



Nonstationary modeling of extreme precipitation in China



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ABSTRACT

The statistical methods based on extreme value theory have been traditionally used in meteorology and hydrology for a long time. Due to climate change and variability, the hypothesis of stationarity in meteorological or hydrological time series was usually not satisfied. In this paper, a nonstationary extreme value analysis was conducted for annual maximum daily precipitation (AMP) at 631 meteorological stations over China for the period 1951–2013. Stationarity of all 631 AMP time series was firstly tested using KPSS test method, and only 48 AMP time series showed non-stationarity at 5% significance level. The trends of these 48 nonstationary AMP time series were further tested using M-K test method. There were 25 nonstationary AMP time series mainly distributed in southern and western China showing significant positive trend at 5% level. Another 5 nonstationary AMP time series with significant negative trends were near northern urban agglomeration, Sichuan Basin, and central China. For these nonstationary AMP time series with significant positive or negative trends, the location parameter in generalized extreme value (GEV) distribution was assumed to be time-varying, and the trends were successfully characterized by the nonstationary GEV models. For the remaining 18 nonstationary AMP time series mainly in the eastern portion of China, no significant trend was detected. The correlation analysis showed that only 5 nonstationary AMP time series were significantly correlated with one or two of the four climate indices EASMI, WPI, SOI, and PDO. Then, the location and scale parameters in the GEV distribution were modeled as functions of the significantly correlated climate indices. The modeling results in this study showed that the nonstationary GEV distributions performed better than their stationary equivalents. Finally, 20-year and 50-year return levels of precipitation extremes at all 631 stations were estimated using the best fitting distribution for the year 1961 and 2013, respectively.

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1. Introduction

Extreme value theory (EVT), one of the important branches of statistics, has been widely used in meteorology and hydrology for a long time (Katz et al., 2002; Soukissian and Tsalis, 2015). Climate or hydrology extremes could be successfully characterized by the probability distributions derived from EVT (Feng et al., 2007; Li et al., 2013). For the most part, EVT applied in meteorology and hydrology assumes that these extreme events are stationary (Katz et al., 2002). However, the stationarity assumption has been gradually challenged due to climate change and variability or human intervention (Salas and Obeysekera, 2014). Then, climatic and hydrological extremes exhibit some type of non-stationarity in the form of trends, shifts or a combination of them (Olsen et al., 1999; Kiem et al., 2003; Villarini et al., 2009). Non-stationarity may affect both the severity and frequency of these extreme events (Olsen et al., 1998; Wigley, 2009; Mika, 2013; Radinović and

Čurić, 2014; Monier and Gao, 2015); therefore, it is suggested that non-stationary probability distribution models need to be identified and possibly used for risk management and engineering design (Katz, 2013; Cheng et al., 2014; Salas and Obeysekera, 2014).

In this paper, we apply nonstationary modeling technique to study the precipitation extremes over China for the period 1951–2013. Precipitation is very crucial to our planet, because it is a major component of the water cycle by depositing most of the fresh water (Radinović and Čurić, 2009). However, extreme precipitation events also cause floods resulting in great loss of lives and properties, especially in extreme seasons (Radinović and Čurić, 2013, 2014). China also suffers from floods caused by precipitation extremes (Zhai et al., 2005); therefore, it is worthy to assess the adverse influences of extreme precipitation events. In recent literatures, changes in trend and frequency have been detected in precipitation extremes in China (Zhai et al., 2005; Su et al., 2006; Qian and Qin, 2008; Xu et al., 2011; You et al., 2011). The non-stationarity in the extreme precipitation time series was also successfully modeled with generalized extreme value (GEV) and generalized Pareto distribution (GPD) by introducing inconstant parameters (Fischer et al., 2012a, 2012b; Feng et al., 2007; Du et al., 2014). These previous studies primarily focused attention on the long term trends of

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precipitation extremes and its correlation with climate change, but non-stationarity in precipitation extremes related to climate change and variability has not been extensively studied.

China is located in East Asia; therefore, the climate is strongly influenced by the important subsystem of Asian monsoon, East Asian monsoon (Ding and Chan, 2005; Zhou et al., 2008). Specifically, it was found that East Asian summer monsoon determined the spatio-temporal variability of summer rainfall over China (Ding and Chan, 2005; Zhao and Zhou, 2009). The Western Pacific subtropical high is also an important weather and climate system in the Asian monsoon region that contributes largely to the complexity and variability of the China's rainfall distribution and precipitation anomalies in summer (Sui et al., 2007; Zhang et al., 2015). The Asian monsoon system is also strongly affected by El Niño Southern Oscillation (ENSO) that has the greatest impact on the year-to-year variability of the global climate (Tanaka, 1997; Wang et al., 2000). Moreover, some low-frequency climate variability such as Pacific Decadal Oscillation (PDO) also influences global precipitation anomalies on decadal timescale (Kiem et al., 2003; Villafuerte et al., 2014). To represent the dependence of meteorological time series on climatic forcing, nonstationary extreme value distribution model taking climate indices as covariates have been applied (Villarini et al., 2010). In this study, we also use nonstationary GEV distribution with time and climate indices as the potential covariates to model the nonstationary precipitation extremes in China.

2. Data

The daily precipitation dataset (1951–2013) that was provided by the National Meteorological Information Center (NMIC) of China Meteorological Administration (CMA) was used to extract extreme precipitation time series. The data quality was also controlled by the NMIC (Qian and Lin, 2005). There are 631 meteorological stations having the good quality and continuous daily records longer than 50 years (Fig. 1). In this study, extreme precipitation is defined as the maximum daily precipitation, and then the annual maximum daily precipitation (AMP) time series at all 631 stations could be simply computed using the daily precipitation dataset. Each station was labeled by a unique ID coded using 6-digit number.

The East Asian summer monsoon index (EASMI, Fig. 2) is defined as an area-averaged seasonally (JJA) dynamical normalized seasonality (DNS) at 850 hPa within the East Asian monsoon domain (10° – 40° N, 110° – 140° E) (Li and Zeng, 2003, 2005). The annual EASMI time series was collected by Dr. Li J.P. and can be directly downloaded from the following website (<http://ljp.gcess.cn/dct/page/65577>).

The Western Pacific subtropical high is quantified by WP index (WPI, Fig. 2) that signifies the zonal and meridional variation of the

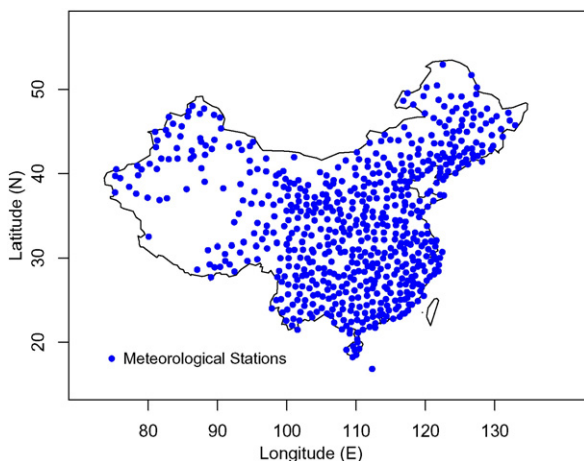


Fig. 1. Geographical distribution of the 631 meteorological stations in China.

location and intensity of the East Asian jet stream entrance region (Barnston and Livezey, 1987). The WPI data (monthly/annual) was provided by the U.S. National Centers for Environmental Prediction (NCEP, <http://www.cpc.ncep.noaa.gov/data/>).

ENSO is generally at its peak during November–January (Trenberth, 1997), and its effect on extreme precipitation is in the following summer (Lin and Lu, 2009). In this study, the Southern Oscillation Index (SOI, Fig. 2), which is a standardized difference between the two barometric pressures between observation stations at Darwin, Australia and Tahiti, is used to quantify ENSO. We computed the average of monthly SOI from November to next January to generate the SOI series from 1950 to 2012. The monthly SOI index could be directly downloaded from national center for environmental information, NOAA (<http://www.ncdc.noaa.gov/>).

PDO index (Fig. 2) is the standardized principal component time series, and the monthly time series of PDO index since 1900 can be obtained from the following website <http://research.jisao.washington.edu/pdo/PDO.latest>. In this study, the annual PDO index was based on the average November–March leading principal component of monthly SST anomalies poleward of 20° N in the Pacific Ocean (Mantua and Hare, 2002).

3. Methodology

Stationarity and trend of the AMP time series will be firstly tested. Only nonstationary AMP time series are modeled by nonstationary GEV distribution. For nonstationary AMP time series with significant trends, time will be chosen as covariate in location parameter of GEV distribution. Otherwise, significant correlated climate indices are used as covariates in both location and scale parameter in GEV distribution, respectively. With the best fitting GEV distribution model, return levels are also estimated.

3.1. Test methods

The stationarity test is carried out using KPSS test method (Kwiatkowski et al., 1992). The objective time series is assumed to be the sum of deterministic trend, random walk, and stationary error with the following linear regression model

$$x_t = r_t + \beta_t + \varepsilon_t \quad (1)$$

where r_t is a random walk, β_t is a deterministic trend, and ε_t is a stationary error. Here, $r_t = r_{t-1} + u_t$, and u_t is independent and identical distributed $N(0, \sigma_u^2)$. If the time series is stationary around a deterministic trend, the null hypothesis is $\sigma_u^2 = 0$, while the alternative hypothesis is $\sigma_u^2 > 0$. In another case, if the time series is stationary around a fixed level, the null hypothesis will be $\beta_t = 0$. In this study, the stationarity test will be implemented using package “tseries” in R environment (R Development Core Team, 2014).

The Mann–Kendall (M-K) test method is applied for detecting monotonic trends in the AMP time series. The M-K test is a rank-based nonparametric trend detection method that is less sensitive to outliers than parametric statistics, such as Pearson's correlation coefficient (Kendall, 1938; Mann, 1945). The null hypothesis in M-K test states that there is no trend in the time series and observations are randomly ordered. On the contrary, the alternative hypothesis means that there are increasing or decreasing monotonic trends. In this study, the detection of trend will be completed using the package “Kendall” in R environment.

The statistical dependence of AMP time series on climate indices (EASMI, WPI, SOI, and PDO) is tested using Spearman's correlation test method. Assuming there are two time series of X_t and Y_t of size n , x_i and y_i are the corresponding ranks, then the difference between ranks

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