Statistical spatiotemporal analysis of hydro-morphological processes in China during 1950–2015

Nan Wang^{1,2} · Weiming Cheng^{1,2,3,4} · Luigi Lombardo⁵ · Junnan Xiong^{1,6} · Liang Guo⁷

Accepted: 18 March 2021

© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2021

Abstract

Hydro-morphological processes (HMPs) are some of the most destructive natural disasters. Understanding the spatiotemporal characteristics of HMPs across China is important for enabling better disaster estimation and prevention at the national scale. However, few studies have focused on the spatiotemporal HMP characterization under various geomorphic settings in China, which may shed light on their regional/national evolution. To bridge this research gap, we analysed the longest HMP time series available in China, which including 47,483 HMP records, to detect spatiotemporal patterns. Specifically, we run several tests namely, Mann–Kendall test, wavelet analysis, Monthly Frequency, and Index of Dispersion, with the objective of detecting the temporal evolution, trends, period, and clustering of HMPs in six geomorphological regions (geomorphic-regions): Eastern Plain, South Eastern Mountain (SEM), North Central Plateau, North Western Basin, South Western Mountain (SWM), and Tibetan Plateau. Our results show that in the last decades have been associated with a marked increase in HMPs and this should be accounted for, especially in those areas where we have retrieved high spatiotemporal clustering (e.g., SEM, SWM). Besides, the main periodicity of HMPs is approximately 12–25 years for most of China since the 1980s, which showed analogous patterns with precipitation anomalies. This study provides a preliminary reference for revealing the spatiotemporal characteristics of HMPs in the context of climate change; therefore, the information provided can be crucial to plan engineering applications with specific return period.

Keywords Hydro-morphological processes · Spatiotemporal distribution · Periodicity · Clustering

✉ Weiming Cheng
chengwm@lreis.ac.cn

¹ State Key Laboratory of Resources and Environmental Information Systems, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

² University of Chinese Academy of Sciences, Beijing 100049, China

³ Jiangsu Center for Collaborative Innovation in Geographic Information Resource Development and Application, Nanjing 210023, China

⁴ Collaborative Innovation Center of South China Sea Studies, Nanjing 210093, China

⁵ Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, PO Box 217, 7500 Enschede, AE, Netherlands

⁶ School of Civil Engineering and Architecture, Southwest Petroleum University, Chengdu 610500, China

⁷ State Key Laboratory of Simulation and Regulation of Water Cycle in River Basin, China Institute of Water Resources and Hydropower Research, Beijing 100038, China

1 Introduction

Hydro-morphological processes (HMPs, including water floods, debris floods, debris flows, etc.) are some of the most destructive natural disasters, due to the number of people affected and the amount of regional and global property loss (Borga et al. 2011). HMPs are triggered by high-intensity and short-duration rainfall and often of a spatially confined and convective origin (Faccini et al. 2018; Saharia et al. 2017). HMPs are expected to increase in frequency and severity due to the impacts of climate change on severe weather events (especially in the form of heavy rainfall) and river discharge conditions (Kleinen and Petschel-Held 2007). This effect is also expected to act at the global scale, therefore involving different landscapes and environmental conditions (Audru et al. 2010). Consequently, mitigation of HMPs in mountainous areas is an important part of public safety management and social development (Borga et al. 2011).

Some researchers have undertaken studies to detect the spatiotemporal characteristics of flood-related disasters. For instance, Mediero et al. (2015) collated a dataset consisting of the longest flow series available for Europe and revealed an over-dispersion in the Atlantic and Continental regions as well as an under-dispersion in the Scandinavian region. Similarly, based on a pan-European database, Blöschl et al. (2017) detected flood timing patterns over Europe in the past five decades and they highlighted the evident climate signal in floods at the continental scale. A clear upward trend in flood frequency in Germany was proven to be driven by extreme precipitation and atmospheric circulation (Petrow and Merz 2009); and the same applies to the Mediterranean area (De Waele 2008). However, a divergent trend was found in the annual flood rate in southeast and southwest Australia, and the significant downward trend was mentioned to be associated with the El Niño Southern Oscillation (Ishak et al. 2013). Several recent studies showed that floods exhibit nonstationary behaviours due to climate change, urbanization, land-use change, and water resources (e.g., Liu and Zhang 2017). Because of this, most studies where a HMP susceptibility analysis is carried out may have ignored the nonstationary spatiotemporal effect (e.g., Zhao et al. 2018). The non-stationarity can be captured via different descriptive tools able to detect temporal clustering behaviour and its variations in frequency or rates. Temporal clustering of HMPs may have considerable consequences for estimation, design, and risk management of HMPs (Merz et al. 2016). Additionally, the clustering of catastrophic events is an important issue for the insurance industry when modelling the price of insurance contracts (Khare et al. 2015). Hence, it is of utmost importance to

understand not only if clustering exists but how clustering changes across space and time. HMP clustering is typically explained through linkages between HMP frequency or magnitude and climate. There are well-organised modes of inter-annual, inter-decadal, and low-frequency climate variability (Barnston and Livezey 1987). Non-parametric tests are particularly suitable for HMP series, as hydrological data are generally not normally distributed and are serially correlated (Kundzewicz and Robson 2004). Moreover, they are more robust to outliers and do not require any assumptions related to distribution (Hamed and Rao 1998). A better understanding on the intra-annual clustering of HMPs and hence the most probable HMP generation processes can therefore assist in identifying the dominant season of HMPs in the regions under the similar environmental conditions (Hall and Blöschl 2018).

According to a report by the Ministry of Water Resources of China, up to 72.4% of flood-related deaths are attributed to HMPs occurred in mountainous areas (MWR 2014). A large number of articles have been published on HMP occurrences in China. For instance, He et al. (2018) and Ma et al. (2018) provide descriptive statistics of HMPs for the whole Chinese territory. However, they focused more on the distribution of the resulting victims in space and time. Kundzewicz et al. (2019) and Wang et al. (2014) also worked at the national level although the former primarily focused on changes in precipitation regimes and river flows whereas the latter dove onto the economic impact. Several studies have also been conducted to understand the spatiotemporal behaviour of HMPs at the national scale. For instance, Liu et al. (2018) reported the geographical location of the centroids, degrees of aggregation, and associated movement tendencies of HMPs during 1951–2015. At the provincial scale, the spatiotemporal distribution and driving factors of HMPs were analysed in several specific region and time span. For instance, Xiong et al. (2019, 2020) analysed the long period (1949–2015) but the area they cover is limited to the Yunnan and Fujian provinces, respectively. Liu et al. (2017) focused on the driving factors of HMPs in Sichuan province during 1949–2015, and pointed out that human activities and precipitation showed the most importance in the spatiotemporal distribution of HMPs. The changing flood frequency of the Pearl River Basin has also been evaluated for the period of 1951–2014, and the results showed that the abrupt changes of peak flood flow attribute both precipitation extremes and the human activities (Zhang et al. 2018). Despite data-specific differences, these articles tried to provide descriptive spatiotemporal statistics of HMPs. Conversely, other contributions have tried to build predictive models on the basis of HMP database. Zhao et al. (2018) assessed the HMP susceptibility of China via Random Forest and Ragetti et al. (2017) did the

same via a more generic Decision Tree. Many more articles apply the same susceptibility criterion but on single regions and with different algorithms. This is the case for Wang et al. (2019) in Dingnan county and Lin et al. (2020) in Guangdong province. Ultimately, our review highlighted articles where the prediction is based on physically based models. Therefore, the scale is much more local and corresponds to single catchment (e.g., Jia et al. 2019). Out of the very large number of articles, however, there is a lack of research focusing on the spatiotemporal changes of HMPs across different geomorphological regions in China. The geomorphological diversity of China contributes to increase the spatial heterogeneity of spatiotemporal HMP characteristics, which hinders HMP estimation and forecasts at the national scale (Liu and Huang 2020). Therefore, to reveal the distinct spatiotemporal characteristics of HMPs under different geomorphic settings, we studied the evolution of HMPs in China from 1950 to 2015.

Credible first-hand information obtained from hazard observations is the basis for any kind of scientific study and assessment (Wirtz et al. 2014). In this study, the spatiotemporal HMP series, which consists of the longest available time series in China, has been compiled to address the need for national HMP information based on the first national investigation held by the China Institute of Water Resources and Hydropower Research (Liu and Huang 2020; Liu et al. 2018). Although some studies already exploited the same database we use here (Liu et al. 2018; Xiong et al. 2019, 2020), few of them has share some degree of commonality with the present contribution. More specifically, we analysed the spatial and temporal characteristics of HMPs for the whole Chinese territory, according to six geomorphological regions (geomorphic-regions): Eastern Plain (EP), South Eastern Mountain (SEM), North Central Plateau (NCP), North Western Basin (NWB), South Western Mountain (SWM), and Tibetan Plateau (TP). Based on the Chinese HMP dataset, the temporal evolution, trends, period, and clusters were analysed in detail together with the correlation between HMPs and climatic indicators to reveal the potential dependence of HMPs with respect to climatic changes. To the best of our knowledge, seasonal and annual characteristics of HMPs in China are mapped for the first time in this study. We address this gap in knowledge through our analysis of HMP evolution over the past 66 years in China. Thanks to the unique dataset we analysed, the main contribution we bring with respect to other articles is brought by the vast spatiotemporal domain we investigated. Therefore, this manuscript is intended to investigate HMPs across a uniquely large spatio-temporal domain covering not only 66 years but also a continental-scale extent corresponding to the whole Chinese territory. Beside this, we present an analytical protocol aimed at estimating how HMPs are

distributed over time in China. To do so, we carried out analyses sensitive to spatiotemporal clustering, estimated the non-stationarity of HMP occurrences and finally correlated our results with respect to climatic indicators. We stress that the protocol we developed chiefly focuses on the spatiotemporal dimension of the HMP distribution. Thus, the spatial component does not explicitly interact with the temporal one. We chose this framework specifically to estimate spatiotemporal variations and trends in HMPs that may be linked to large scale climate changes experienced during the Anthropocene.

The paper is organised as follows. Section 2 introduces the datasets and study area used in this study. Section 3 then describes the method used to detect the spatiotemporal variations in HMPs in China. This is followed by the analysis of spatiotemporal characteristics of HMPs, including spatiotemporal evolution, trends, period, and clustering in Sect. 4. Finally, Sect. 5 discusses the anomalies detected in HMP series and interprets its spatiotemporal trends.

2 Study area and data source

2.1 Study area

China lies between latitudes 18° and 54°N, and longitudes 73° and 135°E, with the mountainous areas covering about two-thirds of its territory. The landscape varies significantly across China, ranging from the hilly and mountainous terrain in southeast to the Gobi and deserts in the northwest. The southwest of the country is the towering massifs and rolling plateaus, including part of the highest tableland on earth, the Tibetan Plateau. Most of the China's agricultural land and settlements locate in the eastern plains and southeast coastal area.

In geosciences and especially when dealing with natural hazards, partitioning the geographic space is a fundamental step because it ensures that the mapping unit (Hansen 1984), subdivides the landscape according to specific rules and objectives. Commonly, one can partition space into a regular lattice (be it a square grid cell or a hexagon), into a geomorphological unit (slope units, catchments or larger geomorphological units), or into an administrative unit (municipalities, regions or countries) (Lombardo et al. 2018). In this work, we chose a hierarchical space partition based on two scales corresponding to local catchments and larger geomorphic-regions. For a vast area such as the whole Chinese territory and for studying the hydro-geomorphological processes resulting from HMPs, a geomorphic-region provides the appropriate spatial partition to differentiate between natural environments. Here we adopted the same geomorphic-region proposed by the

Table 1 Description of the six geomorphic-regions in China

Geomorphological region	Description
EP	<p>This region is in the northern part of China. It comprises low terrains and the largest plain areas. Plains and platforms are dominant features of this region, along with well-developed fluvial accumulation landforms. Major watersheds in this region include the Songhua River Watershed, the Tumen River Watershed, and the Huai River Watershed. HMPs in the Songhua River watershed are mostly caused by heavy storms, 80% of HMPs occur in July and August (especially in August). HMPs in the Huai River Watershed can be caused by Meiyu and heavy storms, and the HMPs are generally concentrated from June to September.</p>
SEM	<p>This region is located in the southern part of the low terrain topography, and it is dominated by low elevation hills and low or middle relief mountains, with only 30% of its area occupied by plains and platforms. Major watersheds in this region include the middle and lower reaches of the Yangtze River Watershed and the Poyang Lake Watershed. HMPs are the most frequent and serious in middle and lower reaches of the Yangtze River Watershed because of the Meiyu and heavy storms.</p>
NCP	<p>This region is located in the north-eastern part of China's middle terrain topography and is characterised by a plateau landform composed of low or middle relief mountains, hills, platforms, and plains. The loess landform is well developed in this region. Major watersheds in this region include the middle reaches of the Yellow River Watershed and the Wei River Watershed. HMPs concentrate in late July to early August and are caused by heavy storms. Ice floods are easily caused by ice jams, ice dams, etc. in the middle and lower reaches of the Yellow River.</p>
NWB	<p>This region is located in the north-western part of China with the middle terrain topography. It is composed of middle to high mountains with flattened basins interposed between them. It is characterised by an arid desert geomorphology, such as Taklamakan desert. Mountains with basins are made up of plains, platforms, and hills. Major watersheds in this region include the Tarim River Watershed and the Ili River Watershed. HMPs in this region can be caused by local heavy storms or the combination of heavy storms and snowmelt.</p>
SWM	<p>This region is located in the southern part of the middle terrain topography. Evidencing a typical karst landform, middle or high mountains with middle or high reliefs are widespread with wide valley basins interspersed between them. Major watersheds in this region include the upper and middle reaches of the Yangtze River Watershed and the Jialing River Watershed. Influenced by the plateau monsoon climate, the storm period in this region is long and usually multi-peaked.</p>
TP	<p>This region encompasses China's high terrain topography. It is composed of plains and high mountains at elevations above 4,000 m which account for three-fourths of the area in this region. It is characterised by glacial and periglacial landforms. Major watersheds in this region include the Yarlung Zangbo River Watershed, Nu River Watershed, and Shiquan River Watershed. Local persistent heavy rain is the main cause of HMP in the middle reaches of the Yarlung Zangbo River Watershed.</p>

Chinese State Key Laboratory of Resources and Environmental Information Systems (Wang et al. 2020). Therefore, we subdivided the Chinese territory into six major geomorphic-regions (Table 1 and Fig. 1).

2.2 Hydro-morphological processes inventory

HMPs in China for the period of 1950–2015 were provided by the National Flash Flood Disasters Investigation and Evaluation Project (Liu et al. 2017 and 2018). The project was conducted at the national scale using data collection, field investigation, and information checking. HMP records (occurrence time and location) were collected from multiple sources, including local chronicles, bulletins of flood and drought disasters in China (a database released by the MWR) together with official documents issued by local governmental departments. As a result, the HMP spatial information (longitude and latitude), temporal location (date and time), together with additional metadata (number of victims and total economic loss) were collated across the country. However, because of the lack of technical description especially in the earliest reports, the HMP dataset does not differentiate between water floods, debris floods and debris flows, and they all fall within the same description indicating fast hydro-geomorphological

disasters, mostly occurring in mountainous areas. In this study, we will refer to each occurrence in our dataset as HMPs to generalize the disasters' characteristics.

In addition to the nomenclature issue of the specific disaster type within the Chinese HMP archive, at times some disasters are repeated at the same time and at the same location. Therefore, prior to any analytical step, filtering out repeated instances is required. We did this by deleting any event recorded with the same date and time and within the same administrative village (which is the smallest administrative unit in China). Besides, the same HMP occurred in the upper stream may induce damage to different villages or catchments. In that case, we maintained the records and identified them as different disasters to respect the spatial information. It is important to note that such procedure may induce spatial clustering, which we have not fully accounted for in this manuscript.

To the best of our knowledge, this inventory is the first dataset focusing on national HMPs in China and consists of the longest available temporal records. In this study, we selected the HMPs with full date records in the form of year-month-day or year-month since 1950, and totally 47,483 events were used for the subsequent research (Fig. 1).

Fig. 1 Location and inter-year and intra-year series of HMPs in China during 1950–2015. **a** The spatial location of the study area, and the distribution of HMPs. **b** The inter-year series of HMPs. **c** The intra-year series of HMPs

Notably, the number of HMPs strongly changes through time (Fig. 1b). In this work, we did not want to dismiss the initial 30 years analogic records, hence we included this information in our analyses, and we consider the potential presence of a mapping bias in our interpretation.

2.3 Watersheds delineation

The watershed was adopted as the highest resolution mapping unit in this study for calculating temporal trends and clustering. Based on the third-order stream provided by the Resource and Environment Data Cloud Platform (<http://www.resdc.cn/>), the entire study area was divided and merged into 133 watersheds, with the watershed area ranging from 0.3×10^4 to 60×10^4 km².

2.4 Climate indicators

Daily precipitation data were provided by the China Meteorological Administration (<http://data.cma.cn/>). In this study, only the stations (there are 541 out of 824 basic meteorological stations) with complete data from

1980–2010 were selected (see Fig. 2 to check the meteorological stations' distribution in China).

3 Methods

To get the persistent trending of HMPs over a long time span in China, we firstly calculated 5-year and 10-year moving average of the whole time series within each geomorphic-region; then, to further obtain the upward/downward trending together with its magnitude of HMPs on catchment scale, we performed the Mann–Kendall test and Sen's slope estimator; besides, we took advantage of wavelet analysis to obtain the periodicity of HMPs on different scales, which could contribute to the understanding on return periods of HMPs; finally, with the assumption of nonstationary in HMP series, we implemented the Index of Dispersion and Monthly Frequency to find out the potential inter-year and intra-year clustering pattern for HMPs. Below we dedicate one separate subsection to each analytical test we have run to explore the spatiotemporal characteristic of the Chinese HMP dataset.

Fig. 2 Distribution of meteorological stations in China

3.1 Mann–Kendall test and Sen’s slope

The nonparametric Mann–Kendall test is an efficient method for identifying the upward or downward trends of a time series, with the advantage of being insensitive to outliers (Kendall 1948; Mann 1945). It has been widely applied to assess the significance of the trends in climatic and hydrologic data (Donat et al. 2013). In this study, we performed the Mann–Kendall test to detect the HMP changing trends in a long time series. The equation for Mann–Kendall test statistic (S) is as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(X_j - X_i) \quad (1)$$

$$\text{sign}(x_j - x_i) = \begin{cases} 1 & x_j - x_i > 0 \\ 0 & x_j - x_i = 0 \\ -1 & x_j - x_i < 0 \end{cases} \quad (2)$$

where S is defined as the Mann–Kendall test statistic; X_i and X_j are the sequential data values at the time of i and j ($i < j$), respectively; and n is the length of the time series. A positive S indicates an upward trend and negative S reveals a downward trend in the time series (Shahid 2011).

$$E(S) = 0 \quad (3)$$

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{p=1}^q t_p(t_p-1)(2t_p+5)}{18} \quad (4)$$

where $E(S)$ and $\text{Var}(S)$ are the mean and variance of S , and t_p indicates the number of ties for the p value, and q is the number of tied values. Then, the standard test statistic Z can be computed using the following formula (5) to evaluate the presence of a statistically significant trend.

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & S < 0 \end{cases} \quad (5)$$

where positive Z indicates an upward trend and negative value reveals a downward trend. In a two-tailed test, if the calculated value of Z is between $-Z_{1-\alpha/2}$ and $Z_{1-\alpha/2}$, it is accepted that the data are independent and randomly distributed. Therefore, the absolute value of Z is compared with the critical value $Z_{1-\alpha/2}$ in a two-tailed test for testing the upward or downward trend at a significance level. In this study, 1.28, 1.64, and 2.32 is used to test the changing trend at 90%, 95%, and 99% significance level. The magnitude of the HMP changing trend in the time series was estimated by Sen’s slope (Sen 1968).

$$\beta = \text{median}\left(\frac{X_j - X_i}{j - i}\right) \forall j < j \quad (6)$$

where β is defined as the Sen’s slope estimator test; X_i and X_j are the sequential data values at the time of i and j ($i < j$), respectively. The positive β value represents an upward trend, while a negative value indicates a downward trend over the study period. Sen’s slope is tested by the significance test at the 90% confidence level.

3.2 Wavelet analysis

Wavelet analysis provides a flexible way to reveal the periodicity in a time series at different time scales by decomposing it into time and frequency domains simultaneously (Torrence and Compo 1998). It is known for the advantage in detecting nonstationary behaviour in the time series, such as geophysical processes (Grinsted et al. 2004). The continuous wavelet transformation of a signal is the convolution of the signal with a set of scaled and translated wavelets, given as:

$$W_f(a, b) = a^{-\frac{1}{2}} \int_{-\infty}^{\infty} f(t) \psi^*\left(\frac{t-b}{a}\right) dt \quad (7)$$

where $W_f(a, b)$ denotes the wavelet coefficient; $f(t)$ is a signal or a square-integrable function; ψ is the mother wavelet function (the Morlet wavelet was chosen as the mother wavelet function in this study); $*$ denotes the complex conjugate; and a, b are the scale and translation parameters, which denote the period and time shift, respectively. The real part of the wavelet coefficients indicates the distribution and phase of the different characteristic time scale signals at different times. The modulus of the wavelet represents the strength of the characteristic time scale signals.

The relationship between the period T and the scale parameter a of Morlet wavelet is as follows:

$$T = \frac{4\pi a}{c + \sqrt{2 + c^2}} \quad (8)$$

where a and b are the scale and translation parameters; c is the centre frequency of a wavelet.

3.3 Monthly frequency

The recorded monthly frequency of HMPs can be corrected to account for months with different numbers of days (Macdonald and Black 2010). If no seasonality is assumed, the occurrence probability of the HMPs in a given month is equal to 1/12. However, if HMPs do not follow an annual uniform distribution and a seasonal pattern exists, the monthly frequency is supposed to be departure from 1/12.

Fig. 3 Time series of the annual mean number of HMPs in six geomorphic-regions in China from 1950 to 2015. The grey line is the original time series; the yellow and blue lines are the 5-year and 10-year moving averages, respectively; the red line is the cumulative

number of HMPs; and the black dashed line is the trend line based on the least-squares linear regression for **a** EP, **b** SEM, **c** NCP, **d** NWB, **e** SWM, and **f** TP

Table 2 the growing rate of HMPs in each geomorphic-region

Region	Growing rate	Region	Growing rate	Region	Growing rate
EP	3.34	SEM	9.32	NCP	1.86
NWB	1.21	SWM	8.05	TP	1.86

Table 3 Statistics on watersheds showing upward/downward trends (at 90%, 95%, or 99% significance levels) within each geomorphic-region

Trends	EP	SEM	NCP	NWB	SWM	TP	Entire China
Upward	4(12%)	13(68%)	2(10%)	5(26%)	16(89%)	3(13%)	44(33%)
Downward	1(3%)	0(0%)	0(0%)	0(0%)	0(0%)	0(0%)	1(1%)
Total	34	19	20	19	18	23	133

The numbers indicate of watershed with an identified significance level for upward or downward trends, and the percentage indicates the partition of watersheds showing upward/downward within each geomorphic-region

Fig. 4 Trends of HMPs detected via the Mann–Kendall test and Sen's slope estimation

$$FF_m = \frac{F_m}{N} \frac{30}{n_m} \quad (9)$$

$$L_U^N = \frac{N + 11.491}{0.048N^{1.131}} \quad (10)$$

$$L_L^N = \frac{N - 27.832}{0.199N^{0.964}} \quad (11)$$

where FF_m is the monthly frequency of the HMPs in the month m ; F_m is the number of HMPs recorded in the month m ; N is the number of HMPs; n_m is the number of days in month m (28.25 in February to account for leap years); L_U^N and L_L^N are the upper and lower bounds of 95% significance level, respectively (Cunderlik et al. 2004). If HMPs follow a uniform distribution along the year at a significance level of 95%, the monthly frequency is supposed to distribute between L_U^N and L_L^N . However, if a monthly frequency is out of these bounds, HMPs do not follow an annual uniform distribution and a seasonal pattern exists at the 95% significance level.

3.4 Index of dispersion

Usually, the occurrence of extreme events can be interpreted as a realisation of a point process (Diggle 1983; Cox and Isham, 2000). If the HMPs occurring at one time point are independent of the HMPs occurring at any previous time, the process is defined as a homogeneous Poisson process. Therefore, the degree of HMPs cluster or departure from a homogeneous Poisson process can be described by the index of dispersion (Mailier et al. 2006). It relates the variability of HMP numbers to the expected value of the counts:

$$D = \frac{\text{Var}(Z(T))}{E(Z(T))} - 1 \quad (12)$$

where D is the index of dispersion; $Z(T)$ is the series of HMP numbers within a time window with length T (here, T was set as 1 year); $\text{Var}(Z(T))$ is the variance of the HMP numbers; and $E(Z(T))$ is the expected value of the HMP numbers.

Fig. 5 The real part of the wavelet coefficient in six geomorphic-regions of China: **a** EP, **b** SEM, **c** NCP, **d** NWB, **e** SWM, and **f** TP

For a homogeneous Poisson, D is equal to zero. Negative D values represent under-dispersion and characterise a more regular pattern of HMP occurrence. Positive D values stand for over-dispersion and they also characterise the clustering of HMP occurrence (Merz et al. 2016).

4 Results

4.1 Temporal evolution analysis

In this section, we analysed the large-scale evolution pattern for the six geomorphic-regions using the number of HMPs in each geomorphic-region from 1950 to 2015 based on the 5-year and 10-year moving averages of the time series. The results show a marked rise in the number of HMPs in China, with a growth rate of ~ 25.63 HMPs per

Fig. 6 The modulus of wavelet coefficients in six geomorphic-regions of China: **a** EP, **b** SEM, **c** NCP, **d** NWB, **e** SWM, and **f** TP

year since 1950 ($y = 25.63(t-1950) - 151.48$, $R^2 = 0.39$). The six geomorphic-regions show a similar overall increasing trend, while each geomorphic-region displays divergent trending patterns. As the original time series indicates, the number of HMPs reach two obvious peaks for 1998 and 2010 in all six geomorphic-regions; EP, SEM, and SWM contain two significant peaks and show slight fluctuates in other periods (Fig. 3a, b, e). However, NCP and NWB show growth with more nonstationary changes (Fig. 3c, d), and the number of HMPs in TP increases drastically, especially in the last two decades (Fig. 3f). Based on the 5-year and 10-year moving averages, intensities in most regions can be divided into two phases: 1985–1998 and 2000–2010. The mean growth rates of NCP, NWB, and TP are ~ 1.86 HMPs per year, ~ 1.21 HMPs per year, and ~ 1.86 HMPs per year, respectively. EP shows a consistent and significant increasing trend with a mean change rate of ~ 3.34 HMPs per year; while SEM and SWM increase sharply with mean growth rates of ~ 9.32 HMPs per year and ~ 8.05 HMPs per year, respectively (Table 2). Additionally, the accumulated number for 1950–2015 indicates that the rate of change for the HMPs follow three forms: EP and NCP display a linear pattern; SEM and SWM increase at a speeding rate geometrically; and the number of HMPs increase exponentially in TP and NWB.

4.2 Temporal trends analysis

Based on the number of HMPs in each watershed from 1950 to 2015, the HMP trends within each geomorphic-region are verified via Mann–Kendall test, and the associated magnitude is estimated by Sen's slope. As shown in Table 3, the significant upward trends are detected for all six geomorphic-regions at 90%, 95%, and 99% significance level and for 33% of all watersheds nationally (Table 3). The watersheds with significant upward trends are scattered throughout SWM or located along the southeast coastal area within SEM, which account for 89% and 68% of all watersheds in these geomorphic-regions, respectively (Table 3). The most significant upward trends (at 99% significance level) are detected in the two watersheds located in the central and southern of SEM (Fig. 4). In NCP, significant upward trends are only detected in two watersheds (10%), which are located in the northern part of NCP. In contrast, the watershed with a 90% significant downward trend is found in the eastern portion of EP (Fig. 4).

The size of the circles in Fig. 4 indicates the magnitude of HMP trending. The results of the Sen's slope estimator test demonstrate that the regional increasing rate of HMPs in EP, SEM, NCP, NWB, SWM, and TP are 0.37, 2.37, 0.03, 0.23, 2.23, and 0.18 per year, respectively. The watersheds with the strongest growth trends are mainly distributed in SWM and the southeast SEM as shown in Fig. 4. For the specific watershed, the most obvious

Fig. 7 The wavelet variance analysis of HMPs in six geomorphic-regions of China

Fig. 8 Monthly frequency of HMPs in six geomorphic-regions. The grey line is the monthly frequency of the watersheds within each geomorphic-region, the red line is the mean monthly frequency of

each geomorphic-region, and the horizontal blue dashed line is the confidence intervals of 95% in the case of a non-seasonality pattern

Table 4 Intra-annual clustering characteristics of HMPs identified in six geomorphic-regions

Region	HMP-rich months	HMP-poor months	Clustering type
EP	July and August	September to May	Right-skewed
SEM	June to August	October to April	Left-skewed
NCP	June to August	September to April	Right-skewed
NWB	June to August	September to April	Left-skewed
SWM	June to August	October to April	Symmetrical
TP	June to August	October to April	Right-skewed

increasing trends are detected in southern and central SEM, and they each indicate a Sen's slope value of 0.5.

4.3 Temporal period analysis

4.3.1 Period scales identification

The real part of the wavelet coefficient reflects the periodic variation in the sequence of HMPs. Its distribution in the time domain indicates the change in HMP trends at different time scales. The frequency distributions of the real part of the wavelet transform coefficients in each geomorphic-region are shown in Fig. 5. The wavelet plots highlight different HMP recurrence through time, this being repeated for each geomorphic-region. More specifically, temporal trends are shown with different sizes and recurrence time. For instance, Fig. 5e (or SWM), shows

from the bottom-right corner upward, three different sizes of the real part of the wavelet. Small clusters are shown with a periodicity (left y-axis) of 2–8 years. We stress that the alternation between wavelet transform coefficients of opposite signs (red and blue clusters of equal size for clarity) corresponds to the oscillation that the temporal HMP behaviour can exhibit through time, being either present or absent. Moreover, the second set of clusters are shown with a periodicity of 10–25 years whereas the last cluster set shows a periodicity of at least 30 years.

These variations occur in every geomorphic-region with different temporal HMP characteristics. For instance, EP, SEM, and SWM follow a similar evolution periodic pattern, while NCP, NWB, and TP exhibit quite different periods. The main periodicity characteristics of EP, SEM, and SWM are approximately 12–25 years with three oscillation periods, and they tend to be stable since 1980. Another prominent time scale for EP, SEM, and SWM is 2–8 years, which contains two oscillation periods and began to stabilize around 2006. The most striking wavelet plot corresponds to the NCP (Fig. 5c), where the 10–25 years HMP periodicity and associated oscillation can be detected since the 1950s and until 2015. Here, the 8–12 years periodicity can be detected from the 1990s onward, and the 5–8 years periodicity can be detected from the beginning of 2005. In NWB, the 10–22 years periodicity began in 1975 with four oscillation periods (Fig. 5d). However, no obvious periodicity can be detected on a large scale for TP (Fig. 5f).

Fig. 9 Monthly frequency of HMPs. The colour bar represents the monthly frequency for each month; the yellow to red areas contain watersheds which are HMP-rich (monthly frequency larger than

0.11), while the blue areas contain the watersheds which are HMP-poor (monthly frequency lower than 0.05)

Fig. 10 Percentage of watersheds with significant HMP clustering at a 95% significant level in the six geomorphic-regions. T indicates the time scale (1 year, 2 years, 3 years, 4 years, and 5 years), and the x-axis indicates the shifting start time of the aggregation time window

	T=1			T=2			T=3			T=4			T=5			
EP	70	74	78	78	70	74	78	74	74	78	78	74	74	70	70	95% 90% 85% 80% 75% 70%
SEM	88	88	88	94	94	88	94	94	94	94	94	94	94	94	94	
NCP	84	79	84	84	79	79	84	79	79	84	79	79	79	74	74	
NWB	88	81	81	88	75	81	81	81	81	81	94	88	88	69	81	
SWM	89	89	89	89	89	89	89	89	89	89	89	89	89	89	89	
TP	83	87	91	87	91	87	91	96	83	87	91	87	87	87	91	
	1	1	2	1	2	3	1	2	3	4	1	2	3	4	5	
The start of the aggregation time window (years)																

In Fig. 6, we summarized the modulus of the Morlet wavelet. The modulus of the Morlet wavelet coefficients is the reflection of the energy density distribution which corresponds to the period variation in the time domain. To put it simple, Fig. 6 shows another signal associated with the signal shown in Fig. 5. The way one should interpret it, is that Fig. 5 shows the period of HMPs and their oscillation through time whereas, Fig. 6 shows how strong the

signal (periodicity and oscillation) appears to be in the data. The larger the coefficient modulus is, the more apparent the periodicity of the corresponding time period or scale.

In EP, SEM, and SWM (Fig. 6a,b,e), the largest and well determined time scale is 15–20 years, which exhibits the clearest temporal scale patterns, followed by the period of the 2–6 years which ranks the second place and contains

Fig. 11 Index of dispersion of HMPs in watersheds for the period of 1950–2015. The solid circles indicate the clustering at 95% significance level, and the circles with white holes indicate the non-significant index of dispersion

smaller periodic variation. In NCP, the most significant periodic variation is 10–20 years, and the second most is 5–8 years (Fig. 6c) whereas in NWB, the temporal scale of 10–20 years lasts for the longest period (from 1985) (Fig. 6d).

4.3.2 Periodic component analysis

We completed our wavelet analyses by also computing the wavelet variance map. This map reflects the distribution of the energy fluctuation of the HMP time series with different time scales. It can be practically used to determine the main periodicity of HMPs. Based on the wavelet variance map, we can calculate the mean period throughout the entire study period. In Fig. 7, all geomorphic-regions except TP demonstrate the most obvious peak of 18–19 years, indicating the strongest and the first main period of HMPs occurrence. As for less evident periodicities or smaller peaks, we have found a quite peculiar characteristic. By computing the average period of each peak smaller than the 18–19 years one, for each of the geomorphic-regions, the resulting value corresponds to

7–7.5 years with the exception of the TP region, which only shows two small peaks corresponding to a periodicity of 1 and 8 years, respectively.

4.4 Temporal clustering detection

4.4.1 Intra-annual clustering

To assess the HMP-rich or HMP-poor months within one year, the seasonality pattern of the monthly frequency of HMPs in six geomorphic-regions are analysed based on their mean values in the period 1950–2015. The proposed method tests the significance of seasonal clustering by comparing the observed monthly variance with the theoretical monthly variance in a nonseasonal model. Figure 8 shows the intra-annual monthly frequency for all watersheds and the averaged intra-annual trends for each geomorphic-region (or monthly frequency, see Sect. 3.3).

Based on the distribution patterns shown in Fig. 8 and Table 4, the peak location (with the highest monthly frequency) can be categorized into three types, namely, right-skewed, left-skewed, and symmetrical. EP, NCP, and TP

Table 5 The numbers of HMPs distributed within each precipitation anomaly zone

Anomalies of precipitation (%)	1998						2010					
	May	Jun	Jul	Aug	Sep	Oct	May	Jun	Jul	Aug	Sep	Oct
< -40	1	14	25	48	15	2	1	45	22	46	2	1
-40 ~ -20	6	9	75	42	13	3	15	21	55	32	2	0
-20 ~ 0	30	39	209	29	9	3	22	32	66	54	19	24
0 ~ 20	30	53	143	68	7	0	19	60	130	144	31	170
20 ~ 40	13	60	137	97	4	0	31	65	294	52	24	119
40 ~ 60	6	75	149	57	1	0	28	103	381	28	43	184
60 ~ 80	9	107	133	67	1	1	31	161	457	11	13	283
80 ~ 100	5	231	95	31	2	0	6	92	417	5	11	77
≥ 100	21	239	261	140	0	3	5	110	613	6	25	32

The bold numbers indicate the top three anomalies of precipitation for each month. The red colour indicates the anomalies of precipitation below zero, and the blue colour indicates the anomalies of precipitation above zero

tend to be right-skewed distributions, with a high frequency of HMPs being more likely to appear after July (Fig. 8a,c,f). SEM and NWB are left-skewed, indicating that the HMPs usually occur earlier than July (Fig. 8b,d). In addition, SWM is identified as a symmetrical distribution throughout the summer (May to October) (Fig. 8e). However, some inconsistencies of the intra-annual frequency within the same geomorphic-region can be detected. In NWB, HMPs occurring in June to August can be detected in most watersheds, while some watersheds exhibit a high frequency in March to May. In SWM, diverse patterns and long-lasting periods of HMP-rich periods in different watersheds can be detected. In TP, HMPs are most likely to occur between June and August with some peaks scattered in different months. To summarize the analogous information in map form, the geographic conversion of monthly frequency shown in Fig. 9.

The mean monthly frequency in the six geomorphic-regions present the similar bell-shape and the highest monthly frequency usually show up in summer (Fig. 9, Table 4). In EP, July and August are identified as HMP-rich months; while, a longer HMP-rich season, from June to August, is observed for the other five geomorphic-regions. For HMP-poor seasons, there is an obvious differentiation between the geomorphic-regions in northern China (EP, NCP, and NWB), and those in southern China (SEM, SWM, and TP). The HMP-poor season period in EP is the longest, which begins in September and ends in May. The period between September and April is shown to be the HMP-poor season in the regions located at higher latitudes. Furthermore, for the regions located at lower

latitudes, the HMP-poor seasons are shorter than those at higher latitudes (from October to April).

4.4.2 Inter-annual clustering

To examine the inter-annual HMP clusters, we calculated the index of dispersion (see Sect. 3.4). However, the calculation on the index of dispersion is sensitive to the selection combinations of two parameters, the time scale and the start time of the aggregation time window. Therefore, we firstly performed a sensitivity test by changing both the time scale and the start time of the aggregation time window. Figure 10 summarizes the percentage of watersheds detected as clustering (at 95% significant level) within each region. In SWM, there is no difference showing in the percentage of watersheds detected via different schemes, while in EP there is a slight difference with various time scales. Besides, in SEM, NCP, NWB, and TP, the percentage of watersheds detected as significant clustering vary while using different parameter combinations. In SEM, an increasing clustering percentage is detected at the larger time scale, while in NCP the clustering percentage decreases at larger time scales. In TP, the highest clustering percentage is obtained at a time scale of 4 years ($T = 4$). In NWB, the highest (94%) and lowest (69%) clustering percentages are both detected at a time scale of 5 years ($T = 5$). These results demonstrate a limited sensitivity to shifts in the start of aggregation time windows.

Given the insensitivity detected above, we set the time scale as 1 year and tried to use the aggregation time

Fig. 12 Percentage anomalies of precipitation averaged in May–October, for (a–f) May–October of 1998 and (g–l) May–October of 2010. The red points are the locations of HMPs

window without shifting. The index of dispersion quantifies the deviation of annual occurrence rates from the expected occurrence rates. In other words, as the index of dispersion increases, the clustering for HMPs is detected. Index of dispersion larger than 0 is obtained in all six geomorphic-regions across China, indicating that inter-

annual clustering plays a dominant role in HMP occurrence (Fig. 11). In this study, the extensive significant cluster or large index of dispersion is up to 4 and can be detected in SEM, SWM, and TP geomorphic-regions. The largest index of dispersion ($D = 12$) is found in the Wujiang River Catchment, which is in the middle of the Yangtze River.

Such value indicates that HMPs occur on average 12 times more often in HMP-rich years than it would be expected from the Poisson distribution. Also, the cluster strength diminishes from eastern to western China. Nevertheless, six watersheds are exhibiting a statistically significant negative index of dispersion, which indicates that the inter-annual occurrence of HMPs in these watersheds are under-dispersed. In this study, the under-dispersion characteristic is mainly identified in western China, and more specifically in NWB, NCP, TP, and SWM which appear to have a more homogenous temporal pattern over the study period.

5 Discussion

The long-term evolution trends indicate that the number of HMPs in all six geomorphic-regions was relatively low before the 1980s. On one hand, this variation might be attributed to the poorly data acquisition methods and inadequate data records before the 1980s, which might have resulted in the lower occurrence observations in the historical period. On the other hand, the change in some hydro-climatic factors, e.g., precipitation, may have positively globally contributed to increase the occurrences of HMPs. Researchers have indicated that climate change contributed to much of the occurrence and magnitude of hydro-geomorphological hazards in recent years (e.g., Liu et al. 2019; Sampson et al. 2015; Ward et al. 2014).

In this section, we further discussed the potential factors associated with the HMP trends and the anomalies showing up in the HMP time series.

5.1 Anomalies of the HMP series

In this study, a general trend of increasingly frequent HMPs is detected for the period of 1950–2015 with even more notable evidence in the period of 2005–2010. Two obvious peak of HMP occurrence in 1998 and 2010 were detected from the time series throughout the study period. To reveal the detailed relation between extreme precipitation and HMPs in 1998 and 2010 (see Fig. 3), we calculated the precipitation anomalies in the light of the definition by World Meteorological Organization. The average value of a meteorological element over 30 years is defined as a climatological normal (WMO 2017). Therefore, the precipitation anomalies in this study were derived based on the mean precipitation of 1981–2010. The statistical results on the spatial distribution of HMPs overlapping with the precipitation anomaly zones are listed in Table 5. Here, the bold number with blue shade is used to indicate the close relationship between HMPs and anomalies precipitation as a preliminary tool.

In 1998, approximately 80% of total HMPs (the bold number with blue shade) located in the zone with precipitation anomalies above zero (see Table 5). The precipitation anomalies together with the rainfall belt moving from the lower, middle to upper reaches of the Yangtze River from June to August (Fig. 12b–d). During this period, the main rainfall belt extended over the Yangtze River, with most HMPs occurred in the heavy rainfall anomaly zone precipitation (here, the heavy rainfall anomaly zone indicates the region with the precipitation anomalies greater than 100%). The circulation anomalies might be attributed to the tropical sea surface temperature anomaly patterns of the preceding seasons, i.e., the super El Niño and strong warming of the tropical Indian Ocean (Yuan et al. 2017). However, the HMPs occurring in September and October are not detected in the heavy rainfall anomaly zone, as shown in Fig. 12e,f. This indicates that, apart from the precipitation, some other potential factors might contribute to the formation of HMPs.

In 2010, more than 90% of the HMPs were distributed in the precipitation anomaly zone, with the zone of 60–80% and greater than 100% ranking in the top two (Table 5). Studies indicate that an El Niño Modoki (a particular ocean–atmosphere phenomenon in the tropical Pacific Ocean, which is a part of the El Niño Southern Oscillation) with strong warming effects in the central Pacific is detected, which causes the rainfall belt to shift northward (Feng et al. 2011). The extreme precipitation appears in the Huai–Yellow River along with a weakened Indian summer monsoon and strengthened East Asian monsoon (Wang et al., 2012). The cluster centre of HMPs moves from the Yangtze River to the Yellow River from May to July (Fig. 12g–i), demonstrating the close connection with precipitation anomalies.

The variation in atmospheric circulations and monsoon activities on a large scale has a great influence on regional precipitation. The anomalies of atmospheric circulations prompt the changing intensity frequency of extreme precipitation in China (Lv et al. 2019). Besides, the fluctuations in El Niño and East Asian monsoon activities also indicating the global climate change effects correspond well with the variation of HMPs in China (Kundzewicz et al. 2019).

There is also a vast literature globally indicating the link between the periods of HMP and the circles of climate variables (e.g., Kundzewicz et al. 2019; Ward et al. 2014). The Pacific Decadal Oscillation phenomenon presents above the Pacific Ocean with alternating positive (warm) and negative (cold) phases, and it has a clear impact on natural disasters as confirmed in multiple studies (e.g., Xiao et al. 2015). It has greatly affected periodic climate change, resulting in the flood and drought episodes in China in the last decades (Shan et al. 2018; Liu et al. 2016),

which could partially explain the inter-annual clustering of HMPs (Kundzewicz et al., 2014; Blöschl and Montanari 2010). Studies have demonstrated that the warm phase of Pacific Decadal Oscillation promoted positive precipitation anomalies in eastern China for the 1960–2010s time period (Zhu et al. 2015). Moreover, El Niño and La Niña induced an alternative variation in floods and droughts, and the study in Yangtze River catchment reported the associated flood/drought periods of 16.69, 5.09 and 10.47 years (Tong et al., 2006). While, the temporal periodic analysis in our study indicates that the 12–25 years periodicity of HMPs tend to be stable for most of China since the 1980s. To be more specific, the main periodicity detected via the wavelet variance is 18–19 years, which shows a consistent accordance with the rich-poor oscillations detected in the previous study.

5.2 Regional differences on the spatiotemporal characteristics of HMPs

Although the results in this study show that the variations of HMPs present relatively obvious regional patterns, the role of climatic controls and subsurface properties (i.e., catchment storage) in the prediction of HMPs have not yet been discussed previously at the geomorphic-regional scale. In the light of the complex interplay of terrain, soil, and other underlying surface features, HMPs are usually induced by the localized extreme precipitations with various durations and intensities. Among the climate indicators, precipitation and soil moisture are the two prominent factors which could induce HMPs (Lombardo et al. 2018). As for the precipitation, most of the Chinese territory suffer from the Asian monsoon, including South Asian monsoon from Indian Ocean and East Asian monsoon from Pacific Ocean, or the interact of both (Kundzewicz et al. 2019). Among them, the East Asian monsoon has been proven to be one of the key controlling factors of the climate system which dominates the precipitation over most of the Chinese territory (e.g., EP, SEM, SWM, and NCP) (Loo et al. 2015). Additionally, the movement of the rainfall belt is closely connected to the advance and retreat of the East Asia summer monsoon (Lu et al. 2013). For instance, the lower reach of Yangtze River Basin (mainly located in SEM) is greatly affected by the East Asia summer monsoon in mid-June (Huang et al., 2017), while the Huai River Basin and Liao River Basin (located in EP) suffer more from the monsoon in late-July (Lau et al. 1988).

As previously mentioned, the East Asia summer monsoon affects most regions (SEM, EP, SWM and southern NCP) in China leading them to display similar inter-annual temporal patterns. However, apart from the hydro-climatic influence on a large scale, the localized terrain characteristics varying greatly across China, with Karst in its south-

western region, loess covering its central part, as well as the desert and Gobi extended through the broaden north-western China (Wang et al. 2020). Besides, the regional differences in soil features, vegetation, human activities, etc. also contributes to the spatial differentiation in each localized region (Liu and Huang 2020). The various underlying conditions together with extreme rainfall result in the great difference in the intra-clustering behaviour as well as its associated frequency and magnitude for HMPs in China.

5.3 Contributions, limitations, and future work

Our contribution aims to develop an analytical protocol for examining the HMP signal via well-established statistical tools able to summarize several aspects of the spatiotemporal HMPs distribution and associated trends. This significantly differs from the articles mentioned in previous, where the investigation is focused on specific aspects rather than seeking a holistic data-driven description. In fact, we investigate the spatiotemporal evolution of HMPs in China during the last six decades, highlighting the persistent and abrupt changing patterns, and we link our observations (the abnormal high value in 1998 and 2010) to precipitation anomalies. This is something that has been partially investigated either in regional or short time-span in previous contributions. For this reason, our interpretation brings an added value of scientific validity in a much broader context. Notably, a longer time span comes with the limitations of bias in the collection of data in the earliest years of this catalogue.

Additionally, we detected the abnormal pattern of HMPs, such as, the period and clustering behaviours, which is supposed to be linked with the climate variability indices. It is possible to find out the return time and the recurrence rate for HMPs in the near future under the climate change context. Also, our investigation follows the natural landscape of China, being divided into six geomorphic-regions, rather than either encompassing the whole Chinese territory or single provinces, whose boundaries we remind here are due to administrative choices. By performing the analysis listed above, we are trying to make a contribution to the HMP management as well as the long-term planning for engineering project. For instance, in the mountainous area, road and/or bridge constructions, mineral mining, dam engineering will severely be affected by HMPs. Because of this, understanding the spatiotemporal evolution of HMPs based on the historical records can contribute to the advisable engineering planning for current and future conditions. Specifically, any engineering application commonly relies on return time information for which structures are built and a spatiotemporal description of HMPs can contribute to

better define exposure and ultimately lead to better plan construction and maintenance actions.

The spatiotemporal characteristics of HMPs detected in this work may be valid because of the intervention of climatic changes, however, it is realistic to assume that there is also a bias in the way the disasters have been recorded. In fact, data management in recent years have become much easier because the Chinese archiving system has been made digital. As a result, HMPs are directly inputted in the platform whereas old data suffers from inaccuracies in the spatial connotation as well as in the frequency of the reports. In this study, we pointed out a few climatic variability factors which may underlie the connection between HMP trends and climate change. However, there is still a lack of definitive research on the driving factors of the temporal characteristics of HMPs. Additionally, the association detected between climatic factors and HMPs is not necessarily the causative factors. Our research may have not provided the exact evidence to support whether climate change will mitigate or propagate HMPs in the future. Although, the increasing of HMPs in the last decades could be linked to climate changes but also to the increased human presence and activity in southeast China, or to a combination of both. For instance, soil conservation implemented under the guidance of the Chinese government in recent years may reduce the peak flow in summer (Liu et al. 2019). Despite the underlying conditions within the specific geomorphic-region are somewhat similar, the spatial differentiation of some factors, such as population density, geology, vegetation, and soil may greatly affect HMPs (e.g., Liu et al. 2017; Xiong et al. 2019). Furthermore, there are intricate relationships among HMPs due to the potential upstream–downstream connection within or between watersheds. This will also have an impact on the assumption that HMPs are independent for statistical analysis. Therefore, a more in-depth and detailed analysis of the driving factors of HMPs must be completed. This can be done with more complex spatiotemporal clustering tools which should be able to jointly capture persistent HMP patterns in close spatial proximity and in subsequent temporal intervals, which is beyond the scope of the present study.

6 Conclusions

To assess the spatiotemporal characteristics of the longest available time series of HMPs in China, we analysed the temporal evolution, trends, periods, and clustering behaviours of HMPs at the national and regional scales. Due to the great diversity of the Chinese landscape, a study to distinguish these detected trends is conducted in six geomorphological regions (geomorphic-regions: the EP, SEM,

NCP, NWB, SWM, and TP) for a 66-years period between 1950 and 2015. As a result, we observed:

1. The notable increasing of HMP occurrence could be detected between 2005 and 2010. The six geomorphic-regions exhibit an overall increasing trend, although each geomorphic-region displays the site-specific pattern. The most obvious anomalies in 1998 and 2010 are identified in all six geomorphic-regions.
2. Approximately one thirds of all watersheds display a significant upward trend over 1950–2015. The most striking upward trend is detected in SWM, while a downward trend is only found in eastern EP. In addition, the changing magnitudes of HMP frequency are more significant in SEM and SWM than in the other regions.
3. The obvious periodicity of HMPs can be detected in all geomorphic-regions except for TP. The HMP frequency in EP, SEM, and SWM follow a similar periodic pattern, while NCP, NWB, and TP indicate diverse variation periods. The main periodicity characteristics in EP, SEM, and SWM are approximately 12–25 years, and they tend to stabilize after 1980. In NCP, the alternative 10–25 years periodicity of HMPs can be detected throughout the 1950–2015 period. In NWB, the 10–22 years periodicity started in 1975.
4. The intra-annual HMP trends demonstrate clear seasonal patterns in the six geomorphic-regions. In SWM, the highest monthly frequency of HMPs is detected in July. The highest monthly frequency is more likely to appear after July in the watersheds located in EP, NCP, and TP, while it is prone to appear prior to July in SEM and NWB.
5. Inter-annual clustering plays a dominant role in the HMP occurrences across China, whereas only 5% watersheds are detected as under-dispersion. The inter-annual occurrence of HMPs in SEM, SWM, and TP extensively clustered, while the HMPs occur randomly in western China.

This research contributes toward a better understanding of the spatiotemporal characterization of HMPs in China. The information we provide can be of use to Chinese institutions that focus on master planning and investments on natural hazard prevention. Our results show that recent years have been associated with a marked increase in HMPs and this should be accounted for, especially in those areas where we have retrieved high spatiotemporal clustering. In fact, whenever an engineering project includes structure design able to sustain damages over long periods of time, it does not account for reiterated disasters, whose damaging effects can accumulate leading to large economic and life losses. Because of this, studying clustering behaviour in spatiotemporal HMP series is of fundamental

importance and it is also the direction of future works. Our contribution does not strictly address this issue but it offers a clear view of how persistent meteorologically-driven disasters have been, are and may be in the future of the Chinese territory.

Taking aside the Chinese context, this research can be of relevance in the context of climate change studies. The resulting disasters are a global threat nowadays, and especially in areas such as the southeast Asia where monsoon anomalies have been shown to control spikes in the disaster frequency distribution. Ultimately, a greater awareness of the spatiotemporal evolution of HMPs is crucial to inform master planners and engineers aiding their project work in mountainous areas and we believe this to be the direction that the scientific community should take to improve our understanding of the Anthropocene and the processes we will face as a society. Large information is contained in historical archives and by homogenizing and collating them globally, we can better learn what to expect and how to respond as a society.

Acknowledgements This work was supported by the National Natural Science Foundation of China, grant number No. 41590845 and the China National Flash Flood Disasters Prevention and Control Project, grant number No. SHZH-IWHR-57 from the China Institute of Water Resources and Hydropower Research (IWHR).

Author contributions NW and WC conceived and designed the experiments; NW performed the experiments; NW and JX analyzed the results; NW and WC wrote the paper; LL and LG revised the paper.

Declarations

Conflicts of interest The authors declare no conflict of interest.

References

- Audru JC, Bitri A, Desprats JF, Dominique P, Terrier-Sedan M (2010) Major natural hazards in a tropical volcanic island: a review for mayotte island, comoros archipelago, indian ocean. *Eng Geol* 114(3):364–381
- Barnston AG, Livezey RE (1987) Classification, seasonality and persistence of low-frequency atmospheric circulation patterns. *Mon Weather Rev* 115(6):1083–1126
- Blöschl G, Montanari A (2010) Climate change impacts—throwing the dice? *Hydrol Process Int J* 24(3):374–381
- Blöschl G, Hall J, Parajka J, Perdigão RA, Merz B, Arheimer B, Čanjevac I (2017) Changing climate shifts timing of European floods. *Science* 357(6351):588–590
- Borga M, Anagnostou EN, Blöschl G, & Creutin, J. D. (2011) Flash flood forecasting, warning and risk management: the hydrate project. *Environ Sci Policy* 14(7):834–844
- Cox DR, Isham V (1980) Point processes. *Monogr Stats Appl Probability* 65(432):47–98
- Cunderlik JM, Ouarda TBMJ, Bobée B (2004) On the objective identification of flood seasons. *Water Resour Res* 40(1):1520
- Diggle PJ (1983) Statistical analysis of point processes. Chapman & Hall, London
- Donat MG, Alexander LV, Yang H, Durre I, Vose R, Dunn RJH, Hewitson B (2013) Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: the HadEX2 dataset. *J Geophys Res Atmos* 118(5):2098–2118
- Faccini F, Luino F, Paliaga G, Sacchini A, Turconi L, de Jong C (2018) Role of rainfall intensity and urban sprawl in the 2014 flash flood in Genoa City, Bisagno catchment (Liguria, Italy). *Appl Geogr* 98:224–241
- Feng J, Chen W, Tam CY, Zhou W (2011) Different impacts of El Niño and El Niño Modoki on China rainfall in the decaying phases. *Int J Climatol* 31(14):2091–2101
- Grinsted A, Moore JC, Jevrejeva S (2004) Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlin Processes Geophys* 11:561–266
- Hall J, Blöschl G (2018) Spatial patterns and characteristics of flood seasonality in Europe. *Hydrol Earth Syst Sci* 22(7):3883–3901
- Hamed KH, Rao AR (1998) A modified Mann-Kendall trend test for autocorrelated data. *J Hydrol* 204(1–4):182–196
- Hansen, A (1984). Landslide hazard analysis. *Slope Instability*, 523–602.
- He B, Huang X, Ma M, Chang Q, Tu Y, Li Q, Hong Y (2018) Analysis of flash flood disaster characteristics in China from 2011 to 2015. *Nat Hazards* 90(1):407–420
- Huang Q, Cervone G, Zhang G (2017) A cloud-enabled automatic disaster analysis system of multi-sourced data streams: an example synthesizing social media, remote sensing and Wikipedia data. *Comput Environ Urban Syst* 66:23–37
- Ishak EH, Rahman A, Westra S, Sharma A, Kuczera G (2013) Evaluating the non-stationarity of Australian annual maximum flood. *J Hydrol* 494:134–145
- Jia P, Liu R, Ma M, Liu Q, Wang Y, Zhai X, Wang D (2019) Flash flood simulation for ungauged catchments based on the distributed hydrological model. *Water* 11(1):76
- Kendall, M. G. (1948). Rank correlation methods.
- Khare S, Bonazzi A, Mitas C, Jewson S (2015) Modelling clustering of natural hazard phenomena and the effect on re/insurance loss perspectives. *Nat Hazard* 15(6):1357–1370
- Kleinen T, Petschel-Held G (2007) Integrated assessment of changes in flooding probabilities due to climate change. *Clim Change* 81(3–4):283–312
- Kundzewicz ZW, Robson AJ (2004) Change detection in hydrological records—a review of the methodology/revue méthodologique de la détection de changements dans les chroniques hydrologiques. *Hydrol Sci J* 49(1):7–19
- Kundzewicz ZW, Su B, Wang Y, Xia J, Huang J, Jiang T (2019) Flood risk and its reduction in China. *Adv Water Resour* 130:37–45
- Lau KM, Yang GJ, Shen SH (1988) Seasonal and intraseasonal climatology of summer monsoon rainfall over East Asia. *Mon Weather Rev* 116(1):18–37
- Lin K, Chen H, Xu CY, Yan P, Lan T, Liu Z, Dong C (2020) Assessment of flash flood risk based on improved analytic hierarchy process method and integrated maximum likelihood clustering algorithm. *J Hydrol* 584:124696
- Liu Y, Huang Y (2020) Why flash floods occur differently across regions? *Spatial Anal China Water* 12(12):3344
- Liu J, Zhang Y (2017) Multi-temporal clustering of continental floods and associated atmospheric circulations. *J Hydrol* 555:744–759
- Liu Z, Menzel L, Dong C, Fang R (2016) Temporal dynamics and spatial patterns of drought and the relation to ENSO: a case study in Northwest China. *Int J Climatol* 36(8):2886–2898

- Liu Y, Yuan X, Guo L, Huang Y, Zhang X (2017) Driving force analysis of the temporal and spatial distribution of flash floods in Sichuan Province. *Sustainability* 9(9):1527
- Liu Y, Yang Z, Huang Y, Liu C (2018) Spatiotemporal evolution and driving factors of China's flash flood disasters since 1949. *Sci China Earth Sci* 61(12):1804–1817
- Liu S, Huang S, Xie Y, Wang H, Leng G, Huang Q, Wang L (2019) Identification of the non-stationarity of floods: changing patterns, causes, and implications. *Water Resour Manage* 33(3):939–953
- Lombardo L, Opitz T, Huser R (2018) Point process-based modeling of multiple debris flow landslides using INLA: an application to the 2009 Messina disaster. *Stoch Env Res Risk Assess* 32(7):2179–2198
- Loo YY, Billa L, Singh A (2015) Effect of climate change on seasonal monsoon in Asia and its impact on the variability of monsoon rainfall in Southeast Asia. *Geosci Front* 6(6):817–823
- Lu XY, Zhang XZ, Chen JN (2013) The interdecadal variability of advance and retreat of east Asian summer monsoon and the effect on the regional rainfall over China. *J Trop Meteorol* 19(4):340
- Lv A, Qu B, Jia S, Zhu W (2019) Influence of three phases of El Niño-Southern Oscillation on daily precipitation regimes in China. *Hydrol Earth Syst Sci* 23(2):883–896
- Ma M, He B, Wan J, Jia P, Guo X, Gao L, Hong Y (2018) Characterizing the flash flooding risks from 2011 to 2016 over China. *Water* 10(6):704
- Macdonald N, Black AR (2010) Reassessment of flood frequency using historical information for the River Ouse at York, UK (1200–2000). *Hydrol Sci J* 55(7):1152–1162
- Mailier PJ, Stephenson DB, Ferro CA, Hodges KI (2006) Serial clustering of extratropical cyclones. *Mon Weather Rev* 134(8):2224–2240
- Mann HB (1945) Nonparametric tests against trend. *Econom J Econom Soc* 13:245–259
- Mediero L, Kjeldsen TR, Macdonald N, Kohnova S, Merz B, Vorogushyn S, Castellarin A (2015) Identification of coherent flood regions across Europe by using the longest streamflow records. *J Hydrol* 528:341–360
- Merz B, Nguyen VD, Vorogushyn S (2016) Temporal clustering of floods in Germany: do flood-rich and flood-poor periods exist? *J Hydrol* 541:824–838
- Ministry of Water Resources of China (MWR). (2014). Bulletin of flood and drought disaster in China. <http://www.mwr.gov.cn/>
- Organization W M. (2017). WMO guidelines on the calculation of climate normals. In: World Meteorological Organization Geneva, Switzerland.
- Petrow T, Merz B (2009) Trends in flood magnitude, frequency and seasonality in Germany in the period 1951–2002. *J Hydrol* 371(1–4):129–141
- Ragettli S, Zhou J, Wang H, Liu C, Guo L (2017) Modeling flash floods in ungauged mountain catchments of China: a decision tree learning approach for parameter regionalization. *J Hydrol* 555:330–346
- Saharia M, Kirstetter PE, Vergara H, Gourley JJ, Hong Y (2017) Characterization of floods in the United States. *J Hydrol* 548:524–535
- Sampson CC, Smith AM et al (2015) A high-resolution global flood hazard model. *Water Resour Res* 51:7358–7381
- Sen PK (1968) Estimates of the regression coefficient based on Kendall's tau. *J Am Stat Assoc* 63(324):1379–1389
- Shahid S (2011) Trends in extreme rainfall events of Bangladesh. *Theoret Appl Climatol* 104(3–4):489–499
- Shan L, Zhang L, Song J, Zhang Y, She D, Xia J (2018) Characteristics of dry-wet abrupt alternation events in the middle and lower reaches of the Yangtze River Basin and the relationship with ENSO. *J Geog Sci* 28(8):1039–1058
- Torrence C, Compo GP (1998) A practical guide to wavelet analysis. *Bull Am Meteor Soc* 79(1):61–78
- Waele JD (2008) Interaction between a dam site and karst springs: the case of supramonte (central-east sardinia, italy). *Eng Geol* 99(3–4):128–137
- Wang YJ, Gao C, Zhai JQ, Li XC, Hartmann H (2014) Spatio-temporal changes of exposure and vulnerability to floods in China. *Adv Clim Chang Res* 5(4):197–205
- Wang N, Cheng W, Wang B, Liu Q, Zhou C (2020) Geomorphological regionalization theory system and division methodology of China. *J Geog Sci* 30(2):212–232
- Ward PJ, Eisner S, Flörke M, Dettinger MD, Kummer M (2014) Annual flood sensitivities to El Niño-Southern Oscillation at the global scale. *Hydrol Earth Syst Sci* 18(1):47–66
- Wirtz A, Kron W, Löw P, Steuer M (2014) The need for data: natural disasters and the challenges of database management. *Nat Hazards* 70(1):135–157
- Xiao M, Zhang Q, Singh VP (2015) Influences of ENSO, NAO, IOD and PDO on seasonal precipitation regimes in the Yangtze River basin China. *Int J Climatol* 35(12):3556–3567
- Xiong J, Ye C, Cheng W, Guo L, Zhou C, Zhang X (2019) The spatiotemporal distribution of flash floods and analysis of partition driving forces in Yunnan Province. *Sustainability* 11(10):2926
- Xiong J, Pang Q, Fan C, Cheng W, Ye C, Zhao Y, Cao Y (2020) Spatiotemporal characteristics and driving force analysis of flash floods in Fujian Province. *ISPRS Int J Geo Inf* 9(2):133
- Yuan Y, Gao H, Li W, Liu Y, Chen L, Zhou B, Ding Y (2017) The 2016 summer floods in China and associated physical mechanisms: a comparison with 1998. *J Meteorol Res* 31(2):261–277
- Zhang Q, Gu X, Singh VP, Shi P, Sun P (2018) More frequent flooding? Changes in flood frequency in the Pearl River basin, China, since 1951 and over the past 1000 years. *Hydrol Earth Syst Sci* 22(5):2637–2653
- Zhao G, Pang B, Xu Z, Yue J, Tu T (2018) Mapping flood susceptibility in mountainous areas on a national scale in China. *Sci Total Environ* 615:1133–1142
- Zhu Y, Wang H, Ma J, Wang T, Sun J (2015) Contribution of the phase transition of Pacific Decadal Oscillation to the late 1990s' shift in East China summer rainfall. *J Geophys Res Atmos* 120(17):8817–8827