Projected Changes in Temperature and Precipitation Extremes in China by the CMIP5 Multimodel Ensembles

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ABSTRACT

This paper presents projected changes in temperature and precipitation extremes in China by the end of the twenty-first century based on the Coupled Model Intercomparison Project phase 5 (CMIP5) simulations. The temporal changes and their spatial patterns in the Expert Team on Climate Change Detection and Indices (ETCCDI) indices under the RCP4.5 and RCP8.5 emission scenarios are analyzed. Compared to the reference period 1986–2005, substantial changes are projected in temperature and precipitation extremes under both emission scenarios. These changes include a decrease in cold extremes, an increase in warm extremes, and an intensification of precipitation extremes. The intermodel spread in the projection increases with time, with wider spread under RCP8.5 than RCP4.5 for most indices, especially at the subregional scale. The difference in the projected changes under the two RCPs begins to emerge in the 2040s. Analyses based on the mixed-effects analysis of variance (ANOVA) model indicate that by the end of the twenty-first century, at the national scale, the dominant contributor to the projection uncertainty of most temperature-based indices, and some precipitation extremes [including maximum 1-day precipitation (RX1day) and maximum 5-day precipitation (RX5day), and total extremely wet day total amount (R95p)], is the difference in emission scenarios. By the end of the twenty-first century, model uncertainty is the dominant factor at the regional scale and for the other indices. Natural variability can also play very important role.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) in its Fifth Assessment Report (AR5) states that “warming of the climate system is unequivocal” and that “continued emissions of greenhouse gases will cause further warming and changes in all components of the climate system” (Stocker et al. 2013). The warming has exerted profound impacts over the globe on human society, ecosystems, and the environment across the globe, mainly through changes in climate extremes (Field et al. 2012). To better adapt to the changing climate, the public and policy makers now frequently demand information concerning future changes in climate extremes. The World Meteorological Organization (WMO) has initiated the Global Framework for Climate Services (GFCS) for managing climate risks (WMO 2009).

China is particularly vulnerable to climate extremes such as droughts, floods, cold temperatures, and heat waves. Disasters caused by meteorological and climatic
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events are estimated to have caused more than 200 billion Yuan per year in economic loss since 1990, accounting for 2.37% of China’s gross domestic product (Wang and Zheng 2012). Thus, changes in climate extremes anticipated from global warming are of particular concern for Chinese policy makers. Scientifically sound projections of future changes in climate extremes are crucial for developing adaptation strategies to reduce climate risks and for a successful implementation of the GFCS in China.

Several studies have investigated future changes in climate extremes anticipated for East Asia and China under different scenarios of greenhouse gas emissions (e.g., Ma et al. 2012; Chen et al. 2002, 2010; Jiang et al. 2004; Ding et al. 2007; Xu et al. 2009b; Sun et al. 2007; Chen et al. 2012; Jiang et al. 2012; Wang et al. 2012; Wu et al. 2012; Xu et al. 2013). The most recent of these results are based mainly on the global climate model (GCM) simulations available from the Coupled Model Intercomparison Project phase 3 (CMIP3). The results show increases in daily maximum and minimum temperatures with stronger warming at higher latitudes (Jiang et al. 2004). Xu et al. (2009b) also showed that CMIP3 models projected longer heat waves, accompanied with more frequent warm nights in the Yangtze River valley of China in the twenty-first century. More frequent and intense precipitation is projected for the middle and lower reaches of the Yangtze River valley, the southeast coastal region, the western part of northwest China, and the Tibetan Plateau (Jiang et al. 2012). Sun et al. (2010) showed that the frequency of intense snowfall events will decrease over southern China in the twenty-first century. In northern China, snowfall events are projected to increase initially and then subsequently decrease over the mid and late twenty-first century (Sun et al. 2010).

To facilitate research on climate extremes, the Joint WMO Commission for Climatology (CCL)–Climate Variability and Predictability (CLIVAR)–Joint Commission for Oceanography and Marine Meteorology (JCOMM) Expert Team on Climate Change Detection and Indices (ETCCDI) defined a set of climate change indices focusing on extremes that can be described from daily temperature and precipitation across different parts of the world (Frich et al. 2002; Klein Tank et al. 2009; Zhang et al. 2011). These indices have been widely used in detection, attribution, and projection of changes in climate extremes (e.g., Alexander et al. 2006; Min et al. 2011; Orlowsky and Seneviratne 2012; Donat et al. 2013; Sillmann et al. 2013a,b; Wen et al. 2013; Xu et al. 2013). Sillmann et al. (2013a) compared ETCCDI indices computed from observations and model simulations by the Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al. 2012) and found that CMIP5 models are generally able to reproduce the historical trend patterns of these climate extreme indices. Compared with CMIP3, CMIP5 features substantial model improvements (Taylor et al. 2012) and adopts a new set of emission scenarios called representative concentration pathways (RCPs) (Moss et al. 2010; van Vuuren et al. 2011) for future climate simulations. Sillmann et al. (2013b) compared CMIP5 with CMIP3 and found that CMIP5 models are generally able to reproduce the historical trend patterns of these climate extreme indices. Compared with CMIP3, CMIP5 features substantial model improvements (Taylor et al. 2012) and adopts a new set of emission scenarios called representative concentration pathways (RCPs) (Moss et al. 2010; van Vuuren et al. 2011) for future climate simulations. Sillmann et al. (2013b) studied the projected future changes in climate extremes at the global, continental, and subcontinental scales. More detailed regional analysis is of particular value for regional policy making. However, detailed analysis of CMIP5 projected future changes in climate extremes for China is still lacking. This study aims at addressing this gap. We follow the global study of Sillmann et al. (2013b) and extend the methods to China and its subregions. Additionally, we attempt to provide some
understanding of the relative importance of various factors that contribute to the uncertainty in the future projections.

The remainder of this paper is organized as follows. The data and methods are described in section 2. The projected spatiotemporal changes in temperature and precipitation indices are presented in sections 3 and 4, respectively. Uncertainties in the projection are quantified using a mixed-effects analysis of variance (ANOVA) model and discussed in section 5, followed by conclusions and discussion in section 6.

2. Data and methods

a. CMIP5 simulations and climate extremes indices

The CMIP5 models produced simulations under some or all of the four RCPs: RCP2.6, RCP4.5, RCP6.0, and RCP8.5 (Taylor et al. 2012). We focus on RCP4.5 and RCP8.5, which are respectively a medium-low and high radiative forcing scenario. The two scenarios have the radiative forcing peaking at 4.5 and 8.5 W m\(^{-2}\) by 2100 respectively. More details on the models and the forcing can be found at the CMIP5 website (http://cmip-pcmdi.llnl.gov/cmip5/availability.html, accessed March 2014).

The ETCCDI indices from CMIP5 simulations were analyzed by Sillmann et al. (2013a,b) and are available online (at http://www.cccma.ec.gc.ca/data/climdex/index.shtml, accessed July 2013) for the twentieth and twenty-first centuries. Index data computed from 24 models (see Table 1, which includes expansions for all model names) were available at the time of this analysis. These indices can be generally classified into four categories, namely absolute indices, threshold indices, duration indices, and percentile indices (Sillmann et al. 2013a). The absolute indices describe, for instance, the hottest or coldest day of a year, or the annual maximum 1-day or 5-day precipitation amounts. The threshold indices count the number of days when a fixed temperature or precipitation is exceeded. The duration indices describe the length of wet or dry spells, or warm and cold spells. The percentile indices depict the exceedance rates below or above a threshold, which is defined as the 10th or 90th percentiles from the 1961–90 base period. Detailed definitions of these indices are summarized in Table 2, which can also be found in Klein Tank et al. (2009), Sillmann et al. (2013a), and Zhang et al. (2011), or at the ETCCDI website (etccdi.pacificclimate.org/list_27_indices.shtml, accessed March 2014).

b. Data processing and analysis method

The CMIP5 models have different spatial resolutions. Data from the different GCMs are converted to a common 1° × 1° grid using a bilinear interpolation scheme before further processing. The projected change for a region is taken to be the median from the multimodel ensemble. Since the number of ensemble runs from different models differs, we use the model ensemble mean to represent the projections from a particular model if there is more than one run available. The analysis of projection uncertainty is based on individual runs. For this reason, we require at least two runs for a model to be included in this analysis in order to estimate contribution of internal variability to uncertainty. This leaves only 8 GCMs from the 24 models for the uncertainty analysis.

We examine the spatial patterns of change by dividing China into eight regions (Fig. 1) used in China’s National Assessment Report on Climate Change (National Report Committee 2007). These regions were determined according to administrative boundaries and societal and geographical conditions.

The projected changes in the annual and seasonal indices are summarized using box-and-whisker plots. These plots consist of the multimodel median, the interquartile model spread (the range between the 25th and 75th quartiles, box), and the full intermodel range (whiskers). The multimodel median is taken to be the projected change, while interquartile model spread and the intermodel range visualize uncertainties in the projection, and can also indicate model agreement or disagreement on the direction of the projected change.

Uncertainty in the projection has three distinct sources: uncertainty due to different emission scenarios, uncertainty due to difference (both in structure and parameters) in GCMs, and uncertainty due to internal variability of the climate system. Hawkins and Sutton (2009, 2011) attempted to separate and quantify these sources. To understand the relative importance of the different sources to the uncertainty in the future projection, we use a mixed-effects ANOVA approach, which is similar to the one proposed in Li et al. (2012), to partition the variance of the projection to each source. We consider a two-factor model, with the two factors representing uncertainty caused by differences in scenarios and GCMs, respectively. More specifically, let

\[ Y_{ijk} = \mu + \alpha_i + \beta_j + \epsilon_{ijk}, \]

where \( Y_{ijk} \) denotes a certain extreme index projected by the \( k \)th run of the \( j \)th model under the \( i \)th forcing scenario, \( \mu \) represents the grand mean of projection ensembles, \( \alpha_i \) represents effect on the projection associated with the \( i \)th \((i = 1, 2) \) forcing scenario, \( \beta_j \) represents the effect on the projection associated with the \( j \)th \((j = 1 \ldots 8) \) GCM simulation, and the noise term \( \epsilon_{ijk} \) represents projection uncertainty caused by the difference among different runs from a GCM (i.e.,
As in Li et al. (2012), we assume the effect of emission scenarios $\alpha_i$ to be fixed because it is not possible to know the probability distribution of possible future emission, and the inter-GCM effect $\beta_j$ to be random. This setting allows us to estimate the effect of GCM differences, although we realize that the eight GCMs used here or even the larger set of CMIP5 models may not represent the plausible GCM population (Knutti et al. 2013). While the results by no means provide a precise partitioning of the contribution to uncertainty from different factors, they should nevertheless give us a general picture of the effects of various factors on future projections. The design is not orthogonal because different models may have a different number of runs available, and thus an explicit formula of its statistical inference is not available. Since our major objective is to quantify the relative contribution of each factor in the model, we employ the expected mean squares (EMS) for each factor as a rough indicator of its relative contribution to the total projection uncertainty. To account for the unbalanced nature of the problem, we use the type II weighted sum of squares (Langsrud 2003) instead of the ordinary type I sum of squares in the analysis to calculate the mean squares.

c. Performance of CMIP5 models at regional scale

Sillmann et al. (2013a) evaluated the performance of the CMIP5 models in simulating those extremes at the global scale based on the root-mean-square errors (RMSEs). Their results showed that the CMIP5 models are generally able to simulate global climate extremes. Following their approach, we assess model performance at regional for China. For this purpose, we compare climates of the indices from the models and from the observations. The observation data are based on gridded daily precipitation and temperature at $0.5^\circ$ resolution constructed from 2416 observation stations over China by the National Climate Center, China Meteorological Administration (Xu et al. 2009a; Wu and Gao 2013). Indices were computed from this gridded datasets and then averaged to $1^\circ$ resolution. The period for computing climatology is 1986–2005. The RMSE is calculated as

$$RMSE = \sqrt{\langle (X - Y)^2 \rangle}, \hspace{1cm} (2)$$
where \( X \) represents the model climatology of an index, \( Y \) is the corresponding climatology from the observational data, and the angular bracket denotes spatial averaging over China on the 1° × 1° grid. The collection of RMSEs for all individual models is used to derive the relative model error for each model, RMSE', defined as

\[
\text{RMSE}' = \frac{\text{RMSE} - \text{RMSE}_{\text{median}}}{\text{RMSE}_{\text{median}}},
\]

where RMSE_{median} is the median of RMSEs for all individual models.

RMSE' provides a metric to measure a model’s performance relative to the other models, with respect to the observation. Negative RMSE' indicates that the corresponding model performs better than the majority (50%) of models. Figure 2, similar to Fig. 10 of Sillmann et al. (2013a), summarizes the RMSE' values for all models (rows) and all indices (columns) relative to the observation. This figure depicts the overall performance of individual models, with colder (warmer) colors indicating models that perform better (worse) than others on average. Despite the fact that the simulation ability of individual models is somehow different for different indices, most models generally perform reasonably well for most temperature indices, particularly CCSM4, CESM1-BGC, CMCC-CM, CSIRO-Mk-3.6.0, IPSL-CM5A-MR, MPI-ESM-LR, and MPI-ESM-MR. Models that perform relatively well for all precipitation indices include CSIRO-Mk-3.6.0, IPSL-CM5A-LR, IPSL-CM5A_ML, and MRI_CGCM3 (see Table 1 for information on models). Moreover, the ensemble median performs well.

Fig. 1. Domains of eight subregions in China—NEC: northeast China; NC: north China; EC: east China; CC: central China; SC: south China; SWC1: southwest China, region 1; SWC2: southwest China, region 2; and NWC: northwest China. CN refers to China as a whole.

Fig. 2. The “portrait” diagram of relative RMSEs for the 1986–2005 climatologies of climate extreme indices simulated by the CMIP5 models with respect to the observation. The RMSEs are spatially averaged over China and the magnitude of the relative RMSEs is shown as colors.
and outperforms individual models because some of the systematic errors in individual models are canceled out in the multimodel median. It shows better skill from the ensemble median, providing justification of the use of ensemble median for the future projection.

3. Changes in temperature indices
   a. Absolute and threshold indices
      1) TEMPORAL EVOLUTION

      Figures 3a and 3b illustrate the temporal evolution of annual minimum daily minimum temperature (TNn) and annual maximum daily maximum temperature (TXx) under RCP4.5 and RCP8.5. Warming is observed in both TNn and TXx, with larger increases under RCP8.5 than that under RCP4.5, and a slightly larger increase in TNn than in TXx under each emission scenario. Relative to the reference period 1986–2005, the projected ensemble median increases by the end of the twenty-first century in TNn and TXx are 2.9° and 2.7° C under RCP4.5, and 5.8° and 5.5° C under RCP8.5, respectively.

      Consistent changes are found in the temperature threshold indices; specifically, these indices are frost days (FD) and tropical nights (TR), which are derived from daily minimum temperature (Figs. 3c,d), and ice days (ID) and summer days (SU), which are derived from daily maximum temperature (Figs. 3e,f). Under both emission scenarios, decreases in FD and ID are projected whereas increases in TR and SU are
projected. By the end of the twenty-first century and under RCP4.5, the projected ensemble median of FD and ID will decrease by 21 days and 17 days while that of TR and SU will increase by 18 days and 25 days, respectively. Projected median changes under RCP8.5 are larger than those under RCP4.5 with a decrease of 43 days for FD and 32 days for ID, and an increase of 38 days for TR and 44 days for SU, respectively.

2) SPATIAL PATTERNS

Figure 4 displays spatial distributions of the projected changes for annual TNn and TXx by the end of the twenty-first century. TNn and TXx are projected to increase in all subregions with stronger warming under RCP8.5. Projections under RCP8.5 are also associated with larger interquartile model spread (Fig. 5) due to different climate sensitivity in the models and/or positive regional land–atmosphere feedbacks. There are some spatial differences in the projected changes in TNn and TXx. For instance, under RCP8.5, the largest changes in TNn, exceeding 7°C, occur at higher latitudes and higher elevations including in northeast China, the northern part of northwest China, and the southern flank of southwest China (Fig. 4b), reflecting the influence of diminished snow cover. However, the most intense warming in TXx is mainly projected in eastern China, with a magnitude around 6°C (Fig. 4d). The projected increases in TXx are also spatially more uniform than those for TNn. From a seasonal perspective, the projected median increase of TNn for RCP8.5 is generally greatest in DJF but is most spatially uniform across China in JJA (as is illustrated in Fig. 5). The projected increases of TXx for RCP8.5 in DJF are only slightly larger than those in JJA and are smaller than the projected TNn increase in DJF. A similar pattern of seasonal and regional changes in TNn and TXx is seen for RCP4.5, albeit less pronounced when compared to RCP8.5.

FD and ID are both projected to decrease everywhere by the end of the twenty-first century under both RCP4.5 and RCP8.5, with strong model agreement (Figs. 6a,c), particularly in western China. The projections indicate that the SWC1 region will experience the
Fig. 5. Projected changes in annual (ANN), summer (JJA), and winter (DJF) TNn and TXx over the period 2081–2100 relative to the reference period 1986–2005 under RCP4.5 (blue) and RCP8.5 (red). Boxes indicate the interquartile model spread (25th and 75th quantiles) with the horizontal line indicating the ensemble median and the whiskers showing the extreme range of the CMIP5 ensemble.
greatest decrease of FD and ID, with FD decreasing by 55 days and ID by 51 days under RCP8.5. Decreases for the NWC region under RCP8.5 are also substantial with 49 days decrease in FD and 43 days decrease in ID. The smallest projected change of FD occurs in SC (14 days for RCP8.5) where the fewest frost days were observed during the reference period 1986–2005.

FIG. 6. As in Fig. 5, but for changes in annual FD, TR, ID, SU, and GSL.
TR and SU are projected to increase by more than 16 and 21 days under RCP4.5 and 38 and 42 days under RCP8.5 in all subregions respectively except SWC1, which includes the Tibetan Plateau (Figs. 6b,d). The largest projected change occurs in SWC2, with an increase of TR and SU by 41 and 50 days under RCP4.5 and by 89 and 93 days under RCP8.5, respectively. This means that if the future emissions follow the path of RCP8.5, Yunnan province located in the SWC2 could experience nighttime temperatures above 20°C and daytime temperatures above 25°C during the entire summer season. In addition, projected increases of TR (62 days) and SU (57 days) for SC under RCP8.5 are larger, even though projected changes of TNn and TXx in SC are actually less than those for other subregions. This may be due to the high local temperature climatology in SC. Small increase in temperature extremes in SC can cause significant impacts on SU and TR in that region.

The growing season length (GSL) is projected to be much longer in the future. Both RCP4.5 and RCP8.5 will result in an increase in GSL across China (Fig. 6c). The largest increase under RCP8.5 occurs in SWC1 (67 days) followed by CC (50 days). The smallest increase of GSL occurs in SC (10 days), because this region is comparatively warm and the GSL itself is already very large during the reference period.

### b. Duration and percentile indices

The projected changes in temperature duration indices are consistent with what would be expected from warming and changes in absolute and threshold indices. That is, cold spell duration index (CSDI) is projected to decrease and warm spell duration index (WSDI) to increase (Fig. 7). The projected magnitude of increase in WSDI is much larger under RCP8.5 at 136 days than RCP4.5 at 49 days. The projected amplitude of decrease in CSDI is more comparable under RCP4.5 and RCP8.5, with the median projected decrease being 3 days and 4 days, respectively. The asymmetry in the projected change of CSDI is due to the fact that the projected CSDI under the two RCPs would be mostly zero by the end of the twenty-first century. Under RCP8.5, the largest increases in WSDI, which exceed 150 days, are mainly projected in western China, while projected

![Image](https://example.com/image.png)
decreases in CSDI that exceed 4 days are concentrated in Xinjiang, Tibet, and southern China where the climatological CSDI is larger in the reference period 1986–2005.

Projected changes of cold nights (TN10p) and cold days (TX10p), warm nights (TN90p), and warm days (TX90p) are shown in Fig. 8. Consistent with warming and projections of the absolute and threshold temperature indices, a decrease in TN10p and TX10p and an increase in TN90p and TX90p are projected. Changes in nighttime temperature indices (TN10p and TN90p) are projected to be stronger than those in daytime temperature indices (TX10p and TX90p). TN10p (TX10p) decreases from about 10% in 1961–90 to 1.7% (2.6%) by the end of this century under RCP4.5 and to 0.4% (0.9%) by the end of this century under RCP8.5. These changes indicate that cold temperatures that occurred once every 10 days in the late twentieth century are projected to occur less than once in 200 days for TN10p and 100 days for TX10p by the end of the twenty-first century under RCP8.5. Projections from different models converge as the projection approaches the zero exceedance rate (i.e., all models project fewer and fewer cold nights and days toward the end of the twenty-first century). For TN90p and TX90p, the median projected increases are from about 10% in the base period to 41% and 36% under RCP4.5, and 67% and 59% under RCP8.5 by the end of the twenty-first century, respectively. That is, hot temperatures that occurred once every 10 days in the late twentieth century would become everyday weather by the end of the twenty-first century under RCP8.5.

Figure 9 shows the spatial distribution of projected changes in TN10p, TN90p, TX10p, and TX90p, which are rather uniform across all subregions in China. Under RCP8.5, TN10p will be in the range from 0.1% (NEC) to 0.5% (SC), TN90p from 61% (NEC) to 75% (SWC2), TX10p from 0.4% (NEC) to 1.6% (SWC2), and TX90p from 51% (NEC) to 68% (SWC1).

### 4. Changes in precipitation indices

In the following, changes in precipitation indices except the number of wet days (R1mm) and consecutive days (CDD) are expressed as percentage change relative to the reference period 1986–2005.

#### a. Temporal evolution

Figure 10 shows the temporal evolution of projected changes in precipitation indices. Overall, precipitation amount, including wet day annual total amount (PRCPTOT), averaged wet day daily amount (SDII), and total extremely wet day total amount (R95p) are all projected to increase in the twenty-first century. Under RCP8.5 (RCP4.5), PRCPTOT and SDII are...
projected to increase by 14% (8%) and 15% (8%), respectively. The percentage changes are very similar for PRCPTOT and SDII, indicating that increases in total precipitation are projected to be mainly due to increases in precipitation intensity across the precipitation distribution rather than changes in precipitation frequency.

The projected percentage increases in maximum 1-day precipitation (RX1day) and maximum 5-day precipitation (RX5day), indicators of the extreme aspect of precipitation, are larger than those for PRCPTOT and SDII. Under RCP8.5 (RCP4.5), the increase is projected to be 21% (11%) for RX5day and 26% (13%) for RX1day by 2100, suggesting larger increases in more extreme daily precipitation. The number of wet days (i.e., R1mm) is projected to change little, and the number of consecutive dry days is projected to decrease during the second half of the twenty-first century.

Time series of precipitation indices under RCP8.5 start to deviate from those under RCP4.5 in the early 2040s, indicating that the difference in the impacts of emission scenarios on precipitation indices is very small before that time. This finding is consistent with changes in temperature indices.

b. Spatial patterns

Figure 11 presents the spatial distribution of projected median changes in PRCPTOT and R95p under RCP4.5 and RCP8.5. By the end of the twenty-first century, PRCPTOT is projected to increase uniformly across the country (Figs. 11a,b). The projected PRCPTOT changes have large spread among models, but the majority
models agree on the sign of change in all subregions (Fig. 14a). The projected percent increase is larger in northern China than in southern China. The largest increase is projected for western China, due to the drier climate toward the north and northwest. The spatial distribution of R95p changes is similar to that of PRCPTOT, especially in western and northern China (Figs. 11c,d). The percentage increase in R95p is larger than that of PRCPTOT, implying a disproportionally larger contribution to the total precipitation change from an increase in precipitation falling on very wet days. Additionally, models have better agreement in the sign of projected changes in R95p than in PRCPTOT (Fig. 14).
Figure 12 summarizes changes in annual and seasonal RX1day and RX5day in the eight subregions. The projected changes for these two indices are similar in space with slightly wider spread for RX1day in most cases. For annual indices, the median RX5day projection shows increases from 19% (CC and SC) to 28% (NEC) under RCP8.5 and RX1day increases from 22% (SC) to 32% (NC and SWC2). In northern China (i.e., NEC, NC, and NWC), the median projected increases of RX1day and RX5day are more pronounced in December–February (DJF) than in June–August (JJA). For example, the strongest increase of RX1day (RX5day) in DJF is 53% (51%) compared with 27% (19%) increase in JJA in NC. The opposite seasonal pattern is noticed in southern China such as in SC, SWC1, and SWC2, where the projected increases in JJA are larger than those in DJF. This may not necessarily reflect the absolute change in the extreme values because of seasonal variability in precipitation climatology. There do not appear to be seasonal differences in the projected changes in extreme precipitation in other subregions (e.g., EC and CC).

Figure 13 displays projected changes in the number of wet days (R1mm) and consecutive dry days (CDD). The number of wet days increases north of ~30°N and decreases in the south. The maximum number of consecutive dry days is projected to decrease in the north including NC, NWC, and NEC (Fig. 14e) but increase in other regions.

5. Relative importance of different factors contributing to the uncertainty in the projections

The main results of uncertainty assessment are summarized in Fig. 15. For temperature-based indices, forcing uncertainty is a dominant factor for China as a whole; however, internal variability and differences between models also play important roles at the regional scale. For example, for the relatively small region SWC1, the effect of model differences is as strong as that of the difference in scenarios for indices such as TR, ID, SU, and GSL. Another example is that internal variability has the largest contribution to the uncertainty in projected changes of ID in CC. For the precipitation-based indices,
Fig. 12. As in Fig. 5, but for (left) RX5day and (right) RX1day.
the major sources of uncertainties are diverse for different indices at both national and regional scales. Differences in both models and forcing scenarios have a large influence on projected changes in PRCPOT for the country, but the main contributors vary among sub-regions. For example, it appears that the dominant contributors are forcing scenarios in NEC and SWC1, internal variability in EC, and differences in GCMs in CC and SWC2.

The differences between forcing scenarios appear to be the most important contributor to projection uncertainty in R95P, SDII, RX1day, and RX5day, similar to those of temperature indices. This is consistent with other studies that show that precipitation rate and extreme precipitation in particular are strongly influenced by the availability of atmospheric moisture (Kharin et al. 2013; Zhang et al. 2013). For example, over Northern Hemispheric land, projected changes in RX1day and RX5day scale well with projected temperature increases (Zhang et al. 2013), and this is also the case for projected changes in 20-yr return values of annual maximum daily precipitation (Kharin et al. 2013).

6. Summary and concluding remarks

In this study, we examined projected changes in ETCCDI extreme indices that are based on daily temperature and precipitation data in China as simulated by the CMIP5 multimodel ensemble under RCP4.5 and RCP8.5 forcing scenarios. Results generally show decreases in cold extremes, increases in warm extremes, and an intensification of precipitation extremes in the future warmer world. They are in agreement with previous CMIP3-based studies (e.g., Chen et al. 2012; Jiang et al. 2012; Wang et al. 2012; Xu et al. 2013). The larger changes in the climate extreme indices corresponding to stronger radiative forcing changes are also in agreement with previous findings. However, compared with earlier studies, this study is more comprehensive, providing more detailed information on the future changes in climate extremes for China and its subregions based on multiple aspects, new scenarios, and the new generation of climate models. We also quantified the relative contribution of various factors to the uncertainty in the projections. The main findings are summarized below:
FIG. 14. As in Fig. 5, but for annual PRCPTOT, SDII, R95p, R1mm, and CDD, respectively.
1) TNn and TXx are projected to have larger increase and interquartile model spread under RCP8.5 than RCP4.5. The spatial pattern of changes in TNn and TXx differ slightly with a larger increase in TNn than in TXx in general. The greatest projected TNn change occurs in the higher latitudes and higher elevation regions of northeast China, the northern part of northwest China, and the southern flank of southwest China. The largest warming in TXx is projected for eastern China and the northern part of northwest China. Projected changes in other temperature extremes indices are consistent with those of TNn and TXx. The number of frost days and ice days are expected to decrease with the largest decrease projected in SWC1 and NWC. More tropical nights and summer days are expected toward the end of the twenty-first century, especially in SWC2 and SC. The growing season length (GSL) is also projected to become longer in China, particularly in SWC1. Cold spell duration index (CSDI) is projected to decrease and warm spell duration index (WSDI) to increase. The strongest increases of WSDI are mainly projected for western China, and the decreases of CSDI are mainly projected in Xinjiang, Tibet, and southern China. Decreases in TN10p and TX10p and increases in TN90p and TX90p are also predominant features. Moreover, changes in warm and cold nights are more remarkable than warm and cold days. For example, under the RCP8.5 scenario, cold nights or days that are defined based on 1961–1900 climate would be very rare by the end of the twenty-first century.

2) Annual total precipitation amount (PROPTOT), average daily precipitation rate (SDII), the proportion of heavy precipitation in total annual precipitation (R95p), and extreme precipitation including both RX1day and RX5day are all projected to increase. Percent changes in extreme precipitation RX1day and RX5day are larger than projected for other aspects of precipitation examined, indicating larger disproportionately increases in extremes as compared to other aspects of precipitation. The percent increase in precipitation extremes is more pronounced in DJF than in JJA in northern China (e.g., NEC, NC, and NWC) whereas the seasonal difference is opposite in southern China (e.g., SC, SWC1, and SWC2). This difference may be related to the difference in the seasonal amount of precipitation rather than an indication of larger increase in the magnitude of extreme precipitation. It may also reflect possible changes in circulations. The number of wet days appears to increase in the north (north of 30°N) and decrease in the south (south of 30°N). However, the changes are small in general and model agreement on the sign of projected change is poor.
3) Uncertainties in the projection are larger under RCP8.5 than under RCP4.5 at a given future time (except TN10p and TX10p) and increase over time under both forcing scenarios. In addition, differences in projected change under the two forcing scenarios start to emerge only in the 2040s. Two factors including the committed warming from emissions already made and the time that it takes for the RCPs to diverge are at play. Three factors—natural climate variability, difference in forcing scenarios, and uncertainty in climate models—contribute to the uncertainty in the projections. Their relative contributions differ depending on indices, spatial scale, and time period. At the national scale and by the end of the twenty-first century, differences in the forcing scenarios play the dominant role. This is also the case for extreme precipitation indices, notably RX1day, RX5day, and R95p, which are more temperature sensitive than other indices such as total precipitation. At the regional scale, differences among climate models become another important contributor for most indices even at the end of the twenty-first century. However, it is unclear if the elevated importance in model uncertainty compared with forcing uncertainty is due to larger variability at smaller spatial scales or is an indication of a lack of ability in models in simulating climate at regional scales.

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