Quantile Regression–Based Spatiotemporal Analysis of Extreme Temperature Change in China

MENG GAO
Yantai Institute of Coastal Zone Research, Chinese Academy of Sciences, Yantai, China

CHRISTIAN L. E. FRANZKE
Meteorological Institute, and Center for Earth System Research and Sustainability, University of Hamburg, Hamburg, Germany

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ABSTRACT

In this study, temporal trends and spatial patterns of extreme temperature change are investigated at 352 meteorological stations in China over the period 1956–2013. The temperature series are first examined for evidence of long-range dependence at daily and monthly time scales. At most stations there is evidence of significant long-range dependence. Noncrossing quantile regression has been used for trend analysis of temperature series. For low quantiles of daily mean temperature and monthly minimum value of daily minimum temperature (TNn) in January, there is an increasing trend at most stations. A decrease is also observed in a zone ranging from northeastern China to central China for higher quantiles of daily mean temperature and monthly maximum value of daily maximum temperature (TXx) in July. Changes of the large-scale atmospheric circulation partly explain the trends of temperature extremes. To reveal the spatial pattern of temperature changes, a density-based spatial clustering algorithm is used to cluster the quantile trends of daily temperature series for 19 quantile levels (0.05, 0.1, ..., 0.95). Spatial cluster analysis identifies a few large clusters showing different warming patterns in different parts of China. Finally, quantile regression reveals the connections between temperature extremes and two large-scale climate patterns: El Niño–Southern Oscillation (ENSO) and the Arctic Oscillation (AO). The influence of ENSO on cold extremes is significant at most stations, but its influence on warm extremes is only weakly significant. The AO not only affects the cold extremes in northern and eastern China, but also affects warm extremes in northeastern and southern China.

1. Introduction

Climate change and global warming, especially changes in climate extremes, are of concern because of their severe societal and ecological impacts (Kharin et al. 2007; Hansen et al. 2012; Fyfe et al. 2013; Zhang and Zwiers 2013; Ji et al. 2014; Robeson et al. 2014; Lin and Franzke 2015; Franzke 2015, 2017). Climate extremes have already been extensively studied at global, regional, and local scales. Specifically, changes in temperature extremes have been identified in many parts of the world (Brown et al. 2008; You et al. 2011; Mika 2013; Monier and Gao 2015). At regional and local scales, unlike the warming trend of global mean temperature, a wide variety of changes in temperature extremes is possible (Alexander et al. 2006; Brown et al. 2008).

Local changes in temperature extremes not only influence individuals’ perceptions but also affect practical planning and ultimately drive mitigation policy (Chapman et al. 2013). It is therefore important to detect the changes in temperature extremes at regional and local scales and identify their connections to global climate change (Capparelli et al. 2013). In this study, we focus on the spatiotemporal variations of temperature extremes in China.

Trend identification and significance tests in climate time series are important issues in climate research (e.g., IPCC 2007; Franzke 2012). The traditional methodology for trend identification and significance test is by using linear regression or the nonparametric Mann–Kendall (M-K) test (Mann 1945; Kendall 1975). Long-range dependence (LRD; also called long memory or long-term persistence) refers to a serial correlation between distant observations of a time series that decays according...
to a power law. LRD may induce trendlike behaviors; therefore, the statistical uncertainty of the trend identification will significantly increase (Yue et al. 2002; Fatichi et al. 2009; Lennartz and Bunde 2009; Franzke 2010, 2012, 2013; Bunde et al. 2014; Ludescher et al. 2016). In previous studies, LRD has already been detected in multidecadal daily or monthly temperature time series (Caballero et al. 2002; Blender and Fraedrich 2003; Király et al. 2006; Vyushin and Kushner 2009; Franzke 2010, 2012) and even in millennial yearly temperature time series (Östvand et al. 2014, Nilsen et al. 2016). The first objective of this study is to examine the temperature series at different time scales for evidence of LRD.

Quantile regression, initiated by Koenker and Bassett (1978), offers an alternative trend-detection approach for identifying changes over time of any percentile values of climate variables (Barbosa 2008; Donner et al. 2012). Koenker and Schorfheide (1994) used quantile regression to reanalyze the global surface air temperature. Barbosa et al. (2011) examined the changes in daily mean air temperature over central Europe using quantile regression and found considerable spatial diversity. Shiau and Huang (2015) and Tan and Shao (2017) also proposed to detect the distributional changes of precipitation indices by estimating the regression coefficients of linear quantile regression at dense quantiles. For serially correlated temperature time series, Franzke (2013) proposed a new method to test the statistical significance of trends of extreme values in daily temperature time series with LRD based on quantile regression and surrogate data. The 5th and 95th percentiles of daily temperature were defined as the cold and warm temperature extremes, respectively. The second objective of this study is to test the statistical significance of trends of temperature extremes using quantile regression as in Franzke (2013), if there is evidence of LRD in temperature time series.

A few methods have been applied to investigate the spatial variation quantile trends at multiple percentiles. Reich (2012) developed a spatiotemporal quantile regression model by assuming that each quantile level changes linearly in time. Unlike Reich’s model-dependent method, Chapman et al. (2013) and Stainforth et al. (2013) derived a local trend parameter of temperature change; thus, the relative changes of temperature between different quantiles and between different geographical locations for the same quantiles could be evaluated. An alternative approach to detect spatial variation patterns of climate extremes is by combining quantile regression and cluster analysis (Barbosa et al. 2011; Shiau and Lin 2016). In previous studies, different distance metrics have been proposed to better measure the similarity of climate change patterns (Scotto et al. 2010, 2011). The spatial clustering was implemented using an agglomerative hierarchical method (Scotto et al. 2010, 2011; Barbosa et al. 2011; Shiau and Lin 2016), where spatial proximity between different sites was not included. When spatial variations of quantile trends of temperature are studied, it is more reasonable to apply spatial clustering algorithms that consider both geometrical properties and attributes simultaneously rather than agglomerative hierarchical methods. Our third objective is to investigate the spatial pattern of temperature changes in China by combining quantile regression and spatial clustering to consider both geometrical properties and attributes simultaneously.

Quantile regression can also be used for detecting the relation between climate extremes and large-scale climate patterns (Tareghian and Rasmussen 2013; Fan and Xiong 2015; Tan and Shao 2017). In China El Niño–Southern Oscillation (ENSO) is considered as an important factor for summer climate anomalies (Wang et al. 2008; Wu et al. 2010). Additionally, it has been found that winter temperature extremes in eastern China are also affected by ENSO (Chen et al. 2012). The Arctic Oscillation (AO) is one of the most dominant patterns of Northern Hemispheric climate variability (e.g., Feldstein and Franzke 2017), and it is most prevalent in winter and in the middle and high latitudes (Ramos et al. 2010; You et al. 2013). Recent studies have illustrated a strong positive correlation between winter temperature extremes and the AO in northern China (Gong and Wang 2003; You et al. 2013). The above teleconnections between ENSO/AO and temperature extremes in China are usually investigated by correlation analysis (Gong and Wang 2003; Wu et al. 2010; You et al. 2013); however, to our best knowledge, quantile regression has not been applied. Using quantile regression to explore the statistical connections of temperature extremes in China with ENSO/AO is the fourth objective of this study.

The paper is organized as follows. In section 2, we present the daily temperature data, the deseasonalized daily temperature, and the aggregated monthly anomaly temperature time series. The monthly time series of climate indices representing ENSO and AO are also described. Section 3 shows all the methods used in this study. Results and discussion are respectively presented in sections 4 and 5, and finally conclusions are given in section 6.

2. Data

The time series of daily mean, maximum, and minimum temperatures are provided by the Climate Data
The RHTest software, developed at the Climate Research Branch of Meteorological Service of Canada (available at http://etccdi.pacificclimate.org/software.shtml), is applied to assess data homogeneity. After homogeneity assessment, there are a total of 352 meteorological stations having good quality and continuous daily records of surface air temperature in the period 1956–2013. These 352 meteorological stations are not evenly distributed and most of them are located in central and eastern China (Fig. 1).

As in Franzke (2013), quantile regression could be directly used for trend detection in the original daily mean temperature time series. However, the daily mean temperature time series are obviously affected by seasonality, resulting in quasi-periodic variations of statistics such as the sample mean and variance (Fatichi et al. 2009). Here we use the classical approach by subtracting the mean annual cycle resulting in the deseasonalized daily temperature time series (Fatichi et al. 2009; Franzke 2010, 2012). By averaging the deseasonalized daily temperature time series, we can obtain the monthly anomaly temperature time series (Franzke 2010, 2012). The two Expert Team on Climate Change Detection and Indices (ETCCDI) variables, monthly minimum value of daily minimum temperature (TNN) and monthly maximum value of daily maximum temperature (TXx), are also computed using the dataset of daily maximum and minimum temperature, respectively. Specifically, annual temperature series of TNn in January and TXx in July are developed, because in China’s mainland warm extremes usually occur in July and cold extremes occur in January. Trends in annual extreme temperature series, TXx (July) and TNn (January), are also analyzed.

Moreover, TXx and TNn are also used as the response variable in quantile regression to detect the relationships between temperature extremes and large-scale climate patterns. The Niño-3.4 (5°S–5°N, 170°–120°W) SST is used as an index for ENSO (Wu et al. 2010; Chen et al. 2013), and the monthly Niño-3.4 index can be accessed from https://www.esrl.noaa.gov/psd/data. The monthly time series of the AO index, which is extracted from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC; http://www.cpc.ncep.noaa.gov/products), is used to represent the AO (You et al. 2013). Before applying quantile regression, monthly time series of Niño-3.4 and AO indices are standardized by subtracting the mean and dividing by the standard deviation over the entire study period.

To understand the changing patterns of the large-scale atmospheric circulation, the reanalysis data of monthly mean geopotential height and wind fields at 850 hPa are downloaded from the National Centers for Environmental Prediction (NCEP)–National Center for Atmospheric Research (NCAR) and analyzed. The NCEP–NCAR Reanalysis-1 project data assimilation system is using past data from 1948 to the present. The spatial resolution of the global dataset is 2.5° × 2.5° (Kalnay et al. 1996).

3. Methods

a. Detection of long-range dependence and serial correlation

Theoretically, an LRD process can be expressed either in the time or in the frequency domain. In the time domain, LRD is characterized by a hyperbolically decaying autocorrelation function (Hosking 1981), while in the frequency domain LRD manifests itself as an unbounded spectral density at zero frequency (Hurst 1951; Franzke et al. 2012). To describe the serial correlation in a time series, a number of models have been proposed. The fractional integrated autoregressive and moving average model, ARFIMA(p, d, q), is one of the most flexible models (Granger and Joyeux 1980; Hosking 1981). Here d is denoted as the long-range parameter or the fractional differencing parameter, which is a measure of the strength of the temporal dependence of a time series.

Many methods are available to detect the existence of LRD and to estimate the long-range parameter d including graphical methods, parametric methods, and
semiparametric methods (Beran 1994). In this study, the Geweke and Porter-Hudak (GPH) semiparametric estimator (Geweke and Porter-Hudak 1983; Franzke 2010, 2012) is used to estimate the long-range parameter $d$ as well as the corresponding 95% confidence interval. If the 95% confidence interval does not contain 0, $d$ is considered to be significantly different from 0 at the 5% significance level. The estimation of the long range parameter $d$ is implemented using the R package “fracdiff.” Evidence of LRD and trends will be detected for daily and monthly temperature series.

LRD is not detected for annual temperature series, TNn in January and TXx in July, because the lengths of the series are too short. Alternatively, lag-1 and lag-2 autocorrelation coefficients are computed to measure the serial correlations (Rao and Bhattacharya 1999). If the estimated lag-1 or lag-2 autocorrelation coefficient falls inside the 95% confidence interval, serial correlation at lag 1 or lag 2 is considered to be not significant at the 5% significance level. Autocorrelation coefficients are also computed using R.

b. Quantile regression

Quantile regression is proposed as an extension to the traditional linear regression, which approximates quantiles of the response variable (Koenker and Bassett 1978). The widely used linear quantile regression minimizes the functional

$$\sum_{i=1}^{n} \rho_{\tau}(y_{i} - X_{i}^T \beta),$$

(1)

where $\rho_{\tau}(\mu) = \tau \mu I_{(0,\infty)}(\mu) - (1 - \tau)\mu I_{(-\infty,0)}(\mu)$ is the check function; $I_{A}(\mu)$ is the indicator function that equals to 1, if $\mu \in A$; $n$ is the length of the observed time series $y$; $X_{i} = (X_{i1}, \ldots, X_{in})^T$ ($m$ is the number of covariates minus one), where $X_{i1} = 1$ for the intercept and $X_{ij}$ is a vector of the time points but can also contain external factors such as climate indices; $\beta$ denotes the parameter vector to be estimated; and $\tau$ is the quantile level [see Yu et al. (2003) and Koenker (2005) for more details].

In this study, quantile regression is used for different percentiles; therefore, the estimated quantile curves might cross, leading to an invalid distribution for the response (Wu and Liu 2009; Bondell et al. 2010). To solve the crossing problem in quantile regression, a few methods have been proposed. We adopt the method of Bondell et al. (2010), which is also applicable to multivariate quantile regression. The estimated coefficients are considered to be significantly different from 0 at the 5% significance level, only 0 is outside of the 95% confidence interval. In this study, all quantile regressions are carried out using R.

c. Trend identification and significance test

Following Franzke (2013), linear quantile regression trends for the 5th (cold extremes), 50th (median), and 95th percentiles (warm extremes) of daily mean temperatures are estimated, respectively. The change rate is measured in degrees Celsius per decade. Analogously, the statistical significance of the quantile trends is also tested using the surrogate data generating method proposed by Schreiber and Schmitz (1996). The readers are referred to Schreiber and Schmitz (1996) and Franzke (2013) for further details. For each daily temperature time series, we generate 1000 surrogate time series with the same autocorrelation function and the same probability density function. Linear quantile regression trends for the 0.05, 0.5, and 0.95 quantiles of each surrogate time series have also been estimated, respectively. If the linear quantile regression trend of the observed daily temperature time series is outside the 2.5% or 97.5% percentiles of the quantile trends computed from the ensemble of surrogate data, we claim that the observed trend is statistically significant (Franzke 2013).

For comparison purposes, we also apply two traditional methods, robust linear regression and nonparametric M-K test, to identify the temperature trends. The robust regression is used to detect the linear trends of deseasonalized daily temperature time series, monthly anomaly temperature time series, and annual temperature time series of January TNn and July TXx, respectively. Robust regression is a form of weighted least squares regression and is done iteratively (Holland and Welsch 1977). In the first iteration, equal weights are assigned to all points and the ordinary least squares method is used to estimate the model coefficients. At subsequent iterations, weights are recomputed so that points farther from model predictions in the previous iteration are given lower weight. Model coefficients are then recomputed using weighted least squares. The process continues until the values of the coefficient estimates converge within a specified tolerance. Here, we use the bisquare weighting (Holland and Welsch 1977) and the weighting function $w$ is given by

$$w = [(r)(1 - r^2)^2], \text{ if } |r| < 1,$$

(2)

where $r$ is given by

$$r = R/(Ts\sqrt{1 - h}),$$

(3)

and $R$ represents the residuals from the previous iteration, $h$ represents the leverage values from a least squares fit, $s$ is an estimate of the standard deviation of the error term, and $T = 4.685$ is the default tuning constant. The robust regression (RR) is computed using the Matlab Statistics Toolbox.
When the M-K test is used for trend identification, the presence of serial correlation in time series will affect the ability of the test to correctly assess the significance of trend (von Storch and Navarra 1995; Douglas et al. 2000). Because M-K test is not designed for trend analysis of extremes, it is not used to detect the trends of daily temperature series and the annual temperature series of January TNn and July TXx in this study. Instead, a modified M-K test is only used to detect the trend of monthly anomaly temperature time series and test its statistical significance (Yue and Wang 2004). This method uses a nonparametric method to account for the presence of serial correlations. Additionally, Sen’s slope is estimated to quantify the trend (Sen 1968). An identified trend is considered to be statistically significant only if it is significant at the 5% level. The modified M-K test is completed using the R package “fume.”

d. Spatial cluster analysis

In this study, spatial cluster analysis of quantile trends of temperatures is realized using a newly proposed density-based spatial clustering (DBSC) algorithm (Liu et al. 2012), which considers spatial proximity and attributes similarity simultaneously. For each daily temperature time series, linear quantile regression trends are estimated first at 19 quantile levels (0.05, 0.1, \ldots, 0.95). A vector consisting of 19 quantile trend values is considered as the attribute of the station, and the attribute similarity is measured as the Euclidean distance (Shiau and Lin 2016). The spatial proximity between stations is measured by the geometrical distances. Here, we introduce this algorithm briefly; the reader is referred to the original references for further details (Liu et al. 2012). Delaunay triangulation with edge length constraints is first employed for modeling the spatial proximity relationships among stations. A modified density-based clustering strategy is then designed and used to identify spatial clusters. By combining quantile regression and spatial cluster analysis, both temporal and spatial changes in temperatures in China can be summarized. In this study, the computer code to implement DBSC is written in Matlab.

4. Results

a. Evidence of long-range dependence

First the deseasonalized daily temperature time series and monthly anomaly temperature time series at all 352 stations are examined for evidence of LRD by using the GPH method. The test results are shown in Figs. 2a,b. At the daily time scale, all $d$ values are positive ranging from 0.075 to 0.47 with a median value of 0.29 (Table 1). At 350 stations, the $d$ values are significantly different from zero confirming the universality of LRD in temperature time series (Fig. 2a). At the remaining two stations, the $d$ values are not significantly different from zero. Since all $d$ values are smaller than 0.5, all these daily temperature time series are considered to be persistent. Figure 2b shows that the intensity of the dependence decreases: LRD at the monthly time scale is lower than that at the daily time scale. The range of $d$ values is from $-0.035$ to 0.397, and the median value is 0.226. Figures 2a and 2b also show that stations with stronger serial correlations are mainly located in northern and southwestern China as well as the southeastern coastal area. Thus, LRD in daily and monthly temperature series should be considered in the following trend analysis and significance test.

The lag-1 and lag-2 autocorrelation coefficients of all annual time series of January TNn and July TXx are presented in Figs. 2c–f and Table 2. For annual time series of January TNn, significant serial correlations at lag 1 and lag 2 are detected at 91 and 92 stations, respectively. For annual time series of July TXx, there are only 48 stations showing significant autocorrelation at lag 1 and lag 2. From Fig. 2, we conclude that the serial correlation decreases as the time scale increases at most stations in China.

b. Trend analysis and statistical significance

The trends in monthly anomaly temperature time series at all 352 stations are first identified using two traditional methods, robust linear regression and the nonparametric M-K test. Figures 3a and 3b show the spatial distribution patterns of the temperature trends at the 352 stations, and Table 1 provides the descriptive statistics of all trends. The results of the trend identification using the robust linear regression and nonparametric M-K test are very similar (Figs. 3a,b and Table 1), suggesting that they are robust. Positive trends are detected at most stations, whereas negative trends are detected at only a few stations. At the monthly time scale, both robust linear regression and nonparametric M-K test have detected significant warming trends over China.

Next, robust linear regression and Franzke’s (2013) method are used to test the trend of the original daily temperature series (nondeseasonalized). Figure 3c and Table 1 show the results of the trend analysis using robust linear regression. The detected trends of the original daily mean temperature series are quite similar to that of monthly anomaly temperature time series (deseasonalized and aggregated). Following Franzke’s (2013) method, trends are also detected using the noncrossing quantile regression technique at the three
quantile levels 0.05, 0.5, and 0.95, corresponding respectively to lowest 5th, 50th, and 95th percentiles of daily temperature. The detected trends and their statistical significance are also presented in Figs. 3d–f and summarized in Table 1. For the lowest percentile, there are 135 and 214 stations showing significant and non-significant positive trends, respectively. Only three stations show a nonsignificant negative trend. The rate of change of cold extremes ranges from $-0.156^{\circ}\text{C decade}^{-1}$ to $1.5^{\circ}\text{C decade}^{-1}$, and the median value is $0.288^{\circ}\text{C decade}^{-1}$ (Table 1). Large trends (more than $0.4^{\circ}\text{C decade}^{-1}$) are mainly located in northern and eastern China (Fig. 3d). For the median daily temperatures, there are 117 and 230 stations showing significant and nonsignificant positive trends, but only 5 stations showing nonsignificant negative trends. The rates of change range from $-0.125^{\circ}\text{C decade}^{-1}$ to $0.882^{\circ}\text{C decade}^{-1}$ with a median value of $0.285^{\circ}\text{C decade}^{-1}$ (Table 1). Stations with significant positive trends are mainly distributed in central and eastern China (Fig. 3e). For the 95th percentile, the numbers of
stations with significant positive, nonsignificant positive, significant negative, and nonsignificant negative trends are 128, 196, 5, and 23 (Fig. 3f), respectively. The minimum, median, and maximum change rates are $-0.34^\circ$, $0.154^\circ$, and $0.817^\circ$ decade$^{-1}$ (Table 1), respectively. Significant positive trends are mainly located in northern and southern China, while negative trends are distributed in central China (Fig. 3f).

Finally, the robust linear regression and the non-crossing quantile regression methods are applied for trend analysis of the annual temperature series of January TNn and July TXx. Because the length of the annual temperature series is short (58 yr), quantile levels 0.05 and 0.95 are replaced by 0.1 and 0.9 to reduce the uncertainty of quantile regression (the estimation of quantile coefficients can be reduced to a linear programming problem, which might return null estimation if the length of the series is short and the quantile is too low or high). Figure 4 presents the quantile evolutions of the January TNn and July TXx at quantile levels $\tau = 0.1$, 0.5, and 0.9 during 1956–2013 and their comparisons to the results derived from the robust linear regressions. The estimated change rates are also summarized in Table 2. For the January TNn temperature series, we find that the numbers of stations with significant positive trends identified using robust linear regression and quantile regression at multiple quantile levels are similar (Figs. 4a–d). However, a few of the stations located in northern China with significant negative trends are identified by using quantile regression at the quantile level of 0.1 (Fig. 4b). For July the TXx temperature series trends, detected using robust regression and quantile regression at median levels, are similar (Figs. 4e,g). Compared with Fig. 3f, significant negative trends of warm extremes are detected at more stations, which are mainly located in central and northeastern China (Fig. 4h).

c. Spatial pattern of quantile trends

To reveal the spatial pattern of quantile trends of daily temperature, the DBSC algorithm is applied to implement spatial clustering of vectors consisting of quantile trends at the following quantile levels: 0.05, 0.1, . . . , 0.95. As shown in Fig. 5, there are six main clusters discovered by the DBSC algorithm. The largest cluster is cluster C1, which contains 176 stations and is located over central and southern China. The second largest cluster is C2 with 121 stations, which are distributed over northern China. The other main clusters are C3 and C4. Cluster C3 is located over the Yangzi River delta and the eastern coast, while cluster C4 is located over the northern coast of China. C5 and C6 are two small clusters located in the

| TABLE 1. Summary of LRD detection and trend analysis of temperature series at daily and monthly time scales at 352 stations in China. The last three columns correspond to the quantile trends at three quantile levels $\tau = 0.05$, 0.5, and 0.95. The change rate is measured by $^\circ$C decade$^{-1}$. Each column corresponds to the descriptive statistics of all 352 LRD parameters or temperature trends. |
|-----------------------------------------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Monthly temp series | Daily temp series |
|                      | $d$ RR Modified M-K | $\tau = 0.05$ RR $\tau = 0.5$ RR $\tau = 0.9$ RR |
| Min                  | $-0.035$ $-0.131$ $-0.129$ | $0.075$ $-0.113$ $-0.156$ $-0.125$ $-0.34$ |
| 1st quartile         | 0.17 0.142 0.151 | 0.235 0.149 0.199 0.199 0.078 |
| Median               | 0.227 0.211 0.215 | 0.29 0.219 0.288 0.285 0.154 |
| Mean                 | 0.215 0.222 0.226 | 0.287 0.23 0.328 0.285 0.165 |
| 3rd quartile         | 0.275 0.295 0.296 | 0.341 0.302 0.429 0.38 0.242 |
| Max                  | 0.397 0.884 0.871 | 0.47 0.89 1.5 0.882 0.817 |

| TABLE 2. Summary of autocorrelation coefficients and trend analysis of annual temperature series January TNn and July TXx at 352 stations in China. Quantile regressions are implemented at three quantile levels, $\tau = 0.1$, 0.5, and 0.9. The change rate is measured by $^\circ$C decade$^{-1}$. Each column corresponds to the descriptive statistics of all 352 autocorrelation coefficients or temperature trends. |
|-----------------------------------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| January TNn | July TXx |
| Autocorrelation | Lag 1 | Lag 2 | RR | $\tau = 0.1$ | $\tau = 0.5$ | $\tau = 0.9$ |
| Lag 1 | $-0.177$ | $-0.3$ | $-0.665$ | $-0.75$ | $-0.6$ | $-0.7$ |
| Lag 2 | $0.072$ | $-0.19$ | $0.288$ | $0.195$ | $0.263$ | $0.207$ |
| RR | $0.161$ | $0.089$ | $0.464$ | $0.482$ | $0.433$ | $0.433$ |
| $\tau = 0.1$ | $0.174$ | $0.102$ | $0.504$ | $0.51$ | $0.492$ | $0.52$ |
| $\tau = 0.5$ | $0.261$ | $0.203$ | $0.658$ | $0.726$ | $0.687$ | $0.802$ |
| $\tau = 0.9$ | $0.848$ | $0.796$ | $1.815$ | $2.36$ | $1.854$ | $2.08$ |
| Mean | $0.557$ | $0.576$ | $0.939$ | $0.945$ | $1.07$ | $1.174$ |
Qinghai–Tibetan Plateau and Xingjiang, respectively. The average of quantile trends and the associated confidence intervals (mean value plus and minus standard deviations) of each cluster are shown in Fig. 6. We see that there is an obvious difference between adjacent clusters (e.g., C1 and C3 or C2 and C4). For clusters C2, C3, and C5, the quantile trends at lower quantiles \( t < 0.3 \) are much higher than that at higher quantiles \( t > 0.6 \). This result is consistent with the rapid warming trends of cold extremes in northern and the Qinghai–Tibetan Plateau presented in Fig. 3d.

d. Relationship of temperature extremes with ENSO and the AO

The potential teleconnections between temperature extremes in China and ENSO (the AO) are investigated by computing the correlations between monthly anomaly temperatures and the Niño-3.4 index (AO index). Figure 7
shows the Kendall’s $\tau$ between the monthly mean temperature anomalies and standardized climate indices for 1956–2013 in China with a 0–5-month lag. Correlation analysis shows that the number of stations at which the Niño-3.4 index is significantly correlated to monthly anomaly temperature is highest when the time lag is 5 months. The AO index is highly correlated with monthly anomaly temperature at the 0-month lag at 161 stations, with coefficients as high as 0.27. The two time lags, 5-month and 0-month, are further used in the following multivariate noncrossing quantile regression. In each quantile regression model, January TNn or July TXx is used as response variable and the two normalized climate indices, the Niño-3.4 index (5 months ahead of January or July) and the AO index, are taken as predictors.

Figure 8 shows the spatial distribution of quantile slopes estimated using noncrossing quantile regression (QR) for January TNn at quantile levels $\tau = 0.1, 0.5,$ and 0.9 as well as the slopes estimated using robust regression. The results of statistical significance are also summarized in Table 3. Using robust regression, significant influence of ENSO on January TNn has only been identified at 26 stations (Fig. 8a). When the quantile regression method is applied, the number of stations with significant quantile slopes increases notably (Figs. 8b–d). From Figs. 8a–d, we find that ENSO mainly affects cold extremes at the northeastern and southeastern coastal zones in China. The relationships between January TNn and the AO revealed by robust regression and quantile regression are consistent (Figs. 8e–h). These findings indicate that cold
extremes in northern and eastern China are significantly affected by the AO. Similarly, quantile regression detects more significant positive quantile slopes than robust regression.

Figure 9 presents the spatial distribution of quantile slopes for July TXx versus the Niño-3.4 index and AO index, and the descriptive statistics are shown in Table 4. Using robust regression, a significant influence of ENSO on July TXx has been identified at 11 stations (Fig. 9a). From Figs. 9b–d, we find that the quantile slopes at most stations are negative, and the positive trends are mainly distributed at eastern China. Specifically, the July TXx at the 0.9 quantile is significantly affected by the ENSO at 35 stations positively and 69 stations negatively. Similarly, the statistical connections between the AO and July TXx have also been verified at a few stations (Figs. 9f–h) using quantile regression. Taken the quantile level of 0.9 as an illustration, stations with significant negative quantile slopes are located in southern and northeastern China, while those with significant positive stations are mainly distributed in central and northwestern China (Fig. 9h). However, robust regression only detects two significant positive slopes and nine significant negative slopes (Fig. 9a). We note that the teleconnections between temperature extremes can be more effectively detected using quantile regression than robust regression.
5. Discussion

Traditionally, the analysis of changes of climate extremes is based on either climate extreme indices (Alexander et al. 2006; You et al. 2011) or extreme value theory (Kharin et al. 2007, 2013; Brown et al. 2008). The ETCCDI have defined as many as 27 indices for extreme weather and climate events including 16 indices for temperature extremes and 11 indices for precipitation extremes (Alexander et al. 2006). Then, monthly or yearly
time series of these indices can be extracted from daily observations of temperature and precipitation, and a trend analysis follows (Alexander et al. 2006). When LRD is present in climate time series, the statistical uncertainty of the trend identification will significantly increase (Fatichi et al. 2009; Franzke 2010, 2012; Ludescher et al. 2016).

Detecting the existence of LRD in temperature time series is the preliminary procedure in the time series

Table 3. Descriptive statistics of slopes estimated using robust regression as well as quantile slopes estimated using quantile regression of January TNn with respect to the two normalized climate indices, Niño-3.4 index (5 months ahead of January) and AO index at quantile levels $\tau = 0.1, 0.5,$ and 0.9. Filled circles represent statistically significant slopes at 5% level. (Legend acronyms are defined in Fig. 2.)

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Descriptive statistics of slopes estimated using robust regression as well as quantile slopes estimated using quantile regression of January TNn with respect to the two normalized climate indices, Niño-3.4 index (5 months ahead of January) and AO index at quantile levels $\tau = 0.1, 0.5,$ and 0.9.</th>
</tr>
</thead>
<tbody>
<tr>
<td>January TNn vs Niño-3.4</td>
<td>January TNn vs AO index</td>
</tr>
<tr>
<td>RR</td>
<td>$\tau = 0.1$</td>
</tr>
<tr>
<td>Min</td>
<td>-0.983</td>
</tr>
<tr>
<td>1st quartile</td>
<td>-0.047</td>
</tr>
<tr>
<td>Median</td>
<td>0.208</td>
</tr>
<tr>
<td>Mean</td>
<td>0.234</td>
</tr>
<tr>
<td>3rd quartile</td>
<td>0.513</td>
</tr>
<tr>
<td>Max</td>
<td>1.363</td>
</tr>
</tbody>
</table>

Fig. 8. Slopes estimated using robust regression as well as quantile slopes estimated using quantile regression of January TNn with respect to the two normalized climate indices, Niño-3.4 index (5 months ahead of January) and AO index at quantile levels $\tau = 0.1, 0.5,$ and 0.9. Filled circles represent statistically significant slopes at 5% level. (Legend acronyms are defined in Fig. 2.)
For temperature time series, a number of studies have been devoted to investigate the possibility of LRD at either global or regional scales (Caballero et al. 2002; Blender and Fraedrich 2003; Franzke 2010, 2012; Mann 2011). The detection of the presence of LRD in temperature time series relies on the method that is employed. Vyushin and Kushner (2009) found that different LRD detection

**Fig. 9.** Slopes estimated using robust regression as well as quantile slopes estimated using quantile regression of July TXx with respect to the two normalized climate indices, Niño-3.4 index (5 months ahead of July) and AO index at quantile levels \(\tau = 0.1, 0.5,\) and 0.9. Filled circles represent statistically significant slopes at 5% level. (Legend acronyms are defined in Fig. 2.)

**Table 4.** Descriptive statistics of slopes estimated using robust regression as well as quantile slopes estimated using quantile regression of July TXx with respect to the two normalized climate indices, Niño-3.4 index (5 months ahead of July) and AO index at quantile levels \(\tau = 0.1, 0.5,\) and 0.9.

<table>
<thead>
<tr>
<th></th>
<th>July TXx vs Niño-3.4</th>
<th></th>
<th>July TXx vs AO index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RR</td>
<td>(\tau = 0.1)</td>
<td>(\tau = 0.5)</td>
</tr>
<tr>
<td>Min</td>
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<td>-0.726</td>
<td>-0.758</td>
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<tr>
<td>1st quartile</td>
<td>-0.185</td>
<td>-0.207</td>
<td>-0.171</td>
</tr>
<tr>
<td>Median</td>
<td>-0.05</td>
<td>-0.042</td>
<td>-0.043</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.055</td>
<td>-0.042</td>
<td>-0.036</td>
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<tr>
<td>3rd quartile</td>
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<td>0.122</td>
<td>0.118</td>
</tr>
<tr>
<td>Max</td>
<td>0.434</td>
<td>0.652</td>
<td>0.493</td>
</tr>
</tbody>
</table>
methods could not generate robust estimation when they were applied to empirical time series due to the problems of frequency range choices and filtering properties of the methods. In addition, the detection is also affected by the time scale of the time series (the length or interval of time series). In this study, the semiparametric GPH method (Geweke and Porter-Hudak 1983) is applied to examine the evidence for LRD in multidecadal daily and monthly temperature series, which have been deseasonalized by removing the annual cycle. In previous studies, the GPH method has already been successfully applied in detecting LRD in temperature time series (Franzke 2010, 2012). Analogously, we also find evidence of LRD at daily and monthly time scales; therefore, the statistical significance of trends in temperature extremes should be tested using a proper method. However, for short time series with few samples, there is uncertainty in LRD detection (Rao and Bhattacharya 1999). As LRD can be characterized by a slowly decaying autocorrelation, lag-1 and lag-2 autocorrelation are computed as a measure of serial correlation of the annual extreme temperature series, TNn in January and TXx in July. Our findings verify that serial correlations are not significant for most annual extreme temperature series. The detection of LRD also shows that the intensity of serial correlation decreases as the time scale is increased (daily, monthly, and annual).

In the present paper, quantile regression has been extensively applied to conduct a spatiotemporal analysis of extreme temperature changes at 352 meteorological stations over China. Primarily, quantile regression has been applied for trend identification in daily temperature time series with significant LRD, then, the surrogate data generating method proposed by Franzke (2013) is used to test the statistical significance of quantile trends. We find that linear, quadratic, and cubic quantile regression trends are similar at most stations (not shown). For simplicity, only linear quantile regression trends are estimated in the observed temperature time series and surrogate time series. Moreover, the noncrossing quantile regression method has also been used for detecting the trends of annual extreme temperature series, TNn in January and TXx in July. As we know, China has already experienced significant temperature changes during the past few decades (Ding et al. 2007). It has been estimated that the daily maximum and minimum air temperatures increased at rates of 0.13° and 0.32°C decade^{-1} from 1955 to 2000, respectively (Wang and Gong 2000). For mean maximum temperatures, the increasing trends have occurred in northern China, while weak decreasing or insignificant trends have occurred in southern China (Zhai and Pan 2003; You et al. 2011). A general conclusion states that winter temperature extremes is warming faster than annual mean warm extremes (Wang and Gong 2000; Zhai and Pan 2003; You et al. 2011). Results of trend identification and significance tests in this study are consistent with the above general conclusion. The robust linear regression and M-K test also show significant warming trends over China. When Franzke’s (2013) method has been used to test the statistical significance of quantile trends, the numbers of stations with significant positive trends at quantiles 0.05, 0.5, and 0.95 decrease to 125, 117, and 128, respectively. Compared with the traditional robust regression and Mann–Kendall methods for trend identification, the warming extent tested using the quantile regression and surrogate data method is lower over China suggests that the shape of the temperature distribution is changing because of global warming; that is, global warming is not just a simple shift to warmer temperatures. Moreover, significant negative trends in warm extremes are also detected in central China, which is consistent with the decreasing trends shown in some previous studies (Zhai and Pan 2003; Zhang et al. 2011; Zhou and Ren 2011; You et al. 2011). In conclusion, quantile trends have provided a more complete description of temperature change in China, where temperature variability not only in the mean but also in extreme values has been investigated.

To investigate the role of large-scale atmospheric circulation change in climate change, atmospheric circulation composite analysis is usually conducted (You et al. 2011), where composite circulation maps showing the differences of wind fields and geopotential height between two periods are consequently created to represent the change in circulation. Figure 10 shows the mean difference of wind fields and geopotential height at 850 hPa in January and July between 1981–2013 and 1956–80. In January, two enhanced anticyclonic circulations developed in northern China and the Qinghai–Tibetan Plateau. This would partly explain why the cold temperature extremes have consistently decreased in northern China, which was consistent with rapid warming in these two regions in January (Figs. 3d and 4a–d). As shown in Fig. 10b, the largest differences of geopotential height (approximately 50 gpm) occurs near 45°N, 100°E in July (Fig. 8a), and enhanced anticyclonic circulation develops over the Eurasian continent, centered on Mongolia. The increased geopotential height over Mongolia is consistent with the rapid warming in northern China in July (Figs. 3f and 4h). The north-easterly wind in northern and eastern China has strengthened, and in turn weakens the northern and eastern extent of the westerly jet stream and any...
southwesterly flow from the ocean. This may partly explain the decreasing trend of warm extremes in July in northeastern and central China. The association between large-scale circulation patterns and temperature extremes is an important research topic in climatology. Loikith and Broccoli (2012) proposed to identify this association based on composite analysis. Identifying the association between regional atmospheric circulation patterns and temperature extremes in China is not the main objective of this study but deserves to be studied in an independent paper.

The spatiotemporal temperature variations in China have been summarized by combining quantile regression and spatial cluster analysis. Unlike Barbosa et al. (2011), both spatial proximity and quantile trends similarity have been considered in spatial clustering by using the DBSC algorithm. Spatial clustering of quantile trends of temperatures is helpful to reveal the physical mechanism of local temperature change. Two large clusters have been identified showing significant differences of quantile trends in southern and northern China. Hu et al. (2010) and Yang et al. (2011) both found that the warming trend at Yangzi River delta was attributable to urbanization. In this study, a cluster C3 located at Yangzi River delta and the eastern coast has also been identified with larger quantile slopes than that at the nearby cluster C1 showing the contribution of urbanization to local warming.

Finally, the influences of two important large-scale climate patterns, ENSO and the AO, on temperature extremes are investigated through quantile regression. Chen et al. (2013) showed that cold extremes in the southern part of eastern China were correlated to ENSO. In this study, both robust regression and quantile regression verify the above findings (Figs. 8a–d). Moreover, we also find strong correlations between ENSO and cold extremes in northeastern China. Compared to the robust regression, quantile regression identifies more significant correlations between cold extremes and Niño-3.4 index. The Arctic Oscillation, also known as the northern annular mode, strongly influences surface air temperatures over the Eurasian continent (Thompson and Wallace 1998). Specifically, the AO has significant influence on both temperature and precipitation in northern China at the interdecadal time scale (Gong and Wang 2003). Chen et al. (2013) demonstrated that interannual variation of winter temperature extremes in the northern part of eastern China was closely linked to the AO. Analogously, You et al. (2013) found that the AO could explain more than 50% of the winter temperature extreme change in China. In this study, the significant correlations between AO and cold extremes in northern and eastern China are also identified by robust regression and quantile regression (Figs. 8e–h). In addition, impacts of ENSO on the summer temperature in northeastern China have been recognized in previous studies (Wu et al. 2010). This teleconnection is also identified by quantile regression in northeastern China; however, the impact of ENSO on warm extremes is not significant at most stations in China (Figs. 9a–e). Alternatively, ENSO plays a more important role in determining the spatial distribution of summer precipitation in China (Lin and Lu 2009). Additionally, we also find evidence of the AO’s significant impact on warm extremes in northeastern and southern China (Fig. 9h). Zhu and Wang (2016) found that there was interannual variation in the correlation between the AO and ENSO in boreal winter. Our research indicates that further investigation of the mechanical linkage between the AO and ENSO and their joint influence on climate extremes in China is worthwhile.

6. Conclusions

In this study, we have conducted a spatiotemporal analysis of temperature extreme changes based on quantile regression at 352 meteorological stations over China in the period 1956–2013. Before the trend identification, temperature time series at daily and monthly time scales have been examined for evidence of long-range dependence. We find evidence for long-range
dependence for most temperature time series. Then, the statistical significance of linear quantile trends of temperature extremes is tested against quantile trends of 1000 surrogate time series. We find evidence for a significant positive trend in cold extremes for 135 stations, which are mainly located in northern and eastern China. For warm extremes, significant positive and negative trends have been detected for 128 and 8 stations, respectively. This spatial variability of quantile trends represents different patterns of temperature extreme change in China. More specifically, the trends of two ETCCDI variables, T\(n\) in January and T\(x\) in July, are also analyzed using quantile regression that has identified changes of temperatures at more quantiles. Changes of large-scale atmospheric circulation partly explain the trends of temperature extremes in China.

Spatial cluster analysis has identified a few large clusters indicating different warming patterns in different parts of China. These clusters are located in southern China, northern China, and the Yangzi River delta. Correlation analysis reveals that the time lag of influence of AO on monthly temperature anomaly is 0 months, whereas the time lag of influence of ENSO on monthly temperature anomaly is 5 months. Finally, quantile regression also reveals the teleconnection between temperature extremes and two large-scale climate patterns, ENSO and the AO. The influence of ENSO on cold extremes is significant at most stations over China, but its influence on warm extremes is not so significant. The AO affects not only cold extremes in northern and eastern China but also warm extremes in northeastern and southern China.

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REFERENCES


