Future Projection of Extreme Precipitation Indices over the Indochina Peninsula and South China in CMIP6 Models

BIN TANG,^{a,b} WENTING HU,^{a,b} AND ANMIN DUAN^{a,b}

^a *State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG),
Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China*

^b *University of Chinese Academy of Sciences, Beijing, China*

(Manuscript received 9 December 2020, in final form 23 July 2021)

ABSTRACT: A future projection of four extreme precipitation indices over the Indochina Peninsula and South China (INCSC) region with reference to the period 1958–2014 is conducted through the application of a multimodel ensemble approach and a rank-based weighting method. The weight of each model from phase 6 of the Coupled Model Intercomparison Project (CMIP6) is calculated depending on its historical simulation skill. Then, the weighted and unweighted ensembles are used for future projections. The results show that all four extreme precipitation indices are expected to increase over the INCSC region, both in the middle (2041–60) and at the end (2081–2100) of the twenty-first century, under three Shared Socioeconomic Pathway (SSP) scenarios. The increases in total extreme precipitation (R95p), extreme precipitation days (R95d), and the fraction of total rainfall from events exceeding the extreme precipitation threshold (R95pT) in the Indochina Peninsula are more significant than those in South China. The occurrence of extreme rainfall events may become more frequent in the future over the INCSC region, since the probability that R95pT increases is larger than 0.7 in the whole INCSC region. A comparison between the weighted and unweighted ensemble means shows that the uncertainty over South China is almost always reduced after applying the weighted scheme to future probabilistic projection, while the reductions in uncertainty over the Indochina Peninsula may depend on SSPs. The more extreme precipitation over the INCSC region in the future may be related to the larger water vapor supply and the more unstable local atmospheric stratification.

KEYWORDS: Extreme events; Model comparison; Model evaluation/performance

1. Introduction

Global warming has profoundly affected the climate in the last few decades, not only in terms of the mean climate but also with respect to extreme events in different regions of the world (Christensen and Christensen 2004; Shiu et al. 2012; Papalexiou and Montanari 2019). In addition, extreme wet events are projected to occur more frequently in many land areas against the background of global warming (Meehl et al. 2007; Allan and Soden 2008). In the Asia-Pacific region, there is an increase in the frequency of dry days and a shift toward heavier rain for the land domain (Watterson 2020). Located in the tropical monsoon area, the Indochina Peninsula and South China (INCSC) region has a population of more than half a billion, making it especially vulnerable to extreme precipitation hazards such as widespread flooding (Villafuerte and Matsumoto 2015; Supari et al. 2020). According to Ge et al. (2019), the flood risk over the INCSC region is expected to grow, driven by an increase in the frequency of extremely wet days, under scenarios with a 1.5° or 2°C global

warming above preindustrial conditions. Therefore, efforts to project precipitation extremes in the INCSC region under global warming scenarios are crucial for risk assessment and policymaking aimed at coping with the future climate change experienced by any of the region's countries (Weiss 2009; IPCC 2014).

Global climate models are regarded as effective tools to project future changes in mean climate and extremes (Chen et al. 2010; Chen 2013). Multiple studies have been conducted based on model assessments to reveal the future climate changes in extreme precipitation in different regions, such as South Asia (Kripalani et al. 2007), East Asia (Lee et al. 2020), Australia (Watterson and Rafter 2017), the northeast United States (Thibeault and Seth 2014), and China (Li et al. 2016). However, large uncertainties still exist in model projections, at both regional and global scales. Among these uncertainties, there are three main causes: model uncertainty, scenario uncertainty, and random internal variability in the climate itself (Hawkins and Sutton 2010). Probabilistic projection methods have been widely used in climate projections (Giorgi and Mearns 2002; Giorgi and Mearns 2002, 2003; Giorgi and Bi 2005; Xu et al. 2010; W. Chen et al. 2011; Li et al. 2016). In addition, to increase the level of reliability, the multimodel ensemble (MME) method has also been widely used for future climate projections (Fowler et al. 2007; Watterson 2008; Yang et al. 2011; Villarini and Vecchi 2012; Sillmann et al. 2013; Zhou et al. 2014). For example, using seven models from phase 3 of the Coupled Model Intercomparison Project (CMIP3), Jiang et al. (2012) showed that both the frequency and intensity of extreme precipitation would increase by the end of

Denotes content that is immediately available upon publication as open access.

Supplemental information related to this paper is available at the Journals Online website: <https://doi.org/10.1175/10.1175/JCLI-D-20-0946.s1>.

Corresponding author: Wenting Hu, hwt@lasg.iap.ac.cn

DOI: 10.1175/JCLI-D-20-0946.1

© 2021 American Meteorological Society. For information regarding reuse of this content and general copyright information, consult the AMS Copyright Policy (www.ametsoc.org/PUBSReuseLicenses).

the twenty-first century across China, especially over the Tibetan Plateau and southeast coastal regions. For South China, the precipitation extremes were projected to increase, in terms of both the annual number of days and the intensity, by the CMIP5 models (Guo et al. 2016; Qin and Xie 2016; Peng et al. 2018). For the Indochina Peninsula, a wetting tendency was projected using CMIP5 models, as manifested by the frequency of extremely heavy rainfall being projected to increase in all seasons under the representative concentration pathway (RCP) scenarios RCP4.5 and RCP8.5 (Supari et al. 2020). Most of the studies mentioned above used a simple MME approach in which equal weight was assigned to each model participating in the future projection of precipitation extremes.

However, the overall skill of climate projection using the simple MME approach may be degraded when models with poor simulation capacities are used (Li et al. 2016). Therefore, it is desirable to break the democracy among models and assign different weights to different models to obtain a more reliable projection result. However, the selection of which method to use to determine the corresponding weights of different models is also a key problem that still needs to be solved. In this respect, Giorgi and Mearns (2002) proposed the reliability ensemble average (REA) method, which assigns each model a corresponding weight based on reliability criteria, including model performance and model convergence. The former of these two criteria is based on the model capacity to reproduce different aspects of present-day climate, while the latter is based on the simulation convergence of different models (Giorgi and Mearns 2002, 2003; Giorgi and Bi 2005). Xu et al. (2010) further improved the REA method by employing a comprehensive criterion that considers both multiple variables and statistical characteristics, which can produce finer-scale structures compared with the original one. W. Chen et al. (2011) were the first to propose a rank-based weighting method and used it to conduct a probabilistic projection of mean temperature and mean precipitation over China. Li et al. (2016) also applied this method for probabilistic projection in China but concentrated on extreme precipitation indices. The rank-based weighting method (W. Chen et al. 2011) can sort models into a ranked list by considering both the mean state and variability of the climate. In addition, it has smaller uncertainties for future projection compared to the original REA method (W. Chen et al. 2011). However, the application of the rank-based method to the future projection of extreme precipitation indices in the INCSC region has not yet been tested. Therefore, this approach is utilized in the present study to conduct the future projection of four extreme precipitation indices under different Shared Socioeconomic Pathway (SSP) scenarios in phase 6 of CMIP (CMIP6) over the INCSC region. It is hoped that the results will provide useful information for risk assessment and policymaking related to global warming.

Our main goal in conducting this study is to construct future projections of extreme precipitation indices over the INCSC region by using CMIP6 models under different SSPs for the middle (2041–60) and the end (2081–2100) of the twenty-first century. The ranking of the CMIP6 models is

FIG. 1. Map showing the location and altitudes (shading; m) of the INCSC region.

obtained from the capacities of the models to simulate extreme precipitation indices over South China and the Indochina Peninsula in terms of present-day climate. The reasonable but unverified assumption here is that a better agreement with present-day climate corresponds to a higher reliability of the model's future projection (Whetton et al. 2007). On the basis of this assumption, the weights determined by model performances in simulating historical precipitation extremes are assigned to the CMIP6 models, and then the future projections of extreme precipitation in the INCSC region under different SSPs are presented. Furthermore, the possible reasons for the identified future changes in precipitation extremes over the INCSC region are also discussed.

The remainder of the paper is organized as follows. The data and methods are briefly described in section 2. Section 3 presents the ranking of the CMIP6 models based on their simulation skills with respect to historical extreme precipitation indices over the INCSC region. The future projections of extreme precipitation indices in the INCSC region under three SSPs for the middle (2041–60) and end (2081–2100) of the twenty-first century are presented in section 4. In addition, a comparison between the weighted and unweighted ensemble means is also given in this section. The possible reasons for the identified changes in precipitation extremes over the INCSC region are further discussed in section 5. Finally, a summary and discussion are provided in section 6.

2. Data and methods

a. Description of the study area

The INCSC is a region located within 0°–30°N, 90°–120°E, including mainly South China, Myanmar, Thailand, Laos, Vietnam, Cambodia, and the Malaysian Peninsula (Fig. 1), and is extremely susceptible to extreme precipitation events owing to the abundant water vapor supply (Buckley et al.

2014). The economic activity and everyday lives of the human population living in the INCSC region have been greatly influenced in the last few decades by large-scale flooding (Weiss 2009). Therefore, there is a strong need for projections of extreme precipitation indices over the INCSC region toward a better understanding and risk assessment of the possible future changes in extreme precipitation.

b. Observations and CMIP6 model output

Daily gridded precipitation data with a resolution of $0.25^\circ \times 0.25^\circ$ provided by the Asian Precipitation–Highly Resolved Observational Data Integration Toward the Evaluation of Water Resources (APHRODITE) project (Yatagai et al. 2012) based on the rain gauge dataset were employed as observational data to evaluate the historical simulations of the CMIP6 models in this study. The APHRODITE dataset is quality controlled and thoroughly checked for errors and inconsistencies (Yatagai et al. 2012). It was also shown that these data can serve as a good evaluation tool for climate model performance (Yatagai et al. 2008, 2012). The data can be obtained at <http://aphrodite.st.hirosaki-u.ac.jp/download/>.

For integrity, 26 CMIP6 models (Table 1) were used in this study. As the period 1958–2014 is covered by both APHRODITE data and historical experiments of CMIP6 models, the daily precipitation in both the observations and historical model outputs for that period was used for the model assessments. For future emission scenarios, the CMIP6 Scenario Model Intercomparison Project provides a new set of emission and land-use scenarios. The SSP is a combination of the RCP and alternative pathways of socioeconomic development (O'Neill et al. 2016; Eyring et al. 2019). In addition, SSP126, SSP245, and SSP585 represent radiative forcings stabilized at 2.6, 4.5, and 8.5 W m^{-2} by the end of the twenty-first century, respectively. Thus, we used SSP126, SSP245, and SSP585 in CMIP6 for future projections. Monthly horizontal wind, air temperature, specific humidity, relative humidity, sea level pressure, surface air pressure, and 2-m air temperature were also employed to explore the possible reasons for the future change in extreme precipitation indices over the INCSC region. Only the first realization (usually r1i1p1f1, except r1i1p1f2 for CNRM-CM6-1-HR, CNRM-CM6-1, CNRM-ESM2-1, MIROC-ES2L, and UKESM1-0-LL, r1i1p1f3 for HadGEM3-GC31-LL) of each model was used in this study in order to have as many models as possible. Given the different mechanisms behind extreme precipitation over South China and the Indochina Peninsula (Kanae et al. 2001; Chi et al. 2005; Buckley et al. 2014), the analyses of these two subregions' extreme precipitation indices were conducted separately.

c. Extreme precipitation indices

In this study, we calculated the extreme precipitation threshold by using percentiles, following the method of Zhai et al. (2005), which has been widely used in previous studies (Qian and Lin 2005; Wu et al. 2007; Li et al. 2012; Wang et al. 2012; Wu et al. 2013; Zhang et al. 2014; Cui et al. 2018). At each grid point, the annual precipitation data (daily precipitation $\geq 1 \text{ mm}$) were sorted in ascending order to obtain the annual precipitation sequence for every year

from 1980 to 2009. Then, the average of the 95th percentile for the 30-yr precipitation sequence at each grid point was defined as the extreme precipitation threshold (R_{95p} in Table 2). It should be noted that the extreme precipitation thresholds for observations and models were calculated separately from the APHRODITE data and from each CMIP6 model.

Based on this extreme precipitation threshold, four extreme precipitation indices with details given in Table 2 were calculated, which were developed by the World Meteorological Organization, the Climatological Commission, and the Climate Change and Forecasting Program Recommendations. In addition, these indices have been widely used to reflect the basic characteristics of extreme precipitation (Yang et al. 2008; Choi et al. 2009; Faticchi and Caporali 2009; Zhang et al. 2011; Peng et al. 2018). Total extreme precipitation ($R95p$), extreme precipitation days ($R95d$), and extreme precipitation intensity (AEPI) are the basic statistical variables describing extreme precipitation; the fraction of total rainfall from events exceeding the extreme precipitation threshold ($R95pT$) reflects the proportion of extreme precipitation in total precipitation. To facilitate the intercomparison of different CMIP6 models, the four extreme precipitation indices were first calculated for the observation and models on their native grids and then interpolated to a common 1° latitude $\times$ 1° longitude grid via bilinear interpolation that the data are interpolated from one rectilinear grid to another (Ou et al. 2013; Zhang et al. 2013; Jiang et al. 2016; Wang et al. 2018). Note that when extreme precipitation indices were interpolated to 1° through bilinear interpolation, the extreme precipitation indices may be smoothed with an increase in the minima and reduction in the maxima (Accadia et al. 2003). However, compared with other interpolation methods (e.g., conservative interpolation), a bilinear interpolation algorithm may be more suitable for this study, given that most of CMIP6 models have a native resolution lower than $1^\circ \times 1^\circ$ (Jiang et al. 2016; Wang et al. 2018).

We notice that there are some biases in the mean and interannual variation of four extreme precipitation indices between station and APHRODITE within the INCSC region (figures not shown). However, since APHRODITE incorporated as much gauge-observation data as possible, it is hard to find independent gauge-observation data to correct APHRODITE (Yatagai et al. 2012; Lai et al. 2020). Furthermore, correcting or modifying the APHRODITE needs a reliable observation as a reference when employing a certain bias correction method (Leander et al. 2008; Teutschbein and Seibert 2012; Sunyer et al. 2015; Smitha et al. 2018; Gumindoga et al. 2019; Voropay et al. 2021). However, large uncertainties exist among various precipitation datasets for Indochina Peninsula, due to the lack of perfect and robust site observations there (e.g., Sunyer et al. 2015; Turco et al. 2013; Kim et al. 2018). Thus, we still utilized APHRODITE gridded precipitation dataset as observation for model evaluation, which is based on gauge-observation data with an appropriate homogenization and interpolation methodology and may be more appropriate for evaluating model simulations (Kiktev et al. 2003; Alexander et al. 2006; Yatagai et al. 2012; Jiang et al. 2015).

In this study, the changes of extreme precipitation indices in future projection were expressed in percentage with reference to

TABLE 1. Model institution identification (ID), modeling center and country, model name, and atmospheric resolution of the 26 CMIP6 models employed in this study. (Expansions of most acronyms are available online at <http://www.ametsoc.org/PubsAcronymList>.)

Institution ID	Modeling center and country	Model name	Atmospheric resolution (lat $\times$ lon)
CSIRO-ARCCSS	Commonwealth Scientific and Industrial Research Organization, Australian Research Council Centre of Excellence for Climate System Science, Australia	ACCESS-CM2	$1.25^{\circ} \times 1.875^{\circ}$
CSIRO	Commonwealth Scientific and Industrial Research Organization, Australia	ACCESS-ESM1-5	$1.25^{\circ} \times 1.875^{\circ}$
BCC	Beijing Climate Center, China	BCC-CSM2-MR	$1.125^{\circ} \times 1.225^{\circ}$
CCCma	Canadian Centre for Climate Modeling and Analysis, Environment and Climate Change Canada, Canada	CanESM5	$1.406^{\circ} \times 1.406^{\circ}$
NCAR	National Center for Atmospheric Research, Climate and Global Dynamics Laboratory, United States	CESM2-WACCM CESM2	$0.938^{\circ} \times 1.25^{\circ}$ $0.938^{\circ} \times 1.25^{\circ}$
CNRM-CERFACS	Centre National de Recherches Meteorologiques, Centre Europeen de Recherche et de Formation Avancee en Calcul Scientifique, France	CNRM-CM6-1 CNRM-ESM2-1	$1.406^{\circ} \times 1.406^{\circ}$ $1.406^{\circ} \times 1.406^{\circ}$
EC-Earth-Consortium	EC-EARTH consortium	EC-Earth3 EC-Earth3-Veg	$0.703^{\circ} \times 0.703^{\circ}$ $0.703^{\circ} \times 0.703^{\circ}$
CAS	Chinese Academy of Sciences, China	FGOALS-g3	$2.25^{\circ} \times 2^{\circ}$
NOAA-GFDL	National Oceanic and Atmospheric Administration, Geophysical Fluid Dynamics Laboratory, United States	GFDL-ESM4	$1^{\circ} \times 1.25^{\circ}$
MOHC	Met Office Hadley Centre, United Kingdom	HadGEM3-GC31-LL UKESM1-0-LL	$1.25^{\circ} \times 1.875^{\circ}$ $1.25^{\circ} \times 1.875^{\circ}$
INM	Institute for Numerical Mathematics, Russian Academy of Science, Russia	INM-CM4-8 INM-CM5-0	$1.5^{\circ} \times 2^{\circ}$ $1.5^{\circ} \times 2^{\circ}$
IPSL	Institute Pierre Simon Laplace, France	IPSL-CM6A-LR	$1.259^{\circ} \times 2.5^{\circ}$
NIMS-KMA	National Institute of Meteorological Sciences/Korea Meteorological Administration, South Korea	KACE-1-0-G	$1.25^{\circ} \times 1.875^{\circ}$
MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, The University of Tokyo, National Institute for Environmental Studies, RIKEN Center for Computational Science, Japan	MIROC6 MIROC-ES2L	$1.406^{\circ} \times 1.406^{\circ}$ $1.25^{\circ} \times 1.875^{\circ}$
DKRZ	Deutsches Klimarechenzentrum, Germany	MPI-ESM1-2-HR	$0.938^{\circ} \times 0.938^{\circ}$
MPI-M	Max Planck Institute for Meteorology, Germany	MPI-ESM1-2-LR	$1.875^{\circ} \times 2.5^{\circ}$
MRI	Meteorological Research Institute, Japan	MRI-ESM2-0	$1.125^{\circ} \times 1.125^{\circ}$
NUIST	Nanjing University of Information Science and Technology, China	NESM3	$1.875^{\circ} \times 1.875^{\circ}$
NCC	NorESM Climate modeling Consortium, Norway	NorESM2-LM NorESM2-MM	$1.875^{\circ} \times 2.5^{\circ}$ $0.938^{\circ} \times 1.25^{\circ}$

the historical period, rather than presenting absolute numbers of changes. This is because without bias correction, the absolute numbers of changes especially for the threshold-based indices may be affected using the raw CMIP6 model simulations when the simulated climatology has large biases. Nevertheless, bias correction is known to alter the climate change signals but without physical justification (e.g., Hempel et al. 2013; Maraun 2016) and it has been criticized for being used more from the perspective of necessity rather than validity (Ehret et al. 2012).

Thus, percentages are used to give a more objective picture of what the models project. It should be mentioned that in section 4b, mean absolute change was used in order to conduct clear and intuitive comparisons.

d. Model evaluation metrics

1) TAYLOR DIAGRAM

The Taylor diagram was used in this study to quantitatively evaluate the capacities of the CMIP6 models for reproducing the

TABLE 2. Brief description of the four extreme precipitation indices used in this study.

Index	Descriptive name	Definition	Units
R95p	Precipitation due to very wet days	Annual total precipitation when the daily precipitation exceeds the extreme precipitation threshold. Let R_{wj} be the daily precipitation amount on wet days ($R > 1$ mm) of period j and R_{wn95} be the extreme precipitation threshold, then R95p is determined as $R95p_j = \sum_{w=1}^W R_{wj}$, $R_{wj} > R_{wn95}$.	mm
R95d	Extreme precipitation days	Number of days with daily precipitation exceeding the extreme precipitation threshold during the whole year.	days
AEPI	Extreme precipitation intensity	Absolute intensity of extreme precipitation. $AEPI = R95p/R95d$.	mm day ⁻¹
R95pT	Extreme precipitation ratio	Ratio of annual extreme precipitation to annual rainfall on rainy days (daily precipitation ≥ 1 mm). Let R_j be the sum of daily precipitation amount for period j , and let R_{wj} be the daily precipitation amount on wet days ($R > 1$ mm) of period j and R_{wn95} be the extreme precipitation threshold, then R95pT is determined as $R95pT_j = \sum_{w=1}^W R_{wj}/R_j$, $R_{wj} > R_{wn95}$.	%

historical spatial variation in the four extreme precipitation indices by examining the pattern correlation, centered normalized root-mean-square (RMS) difference, and spatial standard deviation ratio of the modeled and observed values (Taylor 2001). The more skillful the CMIP6 model is in reproducing the spatial variation in the observational extreme precipitation indices, the closer both the pattern correlation and spatial standard deviation ratio are to 1, and the closer the centered normalized RMS difference is to 0.

2) INTERANNUAL VARIABILITY SKILL SCORE

To quantitatively evaluate the capacities of the CMIP6 models for reproducing historical temporal variations, we used the interannual variability skill (IVS) score described by W. Chen et al. (2011) as follows:

$$IVS = \left(\frac{STD_m}{STD_o} - \frac{STD_o}{STD_m} \right)^2, \quad (1)$$

in which STD_m and STD_o are the interannual standard deviations of the model simulations and observations, respectively. The IVS of each extreme index is first calculated at each grid point and then averaged over South China and the Indochina Peninsula. The IVS value calculated through this method might become unduly dominated by individual grid points (e.g., in dry areas), where the relative difference between the simulated and the observed standard deviations is very large. However, this calculating method can provide the most stringent test for models compared with other calculating methods, such as using the area mean values to obtain the interannual standard deviations and then calculating IVS. A smaller IVS

value indicates better agreement in terms of the interannual variability between the model simulation and observations.

3) COMPREHENSIVE RATING METRICS

According to the Taylor diagram and the IVS values, each extreme precipitation index was used to rank the CMIP6 models in this study based on their historical spatial and temporal simulation capabilities. Then, a comprehensive ranking metric, MR, defined in Jiang et al. (2015), was used. MR is defined as follows:

$$MR = 1 - \frac{1}{nm} \sum_{i=1}^n \text{rank}_i. \quad (2)$$

In this formula, m is the number of models, n is the number of extreme precipitation indices, and rank_i is the rank of the model for the i th extreme precipitation index. Better model performance accompanies a smaller value of rank_i .

e. Probabilistic projection scheme

1) CALCULATION OF MODEL WEIGHTS

From Eqs. (1) and (2), the ranks of Taylor (the rank of MRs based on the three statistics of the Taylor diagram) and IVS (the rank of MRs based on the IVS) were obtained. The sum of the ranks of Taylor and IVS represents the overall ranking of historical simulation capacity of each CMIP6 model. Then, the model's corresponding weight was calculated following the method of W. Chen et al. (2011). The formula is as follows:

$$R_i = \frac{\sum_{i=1}^N S_i}{S_i}, \quad (3)$$

$$W_i = \frac{R_i}{\sum_{i=1}^N R_i}, \quad (4)$$

where S_i is the sum of the ranks of each CMIP6 model considering its simulation skills in both spatial pattern and interannual variability, and N is the total number of models. Therefore, R_i can be regarded as a combined performance indicator for model i . Models with better simulation skills will have higher R_i values. Through R_i , the W_i can be obtained using Eq. (4). In short, W_i is the normalized value of R_i .

2) PROBABILITY OF CHANGES EXCEEDING THE GIVEN THRESHOLD

According to the W_i of each model, the probability P of the change in extreme precipitation index Δpr exceeding the given threshold Δpr_{th} can be calculated as follows:

$$P^{\Delta pr > \Delta pr_{th}} = \sum_i W_i, \quad \Delta pr_i > \Delta pr_{th}. \quad (5)$$

When Δpr is less than the given threshold, the probability can be calculated by $1 - P$.

3) ROOT-MEAN-SQUARE DIFFERENCE

The weighted average change is given using the formula described in W. Chen et al. (2011). For each extreme precipitation index, it can be defined as follows:

$$\Delta P = \frac{\sum_i W_i \Delta P_i}{\sum_i W_i}, \quad (6)$$

where ΔP_i is the projected change in model i and W_i is its corresponding weight defined in Eq. (4).

The root-mean-square difference (RMSD) of projected change is used here to measure the uncertainty in projection (J. Chen et al. 2011). Note that the term “difference” here means the difference in projected change between individual models and the MME. The RMSD of projected change by weighted mean and unweighted mean are defined separately by Eqs. (7) and (8) as follows:

$$\delta_{\Delta P} = \left[\frac{\sum_i W_i (\Delta P_i - \Delta P)^2}{\sum_i W_i} \right]^{1/2}, \quad (7)$$

$$\bar{\delta}_{\Delta P} = \left[\frac{1}{N} \sum_{i=1, N} (\Delta P_i - \bar{\Delta P})^2 \right]^{1/2}. \quad (8)$$

In these two formulas, ΔP is the weighted mean change defined by Eq. (6) and $\bar{\Delta P}$ is the equally weighted average.

3. Model evaluation

In this section, we focus on the simulation skills of CMIP6 models with respect to historical extreme precipitation indices over the INSCS region based on the two evaluation metrics introduced in section 2d.

a. Evaluation of spatial variation

Figure 2 displays the CMIP6 model rankings for each of the four extreme precipitation indices with regard to the three aspects of the Taylor diagram: pattern correlation (left-hand column), spatial standard deviation ratio (central column), and centered normalized RMS difference (right-hand column). The exact values of each statistic are shown in Tables S1 and S2 in the online supplemental material for reference. The ranks of the three metrics obtained from the Taylor diagrams for each extreme precipitation index are averaged model by model first. Then, the obtained ranks are sorted as the basis for the MR calculation to quantify the capability of each CMIP6 model in reproducing the spatial pattern of observations. The application of MR introduced in section 2 provides a comprehensive spatial ranking for each model. According to the values of the spatial MR, model capabilities are ordered from top to bottom, with more red boxes indicating better model simulation skills for extreme precipitation indices. The five leading models for the simulations in South China are EC-Earth3-Veg, EC-Earth3, NorESM2-MM, CESM2, and NESM3. For the Indochina Peninsula, EC-Earth3, EC-Earth3-Veg, NorESM2-MM, HadGEM3-GC31-LL, and CESM2 are the five models with the best skill in simulating the spatial pattern.

b. Evaluation of interannual variability

The IVS score described in section 2d was used to measure the similarity of interannual variability between models and observations. Figure 3 shows the IVS score of the four extreme precipitation indices averaged over South China and the Indochina Peninsula for the period 1958–2014. The extreme precipitation indices are not equally well simulated in the two subregions. The two indices with relatively high IVS values (R95p and AEPI) are poorly simulated compared with the other two. This may be because R95p and AEPI are directly affected by biases in precipitation intensity, but these biases are partly factored out in R95d (e.g., by the model-dependent definition of the extreme precipitation threshold value) and in R95pT (as models with larger extreme precipitation also tend to have larger total precipitation). The MRs based on the IVS values of the four extreme precipitation indices were further calculated to obtain the rankings of the CMIP6 models in terms of interannual variability. Overall, the five top models for South China are MRI-ESM2-0, NorESM2-LM, GFDL-ESM4, NorESM2-MM, and EC-Earth3-veg, while MRI-ESM2-0, NorESM2-MM, ACCESS-ESM1-5, NorESM2-LM, and MIROC6 are the five leading models for the Indochina Peninsula.

c. Calculation of weights

The model rankings of the 26 CMIP6 models were determined by the MRs based on both the Taylor diagram and IVS. Then, their corresponding weights were calculated using Eq. (6). Table 3 details the rankings of Taylor and IVS, as well as the sum of the ranks and the corresponding weights, of the 26 CMIP6 models, in which the boldface values denote that the weights of the corresponding models are larger than the value of equally weighted models (0.038). In other words, these models with higher rankings will have a greater impact on the future

FIG. 2. Portrait diagram of the model rankings (given by the colors) for each extreme precipitation index based on the pattern correlation (left columns), the spatial standard deviation ratio (center columns), and the centered normalized RMS difference (right columns) for (a) South China and (b) the Indochina Peninsula. In each plot, the model names listed on the left from top to bottom follow their ranks of MRs based on the Taylor diagram.

probabilistic projection of extreme precipitation indices in the INCSC region. Note that the model horizontal resolution is not the only factor determining the model skill in simulating extreme precipitation indices over the INCSC region. Because not all the models with above-average weight (>0.038) are high-resolution models. For instance, the resolution of IPSL-CM6A-LR is lower than that of CESM2-WACCM, but with larger weight for South China. The improvements in physical processes are also required (Bador et al. 2020).

4. Future projection

In this section, we explore the future changes in the four extreme precipitation indices. Two future time periods are focused on under the three SSPs: 2041–60, representing the middle of the twenty-first century (also referred to as the mid-twenty-first century), and 2081–2100, which represents the end of the twenty-first century (also referred to as the late twenty-first century).

a. Future projection of the four extreme precipitation indices

The projected changes (expressed in percentage) in the four extreme precipitation indices in the middle and the end of the twenty-first century with respect to the period 1958–2014 under three SSPs over South China and the Indochina Peninsula are shown in Figs. 4 and 5. The projected changes in the four extreme precipitation indices are presented in the form of a box-and-whisker plot in which the upper and lower limits of each box

represent the 75th and 25th percentile values, respectively, while the horizontal line in each box shows the median of the distributions, and the upper and lower whiskers indicate the 95th and 5th percentile values, respectively. Note that Figs. 4 and 5 are derived from 26 CMIP6 models with equal weights, in which the range of future change is represented by the ensemble of those models. It should be mentioned that the extreme precipitation indices were first averaged over all grid boxes, and then the percent change was calculated based on the area-mean extreme precipitation indices. The increase in the four extreme precipitation indices in the INCSC region is almost certain during the mid-twenty-first century (Fig. 4), given that the 25th percentiles of the change are all larger than zero. R95p shows the largest increase, while the AEPI increase is relatively slow compared with the other three indices. This may be because the frequency of extremes nearly always increases faster than the magnitude of extremes and the number of days exceeding the threshold increases. Since the threshold is unchanged from the base climate, AEPI statistics for future climate includes fewer rare events than in the present climate. Therefore, the change in AEPI is smaller than the change in any fixed high percentile of the precipitation distribution. Moreover, the changes in the four extreme precipitation indices are larger with increasing greenhouse gas emissions. In addition, more substantial changes in all extreme precipitation indices except AEPI can be expected in the Indochina Peninsula than in South China.

For the late twenty-first century (Fig. 5), the changes in extreme precipitation indices are similar to those in the mid-twenty-first century but with consistently larger magnitudes. For instance, the

FIG. 3. The IVS scores of CMIP6 models for four extreme precipitation indices over (a) South China and (b) the Indochina Peninsula.

median of the change distribution under SSP585 for all extreme precipitation indices except AEPI is larger than 20% in the late twenty-first century, in contrast to the mid-twenty-first century, when the median is almost always close to or less than 20%. Meanwhile, the same extreme precipitation index is predicted to change by similar ranges in the mid-twenty-first century under different warming scenarios (Fig. 4). However, there is a great variation between the scenarios in the late twenty-first century (Fig. 5). In addition, the distances between the 5th and 95th percentiles with respect to all the indices are the largest in both South China and Indochina during the late twenty-first century under SSP585, which means that large differences exist in the projected changes in extreme precipitation indices by CMIP6 models during the late twenty-first century under SSP585 over the INCSC region.

The future projections of the four extreme precipitation indices are similar among the three SSPs but with different magnitudes. Therefore, the results under only one scenario (SSP245) are shown below, while those under the other two

scenarios are included in the supplemental material (see Figs. S1 and S2). Figures 6 and 7 show the spatial patterns of the probabilities that the increase in the four extreme precipitation indices exceeds zero and the distribution of median change (expressed in percentage) over the INCSC region under SSP245 in the middle and late twenty-first century. It should be mentioned that the probabilities in the left columns of Figs. 6 and 7 were calculated based on the rank-based weighting method to have a more realistic estimation of the probabilities of increase for extreme precipitation indices, while the right columns are based on the simple multimodel average to characterize the most likely magnitude of the change. For the mid-twenty-first century, the probabilities that the increase in the four extreme precipitation indices exceeds zero are almost all larger than 0.7 over the whole INCSC region (Figs. 6a,c,e,g), which means that the annual extreme precipitation, annual extreme precipitation days, extreme precipitation intensity, and extreme precipitation ratio are highly likely to increase in the mid-twenty-first

TABLE 3. Ranks and corresponding weights of 26 CMIP6 models according to their comprehensive performance considering both the Taylor diagram and interannual variability over South China and the Indochina Peninsula. The boldface values indicate those models with weights larger than the value of equally weighted models (0.038).

South China					Indochina Peninsula				
Model	Rank of Taylor	Rank of IVS	Sum of the ranks	Weight	Model	Rank of Taylor	Rank of IVS	Sum of the ranks	Weight
EC-Earth3	1	8	9	0.0891	EC-Earth3	1	6	7	0.1131
MIROC6	8	2	10	0.0802	HadGEM3-GC31-LL	5	5	10	0.0792
NESM3	3	7	10	0.0802	NorESM2-MM	3	8	11	0.0720
EC-Earth3-Veg	2	10	12	0.0668	MPI-ESM1-2-HR	11	1	12	0.0660
MPI-ESM1-2-HR	11	5	16	0.0501	EC-Earth3-Veg	2	11	13	0.0609
MPI-ESM1-2-LR	13	3	16	0.0501	UKESM1-0-LL	7	6	13	0.0609
NorESM2-MM	4	12	16	0.0501	NESM3	12	4	16	0.0495
GFDL-ESM4	12	5	17	0.0472	CESM2	4	18	22	0.0360
IPSL-CM6A-LR	16	1	17	0.0472	MIROC-ES2L	20	2	22	0.0360
CNRM-ESM2-1	14	4	18	0.0445	ACCESS-ESM1-5	8	15	23	0.0344
ACCESS-ESM1-5	6	14	20	0.0401	MPI-ESM1-2-LR	14	9	23	0.0344
MRI-ESM2-0	10	11	21	0.0382	INM-CM5-0	23	2	25	0.0317
CNRM-CM6-1	15	8	23	0.0349	NorESM2-LM	15	10	25	0.0317
CESM2	5	26	31	0.0259	KACE-1-0-G	13	13	26	0.0304
CESM2-WACCM	7	24	31	0.0259	MRI-ESM2-0	10	18	28	0.0283
MIROC-ES2L	9	22	31	0.0259	CESM2-WACCM	6	23	29	0.0273
UKESM1-0-LL	20	12	32	0.0251	ACCESS-CM2	17	13	30	0.0264
NorESM2-LM	17	19	36	0.0223	MIROC6	9	21	30	0.0264
HadGEM3-GC31-LL	18	21	39	0.0206	GFDL-ESM4	18	17	35	0.0226
INM-CM4-8	22	17	39	0.0206	INM-CM4-8	24	11	35	0.0226
INM-CM5-0	25	14	39	0.0206	CNRM-CM6-1	16	22	38	0.0208
ACCESS-CM2	26	14	40	0.0200	IPSL-CM6A-LR	25	15	40	0.0198
FGOALS-g3	23	18	41	0.0196	BCC-CSM2-MR	21	20	41	0.0193
BCC-CSM2-MR	19	24	43	0.0186	CanESM5	19	24	43	0.0184
CanESM5	21	23	44	0.0182	CNRM-ESM2-1	22	26	48	0.0165
KACE-1-0-G	24	20	44	0.0182	FGOALS-g3	26	25	51	0.0155

century. However, the distribution of median change show some differences for different extreme precipitation indices (Figs. 6b,d,f,h). For R95p (Fig. 6b), R95d (Fig. 6d), and R95pT (Fig. 6h), the regions with relatively larger increase are mainly located in the south region of South China, southern Myanmar, Cambodia, and the Malay Peninsula. This indicates that the annual extreme precipitation, annual extreme precipitation days, and extreme precipitation ratio in the south region of South China, southern Myanmar, Cambodia, and the Malay Peninsula are likely to increase with a larger amplitude than other regions over the INCSC region in the mid-twenty-first century. Different from the other three extreme precipitation indices, the median changes of AEPI in the mid-twenty-first century are almost all less than 4% over the whole INCSC region (Fig. 6f), which means that the amplitude of extreme precipitation intensity increase is relatively small in the mid-twenty-first century.

For the late twenty-first century (Fig. 7), the probabilities are consistently larger than those in the mid-twenty-first century, but similar spatial distributions remain. The median change of R95p (Fig. 7b) over most region of INCSC in the late twenty-first century is larger than 20%, which is similar with the results derived from CMIP5 models shown by Watterson (2020). Furthermore, the median change of AEPI is likely to increase exceeding 4% in some regions of South

China, Myanmar, northern Laos, and northern Vietnam in the late twenty-first century (Fig. 7f).

b. Comparison between the rank-based weighting average and simple multimodel average

In the previous part, we reported the future projections of the four extreme precipitation indices in the middle and late twenty-first century under the three SSPs and the spatial pattern of the probability that the change exceeds zero and the spatial pattern of most likely magnitude of the change. These were partly based on the assumption that a better agreement with present-day climate always leads to a higher reliability of the model's future projection. However, what are the effects of the weighting on the projection? To answer these questions, we next compare the projected mean changes in the four extreme precipitation indices over the INCSC region as determined by (i) the rank-based weighted average of the 26 CMIP6 models and (ii) simple multimodel averaging.

Figure 8 depicts the geographic distributions of the projected mean changes in the four extreme precipitation indices relative to 1958–2014 for the period 2081–2100 under SSP245, as obtained from the weighted and unweighted schemes and the difference between these two schemes (difference = weighted scheme – unweighted scheme). The results show that the main spatial patterns of the changes in

FIG. 4. Box-and-whisker plots for the projected changes (expressed in percentage) of four extreme precipitation indices in the period 2041–60 with respect to the period 1958–2014 under three SSPs over South China and the Indochina Peninsula. The upper and lower limits of each box represent the 75th and 25th percentile values, respectively, while the horizontal line in each box shows the median of the distributions. The upper and lower whiskers indicate the 95th and 5th percentile values, respectively. The horizontal gray line indicates that the change is zero. Note that the distribution is derived from 26 CMIP6 models with equal weights, in which the range of future change is represented by the ensemble of those models.

the four extreme precipitation indices relative to 1958–2014 are quite consistent between the two schemes in the late twenty-first century. However, slight differences in the magnitudes and locations of the largest index changes still exist between the two schemes. The projected changes in AEPI obtained from the weighted scheme are smaller than those from the unweighted scheme over all of South China (Fig. 8i), while the changes in the other three extreme precipitation indices are larger in most regions of the INCSC (Figs. 8c,f,i). The results are similar to those in Fig. 8 in the 2041–60 period under SSP245 and the two periods under SSP126 and SSP585 (see Figs. S3–S7). Although the projection results of the four extreme precipitation indices using the weighted and

unweighted schemes under each SSP are similar, the RMSDs of the four extreme precipitation indices area-averaged over South China and the Indochina Peninsula, based on Eqs. (7) and (8), were further calculated to compare these two schemes.

Table 4 summarizes the ratio between the weighted and unweighted RMSDs for South China and Indochina Peninsula by the middle and end of the twenty-first century (ratio = RMSD with weighted scheme/RMSD with unweighted scheme). Note that the RMSDs of projected change by weighted mean and unweighted mean are first calculated at each grid point and then averaged over the South China and Indochina Peninsula regions. The RMSDs

FIG. 5. As in Fig. 4, but for the period 2081–2100.

FIG. 6. (left) The spatial pattern of the probability that the increase in four extreme precipitation indices exceeds zero and (right) the median change (expressed in percentage) distribution during the period 2041–60 over the INCSC region under SSP245: (a),(b) R95p, (c),(d) R95d, (e),(f) AEPI, and (g),(h) R95pT. Note that the probabilities in the left columns are calculated based on the rank-based weighting method to have a more realistic estimation of the probabilities of increase for extreme precipitation indices, while the right columns are based on the multimodel ensemble approach to characterize the most likely magnitude of the change.

FIG. 7. As in Fig. 6, but for the period 2081–2100.

FIG. 8. Geographic distributions of projected mean changes in four extreme precipitation indices [(a)–(c) R95p; (d)–(f) R95d; (g)–(i) AEPI; (j)–(l) R95pT] relative to 1958–2014 under the SSP245 scenario in 2081–2100 obtained from the weighted and unweighted schemes and the difference between the two schemes (difference = weighted – unweighted). The mean changes are given in absolute units (R95p: mm; R95d: day; AEPI: mm day⁻¹; R95pT: %).

TABLE 4. The ratio between the weighted and unweighted RMSDs area-averaged over South China and the Indochina Peninsula for the middle (2041–60) and end (2081–2100) of the twenty-first century (ratio = RMSD with weighted scheme/RMSD with unweighted scheme). The boldface values indicate that the weighted scheme has decreased the uncertainty in future projection compared to the unweighted scheme.

Extreme index	South China	Indochina Peninsula	South China	Indochina Peninsula
	2041–60 (SSP126)		2081–2100 (SSP126)	
R95p	0.947	1.029	0.884	1.031
R95d	1.128	1.054	1.059	1.089
AEPI	0.882	0.874	0.870	0.892
R95pT	0.996	1.047	0.952	1.055
	2041–60 (SSP245)		2081–2100 (SSP245)	
R95p	0.895	0.992	0.917	0.968
R95d	1.055	1.053	1.059	0.991
AEPI	0.861	0.885	0.876	0.876
R95pT	0.953	1.027	0.959	0.985
	2041–60 (SSP585)		2081–2100 (SSP585)	
R95p	0.903	0.979	0.910	1.004
R95d	1.061	1.003	1.050	0.959
AEPI	0.871	0.878	0.900	0.891
R95pT	0.962	1.002	0.961	1.007

of the extreme precipitation indices obtained from the weighted scheme generally show reductions compared with the unweighted scheme under the three SSPs. However, there are some differences in the reductions in RMSDs over South China and the Indochina Peninsula. For South China, the RMSDs of the extreme precipitation indices (except R95d) obtained from the weighted scheme nearly always have certain reductions. For the Indochina Peninsula, the reductions in RMSDs vary under different SSPs. For example, only the RMSD of the AEPI obtained from the weighted scheme decreases under SSP126 at the end of the twenty-first century, while the RMSDs of all extreme precipitation indices decrease after applying the weighted scheme under SSP245 by the end of the twenty-first century.

To increase the credibility of the ratio between the weighted and unweighted RMSDs, a statistically significant connection between the present-day performance and climate changes should be demonstrated. Therefore, we use the pool permutation procedure proposed by MacKay (2000) to obtain the distributions of the ratios between the weighted and unweighted RMSDs. The specific steps are as follows: 1) scramble the climate changes in random order between the 26 models to break the connection between the present-day climate and the climate changes; 2) calculate the ratio between the weighted and unweighted RMSDs, retaining the model weights as reported in Table 3; and 3) repeat steps 1 and 2 a larger number of times (here we repeat 10 000 times) to obtain the sampling distribution of the RMSD ratio when there is no real present-climate change connection. The actual ratios in Table 4 are generally in the lower tails of the distribution (see Figs. S8–S10). Therefore, one can conclude that there is a connection between present-day performance and climate change, which is unlikely to be caused by chance alone. Although the reduction in uncertainty after applying the weighted scheme to future probabilistic projection may depend on regions and emission scenarios, it is meaningful to use the rank-based

weighting method in future probabilistic projections for some study areas.

5. Possible reasons for changes in precipitation extremes

The possible causes of the future change in precipitation extremes in South China and the Indochina Peninsula are further investigated. As the extreme precipitation from June to August accounts for approximately half of the total annual amount in the observations and most of the CMIP6 models over the INCSC region (see Tables S3 and S4), the following analyses are mainly focused on the summer season.

Figure 9 shows the spatial distributions of the changes in summer-mean 2-m air temperature, sea level pressure, and 850-hPa horizontal winds (Fig. 9a); summer-mean SST (Fig. 9b); precipitable water content and vertically integrated water vapor flux from the surface to 300 hPa (Fasullo and Webster 2002; Fig. 9c); and K-index (Fig. 9d) under SSP245 at the end of the twenty-first century based on the 26 CMIP6 model ensemble mean. It is clear that the 2-m air temperature increases significantly in the late twenty-first century under SSP245. According to theoretical arguments, the atmospheric moisture content will increase at a rate of $\sim 7\% \text{ K}^{-1}$ of global warming following the Clausius–Clapeyron relation, therefore leading to more intense extreme precipitation (Allen and Ingram 2002; Trenberth et al. 2007; Zhang and Zhou 2019). Furthermore, the increases in 2-m air temperature (shading) over the land areas of East Asia are greater than those over the western North Pacific at the same latitude, causing the strengthened east–west thermal contrast. Correspondingly, the east–west pressure gradient (contours) is strengthened (Fig. 9a). In addition, the warming over the land areas of China is larger than that over the South China Sea, causing the strengthened south–north thermal contrast (Fig. 9a). Therefore, both thermal contrasts between land and sea induce a strengthening of the southwesterly winds

FIG. 9. Projected changes in (a) summer-mean 2-m air temperature (shading; K), sea level pressure (contours; hPa), and 850-hPa horizontal winds (vectors; m s⁻¹); (b) summer-mean SST (°C); (c) precipitable water content (shading; kg m⁻²) and vertically integrated water vapor flux (vectors; 50 kg m⁻¹ s⁻¹) from the surface to 100 hPa; and (d) K index (°C) over East Asia in the period 2081–2100 with respect to the period 1958–2014 under SSP245.

(vectors) in South China (Fig. 9a), which is similar to the findings of Chen (2013). The accelerated southwesterly winds over South China as well as the enhanced land–sea contrast between East Asia and adjacent oceans in 2081–2100 under SSP245 can be clearly seen in Fig. 9a. Furthermore, the projected change in sea surface temperature (SST) shows greater warming in the northwest Indian Ocean in the Northern Hemisphere than in the southwest Indian Ocean in the Southern Hemisphere in the late twenty-first century under SSP245 (Fig. 9b). The northwest–southeast SST contrast in the Indian Ocean will cause strengthened Somali cross-equatorial flow, leading to strengthened westerly winds that stretch eastward from the Arabian Sea through the Indochina Peninsula and extend farther to South China (Fig. 9a). The increases in 2-m air temperature and intensification of westerlies and southwesterlies lead to higher precipitable water content over the INCSC region in the late twenty-first century under SSP245 (Fig. 9c). Hence, abundant water vapor is conducive to the increase in precipitation and its related extremes over the INCSC region under the global warming scenario.

Atmospheric stability is also an important driver of the occurrence of precipitation and its related extremes (Chen 2013). The K index [$K \text{ index} = (T_{850} - T_{500}) + T_{d850} - (T - T_d)_{700}$] is widely used as a diagnostic factor for the occurrence of precipitation, given that it can depict the stability of the atmosphere (Chen et al. 2010). Specifically, larger K index values usually favor more precipitation and its related extremes (Chen 2013). In the late twenty-first century, the projections from the 26 CMIP6 model ensemble mean indicate a significant

increase in the K index over the INCSC region under SSP245 (Fig. 9d). All 26 CMIP6 models show a consistent increase in the K index area-averaged over the whole INCSC region under the three SSPs (Table S5). The increase in the K index means that atmospheric stratification will become more unstable in the future, providing a background that is more conducive to increases in precipitation and its extremes under the global warming scenario. Similar results apply to the projected changes in circulation, moisture conditions, and atmospheric stability in the mid-twenty-first century and under the other two SSPs (see Figs. S11–S14).

In summary, the larger supply of water vapor and the more unstable atmospheric stratification in the future will provide a background that is more conducive to increases in precipitation and its extremes over the INCSC region under the global warming scenario.

6. Summary and conclusions

Based on the overall rankings of the historical simulation capacities of 26 CMIP6 models in the INCSC region, the corresponding weights of each CMIP6 model were obtained. Then, with the application of this rank-based weighting method, a future projection of four extreme precipitation indices in the INCSC region in the middle and late twenty-first century under three SSPs is presented in this study. In addition, the differences in the projections between the weighted and unweighted schemes, and the possible reasons behind the identified changes in the precipitation extremes over the INCSC region are also discussed. The main findings from the probabilistic projections are as follows:

- 1) The four extreme precipitation indices in the INCSC region under the three SSPs are expected to increase in both periods (2041–60 and 2081–2100). The increases in total extreme precipitation (R95p), extreme precipitation days (R95d), and the fraction of total rainfall from events exceeding the extreme precipitation threshold (R95pT) in the Indochina Peninsula are more significant than those in South China in both periods (2041–60 and 2081–2100) under each SSP.
- 2) There are high probabilities (greater than 0.7) of future increases in R95p, R95d, extreme precipitation intensity (AEPI), and R95pT over the INCSC region under the three SSPs. Taking SSP245 as an example, R95pT is projected to increase with a probability larger than 0.7 in nearly the whole INCSC region, indicating that the occurrence of extreme rainfall events may become more frequent over the INCSC region in the future. However, the distribution of the median change varies with different extreme precipitation indices. R95p, R95d, and R95pT increase with larger amplitude in the south region of South China, southern Myanmar, Cambodia, and the Malay Peninsula compared with other regions over the INCSC. AEPI increases with a relatively small amplitude over the whole INCSC in the middle and late twenty-first century.
- 3) Although the projection results of the four extreme precipitation indices calculated by the weighted and unweighted schemes under the three SSPs are generally similar, reductions in model uncertainty are almost always found in South China after applying the weighted scheme to future probabilistic projection. However, the reductions in uncertainty over the Indochina Peninsula may depend on SSPs. The utilization of the pool permutation procedure also demonstrates that the reductions in model uncertainty by the weighted scheme are unlikely to be caused by chance alone. Thus, it is meaningful to use the rank-based weighting method in future probabilistic projections for some study areas.
- 4) The increased land–sea contrast between East Asia and adjacent oceans leads to strengthened southwesterly winds across South China. The northwest–southeast SST contrast in the Indian Ocean will cause strengthened Somali cross-equatorial flow, leading to strengthened westerly winds across the Indochina Peninsula and farther to South China. The intensification of winds as well as the direct influence of temperature increase leads to higher precipitable water content over the INCSC region. Correspondingly, more water vapor is conducive to an increase in precipitation and its related extremes over the INCSC region under the global warming scenario. In addition, atmospheric stratification is projected to become more unstable in the future, which also provides a favorable background for increases in precipitation and its extremes under the global warming scenario.

According to the probabilistic projections of extreme precipitation indices in our study, the risks of extreme rainfall events may increase significantly in most subregions of the INCSC region in the future. However, it should be mentioned here that the weights assigned to each model were obtained by

considering model simulation skills in both spatial patterns and interannual variability for present-day climate. Accordingly, subjective factors, such as the selection of extreme precipitation indices, the different members (realizations) of the same model, and the selection of evaluation metrics, might have influenced the weighting assignment results for the CMIP6 models to a certain degree (Räisänen and Palmer 2001; Weigel et al. 2010). More efforts will be undertaken in future work to refine the weighting method. Besides, we only focused on the basic features (e.g., frequency and density) of extreme precipitation in this study, thus other extreme indices such as extreme annual daily rain would be included in our future work. In addition, generalized extreme value distribution (GEVD) and generalized Pareto distribution (GPD) have been found to be suitable as a fit to the tails of the distribution for precipitation and could provide systematic, probabilistic interpretation for predicting future climate (Jones et al. 2013; Li et al. 2018; Mandapaka and Lo 2018). Therefore, the applications of GEVD and GPD in projecting extreme precipitation indices over the INCSC region are also worthy of further investigation.

Acknowledgments. This work was jointly supported by the National Natural Science Foundation of China (41861144014 and 41875076).

REFERENCES

- Accadia, C., S. Mariani, M. Casaioli, A. Lavagnini, and A. Speranza, 2003: Sensitivity of precipitation forecast skill scores to bilinear interpolation and a simple nearest-neighbor average method on high-resolution verification grids. *Wea. Forecasting*, **18**, 918–932, [https://doi.org/10.1175/1520-0434\(2003\)018<0918:SOPFSS>2.0.CO;2](https://doi.org/10.1175/1520-0434(2003)018<0918:SOPFSS>2.0.CO;2).
- Alexander, L. V., and Coauthors, 2006: Global observed changes in daily climate extremes of temperature and precipitation. *J. Geophys. Res.*, **111**, D05109, <https://doi.org/10.1029/2005JD006290>.
- Allan, R. P., and B. J. Soden, 2008: Atmospheric warming and the amplification of precipitation extremes. *Science*, **321**, 1481–1484, <https://doi.org/10.1126/science.1160787>.
- Allen, M. R., and W. J. Ingram, 2002: Constraints on future changes in climate and the hydrologic cycle. *Nature*, **419**, 224–232, <https://doi.org/10.1038/nature01092>.
- Bador, M., and Coauthors, 2020: Impact of higher spatial atmospheric resolution on precipitation extremes over land in global climate models. *J. Geophys. Res. Atmos.*, **125**, e2019JD032184, <https://doi.org/10.1029/2019JD032184>.
- Buckley, B. M., R. Fletcher, S.-Y. S. Wang, B. Zottoli, and C. Pottier, 2014: Monsoon extremes and society over the past millennium on mainland Southeast Asia. *Quat. Sci. Rev.*, **95**, 1–19, <https://doi.org/10.1016/j.quascirev.2014.04.022>.
- Chen, C. T., and T. Knutson, 2008: On the verification and comparison of extreme rainfall indices from climate models. *J. Climate*, **21**, 1605–1621, <https://doi.org/10.1175/2007JCLI1494.1>.
- Chen, H., 2013: Projected change in extreme rainfall events in China by the end of the 21st century using CMIP5 models. *Chin. Sci. Bull.*, **58**, 1462–1472, <https://doi.org/10.1007/s11434-012-5612-2>.
- , J. Sun, X. Chen, and W. Zhou, 2010: CGCM projections of heavy rainfall events in China. *Int. J. Climatol.*, **32**, 441–450, <https://doi.org/10.1002/joc.2278>.
- Chen, J., F. P. Brissette, and R. Leconte, 2011: Uncertainty of downscaling method in quantifying the impact of climate

- change on hydrology. *J. Hydrol.*, **401**, 190–202, <https://doi.org/10.1016/j.jhydrol.2011.02.020>.
- Chen, W., Z. Jiang, and L. Li, 2011: Probabilistic projections of climate change over China under the SRES A1B scenario using 28 AOGCMs. *J. Climate*, **24**, 4741–4756, <https://doi.org/10.1175/2011JCLI4102.1>.
- Chi, Y., J. He, and Z. Wu, 2005: Features analysis of the different precipitation periods in the pre-flood season in South China. *J. Nanjing Inst. Meteor.*, **28**, 163–171.
- Choi, G., and Coauthors, 2009: Changes in means and extreme events of temperature and precipitation in the Asia-Pacific network region, 1955–2007. *Int. J. Climatol.*, **29**, 1906–1925, <https://doi.org/10.1002/joc.1979>.
- Christensen, O. B., and J. H. Christensen, 2004: Intensification of extreme European summer precipitation in a warmer climate. *Global Planet. Change*, **44**, 107–117, <https://doi.org/10.1016/j.gloplacha.2004.06.013>.
- Cui, D., C. Wang, and J. Santisirisomboon, 2018: Characteristics of extreme precipitation over eastern Asia and its possible connections with Asian summer monsoon activity. *Int. J. Climatol.*, **39**, 711–723, <https://doi.org/10.1002/joc.5837>.
- Ehret, U., E. Zehe, V. Wulfmeyer, K. Warrach-Sagi, and J. Liebert, 2012: HESS opinions: “Should we apply bias correction to global and regional climate model data?” *Hydrol. Earth Syst. Sci.*, **16**, 3391–3404, <https://doi.org/10.5194/hess-16-3391-2012>.
- Eyring, V., and Coauthors, 2019: Taking climate model evaluation to the next level. *Nat. Climate Change*, **9**, 102–110, <https://doi.org/10.1038/s41558-018-0355-y>.
- Fasullo, J., and P. J. Webster, 2002: Hydrological signatures relating the Asian summer monsoon and ENSO. *J. Climate*, **15**, 3082–3095, [https://doi.org/10.1175/1520-0442\(2002\)015<3082:HSRTAS>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<3082:HSRTAS>2.0.CO;2).
- Faticchi, S., and E. Caporali, 2009: A comprehensive analysis of changes in precipitation regime in Tuscany. *Int. J. Climatol.*, **29**, 1883–1893, <https://doi.org/10.1002/joc.1921>.
- Fowler, H. J., M. Ekström, S. Blenkinsop, and A. P. Smith, 2007: Estimating change in extreme European precipitation using a multimodel ensemble. *J. Geophys. Res.*, **112**, D18104, <https://doi.org/10.1029/2007JD008619>.
- Ge, F., and Coauthors, 2019: Risks of precipitation extremes over Southeast Asia: Does 1.5°C or 2°C global warming make a difference? *Environ. Res. Lett.*, **14**, 044015, <https://doi.org/10.1088/1748-9326/aaff7e>.
- Giorgi, F., and L. O. Mearns, 2002: Calculation of average, uncertainty range, and reliability of regional climate changes from AOGCM simulations via the “reliability ensemble averaging” (REA) method. *J. Climate*, **15**, 1141–1158, [https://doi.org/10.1175/1520-0442\(2002\)015<1141:COAURA>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<1141:COAURA>2.0.CO;2).
- , and —, 2003: Probability of regional climate change based on the reliability ensemble averaging (REA) method. *Geophys. Res. Lett.*, **30**, 1629, <https://doi.org/10.1029/2003GL017130>.
- , and X. Bi, 2005: Updated regional precipitation and temperature changes for the 21st century from ensembles of recent AOGCM simulations. *Geophys. Res. Lett.*, **32**, 365–370, <https://doi.org/10.1029/2005GL024288>.
- Gumindoga, W., T. Rientjes, A. T. Haile, H. Makurira, and P. Reggiani, 2019: Performance of bias-correction schemes for CMORPH rainfall estimates in the Zambezi river basin. *Hydrol. Earth Syst. Sci.*, **23**, 2915–2938, <https://doi.org/10.5194/hess-23-2915-2019>.
- Guo, X., J. Huang, Y. Luo, Z. Zhao, and Y. Xu, 2016: Projection of precipitation extremes for eight global warming targets by 17 CMIP5 models. *Nat. Hazards*, **84**, 2299–2319, <https://doi.org/10.1007/s11069-016-2553-0>.
- Hawkins, E., and R. Sutton, 2010: The potential to narrow uncertainty in projections of regional precipitation change. *Climate Dyn.*, **37**, 407–418, <https://doi.org/10.1007/s00382-010-0810-6>.
- Hempel, S., K. Frieler, L. Warszawski, J. Schewe, and F. Piontek, 2013: A trend-preserving bias correction—The ISI-MIP approach. *Earth Syst. Dyn.*, **4**, 219–236, <https://doi.org/10.5194/esd-4-219-2013>.
- IPCC, 2014: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects*. Cambridge University Press, 688 pp., http://www.ipcc.ch/pdf/assessment-report/ar5/wg2/WGIIAR5-PartB_FINAL.pdf.
- Jiang, D., S. Yue, and X. Lang, 2016: Timing and associated climate change of a 2°C global warming. *Int. J. Climatol.*, **36**, 4512–4522, <https://doi.org/10.1002/joc.4647>.
- Jiang, Z., J. Song, L. Li, W. Chen, Z. Wang, and J. Wang, 2012: Extreme climate events in China: IPCC-AR4 model evaluation and projection. *Climatic Change*, **110**, 385–401, <https://doi.org/10.1007/s10584-011-0090-0>.
- , W. Li, J. Xu, and L. Li, 2015: Extreme precipitation indices over China in CMIP5 models. Part I: Model evaluation. *J. Climate*, **28**, 8603–8619, <https://doi.org/10.1175/JCLI-D-15-0099.1>.
- Jones, M. R., S. Blenkinsop, H. J. Fowler, and C. G. Kilsby, 2013: Objective classification of extreme rainfall regions for the UK and updated estimates of trends in regional extreme rainfall. *Int. J. Climatol.*, **34**, 751–765, <https://doi.org/10.1002/joc.3720>.
- Kanae, S., T. Oki, and K. Musiake, 2001: Impact of deforestation on regional precipitation over the Indochina Peninsula. *J. Hydrometeorol.*, **2**, 51–70, [https://doi.org/10.1175/1525-7541\(2001\)002<0051:IODORP>2.0.CO;2](https://doi.org/10.1175/1525-7541(2001)002<0051:IODORP>2.0.CO;2).
- Kiktev, D., D. M. H. Sexton, L. Alexander, and C. K. Folland, 2003: Comparison of modeled and observed trends in indices of daily climate extremes. *J. Climate*, **16**, 3560–3571, [https://doi.org/10.1175/1520-0442\(2003\)016<3560:COMAOT>2.0.CO;2](https://doi.org/10.1175/1520-0442(2003)016<3560:COMAOT>2.0.CO;2).
- Kim, I.-W., J. Oh, S. Woo, and R. H. Kripalani, 2018: Evaluation of precipitation extremes over the Asian domain: Observation and modelling studies. *Climate Dyn.*, **52**, 1317–1342, <https://doi.org/10.1007/s00382-018-4193-4>.
- Kripalani, R. H., J. H. Oh, A. Kulkarni, S. S. Sabade, and H. S. Chaudhari, 2007: South Asian summer monsoon precipitation variability: Coupled climate model simulations and projections under IPCC AR4. *Theor. Appl. Climatol.*, **90**, 133–159, <https://doi.org/10.1007/s00704-006-0282-0>.
- Lai, S., Z. Xie, C. Bueh, and Y. Gong, 2020: Fidelity of the APHRODITE dataset in representing extreme precipitation over Central Asia. *Adv. Atmos. Sci.*, **37**, 1405–1416, <https://doi.org/10.1007/s00376-020-0098-3>.
- Leander, R., T. A. Buishand, B. J. J. M. van den Hurk, and M. J. M. de Wit, 2008: Estimated changes in flood quantiles of the river Meuse from resampling of regional climate model output. *J. Hydrol.*, **351**, 331–343, <https://doi.org/10.1016/j.jhydrol.2007.12.020>.
- Lee, Y., J. Paek, J.-S. Park, and K.-O. Boo, 2020: Changes in temperature and rainfall extremes across East Asia in the CMIP5 ensemble. *Theor. Appl. Climatol.*, **141**, 143–155, <https://doi.org/10.1007/s00704-020-03180-w>.
- Li, J., W. Dong, and Z. Yan, 2012: Changes of climate extremes of temperature and precipitation in summer in eastern China associated with changes in atmospheric circulation in East Asia during 1960–2008. *Chin. Sci. Bull.*, **57**, 1856–1861, <https://doi.org/10.1007/s11434-012-4989-2>.
- Li, W., Z. Jiang, J. Xu, and L. Li, 2016: Extreme precipitation indices over China in CMIP5 models. Part II: Probabilistic

- projection. *J. Climate*, **29**, 8989–9004, <https://doi.org/10.1175/JCLI-D-16-0377.1>.
- , —, X. Zhang, L. Li, and Y. Sun, 2018: Additional risk in extreme precipitation in China from 1.5°C to 2.0°C global warming levels. *Sci. Bull.*, **63**, 228–234, <https://doi.org/10.1016/j.scib.2017.12.021>.
- MacKay, M. D., 2000: A modified pool permutation procedure for short regional climate model simulations nested within analyzed fields. *Geophys. Res. Lett.*, **27**, 2525–2528, <https://doi.org/10.1029/1999GL011332>.
- Mandapaka, P. V., and E. Y. M. Lo, 2018: Assessment of future changes in Southeast Asian precipitation using the NASA Earth Exchange Global Daily Downscaled Projections data set. *Int. J. Climatol.*, **38**, 5231–5244, <https://doi.org/10.1002/joc.5724>.
- Maraun, D., 2016: Bias correcting climate change simulations—A critical review. *Curr. Climate Change Rep.*, **2**, 211–220, <https://doi.org/10.1007/s40641-016-0050-x>.
- Meehl, G. A., and Coauthors, 2007: Global climate projections. *Climate Change 2007: The Physical Science Basis*, S. Solomon et al., Eds., Cambridge University Press, 747–846.
- O'Neill, B. C., and Coauthors, 2016: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.*, **9**, 3461–3482, <https://doi.org/10.5194/gmd-9-3461-2016>.
- Ou, T., D. Chen, H. W. Linderholm, and J.-H. Jeong, 2013: Evaluation of global climate models in simulating extreme precipitation in China. *Tellus*, **65A**, 19799, <https://doi.org/10.3402/tellusa.v65i0.19799>.
- Papalexiou, S. M., and A. Montanari, 2019: Global and regional increase of precipitation extremes under global warming. *Water Resour. Res.*, **55**, 4901–4914, <https://doi.org/10.1029/2018WR024067>.
- Peng, Y., X. Zhao, D. Wu, B. Tang, P. Xu, X. Du, and H. Wang, 2018: Spatiotemporal variability in extreme precipitation in China from observations and projections. *Water*, **10**, 1089, <https://doi.org/10.3390/w10081089>.
- Qian, W., and X. Lin, 2005: Regional trends in recent precipitation indices in China. *Meteor. Atmos. Phys.*, **90**, 193–207, <https://doi.org/10.1007/s00703-004-0101-z>.
- Qin, P., and Z. Xie, 2016: Detecting changes in future precipitation extremes over eight river basins in China using RegCM4 downscaling. *J. Geophys. Res. Atmos.*, **121**, 6802–6821, <https://doi.org/10.1002/2016JD024776>.
- Räisänen, J., and T. N. Palmer, 2001: A probability and decision-model analysis of a multimodel ensemble of climate change simulations. *J. Climate*, **14**, 3212–3226, [https://doi.org/10.1175/1520-0442\(2001\)014<3212:APADMA>2.0.CO;2](https://doi.org/10.1175/1520-0442(2001)014<3212:APADMA>2.0.CO;2).
- Shiu, C.-J., S. C. Liu, C. Fu, A. Dai, and Y. Sun, 2012: How much do precipitation extremes change in a warming climate? *Geophys. Res. Lett.*, **39**, L17707, <https://doi.org/10.1029/2012GL052762>.
- Sillmann, J., V. V. Kharin, F. W. Zwiers, X. Zhang, and D. Bronaugh, 2013: Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. *J. Geophys. Res. Atmos.*, **118**, 2473–2493, <https://doi.org/10.1002/jgrd.50188>.
- Smitha, P. S., B. Narasimhan, K. P. Sudheer, and H. Annamalai, 2018: An improved bias correction method of daily rainfall data using a sliding window technique for climate change impact assessment. *J. Hydrol.*, **556**, 100–118, <https://doi.org/10.1016/j.jhydrol.2017.11.010>.
- Sunyer, M. A., and Coauthors, 2015: Inter-comparison of statistical downscaling methods for projection of extreme precipitation in Europe. *Hydrol. Earth Syst. Sci.*, **19**, 1827–1847, <https://doi.org/10.5194/hess-19-1827-2015>.
- Supari, and Coauthors, 2020: Multi-model projections of precipitation extremes in Southeast Asia based on CORDEX-Southeast Asia simulations. *Environ. Res. Lett.*, **184**, 109350, <https://doi.org/10.1016/j.envres.2020.109350>.
- Taylor, K. E., 2001: Summarizing multiple aspects of model performance in a single diagram. *J. Geophys. Res.*, **106**, 7183–7192, <https://doi.org/10.1029/2000JD900719>.
- Teutschbein, C., and J. Seibert, 2012: Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *J. Hydrol.*, **456–457**, 12–29, <https://doi.org/10.1016/j.jhydrol.2012.05.052>.
- Thibeault, J. M., and A. Seth, 2014: Changing climate extremes in the Northeast United States: Observations and projections from CMIP5. *Climatic Change*, **127**, 273–287, <https://doi.org/10.1007/s10584-014-1257-2>.
- Trenberth, K. E., and Coauthors, 2007: Observations: Surface and atmospheric climate change. *Climate Change 2007: The Physical Science Basis*, S. Solomon et al., Eds., Cambridge University Press, 235–336.
- Turco, M., A. L. Zollo, C. Ronchi, C. De Luigi, and P. Mercogliano, 2013: Assessing gridded observations for daily precipitation extremes in the Alps with a focus on northwest Italy. *Nat. Hazards Earth Syst. Sci.*, **13**, 1457–1468, <https://doi.org/10.5194/nhess-13-1457-2013>.
- Villafuerte, M. Q., II, and J. Matsumoto, 2015: Significant influences of global mean temperature and ENSO on extreme rainfall in Southeast Asia. *J. Climate*, **28**, 1905–1919, <https://doi.org/10.1175/JCLI-D-14-00531.1>.
- Villarini, G., and G. A. Vecchi, 2012: Twenty-first-century projections of North Atlantic tropical storms from CMIP5 models. *Nat. Climate Change*, **2**, 604–607, <https://doi.org/10.1038/nclimate1530>.
- Voropay, N., A. Ryazanova, and E. Dyukarev, 2021: High-resolution bias-corrected precipitation data over south Siberia, Russia. *Atmos. Res.*, **254**, 105528, <https://doi.org/10.1016/j.atmosres.2021.105528>.
- Wang, X., D. Jiang, and X. Lang, 2018: Extreme temperature and precipitation changes associated with four degree of global warming above pre-industrial levels. *Int. J. Climatol.*, **39**, 1822–1838, <https://doi.org/10.1002/joc.5918>.
- Wang, Y., Y. Y. Ding, and Q. L. Miao, 2012: Spatial and temporal variations of extreme precipitation events in Northeast China. *Adv. Mat. Res.*, **573–574**, 395–399, <https://doi.org/10.4028/www.scientific.net/AMR.573-574.395>.
- Watterson, I. G., 2008: Calculation of probability density functions for temperature and precipitation change under global warming. *J. Geophys. Res.*, **113**, D12106, <https://doi.org/10.1029/2007JD009254>.
- , 2020: Influence of sea surface temperature on simulated future change in extreme rainfall in the Asia-Pacific. *Asia-Pac. J. Atmos. Sci.*, **56**, 349–366, <https://doi.org/10.1007/s13143-019-00141-w>.
- , and T. Rafter, 2017: The distribution of daily rainfall in Australia and simulated future changes. *J. Southern Hemis. Earth Sys. Sci.*, **67**, 160–180, <https://doi.org/10.22499/3.6703.002>.
- Weigel, A. P., R. Knutti, M. A. Liniger, and C. Appenzeller, 2010: Risks of model weighting in multimodel climate projections. *J. Climate*, **23**, 4175–4191, <https://doi.org/10.1175/2010JCLI3594.1>.
- Weiss, J., 2009: *The Economics of Climate Change in Southeast Asia: A Regional Review*. Asian Development Bank, 223 pp., <https://hdl.handle.net/11540/179>.
- Whetton, P., I. Macadam, J. Bathols, and J. O'Grady, 2007: Assessment of the use of current climate patterns to evaluate

- regional enhanced greenhouse response patterns of climate models. *Geophys. Res. Lett.*, **34**, L14701, <https://doi.org/10.1029/2007GL030025>.
- Wu, C., G. Huang, H. Yu, Z. Chen, and J. Ma, 2013: Spatial and temporal distributions of trends in climate extremes of the Feilaixia catchment in the upstream area of the Beiji River Basin, South China. *Int. J. Climatol.*, **34**, 3161–3178, <https://doi.org/10.1002/joc.3900>.
- Wu, Y., S. Wu, and P. Zhai, 2007: The impact of tropical cyclones on Hainan Island's extreme and total precipitation. *Int. J. Climatol.*, **27**, 1059–1064, <https://doi.org/10.1002/joc.1464>.
- Xu, Y., X. Gao, and F. Giorgi, 2010: Upgrades to the reliability ensemble averaging method for producing probabilistic climate-change projections. *Climate Res.*, **41**, 61–81, <https://doi.org/10.3354/cr00835>.
- Yang, J. H., Z. H. Jiang, P. X. Wang, and Y. S. Chen, 2008: Temporal and spatial characteristic of extreme precipitation event in China. *Climate Environ. Res.*, **13**, 75–83, <https://doi.org/10.4236/gep.2020.86004>.
- Yang, T., X. Wang, C. Zhao, X. Chen, Z. Yu, Q. Shao, and W. Wang, 2011: Changes of climate extremes in a typical arid zone: Observations and multimodel ensemble projections. *J. Geophys. Res.*, **116**, D19106, <https://doi.org/10.1029/2010JD015192>.
- Yatagai, A., P. Alpert, and P. Xie, 2008: Development of a daily gridded precipitation data set for the Middle East. *Adv. Geosci.*, **12**, 165–170, <https://doi.org/10.5194/adgeo-12-165-2008>.
- , K. Kamiguchi, O. Arakawa, A. Hamada, N. Yasutomi, and A. Kitoh, 2012: APHRODITE: Constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges. *Bull. Amer. Meteor. Soc.*, **93**, 1401–1415, <https://doi.org/10.1175/BAMS-D-11-00122.1>.
- Zhai, P., X. Zhang, H. Wan, and X. Pan, 2005: Trends in total precipitation and frequency of daily precipitation extremes over China. *J. Climate*, **18**, 1096–1108, <https://doi.org/10.1175/JCLI-3318.1>.
- Zhang, H., Fraedrich, K., Blender, R., and Zhu, X., 2013: Precipitation extremes in CMIP5 simulations on different time scales. *J. Hydrometeorol.*, **14**, 923–928, <https://doi.org/10.1175/JHM-D-12-0181.1>.
- Zhang, K., S. Pan, L. Cao, Y. Wang, Y. Zhao, and W. Zhang, 2014: Spatial distribution and temporal trends in precipitation extremes over the Hengduan Mountains region, China, from 1961 to 2012. *Quat. Int.*, **349**, 346–356, <https://doi.org/10.1016/j.quaint.2014.04.050>.
- Zhang, W., and T. Zhou, 2019: Significant increases in extreme precipitation and the associations with global warming over the global land monsoon regions. *J. Climate*, **32**, 8465–8488, <https://doi.org/10.1175/JCLI-D-18-0662.1>.
- Zhang, X., and Coauthors, 2011: Indices for monitoring changes in extremes based on daily temperature and precipitation data. *Wiley Interdiscip. Rev.: Climate Change*, **2**, 851–870, <https://doi.org/10.1002/wcc.147>.
- Zhou, B., Q. H. Wen, Y. Xu, L. Song, and X. Zhang, 2014: Projected changes in temperature and precipitation extremes in China by the CMIP5 multimodel ensembles. *J. Climate*, **27**, 6591–6611, <https://doi.org/10.1175/JCLI-D-13-00761.1>.