Trends in extreme precipitation indices across China detected using quantile regression

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Abstract
For China, long-term changes are detected not only in the means of eight extreme precipitation indices, but also in their distribution shapes by quantile regression. This resulted in different trends for the means and other aspects of the index distributions. The differences between changes in the means and upper/lower extremes vary with region and index. A noteworthy feature is that changes in upper tails of the index distributions across a broad area, especially in the south, are at a much higher rate than mean trends estimated by the traditional linear regression model. This has practical implications for disaster risk management.

Keywords: extreme precipitation indices; quantile trend; quantile regression; China

1. Introduction

In recent decades, changes in climatic extremes have attracted widespread attention, owing to their huge impact on human life, environment, economy, and society (IPCC, 2012; Chen et al., 2015). Numerous studies of trends in extreme precipitation events have been made for various regions of the world (Jones et al., 1999; Klein Tank et al., 2006; Vincent and Mekis, 2006; Donat et al., 2013).

In China, a number of studies on extreme precipitation indices have been conducted (Wang and Zhou, 2005; Zhai et al., 2005; Fu et al., 2008; You et al., 2011). These studies have reported trends in several precipitation indices over the last few decades. Annual total precipitation, average wet-day precipitation, maximum 1- and 5-day precipitation, and number of heavy precipitation days show weak increasing trends, whereas a decreasing trend has been observed for number of consecutive dry days (CDD). For all precipitation indices except number of CDD, stations in the Yangtze River Basin and southeastern and northwestern China have the largest positive trends, whereas stations in the Yellow River Basin, central China, and the Sichuan Basin have the largest negative trends.

Most of the studies above have paid much attention to the mean trend of extreme precipitation indices, e.g. that estimated by linear regression models based on ordinary least squares regression (LSR). Although LSR is a commonly used method in studying linear trends, they have limitations. For example, they only provide information on linear trend of the mean condition of the indices, but trends of other aspects (e.g. upper tails) of the index distributions, which are generally more valuable than the mean trend in climate risk studies (Tareghian and Rasmussen, 2012), cannot be properly addressed.

Quantile regression (QR) was developed as an extension to LSR (Koenke and Basset, 1978). This method has the ability to estimate slopes of changes not only in the mean but in all parts of the distribution of a time series. Therefore, this method can provide a more complete picture of long-term temporal trend in those series (Barbosa, 2008).

In contrast to past research, this study focuses on investigating slopes of trends in different quantiles of the conditional distributions of eight extreme precipitation indices in China, particularly those in the upper tails of those distributions, using QR. Although this method has been recently introduced in climate change studies (Barbosa, 2008; Tareghian and Rasmussen, 2012; Lee et al., 2013; Wasko and Sharma, 2014), to the author’s knowledge, its application to extreme precipitation indices in China is new. Comparison between quantile and mean trends of the indices can aid understanding of the merits of QR. More importantly, application of this method is helpful for comprehensive understanding of long-term trends of precipitation extremes in China, in terms of extent and magnitude. Furthermore, investigation of changes in upper tails of the distributions of precipitation extremes, which often cause great climate disasters, is more interesting and useful in climate risk assessment, in comparison with the central tendency of precipitation extremes.

The structure of this article is as follows. The data and method used are described in Section 2. Results of quantile trends are presented in Section 3. Key findings are summarized in Section 4.
2. Data and method

2.1. Data

An observed daily precipitation data set from 825 stations in China for the period 1961–2013 was collected from the China Meteorological Data Sharing Service System. This data set is quality controlled, including check and correction of internal and spatial consistency and potential outliers (http://data.cma.cn for details). A homogeneous long-term climate series is the basis in climate change research. It is defined as one time series where variations are caused by variations in weather and climate only. Unfortunately, most climatic time series are affected by a number of non-climatic factors (e.g. instrument change, different observing practices, and station relocations) that make these data unrepresentative of the actual climate variation with time (Peterson et al., 1998). Zhang et al. (2012) found that homogeneity of the monthly precipitation data is satisfactory at most stations in China using the RHtest method established by Wang et al. (2007) to be used to test the homogeneity of yearly, monthly, and daily time series and to adjust the series with lag-1 autocorrelation error and multiple change points. They also found that relocation of stations is one of the main causes of inhomogeneity in the precipitation data. Wijngaard et al. (2003) concluded that inhomogeneity could be caused by true local climate variations and may impact the analysis of trends and variability in climatic extremes. Considering that our analysis concentrates on upper-tail trends of precipitation extremes, we only removed stations with obvious relocation and incomplete time series for the period 1961–2013. Finally, we retained a total of 578 stations for use in the analysis.

2.2. Definition of extreme precipitation indices

Eight indices of precipitation extremes, which are recommended by the Expert Team on Climate Change Detection Monitoring and Indices (Klein Tank et al., 2006), were selected. These are numbers of days with heavy [Precipitation (Pr) > 10 mm] and very heavy (Pr > 20 mm) precipitation (R10MM and R20MM), maximum numbers of consecutive wet days (CWD) (Pr ≥ 1 mm) and CDD, total precipitation on very wet (Pr > 95th percentile) and extreme wet (Pr > 99th percentile) days (R95PTOT and R99PTOT, mm), and finally, maximum 1- and 5-day precipitation (RX1DAY and RX5DAY, mm). A detailed description of the indices is in Donat et al. (2013). The indices were calculated using the RclimDex software package, developed at the Meteorological Service of Canada (available from http://etccdi.pacificclimate.org/software.shtml). The 95th and 99th percentiles of precipitation are calculated during the period of 1961–1990, which is defined as the latest global normal period currently used for climate reference by World Meteorological Organization (http://public.wmo.int for details). The indices were calculated on an annual basis at each station.

2.3. Quantile regression

QR is generally regarded as an extension of LSR. Within the LSR framework, the response variable (Y) is linearly related to time (t): \( Y = f(\alpha, \beta, t) = \alpha t + \beta \), with \( \alpha \) denoting the linear slope and \( \beta \) the constant intercept. That is, the variable Y can be described as a function of time \( t \) and parameters \( \alpha \) and \( \beta \). The two parameters are assessed from the ordinary least squares estimate of the expected value of response variable \( Y \) conditional on \( t \) \( [E(Y|t)] \), and thereby calculated by minimizing the sum of squared residuals

\[
\sum_i [y_i - f(\alpha, \beta, t)]^2
\]  

(1)

Let \( Y \) be a random variable with cumulative distribution function \( F_y(y) \). The \( \tau \)th quantile of \( Y \) is defined \( Q_y(\tau) \) such that \( P(Y \leq Q_y(\tau)) = \tau \), where, \( \tau \in [0, 1] \). The quantile function \( \tilde{Q}_y(t) \) is defined as \( \tilde{Q}_y(t) = F_y^{-1}(t) \). Considering the conditional distribution \( Y \) given \( T=t \), the conditional quantile function is defined as \( Q_y(\tau|t) \). Therefore, QR can be interpreted in a similar way, by replacing \( E(Y|t) \) with the quantile of the response variable \( Q_y(\tau|t) \). For quantile \( \tau \), the linear QR model can be written as

\[
y(\tau|t) = f'(\alpha\tau, \beta\tau, t) = \alpha t + \beta \tau + \xi
\]  

(2)

where \( \alpha \) is the quantile slope and \( \beta \) is the intercept for each \( \tau \). \( \xi \) is the error with the expectation of zero. Instead of LSR, the two parameters are estimated from the conditional quantile function by minimizing the sum of asymmetrically weighted absolute residuals.

\[
\sum_i \rho_{\tau} |y_i - f'(\alpha\tau, \beta\tau, t)|
\]  

(3)

where \( \rho_{\tau} \) is the tilted absolute value function (Barbosa, 2008).

Detailed description of the QR method can be found in the literature (Barbosa, 2008; Tareghian and Rasmussen, 2012; Lee et al., 2013).

2.4. Trend analysis

The QR method was used to estimate slopes of trends in quantiles 0.01–0.99 (in steps of 0.01) of the annual extreme precipitation indices for all stations. The ‘quantreg’ package within R software was run for QR analysis. The mean trend was calculated by LSR, based on ordinary least squares. Confidence intervals (CIs) for the slopes of mean and quantiles were assessed using ordinary bootstrap method. The adjusted bootstrap percentile intervals were generated using the ‘boot’ package within R software (Davison and Kuanon, 2002). Statistical significances were defined using whether zero lies in the CI at the 5% level. Regional time series of the indices were calculated as their arithmetic average over all the stations. Trends in quantiles 0.05, 0.50 and 0.95 for each index were compared with the mean trend to investigate their similarities and differences. Finally, we chose slopes...
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3. Results

3.1. Quantile trends of regional precipitation indices

Figure 1 displays regional mean time series of the eight extreme precipitation indices in China, along with mean trends estimated by LSR and trends in 0.05 (lower), 0.50 (median), and 0.95 (upper) quantiles estimated by QR. These correspond respectively to 5% (minima), 50% (median), and 95% (maxima) of the ordered observations. Table 1 lists trends in Figure 1 and their corresponding significance levels. The mean and median trends can be understood as a measurement of central tendency for the indices, whereas those of the lower and upper quantiles reflect long-term trend in the lower and upper tails of the conditional distributions of the indices. As can be seen in the figure, trends of the median for all indices are very close to those of the mean, whereas the upper and lower quantiles show significantly different trends from the mean slopes. Specifically, for very wet days (R95PTOT) and extremely wet days (R99PTOT), there are increasing trends in the upper quantile, with larger slopes than those of the lower, median, and mean quantiles (Figure 1(a) and (b)). For consistency of dry days, CDD shows no substantial change in central tendency with time, but there is evidence that its distribution narrows (Figure 1(c)). For CWD, there is a significantly decreasing trend in the median and mean. However, trend lines in the lower and upper quantiles are almost parallel, suggesting that although the mean trends can be understood as a measurement of central tendency for the indices, whereas those of the lower and upper quantiles reflect long-term trend in the lower and upper tails of the conditional distributions of the indices. As can be seen in the figure, trends of the median for all indices are very close to those of the mean, whereas the upper and lower quantiles show significantly different trends from the mean slopes. Specifically, for very wet days (R95PTOT) and extremely wet days (R99PTOT), there are increasing trends in the upper quantile, with larger slopes than those of the lower, median, and mean quantiles (Figure 1(a) and (b)). For consistency of dry days, CDD shows no substantial change in central tendency with time, but there is evidence that its distribution narrows (Figure 1(c)). For CWD, there is a significantly decreasing trend in the median and mean. However, trend lines in the lower and upper quantiles are almost parallel, suggesting that although the mean
Upper-quantile trend slopes of the index distribution shapes to obtain statistically used quantile 0.95 to reflect changes in upper tails quantile 0.99 of the index distributions has a much upper-quantile trends of the conditional distribu-

In this section, we examine spatial patterns of precipitation extremes

3.3. Spatial patterns of upper-quantile trends of precipitation extremes

Table 1. Quantile and mean trends of precipitation indices during 1961–2013 for China as a whole.

<table>
<thead>
<tr>
<th>Indices</th>
<th>Units</th>
<th>Mean</th>
<th>0.05</th>
<th>0.50</th>
<th>0.95</th>
</tr>
</thead>
<tbody>
<tr>
<td>R95PTOT</td>
<td>mm decade⁻¹</td>
<td>4.83</td>
<td>2.66</td>
<td>6.27</td>
<td>7.16</td>
</tr>
<tr>
<td>R99PTOT</td>
<td>mm decade⁻¹</td>
<td>3.03</td>
<td>3.54</td>
<td>2.20</td>
<td>4.68</td>
</tr>
<tr>
<td>CDD</td>
<td>days decade⁻¹</td>
<td>-0.63</td>
<td>1.66</td>
<td>-1.04</td>
<td>-3.30</td>
</tr>
<tr>
<td>CWD</td>
<td>days decade⁻¹</td>
<td>-0.11</td>
<td>-0.01</td>
<td>-0.11</td>
<td>-0.03</td>
</tr>
<tr>
<td>R10MM</td>
<td>days decade⁻¹</td>
<td>-0.16</td>
<td>-0.28</td>
<td>-0.15</td>
<td>-0.30</td>
</tr>
<tr>
<td>R20MM</td>
<td>days decade⁻¹</td>
<td>0.02</td>
<td>-0.01</td>
<td>0.06</td>
<td>-0.20</td>
</tr>
<tr>
<td>RX1DAY</td>
<td>mm decade⁻¹</td>
<td>0.80</td>
<td>1.16</td>
<td>0.46</td>
<td>1.40</td>
</tr>
<tr>
<td>RX5DAY</td>
<td>mm decade⁻¹</td>
<td>0.69</td>
<td>-1.03</td>
<td>0.40</td>
<td>2.54</td>
</tr>
</tbody>
</table>

Significant trends (at the 5% significance level) are indicated in bold.

trend decreased, trends in the extreme quantiles did not change dramatically (Figure 1(d)). For both RX1DAY and RX5DAY, the upper-quantile slopes are signifi-
cant and greater than those of the median and mean (Figure 1(g) and (h)). For R10MM and R20MM, there are no significant changes in the mean and quantiles (Figure 1(e) and (f)).

3.2. Number of stations with significant trends on quantile

If trend of an index in a given quantile for a given station is significant at the 5% level, we consider that the index in this quantile has a significant impact on this station. The more the number of stations with significant trends, the wider the impact of this index in a given quantile on the country. Thus, we investigated the dependence of number of stations with significant trends on quantile for each index. The QR method was implemented for a range of quantiles 0.01–0.99 (in steps of 0.01) for all stations and indices. As can be seen in Figure 2, number of stations at which trends are statistically significant (at the 5% significance level) varies by quantile. In particular, for quantiles greater than 0.90 or less than 0.10, number of stations rapidly increases with quantile. Compared with ~50 stations having significant mean trends (dots), upper quantiles show significant trends at ~150 stations. This finding implies that change in the upper and lower quantiles of the distributions of the extreme precipitation indices has a more widespread influence than that of their means across the country.

3.3. Spatial patterns of upper-quantile trends of precipitation extremes

In this section, we examine spatial patterns of upper-quantile trends of the conditional distributions of the indices. Although long-term changes in quantile 0.99 of the index distributions has a much wider influence over the entire region (Figure 2), we used quantile 0.95 to reflect changes in upper tails of the index distribution shapes to obtain statistically stable and reliable results. Upper-quantile trend slopes were compared with mean trends to examine their similarities and differences in terms of spatial pattern. To facilitate description of our result, we separated China into seven regions: northwestern (NW), southwestern (SW), southern (S), central (C), eastern (E), northern (N), and northeastern (NE) (Figure 3(a)).

For R95PTOT and R99PTOT, upper-quantile and mean trends display consistently spatial patterns across the country. Increasing trends were detected in northwestern, northeastern, eastern and southern China. There are declining trends in northern and central China and the western part of southern China, in line with You et al. (2011). However, upper-quantile trends have greater magnitudes and are statistically significant at more stations than the mean trends. The strongest increasing trend in upper quantile was seen in eastern and southern China, with magnitudes up to 200 mm decade⁻¹ for R95PTOT (Figure 3(a) and (b)), and 150 mm decade⁻¹ for R99PTOT. Comparing these with the mean trend for R95PTOT (<50 mm decade⁻¹), we found that rates of changes in upper quantile greatly strengthened. Since most Chinese people are living in the east, this significant increasing trend of the sever extreme precipitation has put a great pressure on the society. On the other hand, it also raises an important scientific question about the causes of this change and how this will evolve in the future. A recent study (Ou et al., 2013) compared the observed trends for the means in a number of extreme precipitations in China, which reveals that while the temporal trend in the extreme precipitation for western China is well captured by most models, the trends of the extreme precipitation in eastern China are poorly captured by most models. This is especially true for the so-called southern flood and northern drought pattern. Eastern China is strongly influenced by Asian summer monsoon and human activities. Further studies are needed to identify processes that are responsible for this change and to reliably project the future changes.
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Figure 3. Comparison of mean and upper (0.95) quantile trends for four precipitation indices. Units of panels (a) and (b) are 50 mm decade$^{-1}$; (c) and (d) 10 days decade$^{-1}$; (e) and (f) days decade$^{-1}$; (g) and (h) 10 mm decade$^{-1}$. To facilitate discussion, the region is separated into seven subregions in panel (a). Positive and negative values denote increasing and decreasing trends, respectively.

For CDD, there are decreasing trends in the upper quantile in northwestern, northeastern, and eastern regions while there are increasing trends in northern, central, and southern regions, in accordance with the spatial distribution of mean trends estimated by LSR. However, significant changes were detected by LSR only at stations in the northwest and northeast. There are larger magnitudes in upper-quantile trends at most stations in China, notably in the northwest, with trend $\sim$20 days decade$^{-1}$, compared to the mean trend with <10 days decade$^{-1}$ (Figure 3(c) and (d)). For CWD, the differences are minor between the upper-quantile and mean trends in the north, where weak or no trends were observed. Interestingly, great differences are visible between these in the central and south areas. There are decreasing trends in central and southern China.
and rising trends in eastern China for the two types of trends. However, the largest trends in the upper quantile are up to 4 days decade\(^{-1}\), relative to those of the mean (<1 day decade\(^{-1}\)).

For R10MM, pronounced decreasing trends were detected by LSR, mainly in central China and the western part of southern China, at a rate of \(~2\) days decade\(^{-1}\). For the upper quantile, there are larger negative trends (\(~5\) days decade\(^{-1}\)), mainly in central China and the western part of southern China, and positive ones (\(~5\) days decade\(^{-1}\)) in eastern China (Figure 3(e) and (f)). The R20MM results are similar to those of R10MM, but with weaker trends (\(~3\) days decade\(^{-1}\)) in the upper quantile.

For RX1day, there are no evident trends in the mean state. In contrast, the upper quantile has much stronger positive (in central and southern China) and negative (in northern China and eastern coastal part of China) trends, with magnitudes up to 70 mm decade\(^{-1}\), along with more stations with significant change (Figure 3(g) and (h)). The findings for RX5day agree with those of RX1day, but trends in the upper quantile reach 100 mm decade\(^{-1}\) for the former.

4. Summary and conclusion

The QR method was used to study trends in various quantiles of the conditional distributions of eight indices of precipitation extremes in China. Major findings are as follows.

1. The distributions of precipitation extremes in China have experienced variable changes in recent decades. For China as a whole, the entire distribution of CDD narrows with time, while that of RX5DAY widens. CWD shows a remarkable decline in the mean, but no obvious trends in the upper and lower quantiles. R95PTOT, R99PTOT, and RX1DAY show increases in the mean and three quantiles, with the upper quantile having a much higher trend. R10MM and R20MM do not have significant trend in the mean and three quantiles.

2. The number of stations with significant trends varies depending on quantile for each index. More stations with obvious changes were detected in the lower and upper tails of the distributions of the indices. This suggests that change in the extreme parts of the distributions of precipitation extremes occurs over a much broader region of China than those of the mean.

3. Change in maxima of the indices exhibits spatial patterns coherent with those of the means estimated by LSR. However, rates of such change are dramatically higher than those of the mean. The strengthened magnitude in rate varies by index and region. There are decreasing trends of CDD in northwestern, northeastern, and eastern China, and increasing ones in northern, central, and the western region of southern China. Region-wide, there are larger magnitudes of upper-quantile trends of CDD than those of the mean. There are increases for the other seven indices in northwestern, northeastern, and eastern China, but declines in northern, central, and southern China. However, the most remarkable changes in the rate of the upper-quantile trend concentrate in the south of China, relative to that of the mean trend.

Compared with LSR, the QR method provides a more complete picture of long-term trend of the conditional distributions of precipitation extremes. Change of precipitation extremes appears not only in the mean but also in various parts of their distributions. This indicates that analysis of the mean variability of extreme climate events is far from adequate in the study of extreme climate change. Given its advantage over LSR, QR should be considered for research into long-term climatic trend and risk assessment.

Our findings reveal that changes in upper extremes of the distributions of the extreme precipitation indices, which very often cause serious weather and climate risks, have occurred in a broader area of China and at a much higher rate than previously believed. No matter what processes are behind this change, we need to take the identified differences between upper-quantile and mean long-term trend of precipitation extremes seriously.

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