Changes in magnitude and frequency of heavy precipitation across China and its potential links to summer temperature

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Changes in magnitude and frequency of heavy precipitation across

China and its potential links to summer temperature

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Abstract: Changes in the magnitude, frequency and timing of heavy precipitation are closely related to the occurrence of floods and droughts, which hold a great deal of significance for management of agricultural irrigation and water resources. Records of daily precipitation and temperature from 728 stations across China were used to assess changes in the magnitude, frequency and timing of heavy precipitation using the Peak-over-Threshold (POT) with 95th percentile as the threshold. Because of the continuous nature of the magnitude and timing of heavy precipitation, the “change point” method and the modified Mann-Kendall trend test method were used to detect change points (CPs) and slowly-varying changes, respectively. In addition, the segmented regression and Poisson regression methods were used to detect CPs and

temporal trends in the frequency of heavy precipitation, respectively, with consideration of the count nature of the data. The results showed that 55% and 36% of the stations had CPs in mean and/or variance of the magnitude and timing, respectively, while the percentage is only 5.8% in the frequency. However, while there is limited evidence of significant trends in the magnitude and timing, strong evidence points to a significant increasing frequency in most regions of China. These changes may be partly explained by changes in summer temperature. Examination of the summer surface temperature records suggests that the areas, where the frequency of heavy precipitation has a significant increase, are also mostly characterized by significant increasing temperature. In addition, trends of the frequency vary between the periods before and after the turn point (TP) of summer temperature trends, especially in northern China where both the summer temperature and the frequency have shifted significantly decreasing trends to significantly increasing trends. A possible interpretation of these findings is that storms tend to be more frequent without significant changes in water vapor content.

Key words: Heavy precipitation; Change points (CPs); Trend analyses; Summer temperature; China

1. Introduction

Spatio-temporal changes in precipitation reflect some of the impacts of climate change on the hydrological cycle at regional and global scales. Precipitation changes affect the management of water resources, agricultural irrigation, and flood/drought

forecasting (Zhang et al., 2015). Hence, these changes, especially under climate change, have drawn much attention in recent years (Wang and Zhou, 2005; Chou et al., 2007; Yang et al., 2010; Zhang et al., 2011a). Numerical climate model simulations (e.g. Hulme et al., 1998) and observational records (e.g. Easterling et al., 2000; Allan and Soden, 2008) show globally averaged precipitation increase with increasing global-mean temperature, perhaps due to the intensification of the hydrological cycle. In addition, there is more extreme precipitation in the world's dry and wet regions (Donat et al., 2016), and the extreme precipitation will continue to increase as global warming continues (Ingram, 2016). This intensification in extreme precipitation has increased the risk of flooding particularly in the world's dry regions (Hirabayashi et al., 2013; Donat et al., 2016), such as Northwestern China (Zhang et al., 2016).

Thus, extreme rainfall is expected to increase in warming at the global and regional scales, but regional changes over land have been less certain (Zhang et al., 2013; Ingram, 2016). Therefore, it is necessary to assess whether there have been increasing trends in heavy precipitation over China, because China is the largest agricultural country in the world and development of agriculture significantly depends on the availability of water resources (e.g. Zhang et al., 2012b) and has experienced an increased frequency of extreme precipitation and flooding events over the last century (Xu et al., 2011; Zhang et al., 2014a; Chi et al., 2016; Gu et al., 2016). In addition, heavy precipitation has potential to trigger the occurrence of most destructive natural hazards in China, such as floods, which often cause adverse

societal consequences particularly for agricultural development (Zhang et al., 2012b, 2015).

Previous studies have examined the presence of trends in extreme precipitation over China (e.g., Yang et al., 2013; Zhang et al., 2012a, 2014a; Chi et al., 2016). Chi et al. (2016) divided China into four regions and have found that extreme precipitation magnitude and frequency have risen with regional differences since 1970. Yang et al. (2013) examined the validity of the stationarity assumption in annual and seasonal daily maximum precipitation on three sub-regions of China. These results are generally areal-averaged over spatially homogeneous regions and a linear trend (computed using ordinary least squares or a nonparametric counterpart) was fitted to these time series. However, few studies focused on heavy precipitation across China. Heavy precipitation is often defined using a peaks-over-threshold (POT) approach (e.g. Villarini et al., 2011, 2013), in which the number of days exceeding a selected threshold is counted for every year (i.e. the frequency). In addition, the implications of aggregating stations over a large spatial domain on the trend analysis are unclear (Villarini et al., 2013). In this study, we analyze changes in heavy precipitation from individual stations to avoid the region to be divided.

Another overlooked point is the possible influence of change points (CPs) in heavy precipitation on results of trend test (Villarini et al., 2009; Yang et al., 2013; Zhang et al., 2014b). The CPs are the presence of possible abrupt changes in heavy precipitation distribution, which may associate with climate variations (e.g., Alley et al., 2003; Swanson and Tsonis, 2009) or inhomogeneities (e.g. Dai et al., 2011) with

big impacts on the trend results (Villarini et al., 2009; Zhang et al., 2014b). Significant trends in heavy precipitation could also be attributed to the undetected CPs (Villarini et al., 2009; Zhang et al., 2014b). Moreover, the reliability of the CPs and trends detection may also be disturbed by the noise signal (Frei and Schar, 2001). Therefore, selecting appropriate statistical tools is important to enhance the capability of detecting CPs and trends with adequate consideration for the continuous or discrete data.

Previous studies mainly focused on the changes in extreme precipitation defined by the largest 1-day or n -day accumulation. There is a gap that little attention was paid to examine the changes in heavy precipitation defined using a peaks-over-threshold (POT) approach (e.g. Villarini et al., 2011, 2013). Using heavy precipitation, not only the magnitude and timing of precipitation extremes (i.e. the day of the year where heavy precipitation is observed), but also the frequency of extreme precipitation (i.e. the number of days exceeding a selected threshold value for every year) can be obtained together. Therefore, changes in the magnitude, frequency and timing can be examined, respectively. Based on the above introduction, there are two hypotheses of this study: (1) temporal trends in magnitude, frequency and timing of heavy precipitation can be influenced by change points; and (2) more heavy precipitation could happen in the dry and wet regions of China due to warming climate. As has been confirmed that a wetting tendency in winter should be the result of increasing temperature (Zhang et al., 2013a), the goal of our study is to examine whether there is any relationship between the magnitude, frequency and timing of heavy precipitation

and summer surface temperature. To identify the potential relations would be of great practical value to understand weather extremes in the warming climate and hence in the mitigation to catastrophic weather events. Thus, the main issues that will be addressed are: (1) the presence of temporal nonstationarities (both in terms of CPs and slowly varying changes) in heavy precipitation; and (2) the relationship between changes in heavy precipitation and surface temperature.

2. Data

Daily precipitation and temperature data from 728 meteorological stations covering 1951-2014 were collected from National Climate Center (NCC) of China Meteorological Administration (CMA). Daily temperature dataset involved daily maximum, minimum and daily average temperature. For data quality control, gaps in the data were identified in the precipitation series of 728 stations and the numbers of total missing values were less than 365 at all stations. Locations of these meteorological data are shown in Fig. 1. Missing data were processed, based on Zhang et al. (2011b). The missing values of 1–2 days were replaced by the average values of neighboring days. If consecutive days had missing data, the missing values were replaced with long term averages of the same days. On the basis of the objectives of this study, the gap-fill method did not significantly affect the final results (Zhang et al., 2011b). The minimum meteorological series length was 55 years and the maximum one was 64 years (Fig. 2). Note that due to different record lengths of stations, the statistical estimators will have varying precision. However, a minimum

precision was enforced by the requirement of having at least 55 years of data in the record (Fig. 2).

3. Methodology

In this section we provide an overview of the tools used to perform Peak-over-Threshold (POT) sampling, and analyses of CPs and trends. The reason why POT sampling technique was selected is that not only the magnitude and timing but also the frequency of heavy precipitation will be obtained in this study. In addition, when detecting the signal of CP and trend in extreme events, the presence of signal may be buried in the noise (e.g., Frei and Schar, 2001), complicating the signal detection (Villarini et al., 2013). Therefore, based on the continuous/discrete nature of records, different methods were selected to detect the CP and trend shown as follows.

3.1 Peak-over-Threshold (POT) sampling technique

With a way similar to Villarini et al. (2013), heavy rainfall is defined using a peaks-over-threshold (POT) approach. Setting a threshold for POT-based sampling, the magnitude, frequency and timing of heavy precipitation were analyzed, which are defined as precipitation extremes over the threshold, the number of days exceeding the threshold every year, and date of occurrence of precipitation extremes, respectively. Generally, a threshold is quantified in two ways, i.e. taking an absolute value; or taking a value based on a percentile. In this study, the threshold was set as the 95% percentile of the non-zero precipitation series, as shown in Fig. 3. The choice of 95% percentile was justified by Villarini et al. (2011, 2013). In addition, the threshold (i.e. 95% percentile) varies significantly with a decreasing way from 75 mm/day in southeast China to 5 mm/day in northwest China (Fig. 3). Spatial interpolation was performed by means of the inverse distance weighted method.

3.2 CP analysis

CP analysis provides a tool to check the presence of abrupt changes in the distribution of variables. For the magnitude and timing of heavy precipitation, a test method named “change point” by R package was used to detect CPs due to the continuous nature of these data (Killick and Eckley, 2014). This method is a kind of a likelihood function framework with large flexibility without assuming that the series follows a Gaussian distribution and without assuming the location of CP before test analysis. Compared to other tests, the advantages of this method over available ones are that: (1) it is less sensitive to outliers and skewed distributions; (2) both single CP and multiple CPs can be tested; (3) the significance of the test can be obtained; and (4) it can be used to detect CPs in mean (first moment) and variance (second moment). In general, most of the CP tests are designed to detect CP in the first moments of the distribution of the variable (i.e., the mean). However, some studies have emphasized the importance of the CP in the second moment of the distribution of the variable (e.g., Villarini et al., 2009, 2011). In this study, the “change point” method was used to detect the CP in both the mean and variance of magnitude and timing of heavy precipitation. The significance level of the CP was set as 0.05. More information about the method of “change point” can be found in Killick and Eckley (2014).

The method of “change point” was developed, assuming a continuous distribution of the data. However, the frequency of heavy precipitation that is the number of days exceeding the threshold every year is discrete. Therefore, the segmented regression method was used to address the above-mentioned issue (Toms and Lesperance, 2003; Villarini et al., 2013):

$$y = \begin{cases} \beta_0 + \beta_1 t + \varepsilon & t \leq \alpha \\ \beta_0 + \beta_1 t + \beta_2(t - \alpha) + \varepsilon & t > \alpha \end{cases} \quad (1)$$

where t is the time (year); y is the response variable such as frequency of heavy precipitation in this study; β_0 , β_1 , and β_2 are regression coefficients; and α is the location where the CP of the response variable y occurs. The location α of the change point needs to be set ahead. For each time series, we first fit the data using locally weighted regression (loess with a span of 0.75) (Cleveland, 1979) to guide the choice of the initial guess. In segmented regression, the relation between the response and the predictor is piecewise linear. Thus, the shift in the frequency of heavy precipitation can be well detected. If the significance level of the shift is at the 5%, the shift will be called as the CP; if not, the shift will be called as the turn point (TP) (e.g., Wang et al., 2011).

3.3 Trend detection

For detecting the slowly varying monotonic patterns of the magnitude and timing of heavy precipitation, the non-parametric trend detection method is chosen not only because of its advantages over parametric statistics in handling outliers but also because of the continuous distributions of magnitude and timing of heavy precipitation (e.g. Daufresne et al., 2009). Hamed and Rao (1998) recommended the modified Mann-Kendall (MMK) statistic with amended variance when the lag- i autocorrelation coefficients were significantly different from zero at the 5% confidence level. If the lag-1 autocorrelation coefficient, c , is larger than 0.1, the pre-whitening procedure is accepted, and then the time series $(x_1, x_2, \dots, x_n)$ should be $(x_2 - cx_1, \dots, x_n - cx_{n-1})$. However, the pre-whitening procedure tends to underestimate the

trend of the time series (e.g. Yue et al., 2002). Moreover, significant lag-1 autocorrelation is often detected even after pre-whitening is done (e.g. Yue et al., 2002). 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 magnitude and timing of heavy precipitation in this study. The significance level for MMK was set at 5%.

The MMK method was developed, assuming continuous distributions of the data. However, the frequency of heavy precipitation obtained by POT sampling is discrete. Moreover, the frequency (i.e., the number of days exceeding the selected threshold for every year) is a kind of point process which can be described by Poisson distribution (Villarini et al., 2013). Therefore, the trend of the frequency was detected using Poisson regression technique (Dobson, 2001; Villarini et al., 2013):

$$P(N_i = k | \lambda_i) = \frac{e^{-\lambda_i} \lambda_i^k}{k!} \quad (k = 0, 1, 2, \dots) \quad (2)$$

where N_i is the number of counts in year i , and λ_i denotes the rate of occurrence parameter. The decreasing or increasing trend was identified by verifying the assumption of linear relation between λ_i and time t , i.e.,

$$\lambda_i = \exp(\beta_0 + \beta_1 t_i) \quad (3)$$

In Equation (3), $\beta_1 > 0$ denotes an increasing trend, and $\beta_1 < 0$ denotes a decreasing trend. Besides, when β_1 is different from 0 at the 5% significance level, the trend is significant.

Some studies have pointed out that the presence of CP can have an important influence on the results of monotonic trend analyses (e.g., Zhang et al., 2014; Villarini et al., 2009). Thus, with a similar approach, the monotonic trend analysis was performed with three types, which is behind the CP analysis. Type I, we first detected the trends in the entire records of all stations ignoring the existing of CP. Type II, we secondly detected the trends for the entire records at the stations without CP. Type III, if a CP was detected, we subdivided the record into two subseries (before and after the CP) and detected trends in each subseries separately. The CP used to subdivide the entire record into two subseries (i.e. final CP) was selected with following criterions. Considering the reliability of trend detection results of two subseries, we also restricted the presence of CP so that the smallest subperiod had a length of 10 years in line with the previous studies (e.g., Villarini et al., 2009; Schmocker-Fackel and Naef, 2010). In addition, if there were CPs in both mean and variance, the CPs in mean were given the highest priority because the CPs in variance have a higher moment than that in mean with a consequence of bigger uncertainty.

4. Results

4.1 Changes in the magnitude of heavy precipitation

In this section, we examine the changes in the magnitude of heavy precipitation by detecting CPs both in the mean and variance (Fig. 4), as well as monotonic trends (Fig. 5). There were 353 stations out of 728 with CPs in mean, and 291 stations out of 728 with CPs in variance. Moreover, a CP was observed at 167 stations in mean and variance and at least a CP was detected at 404 stations, accounting for 55% of total stations, in mean or variance. 166 (187) stations had a CP in mean before (after) 1980

with a tendency of the CPs to occur in the northern and coastal regions of China (central part of China); while 121 (170) stations have CP in variance before (after) 1980 with a tendency of the CPs to occur in the northern and coastal regions of China (central part of China). However, it should be noted that no strongly discernible spatial patterns can be identified for CPs in the mean and/or variance. The one thing we can confirm is that more than half of stations had a significant shift in the magnitude of heavy precipitation, though it is not clear whether these changes are associated with data inhomogeneity or shifts from one climate regime to another.

Following CPs analysis, trends in the magnitude of heavy precipitation for the entire series or subseries divided by the CPs were analyzed (Fig. 5). Firstly, we detected the trends at all stations and the stations without consideration of a CP in mean and/or variance, respectively, with results that only less than 5% of stations were found with significant trends. Secondly, for eliminating the influence of the CPs on the results of trends, the trends in subseries before and after the CPs had also been examined with results that significant trends were detected at few stations only in a similar way with the results in all stations.

4.2 Changes in the frequency of heavy precipitation

The segmented regression and Poisson regression were used to evaluate the presence of shifts and trends in the frequency of heavy precipitation events, respectively (Figs. 6 and 7). Most regions of China are dominated by TPs (shifts not significant at 5% significance level) after 1980, while regions dominated by TPs with a tendency before 1980 distributed sporadically in central, southwestern and

northwestern China (Fig. 6). For the stations with CPs (shifts significant at 5% significance level), there were only 42 stations, accounting for less than 6% of total stations, dominated by a tendency in northern China (Fig. 6). Spatial interpolation was performed by means of inverse distance weighted method.

Similarly, trends in the magnitude of heavy precipitation were quantified, and the slowly varying monotonic patterns of the frequency of heavy precipitation were also examined (Fig. 7). In all records, statistically significant increasing trends were dominant over the negative ones across China, which is consistent with the results at the stations without CPs. Most of these stations are located in northern China and southeastern China, while the remaining stations with significant decreasing trends are mainly concentrated in northeastern China and southwestern China. In addition, trends in subseries divided by CPs were also detected to exclude the influence of CPs on the results of trend detection. Most of the stations exhibited significant decreasing trends prior to the year of CPs with a tendency in northern China, while the trends of these stations were reversed to show significant increasing trends posterior to the year of the CPs. Overall, these results pointed out that the occurrence of heavy precipitation events was more often over large areas of China, in particular over northern China.

4.3 Changes in the timing of heavy precipitation

After analyzing the changes in the magnitude and frequency of heavy precipitation, we turned to pay our attention to the changes in timing of heavy precipitation (Figs. 8 and 9). There were 263 stations, accounting for 36% of the total stations, with a CP mainly in the mean of the timing of heavy precipitation (Fig. 8). Most of these stations with CPs before 1990 were located in the

southeastern China. However, there is no strong spatially coherent pattern associated with the results of CP analysis in the timing of heavy precipitation.

In all of the records, there was a general tendency towards increasing trends in northwestern China and central-south China, while the stations mainly exhibited decreasing trends in northeastern China and southwestern China (Fig. 9a). Results of trend analysis in all records were consistent with those in the records without CPs (Fig. 9b). It should be pointed out here that significant increasing trends were observed in central-south China, which indicated that obviously delayed phenomenon in occurrence time of heavy precipitation events had happened in this region. After excluding the influence of CPs on the trend detection in the timing of heavy precipitation, significant increasing trends in both the subseries before and after the CPs were detected at few stations (Fig. 9c, d). These results indicated that the CPs were potentially responsible for the significant increasing trends in central-south China. In other words, the occurrence time of heavy precipitation may have a shift in which more heavy precipitation events happened from summer towards autumn.

Possible causes behind the changes in the timing of heavy precipitation were analyzed using NCEP/NCAR monthly data during 1955-2014 (Fig. 10). The differences between water vapor flux before and after 30 years (i.e. 1955-1984 and 1985-2014, respectively) during four seasons (i.e. spring, summer, autumn and winter) were calculated with 1985 as a break point due to most of stations with CPs occurring before 1990. The moisture carried by westerlies and East Asian monsoon was convergent in southwestern China and formed an evident vapor convergence center, which might have triggered heavy precipitation in spring and led to earlier occurrence of heavy precipitation in southwestern China in recent 30 years (Figs. 9a

and 10a). For summer, the water vapor flux from South China Sea and related northward propagation of water vapor led to a water vapor divergence center in southeastern China in summer (Fig. 10b), which did not benefit the occurrence of heavy precipitation during summer. Moreover, a strong water vapor convergence center formed in southwestern China during autumn (Fig. 10c), and this water vapor flux behavior can help to cause the occurrence of heavy precipitation during autumn in southern China. These two reasons may lead to the result that less heavy precipitation events occur in summer and more heavy precipitation occurs in autumn which delays the occurrence time of heavy precipitation in central-southern China (Fig. 9). For winter, the difference in the moisture flux was slight and no obvious anomalies were detected in the water vapor flux between two time intervals considered in this study (Fig. 10), and hence no evident influence of water vapor flux changes on the occurrence of heavy precipitation.

4.4 Potential links to summer temperature

The above-mentioned analyses showed that an increase was confirmed in the frequency but not in the magnitude of heavy precipitation over China, in particular over northern China and southeastern China. The subsequent scientific issue is that why these changes happened in heavy precipitation during the past few decades. A hypothesis was made that the variability in the climate system related to climate warming can influence the occurrence of heavy precipitation. In addition, monthly frequency analysis (Macdonald et al., 2010) was used to examine the seasonality of heavy precipitation and results showed that heavy precipitation occurs mainly during the summer (i.e. June-August) (figure not shown here). Therefore, changes in

temperature averaged over summer during the same period (i.e., 1951-2014) with precipitation were also investigated.

First, the spatial patterns of shifts in average values of daily minimum (T_{min}), maximum (T_{max}) and average temperature (T_{ave}) in summer were analyzed, respectively (Fig. 11). Spatial interpolation was performed by means of the inverse distance weighted method. There was a similar spatial pattern of TPs among T_{min} , T_{ave} and T_{max} , especially between T_{ave} and T_{max} . Comparison of spatial distribution between temperature and frequency of heavy precipitation of TPs indicated that the spatial pattern of TPs in the frequency of heavy precipitation clearly matched with that of temperature, especially in T_{min} . Moreover, the area with the highest matching degree mainly located in northern China where the frequency of heavy precipitation shifted from decrease to increase. It should be noted that T_{min} , T_{ave} and T_{max} had a significant shift at 489, 341 and 326 stations, respectively, all of which were much higher than the number of stations with a significant shift in the frequency of heavy precipitation.

Secondly, the spatial distributions of trends in summer temperature during the whole study period, subperiods before and after the TPs of summer temperature are shown respectively (Fig. 12). The majority of China experienced a positive trend of summer temperature, especially in T_{min} . Based on thermodynamic considerations, increasing temperature can cause the saturation water vapor pressure in a roughly exponential way. That may be the reason why the areas dominated by significant increasing frequency of heavy precipitation are those dominated by significant increasing temperature. It can also be observed that trends of temperature were not

temporally homogeneous during subperiods before and after the TPs of summer temperature. Most of the stations experienced a summer cooling trend before TPs, while the decreasing summer temperature was reversed and was becoming warmer significantly. This phenomenon was remarkable in central-southern China, where obviously delayed phenomenon in occurrence time of heavy precipitation events was detected.

Finally, trends in the magnitude, frequency and timing of heavy precipitation were quantified before and after the TPs of summer temperature to further evaluate whether the varying changes in heavy precipitation match those in summer temperature (Fig. 13). Slight changes were observed in the magnitude of heavy precipitation between the two subperiods, which indicated that summer temperature shifted from cooling to warming, may have little influence on the magnitude of heavy precipitation. However, central-southern China was dominated by an increasing trend before the TPs of T_{min} and the increasing trend was much evident after the TPs of T_{min} in the timing of heavy precipitation. It again confirmed that summer temperature warming has the potential to accelerate the delayed occurrence of heavy precipitation. Over the northern parts of China where remarkable cooling changes of summer temperature were observed before TPs, a significant decreasing trend in the frequency was observed. After the TPs of summer temperature, the trends of frequency of heavy precipitation over these regions also reversed, almost exactly in line with the summer temperature trends. This dipole of trends in the frequency of heavy precipitation was remarkably coherent with the summer temperature trends in the north parts of China, which further corroborated

that the occurrence of heavy precipitation was more frequent recently in response to changes in summer temperature warming over northern parts of China.

5. Discussion

Changes in heavy precipitation were the basis of the elaboration of risk maps and played an important role in public safety, storm water infrastructure, and adaptation strategies in a changing climate. Recently, Ingram (2016) indicated that extreme precipitation increases all around with a standpoint of global scale. Because of nobody living on global average, change in heavy precipitation is important for planning and adaptation in a particular region where devastating consequences caused by extreme events happen. Our results pointed out here that the increase is not in the magnitude but in the frequency of heavy precipitation events over large areas of China, in particular northwestern and southeastern China. Our findings relate to a range of heavy precipitation event frequency showing a positive trend, hence they have serious implications on the associated flood risk and design of urban infrastructures and hydraulic structures, and the potential impact on business and society.

Yang et al. (2013) examined trends in the seasonal maximum daily precipitation over China and found no significant changes in the magnitude of the largest 1-day accumulation. These results potentially implied that storms may have become more frequent (Villarini et al., 2013). Heavy precipitation plays an important role in the occurrence of flood. Mallakpour and Villarini (2015) found that the above changes in heavy precipitation are the key factors that lead to moderate changes in the magnitude but remarkable increasing frequency of flooding across the central United States. Therefore, our findings can also provide another evidences shedding

new light on whether there are changes in floods over China, though there are many other factors that may affect floods in addition to heavy precipitation, including changes in land use, water storage or water management (Hirsch and Archfield, 2015).

Many studies have attributed the changes in heavy precipitation to global warming (Collins et al., 2013; Donat et al., 2016; Milly and Dune, 2016). As expected, the overall geographical pattern follows a “wet gets wetter, dry gets drier” trend due to temperature increase (Collins et al., 2013). Milly and Dune (2016) also suggested that atmospheric warming will drive an increase in potential evapotranspiration (PET) with a consequence of continental drying. However, our results showed that the areas with an increase in the frequency of heavy precipitation located in not only wet regions (southeastern China) but also dry regions (northwestern China) over China, which is in line with that by Donat et al. (2016). They found more extreme precipitation both in the world’s dry and wet regions (Donat et al., 2016). In addition, the match of patterns, between the trends of both the summer temperature and the frequency of heavy precipitation during the two subperiods before and after TPs in summer temperature in northern parts of China, is the strongest which indicates that temperature shifting from cooling to warming could contribute to heavy precipitation events occurring more often over dry regions (i.e. northern parts of China). Our findings are consistent with that in a previous study which showed that the northern half of central United States had the largest concentration of increasing trends in heavy precipitation with the most warming (Villarini et al., 2013).

Based on the Clausius–Clapeyron equation, the concentrations of atmospheric water vapor will increase with 6–7% per °C of warming to the saturation

concentrations (Ingram, 2016). Generally speaking, more atmospheric water vapor has better condition to carry more precipitation. There are some ways that the increasing atmospheric water vapor turned to precipitation. One way is that the wetter storms become wettest which make heavy precipitation events more extreme. Another way is that the wetter storms become not wettest but more often which triggers more often occurrence of heavy precipitation events. The previous study has confirmed that increasing temperature trends to trigger the intensification of precipitation across China (Zhang et al., 2013). Our results showed that the latter is the main type in increasing precipitation due to climate warming across China.

However, it also should be noted that there are different meteorological, hydrological and climatological mechanisms behind the occurrence of heavy precipitation (i.e., tropical cyclone, convection, thunderstorm, frontal passages, sea surface temperature (SST) anomalies, and jet streams) (Hischboeck, 1988). It is difficult to identify certain relationships between the above mechanisms and temperature which shows that a direct attribution of summer temperature changes in heavy precipitation is still very challenging. In addition, the complex physical interactions make the prediction of changes in heavy precipitation hardest. For example, some studies suggested that tropical cyclones would become more intense in a warming climate (Knutson et al., 1998; Knutson and Tuleya, 2004; Knutson et al., 2007), while the tropical cyclone frequency generally decreased over China (Ying et al., 2011) with a consequence of tropical cyclone-induced precipitation significantly decreasing during the past few decade (Ren et al., 2006).

Another factor that may have impacts on our findings is the quality of data used in this study. Most of 728 stations used in this study relocated at least one time (Wu, 2005). In addition, the environment around some stations has shifted from

urban-free to urbanized environment before and after the 1970s due to social and economic development (Wu, 2005). For example, the Yellow River basin has undergone tremendous land use and land cover changes due to human activities, particularly during the period 1975-1985 (Liu et al., 2008). Therefore, it is difficult to state whether these changes in heavy precipitation are associated with data inhomogeneity or shifts from one climate regime to another. Despite the above factors causing some uncertainties in the results of heavy precipitation analysis, nothing can replace measuring the real world in situ (Hirsch and Archfield, 2015; Ingram, 2016).

6. Conclusions

In this study, changes in the magnitude, frequency and timing of heavy precipitation were analyzed based on POT sampling with 95% percentile as the threshold. The possible links between the changes in heavy precipitation and summer temperature were also investigated. Results of this study can be summarized as follows.

(1) There are significant shifts in the magnitude of heavy precipitation with 55% stations having a CP. However, no discernible spatial patterns can be identified for CPs. Significantly monotonic trends have not been observed during the whole study period, which is consistent with that in both the two subperiods before and after the CPs.

(2) In contrast with the changes in the magnitude of heavy precipitation, most stations showed a significant increasing trend in frequency of heavy precipitation, while just a few stations had a CP in the frequency of heavy precipitation. The areas with significant increasing frequency were mainly concentrated in northwestern

China and southeastern China. In addition, most of stations with CPs have shown decreasing trends to increasing trends, especially in northern China.

(3) Similar to the results of CPs detection in the magnitude of heavy precipitation, 36% stations with a CP in timing of heavy precipitation have no discernible spatial pattern. However, significant increasing trends were observed in central-southern China during the whole study period, while significant increasing trends were detected at few stations in the two subperiods before and after the CPs in this region. These results pointed out that the occurrence time of heavy precipitation may have a shift in which more heavy precipitation events happen during summer towards autumn. After analyzing the differences between water vapor flux before and after 30 years during four seasons, the water vapor flux behavior does not benefit the occurrence of heavy precipitation during summer but autumn over south China, which delays the occurrence time of heavy precipitation in central-southern China.

(4) Most of stations have a shift in summer temperature and the spatial distribution of TPs is similar with that in the frequency precipitation. In addition, the areas with significant increasing trends in frequency precipitation are those dominated by remarkable warming air temperature. In particular, over northern parts of China, the frequency of heavy precipitation has shifted from significant decreasing trend to significant increasing trend as the summer temperature turns cooling to warming. However, no remarkable changes have been observed in the magnitude of heavy precipitation related to varying summer temperature. A possible interpretation of the findings is that climate warming could make heavy precipitation not more extreme but more frequent. The ongoing work will focus on the heavy precipitation analysis in global climate model (GCMs) simulations from

the Coupled Model Intercomparison Project Phase 5 (CMIP5), which will be used to support the results from observed data.

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Fig. 1 Locations of weather stations across China.

Fig. 2 Information on precipitation/temperature datasets analyzed in the study. (a) Number of stations with between 55 and 64 years of complete data; (b) number of stations with complete data for each year (1951-2014)

Fig. 3 Spatial distribution of threshold values defined by 95th percentile used for POT analyses, unit: mm/day. The colors in the map indicate the magnitudes of the threshold.

Fig. 4 Spatial distribution of change points (CPs) in the magnitude of heavy precipitation across China (significance level of 0.05). The locations of CPs are in (a) the mean, and (b) the variance; and (c) the locations of the selected final CPs in the mean/variance. The stations without CPs are not displayed. The colors indicate the time of CPs within different periods.

Fig. 5 Spatial distribution of trends in the magnitude of heavy precipitation (a) at all stations, (b) at stations without CPs, (c) at stations with time series before CPs, and (d) at stations with time series after CPs across China (significance level of 0.05).

Fig. 6 Spatial distribution of CPs in the frequency of heavy precipitation at annual scale across China. The colors indicate the time of turn points within different periods.

Fig. 7 Spatial distribution of trends in the frequency of heavy precipitation (a) at all stations, (b) at stations without CPs, (c) at stations with time series before CPs, and (d) at stations with time series after CPs across China (significance level of 0.05). The stations without CPs are not displayed.

Fig. 8 Spatial distribution of CPs in the timing of heavy precipitation events (significance level of 0.05). The locations of CPs are in (a) the mean, and (b) the variance; and (c) the locations of the selected final CPs in the mean/variance. The stations without CPs are not displayed. The colors indicate the time of CPs within different periods.

Fig. 9 Spatial distribution of trends in the timing of heavy precipitation (a) at all stations, (b) at stations without CPs, (c) at stations with time series before CPs, and (d) at stations with time series after CPs across China (significance level of 0.05). The stations without CPs are not displayed.

Fig. 10 Differences between water vapor flux before and after 30 years during four seasons (A ~ D indicates spring, summer, autumn and winter, respectively), unit: $\text{kg} / \text{m} \cdot \text{s}$. Shaded areas with positive values show the sources of water vapor and negative values the sink of water vapor.

Fig. 11 Spatial distribution of turn points (TPs) of average values of daily minimum ((a) T_{min}), average ((b) T_{ave}), and maximum temperature ((c) T_{max}) in summer across China. The colors indicate the time of TPs within different periods.

Fig. 12 Spatial distribution of trends in average values of daily minimum (T_{min}), maximum (T_{max}) and average temperatures (T_{ave}) on summer across China.

Fig. 13 Spatial distribution of changes in the magnitude, timing and frequency of heavy precipitation across China under the influence of summer temperature.