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The Sources of Uncertainty in the Projection of Global Land Monsoon Precipitation

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Abstract Policy makers need reliable future climate projection for adaptation purposes. A clear separation of sources of uncertainty also helps narrow the projection uncertainty. However, it remains unclear for monsoon precipitation projections. Here we quantified the contributions of internal variability, model uncertainty, and scenario uncertainty to the ensemble spread of global land monsoon precipitation projections using Coupled Model Intercomparison Project Phase 5 (CMIP5) models and single-model initial-condition large ensembles (SMILEs). For mean precipitation, model uncertainty (contributing ~90%) dominates the projection uncertainty, while the contribution of internal variability (scenario uncertainty) decreases (increases) with time. For extreme precipitation, the results are generally similar except that at the end of 21st century the contribution of scenario uncertainty is comparable to model uncertainty. Reducing model uncertainty can effectively narrow the monsoon precipitation projection. The internal variability estimates differ slightly among models and methods, the uncertainty partitioning is robust in middle-long term.

1. Introduction

The global monsoon (GM) comprises a hierarchy of regional monsoons, including the Asian-Australian monsoon, the African monsoon, and the American monsoon. About two thirds of the Earth’s population has been directly and indirectly influenced by the monsoon systems (Wang et al., 2017; Wang & Ding, 2008; Zhang & Zhou, 2019a). The GM is susceptible to the effects of global warming (Christensen et al., 2013; D’Agostino et al., 2019; Han et al., 2019; Seager et al., 2010; Zhang & Zhou, 2019b). A reliable projection of GM precipitation is crucial for decision makers to develop effective adaptation and mitigation polices.

The projection of GM change has been a focus within the monsoon community (Endo & Kitoh, 2014; Hsu et al., 2013; Kitoh et al., 2013; Lee & Wang, 2014; Stocker et al., 2013; Zhang et al., 2019). While the multimodel ensemble mean indicates that GM is likely to strengthen in the 21st century with increases in its area and precipitation intensity under Representative Concentration Pathway (RCP) 4.5 and RCP8.5 scenarios (Christensen et al., 2013; Seth et al., 2019), a spread across individual projections within a multimodel ensemble is also evident (Figures 1a and 1b). Meanwhile, extreme precipitation over the global land monsoon region is also projected to increase robustly, with a larger magnitude than mean precipitation (Kitoh et al., 2013; Zhang et al., 2018).
Climate projections are subject to several sources of uncertainty, including the scenario uncertainties related to anthropogenic forcing agents, parametric and structural model uncertainty related to the response of the climate model to the specified forcing agents, and natural internal variability which is intrinsic to the climate system (Cox & Stephenson, 2007; Hawkins & Sutton, 2009; Kirtman et al., 2013; Tebaldi & Knutti, 2007). Although a clear separation of the sources of uncertainty would undoubtedly help us to narrow the uncertainty of climate projection and great effort has been devoted to this topic in the recent decade (Dai & Bloecker, 2019; Deser et al., 2012; Knutti et al., 2008; Marotzke, 2019), the contribution of different sources of uncertainty to the ensemble spread of GM projection has never been quantified. This study aims to address the following questions: (1) What are the relative contributions of different sources of uncertainty to the projection of GM? (2) Are the sources of uncertainty for the mean and extreme precipitation projection the same? (3) What is the potential limit to narrow the uncertainty of GM precipitation projection?

2. Data and Methods

We use monthly mean and daily precipitation data from 24 CMIP5 models. The simulations from all forcing historical experiments (1950–2005) and projections under RCP4.5 and RCP8.5 emission scenarios (2006–2100) were analyzed (Table S1 in the supporting information; Taylor et al., 2012). Only the first realization for each model and each scenario was used. In addition, the single-model initial-condition large ensembles (SMILEs) from CESM-LE (Kay et al., 2015), CanESM2-LE (Kirchmeier-Young et al., 2017), and MPI-ESM-GE (Maher et al., 2019), with 35, 50, and 100 members, respectively, were also analyzed (Table S2). The model data were regridded to a common 1° × 1° grids. In our analysis, the baseline is defined as 1986–2005. We present projections for three specific periods in the future, including near-term (2021–2040), mid-term (2041–2060), and long-term (2081–2100) periods.

We focus on both mean state and extreme precipitation changes in global land monsoon domain. The GM region is defined as the area where local “summer minus winter” precipitation rate exceeds 2.0 mm day⁻¹, and local summer precipitation exceeds 55% of the annual total (Wang et al., 2012). Here, local summer refers to May through September for the northern hemisphere and November through March for the southern
hemisphere. The regional monsoons are divided into North American Monsoon (NAM), South American Monsoon (SAM), North African Monsoon (NAF), South African Monsoon (SAF), East Asian Monsoon (EAS), South Asian Monsoon (SAS), and Australian Monsoon (AUS) (Figure S1; Kitoh et al., 2013). The global land monsoon index ($P_{av}$) is defined as the accumulated precipitation in the global land monsoon domain. To quantify future changes in extreme precipitation, the seasonal maximum accumulated 5-day precipitation ($RX_{5day}$) is analyzed. In addition to $RX_{5day}$, two widely used precipitation indices including the simple daily intensity index (SDII) and the consecutive dry days index (CDD), which are defined respectively as the total precipitation divided by the number of days with precipitation greater than or equal to 1 mm and the largest number of consecutive days with daily precipitation less than 1 mm (Zhang et al., 2011), are also analyzed. These indices were calculated over land monsoon domains determined by each model for the local summer season (Text S1; Kitoh et al., 2013).

The source of uncertainty in precipitation projections for the 21st century can be separated into three components including the internal variability, model uncertainty, and scenario uncertainty (Cox & Stephenson, 2007; Tebaldi & Knutti, 2007). We employ the method developed by Hawkins and Sutton (2009, 2011) to separate and quantify the uncertainty arisen from these three components (see supporting information Text S2 for technical details). The method requires that all the models should have exactly same ensemble members. For individual model with multiple realizations, the estimation of internal variability tends to have a spread of ±10%. Since a large part of spread is random across models, it is less significant when averaged over all the CMIP5 models (Hawkins & Sutton, 2009; Yip et al., 2011). The model uncertainty, originating from our incomplete understanding of the climate system and the limitations of implementation of the physical processes, parameterization schemes, etc., also involves the uncertainty related to different model performances in reproducing the climatology of monsoon.

3. Results

We first show the projected changes of mean and extreme precipitation accumulated in global land monsoon domain (Figures 1a and 1c). The CMIP5 models project an increase in both mean and extreme precipitation over the global land monsoon domain, as shown in previous studies (D’Agostino et al., 2019; Endo & Kitoh, 2014; Han et al., 2019; Kitoh et al., 2013; Seager et al., 2010; Zhang et al., 2018). Superimposed on the increasing trend associated with global warming, there is considerable spread among the projections. For the same RCP, different CMIP5 models produce different projections as indicated by the spread along with the thick lines of multimodel ensemble mean; hence, there is clear model uncertainty. The future change of monsoon precipitation depends on the scenario. Higher emission scenarios are followed by stronger increases in monsoon precipitation, indicating an uncertainty related to scenario. There is also uncertainty related to natural internal variability. For example, before ~2040, we cannot distinguish the differences between scenarios, indicating the dominance of internal variability. Across the 21st century, the uncertainty increases with time. The evolution of extreme precipitation ($RX_{5day}$) is like the mean precipitation but with larger spread (Figure 1c).

To reveal how the uncertainty in decadal mean GM precipitation changes over the 21st century, we examine the changes of total uncertainty that is portioned among the three components including internal variability, model uncertainty, and scenario uncertainty (Figures 1b and 1d; see supporting information Text S3 for technical details). The model uncertainty is the dominant contributor to mean monsoon precipitation $P_{av}$ throughout the century, consistent with that for global mean precipitation (Hawkins & Sutton, 2011). The contribution of internal variability is only important at the beginning decades of the century, while the scenario uncertainty is small. The uncertainty of extreme precipitation $RX_{5day}$ shows similar results as the mean precipitation except that the scenario uncertainty becomes more important at the end of the century.

To reveal the changes of uncertainty arisen from three components relative to the projected changes, we examine the fractional uncertainty defined as the projection uncertainty divided by the expected mean changes (Figures 2a and 2b). For the mean monsoon precipitation $P_{av}$, it is evident that the dominant contribution to projection uncertainty is model uncertainty, which falls slowly with lead time and is relatively stable after ~2030. The contribution of internal variability to projection uncertainty is of secondary importance before ~2060, but it falls rapidly with lead time as the signal of anthropogenic forcing strengthens.
After 2060s, the scenario uncertainty is the second largest contribution to projection uncertainty. The total fractional uncertainty decreases with lead time but is relatively stable after ~2030 as the model uncertainty. The relative importance of each component to extreme precipitation is different from that of mean precipitation. While the contribution of model uncertainty is relatively stable, that of internal variability/scenario uncertainty decreases/increases rapidly with time. The contribution of scenario uncertainty is comparable to model uncertainty after ~2080.

To quantify how the contributions of fractional uncertainty vary as a function of projection lead time, we examine the fraction of the total variance in decadal mean projections explained by each source of uncertainties for different lead times in the 21st century (Figures 2c and 2d). For changes of mean monsoon precipitation, consistent with Figures 2a and 2b, model uncertainty (blue) is dominant at all lead times. At shorter lead times (before 2030s), both the internal variability (orange) and model uncertainty (blue) are significant factors, but the importance of internal variability/scenario uncertainty decreases/increases rapidly with the increasing of lead times. The contribution of scenario uncertainty is very small before 2060s and only becomes important at the end of the 21st century. In contrast with mean precipitation, the contribution of scenario uncertainty is more important for extreme precipitation, which is comparable to the model uncertainty after ~2080.

Decision-making needs climate projection information at near term (2021–2040), midterm (2041–2060), and long term (2081–2100), and at regional scales. We examine the regional differences of uncertainties in Figure 3. For the global land monsoon precipitation Pav projection, over 2021–2040, the fraction of total variance explained by model uncertainty is ~86.0%, while that of internal variability is ~13.7%. The percentage contribution of model uncertainty increases to ~91.8%, while that of internal variability decreases to ~5.4% in midterm. The contribution of scenario uncertainty is negligible for both near-term and midterm periods. Over the long-term period (2081–2100), the fraction of total variance contributed by internal variability decreases to less than 2.1%, while the contribution of scenario uncertainty increases to 6.5% and the contribution of model uncertainty keeps unchanged.

We further compare the uncertainty over global land monsoon area with that over the global land (Table S3). While the fraction of total variance explained by model uncertainty decreases with time and that explained by scenario uncertainty increases with time for global land average, the contribution of model uncertainty...
almost keeps unchanged from midterm to long term for the average in global land monsoon area, indicating model uncertainty in the monsoon area is larger than other parts of global land.

At regional scales for the near-term projection (Figure 3a), the contribution of internal variability is less than 20% in most monsoon regions except for the East Asian, South Asian, and Australian monsoon regions, where the contribution of internal variability is larger than 30%. Nonetheless, the model uncertainty explains more than 70% of the variance over all regional monsoon domains. For midterm and long-term projections (Figures 3b and 3c), the contribution of internal variability declines rapidly, while that of model uncertainty increases rapidly. Exceptions are seen in the NAM and SAS regions, where the contribution of scenario uncertainty is larger than that in other monsoon regions.

How does the model performance affect the projection uncertainty and its partitioning? To explore this, we classified the CMIP5 models into two groups based on the skill in simulating the present-day climatology against observations from the Global Precipitation Climatology Centre (GPCC; Schneider et al., 2018; Ziese et al., 2018). For evaluation purpose, we employed the metric of root-mean-square error (RMSE) following Sillmann et al. (2013) (see supporting information Text S4 and Figure S2 for details). Results show that the projection uncertainty and its partitioning in the high-skill models are close to that of 24 models, whereas the low-skill models exhibit larger projection uncertainty (Figure 4). In middle-longterm, for example, the total projection uncertainty in the low- and high-skill models are 3.68% and 2.93% for Pav, respectively. In particular, the larger uncertainty in low-skill models is primarily induced by the component of model uncertainty. Hence, improving model performance and selecting high-skill models can narrow the total projection uncertainty by constraining the component of model uncertainty. The potential gains from improving model representations of precipitation estimated by the signal/noise ratio assuming a zero-model uncertainty also support the conclusion (figure not shown).

The impacts of extreme precipitation on the society are larger than mean precipitation in the vulnerable monsoon regions. We extend our analysis to extreme precipitation RX5day (Figures 3d–3f). For the average over global land monsoon regions, the internal variability is generally small and negligible for midterm and long term. Model uncertainty is dominant for both near term and midterm. The contribution of scenario uncertainty is comparable to that of model uncertainty in the long term, which contrasts with the mean precipitation. The comparable contribution of model uncertainty and scenario uncertainty in global land
The monsoon region is different from that averaged over global land (Table S3), where the contribution of scenario uncertainty (66.0%) is far larger than model uncertainty (33.6%), indicating that the model uncertainty in the monsoon area is larger than other parts of global land in the context of extreme precipitation projection.

At regional scales, while the model uncertainty still dominates across the three time periods, the contribution from internal variability is only relatively larger at near term. The scenario uncertainty is becoming important at long term and comparable to model uncertainty in East Asian and South Asian monsoon regions. The North American monsoon region has the largest contribution from model uncertainty.

**Figure 4.** Evolution of uncertainty components for $P_{av}$ (a, c) and $RX_{5day}$ (b, d) projections in CMIP5 ensemble, for low-(a, b) and high-skill (c, d) models based on evaluations of simulated climatology.

**Figure 5.** Projections of global land monsoon (a) mean ($P_{av}$) and (b) extreme precipitation ($RX_{5day}$) relative to 1986–2005 for historical and RCP8.5 scenario. Red, orange, light blue, and dark blue lines denote CMIP5 multimodels, CESM-LE, CanESM2-LE, and MPI-ESM-GE, respectively. Estimates of the decadal internal variability and model uncertainty of global land monsoon (c) $P_{av}$ and (d) $RX_{5day}$. Unit: %. Note that daily data from MPI-ESM-GE is not available; thus, MPI-ESM-GE is not included in subplots (b) and (d).
Like mean precipitation, high-skill models also exhibit reduced projection uncertainty in extreme precipitation compared to low-skill models (6.07% vs. 8.61% in the middle-longterm), primarily resulting from the reduced model uncertainty (Figures 4b and 4d). This is well supported by a zero-model uncertainty assumption which is found to enhance the signal/noise ratio in extreme precipitation projections (figures not shown).

We extend the analysis to other extreme indices including SDII and CDD (Figures S3–S5). The partitioning of uncertainty is qualitatively consistent with that of RX5day, with a dominant contribution of model uncertainty and increasing (decreasing) contribution from scenario uncertainty (internal variability) with time. Differences are seen for CDD in near term in which the dominance of internal variability is more evident. The dominant model uncertainty is stable with time for SDII but decreases rapidly for CDD (Figure S5).

The SMILE is an emerging way that allows a robust quantification of a model’s forced response and internal variability (Deser et al., 2020; Kay et al., 2015; Lehner et al., 2020). Based on large ensembles of CESM-LE, CanESM2-LE, and MPI-ESM-GE, we quantify the contributions of internal variability and model structural differences to the total projection uncertainty under RCP8.5 in Figure 5 (Text S5). For both Pav and RX5day, the spread among individual model’s multiple realizations is within that of CMIP5 models, while the model structure difference explains the largest part of total projection uncertainty. We further compare the time-evolving model uncertainty with the internal variability estimated from CMIP5 models and SMILEs (Figures 5c and 5d). Although the magnitude of internal variability differs between models and methods, the impact is only evident in the beginning decades. For midterm and long term, the magnitude difference does not affect the point that model uncertainty is the dominant source of uncertainty in the projections of global land monsoon precipitation.

4. Summary and Concluding Remarks

We separated the sources of uncertainty in global land monsoon precipitation projection based on 24 CMIP5 models and three sets of SMILEs. The contributions of internal variability, model uncertainty and scenario uncertainty to the overall ensemble spread of GM projection are quantified. For mean precipitation, the model uncertainty is the dominant contributor throughout the century and explains more than 70% of the variance during near term, midterm, and long term. The contribution of internal variability is only important at the beginning decades, while the scenario uncertainty becomes important at the end of the 21st century, especially in the NAM and SAS regions. The sources of uncertainty for the mean and extreme precipitation mainly differ in long-term projection, when the contribution of scenario uncertainty is comparable to the model uncertainty for extreme precipitation. The model uncertainty in the monsoon area is larger than other parts of global land in terms of both mean and extreme precipitation. Selecting high-skill models could reduce total projection uncertainty for both the mean and extreme precipitation, primarily by constraining the component of model uncertainty. This highlights the importance of model evaluation and selection in climate projections to enhance the robustness of results.

The internal variability can be calculated either as the variance of the residual from the polynomial fit (Hawkins & Sutton, 2009, 2011), or as intermember deviation from single-model large ensemble simulations (Maher et al., 2019). Although the magnitude of internal variability differs between models and methods, the impact is only evident in the early decades and does not affect the point that model uncertainty is the dominant source of uncertainty in the middle-long-term projections of global land monsoon precipitation.

We use the reference period of 1986–2005 that is widely used in IPCC AR5 (Christensen et al., 2013). To explore whether reference period has a pronounced influence, we extended reference period to 27 (1979–2005) and 30 years (1971–2000) (Figure S6). The impact is only evident in a couple of early decades (before 2020s), with a longer-reference period is associated with less contribution from internal variability.

Data Availability Statement

CMIP5 data are available online (https://esgf-node.llnl.gov/search/cmip5/). The monthly and daily precipitation data of GPCC were acquired from https://opendata.dwd.de/climate_environment/GPCC/html/full-data-monthly_v2018_doi_download.html and https://opendata.dwd.de/climate_environment/GPCC/full_data_daily_V2018 websites.
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