Anthropogenic influence on the intensity of extreme precipitation in the Asian-Australian monsoon region in HadGEM3-A-N216

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Abstract
The Asian-Australian monsoon (AAM) region is characterized as abundant summer monsoon rainfall, which provides fresh water resources for high-density population there. The research uses HadGEM3-A-N216 model simulations to compare the change of extreme rainfall intensity in the AAM region with and without anthropogenic influences. Although the anthropogenic forcing exerts a weak impact on the climatological mean distribution of the extreme precipitation, it significantly increases the extreme precipitation intensity at each degree in most parts of the AAM region, especially for the northern East Asia, the Bay of Bengal, and Australia. As the extreme degree increases from the 50–98%, the extreme precipitation intensity in the northern East Asia, the Bay of Bengal, and the Australia increase more and more rapidly, while that in the southern East Asia changes from a decreasing trend to an increasing trend. Overall, the stronger extreme precipitation is accompanied by a stronger growth trend under the anthropogenic forcing.

KEYWORDS
Asian-Australian monsoon region, climate warming, extreme precipitation, quantile regression
1 | INTRODUCTION

Monsoon occurs as a consequence of atmospheric response to the seasonal transition of land-sea thermal contrast, which is characterized by rapid changes in prevailing wind direction and rainfall intensity (Trenberth et al., 2000; Wang and Ding, 2006; Wang et al., 2012; Liu et al., 2014). As an important part of the global monsoon, the Asian-Australian monsoon region (AAM) ranges from 30°S to 40°N, 40°E to 160°E, and it consists of the Asian monsoon in the Northern hemisphere and its corresponding Indonesian-Australian monsoon in the Southern hemisphere (Wang et al., 2014). This region has abundant summer monsoon precipitation, which supplies more than two-thirds of water that are required by the planet’s population (Zhang et al., 2017). Therefore, it is of great importance to investigate the variability and long-term changes of extreme precipitation in the AAM region.

According to the fifth Intergovernmental Panel on Climate Change (IPCC) report, human activities have contributed the most to the global averaged temperature rise since the 1950s. Over the land, the areas with extreme precipitation increasing are much larger than those with decreasing (Trenberth, 2011; Orlowsky and Seneviratne, 2012; Church et al., 2013; Fischer et al., 2013). The increase in global temperature causes the atmosphere to become more and more humid, which results in the increasing extreme precipitation (Cheng and AghaKouchak, 2014). The rate of extreme precipitation increase is closed to the Clausius–Clapeyron relationship (7% °C⁻¹) (Sugiyama et al., 2010; Li et al., 2019). Accordingly, the intensity and frequency of extreme precipitation in most areas represent a significantly increasing trend, and the recurrence interval is shortened (Kharin et al., 2007; Donat et al., 2013; Zhang et al., 2018). In particular for the AAM region, the observational data suggests that human activities have intensified the extreme precipitation intensity there in recent several decades, especially for East Asia and North Australia (Chen and Sun, 2017; Du et al., 2019), where the human influence signal is detectable at 95% confidence level (Dong et al., 2020). Furthermore, based on phase 5 of Coupled Model Intercomparison Project (CMIP5) and phase 6 of Coupled Model Intercomparison Project (CMIP6) projections, previous studies have shown that the heavy precipitation and extreme precipitation will continue to increase in future for both Asian monsoon region (Freychet et al., 2014) and Australian monsoon region (ChevuTuri et al., 2018), although there are large regional differences (Wang et al., 2020).

Previous studies suggest that the extreme precipitation in the most of the AAM region will increase under global warming scenarios (Wang et al., 2014), but the response of the extreme precipitation to temperature rise in historical periods has not been fully understood. On the one hand, the quantitative influence of human activities could not be well separated from the interdecadal variabilities such as the Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation (AMO), which are proved to exert significant impacts on the rainfall in the AAM region (Joshi and Rai, 2015; Sun et al., 2017). On the other hand, the observed daily precipitation has small sample sizes, which add the uncertainties of the extreme precipitation trend. Therefore, this research uses the model multimember simulation to compare the change of extreme precipitation with temperature since 1960s with or without human activities. In the following: Section 2 introduces the methods and data used in this article, Section 3 presents the results, and Section 4 is the conclusion and discussion.

2 | DATA AND METHODS

Anthropogenic forcing is an important factor affecting extreme precipitation events under climate change (Stott et al., 2015). The HadGEM3-A-N216 model simulations is employed to assess the change of extreme precipitation with and without anthropogenic influences, which is one of the highest resolution global models that can be used in attribution research in this field at current stage (Christiansen et al., 2018; Ciavarella et al., 2018; Wilcox et al., 2018). The HadGEM3-A-N216 model conducts two experiments from 1960 to 2013, and each experiment comprises an ensemble of 15 initial-condition simulation members, named as All-Hist simulations and Nat-Hist simulations (Burke et al., 2016; Christidis et al., 2016; Vautard et al., 2019). All-Hist simulations are forced by the observed sea ice concentrations (SIC) and SST from the Hadley Center Sea Ice and Sea Surface Temperature dataset (Rayner et al., 2003), which includes both anthropogenic forcing and natural forcing. Nat-Hist simulations represent the natural forcing, because the human influence on the observed SST and SIC are eliminated. More details about the distinct forcing scenarios for the two experiments can be found in Christidis et al. (2013). The observed daily precipitation used in this research is Rainfall Estimates on a Gridded Network (REGEN) data, The precipitation trend shown in this dataset is consistent with that in the IPCC fifth assessment report (Church et al., 2013), which is suitable for analyzing extreme precipitation (Contractor et al., 2019).

In this research, the annual maximum 1-day precipitation (Rx1day) is used to analyze the extreme precipitation (Zhang et al., 2011). The global land monsoon
area is defined to be an area where summer precipitation accounts for more than 55% of the annual total precipitation, and the summer precipitation minus the winter precipitation rate exceeds +2.0 mm day\(^{-1}\) (Wang et al., 2012). So we calculated the AAM land region using monthly mean precipitation from Global Precipitation Climatology Project during 1979–2010 (Huffman et al., 2009).

Since extreme precipitation has obvious spatial distribution differences, the spatial pool method can obtain a relatively stable extreme precipitation estimation sequence (Kendon et al., 2008). Also, the standard error of parameter estimation via the spatial pool method is significantly lower than that based on only one grid point, especially for the maximum daily precipitation (Hanel et al., 2009).

In previous studies (Li et al., 2018), the extreme value distribution (GEV) is a common method to analyze the change of extreme precipitation with temperature. This method can reflect the general trend of extreme precipitation, but cannot focus on the complete extreme precipitation simulation in different recurrence intervals (Li et al., 2019).

If the probability distribution function of a dependent variable is:

\[ F(y) = P(Y \leq y), \]

then the \(\tau\) quantile corresponding to the \(Y\) value can be written as:

\[ F^{-1}(\tau) = \inf \{y : F(y) \geq \tau\}. \]

For each \(\tau\) quantile, solve by minimizing the sum of the absolute values of the weight residuals,

\[ F^{-1}(\tau) = \arg\min_{\beta \in \mathbb{R}^{p}} \left[ \sum_{i \in \{Y_i \geq \tau\}} \tau|y_i - \zeta| + \sum_{i \in \{Y_i < \tau\}} (1 - \tau)|y_i - \zeta| \right], \]

equivalent to:

\[ F^{-1}(\tau) = \min_{\zeta \in \mathbb{R}} \sum_{i=1}^{n} \rho_{fi}(y_i - \zeta). \]

\[ \rho_{fi}(z) = \tau z I_{(\rho, \infty)}(z) - (1 - \tau) I_{(-\infty, 0)}(z), \]

where \(I_{(\cdot)}\) is the loss function.

For the general linear conditional quantile function is \(Q(\tau | X = x) = x' \beta(\tau)\), so the estimated value can be obtained by solving,

\[ \hat{\beta}(\tau) = \arg\min_{\beta \in \mathbb{R}^{p}} \sum_{i=1}^{n} \rho_{fi}(y_i - x_i' \beta), \]

where \(\hat{\beta}(\tau)\) is the regression coefficient of \(\tau\) quantile.

### 3 RESULTS

In climatology, the regions with large Rx1day in the observations are mainly located in the Bay of Bengal, the Indochina Peninsula, and the southern part of the East Asia, with the largest value exceeding +200 mm day\(^{-1}\) (Figure 1a). Compared with the observations, the climatological mean Rx1day in the All-Hist runs presents similar spatial distribution and comparable intensity over the AAM region, with the pattern correlation coefficient (PCC) between the two data exceeding +0.60 (Figure 1a versus Figure 1b). Accordingly, the regional mean bias of the Rx1day over the AAM region is merely −2.00 mm day\(^{-1}\). However, the All-Hist runs underestimates the intensity of extreme precipitation in the Indian Peninsula and Indochina Peninsula, with the peak underestimation in the western Indian Peninsula exceeding −100 mm day\(^{-1}\) (Figure 1d). On the other hand, the model simulations slightly overestimate the precipitation intensity over the other regions, such as the East Asian monsoon region and the Australian monsoon region (Figure 1d). In general, the HadGEM3-A-N216 model well simulates the climatology of the extreme precipitation in most parts of the AAM region.

Due to the high-density population in Indian Peninsula, Southeastern Asia and Southern China, the potential impact of extreme precipitation on local communities is greater in these areas than other areas. Thus, we divide the AAM region into six subregions. They are the Indian Peninsula, the Bay of Bengal, the Indochina Peninsula, the southern East Asian monsoon region, the northern East Asian monsoon region, and the Australian monsoon region. Figure 2 shows the time series of the regional extreme precipitation intensity for the AAM region and the six subregions. It is clear that the observations in each subregion fall between the maximum and minimum of the model simulations. The ensemble mean of the model simulated extreme precipitation that averaged in the AAM region are almost consistent with the observations, where the differences between them are less than 2.0 mm day\(^{-1}\) in most years. However, there are large regional differences in the six subregions. Specifically, the simulated intensity of the extreme precipitation in the Indian Peninsula and Indochina Peninsula are significantly underestimated, with the averaged underestimation exceeding −27.3 mm day\(^{-1}\) in the Indian Peninsula during the whole period. In contrast, the intensity of the extreme precipitation simulation in the Bay of Bengal, the southern East Asian monsoon region, and the northern East Asian monsoon region are slightly overestimated. The best performance area is the Australian monsoon region with the averaged deviation less than 3.0 mm day in the most years (Figure 2). Correspondingly, the linear correlation coefficient between the time series of averaged Rx1day in the observations and the model simulations exceeds +0.64 (significant at the 99% confidence level). Overall, the HadGEM3-A-N216 model...
well reproduces the interannual variations of the extreme precipitation in most parts of the AAM region. To investigate the influence of human activities on the extreme precipitation intensity in AAM region, we compare the climatology of the extreme precipitation distribution of the All-Hist runs and the Nat-Hist runs. The spatial distributions of extreme precipitation intensity are similar between the All-Hist runs and the Nat-Hist runs, with large values in the Bay of Bengal and southern East Asia and small values in the western Indian Peninsula (Figure 1b vs. Figure 1c). The regional mean bias of the Rx1day over the AAM region in All-Hist runs and the Nat-Hist runs are $-2.10$ mm day$^{-1}$ and $-1.85$ mm day$^{-1}$, respectively (Figure 1d vs. Figure 1e). The PCC between the two bias patterns in All-Hist runs and the Nat-Hist runs exceed +0.92 (Figure 1d vs. Figure 1e). These indicate that the anthropogenic forcing exerts a little impact on the spatial distribution of the climatological mean extreme precipitation intensity in AAM region. Even so, the climatology of extreme precipitation is slightly decreased under the anthropogenic forcing, which accounts for more than 55% of the AAM region, especially in the southern East Asian monsoon region, with the maximum decrease reaching $-15.9$ mm day$^{-1}$. On the contrary, the extreme precipitation climatology is significantly increased in the Bay of Bengal under the anthropogenic forcing, with the maximum increase more than $+27.3$ mm day$^{-1}$ (Figure 1f).

To further assess the impact of human activities on extreme precipitation, we investigate the trend change between extreme precipitation intensity and the global land surface averaged temperature change in different recurrence intervals (hereafter refers to as the scaling). For the extreme precipitation that occurs once every 2 years, the averaged change of scaling in the AAM region is $+0.7\%$ C$^{-1}$ under the anthropogenic forcing, with increasing trend in the northern East Asia, northern Bay of Bengal, and central Australia, and decreasing trend in Indian Peninsula and southeastern East Asia (Figure 3a). In comparison, the extreme precipitation...
mainly shows a decreasing trend with an averaged scaling to be $-2.1\%{\degree} C^{-1}$ under the natural forcing, but the decreasing trends in the Indian Peninsula and southeastern East Asia are weaker than those under the anthropogenic forcing (Figure 3a vs. Figure 3b). Correspondingly, the differences between them show increased scaling in the northern East Asia and the Australia with the maximum value more than $+20\%{\degree} C^{-1}$, while the other regions mainly show slightly decreased scaling (Figure 3c).

For the extreme precipitation that occurs once every 10 years, the AAM region under the anthropogenic forcing mainly present increasing trend with the averaged scaling of $+4.5\%{\degree} C^{-1}$. In contrast, the averaged scaling under the natural forcing reduces to $-2.2\%{\degree} C^{-1}$. This means that anthropogenic forcing has obviously reversed the extreme precipitation intensity scaling in AAM region. Compared with the extreme precipitation that occurs once every 2 years, the distribution of the scaling under natural forcing is quite consistent (Figure 3b vs. Figure 3e), while the scaling in southern East Asia, Indochina Peninsula, and Australia change from negative phase to positive phase under the anthropogenic forcing. Particularly, the extreme precipitation intensity scaling changes from negative sign at 2-year time to more positive sign at 10-year time in southern East Asia (Figure 3a vs. Figure 3d). For extreme precipitation that occurs once every 50 years, the scaling under the without anthropogenic mainly weakens throughout the AAM region with an averaged scaling of $-3.2\%{\degree} C^{-1}$, and Only 34.8% of the area show an increasing trend. On the other hand, the change of scaling under the anthropogenic forcing is completely opposite with an averaged scaling of $+4.3\%{\degree} C^{-1}$, as evidenced by the regions with increasing trend accounts for 73.7% of the total AAM area. Although the spatial distribution of scaling in different recurrence
periods is similar, the scaling is significantly increased from the 50% to the 98% in the AAM region, especially for southern East Asia, southern Indian Peninsula, and the Indochina Peninsula (Figure 3c,f,e). In summary, the anthropogenic forcing has greatly increased the scaling in the AAM area, particularly for the extreme precipitation with higher percentile.

Furthermore, we calculate the probability density distribution analysis (PDF) between the land temperature and the extreme precipitation intensity in All-Hist runs and Nat-Hist runs, and Figure 4 shows the PDFs for the entire AAM region and three subregions of Australia, northern East Asia, southern East Asia that are well simulated by All-Hist runs model. No matter the entire AAM
region or three subregions, the extreme precipitation trends under the All-Hist runs shift right compared with that under the Nat-Hist runs, and most parts of extreme precipitation trends are located to the right of the zero line. Meanwhile, the PDF of All-Hist runs tend to shift right with the increase of the percentiles from 50 to 98% (Figure 4). These results indicate that the anthropogenic forcing contributes to the extreme precipitation intensity increase of the in AAM region, which is featured by the stronger (weaker) extreme precipitation accompanying with a stronger (weaker) growth trend.

4 | CONCLUSIONS AND DISCUSSION

Using the HadGEM3-A-N216 model simulations and the REGEN dataset, in this research we compare the long-term changes of extreme precipitation in the AAM region during the historical period with and without anthropogenic influences. The HadGEM3-A-N216 model simulations well reproduces the climatological mean and interannual variability of extreme precipitation in most parts of the AAM region during 1960–2013, with the linear correlation coefficient between the time series of regional mean Rx1day in the observations and the model simulations exceeding +0.64. In most years, the extreme precipitation intensity difference averaged over the AAM region between model simulations and observations is less than 2.0 mm day$^{-1}$. Except for the extreme precipitation intensity in the Indian Peninsula that is greatly underestimated, the simulated extreme precipitation intensity in other regions is slightly overestimated. Under the anthropogenic forcing, the areas with the climatological mean extreme precipitation intensity decreasing account for more than 55% of the AAM region, and the climatological mean of the extreme precipitation intensity in northern East Asia, the Bay of Bengal, and
Australia are slightly increased. Although the spatial distribution of extreme precipitation intensity trend is almost similar between anthropogenic forcing and without anthropogenic forcing, the anthropogenic forcing promotes the increasing trend of extreme precipitation as the percentage increases from the 50 to 98%. The extreme precipitation intensity in the northern East Asia, the Bay of Bengal, and the Australia increases much larger from the 50 to 98%, while it changes from a decreasing trend to an increasing in the southern East Asia. Correspondingly, the extreme precipitation trends under the anthropogenic forcing relatively shift to the right compared with those without anthropogenic forcing in the AAM region. The general feature is that more extreme precipitation is accompanied by a stronger growth trend under the anthropogenic forcing.

During the historical period of 1960–2013, the current results reveal that the anthropogenic forcing has increased the intensity of extreme precipitation in most of the AAM region. These results add the robustness of the conclusion revealed by the previous studies based on the observations (Chen and Sun, 2017; Du et al., 2019; Dong et al., 2020). It should be noted the growth trend of the Rx1day in southeastern China and India under the anthropogenic forcing is much lower than that under the natural forcing only (Figure 3). The decrease trend of extreme precipitation intensity in the two regions under the anthropogenic forcing may be largely related to the human-induced aerosol emissions (Gu et al., 2006; Bollasina et al., 2011; Salzmann and Cherian, 2015; Ma et al., 2017), which can be proved by the increasing aerosol emissions reducing the rainfall over the AAM region (Li et al., 2015). Meanwhile, the interdecadal variabilities of PDO and AMO may also partly explain the decrease trend of extreme precipitation intensity over the Indian Peninsula, regardless of whether there is anthropogenic forcing or not (Figure 3) (Krishnan and Sugi, 2003; Krishnamurthy and Krishnamurthy, 2014; Joshi and Rai, 2015; Krishnamurthy and Krishnamurthy, 2016). Therefore, we will attempt to investigate the relative contribution of anthropogenic aerosols, greenhouse gases, and interdecadal variabilities to the different degrees of extreme precipitation over the AAM region in future works. Additionally, our conclusions are only based on a single atmosphere model which exists model dependence. To better understand the impact of anthropogenic forcing on the extreme precipitation in the AAM region, a comparison with the estimates from the fully coupled models (Sun et al., 2014; Massey et al., 2015) is needed in future.

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