached a roughly constant number when the ending year is 2002, and it is around 1.7–1.8%/C. This higher  $\eta_a$  tends to confirm the effect of radiative forcings other than anthropogenic GHG lowering the response in GPCP, CMIP6-hist, and AMIP6 during the period.

Figure 4 illustrates the estimated  $\eta_a$  with the same ending year (2014) but varying starting years from 1997 back to 1979. Large fluctuations appear again in GPCP  $\eta_a$  for different starting years, showing the effect of various internal and external factors. GPCP  $\eta_a$  is even negative with 1997 as the starting year, but sharply increases to about 2.5 %/C with 1989, 1990, and 1991 being the starting year, and then decreases to be less than 1.5%/C as the starting year extends back to 1979. AMIP6  $\eta_a$  roughly follows a similar changing tendency but with less variations as the starting year extends back, from negative to positive  $\eta_a$  and finally approaching 1.1%/C for the entire overlap period (1979–2014). It is noted that AMIP6  $\eta_a$  is always smaller than GPCP  $\eta_a$  with only one exception with 1981 being the starting the year. For CMIP6-hist and histGHG, a relatively smaller change in  $\eta_a$  can be found approximately after the starting year is earlier than 1993, though they tend to separate as the starting year approaches 1979. It is also worth mentioning that CMIP6-hist and histGHG  $\eta_a$  values tend to be larger than GPCP and AMIP6  $\eta_a$  if the starting year is earlier than 1985.

Figures 3 and 4 show the consistencies/inconsistencies in  $\eta_a$  and its dependency on the length of data record between GPCP and climate model outputs. It can be concluded that  $\eta_a$  is sensitive to the length of data record due to the involvement of various internal and external physical mechanisms. Furthermore, by comparing with CMIP6-hist and histGHG ensemble-mean results, fluctuations in  $\eta_a$  in GPCP and AMIP6 may be primarily due to internal modes of climate variability including the PDO and AMO, and also possibly ENSO, though volcanic eruptions may have played a role as well. Nevertheless, it is interesting to note that GPCP, AMIP6, CMIP6-hist, and CMIP6-histGHG would approach each other within a narrow  $\eta_a$  range between about 1.1 and 1.9 %/C when the time period considered extends to the full overlap period (1979–2014). This consistency suggests that  $\eta_a$  might be dominated by the anthropogenic GHG effect. It can further be argued that even though the global mean trend in GPCP is still small and obscured likely by intense (interannual) background noises, the GHG-related effect may already be discernible in GPCP. Furthermore, even though  $\eta_a$  is sensitive differently to various forcing agents as shown in past studies (e.g. e.g., Fläschner et al. 2016; Samset et al. 2018), it can still be applied as an important metric for (ensemble-mean and individual) model evaluations and/or comparisons with observed precipitation likely because of the dominance of the GHG effect.

## 4. Regional Precipitation Variability And Trends

### 4.1 Trends in annual mean precipitation

Although the global mean precipitation trends derived from GPCP are weak (Fig. 1 and Table 2), regional trends with large positive/negative values can readily be seen over global ocean and land (Fig. 5a, b; Gu et al. 2016; Adler et al. 2017, 2020). Precipitation increases approximately along the Pacific ITCZ, even more prominent during the longer period (1979–2020), while precipitation reduction hovers south and north of the ITCZ in the central-eastern Pacific. Positive trends also appear in the tropical western Pacific extending northeastward and southeastward along the SPCZ in a horseshoe shape, across the tropical Indian Ocean and tropical southwestern Atlantic, and over northern South America and west Africa. Subtropical drying can generally be observed in the Pacific and Atlantic Ocean basins, and over lands including the southwest US and part of South America roughly between 20–40°S. These rich spatial features of precipitation change during the GPCP period seem to agree with the notion of “wet-get-wetter, dry-get-drier” derived from coupled model simulations (e.g., Held and Soden 2006), especially over deep tropical oceans for the longer GPCP period (1979–2020).

AMIP6 can reproduce most of these spatial patterns of precipitation change (Fig. 5c) relatively well, though detailed differences exist in many regions especially along the central-eastern Pacific ITCZ where a band of precipitation increase in GPCP is generally replaced by weak negative AMIP trends. The spatial correlation of precipitation trends between AMIP6 and GPCP is 0.53 between 40°N–40°S during 1979–2014 (Table 5). In contrast, precipitation trends in CMIP6-hist tend to manifest different spatial distributions from those in GPCP (Fig. 5d). Spatial correlation between the two within 40°N–40°S is only 0.17, and it is even weaker (0.04) between CMIP6-hist and AMIP6 (Table 5), roughly consistent with past studies (e.g., Hoerling et al. 2010). However, regional similarities between CMIP6-hist and either GPCP or AMIP6 can readily be seen in the deep tropics and over the mid-high latitudes. They all have positive trends along the Pacific ITCZ and SPCZ, in the Indian ocean, and along the Atlantic ITCZ extending across part of the West African continent, etc.; and subtropical drying and high-latitude wetting are generally seen as well in all three. These broad similarities strongly imply the anthropogenic-GHG impact on precipitation change on these regional scales. Also, the GPCP trends with longer record (1979–2020) have a stronger spatial correlation (0.17 to 0.32) with CMIP6-hist (1979–2014) trends, but a weaker spatial correlation (0.53 to 0.33) with AMIP6 (1979–2014) trends (Table 5). This further suggests that with the lengthening of the GPCP record, the anthropogenic-GHG effect will become more prominent along with weakened impact from decadal-scale internal modes.

Table 5

Spatial correlations between trends in annual-mean precipitation from GPCP, CMIP6-hist, AMIP6, hist-resIPO, and hist-resAMO within 40°N-40°S.

|                                | <b>GPCP<br/>1979–<br/>2014<br/><br/>(1979–<br/>2020)</b> | <b>CMIP6-hist 1979–<br/>2014</b> | <b>AMIP6<br/>1979–<br/>2014</b> | <b>hist-<br/>resIPO<br/>1979–<br/>2014</b> | <b>hist-<br/>resAMO<br/>1979–<br/>2014</b> |
|--------------------------------|----------------------------------------------------------|----------------------------------|---------------------------------|--------------------------------------------|--------------------------------------------|
| CMIP6-hist (1979–<br>2014)     | 0.17 (0.32)                                              |                                  | 0.04                            | 0.31                                       | 0.56                                       |
| AMIP6<br><br>(1979–2014)       | 0.53 (0.33)                                              | 0.04                             |                                 | 0.63                                       | 0.02                                       |
| hist-resIPO<br><br>(1979–2014) | 0.50 (0.39)                                              | 0.31                             | 0.63                            |                                            | 0.22                                       |
| hist-resAMO<br><br>(1979–2014) | 0.06 (0.22)                                              | 0.56                             | 0.02                            | 0.22                                       |                                            |

It is also noted that the magnitudes of regional trends in CMIP6-hist are generally smaller than those in either GPCP or AMIP6, whereas CMIP6-hist has larger global mean trends than the other two (Fig. 1 and Table 2). To further quantify how different the trend magnitudes in models might be on the regional scale compared to GPCP's, percentile matchings of trends at grids within 40°N-40°S between model (AMIP6 and CMIP6-hist) and GPCP trends are estimated over land + ocean, land, and ocean, respectively (Fig. 6). High correspondences appear between AMIP6 and GPCP especially over ocean, confirming that AMIP6 can generally simulate regional precipitation trends with similar amplitudes as GPCP. The same conclusion can be made over land + ocean because of the oceanic dominance. However, AMIP6 tends to underestimate trends at both positive and negative ends over land. For CMIP6-hist, much weaker trends are seen over either land or ocean compare to GPCP as depicted in Fig. 5 (CMIP6-hist panel has smaller range in scale), further confirming that on regional scales, the anthropogenic GHG effect could still be overwhelmed by the impact of internal modes of climate variability, even though certain similarities in spatial patterns of precipitation change exist between CMIP6-hist and GPCP/AMP6 (Fig. 5). For a further exploration, temperature trends are estimated at grids for both the observation (GISS ts) and model outputs (Fig. 7). Similar spatial patterns of temperature trends, dominated by the PDO/IPO effect particularly in the Pacific basin, appear in AMIP6 and GISS ts as anticipated (Figs. 7a and 7c), though minor subtle differences exist in many regions. Differences over oceans should be ascribed to the different SST forcing data than GISS ts, while over land areas the differences might imply deficiencies in model responses. However, as mentioned above, the global mean temperature trend in AMIP6 is basically the same as the observed. For CMIP6-hist, spatial features of temperature trends are different from those for both GISS ts and AMIP6 (Figs. 7a, 7c, and 7d), especially in the deep tropics. It is apparent that the

differences in temperature trend patterns between the observations (GISS ts)/AMIP6 and CMIP6-hist are the major reason for the differences in the spatial distributions of precipitation trends (Figs. 5 and 7), and the impact of modes of interdecadal variability specifically the PDO/IPO is the primary player. Also, compared to GISS ts and AMIP6, CMIP6-hist shows much weaker horizontal gradients in temperature trends especially in the tropics-subtropics. This weaker gradient generally implies weaker circulation changes and hence might be the primary reason for relatively weaker regional precipitation trends as shown in Fig. 5. It is further noted that the GISS ts trends for the longer record (1979–2020) are less impacted by the decadal-scale internal modes specifically the PDO/IPO than those for the shorter record (1979–2014; Figs. 7a and 7b), and have a stronger spatial correlation with CMIP6-hist temperature trends between 40°N–40°S (0.52 to 0.66 over land + ocean, and 0.29 to 0.52 over ocean). This confirms that with the lengthening of the observational data record, the effect of decadal-scale internal modes will become weaker and both temperature and precipitation trends will become dominated by the anthropogenic-GHG effect.

Comparisons between GPCP and model outputs are further made in terms of zonal profiles of trends in zonal mean precipitation (Fig. 8). We focus on the latitudinal band of 60°N–60°S because of possible data issues in the high latitudes in GPCP (e.g., Adler et al. 2003, 2018). Similar zonal features can be found over ocean and land + ocean between GPCP and AMIP6 especially in the deep tropics. Over ocean, GPCP illustrates a band of intense precipitation increase roughly along the ITCZ, while the band in AMIP6 is weaker with reduction along 10°N and increase north of it, roughly peaking around 20°N. The failure of the AMIP simulations to accurately simulate this very distinctive, and very narrow, feature in the observations may be due to the relatively coarse resolution in the models unable to accurately represent the dynamics in this narrow belt. This poor result for the narrow rainfall feature at this latitude may shift the AMIP trend pattern poleward with compensating, incorrect dynamics resulting in the mismatched pattern with an incorrect AMIP peak at 20°N. South of the Equator with larger scale features, possibly easier to simulate, reductions between the equator and 10°S and a band of increase between 10°S–25°S appear in both GPCP and AMIP6. However, the zonal structures of the trends tend to be different south of about 30°S. Discrepancies can also be seen north of about 20°N. Over land, differences between GPCP and AMIP6 can readily be found in the deep tropics and south of the equator with GPCP manifesting more meridional structures. However, there are still certain similarities between the two, for instance, precipitation increase can be seen in the tropics except right north of the equator where a band of reduction appears in GPCP. Nevertheless, general consistencies between the two can be seen north of about 10°N.

Similarities can also be found between CMIP6-hist and GPCP, despite that CMIP6-hist shows much smoother zonal profiles of trends and the profiles tend to be similar between land and ocean. Specifically, both CMIP6-hist and GPCP have positive trends in the tropics with a maximum north of the equator and drying or weak positive trends in the subtropics, though GPCP shows more complicated meridional structure. Precipitation increase also appears in CMIP6-hist and GPCP in the mid-high latitudes except

over the northern hemispheric ocean where larger uncertainties may exist in GPCP (e.g., Adler et al. 2003, 2018).

As mentioned before, spatial patterns of precipitation trends in GPCP and model outputs (AMIP6 and CMIP6-hist) seem to agree with “wet-get-wetter, dry-get-drier” (e.g., Held and Soden 2006; Zhou et al. 2011). However, previous studies have argued that this notion does not hold over land (e.g., Greve et al. 2014; Byrne and O’Gorman 2015) and does not even exactly hold over tropical ocean (e.g., Chadwick et al. 2013). To further investigate this, spatial correlations between precipitation trends and climatological mean precipitation at grids between 40°N-40°S are estimated for GPCP and the ensemble means of CMIP6-hist and AMIP6 (Table 6). Consistent with Chadwick et al. (2013), correlations are generally weak especially over land in GPCP. Correlation in AMIP6 is also weak over both land and ocean, though it is relatively stronger over land. For CMIP6-hist, correlations over both land and ocean are weak as well, though they are relatively stronger than the respective ones for GPCP, suggesting that the impact of internal modes of climate variability could not be the dominant reason for the weak correlations. Spatial correlations between precipitation trends and mean precipitation within 40°N-40°S are further estimated for all individual model runs in CMIP6-hist and AMIP6. It is noted that the mean spatial correlations for CMIP6-hist and AMIP6 are much weaker than the ones corresponding to their respective ensemble means and those for GPCP (Table 6). There are also large spreads in the spatial correlations from individual model runs for both AMIP6 and CMIP6-hist. For AMIP6, the spatial correlation coefficient can be from 0 to 0.56 over land and from 0.07 to 0.33 over ocean among 28 individual model members. For CMIP6-hist, the spread is even larger with the correlation being from – 0.20 to 0.36 over land and from – 0.31 to 0.39 over ocean; and negative spatial correlations appear for several individual models over land (8 of 28) and ocean (3 of 28). These results generally confirm that circulation changes/shifts related to both anthropogenic GHG forcing and internal modes of climate variability would be the factors controlling the patterns of precipitation change (e.g., Chadwick et al. 2013; Byrne and O’Gorman 2015), a critical source of uncertainty in model outputs (e.g., Shepherd 2014).

Table 6  
Spatial correlations between trends in annual-mean precipitation from GPCP, CMIP6-hist, and AMIP6 and corresponding mean precipitation within 40°N-40°S. Numbers in parentheses for CMIP6-hist and AMIP6 are the averages of their respective individual model runs.

| <b>Trend vs mean precipitation</b> | <b>GPCP</b>        | <b>CMIP6-hist</b> | <b>AMIP6</b>     |
|------------------------------------|--------------------|-------------------|------------------|
|                                    | <b>1979–2014</b>   | <b>1979–2014</b>  | <b>1979–2014</b> |
|                                    | <b>(1979–2020)</b> |                   |                  |
| Land + ocean                       | 0.23 (0.27)        | 0.28 (0.12)       | 0.19 (0.16)      |
| Land                               | 0.10 (0.02)        | 0.17 (0.09)       | 0.30 (0.19)      |
| Ocean                              | 0.28 (0.37)        | 0.33 (0.12)       | 0.18 (0.16)      |

Seasonal difference in global mean precipitation trends is evident based on GPCP, but generally weak in AMIP6 and CMIP6-hist (Fig. 2 and Table 3). It is hence interesting to further explore whether and how spatial patterns of precipitation change would vary with season in GPCP and model outputs. Also, since AMIP6 can generally reproduce the major spatial features of annual mean precipitation trends observed in GPCP (Fig. 5), it is necessary to make further comparisons with GPCP with regards to regional precipitation trends during different seasons. Figure 9 illustrates precipitation trends at grids in GPCP, AMIP6, and CMIP6-hist in four standard seasons during 1979–2014. GPCP trends have many similar spatial features between the four distinct seasons (left panel in Fig. 9), which can also be found in GPCP annual mean precipitation trends (Fig. 5a). For instance, precipitation increase appears in all seasons along the Pacific ITCZ, SPCZ, western Pacific, and part of Indian Ocean and tropical Atlantic; and precipitation reduction just north and south of the equator in the Pacific and in the subtropics can be observed in all seasons. However, large seasonal differences exist in many regions. Detailed patterns of precipitation trends vary with season especially in the tropical Pacific where the magnitudes and spatial distributions of precipitation trend in JJA tend to be different than during three other seasons; positive trend occurs over the Amazon region of South America in DJF and MAM, while a weak negative trend is generally seen in JJA and SON; and also a large seasonal contrast (DJF and MAM vs JJA and SON) is observed in the Southern Hemisphere mid-high latitudes roughly along the 60°S, though the uncertainty of GPCP precipitation might be large in this region (e.g., Adler et al. 2003, 2018). Spatial features of AMIP6 trends also resemble each other between seasons (middle panel in Fig. 9), although seasonal differences do exist especially in the tropics. And similarities between AMIP6 and GPCP can also be found during the four seasons, confirmed by relatively high spatial correlations between 40°N–40°S except for JJA (Table 7). In JJA, unlike GPCP, AMIP6 generally has similar amplitudes of positive/negative trends as in the other three seasons. For CMIP6-hist, the similarities between seasons can generally be found globally (right panel in Fig. 9). However, positive trends in the deep tropics tend to be stronger in JJA and SON, for instance, along the Pacific ITCZ, over western Indian Ocean–West Africa, etc. It is also noted that precipitation trends over the Amazon region of South America vary with season with positive trends in DJF and MAM while weak negative trends in JJA and SON, roughly consistent with the GPCP results. Nevertheless, the spatial correlations between CMIP6-hist and either GPCP or AMIP6 during the four seasons tend to be low (Table 7), further confirming the dominance of internal modes of climate variability during the GPCP era.

Table 7  
Spatial correlations between trends in seasonal mean precipitation from GPCP, AMIP6, and CMIP6-hist within 40°N-40°S during 1979–2014.

|     | GPCP vs AMIP6 | GPCP vs CMIP6-hist | CMIP6-hist vs AMIP6 |
|-----|---------------|--------------------|---------------------|
| DJF | 0.44          | 0.26               | 0.05                |
| MAM | 0.56          | 0.11               | 0.05                |
| JJA | 0.27          | 0.09               | -0.12               |
| SON | 0.51          | 0.12               | 0.10                |

## 4.2 Impact of the PDO and AMO

The impact of internal modes of climate variability, specifically the PDO and AMO, on precipitation trends during the satellite era is further examined by means of two types of CMIP6 historical pacemaker simulations (Zhou et al. 2016). The hist-resIPO and hist-resAMO experiments are driven by the historical radiative forcings used in the CMIP6 historical full forcing runs and the observed SSTs over the main IPO region: 20°S-20°N, 175°E-75°W and over the AMO region: 0-70°N, 0-70°W, respectively. Figure 10 depicts the simulated precipitation trends related to the PDO (hist-resIPO) and AMO (hist-resAMO), respectively, during 1979–2014. Even though only eight ensemble members are available, hist-resIPO manifests very similar spatial patterns of precipitation trends as GPCP and AMIP6 (Figs. 5a, 5c, and 10a). Spatial correlation of precipitation trends between 40°N-40°S is 0.50 between hist-resIPO and GPCP, and even higher (0.63) between hist-resIPO and AMIP6 (Table 5). However, the correlation is weaker between hist-resIPO and GPCP with the longer-record (1979–2020); and it becomes even weaker between hist-resIPO and CMIP6-hist, despite that the historical radiative forcings used in CMIP6-hist had also been applied in hist-resIPO. The results further confirm the dominant role of the PDO in shaping the spatial patterns of precipitation change during the satellite era.

For hist-resAMO, the simulated precipitation trends manifest different spatial structures than those for GPCP (Figs. 5a and 10b) with a very weak spatial correlation (0.06) between the two fields within 40°N-40°S, though certain similarities can still be found in some regions. Its spatial correlation with AMIP6 is even weaker (0.02). However, there are broad similarities in spatial patterns of precipitation change between hist-resAMO and CMIP6-hist (Figs. 5d and 10b) with a relatively high spatial correlation (0.56), in spite of very few model ensemble members (5) available for hist-resAMO. Thus, the AMO effect may actually enhance the spatial patterns of precipitation change related to anthropogenic radiative forcings specifically GHG during the period.

The effects of the PDO and AMO on GPCP precipitation trends are further examined by means of a procedure of multiple linear regression applied in Gu et al. (2016). By regressing against the PDO (Zhang et al. 1997; Mantua and Hare 2002) and AMO indices (Enfield et al. 2001), precipitation anomalies during 1979–2014 are decomposed; and trends associated with either the PDO or the AMO are then estimated

(Fig. 11). With the PDO and AMO effect removed or reduced, the GPCP trends have more similarities to the CMIP6-hist simulated trends (Figs. 5a, 5d, and 11d). Spatial correlations within 40°N-40°S have also increased (Table 8), especially over ocean; however, spatial correlations over land become weaker and even negative, suggesting the limitations of the linear regression method used here. It is also noted that there are high similarities between the trends associated with the PDO and the hist-resIPO simulated trends (Figs. 10a and 11a), confirming the effectiveness of the method in identifying the PDO impact; nevertheless, obvious discrepancies exist between the trends associated with the AMO and the hist-resAMO simulated trends (Figs. 10b and 11b), implying that either the regression method applied here might not be effective in identifying the AMO impact or the AMO effect on precipitation during the period might be weak as suggested in Gu et al. (2016) and can't be identified correctly through linear regression method.

Table 8  
Spatial correlations between trends in annual-mean precipitation from GPCP with/without the effects from PDO and AMO, and from CMIP6-hist within 40°N-40°S.

|                           |              | GPCP                  | GPCP (No PDO or AMO effect) |
|---------------------------|--------------|-----------------------|-----------------------------|
|                           |              | 1979–2020 (1979–2014) | 1979–2020 (1979–2014)       |
| CMIP6-hist<br>(1979–2014) | Land + ocean | 0.32 (0.17)           | 0.35 (0.22)                 |
|                           | Land         | 0.16 (0.06)           | -0.06 (-0.18)               |
|                           | Ocean        | 0.38 (0.14)           | 0.50 (0.29)                 |

## 4.3 Trends in precipitation seasonal range

Possible changes in global precipitation seasonal cycle are investigated in this subsection. We center our calculations on long-term changes/trends in precipitation seasonal range defined as the difference between precipitation in the peak month and the lowest month within each year, though other aspects of seasonal variation are also important. The three-month-running-averages of monthly precipitation are first computed at grids; the months with maximum and minimum precipitation for each year can then be identified and so are precipitation seasonal ranges; finally, linear trends in resulting annual time series of seasonal range are estimated. Trends in precipitation seasonal ranges over land during 1979–2014 are depicted in Fig. 12 for GPCP and model outputs.

Consistent with past studies (e.g., Chou et al. 2013; Marvel et al. 2017), seasonal ranges have increased in many regions during the satellite era as shown in GPCP (Fig. 12a), including central South America, southwest US and Mexico, middle of North America, northern portion of Australia, tropical West Africa and southern part of Africa, northern Eurasia, etc. Globally, the seasonal range increase can generally be ascribed to a “wetter” wet month and a “drier” dry month (not shown). Seasonal range reductions in GPCP can also be found in some other areas, such as southeastern US, part of South America, regions scattered across the Eurasian continent, etc. However, the changes in precipitation seasonal range tend to be dominated by the changes in the wet month over both land and ocean (not shown). Compared to

GPCP, both AMIP6 and CMIP6-hist produce broad similar spatial features of changes in precipitation seasonal range, though the amplitudes of changes in GPCP tend to be larger. These common spatial features of changes may suggest the impact of anthropogenic GHG on regional precipitation change during the period, which seems more discernible and consistent between GPCP and models than mean precipitation trends indicate (Figs. 5 and 12). Therefore, trends in precipitation seasonal range might be a better indicator for regional precipitation change. It should also be mentioned that the discrepancies between GPCP and model outputs are large over ocean with regards to the trends of precipitation seasonal range (not shown), likely associated with weaker oceanic seasonal cycle, model deficiencies, and possible GPCP data issues. Also, widespread and more intense temperature warming over land than over ocean in both the observation and model outputs (Fig. 7) might be another reason for similar changes in precipitation seasonal range over land in GPCP and AMIP6/CMIP6-hist.

## 5. Summary And Concluding Remarks

Global mean precipitation has increased during the satellite era following surface warming based on both GPCP and climate model simulations (CMIP6-hist and AMIP6). The trends in global mean precipitation are relatively weak in GPCP, with the global land + ocean number roughly 0.27% per decade for the overlap period with CMIP6 (1979–2014), compared to the trends in CMIP6-hist (0.36% per decade). Global mean trends in AMIP6 (0.16% per decade) are weaker than both CMIP6-hist and GPCP trends, suggesting the crucial effect of surface temperature variability from internal modes including the PDO and AMO during the satellite era and also possible model deficiencies. However, a roughly same sensitivity to global mean surface temperature warming, the apparent hydrological sensitivity, ( $\eta_a$ ) can be found in GPCP and models for the overlap period (1979–2014): GPCP (1.41%/C) vs CMIP6 (1.52%/C) vs AMIP (1.1%/C). In particular, even though various factors can influence  $\eta_a$  (Figs. 3 and 4), GPCP, AMIP6, CMIP6-hist, and CMIP6-histGHG tend to approach each other eventually within a narrow  $\eta_a$  range, suggesting that  $\eta_a$  might already be dominated by the anthropogenic GHG effect during 1979–2014. Thus, in spite of intense (interannual) background noises, the GHG-related effect may already be discernible in GPCP. Also, even though  $\eta_a$  is dependent upon forcing agents (e.g., Fläschner et al. 2016; Samset et al. 2018), it could still be a good metric for model evaluations and/or comparisons with observations.

Even though the global mean precipitation trend is still weak in GPCP, prominent spatial patterns of precipitation trends can readily be seen across the world. Precipitation increases along the Pacific ITCZ and SPCZ, while decreases south and north of the ITCZ in the central-eastern Pacific. Precipitation increase also occurs in the other regions including tropical western Pacific, Indian Ocean, southwest of tropical Atlantic, etc., while drying can generally be observed especially over subtropical oceans. AMIP6 can generally reproduce these features well in terms of the large-scale spatial structures of precipitation change, while CMIP6-hist doesn't, confirming the importance of internal modes of climate variability (PDO, AMO, etc.) during the satellite era. CMIP6 pacemaker runs further confirm that the PDO might have played a dominant role in spatial patterns of precipitation change during the satellite era, and the AMO may only played a minor role though it seems to enhance the impact of anthropogenic GHG. GPCP trends for a relatively longer-period (1979–2020) or with the PDO and AMO effects removed or limited tend to be

more similar to the CMIP6-hist simulated trends. Hence, the effect of anthropogenic-GHG would become dominant with the lengthening of observations in the near future, resulting from reduced impact from internal modes. This is also generally supported by many similar zonal-mean features of precipitation trends appearing in GPCP, CMIP6-hist, and AMIP6.

Evident changes/trends in precipitation seasonal range are discovered in GPCP across the world, generally confirmed by AMIP6 and CMIP6-hist specifically over global land areas in terms of spatial features of changes. These consistencies tend to support that the impact of anthropogenic GHG on regional scales during the period and might be more discernible in the trends of precipitation seasonal range than in mean precipitation trends. Hence, precipitation seasonal range might be another good indicator for regional and global precipitation change, in addition to (monthly) precipitation intensity as defined in Gu and Adler (2018).

## Declarations

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**Author Contributions:** GG performed the data analysis including drawing the figures and tables. GG and RA contributed to the interpretation of the results and to the manuscript text.

**Data Availability:** The GPCP V2.3 monthly precipitation analysis is available from NOAA/NCEI at <https://www.ncei.noaa.gov/data/global-precipitation-climatology-project-gpcp-monthly/access/> and can also be downloaded from [http://eagle1.umd.edu/GPCP\\_ICDR/GPCP\\_Monthly.html](http://eagle1.umd.edu/GPCP_ICDR/GPCP_Monthly.html). The CMIP6 and AMIP6 data are available at the CMIP6 website (<https://esgf-node.llnl.gov/projects/cmip6/>). The NASA-GISS global surface temperature anomaly product was downloaded from its website at <http://data.giss.nasa.gov/>. The PDO and AMO indices were downloaded from the University of Washington (<http://jisao.washington.edu/pdo/PDO.latest>) and NOAA/ERSL/PSD (<http://www.esrl.noaa.gov/psd/data/timeseries/AMO/>), respectively.

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## Figures

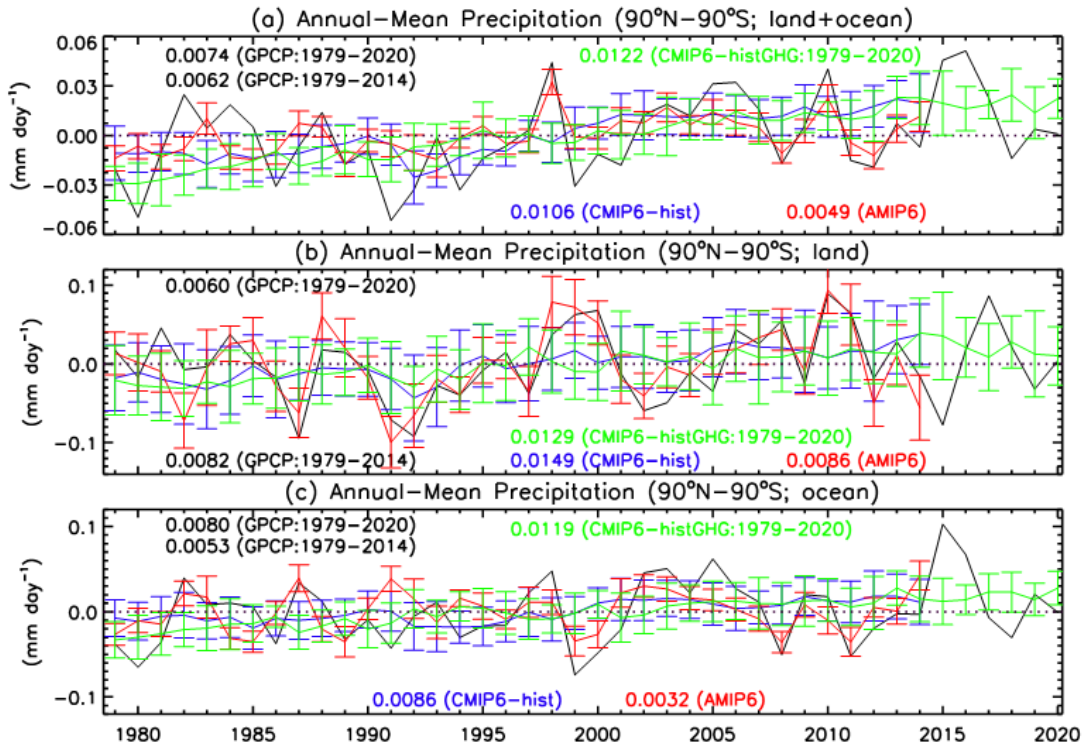


Figure 1

Global annual mean precipitation anomalies in GPCP, AMIP6, CMIP6-hist, and CMIP6-histGHG. For AMIP6, CMIP6-hist, and CMIP6-histGHG, one standard deviation estimated from 28 model outputs is applied to represent the model spread (vertical error bar).

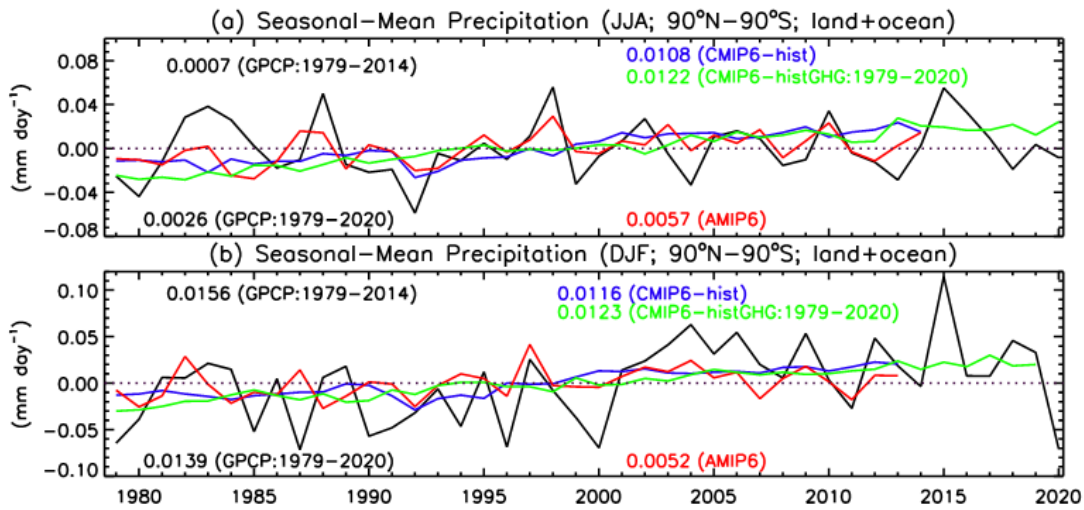
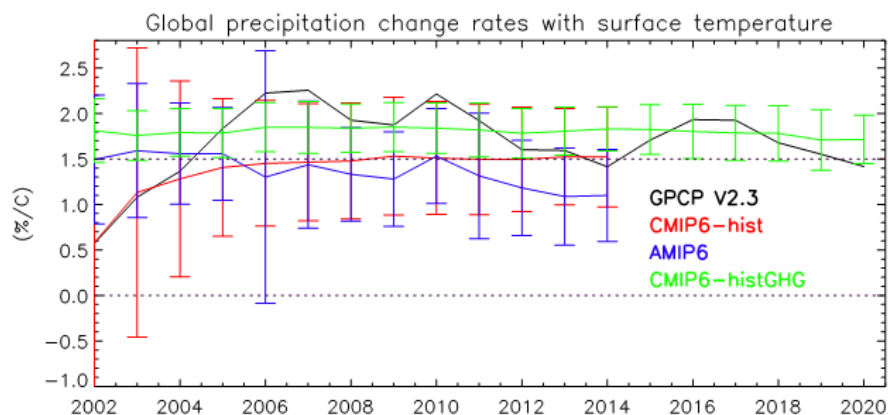


Figure 2

Seasonal-mean times series of global (land+ocean) precipitation in GPCP, AMIP6, CMIP6-hist, and CMIP6-histGHG. (a) JJA, and (b) DJF.



**Figure 3**

Global (land+ocean) precipitation change rates (%/C) with corresponding surface temperature change during the GPCP period as function of the length of varying time periods from 1979 for GPCP, AMIP6, CMIP6-hist, and CMIP6-histGHG. The x axis represents the end years of the time periods in which precipitation change rates are estimated. For instance, 2002 indicates the time period of 1979-2002 (24

years). Also, one standard deviation estimated from multiple model outputs is applied to represent the model spread (vertical error bar).

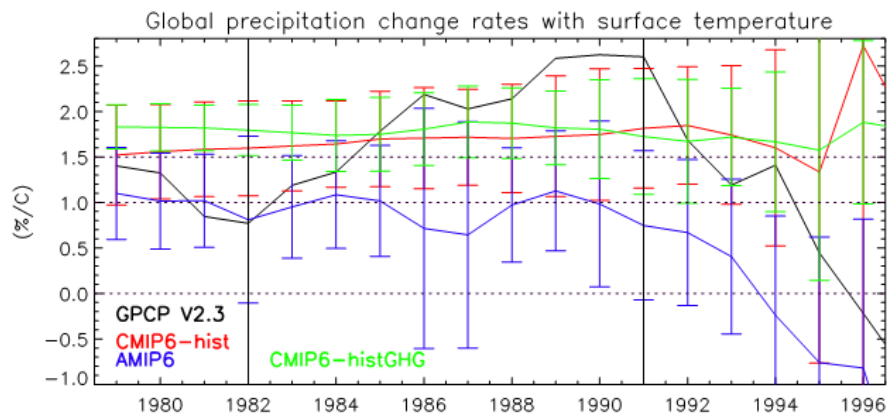


Figure 4

Global (land+ocean) precipitation change rates (%/C) with corresponding surface temperature change during the GPCP period as function of the length of varying time periods to 2014 for GPCP, AMIP6,

CMIP6-hist, and CMIP6-histGHG. The x axis represents the beginning years of the time periods in which precipitation change rates are estimated. For instance, 1980 indicates the time period of 1980-2014 (35 years). Also, one standard deviation estimated from multiple model outputs is applied to represent the model spread (vertical error bar).

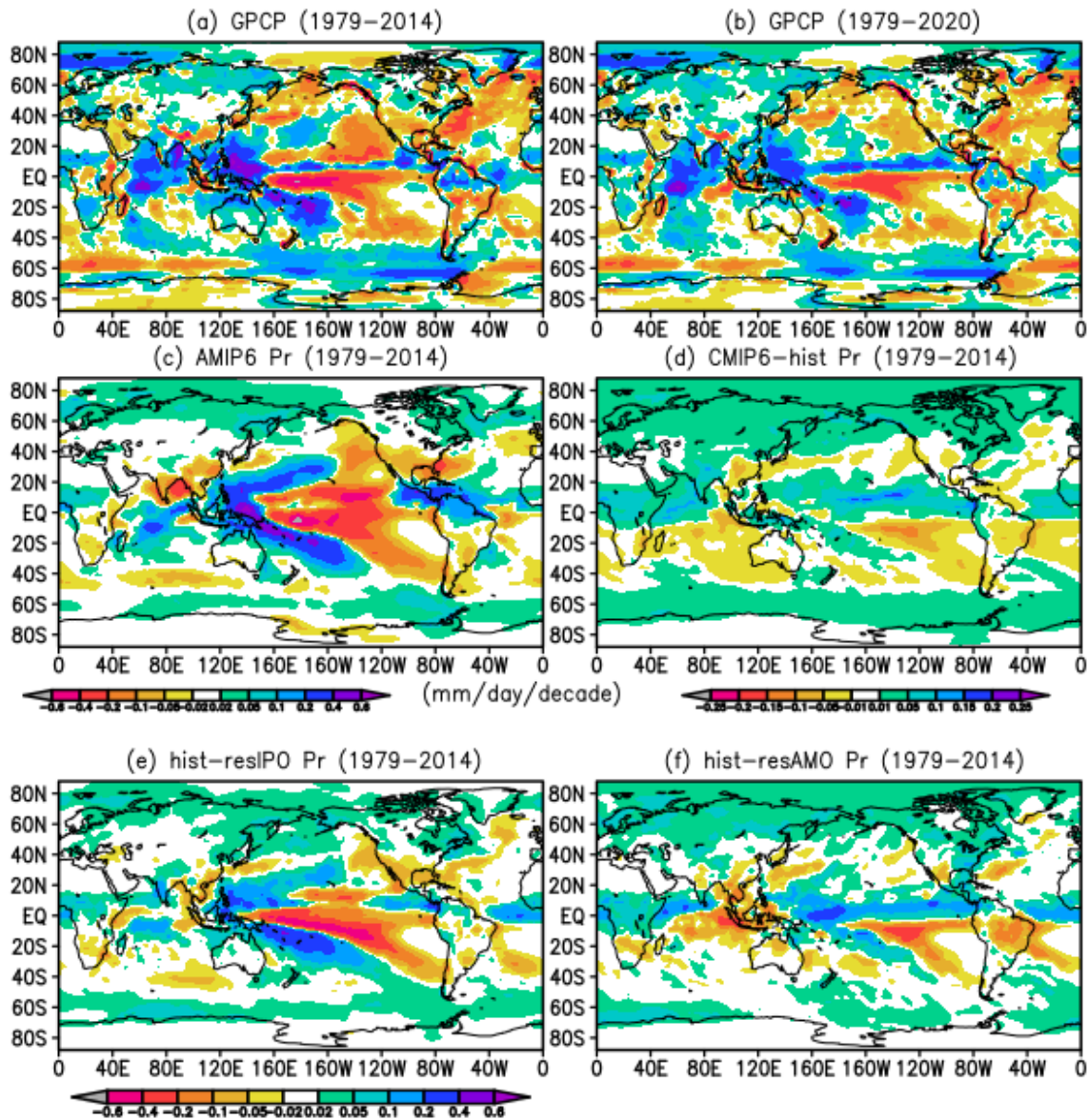


Figure 5

Observed GPCP precipitation trend (mm day<sup>-1</sup>per decade) during (a) 1979-2014 and (b) 1979-2020. (c) AMIP6 and (d) CMIP6 historical full forcing simulated precipitation trend (mm day<sup>-1</sup> per decade) during 1979-2014.

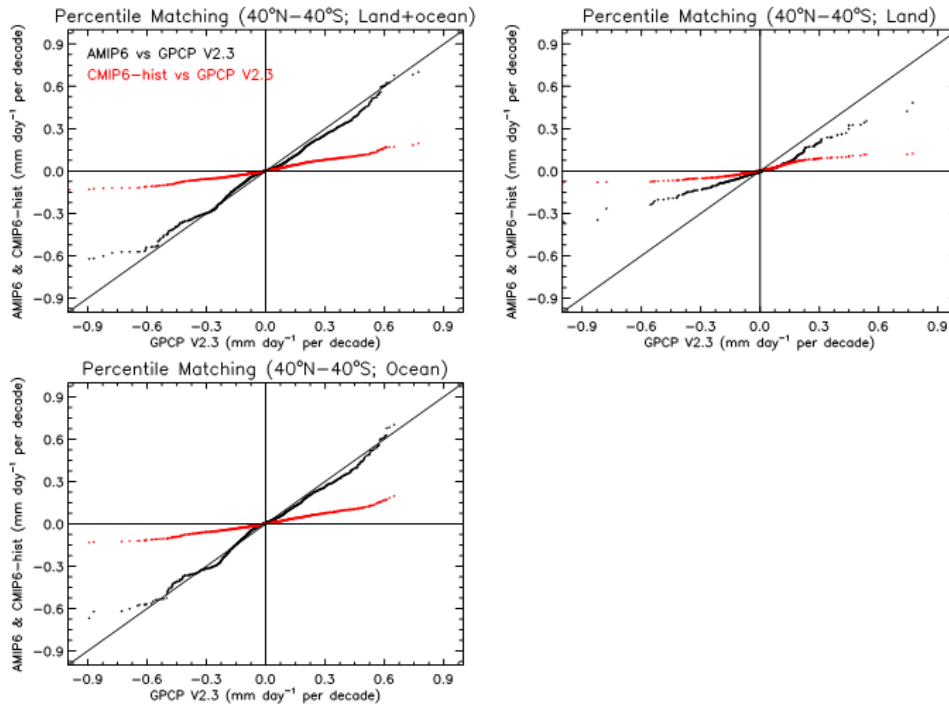


Figure 6

Percentile matching of precipitation trends (mm day<sup>-1</sup> per decade) within 40°N-40°S between AMIP 6 and GPCP (black) and between CMIP6-hist and GPCP (red) during 1979-2014.

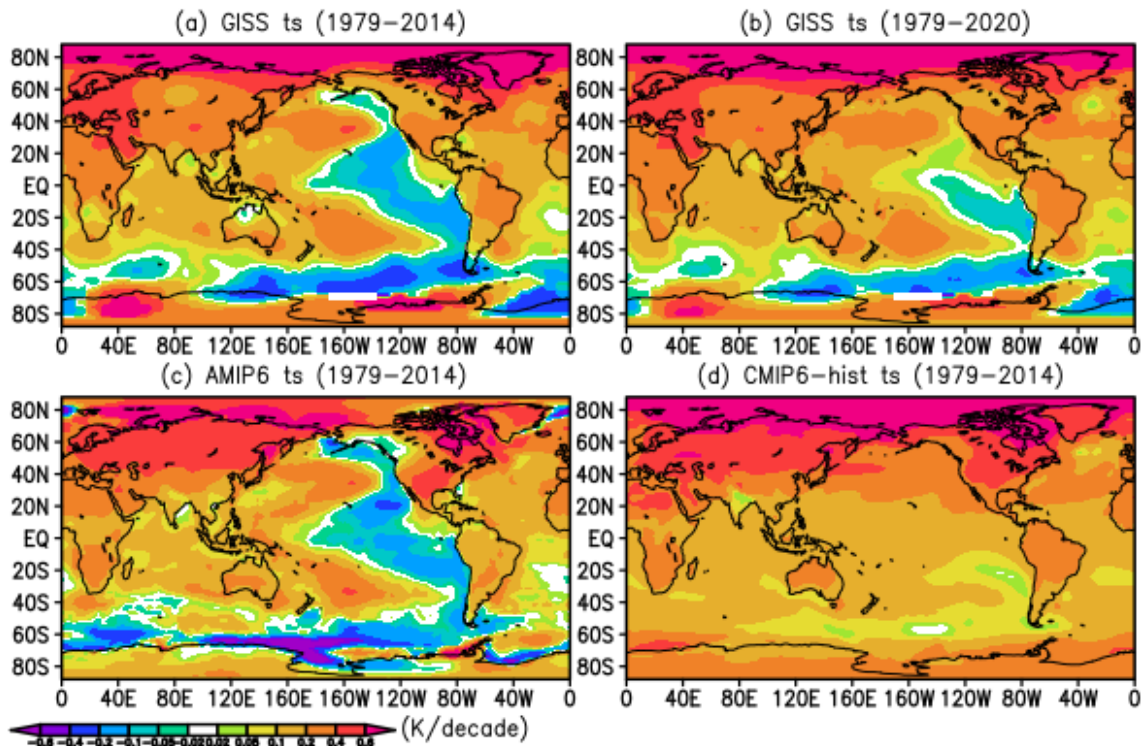
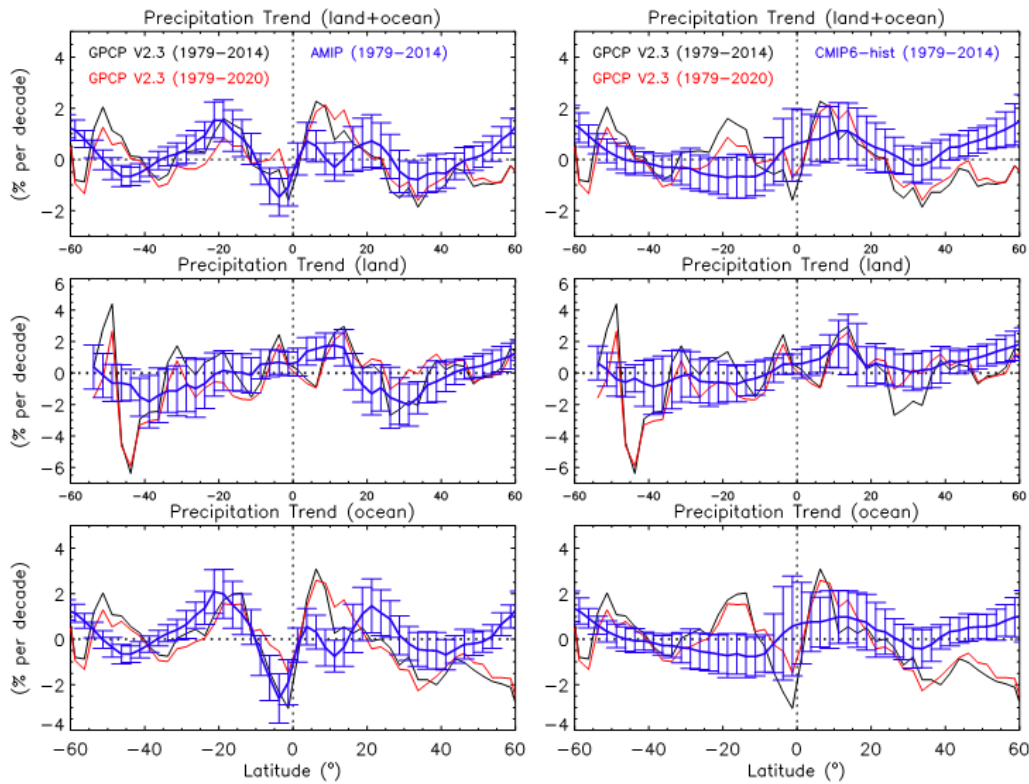


Figure 7

Observed GISS ts trend (K per decade) during (a) 1979-2014 and (b) 1979-2020. (c) AMIP6 and (d) CMIP6 historical full forcing simulated temperature trend (K per decade) during 1979-2014.



**Figure 8**

Zonal profiles of annual-mean precipitation trends (% per decade) in GPCP, AMIP6, and CMIP6-hist. The model spread (vertical error bar) is represented by one standard deviation estimated from 28 model outputs

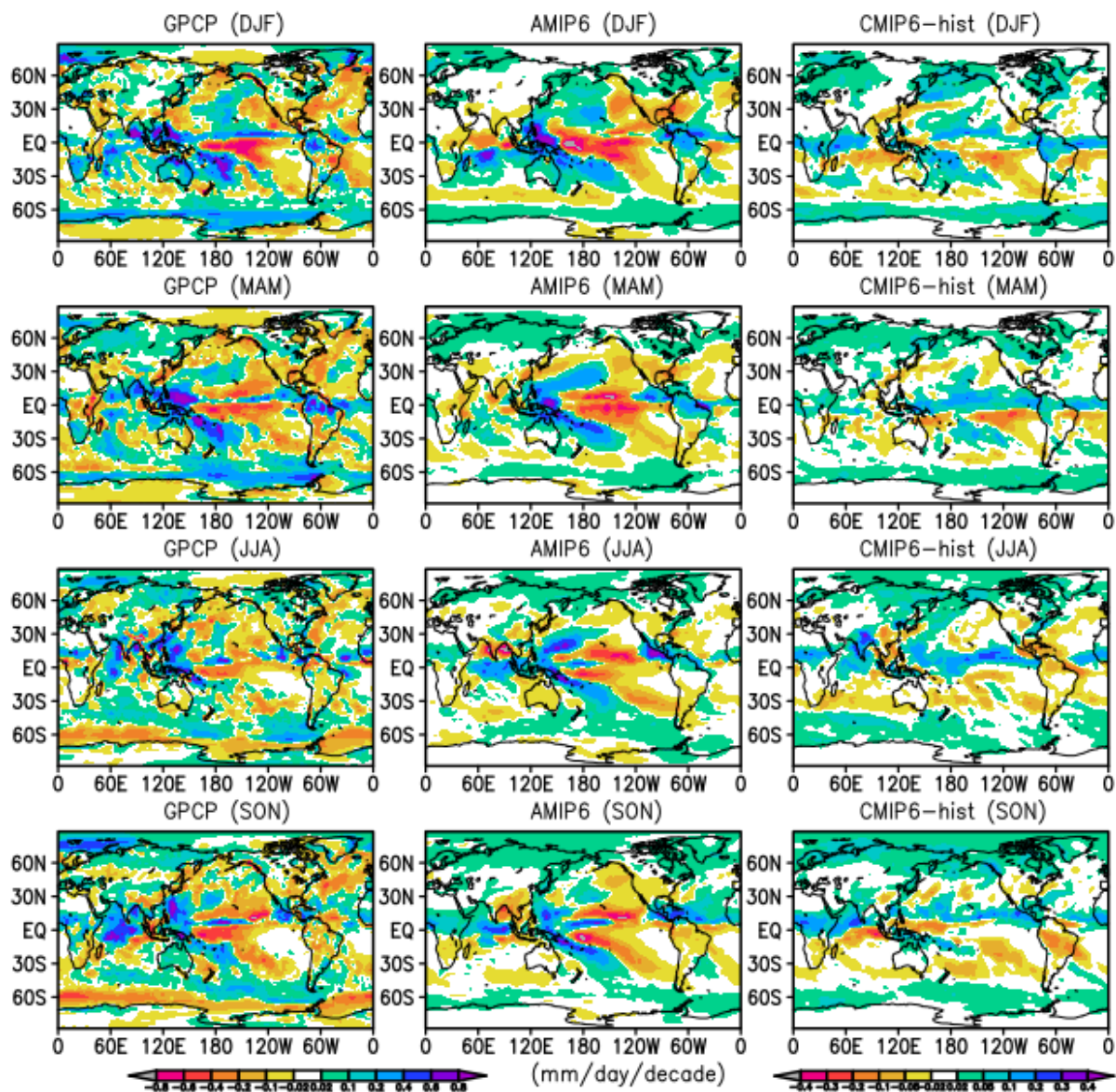


Figure 9

Linear trends in GPCP (left), AMIP6 (middle), and CMIP6-hist (right) seasonal mean precipitation anomalies during 1979-2014.

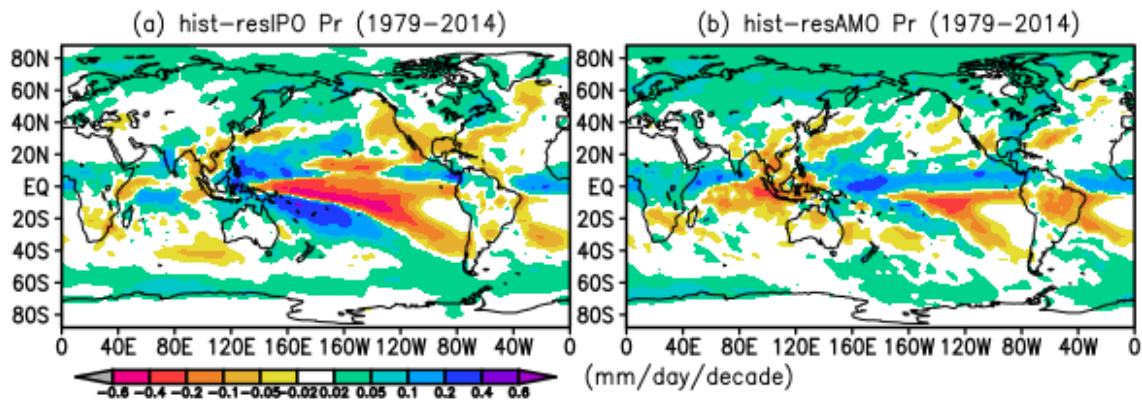
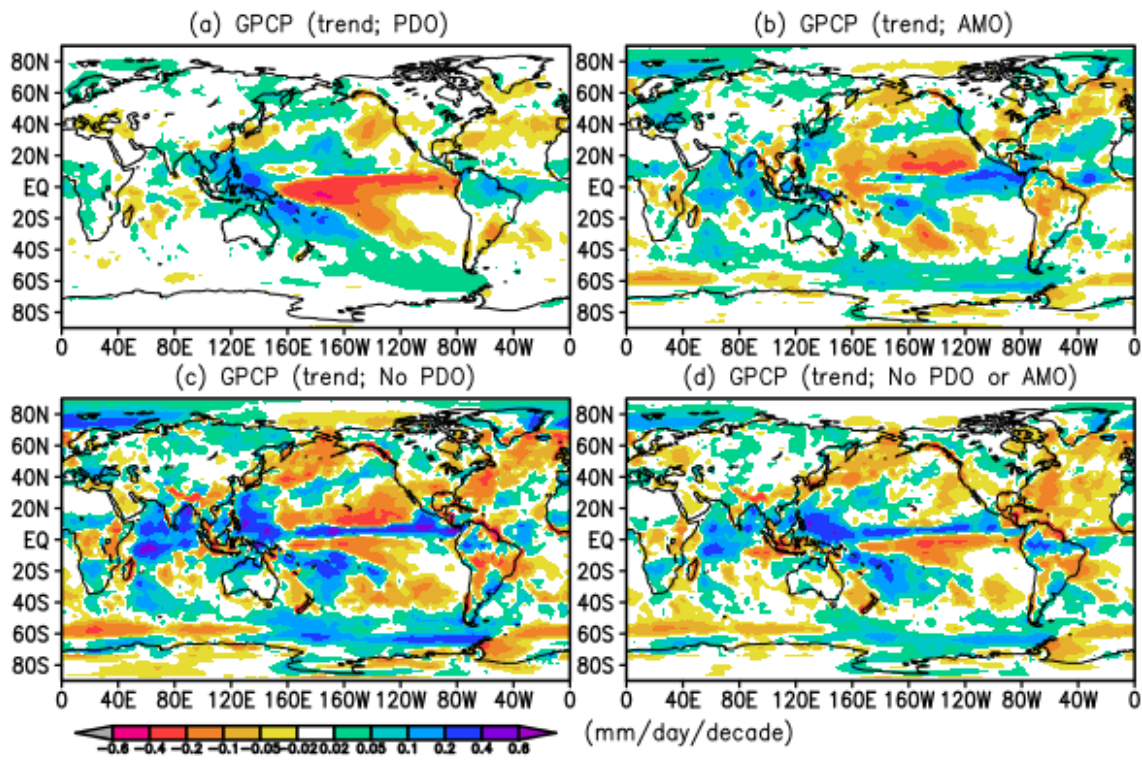


Figure 10

CMIP6 (a) hist-resIPO and (b) hist-resAMO simulated precipitation trend (mm day<sup>-1</sup> per decade) during 1979-2014.



**Figure 11**

Estimated contributions from (a) PDO and (b) AMO to observed GPCP precipitation trend (mm day<sup>-1</sup> per decade) during 1979-2014; (c) GPCP trend without the PDO effect; (d) GPCP trend with both the PDO and AMO effects removed.

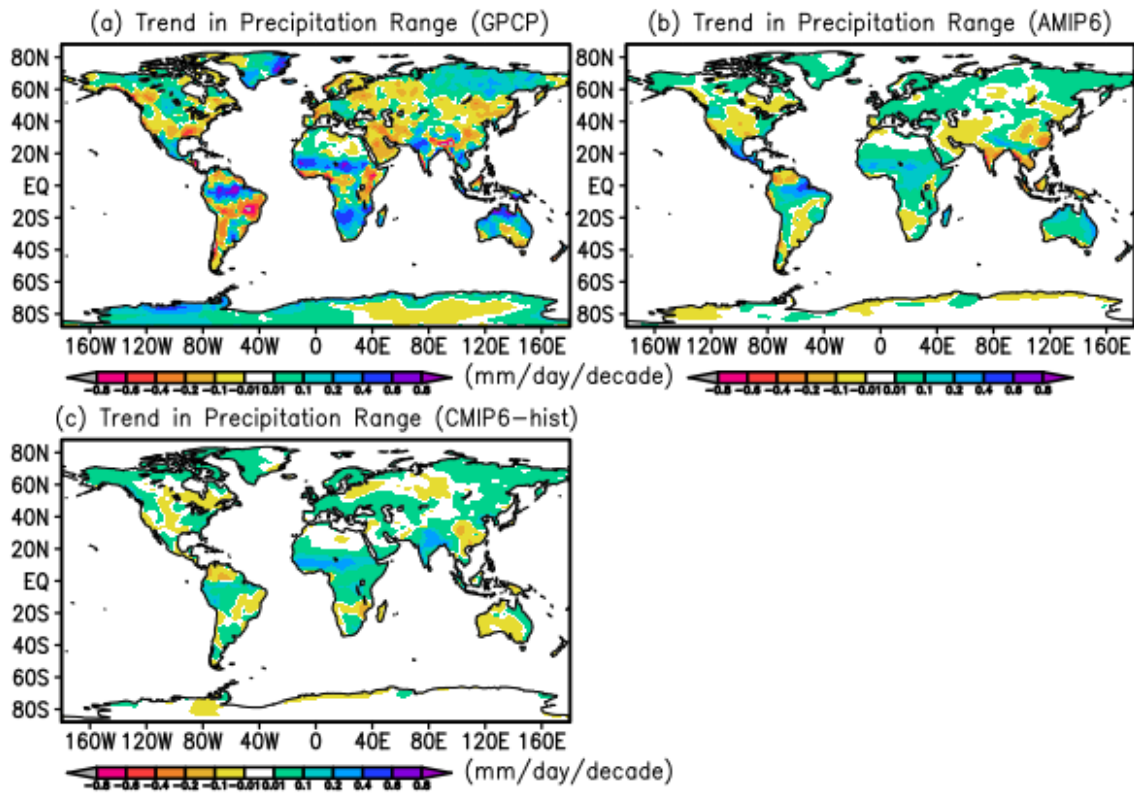


Figure 12

Linear trends in seasonal precipitation range (defined by the difference between precipitation in peak month and lowest month within each year) over land during 1979-2014. (a) GPCP, (b) AMIP6, and (c) CMIP6-hist.