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Nonstationarity in timing of extreme precipitation across China and impact of tropical cyclones

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Abstract: This study examines the seasonality and nonstationarity in the timing of extreme precipitation obtained by annual maximum (AM) sampling and peak-over-threshold (POT) sampling techniques using circular statistics. Daily precipitation data from 728 stations with record length of at least 55 years across China were analyzed. In general, the average seasonality is subject mainly to summer season (June-July-August), which is potentially related to East Asian monsoon and Indian monsoon activities. The strength of precipitation seasonality varied across China with the highest strength being in northeast, north, and

central-north China; whereas the weakest seasonality was found in southeast China. There are three seasonality types: circular uniform, reflective symmetric, and asymmetric. However, the circular uniform seasonality of extreme precipitation was not detected at stations across China. The asymmetric distribution was observed mainly in southeast China, and the reflective distribution of precipitation extremes was also identified the other regions besides the above-mentioned regions. Furthermore, a strong signal of nonstationarity in the seasonality was detected at half of the weather stations considered in the study, exhibiting a significant shift in the timing of extreme precipitation, and also significant trends in the average and strength of seasonality. Seasonal vapor flux and related delivery pathways and also tropical cyclones (TCs) are most probably the driving factors for the shifts or changes in the seasonality of extreme precipitation across China. Timing of precipitation extremes is closely related to seasonal shifts of floods and droughts and which means much for management of agricultural irrigation and water resources management. This study sheds new light on nonstationarity in timing of precipitation extremes which differs from existing ones which focused on precipitation extremes from perspective of magnitude and intensity.

Key words: Extreme precipitation; Circular statistics; Seasonality; Nonstationarity; Tropical cyclones; China

1. Introduction

China is the third largest agricultural country in territory with the largest population in the world. During recent decades, China has been experiencing intensifying precipitation extremes and hence amplifying flooding and droughts (Zhang et al., 2012a, 2013a, 2014, 2016; Chi et al., 2016; Gu et al., 2016). Of natural hazards in China, the most destructive are extreme precipitation which causes huge agricultural losses and directly influences the spatiotemporal availability of water resources (e.g. Zhang et al, 2011, 2012b, 2015a). Hence, changes in extreme precipitation have been receiving increasing attention these days in China (e.g. Li et al., 2013; Xiao et al., 2013; Yang et al., 2013; Shao et al., 2015; Zhou et al., 2016).

There is a significantly growing body of knowledge related to changes in the magnitude and frequency of extreme precipitation across China (Li et al., 2013; Xiao et al., 2013; Yang et al., 2013; Shao et al., 2015; Zhou et al., 2016). However, little attention has been paid to the changes in their seasonality and related spatial distribution properties, which are critical for basin-scale management of water resources, agricultural irrigation, and conservation of fluvial ecosystems. Analyzing seasonal daily maximum precipitation, Yang et al. (2013) found that extreme rainfall in autumn (spring and winter) pointed to a decreasing (increasing) tendency over the majority of China. Zeng et al. (2016) indicated that regional maximum 1-day precipitation had significantly increasing trends in spring and summer, but a slightly decreasing tendency with smaller decreasing magnitude in autumn and winter in Sichuan province. Ma and Zhou (2015) examined the changes in precipitation timing, wet days (WD) and duration of extreme wet (dry) spells (WS/DS), indicating that the

69 timing of wet-/dry-season exhibited significant shifts across the whole country.

70 The above-mentioned studies mostly focused on changes in extreme
71 precipitation at the seasonal time scale with respect to the magnitude, frequency and
72 duration of wet and dry spells of extreme precipitation. To the best of our knowledge,
73 nonstationarity in the timing of extreme precipitation in terms of the calendar date of
74 extreme events has not received enough attention and little has been done on this
75 scientific issue across China, which is potentially challenging for infrastructure and
76 asset management (Milly et al., 2008). Salas (1993) defined a stationary hydrological
77 time series as that “is free of trends, shifts, or periodicity (cyclicality).” According to
78 the definition, many research literatures focused on nonstationarity in magnitude and
79 intensity of precipitation extremes (e.g. Cheng and AghaKouchak, 2014; She et al.,
80 2015). Cheng and AghaKouchak (2014) evaluated the nonstationary
81 Intensity-Duration-Frequency (IDF) curves using Bayesian inference. She et al.
82 (2015) proposed a concept of event-based extreme precipitation to investigate the
83 nonstationarity in precipitation amounts. However, only several studies have
84 investigated the nonstationarity in the timing of extreme events by quantifying trends
85 (Mediero et al., 2014; Wang et al., 2014; Zhang et al., 2016). Wang et al. (2014)
86 formulated a trend analysis approach to detect trends and occurrences of extreme
87 precipitation in a mid-latitude Eurasian steppe watershed in North China. Zhang et al.
88 (2016) directly used the calendar date of flood occurrence to describe the trends in
89 the timing of flooding in the Tarim River basin, China.

90 For the timing of extreme precipitation, the probability distribution tends to be

more often multimodal and less well aligned with calendar months and predefined seasons (Dhakal et al., 2016), which are somewhat not sufficiently discerned by the above-mentioned techniques. Thus, directional/circular statistics were developed and were used to analyze the nonstationarity in the timing of flood and extreme precipitation in recent years (e.g. Parajka et al., 2010; Dhakal et al., 2016; Villarini, 2016). Circular statistics deals with data that can be represented as points on the circumference of a unit circle, e.g. the timing of extreme precipitation with a cycle of 365 or 366 days (Pewsey et al., 2013).

It should be pointed out that impacts of tropical cyclones (TCs) on extreme precipitation regimes and timing of extreme precipitation have been well corroborated (Dare et al., 2012; Knight and Davis, 2009). Knight and Davis (2009) indicated that the contribution of tropical cyclone (TC)-induced precipitation to the total extreme precipitation increased by approximately 5%–10% per decade in southeastern Atlantic coastal states. Chen and Fu (2015) showed that the maximum contribution of TC-precipitation to the total rainfall was ~20% in 1998 along coastal areas in China, where have highly developed economies. Therefore, knowledge of the influence of TC activities on the timing of extreme precipitation along coastal areas will aid the design of hydraulic structures and water resources management.

This study therefore aims at addressing the following questions: (1) What are the seasonality properties of extreme precipitation across China? (2) How does nonstationarity manifest itself in the timing of extreme precipitation? (3) What could be the causes for the seasonality of extreme precipitation? Answers of these

questions will help understand the hydrological behaviors in a changing environment and will be of value in management of water resources and agricultural irrigation and mitigation of water-related natural hazards.

2. Data

Daily precipitation data from 839 meteorological stations for a period of 1951-2014 were collected from National Climate Center (NCC) of China Meteorological Administration (CMA). For data quality control, stations with cumulative missing data reaching 365 days were excluded from analyses in this study. Therefore, meteorological data from only 728 stations were analyzed. Locations of these stations are shown in Fig. 1. Missing data were processed based on Zhang et al. (2015b). The minimum meteorological series length was 55 years and the maximum one was 64 years and more information on the dataset is given in Fig. 2.

In this study, the effects of TCs on the timing of extreme precipitation were also investigated with the aim to understand potential causes for the changes in the timing. Information on the TC tracks during 1951-2014 was obtained from the China Meteorological Administration tropical cyclone database (e.g. Ying et al., 2014). The first step to evaluate the effect of TCs on the timing of extreme precipitation was to quantify the relation between an extreme precipitation event and a particular TC event. In this study, an extreme precipitation event was attributed to a TC if the center of circulation was within 500 km of a precipitation station during a time

window of two days around the occurrence time of extreme precipitation (Knight and Davis, 2009; Villarini and Denniston, 2016).

3. Methodology

In this study, extreme precipitation events of the largest and smallest magnitudes were considered at the annual time scale, and the time series of timing of extreme precipitation at each individual station was obtained using the annual maximum (AM) sampling and peak-over-threshold (POT) sampling techniques with certain threshold values. Generally, a threshold value was set by: (1) taking an absolute value such as 50 mm/day as a threshold value; and/or (2) taking a certain percentile value, such as 95%, as a threshold value. In this study, the threshold value was decided as the 95 th percentile of the non-zero precipitation series (Villarini et al., 2013).

3.1. Circular statistical method

Nonstationarity and seasonality in the timing of extreme precipitation were evaluated using the circular statistical method (Villarni, 2016; Dhakal et al., 2016). The occurrence date of extreme precipitation with a 365 or 366 cycle within a year was dealt with as circular data, which can be represented on a circumference with unit radius with each angle defining a point on the circumference of the unit circle:

$$\theta_i = D_i \times \left(\frac{2\pi}{365} \right) \quad (1)$$

where D is the date of extreme precipitation occurrence for extreme event i , D

= 1 for 1 January and $D = 365$ or 366 for 31 December; θ is the angular value of D .

From a sample of n extreme precipitation events, the x and y coordinates of the mean

extreme precipitation date around the year are determined using (Dhakal et al., 2016):

$$\begin{cases} \bar{x} = \frac{\sum_{i=1}^n \cos(\theta_i)}{n} \\ \bar{y} = \frac{\sum_{i=1}^n \sin(\theta_i)}{n} \end{cases} \quad (2)$$

where $\bar{x}$ and $\bar{y}$ are the x and y coordinates of the mean extreme precipitation date.

Hence, the direction representing mean date of occurrence of n extreme precipitation

events is obtained using (Dhakal et al., 2016):

$$\bar{\theta} = \tan^{-1}\left(\frac{\bar{y}}{\bar{x}}\right) \quad (3)$$

where $\bar{\theta}$ is the sample mean direction (MD), the most widely used measure of location. Without adding a measure of the strength of seasonality, MD can be misleading. The mean resultant length (MRL) was used to quantify the strength of seasonality in the timing of extreme precipitation (Dhakal et al., 2016):

$$\rho = \frac{\sqrt{\bar{x}^2 + \bar{y}^2}}{n} \quad (4)$$

where ρ is a dimensionless measure of the strength of seasonality and the range of

ρ is $[0, 1]$, with values of 0 when the observations are uniformly distributed along

the unit circle, and values of 1 when all the points concentrated at one location.

As with MD and MRL, the circular probability distribution representing the

seasonal distribution of these dates can be described with density estimates,

depending on the selection of smoothing kernel and bandwidth. In our study, the von

Mises distribution selected as the smoothing kernel is a symmetric unimodal

distribution with probability density function:

$$f(\theta; \mu, \kappa) = \frac{1}{2\pi l_0(k)} e^{k \cos(\theta - \mu)}, \quad 0 \leq \theta \leq 2\pi \quad (5)$$

where $\kappa \geq 0$ is a concentration parameter; $l_0(k)$ is the modified Bessel function of the first kind and order zero. More information can be found in Pewsey et al. (2013) and Dhakal et al. (2016). Generally, there are three types of seasonal distribution of extreme precipitation: uniform distribution (with the same probability on any day of the year), reflective symmetric distribution (with a unimodal) and asymmetric distribution (with multimodal, i.e., finite mixtures of unimodal symmetric and asymmetric models). Now we introduce a process similar to Villarni (2016) for examining the types of seasonality. First, the three test methods, including Rayleigh, Kuiper V_n and Watson U^2 , were used to examine whether the null hypothesis of uniformity could be rejected at the 5% significance level. If the null hypothesis was rejected, the asymptotic theory would be used to examine whether the null hypothesis of reflective symmetric at the 5% significance level. After the above-mentioned tests, if these two null hypotheses were not be rejected, the seasonality was considered as an asymmetrically distributed.

3.2. Change points and temporal trends

In this study, the Mann-Whitney U test was used to detect change points in the time series of θ (Zhang et al., 2013b). This test is a nonparametric statistical method (Reeves et al., 2007) and is a rank-based test without knowing the location of change point. Advantages of the test over parametric methods include: (1) it is less sensitive to skewed distributions and outliers; and (2) it enables to compute the p

value of the test statistic. The p value of less than 0.05 means a significant change point, and vice versa; The p value larger than 0.05 means a turn point but not a significant change point.

Non-parametric trend detection methods have advantages over parametric statistics in terms of handling of outliers. Besides, the rank-based nonparametric Mann-Kendall (MK) test (Mann, 1945; Kendall, 1975) can test trends without requiring normality or linearity (Alan et al., 2003). However, negative influences of the persistence on the MK trends have been widely discussed and techniques have been proposed to eliminate persistence effects (von Storch and Navarra, 1995). Hamed and Rao (1998) recommended the modified MK (MMK) statistic with amended variance when the lag- i autocorrelation coefficient was significantly different from zero at the 95% confidence level.

The pre-whitening procedure is accepted, if the lag-1 autocorrelation coefficient, c , is larger than 0.1, and then the time series $(x_1, x_2, \dots, x_n)$ to be studied should be $(x_2 - cx_1, \dots, x_n - cx_{n-1})$. However, pre-whitening tends to underestimate the trend in the time series (e.g. Yue et al., 2002). Moreover, significant lag-1 autocorrelation is often detected even after pre-whitening. This means that pre-whitening with consideration of only lag-1 autocorrelation is insufficient to remove the entire influence of serial correlation. Hamed and Rao (1998) have shown MMK with consideration of lag- i autocorrelation and related robustness to autocorrelation. Due to these advantages, MMK has been widely used (e.g. Daufresne et al., 2009). In this study, MMK was used to detect possible trends in the time series of θ . The confidence level for

MMK was set at 0.05.

In addition, moving window analysis was used to assess the temporal changes in the time series of $\bar{\theta}$ and ρ . For circular data θ , 30 years were set as a window and slid forwardly with 1 year as a time step, for example, from 1951-1980 to 1984-2014 with sliding. The $\bar{\theta}$ and ρ values were calculated with each step and constituted a new time series then. Therefore, MMK was used to evaluate the temporal trends of $\bar{\theta}$ and ρ with the 0.05 significance level.

4 Results and discussion

4.1. Seasonality of extreme precipitation

Fig. 3 illustrates the spatial patterns of MD and MRL, which are two important indices of seasonality of extreme precipitation across China, showing information about the time of the year when extreme precipitation tend to occur and how strong the seasonality is. Fig. 3 shows discernable spatial patterns of both MD and MRL across China (Fig. 3). In general, stations with precipitation extremes that occurred during different months from April to September were distributed sporadically and intermittently across China without any definitive spatial patterns. Specifically, stations with precipitation extremes during June mainly were located in southeast China and those with precipitation extremes during July were found in most regions across the country. Stations with precipitation extremes during August were distributed sporadically and stations with precipitation extremes during July were distributed across China. It can be said that extreme precipitation events occurred

with higher frequency during June and July, and specifically July seemed to have more extreme precipitation events than other months.

The water vapor transport controlled summer precipitation changes in both space and time across China, and spatial patterns of occurrences of extreme precipitation were interpreted by water vapor propagation during June and July. In summer, the Asian summer monsoon region is a dominant moisture sink, and Indian monsoon and East Asian monsoon areas are also the water vapor convergence center (Zhou et al., 2006). The Indian monsoon enhances from May to July carrying water vapor in zonal direction, while East Asian monsoon enhances mainly from June to July with the highest moisture in July and the lowest moisture in September (Zhou et al., 2006). Abundant moisture from the Southern Hemisphere is transported to the Asian monsoon area after monsoon onset, and water vapor from northern boundary of South China Sea to mainland China. These water vapor transport patterns greatly cause significant concentrations of precipitation extremes during June in southeast China. Furthermore, the northward propagation of water vapor flux during July triggers frequent occurrences of extreme precipitation in central and north China during July.

The strength of seasonality of precipitation extremes was also studied in terms of MRL (Figs. 3c, 3d, and 3e). The strongest seasonality was observed in northeast China with MRL larger than 0.85 for AM-based precipitation extremes and 0.75 for POT-based precipitation extremes. Strong seasonality of precipitation extremes implied highly concentrated occurrence of precipitation extremes of the largest and

266 smallest precipitation magnitudes during July in northeast China. It should be noted
267 here that northeast China is one of the main agricultural areas in China, shouldering
268 the heavy responsibility of supply of agricultural products. Thus, strong seasonality
269 of precipitation extreme has the potential to trigger serious flash floods and/or
270 droughts which may inflict negative impacts on the management of agricultural
271 activities, such as agricultural irrigation, and add uncertainty to water supply security.
272 Precipitation anomalies in northeast China is mainly controlled by a northward shift
273 of the local East Asian jet stream in the upper troposphere and the northwestward
274 extension of the western Pacific subtropical high in the lower troposphere (e.g. Shen
275 et al., 2011). Lager MRL of precipitation extremes ($MRL > 0.75$ for AM-based
276 precipitation extremes and $MRL > 0.65$ for POT-based precipitation extremes) was
277 detected in north and central-west China, which was related to the water vapor
278 propagation by Indian summer monsoon, Asian monsoon and westerlies (e.g. Zhou
279 et al., 2008; Liu and Ding., 2008). $MRL < 0.6$ of extreme precipitation was identified
280 in northwest China with almost no difference between AM-based precipitation
281 extremes and POT-based precipitation extremes, where topographical properties had
282 massive impacts on extreme precipitation changes (Zhang et al., 2011b).
283 Inconspicuous seasonality with $MRL < 0.6$ for AM-based precipitation extremes and
284 0.5 for POT-based precipitation extremes was observed in southeast China. When
285 compared to the seasonality of extreme precipitation in other regions of China, the
286 seasonality of extreme precipitation southeast China was not evident, or in other
287 words, extreme precipitation events occurred in a more random way in southeast

China. However, the difference in MRL between AM-based precipitation extremes and POT-based precipitation extremes in southeast China was discernable with a proportion of more than 30% (Fig. 3e). Therefore, the occurrence of extreme precipitation events of smaller precipitation magnitude could be the result of more than one driving factor, such as tropical and extratropical storms and TCs (Chen and Fu, 2015), which resulted in the sporadic and/or random occurrence of extreme precipitation events and hence the relative weak seasonality in southeast China. This relatively random occurrence of extreme precipitation regimes has the potential to pose challenges for management and alleviation of urban waterlogging and it is particularly the case for urban areas in the Yangtze and Pearl River basins.

Types of seasonality, i.e. uniform distribution, reflective symmetric distribution and asymmetric distribution are shown in Fig. 4. It can be observed from Fig. 4 that no uniform distribution can be detected for extreme precipitations across China, implying more evident seasonality or temporal clustering features of extreme precipitation during a year. Fig. 4 shows that seasonality of extreme precipitation follows reflective a symmetric distribution in most regions of China, indicating that, on average, the timing of extreme precipitation was symmetrical and concentrated mainly during June or July (Fig. 3). The stations with seasonality of POT-based extreme precipitation following asymmetric distribution were found mainly in southeast China (Fig. 4b). However, the spatial distribution of stations with extreme precipitation of smaller magnitude was relatively complicated due to extratropical and convective systems from March to May and thunderstorm systems and TCs from

June to September.

For visual comparison of distribution types of seasonality, 4 stations in different locations (Fig. 1) were analyzed as case studies with seasonality of extreme precipitation following reflective symmetric distribution and asymmetric distribution (Fig. 5). Seasonality of extreme precipitation, as shown in Figs. 5a and 5b, was for stations in northeast China where seasonality of extreme precipitation was apparent. Extreme precipitation in southeast China occurred mainly during July and August, following the reflective symmetric distribution. Figs. 5c and 5d illustrate seasonality of extreme precipitation in the south parts of northwest China, and no significant seasonality of extreme precipitation was identified. Relatively even and intermittent occurrences of extreme precipitation can be expected in the south parts of northwest China. Figs. 5e and 5f show seasonality of extreme precipitation changes in southwest China, where the occurrence of extreme precipitation was observed mainly June-August. It can be seen from Figs. 5e and 5f that the seasonality of extreme precipitation was different for AM-based extreme precipitation as well as for POT-based extreme precipitation. Fig. 5e shows more evident seasonality of AM-based extreme precipitation when compared to the seasonality of POT-based extreme precipitation, as shown in Fig. 5f. The occurrence of POT-based extreme precipitation was relatively even during June to September, as shown in Fig. 5f. The seasonality of extreme precipitation in south China was not discernable. The POT-based extreme precipitation events can happen in almost any month of any year. The AM-based extreme precipitation occurred mainly during June and July and

winter involved no extreme precipitation events (Figs. 5h, 5i).

4.2. Nonstationarity in timing of extreme precipitation

Fig. 6 aims at testing the stationarity assumption of the seasonality of extreme precipitation using monotonic trends (Fig. 6) and change points as well (Fig. 7). Trends of θ , MD and MRL for AM-based extreme precipitation and POT-based extreme precipitation were quantified by the modified Mann-Kendall trend test method and results are shown in Fig. 6.

The timing of AM-based extreme precipitation did not exhibit significant trends at most stations across China except for a few stations with significant trends which were distributed sporadically across China (Fig. 6a). However, more stations can be found with increasing or significant increasing trends in the timing of POT-based extreme precipitation in central and south China, implying increasingly late occurrence of extreme precipitation of smaller precipitation magnitude (Fig. 6b). Fig. 6c shows that most stations were characterized by significant trends in MD for AM-based extreme precipitation events. Stations with significant increasing and/or decreasing MD for AM-based extreme precipitation events were distributed interchangeably in northeast, north, central and southeast China (Fig. 6c). Comparatively, relatively fewer stations were characterized by significant trends in MD of POT-based extreme precipitation. Similarly, the distribution of stations with significant increasing or decreasing MD of POT-based extreme precipitation was subject to no confirmed spatial pattern (Fig. 6d). For changes in the strength of

seasonality, stations with stronger seasonality strength were found mainly in central China both for AM-based extreme precipitation and POT-based extreme precipitation, while stations with weaker seasonality strength were found mainly in north China for AM-based extreme precipitation, and northeast, northwest, southwest and southeast parts of central China for POT-based extreme precipitation (Figs. 6e, 6f).

Besides, change points were also detected for the timing of extreme precipitation (i.e., θ) obtained by both AM and POT techniques, as shown in Fig. 7. It can be seen from Fig. 7 that there were 281 and 265 stations with AM-based extreme precipitation and POT-based extreme precipitation, respectively, having significant change points at <0.05 significance level, and other 162 and 189 stations having significant turn points at <0.1 significance level. However, no discernable and confirmed spatial patterns were identified for stations with significant turn points in the AM-based extreme precipitation and POT-based extreme precipitation series.

The timing of change points tended to concentrate during the 1970s and the 1980s, which may be attributed to shifts in observation standards, relocation and changing environment around rain gauges in around 1980 (Wu, 2005). In some instances, it was also possible that these step changes were associated with shifts in the climate regime. Lin (1998) analyzed the climate jumps based on the sea level pressure, the north Pacific sea surface temperature, and precipitation and temperature of China, and found that decadal climate jump happened mainly in the late 1970s and the early 1980s. Increasing temperature tended to trigger the intensification of

precipitation (Zhang et al., 2013c). Temporal and spatial changes of water vapor divergence can aid in the interpretation of seasonal and spatial alterations of precipitation regimes. Temperature changes can influence precipitation changes by altering thermodynamic properties of air mass and hence moisture transportation (Zhang et al., 2013c; Villarini et al., 2013).

The entire study time interval was subdivided into two time blocks, i.e., 1955-1984 and 1985-2014, or the first 30 years and the late 30 years. The stations with CMD for the late 30 years were distributed sporadically across China without confirmed spatial patterns (Fig. 8a). Moreover, CMD of extreme precipitation of smaller precipitation magnitudes was notably different from that of AM-based extreme precipitation and was subject to clear and discernable spatial pattern (Figs. 8a, 8b). Changes of seasonality strength before and after the 1980s were not evident in space. However, the seasonality strength of extreme precipitation tended to be enhancing in recent 30 years in southeast China and northwest parts of Xinjiang, implying increasing temporal concentration of extreme precipitation events and hence high flooding risks in these regions (Fig. 8c). As for changes of extreme precipitation of smaller precipitation magnitudes, the seasonality strength of extreme precipitation of smaller precipitation magnitudes was decreasing in southeast China in the recent 30 years and this decrease was even significant statistically at <0.1 significance level (Fig. 8d). It can be seen from Figs. 8e and 8f that the timing of extreme precipitation and seasonality strength were subject to different changing properties. However, seasonal distribution patterns of extreme precipitation were

similar.

4.3. Atmospheric circulation background, and relation between extreme precipitation and TC activities

Possible causes behind the extreme precipitation behavior in terms of seasonality were analyzed using NCEP/NCAR monthly data for a period of 1955-2014 (Fig. 9). It can be seen from Fig. 9a that the moisture carried by westerlies and East Asian monsoon was convergent in southwest China and formed an evident vapor convergence center, which might have triggered heavy precipitation in spring and led to the average seasonality ahead in southwest China in recent 30 years (Fig. 8b). For summer, Indian monsoon and westerlies converged in the central and west China with abundant moisture (Fig. 9b). This water vapor flux propagation conditions can greatly help cause summer heavy precipitation, and hence stronger seasonality strength in central and west China in recent 30 years (Figs. 8c, 8d). However, water vapor flux from South China Sea and related northward propagation of water vapor led to a water vapor divergence center in southeast China in summer (Fig. 9b), which does not benefit the occurrence of heavy precipitation during summer and hence weaker seasonality strength of extreme precipitation in southeast China (Fig. 8d). Moreover, it can be observed from Fig. 9c that a strong water vapor convergence center formed in southwest China during autumn and spring and summer as well, and this water vapor flux behavior can help cause the occurrence of heavy precipitation during spring, autumn and summer with weaker seasonality strength in

southwest China (Fig. 8d). For winter, the difference in moisture flux was slight and no obvious anomalies were detected in water vapor flux between two time intervals considered in this study (Fig. 9), and hence no evident influence of water vapor flux changes on the occurrence of extreme precipitation.

TCs act as the major driving factor behind the changes of extreme precipitation along coastal regions of east China. Under the influence of TCs, duration of extreme precipitation was prompt and the TC-induced moisture propagation and disturbance energy would collide with mid-latitude circulation, which can benefit the occurrence of extreme precipitation. The spatial distribution of frequency of TC-induced extreme precipitation events, sketched in Fig. 10, shows that the spatial pattern of TC-induced extreme precipitation frequency is subject to remarkable spatial heterogeneity. Roughly, more than 30% of extreme precipitation events along the coastal regions of East China should be attributed to TCs (Fig. 10). In addition, the frequency of TC-induced extreme precipitation gradually decreases to 0, which can be attributed to the decreased accumulated precipitation amount as a result of extratropical transition of tropical cyclones (e.g. Hart and Evans, 2001). Meanwhile, the frequency of TC-induced extreme precipitation defined by AM was much more than in the POT-based extreme precipitation. In this sense, TCs can be taken as one of the principal driving factors causing changes in the average and the strength of seasonality of extreme precipitation in East China.

5. Conclusions

Seasonality and nonstationarity in the timing of extreme precipitation observed at 728 stations across China have been investigated using circular statistics. Two time intervals, i.e. 1955-1984 and 1985-2014, for extreme precipitation are considered in this study. Meanwhile, analysis of water vapor propagation and TC activities is done with the aim to understand possible causes for the seasonality and nonstationarity in the timing of extreme precipitation across China. The following conclusions can be drawn from his study:

(1) The average seasonality of extreme precipitation is mainly concentrated during summer season, i.e. June, July, and August. Specifically, extreme precipitation occurs mainly during June in southeast China, and during July in central and north China. Meanwhile, the strength of seasonality is varying across China. The strongest seasonality of extreme precipitation can be detected in northeast, north, and central-north China; the weakest seasonality of extreme precipitation can be observed in southeast China. Seasonality of extreme precipitation events and related seasonality strength are closely related to water vapor propagation driven by East Asian monsoon and Indian monsoon activities.

(2) The temporal distribution of seasonality of extreme precipitation shows no uniform distribution of extreme precipitation, implying uneven temporal distribution of extreme precipitation. This uneven temporal distribution of extreme precipitation also indicates strong seasonality strength of extreme precipitation across China. Generally, asymmetric distribution of seasonality of extreme precipitation is observed mainly in southeast China, and reflective symmetric distribution in other

regions of China.

(3) Significant change points and trends in the timing of extreme precipitation indicate that the timing of extreme precipitation is not homogeneous. More than 50% of stations are with shifts in the timing of extreme precipitation at <0.1 significance level. Moreover, the average seasonality occurs late in central China, and earlier with relative weak seasonality strength in northeast China.

(4) Differences between circular mean direction (CMD), circular concentration (CC) and circular distribution (CD) during two time intervals, i.e. 1955-1984 and 1985-2014 are evident. Annual maximum daily precipitation is subject to a significant change in CC in central and northwest China. The seasonal availability and delivery pathways of atmospheric moisture are the physical mechanisms behind the above-mentioned differences. Water vapor convergence center forms in southwest China during spring which triggers the earlier occurrence of extreme precipitation. During summer, however, the water vapor flux from South China Sea propagates northward, forming a water vapor divergence center, and this water vapor propagation pattern does not benefit the occurrence of summer extreme precipitation. Also, TCs act as one of the principal driving factors causing the occurrence of extreme precipitation along the coastal regions of China, and more than 50% of extreme precipitation regimes that occur along the coastal regions of China are the result of TC activities.

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Fig. 1 Locations of 728 stations with daily precipitation data across China.

Fig. 2 Histogram of precipitation data length (a) and time series of the number of gage stations available in a given year (b) for the 728 stations considered in the study.

Fig. 3 Spatial distribution of sample mean direction (MD) (a, b), sample mean resultant length (MRL) (c, d) and the difference in MRL between AM and POT (e) across China.

Fig. 4 Spatial distribution of uniform, reflective symmetric and asymmetric distribution of extreme precipitation in AM and POT.

Fig. 5 Case studies showing temporal characteristics of seasonality of extreme precipitation in terms of reflective symmetric and asymmetric based on circular statistics. The 1-4 rows are stations 50425, 51818, 52754 and 57752, respectively (Fig. 1). The blue points on the circle represent the raw data; the gray wedges in the middle of the circles show the rose diagram, with the areas of each sector highlighting the relative frequencies in 16 bins; the black solid line outside the circles indicates the kernel density. The black solid arrow represents the mean resultant vector.

Fig. 6 Temporal trends in the timing of extreme precipitation based on AM (a) and POT (b), moving window trend of MD in AM (c) and POT (d) and moving window trend of MRL in AM (e) and POT (f).

Fig. 7 Spatial distribution of turn points in the timing of extreme precipitation based on AM (a) and POT (b).

Fig. 8 Examination of the differences between before and after 30 years for circular mean direction (CMD), circular concentration (CC) and circular distribution (CD) in the timing of extreme precipitation based on AM and POT.

Fig. 9 Differences between water vapor flux before and after 30 years during four seasons (a ~ d indicates spring, summer, autumn and winter, respectively), unit is $\text{kg}/\text{m}\cdot\text{s}$. Shaded areas with positive values show the sources of water vapor and negative values the sink of water vapor.

Fig. 10 Spatial distribution of frequency of tropical cyclones (TCs)-induced extreme precipitation based on AM and POT.