Global Monsoon Changes with Specific Warming Levels in Two Large-Ensemble Simulations

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Key points:

- Global monsoon area and intensity both show quasi-linear increasing with global warming levels.
- Projection of North American monsoon depend on temperature differences between the equatorial eastern Pacific and the tropical Atlantic.
- Dynamic component plays the dominant role in causing changes in monsoon precipitation, thermodynamic component makes positive contributions.

Abstract

Projection of the global monsoon (GM) system is essential for water resource management, food security, and policymaking. Here we investigate projected changes in global monsoon area (GMA) and global monsoon intensity (GMI) with specific global warming levels, using two datasets of large-ensemble simulations. Both datasets project quasi-linear increases in GMA and GMI with global warming. The GMI over Northern-Hemisphere continents is consistently enhanced, while the GMI over Southern-Hemisphere continents are dominated by opposite changes in the GMI over South America. In addition, both datasets show enhanced monsoon intensity over most parts of regional monsoon domains, except for the North American monsoon. The different changes of the North

American monsoon are up on projected temperature differences between the equatorial eastern Pacific and the tropical Atlantic. Moisture budget shows that the thermodynamic component always makes a large positive contribution to the increase in monsoon precipitation, while evaporation has a smaller positive contribution, except for the East Asian monsoon. The contribution of the dynamic component shows large differences for different regional monsoons. Therefore, the different changes in regional monsoon precipitation are mainly caused by the dynamic component.

Plain Language Summary

Future changes in the global monsoon (GM) have a great impact on human society, water resource management, food security, and policymaking. Using two large-ensemble simulations, we study the changes in global monsoon with specific global mean surface temperature increases, such as 1.5 °C to 5 °C of warming. We find that the global monsoon area and monsoon precipitation intensity will quasi-linearly increase in the future. The global monsoon intensity over Northern-Hemisphere land will be consistently enhanced, while the opposite changes over Southern-Hemisphere land. The intensity changes in the North American monsoon will be up on temperature difference between the equatorial eastern Pacific and the tropical Atlantic in the future. The thermodynamic component always makes a large positive contribution to increasing monsoon rainfall, evaporation only has significant positive effect on the East Asian monsoon, and the dynamic component is most important in determining monsoon precipitation changes in the future.

1 Introduction

Over two-thirds of the global population is influenced by the global monsoon (GM) system, and the GM variability is of essential scientific and social-economic importance (Wang and Ding 2008). During the past two decades, how GM changes in future, in responding to global greenhouse warming, has been a crucial issue for food security, water resource management, and policymaking.

There have been extensive works that investigated GM projections, using Coupled Model Intercomparison Project (CMIP) datasets. Based on CMIP phase 3 (CMIP3), Kim et al. (2008) found that multi-model ensemble means can capture GM precipitation, but model spreads are large. Hsu et al. (2012, 2013) found increases in GM area (GMA) and GM precipitation (GMP) in both the CMIP3 and CMIP5 projection simulations. They attributed it to increases in moisture convergence and surface evaporation. Lee and Wang (2014) showed that CMIP5 models have improved abilities in simulating GMP. They pointed out that Northern-Hemisphere (NH) GMP will increase due to an increase in temperature contrast between the NH and Southern Hemisphere (SH), and atmospheric moistening, against the enhanced troposphere atmospheric stability. The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC-AR6) showed that the GMP will increase in the mid-to long term future, particularly over South and Southeast Asia, East Asia, and West

Africa (IPCC, 2021).

Recently, CMIP6 simulations are used to study future GM changes under global warming. Lee et al. (2019) showed a more significant increase in monsoon precipitation over land than over ocean. Moon and Ha (2020) found lengthened rainy season over most parts of monsoon domains, except for the North and South American monsoons. Wang et al. (2020a) showed that NH monsoon precipitation will increase, whereas SH monsoon precipitation has almost no changes. The projected stronger inter-hemispheric thermal contrast enhanced the NH monsoon (Wang et al. 2020b).

Most of the above works on GM projections are based on multi-model ensembles of transient climate simulations. Considering the problems arising from different climate sensitivities and inconsistent definitions of the global warming levels, Deser et al. (2020) emphasized the advantage of initial-condition large-ensemble simulations of individual climate models. Large-ensemble simulations ensure enough members to investigate climate changes due to greenhouse gas forcing under specific global warming levels, which is one of the central issues in the current international negotiation of climate changes, including the Paris Agreement (Mitchell et al. 2017; Milinski et al. 2020; Zhou et al. 2020).

In this work, we use two state-of-art large-ensemble simulations to investigate GM changes and the relationship between GM indices and global warming levels. We try to find both the similarity and difference between the two large-ensemble simulations and compare the results with those from CMIP6 models. We only focus on the contribution of CO_2 forcing to GM changes, while contributions from natural variabilities are not considered in this work.

The paper is organized as follows: The data and methodology are described in Section 2. Section 3 evaluates the GM simulation ability of two datasets. Future changes in the GM, regional monsoons (RM), and associated physical mechanisms are presented in Section 4. Conclusions are summarized in Section 5.

2 Data and Methods

2.1 Observational and Model Data

The observational datasets used in this study include monthly gridded precipitation from the Global Precipitation Climatology Project (GPCP, 1979-2016; Adler et al. 2003) and the Center for Climate Prediction Merged Analysis of Precipitation (CMAP, 1979-2016; Xie & Arkin, 1997) with a resolution of 2.5º × 2.5º in latitude and longitude.

We use two datasets of large-ensemble simulations. The datasets have been well used in studying monsoon changes under global warming (Li et al. 2019, 2021a, 2021b; Huang et al. 2020; Zhou et al. 2020). The first large-ensemble simulations are by the Canadian Earth System Model version 2 (CanESM2; Arora et al. 2011). CanESM2 large-ensemble simulations expanded each of the 5 ensemble members from the CMIP5 into 10 members, and to form 50-member large-ensemble simulations started with slightly different initial conditions (Fyfe et al. 2017). The 50 simulations are driven by historical anthropogenic and natural external forcing for 1950-2005, the Representative Concentration Pathways (RCP) 8.5 scenario for 2006-2100, with horizontal resolution of T42 (approximately 2.8º). We also use the 5 members from the CMIP5 to obtain the global mean surface temperature (GMST) changes relative to the preindustrial period.

The second large-ensemble simulations are from the Max Planck Institute Earth System Model (MPI-ESM; Maher et al. 2019). It is an updated version of MPI-ESM low resolution from the CMIP5, with horizontal resolution of T63 (approximately 1.9º). Similar to CanESM2, individual ensemble members of MPI-ESM only differ in their initial conditions. The historical simulation period of MPI-ESM is 1850-2005 and the RCP8.5 simulations are performed for 2006-2099. All the datasets were converted to 2º × 2º in latitude and longitude to ensure that they are comparable.

2.2 Global Monsoon Indices and Regional Land Monsoon Domains

Following Wang and Ding (2006, 2008) and Hsu et al. (2011), the GMA is defined as the area in which the local summer-minus winter precipitation (annual range) exceeds 2 mm/day, and the local summer precipitation exceeds 55% of annual total rainfall. In the NH, summer is defined as May-September (MJJAS), and winter is defined as November-March (NDJFM). The definition for the SH is the opposite. The GMP is defined as total summer (June-August for the NH and December-February for the SH) precipitation over the GMA. And the GM intensity (GMI) is defined as the GMP amount per unit area, which means the GMP is divided by the GMA. Because the area of each grid box varies with latitude, we used an area-weight method to calculate these indices.

The GM domain is separated into seven regional land monsoon domains as the Figure 1 in Jin et al. (2020). The seven regional land monsoon domains are East Asia (EA; 105 ºE-140 ºE, 22.5 ºN-65 ºN), South Asia (SA; 60 ºE-105 ºE, 0-40 ºN), North Africa (NAF; 20 ºW-50 ºE, 0-20 ºN), South Africa (SAF; 0-60 ºE, 40 ºS-0), North America (NAM; 120 ºW-50 ºW, 0-30 ºN), South America (SAM; 85 ºW-30 ºW, 40 ºS-0), and Australia (AUS; 100 ºE-155 ºE, 30 ºS-0), respectively. Note that the NAM domain covers not only Mexico but also Central America and Venezuela.

2.3 Global Warming Levels in Two Models

Following Li et al. (2019) and Zha et al. (2021), we use two baseline periods to estimate future changes in GM indices and their relationships with different global warming levels. The first baseline period is the preindustrial period of 1850-1900, which is used to calculate GMST changes relative to the preindustrial period. The second baseline period is the current climate, which is used to compare future changes in GM indices. We define the 1 °C warming period in CanESM2 and MPI-ESM as the current climate, since the observed GMST in 2018-2019 was about 1 °C warming relative to the preindustrial period (WMO 2020). Hence, the six 10-year intervals in CanESM2 are: 1995-2004 (0.983 °C), 2007-2016 (1.454 °C), 2021-2030 (1.981 °C), 2042-2051 (2.958 °C), 2061-2070 (3.978 °C), and 2079-2088 (4.980 °C). The five 10-year intervals in MPI-ESM are: 1995-2004 (1.017 °C), 2015-2024 (1.499 °C), 2031-2040 (1.996 °C), 2055-2064 (2.990 °C), and 2077-2086 (4.016 °C). Hereafter, GMST changes are all relative to the preindustrial period, and changes in GM indices are relative to the current climate (1 °C of warming).

2.4 Method of Moisture Budget

Jin et al. (2020) used a method of simplified moisture budget to analyze the relative contributions of dynamic and thermodynamic components to monsoon precipitation changes:

(1)

Where P denotes the model-output precipitation, denotes the vertical velocity at 500 hPa, denotes the specific humidity at 850 hPa, and g denotes the acceleration of gravity (9.8 m/s^2). This formula is simplified from the complete moisture budget formula, and it has the ability to directly demonstrate the dynamic (vertical motion) and thermodynamic (water vapor) components of the change in monsoon precipitation (see Figure 14 in Jin et al. 2020).

Similar simplified budget decomposition was also found to be sufficient in analyzing tropical and monsoon precipitation changes (Huang et al. 2013; Sooraj et al. 2015; Li et al. 2019; Li et al. 2021a). Because surface evaporation may affect the GMP change (Jin et al. 2020; Wang et al. 2020b), diagnosis equations for projecting the future GMP can be written as:

(2)

(3)

(4)

The overbar and denote the values for the current climate and the difference between future and current climates, respectively. The first term on the right-hand side of Equation 2 indicates the dynamic component (DY), and the second term indicates the thermodynamic component (TH). E denotes evaporation changes. Each item in Equation 2 is calculated at grid points and is area-weighted according to the evolving GMA. Detailed information can be found in Jin et al. (2020).

Besides, locally estimated scatterplot smoothing is used for scatterplot smoothing (LOESS; Cleveland 1979). Two methods are used to examine the significance of GM changes under specific global warming levels. The first is the student t-test at the 0.05 confidence level. The second is defined as over 75% of the results from ensemble members that show consistent changes.

3 Model Evaluation

Firstly, model-simulated 30-year (1977-2006 for CanESM2, 1971-2000 for MPI-ESM) mean precipitation and GM indices are compared with the observations

(1986-2015). GMST changes over the three intervals are all approximately 0.69°C above the preindustrial level. Figure 1 shows the climatological annual-mean precipitation of observations and the ensemble-member mean from the two models. Both models well reproduce the observed annual-mean precipitation in tropical and subtropical regions. The spatial correlation coefficient between observations and CanESM2 and MPI-ESM is 0.85 and 0.79, respectively. However, both models have poor performance in simulating precipitation over the South American continent. This could be because the models underestimate the variability of the SAM monsoon and its sensitivity to climate forcing (Fu et al. 2013). Besides, the double ITCZ problem causes excessive precipitation in the south of the equator, which is a common problem in coupled general circulation models (Zhou et al. 2008; Li and Xie 2014).

As shown in Figure 2, both models well reproduce the climatological annual range of precipitation (shading) and GMA (black contour). The spatial correlation coefficient of the annual range of precipitation between observations and CanESM2 (MPI-ESM) is 0.80 (0.79). The poor performance in simulating GMA over the tropical south Pacific coincides with the spatial pattern of the simulated double ITCZ. As shown in Table 1, the observed standard deviations (STDs) are $46.8{*}10^9$ m^3/day, $5.43{*}10^6$ km^2, and 0.16 mm/day for GMP, GMA, and GMI, respectively. The simulated STDs of the three GM indices are calculated for ensemble-mean from the historical experiments, and the median values and their 5-95% ranges are estimated. The simulated STDs of three GM indices are 41.3 (32.7-51.7) $*10^9$ m^3/day, 4.48 (3.53-5.83) $*10^6$ km^2, and 0.15 (0.12-0.19) mm/day for CanESM2, respectively. They are 33.8 (27.6-45.2) $*10^9$ m^3/day, 3.76 (2.98-4.84) $*10^6$ km^2, and 0.16 (0.13-0.19) mm/day for MPI-ESM, respectively. The observed STDs are generally located in the 5-95% ranges, which indicates the good performance of the two models in reproducing interannual GM variabilities. The above evaluations give us confidence for using these two large-ensemble simulations to estimate GM changes under specific global warming levels.

4 Projection Changes in Global Monsoon

4.1 Relationship between GM and global warming Levels

Figure 3 shows changes in the annual range of precipitation of CanEMS2 when the GMST is increased from 1.5 °C to 5 °C above the preindustrial levels. The change of the annual range is not significant for 1.5 °C of warming in most parts of monsoon domains (Figure 3a). When the warming level reaches 2 °C, however, negative annual ranges over the American continent and positive annual ranges over the NAF become statistically significant (Figure 3b). As GMST is increased more, anomalous values of the annual range become stronger and more significant (Figures 3c-e). The annual range increases over most monsoon domains, except for the NAM and SAM. It indicates a weakening of the NAM monsoon and SAM monsoon in the future. There is a large positive annual range over the near-equator Pacific, which indicates an equatorward movement of the ITCZ and the monsoon convergence zone. Furthermore, the ITCZ movement causes reduced precipitation over large areas of the NAM (Wang et al. 2020a). The changes in GMA well cooperate with the annual range changes, GMA tends to expand (shrink) at the regions where seasonal differences of precipitation are enhanced (weakened), especially at the flank of the monsoon domain. The GMA expands toward high latitudes due to amplified precipitation difference between summer and winter in a warmer world.

Similar to the results in CanESM2, the results in MPI-ESM also show enhanced annual range over Asia, Africa, and Australia (Figures 4a-d). However, the annual range of the SAM monsoon shows a significant increase, which is in contrast with that in CanESM2 (Figure 3). As mentioned in Section 3, both models cannot reproduce the climatological annual range of the SAM monsoon. The inter-model discrepancies for the SAM have been noticed in the CMIP5 models (Fu et al. 2013; Yin et al. 2013), and the risk of strong climatic drying and potential rainforest die-back in the future remains a great concern (Wang et al. 2020b). The above model-dependent results over the NAM and SAM remind us that the analysis of model uncertainty and inter-model difference is necessary for future projections.

Figure 5 shows scatter plots of GMA and GMI indices against GMST changes in the two models. All LOESS regressions of the two GM indices show an increase with global warming levels and the values of the GM indices in MPI-ESM are larger than that in CanESM2. The model ensemble-mean of GMA and GMI will approximately increase from 95 to 107 $*10^6$ km^2 and from 7.10 to 7.65 mm/day through the 150 years for CanESM2, respectively, while they are from 110 to 114 $*10^6$ km^2 and from 7.55 to 7.90 mm/day for MPI-ESM, respectively. The increasing rates of GM indices in CanESM2 are larger than that in MPI-ESM. The simulation spreads for the two models are similar, which are around 16 $*10^6$ km^2 and 1 mm/day for GMA and GMI, respectively. The comparable values between long-term changes and simulation spreads in the GM indices also indicate the contributions from natural variability to the GM changes are large in the near future (Deser et al. 2020; Huang et al. 2020; Zhou et al. 2020; Li et al. 2021b).

We further analyze the probability density functions (PDFs) of GMA and GMI in the two models (Figure 6). The PDFs of the GM indices shift rightward with global warming levels, indicating increases in the mean values of GMA and GMI. In addition, the GMI (Figures 6c-d) in both models shift rightward and spread wider, indicating increases in both the mean GMI and its variabilities with global warming. These results further confirm enhanced frequency and intensity of extreme events of monsoon rainfall in the future (Wang et al. 2020b).

4.2 Changes of GM indices per degree of warming

In this subsection, we quantify the relationship between GM indices and global warming. The change in a GM index over the 95$^{\text{th}}$ (75$^{\text{th}}$) percentage is defined as a strong (weak) change. The GMI in CanESM2 shows quasi-linear increasing (~1 %/°C) with global warming. The GMA shows a larger expansion than the

GMI at lower warming levels (Figure 7a left). Though the increase in GMA of MPI-ESM shows smaller increases compared with that of CanESM2, the GMI shows similar quasi-linear increases around 1 %/°C (Figure 7a right).

Furthermore, we calculate the changes in GM indices over global land, NH land, and SH land (Figures 7b-d), respectively. The GMI over global land generally shows weakly quasi-linear increases (~1 %/°C) in CanESM2, while strongly quasi-linear increases (~2 %/°C) in MPI-ESM. The uncertainty of changes in global land monsoon precipitation may arise from atmospheric circulation changes, which is partly due to model-dependent responses to uniform SST warming (Chen et al. 2020).

Both models show strong enhancement in the GMI over the NH land. The GMI increases from 1 %/°C to 3 %/°C in CanESM2. For MPI-ESM, the GMI shows a quasi-linear increase (~2.2 %/°C) in the future (Figure 7c). This robust change in the GMI over the NH land indicates more extreme events of monsoon precipitation (Wang et al. 2020b). As shown in Figure 7d, there are large diversities of GM indices over the SH land. For CanESM2, there are barely no changes in GMI, and the simulation spreads are large. For MPI-ESM, the GMI show quasi-linear and strong increases with global warming. The unmatched changes in the GM indices over the SH land suggest that the associated physical mechanisms need to be studied in future work, such as contributions from model frameworks and natural variabilities (Deser et al. 2020; Huang et al. 2020). Besides, it is interesting to note that the increasing rate of the GMA over the NH land shows a non-linear weakening with global warming in both models, which indicates that the expanding trend in the GMA will slow down in a warmer world.

Based on the two large-ensemble simulations, changes in regional monsoon indices are shown in Figure 8. For the EA (Figure 8a), both models show large increases in the regional monsoon intensity (RMI). The two models show differences in the regional monsoon area (RMA), with strong expansion in CanESM2 and weak expansion in MPI-ESM. Li et al. (2019) proposed that rapid increasing in monsoon precipitation may be related to the positive feedback between the monsoon circulation and precipitation. For the SA (Figure 8b), the RMI shows strong increasing when the GMST warming is greater than 2 °C, indicating the important impact of the 2 °C thresholds on people living in the SA.

For the NAF (Figure 8c), the increasing trend in RMI is non-linearly weakened with warming levels. The RMA expands mainly northward (Figures 3 and 4), leading to the wetter Sahel. For the SAF (Figure 8d), the RMI shows consistent increases with warming levels, while RMA changes have large uncertainties.

There are large diversities of changes in the NAM and SAM (Figures 8e and 8f), as noticed in Section 3. Both RMA and RMI of the NAM show decreases in CanESM2, while they have little change in MPI-ESM (Figures 8e). Figure 8f shows that the SAM RMI quasi-linearly decreases (increases) in CanESM2 (MPI-ESM). However, the RMA has no significant changes. For the AUS (Figure

8g), the RMI does not change very much because of the large spreads of the RMA in large-ensemble simulations.

In summary, the results in RMI changes over EA, SA, NAF, SAF, and AUS are similar in the two models, and the changes are similar to those based on CMIP6 projections (Chen et al. 2020; Jin et al. 2020; Wang et al. 2020b). In contrast, the changes in RMA and RMI of NAM and SAM are model-dependent.

CMIP6 ensemble projects a drier NAM and a non-significant wetter SAM (Wang et al. 2020b). Following Wang et al. (2020a), we find the difference of surface air temperatures (SAT) between the equatorial eastern Pacific (5 °S-5 °N, 120 °W-80 °W) and the tropical Atlantic (10°N-20 °N, 60 °W-15 °W) increase in both models with warming levels (Figures 9a and 9b). The SAT difference between the two oceans is associated with the movement of ITCZ. When the warming rate of the equatorial eastern Pacific is faster than that of the tropical Atlantic, the El Niño-like warming results in an equatorward shift of the ITCZ and the monsoon convergence zone, which consequently leads to reduced precipitation of the NAM. This relationship is reproduced in both models (Figures 9c and 9d), with a much greater trend in CanESM2 (-1.1 mm/day/°C) than in MPI-ESM (-0.17 mm/day/°C). The SAT difference in CanESM2 increases from -0.25 °C to 0.85 °C, while it changes little in MPI-ESM. It suggests that global warming has a stronger effect on the NAM changes in CanESM2. In addition, the differences of RMA and RMI may partly be due to the too small domain of the NAM monsoon. As for the RMI changes over the SAM, the results from CMIP5 (Yin et al. 2013) and CMIP6 models (Jin et al. 2020) are model-dependent.

4.3 Moisture Budget of the Global Monsoon Precipitation

Changes in atmospheric water vapor, circulation, and evaporation all would contribute to future changes in monsoon precipitation. Using the method of the simplified moisture budget (Equation 2), we estimate monsoon precipitation changes over global land and seven RM domains, respectively. It is found that the TH component always has positive contributions to precipitation increases under global warming, and the inter-member standard deviation is small. It indicates that global warming would lead to a wetter atmosphere and consequently more monsoon precipitation.

It is found that E plays an important positive role in EA monsoon precipitation, a weaker positive role in SA and AUS monsoon precipitation, and a negligible role for other RM domains. The enhanced surface evaporation is mainly caused by the surface temperature increasing, which is a part of the thermodynamic effects (Fasullo 2012). The standard deviations of E are similar to that of TH. In contrast, DY shows very different changes over different regional monsoon domains and between the two models, and its standard deviations are much larger. Our results are consistent with the argument by Wang et al. (2020a), that is, DY plays a more important role than TH in causing changes in monsoon precipitation. DY shows similar changes over SA (Figure 10c) and SAF (Figure 10e) monsoon domains in both models. However, DY makes a positive contribution to monsoon precipitation increases over EA (Figure 10b), NAF (Figure 10d), and AUS (Figure 10h) in CanESM2, whereas DY has little change over these RM domains in MPI-ESM. DY has dominant and negative contributions to monsoon precipitation increases over NAM (Figure 10f) and SAM (Figure 10g) in CanESM2, while it has almost no changes in MPI-ESM.

The uncertainty of monsoon circulations associated with DY changes is closely related to the projected warming pattern and also related to model biases, such as the cold-tongue bias in tropical eastern Pacific (Li and Xie 2014), cloud and water vapor feedbacks (Jalihal et al. 2019), land-atmosphere interaction (Wang et al. 2020b), and so on.

5 Conclusions and Discussion

We use large-ensemble simulations with CanESM2 and MPI-ESM to investigate GM changes associated with global greenhouse warming. Both large-ensemble simulations well reproduce the climatological large-scale features of the GM, except for the poor performance in simulating SAM monsoon. When global warming is over 2 °C, the annual range of monsoon precipitation consistently increases in most parts of the Asian-Australian and African monsoon domains in both models, while the annual range over the NAM and SAM shows opposite changes in the two models. CanESM2 projects a much weaker annual range of the NAM and SAM, while MPI-ESM yields a stronger annual range of precipitation for the SAM and little change for the NAM.

GMA and GMI increase with global warming levels. The increasing rates in CanESM2 are larger than that in MPI-ESM. The GMI increases (~1 %/°C) in both the climatological mean and internal variability. It indicates increasing of frequency and intensity of extreme events of monsoon rainfall. Both models demonstrate consistent enhancement in the GMI over the NH land, which is likely due to the enhanced NH-SH thermal contrast (Lee and Wang 2014; Wang et al. 2020a). For the GM indices over the SH land, the two models generate different projections, and the ensemble-member spreads are large. This is largely due to the combined effects of model biases and internal variabilities of the NAM and SAM.

For RM changes, both models generate similar enhanced RMI of the EA (strong), SA (strong), NAF (weak), SAF (weak), and AUS (slight), which is also similar to the CMIP6 projections (Chen et al. 2020; Jin et al. 2020; Wang et al. 2020b). In contrast, the two models yield different projections of RMA and RMI for the NAM and SAM. The NAM and SAM become drier and weaker in CanESM2, while SAM becomes wetter and stronger in MPI-ESM. RMA and RMI of the NAM have almost no change in MPI-ESM. The discrepancy in NAM monsoon projection between the two models is because of different model projections of SAT differences between the equatorial eastern Pacific and the tropical Atlantic. CanESM2 simulates stronger warming over the equatorial eastern Pacific, which is comparable to the results from CMIP6 ensemble-mean (Wang et al. 2020a). And the El Niño-like warming causes an equatorward shift of the ITCZ, which leads to weakened NAM monsoon. In contrast, SAT difference between the two oceans is weaker in MPI-ESM projections. The model-dependence of NAM and SAM projections needs to be studied with comparison from more models.

The relative contribution of dynamic and thermodynamic components to changes in global and regional land monsoon precipitation are estimated, using a simplified method of moisture budget. The thermodynamic component has a positive contribution to monsoon precipitation increases for all regional monsoons in both models, because of the increase in specific humidity due to greenhouse warming. In contrast, the dynamic component has very different contributions to changes in regional monsoon precipitation, and both model discrepancies and inter-member standard deviation are large. Therefore, the different changes in regional monsoon precipitation are caused by the dynamic component. This is because global greenhouse warming leads to different changes in regional monsoon circulations.

Conflict of Interests

The authors declare no conflicts of interest.

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Table captions

Table 1. The standard deviation (STDs) of global monsoon precipitation (GMP, m^3/day), global monsoon area (GMA, km^2), and global monsoon intensity (GMI, mm/day) from CanESM2 (1977-2006), MPI-ESM (1971-2000), and average of GPCP and CMAP (1986-2015). The STDs of the models are the median values from all members, and the brackets are the 5-95% range of the member spread.

Figure captions

Figure 1. Climatological and annual mean precipitation (mm/day). (a) GPCP and CMAP precipitation averaged 1986-2015, (b) 50 ensemble-member mean CanESM2 precipitation averaged over 1977-2006, and (c) 100 ensemble-member mean MPI-ESM precipitation averaged over 1971-2000. PCC denotes the spatial correlation coefficient between simulations and observations.

Figure 2. Same as Figure 1, except that the shading denotes the annual range of precipitation (mm/day). The annual range is defined as the difference between local summer and winter precipitation. Local summer is May-September in the Northern Hemisphere and November-March in the Southern Hemisphere, and local winter is opposite. The climatological global monsoon domain is enclosed by black solid lines.

Figure 3. Changes in the annual range of precipitation (shading, mm/day) in CanEMS2, relative to the current climate, when the GMST is increased by 1.5 to 5 °C above the preindustrial level. Regions with gray slashes are the places where changes in the annual range of precipitation are statistically significant at the 0.05 confidence level, based on the student t-test. Purple dots denote that the results of more than 75% of the members are consistent. The climatological global monsoon domain is enclosed by black solid lines.

Figure 4. Same as Figure 3, except for changes in MPI-ESM.

Figure 5. Scatter plots of the relationships between (a-b) global monsoon area (10^6 km^2) and GMST, and (c-d) global monsoon intensity (mm/day) and GMST. Plots (a) and (c) are for CanESM2, and plots (b) and (d) are for MPI-ESM. Black solid lines denote model ensemble means with LOESS smoothing.

Figure 6. Smoothed histograms of projected global monsoon changes. (a) and (b) global monsoon area (10^6 km^2), and (c) and (d) global monsoon intensity (mm/day). Plots (a) and (c) are for CanESM2, and plots (b) and (d) are for MPI-ESM. Black, purple, gray, green, orange, and red solid lines represent the histograms of the current climate and GMST increases of 1.5, 2, 3, 4, and 5°C above the preindustrial level, respectively.

Figure 7. (a) Percentage changes of global monsoon area (orange) and global monsoon intensity (green) per 1°C global warming (% /°C), derived from CanESM2 (left) and MPI-ESM (right). The upper (lower) edge of the box denotes the 75^{th} (25^{th}) percentile, and the horizontal line within the box is the ensemble mean. The vertical solid line denotes the range from 5^{th} to 95^{th}. (b)

– (d) Same as (a), except for global land monsoon, NH land monsoon, and SH land monsoon, respectively.

Figure 8. Same as Figure 7, except for regional land monsoons over (a) East Asia, (b) South Asia, (c) North Africa, (d) South Africa, (e) North America, (f) South America, and (g) Australia, respectively.

Figure 9. Scatter plots of relationships between warming levels (°C) and SAT differences (°C) between the equatorial eastern Pacific (5°S-5°N, 120°-80°W) and the tropical Atlantic (10°-20°N, 60°-15W) in CanESM2 (a) and MPI-ESM (b). (c-d) Same as (a-b), but for relationships between the North American land monsoon precipitation (mm/day) and SAT differences (°C) between the equatorial eastern Pacific and the tropical Atlantic. Red solid lines denote the linear regression. Numbers at the top-right denote the regression coefficients.

Figure 10. Moisture budget for precipitation changes (10^9 m^3/day) of global (a) and regional (b-h) land monsoons with different global warming levels. Black, light-blue, blue, red, and pink bars denote the model-simulated precipitation changes (P), diagnosed precipitation changes (sum), dynamic component (DY), thermodynamic component (TH), and evaporation (E), respectively. Green solid lines denote the range of one standard deviation.