Detection of Human Influence on Precipitation Extremes in Asia

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ABSTRACT

This paper examines the possible influence of external forcings on observed changes in precipitation extremes in the mid-to-high latitudes of Asia during 1958–2012 and attempts to identify particular extreme precipitation indices on which there are better chances to detect the influence of external forcings. We compare a recently compiled dataset of observed extreme indices with those from phase 5 of the Coupled Model Intercomparison Project (CMIP5) simulations using an optimal fingerprinting method. We consider six indices that characterize different aspects of extreme precipitation, including annual maximum amount of precipitation falling in 1 day (Rx1day) or 5 days (Rx5day), the total amount of precipitation from the top 5% or top 1% daily amount on wet days, and the fraction of the annual total precipitation from these events. For single-signal analysis, the fingerprints of external forcings including anthropogenic agents are robustly detected in most studied extreme indices over all Asia and for midlatitude Asia but not for high-latitude Asia. For two-signal analysis, anthropogenic influence is detectable in these indices over Asia at 5% or slightly less than 5% significance level, whereas natural influence is not detectable. In high-latitude Asia, anthropogenic influence is detected only in a fractional index, representing a stark contrast to the midlatitude and full Asia results. We find relatively smaller internal variability and thus higher signal-to-noise ratio in the fractional indices when compared with the other ones. Our results point to the need for studying precipitation extreme indices that are less affected by internal variability while still representing the relevant nature of precipitation extremes to improve the possibility of detecting a forced signal if one is present in the data.

1. Introduction

Although intensification of extreme precipitation in response to global warming is a widely accepted projection of future climate, it is difficult to establish a direct causal relationship between anthropogenic climate change and the observed changes in precipitation extremes (Bindoff et al. 2013). This is in particular the case

at impact-relevant regional scales where the inherent internal climate variability in precipitation is high (Deser et al. 2012; Fischer et al. 2013; C. Li et al. 2018; Zhang et al. 2017). At continental to global scales, long-term increases in extreme precipitation have been observed and attributed to anthropogenic climate change. Westra et al. (2013) showed that annual maxima of daily precipitation over global land areas have increased with global mean surface temperature at about the Clausius–Clapeyron rate ($\sim 7.0\% \text{ K}^{-1}$). Min et al. (2011) conducted an optimal detection and attribution analysis on annual maxima of daily and 5-day precipitation accumulations (Rx1day and Rx5day) of Northern Hemisphere land

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(0°–80°N). They found evidence for anthropogenic influences on the average annual maxima over the hemispheric domain, but they were not able to detect human influence at the smaller continental scale. Based on improved observations and climate model simulations, [Zhang et al. \(2013\)](#) confirmed the evidence of human influence at the hemispheric scale, and further detected such evidence in continental regions including North America and Europe, but with increasing difficulty in detection for smaller regions.

At regional spatial scales such as Asia, studies have attempted to attribute the observed changes in precipitation extremes to anthropogenic influences on the climate. Conclusions nevertheless remain less robust. In [Zhang et al. \(2013\)](#), anthropogenic signals were not detected in Rx1day and Rx5day in eastern Eurasia (0°–65°N, 60°–180°E). Because of limitations of data availability, other precipitation detection and attribution studies in Asia have focused mainly on China. For example, [Ma et al. \(2017\)](#) reported an overall shift from weak to intense precipitation regimes in China and attributed this regime shift to anthropogenic emissions of greenhouse gases. [Chen and Sun \(2017\)](#) documented that human activities had intensified daily precipitation extremes over China. While the influence of anthropogenic forcing alone was detected in this study, the influence of the combined anthropogenic and natural forcings was not detected, even though the impacts of natural forcing have been minor during the past decades. [Li et al. \(2017\)](#) also found significant influence of anthropogenic greenhouse gases on annual maxima of daily precipitation in China. Yet, a recent study reported that the changes in annual maxima of daily precipitation in China had not emerged from internal climate variability up to the year 2012 ([W. Li et al. 2018](#)). Although much has been learned, the past results are conflicting and inconclusive.

Among other factors, observational uncertainty is an important factor obscuring our understanding of changes in regional precipitation extremes. Changes in extreme precipitation may exhibit strong spatial and temporal variations that may not necessarily represent responses of extreme precipitation to long-term warming due to the high inherent internal climate variability. Observational data with incomplete spatial coverage or short temporal coverage can therefore produce higher uncertainty in the estimate due to incomplete data samples (e.g., [Wan et al. 2013](#)). An observational dataset of long temporal and complete spatial coverage is critical for a credible detection and attribution analysis.

In March 2013, the World Meteorological Organization (WMO) Expert Team on Climate Change Detection

and Indices (ETCCDI) organized a regional workshop in Nanjing, China. A dataset of ETCCDI extreme temperature and precipitation indices for Asia was compiled in this workshop. This dataset complemented by the Global Historical Climate Network Daily dataset and a dataset maintained by China National Meteorological Information Center has more complete spatial and temporal coverage over Asia than the widely used HadEX2 dataset ([Donat et al. 2013](#)), representing the best-effort observational dataset of weather and climate extremes in Asia. While a detection and attribution analysis of changes in temperature extremes has been conducted based on this dataset ([Dong et al. 2018](#)), no study has analyzed precipitation extreme indices from a detection and attribution perspective. In this study, we analyze changes in precipitation extremes in Asia based on this improved dataset, and investigate whether the observed changes can be linked to anthropogenic climate change. This paper focuses on detection and attribution of changes in six extreme precipitation indices that characterize different aspects of extreme precipitation. The focus is rather different from that of [Dong and Sun \(2018\)](#), who compared the mean and trends in large set of precipitation indices between three different observational datasets and CMIP5 simulations from the lens of model evaluation. [Dong and Sun \(2018\)](#) focused on how the CMIP5 simulations, forced with observed historical forcing, compare with observations. The results showed that differences between the three datasets and CMIP5 models are large for low-latitude regions and for the intensity indices. Here we have two main objectives: to determine 1) whether influences of external forcing including greenhouse gases, aerosols, and natural external forcing can be detected and attributed in the observed changes in extreme precipitation and 2) which of those indices provide better chance for the detection of those influences. Four of the six indices have not been used in previous detection and attribution studies.

We structure the paper as follows. [Section 2](#) introduces the precipitation extreme indices, the observational and model datasets, and methods for detection and attribution analysis used in this study. We then present the results in [section 3](#) and finally conclude the study in [section 4](#).

2. Data and methods

a. Extreme precipitation indices

We employ four precipitation extreme indices developed by the WMO ETCCDI (see definitions in

TABLE 1. Signal-to-noise ratios of six extreme precipitation indices from the observations. The signal and noise are estimated by the precipitation changes from linear trend within the 55-yr period and the corresponding internal variability, respectively.

SNR	Rx1day	Rx5day	R99p	R95p	R99p/PTOT	R95p/PTOT
Mid- + high-latitude region	1.006	0.103	1.360	1.610	1.324	2.318
Midlatitude region	0.913	0.122	1.430	1.723	2.189	2.607
High-latitude region	0.614	−0.162	0.010	1.012	−0.229	1.452

http://etccdi.pacificclimate.org/list_27_indices.shtml). They are the annual maxima of daily and consecutive 5-day precipitation accumulations, denoted respectively by Rx1day and Rx5day, and annual total precipitation accumulations from wet days with precipitation exceeding the 95th and 99th percentiles of daily precipitation during the 1961–90 base period, denoted respectively by R95p and R99p. We also define two new extreme indices reflecting contributions of extreme precipitation to annual total precipitation on wet days, that is, R95p/PRCPTOT and R99p/PRCPTOT, where PRCPTOT is annual precipitation accumulations on days with precipitation amount larger than 1 mm.

We selected these indices because they represent different ways of characterizing precipitation extremes that may be relevant to impacts. Rx1day is typically used to represent extreme precipitation of short duration. It is often used to produce intensity-duration curves, important to many engineering applications. It is also an important indicator for the risk of floods of small spatial scale such as urban flooding. Rx5day represents precipitation extremes of longer (in time) and larger (in space) scale that are more relevant to widespread flooding over a large catchment. Both Rx1day and Rx5day are block maxima, that is, maximum values within a block or period of time (in this case a year). It is argued in statistics that block maxima may not make best use of information available in the daily values, and that the maxima exceeding a certain threshold (or peak-over-threshold) may use the information more efficiently. The use of R95p and R99p indices are similar to the use of peak-over-threshold values in that both may be the sum of multiple daily values in a given year. This not only makes it possible to use the available data more efficiently, but the summation may also have the effect of reducing the coefficient of variance, thereby improving the signal-to-noise ratio (SNR). As annual total precipitation and R95p and R99p can be influenced by anomalies of large-scale circulation, their ratios, R95p/PRCPTOT or R99p/PRCPTOT, can have an even smaller coefficient of variance, providing perhaps an even better SNR for the detection and attribution of human influence in precipitation extremes (Table 1). The six indices together should provide a relatively comprehensive characterization of precipitation extremes. Hereinafter, we refer to them as absolute

indices (Rx1day and Rx5day), percentile-based indices (R95p and R99p), and fractional indices (R95p/PRCPTOT and R99p/PRCPTOT). We note that as PRCPTOT is also an ETCCDI index, the two fractional indices can be calculated by making use of existing datasets of observed and modeled ETCCDI indices.

b. Observational data

We acquire observations of the six precipitation extreme indices from a best-effort ETCCDI dataset compiled from three different data sources. The first source benefited from a regional workshop in March 2013, Nanjing, China, organized by ETCCDI with support from WMO and China Meteorological Administration. Participants from 15 countries in Asia contributed ETCCDI indices (for both precipitation and temperature) that are computed coordinately from station observations using the RClimDex/FClimdex software package (Zhang et al. 2011). As a large proportion of the contributed data is not available elsewhere, this dataset offers a unique opportunity for understanding the historical changes in weather and climate extremes in Asia. This dataset was augmented with the Global Historical Climate Network–Daily (GHCND) dataset to expand the spatial and temporal coverage whenever possible. Considering that only a limited number of Chinese stations are included in the above two datasets, extreme indices calculated from quality-controlled and homogenized temperature and precipitation observations at over 2400 stations in mainland China provided by China National Meteorological Information Center (Cao et al. 2016) were adopted to further augment the dataset. The collected observations were converted to anomalies relative to a 1961–90 baseline period for each extreme index and for stations where there are at least 15 years of data during the baseline period. The resulting anomalies were gridded to a resolution of 5° longitudinally and latitudinally by averaging all station values within each grid cell if that grid cell contains at least one station. The compiled dataset was referred to as ADEX (the new Asian extreme indices dataset; Dong and Sun 2018). We follow this convention in this study. Figure 1 shows the stations where there are enough data for calculating Rx1day. We note that stations used

FIG. 1. Illustration of ADEX station locations used for Rx1day. The grid boxes with sufficient data (1958–2012) are marked by blue dashed lines, and regional boundaries are marked by black lines that separate the two study regions: the midlatitude region (20°–40°N, 65°–140°E) and high-latitude region (40°–60°N, 50°–145°E). Red dots represent excluded stations for which there were fewer than 15 complete years of data during the base period, and black dots represent those used in the calculation of Rx1day. The distributions of stations for the other indices are similar to that shown here.

for calculating other extreme indices are quite similar (not shown). The gridded values we obtain represent the gridbox average of point estimation of extremes, rather than extremes of gridbox mean precipitation. We do so for two reasons. One is the lack of available daily data that are observed from a dense network that allows for a robust estimation of area mean of daily precipitation. The other is uneven spatial distribution of observing stations that may result in inhomogeneity should gridded mean precipitation be produced. This use of point estimates of extremes to compare model extremes that are more representative for area mean is not without caveats. [Chen and Knutson \(2008\)](#) found that extremes calculated from station-based observations of precipitation that represent point estimates have larger values than those calculated from gridded model simulations that represent area estimates. [Dong and Sun \(2018\)](#) found that studied extremes indices in ADEX have higher climatological values than that in the CMIP5 model simulations, and this inconsistency between models and observations may be partly due to different order of operations.

We calculate regional mean time series for the six extreme precipitation indices by averaging all available grid cell anomalies within each predefined region, neglecting grid cells where the fraction of ocean is greater than 25%. We define two regions by dividing all

of Asia (50°–145°E, 20°–60°N) at 40°N into midlatitude and high-latitude Asia. Our choice of the region separation is motivated by the different ratios of extreme precipitation changes to natural internal variability in these two regions, as will be seen later. Further, greater warming has been found in high latitudes due to anthropogenic climate change. It is not clear whether the influence of anthropogenic climate change is also more detectable in high-latitude precipitation extremes than those in midlatitudes. The whole dataset spans years from 1951 to 2012. We analyze only data from 1958 to 2012 because good-quality data prior to 1958 are very limited. We exclude data after 2012 as simulations with known historical forcings, such as natural-only forcing or greenhouse gas-only forcing, for years after 2012 are not available in models from phase 5 of the Coupled Model Intercomparison Project (CMIP5). [Figure 2](#) summarizes the numbers of stations having sufficient data for each region and extreme index. It is seen for all indices that the number of stations varies substantially from 1958 to 2012, with a dramatic increase during the first two decades, particularly in midlatitude Asia.

c. Climate model simulations

To estimate the responses of the precipitation extreme indices to external forcings, we use the relevant ETCCDI indices calculated from CMIP5 climate model

FIG. 2. Number of stations in six intensity indices times series, showing ADEX at midlatitudes (green lines), ADEX at high latitudes (blue lines), and ADEX at both mid- and high latitudes (black lines).

simulations in historical (ALL), historicalGHG (GHG), and historicalNat (NAT) experiments (Sillmann et al. 2013a,b). We choose simulations from climate models having at least three ensemble members under a particular forcing experiment that are available or can be extended to 2012. As many CMIP5 historical simulations end in 2005, we extend them to 2012 using projections under the representative concentration pathway (RCP) 4.5 emissions scenario. The choice of RCP scenarios for data extension is not important because different RCPs have similar radiative forcing during 2006–12 (IPCC 2013). We convert the modeled extreme indices to anomalies relative to 1961–90 and then interpolate to the grid of ADEX. We mask the regridded anomalies by the availability of ADEX

observations to ensure a fair comparison between observations and models. We obtain 116 55-yr chunks from 11 climate models in the preindustrial control experiment (CTL) to estimate internal variability in the extreme indices. These 55-yr chunks emulate the 1958–2012 observations, with the first year representing the observations of 1958. We apply the same processing procedures for the historical simulations on each of the 116 preindustrial control chunks. Table 2 provides details on the climate models and simulations used in this study.

d. Optimal fingerprinting method

Detection and attribution of changes in the climate are typically conducted by comparing observations with

TABLE 2. Available simulations for the different forcing experiments used in this study. Numbers represent simulation ensemble sizes or the number of 55-yr chunks of the CTL simulations. The model that is used only for the calculations of signal is marked with italics, and the models that are used only for the calculation of noise are marked in boldface type. The model simulations that do not extend to 2012 are used for noise estimation [e.g., CESM1(FASTCHEM)], and those with fewer than 110 years of historical simulation data are not used for noise estimation (e.g., MIROC4h). Expansions for the model names can be found online (<https://www.ametsoc.org/PubsAcronymList>).

Model name	ALL	CTL	NAT	GHG
BCC_CSM1.1	3			
BCC_CSM1.1(m)	3	7		
CanESM2	5		5	5
CCSM4			4	3
CESM1(BGC)		8		
CESM1(FASTCHEM)	3			
CNRM-CM5	10		6	6
CSIRO Mk3.6.0	10		5	5
FGOALS-s2	3			
EC-EARTH		8		
GFDL CM3	5		3	3
GFDL-ESM2M		8		
GISS-E2-R	3			
HadCM3	10			
HadGEM2-ES	4	10	4	4
IPSL-CM5A-LR	6	17	3	3
IPSL-CM5A-MR	3		3	3
MIROC-ESM	3	9		
MIROC-ESM-CHEM		4		
MIROC4h	3			
MIROC5	5	11		
MPI-ESM-MR	3	17		
MPI-ESM-LR	3	17		
MRI-CGCM3	5			
NorESM1-M	3			
Sum (models)	82 (17)	116 (11)	26 (6)	23 (5)

expected responses of climate to external forcing (or signals) as simulated by climate models. A simple reasoning is that, if climate models are sufficiently good in simulating the patterns of some aspects of climate response to external forcings and if such a pattern of response can be detected in the observations, we can then have confidence that influence of the external forcings is detectable in those aspects of the climate. While the comparison of the observations and model data is statistical, the conclusion is supported by the physical understanding of the climate system as implemented in the climate models. Flato et al. (2013) concluded that the models had improved ability in reproducing the observed extreme precipitation, although there is still room for improvement in the model simulations.

An optimal fingerprint method based on total least squares regression (Allen and Stott 2003) as implemented in Ribes et al. (2013) was used in this study to provide the

statistical inference. This method regresses the observations $\mathbf{Y}$ onto multimodel mean signal patterns $\mathbf{X}$ as follows: $\mathbf{Y} = (\mathbf{X} - \mathbf{v})\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, where the residual vector $\boldsymbol{\varepsilon}$ and matrix $\mathbf{v}$ represent internal climate variability in the observations and in the modeled signal patterns, respectively, and $\boldsymbol{\beta}$ is a vector of scaling factors to be estimated, with one scaling factor for each signal pattern in $\mathbf{X}$. If the 90% confidence interval of a scaling factor is above 0, this indicates that the signal is detectable in the observations at the 5% significance level. If the signal is detected, while simultaneously the estimated confidence interval also includes 1, this implies that the modeled signal is detectable and attributable in observations. A scaling factor confidence interval that includes 1 but also including 0 implies consistency between the model and observation but no detectable or attributable signal.

We conduct both single-signal and two-signal analyses in this study. The single-signal analysis, which involves modeled response to either ALL forcing or GHG forcing, aims to ascertain if the modeled response to the corresponding external forcing is consistent with the change in observations. We do not conduct the single-signal analysis on the response to NAT forcing as a lack of the inclusion of responses to the primary components of external forcing can render the single-signal analysis invalid (Zhang et al. 2013). The two-signal analysis, which simultaneously involves responses to anthropogenic (ANT) and NAT forcings, is used to determine whether the ANT signal can be detectable in the observations, and if so, whether it can be separated from the NAT signal. We estimate the modeled ANT response as the difference between the modeled ALL and NAT responses. Although this difference is also contaminated by the difference due to different models being used in estimating the ALL and NAT responses, it is verified that the use of ANT responses estimated from models that have both ALL and NAT simulations does not strongly affect our major findings. A residual consistency test is used to examine if modeled internal variability is consistent with that observed as represented by regression residuals.

We implement fingerprinting analyses on nonoverlapping 5-yr mean regional mean anomalies. We confirmed that using 3-yr mean anomalies, which are relatively more affected by internal climate variability, produced almost identical results to the reported ones. We conduct separate analysis for mid- and high-latitude Asia and space-time analysis for all of Asia where the two regions are considered as two spatial dimensions to construct the observed and modeled response patterns. The space-time analysis attempts to determine anthropogenic influence on extreme precipitation on average over Asia, while the separate analysis aims to explore the detectability of

anthropogenic fingerprint in smaller regions of mid- and high-latitude Asia.

3. Results

a. Spatial and temporal patterns of extreme precipitation changes in Asia

Figure 3 presents the observed and modeled 1958–2012 trends in the six precipitation extreme indices and total precipitation amount under different forcing experiments. In the observations, all extreme indices exhibit positive trends or weak negative trends over the majority land of Asia, with the largest positive trends observed in South China (the first column in Fig. 3). There are regions where negative trends are consistently observed in these studied extreme indices, such as northern and southwestern China. The pattern of the percentile-based indices and PRCPTOT are similar, both showing positive trends in most Asian regions and negative trends from southwestern to northeastern China. The fractional indices thus improve comparability among grid boxes, as can be seen by comparing the observed trends in these two types of indices (the third to sixth rows in the first column in Fig. 3). The forced responses to ALL and GHG also show positive or weak negative trends for all extreme indices (the second and third columns in Fig. 3). However, models fail to reproduce the drying trends in these indices in the inland areas of Asia. For the NAT results, the NAT responses exhibit mixed weak positive and negative trends without spatially organized patterns (the fourth column in Fig. 3).

The 5-yr mean anomaly time series provide clearer information about the temporal evolution of these extreme indices on average over regions. Figure 4 presents the 5-yr mean anomaly time series for the observed and modeled precipitation extreme indices averaged over the three considered regions (i.e., all of Asia, midlatitude Asia, and high-latitude Asia). It is found for all studied extreme indices that the observations fall well within the central 90% ranges of the simulated responses of individual models to ALL forcing (black lines vs light pink envelopes) and GHG forcing (not shown). Moreover, the multimodel mean responses to ALL and GHG forcings reproduce reasonably the upward trends in the observations in most cases, especially after 1980s (red and green lines vs black lines in Fig. 4). Although the central 90% ranges of the NAT responses can also include the observations (black lines vs light blue envelopes), the multimodel mean NAT responses exhibit no trend or very weak positive trends that are substantially less than the observed upward trends (black lines vs blue lines). As expected, the

two fractional indices R95p/PRCPTOT and R99p/PRCPTOT appear to show less internal variability than their counterparts R95p and R99p, indicating a potential for larger SNRs and thereby a better chance to detect the influence of external forcings, as will become obvious later. Also, it is noted that despite the relatively larger magnitudes of trends, extreme precipitation in the midlatitudes of Asia tends to be more influenced by internal variability than in the high latitudes, consistent with a previous study (Dong and Sun 2018).

b. Attribution of the observed extreme precipitation changes

Figure 5 summarizes the ALL scaling factor best estimates and their 90% confidence intervals from single-signal analyses. Based on the space–time analyses for all of Asia (middle + high latitudes), it is found that the combined influence of anthropogenic and natural forcings can be detected in all studied precipitation extreme indices except Rx5day at the 5% significance level, as indicated by the scaling factors that are well above zero (right panel in Fig. 5). Moreover, the scaling factors that are greater than zero are also consistent with 1, indicating that the modeled responses of these extreme indices to the combined anthropogenic and natural forcings agree with the changes in observations. We also notice that the 90% confidence intervals of the scaling factors for the two fractional extreme indices are sizably narrower than those for the other indices, indicative of a higher detectability of the ALL responses in the fractional indices. The higher detectability is likely related to the relatively lower internal climate variability and higher SNRs in these fraction indices, as we have already discussed. We find essentially the same results from the analyses for midlatitude Asia (left panel in Fig. 5), suggesting that the signals of the observed midlatitude extreme precipitation changes dominate the signals for the whole region, while the high-latitude signals are weak. The weak high-latitude signals lead the ALL scaling factors to cross 0 for all studied extreme indices in this region except R95p/PRCPTOT (middle panel in Fig. 5), despite the relatively weaker internal climate variability in the studied extreme indices there. Note, however, that the sparse observations in the high latitudes can also affect the results. We obtain similar GHG scaling factors from the corresponding single-signal analyses (Fig. 6), in line with the results shown in Figs. 3 and 4.

Figure 7 shows the best estimates of scaling factors for ANT and NAT as well as their 90% confidence intervals from the two-signal analyses for different regions. We find for all regions that the NAT scaling factors are not significantly different from zero regardless of extreme indices (blue bars in Fig. 7). This implies that the role of

FIG. 3. Comparison of trend patterns for Rx1day [$\text{mm} (10 \text{ yr})^{-1}$], Rx5day [$\text{mm} (10 \text{ yr})^{-1}$], R99p [$\text{mm} (10 \text{ yr})^{-1}$], R95p [$\text{mm} (10 \text{ yr})^{-1}$], R99p/PRCPTOT [$\% (10 \text{ yr})^{-1}$], R95p/PRCPTOT [$\% (10 \text{ yr})^{-1}$], and PRCPOT [$\text{mm} (10 \text{ yr})^{-1}$] in mid- and high-latitude Asia between ADEX and simulation during 1958–2012 for (left) ADEX, (left center) ALL, (right center) GHG, and (right) NAT forcing.

FIG. 4. Time series of 5-yr mean regional average anomalies (millimeters or percent, relative to 1961–90) for Rx1day, Rx5day, R99p, R95p, R99p/PRCPTOT, and R95p/PRCPTOT in the observation (ADEX; black lines) and model simulations. The red, green, and blue lines represent multimodel ensemble means in the ALL, GHG, and NAT simulations, respectively. The light pink and light blue shadings indicate the 5%–95% range of the individual model results under ALL and NAT forcings, respectively. For each index group, the top plot is midlatitudes + high-latitudes (M+H), the middle plot is midlatitudes (M), and the bottom plot is high latitudes (H).

natural forcings is negligible in the observed changes in these studied extreme precipitation indices. In contrast, the ANT scaling factors for all of Asia suggest that anthropogenic influence is detectable in these extreme indices at the 5% significance level or a level that is slightly less than 5%. In midlatitude Asia, anthropogenic influence remains detectable in the two fractional indices, as indicated by the ANT scaling factors for these indices being well above zero. Anthropogenic influence is also marginally detectable in Rx1day. In the high latitudes, anthropogenic influence is detected

in R95p/PRCPTOT. The surprisingly high detectability of the fractional extreme indices, even in smaller subregions of Asia, highlights that it is necessary to conduct detection and attribution analysis on precipitation extreme indices that are less affected by internal variability while still representing relevant features of extreme precipitation so as to enhance the ability to detect a forced signal if one is present in the data. Our results for Rx1day and Rx5day are consistent with those reported in Min et al. (2011) and Zhang et al. (2013), despite the fact that the transformed probability indices

FIG. 5. Best estimates of the scaling factors and their 5%–95% confidence intervals from single-signal analyses, in which the observation are regressed to the model-simulated response to ALL forcing for the period of 1958–2012. Triangles at the bottom and at the top indicate that models may over- or undersimulate observed variability, respectively, according to the residual consistency tests. These show the results for the intensity indices (Rx1day, R99p, R99p/PRCPTOT, Rx5day, R95p, and R99p/PRCPTOT) for (left) the midlatitude, (center) the high-latitude, and (right) the mid- + high-latitude regions.

by a generalized extreme value distribution fitted to Rx1day and Rx5day are analyzed in these studies.

4. Conclusions and discussion

Benefiting from a recently compiled ADEX dataset for temperature and precipitation extreme indices in Asia, we perform optimal detection and attribution analyses on a suite of six precipitation extreme indices for Asia and its two subregions (i.e., mid- and high-latitude Asia). These indices represent different aspects of extreme precipitation changes and are affected in different degrees by internal climate variability. Based on single-signal analyses, we find that the multimodel simulated responses to the combined historical anthropogenic and natural forcings (ALL) and to greenhouse gas-only

forcing (GHG) are nearly detectable and attributable with the observed changes in all the studied extreme indices on average over all of Asia and over midlatitude Asia except Rx5day. We also find that extreme precipitation changes in high-latitude Asia are in general nondetectable, except for R95p/PRCPTOT, for which the multimodel simulated ALL and GHG responses are detectable and attributable in the observations.

From two-signal analyses, we find that anthropogenic influence is detectable in all the studied extreme indices on average over Asia at the 5% significance level or a level that is slightly less than 5%, while natural influence is detectable in none of these indices. In midlatitude Asia, anthropogenic influence remains detectable in the two fractional indices R95p/PRCPTOT and R99p/PRCPTOT and marginally in Rx1day, while in

FIG. 6. As in Fig. 5, but for GHG forcing.

FIG. 7. Similar to Fig. 5, but for scaling factors and 5%–95% confidence intervals for ANT (red) and NAT (blue) from the two-signal analyses for each index.

high-latitude Asia anthropogenic influence is detectable only in R95p/PRCPTOT. Compared to the other extreme indices, the fractional indices are relatively less affected by internal climate variability and thus have relatively larger SNRs, leading to the higher detectability of these indices. The percentile-based and fractional indices, especially the latter, also improve the comparability between observations and model simulations with all observed external forcings. Existing studies have reported the important role of aerosols in affecting precipitation extremes in East Asia (Lin et al. 2016; Sillmann et al. 2017; Wang 2015). Simulations driven by individual forcings agents during the historical period can help to better understand the role of anthropogenic aerosols in extreme precipitation changes in East Asia.

Overall, our results emphasize that it can be useful to conduct detection and attribution analyses on different precipitation extreme indices that are less affected by internal climate variability while still representing relevant information on extreme precipitation so as

to obtain an improved understanding of anthropogenic influence on regional extreme precipitation. Like many other studies that involve the comparison between observed and model simulated extreme precipitation, this study also has important caveats. Extreme precipitation identified from observations at daily time scale is of a small-scale nature while model data represent mean precipitation over a large area (i.e., model grid). In this sense, the observed and model data are not strictly comparable. In addition, the models may not adequately simulate some important processes, such as moist convection, that are needed to properly simulate extreme precipitation on daily time scales. These caveats need to be considered when interpreting results of these studies.

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