Observed Changes in the Distributions of Daily Precipitation Frequency and Amount over China from 1960 to 2013

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ABSTRACT

In this study, daily precipitation (P) records for 1960–2013 from 632 stations in China were homogenized and then applied to study the changes in the frequency of dry (P = 0) and trace (0 < P < 0.1 mm day\(^{-1}\)) days and all precipitation events (P ≥ 0.1 mm day\(^{-1}\)), and the frequency and accumulated amount of precipitation at different intensities. Over China as a whole, very heavy precipitation (P ≥ 50 mm day\(^{-1}\)) events have increased significantly from 1960 to 2013, while light (0.1 ≤ P < 10 mm day\(^{-1}\)) and moderate (10 ≤ P < 25 mm day\(^{-1}\)) events have decreased significantly, accompanying the significant increases of dry days and decreases of trace days. This indicates a shift from light to intense precipitation, implying increased risks of drought and floods over China since 1960. Although the consistent increases of dry days and decreases of trace days and light and total precipitation days are seen over most of China, changes in other precipitation categories exhibit clear regional differences. Over the Yangtze River valley and southeast China, very heavy precipitation events have increased while light precipitation events have decreased. However, positive trends are seen for all precipitation categories over northwest China, while trends are generally negative over southwest, northeast, and northern China. To examine the association with global warming, the dependence of the precipitation change for each intensity category over China on global-mean temperature was analyzed using interannual to decadal variations. Results show that dry and trace days and very light and very heavy precipitation events exhibit larger changes per unit global warming than medium-intensity precipitation events.

1. Introduction

It is unequivocal that the climate system has warmed globally since the mid-twentieth century and human influence is extremely likely the dominant cause (IPCC 2013). Precipitation characteristics [amount, frequency, intensity, and probability distribution functions (PDFs)] are expected to change under greenhouse gas (GHG)-induced global warming (Karl and Knight 1998; Trenberth et al. 2003; Sun et al. 2007; Lau and Wu 2007; Lau et al. 2013; Liu et al. 2009; Chou et al. 2012; Shiu et al. 2012). Since increases in heavy precipitation can lead to more floods, and increases in dry days and decreases of trace and
light precipitation can increase risks of drought, changes in precipitation characteristics are of great concern to water management, agriculture, and ecosystems.

Since the global-mean precipitation rate is coupled to global surface and atmospheric energy balance (Trenberth et al. 2009), the increase rate in global-mean precipitation, which is around 1%–3% K\(^{-1}\) under GHG-induced global warming (Held and Soden 2006; Sun et al. 2007; Vecchi and Soden 2007; IPCC 2013), is determined by the change rate in atmospheric net energy balance (Allen and Ingram 2002; Pendergrass and Hartmann 2014). Precipitation intensity, however, is expected to increase at approximately the same rate as atmospheric water vapor content (\(\sim 7\%\) K\(^{-1}\) with constant relative humidity) because the precipitation rate during a storm is proportional to the low-level moisture convergence (Trenberth et al. 2003). This implies that overall precipitation frequency should decrease in order to offset the large increase in precipitation intensity (Trenberth et al. 2003). Analyses of climate model–simulated daily precipitation changes (Sun et al. 2007; Chou et al. 2012; Lau et al. 2013) qualitatively confirm these theoretical arguments, with large increases in heavy precipitation frequency and intensity and decreases in light to moderate precipitation.

Increases in heavy precipitation have been observed over many land areas with sufficient data (Groisman et al. 2005; Wang and Zhou 2005; Alexander et al. 2006; Goswami et al. 2006; Allan et al. 2010; Westra et al. 2013; Lu et al. 2014). Over the United States, Karl and Knight (1998) showed that the portion of total precipitation derived from heavy and extreme events increased at the expense of moderate events. Over eastern China, both the frequency and amount of light precipitation have decreased in the second half of the twentieth century with high spatial coherency, while both the frequency and amount of heavy precipitation have increased (Liu et al. 2005; Zhai et al. 2005; Qian et al. 2007, 2009; Lu et al. 2014; Fu and Dan 2014). Using gridded precipitation data from observations and atmospheric reanalyses, global heavy precipitation was found to increase by 10% to 100% per 1 K increase in global-mean temperature, while light to moderate precipitation has decreased based on interannual to decadal variations (Liu et al. 2009; Shiu et al. 2012).

Changes in precipitation characteristics have been investigated in previous studies, but the association with global warming remains inconclusive (Trenberth et al. 2003; Chou et al. 2012; Qian et al. 2007; O’Gorman and Schneider, 2009; Qian et al. 2009). Since daily precipitation follows a long-normal or gamma distribution at most locations, a shift in its PDF (without a change in the shape) toward a higher mean value would result in increases in both the frequency and intensity of heavy precipitation. Such a PDF shift could result from increased water vapor content in the air (a thermodynamic effect) that could enhance the intensity of all types of precipitation, especially heavy precipitation due to the feedback of enhanced latent heating within a storm (Trenberth et al. 2003). On the other hand, changes in atmospheric vertical profiles and stability could suppress or enhance the occurrence frequency of storms. An analysis of climate model simulations (Chou et al. 2012) confirmed these simple arguments. Chou et al. (2012) showed that increases in water vapor content lead to increases in both frequency and intensity of heavy precipitation in the tropics, while a more stable tropical atmosphere decreases heavy precipitation frequency and intensity. For precipitation extremes, O’Gorman and Schneider (2009) showed that their changes depend on changes in the moist-adiabatic temperature lapse rate, the upward velocity, and the temperature when precipitation extremes occur in climate models. For annual maximum daily precipitation, Westra et al. (2013) showed that its long-term trends observed during 1900–2009 have a statistically significant positive association with global-mean surface temperature, with a median sensitivity ranging from 5.9% to 7.7% K\(^{-1}\). Over China, Qian et al. (2007) demonstrated that the decreasing trend in the frequency of light precipitation for the summer monsoon season during the second half of the twentieth century is associated with regional warming. Others (e.g., Qian et al. 2009; Fu and Dan 2014) suggested that increased aerosols from air pollution are at least partly responsible for the decreasing light precipitation events over China during the past 50 years.

China is frequently affected by a variety of extreme precipitation and drought events due to its vast territory and strong influence of East Asian monsoon (Zhou et al. 2009, 2013; Qian and Zhou 2014). But changes in precipitation characteristics over China, and in particular the mechanisms responsible, remain unclear. In this study, we select and homogenize daily precipitation records from 632 stations over China to study precipitation characteristics (frequency, intensity, and PDFs) and their long-term changes. We first describe the long-term mean precipitation characteristics over China, and then analyze their long-term changes from 1960 to 2013. Finally, the associations with global warming are discussed.

This study differs from previous analyses (e.g., Liu et al. 2005; Zhai et al. 2005; Qian et al. 2007, 2009; Zhang and Zhai 2011; Lu et al. 2014; Fu and Dan 2014; Lu et al. 2014) in that, instead of focusing on the light or heavy precipitation or the frequency of all daily precipitation events, we examine the changes in both the frequency and the accumulated amount of precipitation for all intensity categories (i.e., the full PDF). Furthermore, we
have performed a homogenization analysis of the daily rain gauge records before applying them to quantify the long-term changes, whereas all the previous studies used these records directly without homogenization. Finally, we also examine the relationship of the precipitation changes with global-mean temperature, which has not been done previously over China.

2. Data and method

a. Daily precipitation dataset

A dataset of daily precipitation ($P$) amount at 756 rain gauge stations over China was obtained from the China Meteorological Administration (CMA; http://cdc.nmic.cn/home.do). This is a quality controlled dataset but no homogenization was done by the CMA. The quality control included the identification of outliers, internal consistency check, spatial and temporal consistency checks, and artificial checks and correction of suspected and erroneous data (Liu and Ren 2005). To reduce errors associated with sampling and record length, we selected 632 stations with at least 40 years of near-complete observations (i.e., $\leq 5\%$ of data were missing each year) during 1960–2013. These 632 stations are shown in Fig. 1. The stations are fairly evenly distributed across China, including the eastern Tibetan Plateau, but large gaps exist in western China.

The daily dataset from CMA has been used to document historical changes in precipitation over China in a number of studies without homogenization (e.g., Liu et al. 2005; Qian et al. 2007; Qian et al. 2009; Fu and Dan 2014). Although the standard 8-in. rain gauges have been used since the stations were established (CMA 1979), artificial effects from urban development, site relocation, and local land use changes may be present in the data. They could potentially cause inhomogeneities and spurious changes in daily precipitation records (Wang et al. 2010; Yan et al. 2010). Here, we performed a homogenization analysis of the dataset before applying it to quantify long-term changes.

b. Homogenization of the daily precipitation data

We applied the penalized maximum $F$ test (Wang 2008) to detect any discontinuities or changepoints in the time series of the monthly occurrence frequency of dry ($P = 0$) days and trace ($0 < P < 0.1$ mm day$^{-1}$) days, and in the monthly time series of very light ($0.1 \leq P < 0.5$ mm day$^{-1}$) precipitation amount and total precipitation amount. These time series were computed at each station using the daily precipitation records. The penalized maximum $F$ test allows a long-term trend and accounts for the first-order autocorrelation, so a reference series is not required. More details about the penalized maximum $F$ test and related issues are discussed in Wang et al. (2010) and Dai et al. (2011).
Table 1. The number and percentage (in brackets) of the 632 stations with statistically significant changepoints; N indicates the total number of changepoints in the time series.

<table>
<thead>
<tr>
<th>Time series</th>
<th>N = 0</th>
<th>N = 1</th>
<th>N ≥ 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry-day freq.</td>
<td>476 (75.3%)</td>
<td>140 (22.2%)</td>
<td>16 (2.5%)</td>
</tr>
<tr>
<td>Trace-day freq.</td>
<td>334 (52.8%)</td>
<td>237 (37.5%)</td>
<td>61 (9.7%)</td>
</tr>
<tr>
<td>0.1–5 mm day$^{-1}$ P amount</td>
<td>605 (95.7%)</td>
<td>27 (4.3%)</td>
<td>0</td>
</tr>
<tr>
<td>Total amount</td>
<td>621 (98.3%)</td>
<td>11 (1.7%)</td>
<td>0</td>
</tr>
</tbody>
</table>

The numbers and corresponding percentages of the 632 stations with statistically significant changepoints are given in Table 1. About 25% (47%) of the stations had at least one detected changepoint in the time series of the monthly frequency of dry (trace) days. However, many stations did not show the same changepoints in the time series for the trace days and dry days. Since an observational change likely induces the same changepoints in both time series, we required the time series of both the trace and dry days to have the same changepoints (within 3 months of each other). This resulted in a total of 35 (5.5%) stations with at least one changepoint in the monthly frequency of dry or trace days. The percentage of stations whose time series of very light precipitation amount and total precipitation amount had one significant changepoint was 4.3% and 1.7%, respectively. Of these, five stations detected changepoints in both the very light precipitation amount and total amount. This resulted in a total of 33 (5.2%) stations with one changepoint in the monthly time series of precipitation amount. We did not detect any stations with more than one changepoint in these time series of precipitation amount (Table 1).

After identifying the significant changepoints, it is desirable to adjust the daily precipitation data series to remove associated artificial changes. In this study, we used the penalized maximum $F$-test method (Wang et al. 2010) to homogenize the monthly frequency series, which then were used to compute long-term changes in these frequencies. We used the quantile-matching method proposed by Wang et al. (2010) to remove the discontinuities in the PDF of daily precipitation around the detected changepoints. This homogenized daily precipitation dataset was then used to quantify the changing characteristics of precipitation over China.

To quantify the impact of this homogenization, results from the original unhomogenized dataset were compared with those from the homogenized dataset. Overall, we found that the impact is noticeable at some stations with significant discontinuities, but averaged regionally and nationally the impact of the homogenization was very small as one would expect based on the small (~5%) number of stations with inhomogeneities. As shown in Fig. 2, at station 51437 (Xinjiang Zhaozhu County), for which a changepoint was detected in October 1995, the annual amount of very light precipitation shows an increasing trend of 3.35 mm decade$^{-1}$ in the unhomogenized data and a decreasing trend of $-3.04$ mm decade$^{-1}$ in the homogenized data, with both trends being statistically significant at the 5% and 10% levels, respectively. At station 56565 (Sichuan Yanyuan County), the annual amount of total precipitation derived from the unhomogenized data increases significantly at a rate of 16.9 mm decade$^{-1}$, but decreases insignificantly at rate of 4.0 mm decade$^{-1}$ in the homogenized data. For the nationally averaged amount of both very light and total precipitation, the differences between the original and homogenized data are negligible (Fig. 2).

Thus, our homogenization analysis suggests that the CMA dataset of daily precipitation is relatively homogeneous, with significant changepoints and discontinuities only at a small fraction (~5%) of the stations, and that these discontinuities do not have a large impact on national and regional averages. This assessment provides much needed confidence in all the previous studies that used the CMA dataset to document long-term precipitation changes over China without homogenization.

c. Regional definitions

The climate over China varies significantly from region to region due to its large geographic extent and complex terrain. Different regions may experience different temporal features, like the southern flood and northern drought pattern of summer precipitation in the past half century, with increased precipitation in the middle and lower valley of the Yangtze River and decreased precipitation in northern China (Yu et al. 2004; Zhou et al. 2009). To better understand the regional features of precipitation change, as in China Climate Bulletin for 2013 (CMA 2014) we divided the contiguous domain of China into six subregions (Fig. 1): northwest China (NW: 35°–50°N, 74°–105°E), southwest China (SW: 20°–35°N, 90°–105°E), northeast China (NE: 42°–55°N, 105°–134°E), northern China (NC: 35°–42°N, 105°–125°E), the Yangtze River valley (YZ: 28°–35°N, 105°–123°E), and southeast China (SE: 18°–28°N, 105°–120°E).

d. Precipitation classification

In this study, a precipitation event is defined as one day with daily precipitation ($P$) equal to or greater than 0.1 mm day$^{-1}$, following Sun et al. (2007). The days with no precipitation ($P = 0$) are considered as dry days. For a given station and year, precipitation frequency in each intensity bin is the ratio (in %) of the number of the days whose precipitation rate is within the
corresponding intensity interval to the number of all days with data; the precipitation amount in each intensity bin is the accumulated precipitation amount over the precipitation days within the corresponding intensity interval. To estimate the regionally and nationally averaged precipitation histograms, at each station, daily precipitation was divided into 100 intensity bins with a bin size of 1 mm day\(^{-1}\), and the annual precipitation frequency and amount at each intensity bin were calculated. Then the station annual precipitation frequency and amount of each intensity bin were interpolated onto a 0.5° \times 0.5° grid using the iterative improvement objective analysis with the search radii of 3°–2°–1°–0.5° [using the “obj_anal_ic_Wrap” function in the NCAR Command Language (NCL); NCAR 2012]. Finally, these 0.5° grid cells were averaged using the area as weight to calculate regional and national averages for each intensity bin.

For the sake of discussion, according to CMA standards, the observed daily precipitation is also categorized into five intensity bins: trace (0 < P < 0.1 mm day\(^{-1}\)), light (0.1 ≤ P < 10 mm day\(^{-1}\)), moderate (10 ≤ P < 25 mm day\(^{-1}\)), heavy (25 ≤ P < 50 mm day\(^{-1}\)), and very heavy (P ≥ 50 mm day\(^{-1}\)). The station precipitation amount (except for trace days) and frequency for these five precipitation categories were also calculated and interpolated onto a 0.5° \times 0.5° grid for displaying the spatial distribution and calculating regional averages.

e. The linear trend analysis method

A linear least squares trend analysis is used in time series (y) of various precipitation characteristics. A linear function of time t can be written as

\[ y = at + b, \]

where a is the regression coefficient that denotes the linear trend and b is a constant. Trends of precipitation parameters are expressed as the percentage of the mean for 1960–2013. Trends are calculated only for precipitation parameters with more than 40 years of events during 1960–2013. The nonparametric Mann–Kendal
(MK) statistical test (Kendall and Gibbons 1981) is used to detect whether the linear trend of a series reaches statistical significance.

f. Analysis method for relationship with global warming

In the literature, two methods have been used to examine changes in precipitation characteristics ($\Delta P$) in association with changes in global-mean temperature ($\Delta T$). One examines the $\Delta P/\Delta T$ ratio using their long-term changes (e.g., Sun et al. 2007; Lau and Wu 2007) and the other (referred to as the interannual method) derives the $\Delta P/\Delta T$ ratio using their interannual to decadal variations (Liu et al. 2009; Shiu et al. 2012). Since the interannual to decadal variations reflect mostly short-term internal climate variability, the two methods may produce different results. Nevertheless, the $\Delta P/\Delta T$ ratios derived from the two methods for the recent decades are qualitatively similar (Lau and Wu 2007; Shiu et al. 2012). Here we follow Liu et al. (2009) and Shiu et al. (2012) and use the interannual method to derive the $\Delta P/\Delta T$ ratio, as our data records are relatively short. As stated above, we first calculated each station’s precipitation frequency and amount and mapped them onto a $0.5^\circ \times 0.5^\circ$ grid, prior to calculating the nationally and regionally averaged precipitation frequency difference ($\Delta F$), amount difference ($\Delta P$), and global-mean surface temperature difference ($\Delta T$) between any two (different) years within 1960–2013. Thus the differences include both interannual (e.g., 1980 vs 1981) and decadal (e.g., 1970 vs 1990) variations and long-term (e.g., 1960 vs 2013) changes. We then converted the nationally and regionally averaged $\Delta P$ and $\Delta F$ into a percentage of its long-term (1960–2013) mean for the corresponding event or precipitation category. Finally, we divided the nationally and regionally averaged $\Delta F$ and $\Delta P$ by the corresponding $\Delta T$, and the convergent point of the $\Delta P/\Delta T$ and $\Delta F/\Delta T$ ratios with increasing $\Delta T$ was used as the response rate of the precipitation amount and frequency to global warming for each type of events. Here, we used the GISTEMP global surface temperature dataset (Hansen et al. 2010) for estimating $\Delta T$.

3. Results

a. Long-term mean precipitation characteristics

To better understand the changing character of precipitation over China, here we briefly discuss the long-term climatology of precipitation amount, frequency, and PDFs. Figure 3 shows the geographic distributions
of long-term (1960–2013) mean annual precipitation amount and the annual number of precipitation events, trace days, and dry days over China. Annual precipitation amount exceeds 1400 mm in SE, but decreases northward and westward to below 500 mm over most of NC and NE, and below 100 mm in NW (Fig. 3a). Taking isohyets of 400 and 800 mm as the climatic dividing lines, China can be divided into three parts: an arid zone (mostly the NW), a subhumid zone (the western SW, NC, and NE), and a humid zone (the eastern SW, YZ, and SE). The pattern of annual total precipitation events (Fig. 3b) is broadly correlated (with pattern correlation $r = 0.80$) with that of annual precipitation amount, with 140–190 precipitation days in SE but only 10–30 precipitating days in NW each year. However, the regions with the maximum precipitating days are located mainly in the Sichuan basin (28°–32°N, 100°–105°E) and regions south of the Yangtze River (25°–28°N, 110°–120°E), but not along the southeastern coastal areas as for the precipitation amount (Fig. 3a). The pattern of the precipitating days is highly correlated negatively ($r = -0.98$) with dry days (Fig. 3d), as the number of trace days is relatively small. There are several regions with 60 or more trace days per year, located along the Tian Shan Mountains (around 44°N, 85°E), the Tanggula Mountains (around 35°N, 92°E), and the Hengduan Mountains (around 30°N, 100°E). Areas with low trace days are mainly located along the latitudes between 35° and 40°N, even spanning to the lower Yangtze River. The pattern of the annual trace days is positively correlated ($r = 0.22$) with the topography in China. One possible reason is that low temperatures over those inland mountains in early morning favor the formation of fog and dew that produce trace condensation, but the atmospheric condition does not produce measureable precipitation. Light precipitation events are observed predominantly over the eastern Tibetan Plateau (33°–35°N, 95°–105°E) and the Sichuan basin, while moderate, heavy, and very heavy precipitation events occur frequently in YZ and SE (figures not shown).

Figure 4 shows the long-term mean histograms of daily precipitation amount and frequency of occurrence (FOC) as a function of precipitation intensity from 0.1 to 100 mm day$^{-1}$ averaged over all of China and the six subregions (i.e., the histograms were derived at each station and then interpolated onto a 0.5° grid for each bin, from which the regional averages were derived). The distribution of daily precipitation amount over China shows a maximum around an intensity of 4–6 mm day$^{-1}$ with a long tail toward high precipitation rates (Fig. 4a). This resembles a gamma distribution. The precipitation amounts are similarly distributed among the six subregions, with the maximum occurring at smaller intensity bins for NW, NC, and NE, and at higher intensity bins for YZ, SW, and SE. The peak for SW is particularly sharp compared with the other lines in Fig. 4a. Light precipitation (0.1 ≤ $P < 10$ mm day$^{-1}$) events occur far more frequently than all other precipitation events (Fig. 4b). The frequency decreases more rapidly with intensity for NW than the other regions, which all converge to about 10% for the lowest bin (of 0.1–1.0 mm day$^{-1}$) and then diverge for the heavy and very heavy precipitation events, with larger frequencies for SE and YZ. In the NW, the frequency of heavy precipitation is very low, and very heavy precipitation is very unlikely to occur. Furthermore, the frequency of dry days is generally higher than that of precipitation days, and the frequency of trace days is the lowest among the three. For example, over China as a whole, the frequencies of dry days, trace days, and all precipitation events are 56%, 12%, and 31%, respectively (Fig. 4b).

The percentage contributions of different category precipitation events to the total precipitation amount and to the number of all precipitation days over China and the six subregions are listed in Table 2. Over China as a whole, light precipitation accounts for nearly 80% of all precipitation events, but only ~26% of total precipitation amount. Moderate and heavy precipitation accounts for about 14% and 5% of all precipitation events and contribute about 30% and 24% to the total precipitation amount, respectively. Although very heavy precipitation rarely occurs, accounting for ~2% of the precipitation events, it contributes significantly (by 21%) to the total precipitation amount. Consistent with Fig. 4a, Table 2 shows that for NW, NE, and SW light precipitation is a relatively high contributor to the total precipitation amount and precipitation days, while very heavy and heavy precipitation have relatively low contributions. As expected, the SE has the highest contributions from very heavy and heavy precipitation and lowest contributions from light precipitation. The contributions by moderate precipitation are relatively similar among the subregions.

b. Changes in precipitation characteristics

Figure 5 compares the mean histograms of precipitation amount and frequency of different decades from 1960 to 2013 averaged over the whole of China and the six subregions. It shows that most of the decadal distributions are similar and overlying, especially the frequency histograms at low intensity levels. Nevertheless, noticeable differences are evident for the precipitation amount histograms, especially for SE and NC (Figs. 5e,g). Long-term changes in these distributions are shown more clearly in Fig. 6. For the whole of China,
histograms for both precipitation amount and frequency show negative trends for intensity bins below about 28 mm day$^{-1}$ and generally positive trends for intensity bins above 28 mm day$^{-1}$. The most significant and clearest changes are found for extreme light precipitation events (0.1 ≤ $P < 1$ mm day$^{-1}$), whose frequency deceased by about 7.4% decade$^{-1}$ and amount decreased by about 0.6 mm decade$^{-1}$. For precipitation bins between 2 and 16 mm day$^{-1}$, decreasing trends of precipitation amount ($-0.16$ to $-0.30$ mm decade$^{-1}$) and frequency ($-0.73$% to $-1.60$% decade$^{-1}$) are also significant at the 10% level, but of smaller magnitudes. For bins between 16 and 50 mm day$^{-1}$, both positive and negative trends are present, though not statistically significant at the 10% level. For extreme intense rainfall bins lager than 50 mm day$^{-1}$, remarkable increasing trends are evident. For example, the increase of extreme heavy precipitation events and accumulated amount is up to 3.39% and 0.34 mm decade$^{-1}$, respectively. Meanwhile, dry days have become more frequent, while trace days and total precipitation events have decreased significantly (see inset of Fig. 6b).

In YZ and SE, the linear trends (Fig. 6) for both precipitation amount and frequency are similar to those of all of China, but with larger magnitudes. In the NW, almost all the binned precipitation amounts and frequencies have increased significantly. In contrast, NC and SW show mostly negative trends for both the precipitation amount and frequency. In NE, the changes are generally small.

Figure 7 shows the spatial patterns of the long-term change (1987–2013 minus 1960–86 expressed as a percentage of the 1960–86 mean) in FOC for dry days, trace days, and the four different types of precipitation (cf. Fig. 3) over China. Dry days have become more frequent over most of China, while trace days have become...
less frequent. Among the 632 stations analyzed, 84% stations had significant increases of dry days and 78% stations had significant decreases of trace days. Light precipitation events show predominantly decreasing trends east of about 100°E, but positive trends west of about 100°E (Fig. 7c). Similar change patterns are seen for the moderate events, although the negative trends are weaker and mainly seen over NC, YZ, and SE.

Table 2. The long-term (1960–2013) mean percentage contributions of different-category precipitation events to the total precipitation amount and to the number of all precipitation days (in brackets) over China and the six subregions.

<table>
<thead>
<tr>
<th>Region</th>
<th>Light ((0.1 \leq P &lt; 10 \text{ mm day}^{-1}))</th>
<th>Moderate ((10 \leq P &lt; 25 \text{ mm day}^{-1}))</th>
<th>Heavy ((25 \leq P &lt; 50 \text{ mm day}^{-1}))</th>
<th>Very heavy ((P \geq 50 \text{ mm day}^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>25.8% (79.4%)</td>
<td>29.5% (13.6%)</td>
<td>23.8 (5.0%)</td>
<td>21.0 (1.9%)</td>
</tr>
<tr>
<td>NW</td>
<td>61.6% (93.4%)</td>
<td>30.4% (6.0%)</td>
<td>7.1% (0.6%)</td>
<td>0.8% (0.04%)</td>
</tr>
<tr>
<td>SW</td>
<td>35.3% (83.1%)</td>
<td>34.7% (12.8%)</td>
<td>19.6% (3.3%)</td>
<td>10.4% (0.8%)</td>
</tr>
<tr>
<td>NE</td>
<td>37.0% (85.9%)</td>
<td>34.0% (10.6%)</td>
<td>20.6% (3.0%)</td>
<td>8.4% (0.6%)</td>
</tr>
<tr>
<td>NC</td>
<td>27.8% (80.9%)</td>
<td>29.8% (12.8%)</td>
<td>23.4% (4.6%)</td>
<td>19.1% (1.7%)</td>
</tr>
<tr>
<td>YZ</td>
<td>22.1% (75.2%)</td>
<td>29.3% (15.8%)</td>
<td>25.6% (6.4%)</td>
<td>23.0% (2.6%)</td>
</tr>
<tr>
<td>SE</td>
<td>18.3% (73.0%)</td>
<td>26.2% (16.0%)</td>
<td>26.8% (7.5%)</td>
<td>28.7% (3.5%)</td>
</tr>
</tbody>
</table>

Fig. 5. Decadal-mean histograms of yearly accumulated precipitation amount (mm) and frequency of occurrence (%; the inset panel) as a function of daily precipitation intensity (bin size is 1 mm day\(^{-1}\)) for (a) all of China, and (b)–(g) the six subregions. Each colored line represents one decadal mean but many of them overlay each other.
Trends in heavy precipitation events exhibit no coherent pattern, although large increases are seen over some regions (Fig. 7e). Very heavy events are mainly located in SE, where its frequency generally has increased (Fig. 7f).

Figure 8 shows the time series of the area-weighted mean of the FOC and precipitation amount for the six different categories shown in Fig. 7, plus the case including all precipitation events. The linear trends for the six subregions are shown in Table 3. For China as a whole, dry days increased linearly at a rate of 3.78% decade$^{-1}$, while trace days decreased almost linearly at a rate of 8.22% decade$^{-1}$ from 1960 to 2013, with both trends exceeding the 1% significance level (Fig. 8a). Meanwhile, light and moderate precipitation frequency and amount (Figs. 8b,c) show clear downward and significant trends ranging from $-1.1$ to $-3.9$% decade$^{-1}$ (Fig. 8b and Table 3). The frequency and amount for heavy precipitation exhibit large interannual variations but no obvious long-term trends (Fig. 8d). However, the time series of very heavy precipitation events show significant increasing trends of 1.5%–2.0% decade$^{-1}$ (Fig. 8e). The precipitation amount of all precipitation events shows an insignificant trend from 1960 to 2013 (Fig. 8f) because the contribution from increasing very heavy events is offset by decreasing light and moderate events. However, the frequency of all precipitation events has decreased significantly, at a rate of $-3.18$% decade$^{-1}$ (Fig. 8f), since the decrease of light precipitation events is much larger than the increase of very heavy precipitation events.

Table 3 shows that the decreasing trends for trace days are statistically significant over all the six subregions, ranging from $-5.56$% in SE to $-11.90$% in NE per decade,
while the increasing trends for dry days are statistically significant for all the subregions, ranging from 1.09% in NW to 6.01% in SW per decade. Decreasing trends are also seen for light precipitation and all precipitation events in all regions except NW (Table 3). Trends for the other categories are less spatially coherent (Table 3). These findings are in tune with model projections (Zhu et al. 2009) that indicate a significant increase in frequencies of nonprecipitation and heavy (≥24 mm day\(^{-1}\)) rainfall days and a significant decrease in relatively weak (1–12 mm day\(^{-1}\)) rainfall days over eastern China under global warming. These changes in daily precipitation distribution also agree with previous results (Jiang et al. 2014) derived using the composite analysis between the five warmest years and coldest years, which suggested a shift of daily precipitation toward heavy precipitation in China under global warming.

c. Relationship with global warming

We found that, averaged over China as whole, there is a strong correlation between the annual number of dry days, trace days, and light precipitation events and the global-mean surface temperature (T) during 1960–2013, with correlation coefficients (r) of 0.89, −0.88, and −0.85, respectively. Very heavy precipitation events are also weakly correlated with global mean T (r = 0.32 with the attained significance p = 0.02). Detrending the data reduces the correlations to 0.28, −0.27, −0.33, and 0.28 for annual number of dry days, trace days, light events, and very heavy precipitation events, respectively.
but they are still statistically significant at the 5% level. This suggests that there are more dry days and very heavy events, and fewer trace days and light precipitation events in warmer years, than in cooler years. Thus, in this section, we analyze the dependence of the changes in precipitation histograms over China and its subregions on global-mean temperature using the interannual method used by Liu et al. (2009) and Shiu et al. (2012) (see section 2e for details).

In Fig. 9, the normalized frequency change ($\Delta F/\Delta T$) for dry days, trace days, and light precipitation events averaged over the whole of China is plotted as a function of $\Delta T$, with the red dots representing the mean of the $\Delta F/\Delta T$ ratio of 40 nonoverlapping data points. From these 40 data points, the $\pm 1$ standard deviation range for both $\Delta T$ and $\Delta F/\Delta T$ ratio was computed, shown in Fig. 9 as the horizontal and vertical bars, respectively. For all three cases shown in Fig. 9, the $\Delta F/\Delta T$ ratio varies wildly for small $\Delta T$ cases, which is expected as the $\Delta F$ is essentially random noise when the two years have similar $T$, and the $\Delta F/\Delta T$ ratio is enlarged due to the small $\Delta T$ values. We found that the data points with small $\Delta T$ (e.g., $<0.2$ K) in Fig. 9 result mainly from short-term (interannual to multiyear) variations, while the larger $\Delta T$ cases primarily arise from decadal and long-term changes (e.g., the 1960s vs the 2000s) as $\Delta T$ values increase with time in the global-mean $T$ series from 1960 to 2013 (IPCC 2013). Furthermore, the mean $\Delta F/\Delta T$ ratio converges to a stable value as $\Delta T$ increases (Fig. 9). Thus, we consider the mean $\Delta F/\Delta T$ ratio of the group (red dots in Fig. 9) with the largest $\Delta T$ (denoted as $\Delta F/\Delta T_c$) as the decadal and long-term response ratio of the frequency to unit global warming. Thus, the $\Delta F/\Delta T_c$ ratio derived here is based on decadal to long-term changes, even though we used the interannual method. However, this ratio should not be equated to the response ratio under GHG-induced global warming, since internal natural variations are likely a significant contributor to the $\Delta F/\Delta T_c$ ratio estimated here, and the $\Delta F/\Delta T$ ratio should be much smaller for the GHG-induced warming case than the internal climate variability case due to cancellations of regional $\Delta T$ with opposite signs in the latter case (see further discussion on this in section 4).
TABLE 3. Linear trends of precipitation frequency and amount for different types of events over China and its six subregions during 1960–2013. The unit is % of the 1960–2013 mean per decade. Bold and italic numbers are statistically significant at the 5% and 10% level, respectively.

<table>
<thead>
<tr>
<th>Region</th>
<th>Light</th>
<th>Moderate</th>
<th>Heavy</th>
<th>Very heavy</th>
<th>Total</th>
<th>Trace</th>
<th>Dry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>China</td>
<td>−3.85</td>
<td>−1.17</td>
<td>0.19</td>
<td>1.51</td>
<td>−3.18</td>
<td>−8.22</td>
<td>3.78</td>
</tr>
<tr>
<td>NW</td>
<td>0.71</td>
<td>3.69</td>
<td>7.73</td>
<td></td>
<td>0.93</td>
<td>−7.39</td>
<td>1.09</td>
</tr>
<tr>
<td>SW</td>
<td>−3.32</td>
<td>−0.98</td>
<td>−0.64</td>
<td>−2.53</td>
<td>−2.92</td>
<td>−8.45</td>
<td>6.01</td>
</tr>
<tr>
<td>NE</td>
<td>−1.80</td>
<td>0.10</td>
<td>−0.22</td>
<td>−0.01</td>
<td>−1.56</td>
<td>−11.90</td>
<td>3.16</td>
</tr>
<tr>
<td>NC</td>
<td>−5.01</td>
<td>−1.18</td>
<td>−1.50</td>
<td>−2.69</td>
<td>−4.32</td>
<td>−10.93</td>
<td>2.95</td>
</tr>
<tr>
<td>YZ</td>
<td>−5.41</td>
<td>−1.30</td>
<td>0.66</td>
<td>3.85</td>
<td>−4.14</td>
<td>−6.69</td>
<td>4.34</td>
</tr>
<tr>
<td>SE</td>
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<td>−1.49</td>
<td>0.95</td>
<td>2.31</td>
<td>−3.70</td>
<td>−5.56</td>
<td>5.68</td>
</tr>
<tr>
<td>Amount</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>China</td>
<td>−1.25</td>
<td>−1.14</td>
<td>0.22</td>
<td>2.01</td>
<td>−0.18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NW</td>
<td>1.81</td>
<td>3.79</td>
<td>7.87</td>
<td>−1.47</td>
<td>2.82</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SW</td>
<td>−0.31</td>
<td>−1.07</td>
<td>−0.61</td>
<td>−2.69</td>
<td>−0.88</td>
<td></td>
<td></td>
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<tr>
<td>NE</td>
<td>−0.08</td>
<td>−0.21</td>
<td>0.24</td>
<td>0.94</td>
<td>−0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NC</td>
<td>−2.23</td>
<td>−1.13</td>
<td>−1.62</td>
<td>−3.17</td>
<td>−1.94</td>
<td></td>
<td></td>
</tr>
<tr>
<td>YZ</td>
<td>−1.78</td>
<td>−1.18</td>
<td>0.82</td>
<td>4.49</td>
<td>0.50</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SE</td>
<td>−2.24</td>
<td>−1.37</td>
<td>0.94</td>
<td>2.98</td>
<td>0.34</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The $\Delta F/\Delta T_c$ ratios of dry days, trace days, and light precipitation events averaged over whole China are 20.63%, −46.53%, and −22.38% K$^{-1}$, respectively, and they have relatively small uncertainty range (Fig. 9). This means that over China dry days would increase by 20.63%, and trace days and light precipitation events would decrease by 46.53% and 22.38%, respectively, for each 1-K increase in global mean temperature. The same method can be used to obtain the $\Delta F/\Delta T_c$ ratios for other precipitation categories over China and the six subregions.

Based on long-term mean histograms of precipitation amount, we binned the daily precipitation for each 0.5° grid box within China or one of its subregions into 10 bins with equal precipitation amount (i.e., 10% contribution from each bin). The ranges of the 10 bins for China as a whole and the six subregions are given in Table 4. As in Liu et al. (2009) and Shiu et al. (2012), we treated each gridded daily precipitation data equally as an independent data point or precipitation event in grouping the precipitation bins and in computing the frequencies over a region. Thus, the histograms created here contain both temporal and spatial variations, in contrast to histograms for precipitation at a fixed location. In particular, the heavy and light precipitation bins for a region (e.g., the whole of China) may be concentrated in certain part of the region (e.g., SE for heavy precipitation and NW for light precipitation). As such, changes in the histograms discussed here and some previous studies can result from changes in precipitation spatial patterns (e.g., increases in tropical/low-latitude precipitation and decreases in subtropical/arid land precipitation), and thus they do not necessarily imply a change in local precipitation PDF. This is very different from analyses of the PDFs at a fixed location (e.g., at each grid box; see Sun et al. 2007). This issue has been largely ignored in previous studies (e.g., Lau and Wu 2007; Liu et al. 2009; Shiu et al. 2012; Lau et al. 2013), and their results are often incorrectly interpreted as what would happen to local precipitation PDF, rather than being due to the above-mentioned precipitation change patterns to a large degree. Nevertheless, changes in the histograms that include both spatial and temporal variations, as discussed below and previously, still provide useful information regarding how light and heavy precipitation would change over a given domain.

Figure 10 compares the $\Delta F/\Delta T_c$ ratios for dry days, trace days, and all precipitation events, as well as for the frequency of precipitation events falling into the 10 bins listed in Table 4 for China and the six subregions. For China as a whole, the $\Delta F/\Delta T_c$ ratios for the top bin (i.e., category 10, the top 10% heaviest precipitation) and the bottom bin (i.e., category 1, the bottom 10% lightest precipitation) are 24% and −27% K$^{-1}$, respectively. For the other bins, the $\Delta F/\Delta T_c$ ratios are relatively small and have large uncertainties, although they do increase from slight negative to small positive values as the intensity increases. Meanwhile, all precipitation events show a decrease of −17% K$^{-1}$, compared with an increase of 21% K$^{-1}$ in dry days and a decrease of −46% K$^{-1}$ in trace days, as already shown in Fig. 9. The shape of the $\Delta F/\Delta T_c$ ratio over the 10 bins is qualitatively consistent with those shown by Liu et al. (2009) and Shiu et al. (2012) using the GPCP pentad (5-day mean) precipitation data, although their magnitude of change is larger, except for the lightest bin for which they show small changes.

It can be seen that the shapes of the $\Delta F/\Delta T_c$ ratio over YZ and SE (Figs. 10f,g) are similar to that for China as a whole (Fig. 10a). In NW, the $\Delta P/\Delta T_c$ ratios are positive for all bins except category 1 (lightest precipitation) and the ratio increases with the intensity. In contrast, the $\Delta F/\Delta T_c$ ratios are negative for all 10 bins in SW. In NE and NC, except for the lowest bin, the $\Delta F/\Delta T_c$ ratio is close to zero. Similar to the whole of China, the $\Delta F/\Delta T_c$ ratio is positive for dry days but negative for trace days and all precipitation events for all the subregions except for NW, where the $\Delta F/\Delta T_c$ ratio is just positive for all precipitation events.

We also examined the normalized precipitation amount change (i.e., $\Delta P/\Delta T_c$) of the 10 bins. The shapes of the $\Delta P/\Delta T_c$ ratio (not shown) are similar to those of the $\Delta F/\Delta T_c$ ratio shown in Fig. 10 for China.
and the six subregions. We emphasize that the intensity categories used in Figs. 9 and 10 are region-dependent (see Table 4), in contrast to the intensity bins used in Figs. 4–7. In particular, all the 10 bins for NW belonged to the light or moderate precipitation categories shown in Table 2 and Fig. 7, which shows increases from 1960 to 2013 for both. This is consistent with the positive $\Delta F/\Delta T_c$ ratio shown in Fig. 10b.

TABLE 4. Ranges of 10 bins with equal total precipitation amount over China and the six subregions. The unit is mm day$^{-1}$. Each bin or range has a lower and upper limit. Shown here are the upper limit of bins 1–9 and the lower limit of bin 10; the lower limit for bin 1 is 0.1 mm day$^{-1}$.

<table>
<thead>
<tr>
<th>Subregion</th>
<th>Bin 1</th>
<th>Bin 2</th>
<th>Bin 3</th>
<th>Bin 4</th>
<th>Bin 5</th>
<th>Bin 6</th>
<th>Bin 7</th>
<th>Bin 8</th>
<th>Bin 9</th>
<th>Bin 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>4.0</td>
<td>7.7</td>
<td>11.6</td>
<td>16.2</td>
<td>21.6</td>
<td>28.4</td>
<td>37.6</td>
<td>51.7</td>
<td>78.4</td>
<td>≥78.4</td>
</tr>
<tr>
<td>NW</td>
<td>1.4</td>
<td>2.7</td>
<td>4.1</td>
<td>5.6</td>
<td>7.4</td>
<td>9.5</td>
<td>12.2</td>
<td>16.0</td>
<td>22.6</td>
<td>≥22.6</td>
</tr>
<tr>
<td>SW</td>
<td>3.1</td>
<td>5.7</td>
<td>8.4</td>
<td>11.4</td>
<td>14.8</td>
<td>19.1</td>
<td>24.9</td>
<td>33.8</td>
<td>51.0</td>
<td>≥51.0</td>
</tr>
<tr>
<td>NE</td>
<td>2.6</td>
<td>5.1</td>
<td>7.8</td>
<td>10.9</td>
<td>14.4</td>
<td>18.7</td>
<td>24.3</td>
<td>32.2</td>
<td>46.3</td>
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</tr>
<tr>
<td>NC</td>
<td>3.7</td>
<td>7.0</td>
<td>10.8</td>
<td>15.0</td>
<td>20.1</td>
<td>26.6</td>
<td>35.2</td>
<td>48.2</td>
<td>72.2</td>
<td>≥72.2</td>
</tr>
<tr>
<td>YZ</td>
<td>4.9</td>
<td>9.0</td>
<td>13.4</td>
<td>18.2</td>
<td>24.0</td>
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<td>40.7</td>
<td>54.8</td>
<td>80.5</td>
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</tr>
<tr>
<td>SE</td>
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<td>16.1</td>
<td>22.0</td>
<td>28.8</td>
<td>37.1</td>
<td>48.2</td>
<td>64.8</td>
<td>97.4</td>
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</tr>
</tbody>
</table>
4. Summary and discussion

a. Summary

In this study, we first homogenized daily rain gauge records for 1960–2013 from 632 stations over China, and then applied this homogenized dataset of daily precipitation ($P$) to study the climatology and long-term changes in the FOC of dry ($P = 0$) days, trace ($0 < P < 0.1 \text{ mm day}^{-1}$) days, and the FOC and accumulated precipitation amount of daily precipitation events of different intensities over China and its six subregions.

Our homogenization analysis showed that the CMA dataset of daily precipitation contains homogeneous records for most of the stations, with only about 5% of the stations needing adjustments that have small impacts on regional and national averages. In addition, we also examined the frequency change in these events relative to changes in global mean temperature ($\Delta F/\Delta T_c$) using the interannual method proposed by Liu et al. (2009) (but our $\Delta F/\Delta T_c$ ratio reflects mostly decadal to long-term changes). Our major findings are summarized in Fig. 11 and are listed below.

Long-term mean precipitation amount and precipitation days are largest in southeast China. They decrease northward and westward, with the lowest values in northwest China. In contrast, dry days are much more...
frequent (>200 days yr$^{-1}$) over northwest and northern China than in southeast and southwest China (all regions and abbreviations are defined in Fig. 1).

Dry (trace) days exhibited significant increasing (decreasing) trends across most of China from 1960 to 2013, with a linear trend of 3.78% ($\pm$8.22%) decade$^{-1}$ for China as a whole. Both the frequency and accumulated precipitation amount of light ($0.1 \leq P < 10$ mm day$^{-1}$) and moderate ($10 \leq P < 25$ mm day$^{-1}$) precipitation events increased (decreased) significantly in western (eastern) China west (east) of about 100$^\circ$E. Changes in heavy ($25 \leq P < 50$ mm day$^{-1}$) precipitation frequency and amount were small over most of China. Very heavy ($P \geq 50$ mm day$^{-1}$) precipitation occurs mainly in southeast China: its area-averaged frequency and accumulated amount increased significantly by $\sim$1.51% and 2.01% decade$^{-1}$, respectively, from 1960 to 2013.

There has been a clear shift from light to heavy precipitation during 1960–2013 over China as a whole, mainly over the YZ and SE subregions. Very heavy precipitation events have become more frequent, while light precipitation events have decreased over eastern China. This was accompanied by significant increases of dry days and decreases of trace days. Large regional differences existed in the changes of precipitation types. Over the NW region, both precipitation amount and frequency of moderate and heavy precipitation increased significantly from 1960 to 2013. Over SW, almost all precipitation categories showed decreasing trends for both precipitation amount and frequency. However, in NC and NE, except for the significant decrease of light precipitation amount and frequency, no significant changes were found for moderate, heavy, and very heavy precipitation.

The bottom (lightest) and top (heaviest) bins of precipitation events had a stronger dependence on global mean temperature than other categories. For China as a whole, the FOC of dry days was found to increase 20.63% per 1-K increase in global mean temperature, while trace days and all precipitation days decreased by 46.53% and 20.89%, respectively, for 1-K warming. This $\Delta F / \Delta T_c$ ratio for the lightest and heaviest precipitation bins showed the largest decrease and increase of $-27.12\%$ and 24.21 K$^{-1}$, respectively, while the $\Delta F / \Delta T_c$ ratio for other bins showed small changes with relatively large uncertainties. Although the shape of the $\Delta F / \Delta T_c$ as a function of the intensity categories differed among the different subregions, the decreases in the lightest bin of precipitation, all precipitation events, and trace days, as well as the large increase of dry days, were robust in all the subregions except NW.

b. Discussion

The above results suggest a shift of the precipitation distribution from light to intense precipitation together with more dry days across the whole of China. Such a change implies increased risks of both drought and flash floods. These results are consistent with the increased...
drought over eastern China since the 1950s (e.g., Dai 2011). They are also in agreement with observed changes over other regions of the world (e.g., Karl and Knight 1998; Groisman et al. 2005; Goswami et al. 2006). Furthermore, the observed changes are qualitatively consistent with model projected changes under increasing GHG concentrations (Sun et al. 2007; Chou et al. 2012), although we should note that the observed changes of precipitation in eastern China are significantly affected by internal climate variability (Zhou et al. 2013; Qian and Zhou 2014). How to distinguish the changes in precipitation characteristics due to internal climate variability and external GHG forcing deserves further study.

We realize that the $\Delta F/\Delta T_c$ ratios shown in Fig. 9 (and in Fig. 10 for some bins) are very large and they may not be applicable to the large (3–4 K) future warming projected by climate models (IPCC 2013). Internal climate variability, such as that associated with El Niño–Southern Oscillation (ENSO; Dai and Wigley 2000) and the interdecadal Pacific oscillation (IPO; Li et al. 2010; Dai 2013; Zhou et al. 2013; Dong and Dai 2015; Qian and Zhou 2014) may also influence the $\Delta F/\Delta T_c$ ratio, despite the $\Delta F/\Delta T_c$ ratio representing primarily decadal and long-term changes as discussed above. These ratios may not be considered solely as a response to GHG-induced global warming, such as those shown by Sun et al. (2007). The internal climate variability often induces large positive and negative regional changes in $T$ and $P$ but with relatively small changes in global mean $T$ due to the cancellation of the regional anomalies with opposite signs. A small global-mean $\Delta T$ would lead to large $\Delta F/\Delta T_c$ ratios. This also applies to global analyses of the $\Delta F/\Delta T_c$ ratio for different intensity categories (e.g., Liu et al. 2009; Shiu et al. 2012), since these precipitation categories usually have regional preferences (e.g., heavy precipitation is concentrated mostly in the tropics, while light precipitation is mostly in the subtropics and high latitudes). This means that the regional changes induced by internal variability such as the ENSO and IPO may have large influences on the $\Delta F$ of different intensity categories, but their contributions to global mean $\Delta T$ may be small due to regional cancellations of the $\Delta T$ anomalies, leading to large $\Delta F/\Delta T_c$ ratios. In contrast, the GHG-induced surface warming is present over the majority of the globe, although its spatial distribution is not uniform, and the associated regional $\Delta P$ changes can be either positive or negative (e.g., decreases in the subtropics) (IPCC 2013). Thus, the regional $P$ changes induced by GHGs could still contribute to the $\Delta F$ change while all the regional $\Delta T$ changes would contribute to the global mean $\Delta T$ (i.e., no regional cancellation). This means that for a similar regional $\Delta T$ change (e.g., over China), which is directly related to the regional precipitation change (e.g., through temperature’s influence on water vapor), the global mean $\Delta T$ would be much larger for the GHG-induced warming case than the case due to internal climate variability. This can help explain why the $\Delta P/\Delta T$ ratio derived using the interannual method (Liu et al. 2009; Shiu et al. 2012), which includes regional variations induced by internal climate variability, often greatly exceeds that derived from climate models under increasing GHGs (Sun et al. 2007). It may also explain why the reanalysis data show much larger $\Delta P/\Delta T$ ratio than the climate models (Shiu et al. 2012), even though the atmospheric models in the two cases are similar. This could be due to the fact that the $\Delta P$ and $\Delta T$ in the reanalyses result largely from internal variability (and thus small global mean $\Delta T$) whereas they mainly come from GHG-induced changes in climate models (i.e., large global mean $\Delta T$).

Extreme light and heavy precipitation events are more easily affected by global warming than moderate and total precipitation (Trenberth et al. 2003; Zhang et al. 2013); moderate precipitation is likely caused by atmospheric internal dynamics (Li and Li 2013). As given in section 3b, dry days, trace days, and extreme light and heavy precipitation events exhibited nationally consistently significant trends (Figs. 6 and 7). But for the changes in medium-intensity precipitation events, large regional differences existed. Meanwhile, dry and trace days and the lightest and heaviest bins of precipitation larger than other categories, but also the corresponding ±1 standard deviation ranges are not across the zero line, indicating that the response of these precipitation characteristics to global warming is robust. Other categories had smaller $\Delta F/\Delta T_c$ values (sometimes close to zero line) and larger uncertainty ranges.

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REFERENCES


