Projected changes in extreme warm and cold temperatures in China from 1.5 to 5°C global warming

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Abstract
Linking regional extreme temperature changes to global warming levels is important for understanding the impacts of global emission targets on regional climate. Here, we investigate how the temperature extremes in China change with different global warming levels using large ensemble runs from Canadian Earth System Model version 2. With the global mean near-surface temperature increasing from 1.5 to 5°C above the preindustrial level, the absolute intensity of the warmest and coldest temperatures in China will change linearly, while the percentile-based frequency of warm and cold temperatures will change nonlinearly. All the changes in the intensity and the frequency show clear regional differences, with the most obvious changes observed in northeastern China. The probability distribution functions (PDFs) for the intensity indices show clear shifts but with little change in shape, while the PDFs for the frequency indices show changes in both position and shape. Quantified analyses of risk ratio show that the risk changes in the frequency of temperature extremes will be larger than those for the intensity indices. The changes in the nighttime extremes are faster than those in the daytime extremes. The rarer the event is, the larger the change in the risk ratio. At the 2°C warming level, the cold days and nights with return periods of 5, 10, and 50 years in the current climate will become almost disappeared. At the 3°C level and beyond, the once-in-5-year, 10-year and 50-year warm events in the current climate will occur every year.

1 INTRODUCTION

With continuous global warming (World Meteorological Organization, 2019), an increasing number of warm extremes and a decreasing number of cold extremes have been observed in many areas across the world over the past several decades. Generally, the changes in daily minimum temperatures are more pronounced than those in daily maximum temperatures (Alexander et al., 2006; Donat et al., 2013; Wang et al., 2017a). The reasons behind these changes have also been investigated. Climate model-based results have shown that most of these changes can be attributed to anthropogenic influences at global and regional scales (Bindoff et al., 2013; Zhang et al., 2013; Dong et al., 2016; Kim et al., 2016; Sun et al., 2016; Wang et al., 2017b). These findings

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indicate that with increased greenhouse gases and human activities, temperature extremes will change obviously in the future, which has been verified by many studies on future projections (Intergovernmental Panel on Climate Change, 2012; Sillmann et al., 2013; Wang et al., 2019).

In China, increasing warm extremes and decreasing cold extremes since the mid-20th century have affected various sectors in society (Qi and Wang, 2012; Wang et al., 2012; Sun et al., 2014, 2016; Luo and Lau, 2016). Many studies have projected future changes in mean and extreme temperatures based on different generations of global climate models (Jiang et al., 2004; Li et al., 2013; Zhou et al., 2014), regional climate models (Gao et al., 2013) and various statistical downscaling methods (Wen et al., 2016). These studies have consistently shown that warm extremes will increase and cold extremes will decrease across the country at the end of the 21st century, although regional differences can be observed in mid-latitudes or high-terrain regions (Li et al., 2011; Gu et al., 2012; Jiang et al., 2012; Zhou et al., 2016). Some authors have also applied the generalized extreme value method and found that the return periods for both warm and cold extremes will change (Wen et al., 2016). For other types of extremes, such as heat waves, a few authors have used an observation-constrained method and found that serious heat wave events will rapidly increase in eastern China (Sun et al., 2018).

In response to the international climate change negotiation on global warming targets, studies on the potential influence of 1.5 and 2°C global mean near-surface temperature (GMST) increase above the preindustrial level have recently become a hot topic. Researchers have highlighted the importance of regional differentiation to incremental increases in the global mean temperature (Schleussner et al., 2016). In China, a few researchers have used CMIP5 data to investigate changes in extreme temperatures and found that extreme temperatures will change at different global warming levels. The extreme temperature frequency will increase for warm extremes and decrease for cold extremes from 2 to 4°C global warming, with a fast increase in the coldest night (TNn) and a slow increase in the warmest night (TX) (Chen et al., 2018). Sui et al. (2018) focused on the changes in temperature extremes under a 2°C global warming and showed that the warm extremes will become more frequent, more persistent and more intense, while the cold extremes will become less frequent than those during the baseline period in the late 1980s. Guo et al. (2017) reported the changes in heat wave characteristics for eight different global warming targets from 1.5 to 5°C using CMIP5 models. These authors used a combination of a relative threshold of the 95th percentile and an absolute threshold of 30°C to define the heat waves and found that both the frequency and the intensity of heat waves will increase with warming. Sun et al. (2018) directly related the definition of heat waves to human health and investigated the changes in three metrics of heat waves with daily maximum temperatures above 35°C. These authors concluded that global warming is associated with more severe heat waves, including more heat wave days, longer heat wave seasons and higher hottest day temperatures, and a expansion of the regions impacted by heat waves in China.

These previous studies have mainly investigated future changes in temperature extremes in China with time under different emission scenarios. The studies on different warming levels mainly focused on the changes in extreme temperatures at 1.5 and 2°C GMST above the preindustrial level. Rare studies investigate the relationship between the temperature extremes and GMST increase and the extreme temperature changes beyond 2°C warming, such as the temperature extreme changes from 2 to 5°C, which have important implications for the emission targets and adaptation to climate change in the future. Two studies (Guo et al., 2017; Sun et al., 2018) that examined the changes in heat waves from 1.5 to 5°C focused on only the characteristics of heat waves based on different definitions. Some basic features of extreme temperature changes, including the intensity and frequency of extreme warm and cold events, still need to be further studied. In this study, we use the large ensemble runs of Canadian Earth System Model version 2 (CanESM2) to investigate the changes in the intensity and frequency of extreme temperatures in China from 1.5 to 5°C global warming. We link these changes to the GMST increase so that their relationship can be established. We also investigate the changes in the distribution and occurrence risk of warm and cold extremes under different warming levels so that the comparison among different types of extremes with different levels of rarity can be quantified. The paper is organized as follows: Section 2 describes the observational and model data, along with the data processing and definition of global warming levels; Section 3 presents the main results, and the discussion and conclusions are given in Section 4.

2 | DATA AND METHODS

2.1 | Definitions of extreme temperature frequency and intensity

Eight extreme temperature indices developed by the Expert Team on Climate Change Detection and Indices (ETCCDI; Alexander et al., 2006) are used here to represent the absolute intensity and percentile-based frequency of extreme temperature (Table 1). The absolute
intensity indices include the maximum and minimum of the daily maximum and minimum temperatures (TXx, TXn, TNx, and TNn). The percentile-based indices are defined by the percentage of days with daily maximum or minimum temperatures greater than its 90th percentile (TX90p, TN90p) and daily maximum or minimum temperatures smaller than its 10th percentile (TX10p, TN10p). One should be cautious that the intensity and frequency indices are not completely from the same category of extreme events but instead represent different aspects of extreme temperature changes. For the sake of simplicity, the absolute intensity indices and percentile-based frequency indices are referred to as intensity and frequency indices hereafter. The calculation of all these indices is based on the RClimDex software package (Zhang et al., 2011, available at http://etccdi.pacificclimate.org/software.shtml).

### 2.2 Observational and model data

The observational daily gridded temperature data are derived from homogenized Chinese station data developed by the China National Meteorological Information Center (Cao et al., 2016), including daily maximum and minimum temperatures at 0.5° × 0.5° for 1961–2015 (http://data.cma.cn/). Only the grid boxes containing at least one observation station are used in this study. Each observation station has at least 20-year non-missing data during the 1961–1990 period. Station data for a particular month are treated as missing if more than seven daily values are missing in that month. Data for a year are treated as missing if any monthly value in that year is missing.

The daily data in the model are extracted from the large ensemble runs of CanESM2 (Arora et al., 2011, https://www.ec.gc.ca/ccmac-cccma/). The coupled model CanESM2 consists of atmospheric, ocean, terrestrial carbon and oceanic carbon models (Arora and Boer, 2010; von Salzen et al., 2013). The model employs T63 triangular truncation with physical processes calculated at 128 × 64 (~2.81°) horizontal grids. The large ensemble runs of CanESM2 consist of 50 simulations under historical forcing (including both anthropogenic and natural external forcings) for 1950–2005 and under the Representative Concentration Pathway (RCP) 8.5 scenario for 2006–2100 (Fyfe et al., 2017). In addition, five ensembles of CanESM2 simulated temperature under the CMIP5 framework are used to estimate the GMST for the preindustrial era of 1850–1900. For all the calculations, the observation and model data are converted to a 2.5° × 2.5° horizontal resolution, with all the model data masked by the observational data. The model grids are treated as missing if there are missing values in the observations.

### 2.3 Definition of global warming level, bias correction and risk ratio

Two baseline periods are used in this study. The first baseline period is the preindustrial period of 1850–1900. This period is used to estimate the global warming levels in the model. The 10-year averaged GMST anomaly is calculated relative to the average of 1850–1900 so the global warming levels from 1 to 5°C are defined. The 10-year periods corresponding to 1.5, 2, 2.5, 3, 3.5, 4, 4.5, and 5°C warming levels above the preindustrial period in the CanESM2 are 2007–2016 (1.45°C), 2021–2030 (1.98°C), 2032–2041 (2.48°C), 2042–2051 (2.96°C).

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**TABLE 1** Extreme temperature indices used in this study recommended by the ETCCDI (see http://etccdi.pacificclimate.org/list_27_indices.shtml)

| ID  | Indicator name | Indicator definition                                             | Category | Units |
|-----|----------------|-----------------------------------------------------------------|----------|-------|
| TXx | Warmest day    | Maximum value of daily maximum temperature                      | Intensity| °C    |
| TNx | Warmest night  | Maximum value of daily minimum temperature                      | Intensity| °C    |
| TXn | Coldest day    | Minimum value of daily maximum temperature                      | Intensity| °C    |
| TNn | Coldest night  | Minimum value of daily minimum temperature                      | Intensity| °C    |
| TX90p | Warm days | Percentage of time when daily maximum temperature >90th percentile | Frequency| %     |
| TN90p | Warm nights | Percentage of time when daily minimum temperature >90th percentile | Frequency| %     |
| TX10p | Cold days   | Percentage of time when daily maximum temperature <10th percentile | Frequency| %     |
| TN10p | Cold nights  | Percentage of time when daily minimum temperature <10th percentile | Frequency| %     |

Note: All indices are calculated annually.
replacing the model climatological values of daily temperature with the observed climatology to reduce mismatch between observed and model-simulated variation. The CanESM2 simulated seasonal cycle during 1977–2006 is replaced by the observed seasonal cycle during 1986–2015, as the simulated and observed 30-year periods have equivalent GMST increases relative to the preindustrial period (1850–1900). The model simulated seasonal cycle is then removed from the individual runs and the observed seasonal cycle is added to the model to obtain the bias adjusted model data. This adjustment can only adjust the model bias in the mean state but not in

Prior to all the analyses for future changes, bias correction is performed on CanESM2 simulations by replacing the model climatological values of daily temperature with the observed climatology to reduce mismatch between observed and model-simulated variation. The CanESM2 simulated seasonal cycle during 1977–2006 is replaced by the observed seasonal cycle during 1986–2015, as the simulated and observed 30-year periods have equivalent GMST increases relative to the preindustrial period (1850–1900). The model simulated seasonal cycle is then removed from the individual runs and the observed seasonal cycle is added to the model to obtain the bias adjusted model data. This adjustment can only adjust the model bias in the mean state but not in

FIGURE 1 Observed and Canadian Earth System Model version 2 (CanESM2) simulated temperature index anomalies in China (relative to the 1961–1990 mean) and their long-term trends in 1961–2015 for (a) TXx, (b) TNx, (c) TXn, (d) TNn, (e) TX90p, (f) TN90p, (g) TX10p, and (h) TN10p. In the three panels of each index, the first row shows the observed (black solid line) and simulated (red solid line for the adjusted data and blue solid line for the original data) time series of national averages of the multi-run mean in China. Shadings with small dots in pink and sky blue represent values from individual runs with and without bias adjustment, respectively. The second row (OBS) shows the observed linear trends of the eight index anomalies during 1961–2015. The third row (ADJ) presents the trends of the adjusted simulations after bias correction. Grids without sufficient observational data are marked in white. A coloured grid marked by crossing lines indicates that the linear trend in the grid exceeds the 5% significance level. Time series are computed over the coloured regions. The units of the panels in the first row are in °C per decade for TXx, TNx, TXn and TNn and in % for TX90p, TN90p, TX10p, and TN10p. The units of the linear trends in the panels of the second and third rows are in °C per decade for TXx, TNx, TXn and TNn and in % per decade for TX90p, TN90p, TX10p, and TN10p
the variability. Therefore, the bias in the model simulated variability will still remain. It can be seen that after this adjustment, the simulated intensity and frequency of extreme temperatures show good consistency between CanESM2 and the observations (Figure 1).

The risk ratio (RR) is defined as the ratio of the probability of a predefined extreme event at different levels of global warming to the probability in the current climate (simulated 1°C warming above the preindustrial level), which provides a simple and clear theoretical foundation for representing the impacts of different global warming levels on the rarity of extreme events (National Academies of Sciences, Engineering, and Medicine, 2016; Kharin et al., 2018; Sun et al., 2018). The RR for the selected indices in China is calculated under different global warming levels at three arbitrarily selected rarity levels with 5-, 10-, and 50-year return periods in the current climate. The RR is defined as $RR = p_1/p_0$, in which $p_0$ is the event probability in the current climate and $p_1$ is the event probability in the future climate. The values of $p_0$ are 0.2, 0.1, and 0.02 for 5-, 10-, and 50-year events, respectively.

3 | RESULTS

3.1 | Verification of CanESM2 performance

Figure 1 shows the observed and CanESM2 simulated extreme temperature intensity and frequency after the model results are bias adjusted. For the comparison, the first row of each column also shows the long-term changes of all the indices with (red lines) and without (blue lines) bias adjustment. It is clear that after the bias adjustment, the simulated intensity and frequency of temperature extremes display good consistency with the observations. The most obvious improvements are seen in the frequency indices, which means the adjustment mainly affects the exceedance probability of temperature extremes, especially the small probability. For the period of 1961–2015, most areas in China experienced more frequent and more intense warm extremes and less frequent and less intense cold extremes. The bias-adjusted model results reasonably reproduce the long-term...
variations in the national averaged indices (first row of each panel) and the distribution of linear trends in 1961–2015 (the second and third rows of each panel). For both the intensity and frequency indices, the adjusted model ensemble means generally show consistent long-term changes with the observations, although a large interannual variability is seen in the observations. This finding is expected since the model ensemble means remove the large internal natural variability. The correlation coefficients between the observed and adjusted simulated time series in China are greater than 0.5 for most intensity indices and greater than 0.7 for all frequency indices. These results indicate that the adjusted model results exhibit good performance in simulating the long-term changes in temperature extremes across China after the bias correction is applied. The bias adjustments remove some warm features related to the high climate sensitivity of CanESM2, so the future projection based on the model should be reasonable. However, one should note that CanESM2 overestimates the long-term trend of the warmest day (TXx) in central eastern China, especially in the past 10 years. This overestimation may lead to an overestimate of future warming of TXx. Some previous studies have shown that the reasons for the negative cooling trends in TXx in central eastern China are still unclear, and the greenhouse gas forcing could not adequately explain the changes in that area (Yin et al., 2017).

### 3.2 | Link between extreme temperature changes and GMST increases

Figure 2 displays the CanESM2 projected future changes in extreme temperatures linked with the GMST increase above the preindustrial level. The absolute intensity indices averaged in China increase approximately linearly with global warming, with a rate of 1.44°C per degree for TNn (coldest
night) and 1.44°C per degree for TXx (warmest day) and 1.24 and 1.20°C per degree for TNx (warmest night) and TXn (coldest day), respectively (Figure 2a,b). This indicates that the intensity of extreme temperature in China will change more rapidly than the GMST increased magnitude. The coldest night (TNn) and warmest day (TXx) show faster increasing rates than the other two indices. The former result is expected because the daily minimum temperature changed faster than the daily maximum temperature over the past 60 years. However, the rapid increasing rate in TXx may be due to the model’s performance, including incomplete parameterization schemes and the lack of some external forcing such as aerosols or land-surface processes, in the RCP8.5 scenario.

The percentile-based frequency indices show an approximately nonlinear relationship with the GMST.

**FIGURE 3** CanESM2 projected changes in eight extreme temperature indices under the 1.5, 2, 3, 4, and 5°C global warming levels. Panels (a) to (h) display the results for TXx, TNx, TXn, TNn, TX90p, TN90p, TX10p, and TN10p, respectively. The projected changes are relative to the current climate (1.0°C). Grids without sufficient observational data are marked in white. Units: °C for TXx, TNx, TXn and TNn and % for TN10p, TX10p, TN90p and TX90p. A coloured grid marked by crossing lines indicates that the changes in the grid exceed the 5% significance level.
increase. The frequency of the warm extremes (TX90p and TN90p) increases rapidly (approximately 3% per degree) from 1.5 to 2°C warming and experiences an accelerated change (more than 4% per degree) for TN90p above approximately 3°C warming. At the end of 2100, the increase in the frequency of warm extremes will reach 22 and 26% relative to the current climate, respectively, which is larger than the linear increase at a rate of 3% per degree. The decrease in the frequency of cold extremes (TX10p and TN10p) is much smaller than the increase in the frequency of warm extremes. The changes experience fast-to-slow processes. The final stable condition above approximately 3°C warming indicates that cold extremes will finally disappear. Cold extremes that are as frequent as those in the current climate will not occur in the near future.

3.3 | Geographical distribution of temperature extremes

Figure 3 shows the regional differences in temperature extreme changes with the GMST increase. For the intensity indices, the warmest extremes (TXx and TNx) increase quite uniformly, while the coldest extremes (TXn and TNn) decrease with obvious regional differences. The increase in the warmest extremes and decrease in the coldest extremes display larger magnitudes than the GMST increase in most areas, especially in northeastern and northwestern China. For example, when the GMST increases from 1.5 to 2°C warming, the intensity indices can increase much more than 1.5°C in these areas. When the GMST increases by 5°C, the warming of the coldest extremes will be more than 8°C. These results indicate that northeastern and northwestern China are the most sensitive regions in response to global warming. The intensity of the coldest extremes in northeastern China will decrease rapidly, while the intensity of the warmest extremes in northwestern China will increase substantially.

For the frequency indices, the occurrence of warm extremes (TX90p and TN90p) will increase rapidly from approximately 10–15% to more than 25% at the 3°C warming level and up to above 60% at the 5°C warming, while the occurrence of cold extremes (TX10p and TN10p) will decrease gradually from 9% at the 1.5°C level to less than 0.5% at the 5°C warming level. Different from the intensity indices, the largest increase in the frequency of warm extremes will be located in Western China, while the strongest changes in the frequency of cold extremes will occur in northeastern China. The changes in the nighttime extremes will be slightly larger than those in the daytime extremes. With each additional 0.5°C warming, the changes will be more obvious than those at the low warming levels.
3.4 Probability distributions of temperature extremes in the future

Figure 4 displays the histograms of all the indices under different global warming levels. For the intensity indices, with the increasing GMST, the warmest extremes shift rightward from weak to intense warm events, while the coldest extremes shift leftward from the intense to weak cold extremes. (Note that the abscissa here shows the large to small negative values.) The shapes of all the intensity indices exhibit few changes, so the variabilities in these indices do not change much under different warming levels. For instance, the estimated median values and their corresponding 5–95% range of TNn in China change from $-19.4^\circ C$ ($-21.2$ to $-17.9^\circ C$), with a variability of 1.01 at the current climate, to $-13.6^\circ C$ ($-15.7$ to $-12.0^\circ C$), with a variability of 1.11 at 5°C global warming level.

For the frequency indices, the distributions of warm days and nights (TX90p and TN90p) shift rightward, and the shapes become wider and more flattened. This result suggests more frequent warm extremes with increased variabilities in a warmer climate. On the other hand, the probability distribution functions (PDFs) of cold days and nights (TX10p and TN10p) shift leftward, and the shapes become narrower, indicating decreasing mean values and variabilities. When the GMST increases by 5°C, the probabilities of TX10p and TN10p with zero values become very high, indicating that the cold extremes as frequent as the current climate will almost disappear in a very warm world. The PDFs also clearly show faster changes in warm extremes than decreases in cold extremes. However, an exception should be paid attention to. After the GMST increase reaches 3°C, the distribution of TN90p becomes narrower, suggesting a saturation of warm nights in parts of the country; that is, very warm nights can occur on any day of the year once the GMST increases by 3°C.

3.5 Risk ratio

Figure 5 shows the changes in RRs under different warming levels for events at three rarity levels with return periods of 5, 10, and 50 years in the current climate. A value of 0.0001 is set as the smallest value (but not zero) to represent the extremely small probability. For the intensity indices, the occurrence risk of the

![FIGURE 5](image-url)  
**FIGURE 5** Box plots of the risk ratios for the annual mean temperature indices in China with 5-year (red), 10-year (blue), and 50-year (green) return periods in the current climate (1.0°C) under different global warming levels for (a) TX, (b) TN, (c) TXn, (d) TNn, (e) TX90p, (f) TN90p, (g) TX10p, and (h) TN10p from the CanESM2 simulations
warmest extremes (TXx and TNx) increases rapidly from 1.5 to 2°C warming and then remains saturated (once-a-year event) at the 3°C warming level for all three types of events. The once-in-5-year warmest night (TNx) will occur almost every year at the 2°C warming level. The once-in-50-year events will become usual events (once every year) at 3°C warming. The occurrence risk for the coldest extremes (TXn and TNn) will gradually decrease. All three types of cold events will become near zero occurrence events at the 4°C warming level for the coldest day (TXn) and at the 2.5°C level for the coldest night (TNn). This shows that the occurrence risk for the nighttime extremes changes more rapidly than that for the daytime extremes, such as TNx versus TXx and TNn versus TXn, indicating a more rapid response of nighttime extremes to global warming. For the rarer events, the RRs show larger changes. For example, the RR for once-in-5-year coldest day (TXn) events decreases gradually from 0.77 at the 1.5°C level to 0.02 at the 4°C level, while the RR for once-in-50-year TXn events decreases rapidly from 1.12 at the 1.5°C level to 0.005 (rarely happens) at the 2.5°C level, meaning that the once-in-50-year TXn events in the current climate will almost disappear throughout the year at the 2.5°C warming level.

For the frequency indices, the changes in the RR are more rapid than those for the intensity indices, suggesting a more sensitive response of frequency to the GMST increase. The RR for the frequency of warm extremes will substantially increase from the current climate to the 1.5°C warming. The 5-, 10-, and 50-year warm days (TX90p) will increase by approximately 4, 6, and 14 times, respectively, compared with the current climate. The RR of warm nights (TN90p) increases more prominently than that of TX90p, indicating a more rapid increase in the frequency of nighttime events. Previous detection and attribution studies (Dong et al., 2018) have indicated that the frequency indices show a more robust response to the external anthropogenic forcing than the intensity indices, which may be one possible reason for the rapid changes in warm days and nights. After the GMST increases to more than the 2.5°C level, the warm days and nights at these three return periods will all become once-a-year events. On the other hand, the RRs of cold days and nights with 5-year and 10-year periods rapidly decrease to less than 0.1 from the current climate to 1.5°C warming. The current 1-in-5-year cold days (TX10p) will become 1-in-137-year events, while the current 1-in-10-year events will become 1-in-195-year events at the 1.5°C warming level. Above the 2°C warming level, the RRs of these three types of cold events will remain stable at 0.005, 0.0001, and 0.0005, respectively, indicating that the current cold events will become very rare events (less than once-in-2000-year events).

4  |  CONCLUSIONS

Understanding the regional climate response to different global warming levels is important for climate change impact adaptation and international climate negotiation. The large ensemble runs of climate models provide a very good opportunity to investigate the changes in climate extremes, including the changes in mean and variability, the probability distribution and the occurrence risk. Here, we use large ensemble runs from CanESM2 to investigate the link between extreme temperature indices and global warming levels, risk changes for different types of extremes, etc. Our results show that CanESM2 shows good performance in simulating the temperature extremes in China after the model results are bias adjusted. The model is able to reproduce the long-term linear changes and spatial distributions of all the investigated indices. The model projects that the intensity indices of extreme temperature will change linearly with global warming, while the frequency indices will change nonlinearly with warming. All the intensity indices in China show faster changing rates than the GMST increase, with the fastest rate at 1.44°C per °C for TNn and TXx, indicating a large regional response of temperature extremes to global warming. The projected TXx increase seems to be overestimated, which may be because of the higher estimate for TXx in the model during the historical period and the lack of some forcings in future scenarios. This result reminds us of the important implications of the model performance and the importance of model bias adjustment for the future projection. The application of some methods, such as the observation-constrained method, may help to reduce the uncertainty in future projections.

The geographical distribution of all the changes in China shows clear regional differences. The largest changes in the intensity indices are observed in northeastern and northwestern China, while the frequency indices show the most rapid changes in warm nights in Western China and cold days in northeastern China. These results indicate that the largest changes in temperature extremes in China are seen in the mid- to high latitudes.

We also examine the changes in the PDFs for all the intensity and frequency indices. The PDFs of the absolute intensity indices show clear shifts but with little change in shape, while those of the frequency indices change in both position and shape. This suggests that the intensity of temperature extremes will mainly experience changes in the mean value, while all the frequency indices will change in both mean value and variability. On the other hand, the quantified results of the RR show that the rarer events will have larger changes in the RR. At the 2°C warming levels, the once-in-5-year warmest night (TNx) will occur almost
every year. The once-in-50-year events will become usual events (once every year) at 3°C warming. At the 3°C level and beyond, the warm events with return periods of 5, 10, and 50 years will occur every year. This proposes great challenge for people to be adapted to all kinds of extreme high temperature events in the future.

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