Detection and attribution of flood responses to precipitation change and urbanization: a case study in Qinhuai River Basin, Southeast China

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ABSTRACT

Both flood magnitude and frequency might change under the changing environment. In this study, a procedure combining statistical methods, flood frequency analysis and attribution analysis was proposed to investigate the response of floods to urbanization and precipitation change in the Qinhuai River Basin, an urbanized basin located in Southeast China, over the period from 1986 to 2013. The Mann–Kendall test was employed to detect the gradual trend of the annual maximum streamflow and the peaks over threshold series. The frequency analysis was applied to estimate the changes in the magnitude and frequency of floods between the baseline period (1986–2001) and urbanization period (2002–2013). An attribution analysis was proposed to separate the effects of precipitation change and urbanization on flood sizes between the two periods. Results showed that: (1) there are significant increasing trends in medium and small flood series according to the Mann–Kendall test; (2) the mean and threshold values of flood series in the urbanization period were larger than those in the baseline period, while the standard deviation, coefficient of variation and coefficient of skewness of flood series were both higher during the baseline period than those during the urbanization period; (3) the flood magnitude was higher during the urbanization period than that during the baseline period at the same return period. The relative changes in magnitude were larger for small floods than for big floods from the baseline period to the urbanization period; (4) the contributions of urbanization on floods appeared to amplify with the decreasing return period, while the effects of precipitation diminish. The procedure presented in this study could be useful to detect the changes of floods in the changing environment and conduct the attribution analysis of flood series. The findings of this study are beneficial to further understanding interactions between flood behavior and the drivers, thereby improving flood management in urbanized basins.

Key words | attribution analysis, flood, frequency analysis, Mann–Kendall test, Qinhuai River Basin, urbanization

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INTRODUCTION

Flood disaster is one of the most serious natural hazards, as floods often result in serious property damage and casualties worldwide (Kundzewicz *et al.* 2013; Ragettli *et al.* 2020; Venvik *et al.* 2020). A better understanding of flood characteristics and their potential driving forces is of importance to manage river flows and effectively mitigate flood disasters. Generally, climate change and human activities are identified as the two primary causes for changes in flood

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regime (Hou *et al.* 2020; Ragettli *et al.* 2020). In recent decades, extreme rainfall events have occurred frequently due to climate change, and the occurrence of flood disasters and the extent of flood-induced damage has an increasing trend (He *et al.* 2017; Ledingham *et al.* 2019). For example, the damage caused by floods in China in 2017 were estimated as US $31 billion (China Floods and Droughts Disasters Bullet in 2017).

Human activities, such as land-use change and urbanization, are important factors influencing the hydrological cycle. Increased urbanization has led to considerable changes in natural catchment characteristics by increasing the amount of impervious surface areas, which reduce infiltration of precipitation during storm events and increase direct runoff (Yao *et al.* 2015; Darabi *et al.* 2019; Li *et al.* 2019; Okoli *et al.* 2019). Additionally, the reduction of forest and wetland coverage due to the urbanization would result in a decrease of the buffering capacity of these ecosystems in flood events. Consequently, runoff increases in proportion to the expansion of impervious areas in a watershed, and the stormflow, peak discharges and flood risk also tend to increase in the urban area (Muis *et al.* 2015; Mahmoud & Gan 2018; Li *et al.* 2020). Moreover, several studies have revealed that a decrease in the infiltration of precipitation due to an increase of impervious areas leads to a higher increase in the volume and flood peak of storm runoff for the medium and small floods than that for the really large and rare events (Braud *et al.* 2013). Kaspersen *et al.* (2015) pointed out that an increase in impervious areas had more effects on the hydrological response for more frequent flood events while only a lesser degree effects for less frequent events. They attributed this difference to the fact that the natural surface was able to reach saturation faster during very extreme events and started to behave like the impervious surface rather quickly after the onset of the events. Inversely, the time to saturation is commonly much longer during less extreme events. However, the effect of land-use change on the flood regime cannot always be straightforwardly investigated. Some studies revealed a specific difficulty in detecting flood trends due to several signals overlapping in the analysis process and found little influence of land-use change predominant urbanization on floods (Blöschl *et al.* 2007; Hannaford *et al.* 2013; Madsen *et al.* 2014). Furthermore, the reality is often further complicated by the impacts of several driving factors. Hence, an intensive study is essential to be conducted in the specific basins before a generalized conclusion can be drawn. This constitutes the motivation for this study.

The question whether the magnitude and frequency of floods have changed in the changing environment is of significance. Amounts of various studies have detected trends in flood changes using a range of statistical tests from long-term flood records (Mediero *et al.* 2014; Yin *et al.* 2015; Stevens *et al.* 2016; Balistrocchi & Bacchi 2017; Mudersbach *et al.* 2017; Kundzewicz *et al.* 2018; Dehghanian *et al.* 2020). Hall *et al.* (2014) stated that in the simplest case of change detection of the flood peak records, the Pettitt test and Mann–Whitney U test were frequently applied for step changes, and Mann–Kendall test and Spearman's test were widely performed for gradual changes. Modarres *et al.* (2016) applied the Mann–Kendall test and two pre-whitening trend tests to detect trends for the annual flood peaks in Iran and found a significant increasing trend in flood magnitude in most hydrological basins. Alternatively, the non-stationary flood frequency analysis has also been widely used to detect the variation characteristics of floods in many studies (Viglione *et al.* 2013; Ahmad *et al.* 2015; Šraj *et al.* 2016; Jiang *et al.* 2019). The basic idea of this approach is that it allows the parameters of the flood frequency distribution to change in time as a function of covariates. Delgado *et al.* (2010) mentioned that the non-stationary generalized extreme value function (NSGEV) is advantageous to detect changes in different flood magnitudes. They found a positive trend in the scale parameter of a fitted distribution, the frequencies of both large floods and small floods increased in the Mekong River. However, the above studies merely focused on the detection of river peak flow variation by performing statistical analyses of flood time series, and more concerted efforts are required for attributing trends in floods, as highlighted by Merz *et al.* (2012).

Quantitatively evaluating the contributions of precipitation change and urbanization to the flood response is essential for managing flood risk and is also of practical importance for designing measures to mitigate hazards. Hydrological modeling and statistical analysis are two widely used approaches to differentiate the individual effect of precipitation change and urbanization on floods. Many studies assessed the impact of urbanization on flood peak using hydrological modeling for different land-use scenarios (Jothityangkoon et al. 2013; Wolski et al. 2014; Aich et al. 2015; Zope et al. 2017). For example, Du et al. (2015) used the Soil Conservation Service model to simulate the hydrological process for three land-use scenarios in the Pearl River Delta to assess the impacts of urbanization on floods. They found a significant increasing trend in floods and attributed this trend to the effect of the expansion of impervious surfaces and the displacement of farmland in forested hills in the urbanization process. Chen et al. (2015) analyzed the effects of urbanization on flood characteristics by setting up the HEC-HMS (Hydrologic Engineering Center's Hydrologic Modeling System) model to simulate flood processes for different land-use scenarios, and they concluded that the peak discharge and flood volume increased in the rapid urbanization expansion process. Furthermore, the non-stationary extreme value statistics are frequently adopted for the attribution of floods. The parameters of the flood frequency distribution are allowed to change by various driving factors that are included as covariates, followed by a test if such a model expansion results in a significantly better fit to the extreme values (López & Francés 2013; Machado et al. 2015; Viglione et al. 2016). For instance, Villarini & Strong (2014) selected precipitation and land cover indicators as external covariates and applied the Generalized Additive Models for Location, Scale and Shape (GAMLSS) to attribute the flood changes to rainfall variations in Iowa. Prosdocimi et al. (2015) used a GEV distribution and considered both precipitation and urbanization as covariates. They found that the increasing urbanization level has the dominant effect on flood peak in the UK. To our knowledge, the hydrological models and non-stationary extreme value statistics have been widely applied in the detection and attribution of changes in floods under the context of the changing environment. However, complex structures, parameters identification of the hydrological models and the uncertainty involved in the simulations are important limitations of the application in the attribution analysis. The far more difficult problem of non-stationary extreme value statistics is the inability to quantify the relative importance of the different drivers in flood time series, which is suggested by Merz et al. (2012) who think that more effort is needed to quantitatively evaluate the attribution for flood time series.

Therefore, the main research aim of the study is to propose a procedure to investigate how flood regime changes under changing precipitation and land-use condition, and quantify the attribution of flood changes to precipitation and urbanization. The specific objectives of this study are (1) to detect changes in characteristics of flood series, (2) to explore the variations of the flood frequency after the urbanization and (3) to separate the contributions of precipitation change and urbanization to flood regime changes.

STUDY AREA AND DATA

The Qinhuai River, one of the tributaries of the lower Yangtze River, is located in the southwest of Jiangsu province (Figure 1). The basin area is 2,631 km^2. It is located in the subtropical monsoon climate zone, where the local climate is controlled by the East Asia summer monsoon. The annual mean air temperature is 15.4 °C, and average annual precipitation is 1,116 mm during the period 1986–2013. The rainy season is from April to October.

As a typical watershed in Yangtze delta plain, the Qinhuai River Basin has a marked advancement of urbanization since the beginning of the 2000s (Du et al. 2012; Chen & Du 2014; Hao et al. 2015). The impervious areas increased from 3.8% to 8.6% from 1986 to 2001; however, from 2002 to 2013, the impervious areas increased from 8.8% to 17.5% (Bian et al. 2017). Details of land use/land cover at different periods can be found in the literature by Hao et al. (2015).

The 28-year (1986–2013) daily rainfall data from seven rain-gauge stations and daily discharge data at the Inner Qinhuai station and Wudingmen station were obtained from the local hydrological bureau. The basin location, elevation, network and the distribution of the two hydrological stations and seven rain-gauge stations are shown in Figure 1, and the two streamflow gauging stations are located at the two outlets of the basin.

METHODS

In this study, the annual maximum streamflow (AMS) series and the peaks over threshold (POT) sampling method were

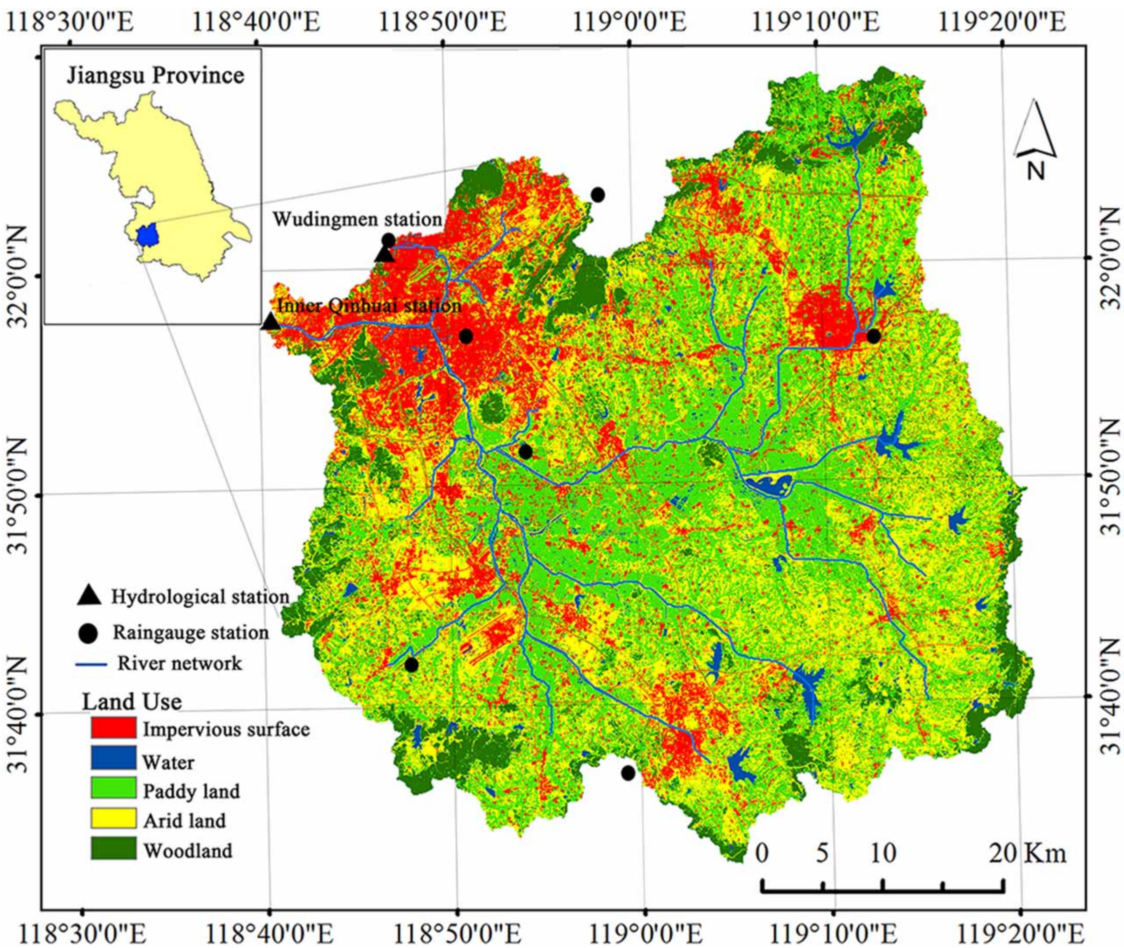

Figure 1 | Locations of Qinhuai River Basin and rain gauge and hydrological stations, and the spatial distributions of the river network and land use (2013) of the basin.

used to obtain the flood series from the daily streamflow data first. Secondly, the nonparametric Mann–Kendall test was applied to detect changes in trends of flood series. Thirdly, the frequency analysis was conducted to assess the frequency variations of flood series. Finally, the attribution analysis proposed in this study was used to quantitatively evaluate the contributions of precipitation change and urbanization to the flood changes.

Selection of flood series

The most common indicator used in flood trend studies is the AMS. In this study, the AMS series were acquired from the daily streamflow data of 1986–2013 for the flood trend analysis. However, this sampling method can result in a loss of information of floods (Bezak *et al.* 2014). For example, some low discharge values in dry years, as the largest flood in a year, could be included in AMS series, and some relatively large floods in wet years may not be considered in AMS series, as they are not the annual largest floods. Therefore, the POT sampling method is also used to overcome those drawbacks by selecting all the floods that exceed a given threshold regardless of the time they occurred (Mediero *et al.* 2014). The first step of the POT method is consideration of the independence of floods. The independence criteria were evaluated following Silva *et al.* (2012):

$$D > 5 + \log(A) \tag{1}$$

$$Q_{\min} < \frac{3}{4}\min(Q_1, Q_2) \tag{2}$$

where D denotes the interval time between two flood peaks in days; A is the basin area in km^2; Q_1 and Q_2 denote the magnitudes of two flood peaks in m^3/s, respectively.

It is commonly assumed that a POT series improves an AMS series in the case of a minimum of two or three events per year on average (Mediero *et al.* 2014). In order to identify the changes of large, medium and small floods under precipitation change and urbanization, we selected daily flood series with one, two and three events on average per year for the POT time series (referred to as POT1, POT2 and POT3 hereafter, respectively).

Detect trend of the flood series

The temporal trends in AMS and POT time series of flood can be detected by nonparametric trend tests which are more robust to outliers and do not need any assumption about the distribution. In this study, the gradual trend test was performed using the rank-based nonparametric Mann–Kendall (MK) test recommended by the World Meteorological Organization (Chebana *et al.* 2013). The MK trend statistic S is calculated following Mann and Kendall (Mann 1945; Kendall 1975). However, if time series data show serial autocorrelation, robust results of the MK test cannot be achieved (Fateh *et al.* 2013). Therefore, a test of the autocorrelation of the time series must be conducted before applying the MK test. If significant autocorrelation is detected, the trend-free pre-whitening procedure proposed by Yue & Wang (2002) will be adopted to remove the effect of serial correlation.

Sen's non-parametric method was applied to calculate the change per year for an existing trend by Sen's slope (Sen 1968). The MK test and Sen's estimation together are also called the Sen-MK test.

Frequency analysis

The flood frequency analysis involves the selection of an appropriate probability density function (PDFs) and a parameter estimation method to modeling the distribution of flood data series. Series studies have shown that the three-parameter Pearson type (P-III) distribution was the most appropriate method to quantify the frequency of AMS series in China (Chen *et al.* 2001; Yin *et al.* 2015). The hydraulic design manual of China also suggests the use of P-III distribution for AMS in China. Hence, the P-III distribution was used to fit the AMS series in our study. The generalized Pareto distribution (GP) was used to fit the distribution of POT series which well fits to partial duration series in almost all cases (Guru & Jha 2015; Solari *et al.* 2017). Due to the short length of the series, the parameters of PDFs were determined by the visual evaluation of the goodness-of-fit.

In the study, the computation formula raised by Rosbjerg (1985) was adopted to convert the frequencies of POT and AMS series to the return period for direct comparison. The changes in the return period with same flood size and changes in flood size with the same return period were also analyzed.

Attribution analysis

The changes in flood regime are generally caused by precipitation change and urbanization. Quantifying the contributions of precipitation change and urbanization to the flood changes is important for flood prediction and flood-induced disaster mitigation. An attribution analysis method, illustrated in Figure 2, was proposed and used to separate the influence of precipitation change and urbanization on floods in this study. This attribution method is

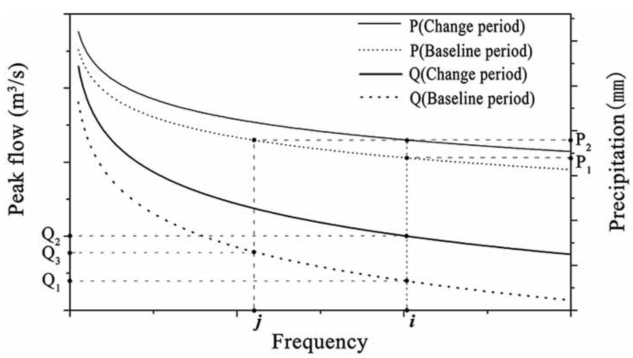

Figure 2 | The separation of precipitation change and urbanization impacts on flood peak. The thick solid and dashed lines are the flood frequency distribution curves of the two periods, respectively. The thin solid and dashed lines are distribution curves of the causative precipitations corresponding to floods for the two periods, respectively. Q_1 denotes the flood size of the baseline period at the frequency i, Q_2 denotes the flood size of the change period at the same frequency i. Q_3 denotes the flood size of the baseline period as the same precipitation condition as Q_2 at the frequency j. P_1 is the precipitation corresponding to the flood size Q_1, and P_2 is the causative precipitation corresponding to the flood size Q_2.

based on the flood frequency curves and the causative precipitation distribution curves in the baseline period and change period. Therefore, the precondition for this method is that the whole study period can be divided into the baseline period and change period. Then, the causative precipitation distribution curves of the two periods were built corresponding to flood series. The ordinate value of any point on the precipitation distribution curve presents the amount of a causative precipitation sample, while the abscissa value presents the corresponding sample's flood frequency.

From Figure 2, we can see that flood size change ΔQ due to precipitation change and urbanization from the baseline period to the change period at the flood frequency i is

$$\Delta Q = Q_2 - Q_1 \tag{3}$$

where Q_1 denotes the flood size of the baseline period at the certain frequency, and Q_2 denotes the flood size of the change period at the same frequency.

The flood size change caused by urbanization ΔQ_{urban} is the difference between Q_2 and Q_3, which can be written as follows:

$$\Delta Q_{urban} = Q_2 - Q_3 \tag{4}$$

where Q_3 denotes the flood size of the baseline period with the same causative precipitation of Q_2.

Then, the precipitation-induced flood size change ΔQ_{pre} can be expressed as

$$\Delta Q_{pre} = \Delta Q - Q_{urban} \tag{5}$$

Detailed notations of Equations (3)–(5) are also defined in the caption of Figure 2.

RESULTS

Previous studies found that the annual runoff coefficient of Qinhuai River abruptly changed around 2002 and 2003, and the change in annual runoff coefficient after 2002 in the area was attributed mainly to land-use/land cover changes predominated by urbanization (Du et al. 2012; Hao et al. 2015; Bian et al. 2017). Therefore, the long-term flood series under the changing environment condition were divided into the baseline period (1986–2001) and urbanization period (2002–2013). The F-test (Mckerchar & Henderson 2003), for the equality of the variances, was performed to test the variance of each of the flood series in the baseline period and urbanization period. In addition, it was found that the results of the F-test are insignificant, which indicated that the variance of each of the flood series in two periods is homogeneous. Then, the statistical methods and flood frequency estimation and attribution analysis were performed for both periods to analyze the flood changes, and the results are discussed in the following sections.

Changes in characteristics of flood series from the baseline period to the urbanization period

Some statistics of all flood series such as mean, standard deviation, coefficient of variation and coefficient of skewness were calculated and shown in Table 1, and threshold values of POT series and lowest values of AMS were also

Table 1 | The mean, standard deviation, coefficient of variation and coefficient of skewness of eight flood series in the baseline period (1986–2001) and the urbanization period (2002–2013)

	AMS		POT1		POT2		POT3	
Flood series	Baseline period	Urbanization period	Baseline period	Urbanization period	Baseline period	Urbanization period	Baseline period	Urbanization period
Mean (m^3/s)	487.7	744.3	706.0	790.0	491.3	588.4	374.6	464.0
Standard deviation (m^3/s)	337.2	245.4	271.2	185.0	290.5	245.5	289.2	267.9
Coefficient of variation	0.69	0.33	0.38	0.23	0.59	0.42	0.77	0.58
Coefficient of skewness	0.84	0.10	0.90	1.20	1.32	0.89	1.39	0.92

identified and shown in Figure 3. It can be seen from Table 1 that the mean values of flood series in the urbanization period are larger than those in the baseline period, while the standard deviation, coefficient of variation and coefficient of skewness of flood series are both higher during the baseline period than those during the urbanization period. It can also be seen from Figure 3 that the threshold values are larger in the urbanization period than those in the baseline period for all POT flood series. In addition, the lowest flood size is larger in the urbanization period than that in the baseline period for AMS series.

The larger threshold and mean values during the urbanization period indicate that the effects of urbanization and precipitation change led to the increase in the flood magnitudes after the year 2002. The decrease in the standard deviation, coefficient of variation and coefficient of skewness of flood series implies the decrease in the differences in flood magnitudes of each flood series during the urbanization period, which is consistent with the results that magnitude of a small flood increased greater than a big flood in the urbanization period. Another possible explanation will be given in the next section.

Trends of flood series from the baseline period to the urbanization period

Four flood series of AMS, POT1, POT2 and POT3 during the baseline period and additional four series during the urbanization period were constructed, respectively, from the daily streamflow of the two periods. The flood series and trends are shown in Figure 3.

The autocorrelation was checked first for all flood series, and no significant autocorrelation data series were found at the 5% significance level. The results of the Sen-MK test for gradual trends of AMS series showed no significant increasing trends at the significance level of 0.1 ($Z < 1.65$ and $\beta > 0$). Moreover, for the whole period, the POT1 and POT2 series show insignificant trends at the significance level of 0.1 ($Z < 1.65$ and $\beta > 0$), but the POT3 series manifested a significant increasing trend at the

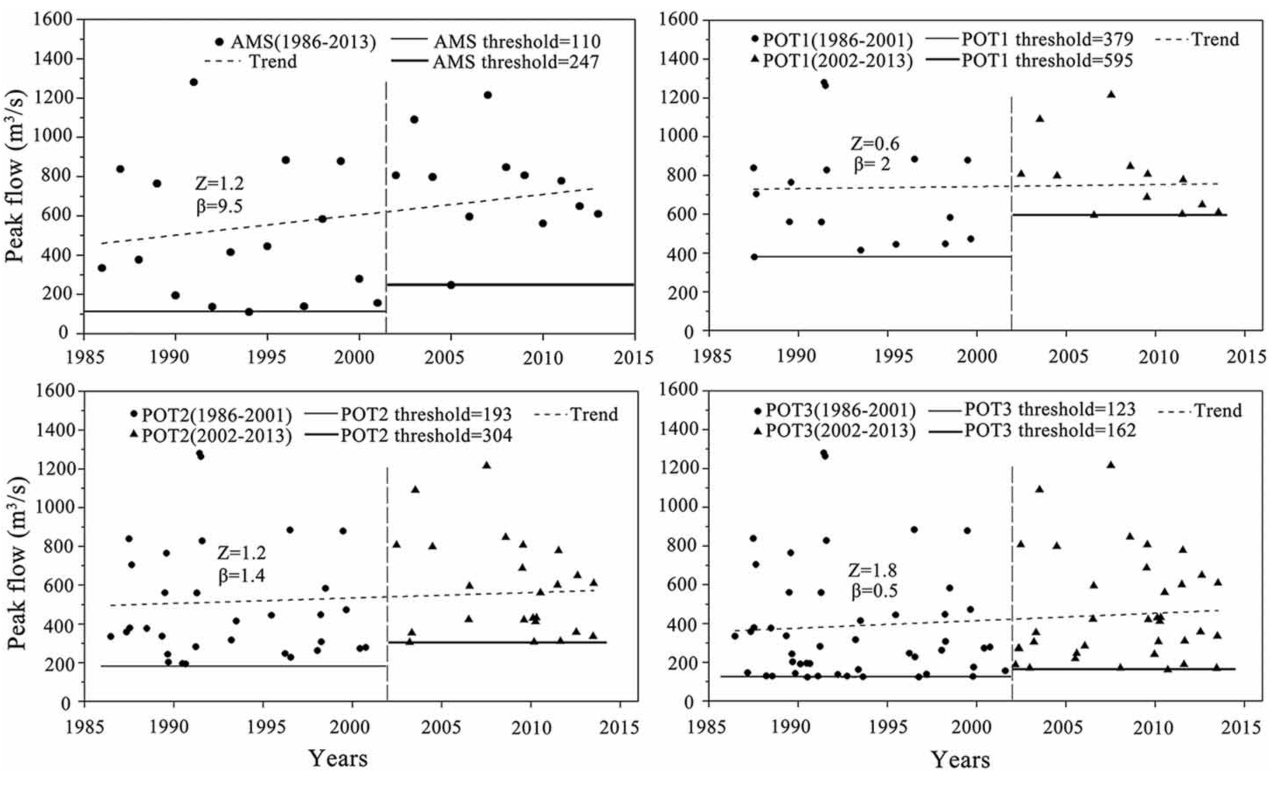

Figure 3 | Flood peaks of POT1, POT2 and POT3 series during the baseline and urbanization periods. Dashed lines show the trends of all series. Thin solid lines show the thresholds in POT1, POT2 and POT3 series during the baseline period. Thick solid lines show the thresholds in POT1, POT2 and POT3 series during the urbanization period.

significance level of 0.1 ($Z > 1.65$ and $\beta > 0$), suggesting that the magnitudes of small floods increased in the urbanization period. To gain more insight into changes in flood frequency, we defined two new times series based on the POT1–3 series. POT1 can be referred as the large flood series, flood sizes between the POT2 and POT1 thresholds can be referred as medium floods, and flood sizes between the POT3 and POT2 thresholds can be referred as small floods. The medium flood series showed a significant increasing trend at the significance level of 0.05 ($Z > 1.96$ and $\beta > 0$), while the small flood series showed a significant increasing trend at the significance level of 0.01 ($Z > 2.56$ and $\beta > 0$) (Figure 4). This indicates that the smaller the magnitude of flood, the larger the increase in the magnitude during the whole period.

Changes in the return period of flood series from the baseline period to the urbanization period

In the previous sections, three different POT series, i.e. POT1, POT2 and POT3 have been selected and analyzed to identify the changes of large, medium and small peak flows under precipitation change and urbanization, respectively. In this section and the following section, in order to quantify and attribute the changes in the return period or the frequency of exceedance of flood series from the baseline period to the urbanization period, two extreme runoff series were investigated, i.e. the AMS series and the standard POT series. The standard POT series are selected based on the optimal threshold values which are determined by the tradeoff of three criteria, i.e. the mean number of over-threshold events, mean exceedance above threshold and dispersion index (Mediero *et al.* 2014). In this study, the optimal threshold values of POT series before and after 2003 were selected to be 139 and 243 m^3/s, respectively, corresponding to an average of 2.3 flood events per year.

The AMS and POT series were fitted to the P-III and GP distributions, respectively, the results are shown in Figure 5. It can be seen from Figure 5 that flood magnitudes for both AMS and POT series are always higher at the same return period during the urbanization period than those during the baseline period.

The root mean square error (RMSE) and probability plot correlation coefficient (PPCC) (Heo *et al.* 2008) were used to evaluate the goodness of fit for AMS and POT series, and the results are shown in Table 2. It can be found that the values of PPCC are more than 0.9 for each flood series in the baseline period and urbanization period, but the values of RMSE for POT series are less than those for AMS series, which indicates that the goodness of fit of GP distribution for POT series is better than P-III distribution for AMS series in both baseline and urbanization periods.

The frequencies of POT and AMS series cannot be directly compared, while they must be converted to the return period by the computational formula raised by Rosbjerg (1985) for the purpose of comparison. Table 3 shows the changes in the return period for the same flood size from the baseline to the urbanization period for both AMS and POT series. The return period decreases for the same flood magnitude from the baseline to the urbanization period in both AMS and POT series. The relative decrease in

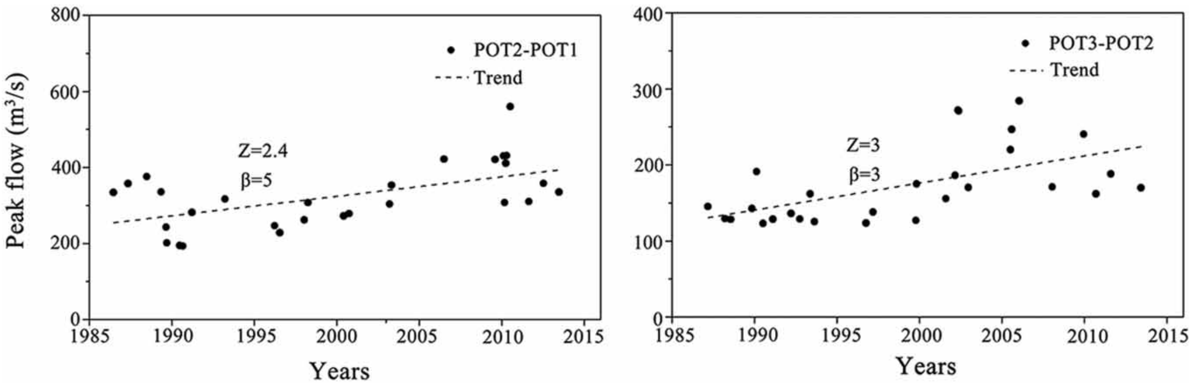

Figure 4 | Flood peaks of medium (the left) and small (the right) flood events derived from two periods, respectively. Dashed lines show the trends of both series.

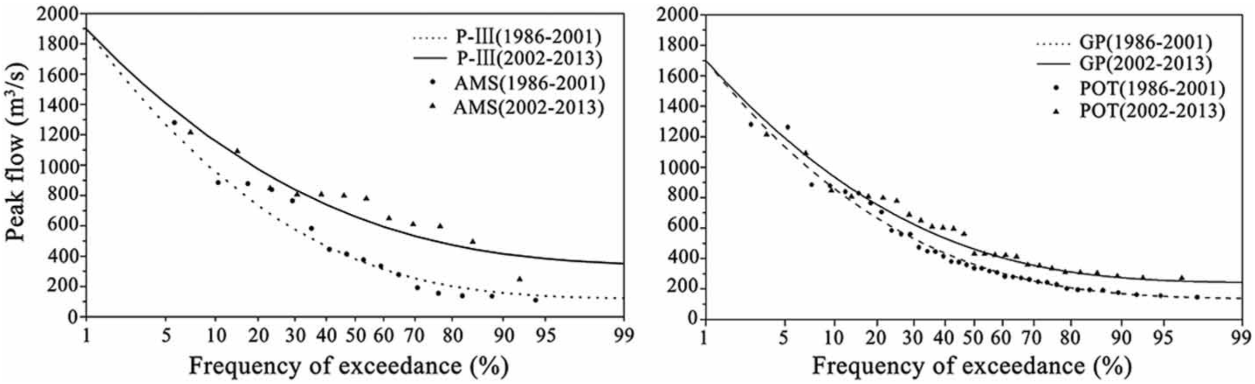

Figure 5 | The frequency distributions of AMS and POT series during the two periods. The dashed lines are fitted frequency distribution curves of POT flood series during the baseline period. The solid lines are fitted frequency distribution curves of POT flood series during the urbanization period.

Table 2 | The test of goodness of fit for AMS and POT series in the baseline period (1986–2001) and the urbanization period (2002–2013)

	AMS		POT	
Indicators	**Baseline period**	**Urbanization period**	**Baseline period**	**Urbanization period**
RMSE (m^3/s)	76.7	87.2	40.8	47.4
PPCC (-)	0.98	0.94	0.99	0.98

Table 3 | Changes in return period with same flood size for AMS and POT series

	AMS		POT	
Peak flow (m^3/s)	**Baseline period (yr)**	**Urbanization period (yr)**	**Baseline period (yr)**	**Urbanization period (yr)**
400	2.1	1.1	1.0	0.7
600	3.5	1.7	1.8	1.3
800	5.9	3.0	3.3	2.5
1,000	10.0	5.4	5.9	4.7
1,200	16.8	10.2	10.6	8.9
1,400	28.1	19.4	18.9	16.7
1,600	47.2	37.5	33.4	31.1

the return period decreased with increasing flood magnitude except for a peak flow of 400 m^3/s in AMS series, indicating that the same flood event will occur more frequently during the urbanization period. In addition, the smaller the flood event, the larger the return period decreases.

Table 4 shows the changes in magnitude with the same return period from the baseline to the urbanization period in AMS and POT series. It can be seen that the flood magnitudes increase for the same return period from baseline to urbanization periods both in AMS and POT series, suggesting that the flood event with larger peak flow will occur during the urbanization period with the same return period of the baseline period. In addition, the relative increments in magnitude increase with the decreasing return period (i.e. with the decrease of flood magnitude). This is why the coefficient of variation and coefficient of skewness of flood series decrease during the urbanization period.

By comparing the results of the frequency analysis for AMS and POT series, we can obtain the following findings: (1) with the same return period, the flood size in AMS series was underestimated compared with those in POT series in both baseline and urbanization periods, as some small floods in dry years are included and several large floods in wet years are usually overlooked in AMS series; (2) the estimated changes in the return period and magnitude of AMS series are apparently larger than those of POT series; (3) due to some small floods in dry years included in the baseline period of AMS series, the flood size with the short return period is much smaller than those in the urbanization period, leading to a remarkable increase in estimated flood size between the two periods. Hence, it should be noted that the results obtained from AMS series could not be sufficiently reasonable because of the smaller sample size of AMS series than that of POT series and the drawback

Table 4 | Changes in flood size with the same return period for AMS and POT series

	AMS			POT		
Return period (yr)	**Baseline period (m^3/s)**	**Urbanization period (m^3/s)**	**Increased by (%)**	**Baseline period (m^3/s)**	**Urbanization period (m^3/s)**	**Increased by (%)**
30	1,426.1	1,533.4	7.5	1,564.8	1,580.7	1.0
20	1,268.8	1,409.5	11.1	1,422.6	1,453.5	2.2
10	1,000.8	1,194.9	19.4	1,182.1	1,235.5	4.5
5	733.3	973.7	32.8	945.0	1,016.8	7.6
2	380.9	661.0	73.5	636.4	726.5	14.1
1	119.2	338.4	183.9	406.8	506.0	24.4

of the sampling strategy as detailed earlier in Selection of flood series.

Evaluation of causative precipitation and urbanization impacts on changes in flood size

The attribution analysis proposed in this study needs causative precipitation corresponding to each flood event. The correlation analysis method was used to find best relationship between the flood size and the accumulated precipitation of one-day, two-day, until seven-day at and before the date of the flood event. The six-day accumulated precipitation series was found to have highest correlation ($r = 0.86$, significant at level of 0.05) with the flood sizes of the POT series. Therefore, the six-day accumulated precipitation was taken as the causative precipitation corresponding for each flood event.

Based on flood frequency curves of the POT series during the baseline and urbanization periods, the two causative precipitation distribution curves of the two periods were built with PDFs of GP distribution, as the causative precipitation series corresponds to POT flood series, and those curves were fitted by visualization evaluation because of short time series (Figure 6).

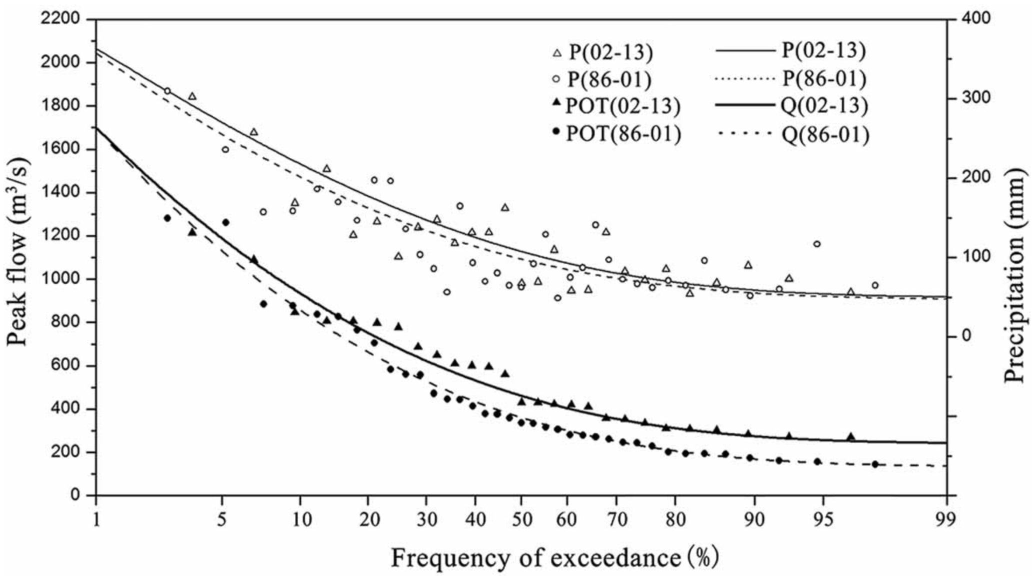

Figure 6 | The separation of the contributions of precipitation change and urbanization to flood sizes. The frequency distributions of flood magnitudes with the thick solid line for the urbanization period (2002–2013) and the thick dashed line for the baseline period (1986–2001). The distribution curves of causative precipitations with the thin solid line for the urbanization period and the thin dashed line for the baseline period.

The individual contribution of urbanization and causative precipitation change was calculated at different return periods based on the four curves by the method described under Attribution analysis, and the results are shown in Table 5. It can be seen that the effects of both causative precipitation change and urbanization are larger on normal floods than those on large floods. However, they exert different degrees of influences on different flood sizes. For example, for the heavy flood with the return period of 30 years, the causative precipitation change and urbanization contributed by 98.8% and 1.2%, to the 1% increase in flood size. However, for small flood with the return period of one year, causative precipitation change and urbanization contributed by 42.4% and 57.6%, to the 24.4% increase of flood size. Therefore, we can conclude that the impacts of urbanization on flood size are larger for small floods and diminish as the flood magnitude increases (i.e. flood frequency decreases).

These results are consistent with findings reported in the literature (Braud *et al.* 2013; Kaspersen *et al.* 2015). They found that the effects of urbanization on floods are proportionally greater for high-frequency events. Sillanpää & Koivusalo (2015) also confirmed this finding by dividing the event data into groups according to the event size and identifying statistically significant differences between the periods for the group of minor rainfall events and no significant differences between the two periods for major events. This difference can be attributed to the fact that the high intensity and large volume of rainfall exceed infiltration capacity of pervious areas in extreme events, causing the natural surface to behave like an impervious surface. Therefore, the relative influence of the urban areas will decrease in large flood events. A reduction in the natural infiltration due to the growth of impervious areas can be expected to lead to an increase in the volume of storm runoff for the medium and small floods.

DISCUSSION

Effects of two different sampling methods on flood change evaluation

The AMS and peak over threshold (POT) sampling are usually used for the flood frequency analysis. The POT sampling has the following advantages over the AMS sampling (Bezak *et al.* 2014; Mediero *et al.* 2014): (1) it provides an approach to control the number of selected floods by choosing an appropriate threshold and thereby use a larger dataset of floods; (2) it ignores useless small floods in dry years and thereby concentrates only on the higher maximum values, which contain most of the information about flood processes. Even though the AMS sampling has many drawbacks compared to the POT sampling, it still remains the most popular approach to analyze flood changes (Bai *et al.* 2015; Yan *et al.* 2017). The AMS sampling is useful and effective in flood trend detection and frequency analysis as long as the time period is long enough.

In this study, the frequency curves derived by P-III distribution based on AMS series are not appropriate to analyze

Table 5 | The attributions of causative precipitation change and urbanization to flood sizes

Return period (yr)	Q_1 (m^3/s)	Q_2 (m^3/s)	P_1 (mm)	P_2 (mm)	Q_3 (m^3/s)	Total (%)	Contribution from urbanization (%)	Contribution from causative precipitation (%)
30	1,564.8	1,580.7	341.8	344.0	1,580.5	1.0	1.2	98.8
20	1,422.6	1,453.5	312.3	321.4	1,453.0	2.2	1.8	98.2
10	1,182.1	1,235.5	267.4	280.3	1,233.7	4.5	3.5	96.5
5	945.0	1,016.8	221.3	235.9	1,006.4	7.6	14.5	85.5
2	636.4	726.5	158.1	171.8	694.0	14.1	36.1	63.9
1	406.8	506.0	108.6	118.8	448.8	24.4	57.6	42.4
0.5	180.3	284.7	57.7	61.6	196.5	57.9	84.5	15.5

Q_1 and Q_2 are the flood sizes of the baseline and urbanization periods with the same frequency, respectively. P_1 and P_2 are the corresponding causative precipitation amount to Q_1 and Q_2, respectively. Q_3 is the flood size during the baseline period which would be contributed by P_2.

the flood changes for a number of reasons (more details have already been given in the above results): the high flood quantiles are underestimated (Table 4), The changes in the return period and magnitudes are overestimated (Tables 3 and 4), and an incredible increase in estimated flood sizes for the short return period (Table 4). All these issues can be attributed to the small datasets (16 and 12 years for the baseline and urbanization periods, respectively) and the sampling strategy (some small floods are included and other large floods are missing) for the AMS. On the contrary, the POT sampling concentrates mainly on the higher maximum values, and it obtains larger number of flood events and selects all large floods. The results based on POT series are reasonable even though the time period is short. Our study shows that the POT sampling is preferred over the AMS sampling when applied to a short time period.

Attribution of trends in flood time series

Studies on flood trend attribution have been of considerable interest because of flood risk in the urbanized area has an increasing trend due to the effects of precipitation change and urbanization. Theoretically, the drivers that may have impacted the flood behavior should be quantitatively investigated. However, the fact that many factors affect flood behavior complicates attribution analysis, and the current state of flood trend attribution is poor as pointed out by Merz *et al.* (2012).

In this study, the attribution analysis method based on the frequency distribution of flood size and causative precipitation distribution curve was proposed and used to separate the contributions of precipitation change and urbanization to flood changes between two periods. Theoretically, the method can quantify the relative contributions of the two factors with a certain degree of accuracy. However, when the method was applied to the case study in this paper, it was found that the causative precipitation distribution curve was more scatter than the flood frequency distribution, which indicates that several other factors might influence the flood sizes, including the duration and variations in intensity during one event as well as antecedent soil moisture condition, changes in land surface patterns and flood control measures. Therefore, the attribution results by this method can provide approximate ratios of the causative precipitation change and urbanization effects on the flood sizes based on the fitted causative precipitation curves. Anyway, the results of the attribution analysis in this study provide evidence that the urbanization had a significant effect on flood peaks for smaller floods, while larger floods are mainly affected by rainfall amounts, which suggests the usefulness and applicability of the proposed method.

It should be noted that one frequency distribution was assigned to each of the flood and causative precipitation series in this paper. We believe that applying different distributions might provide different results and is a topic for further study.

CONCLUSIONS

This study presented a procedure combining statistical methods, flood frequency analysis and attribution analysis to examine the response of floods to urbanization and precipitation change in the Qinhuai River Basin, an urbanized basin located in southeast China, over the period from 1986 to 2013. We analyzed AMS, POT1, POT2 and POT3 series, where the three latter series were created by selecting independent peaks over three different thresholds resulting in 1, 2 and 3, flood events per year, respectively. In addition, we considered floods above the POT1 threshold as large floods, floods between the POT2 and POT1 thresholds as medium floods and flood sizes between the POT3 and POT2 thresholds as small floods. All flood series were constructed from daily streamflow of the baseline period and urbanization period.

The following conclusions can be drawn from this study:

1. The AMS, POT1 and POT2 series showed no significant increasing trends at the significance level of 0.1, and the POT3, medium and small flood series showed significant positive trends at the significance level of 0.1, 0.05 and 0.01, respectively.
2. The mean and threshold values of AMS and different POT series in the urbanization period (1986–2001) were larger than those in the baseline period (2002–2013), while standard deviation, coefficient of variation and coefficient of skewness of AMS and different POT

series were higher in the baseline period than those in the urbanization period.

3. The flood magnitude was higher during the urbanization period than that during the baseline period at the same flood frequency (or return period) of exceedance. The changes in magnitudes of small floods were relatively larger than those of large floods from the baseline period to the urbanization period.
4. The precipitation changes and urbanization are the main driving factors leading floods change in the Qinhuai River Basin. The contributions of urbanization on floods appeared to amplify with decreasing flood size, while the effects of precipitation diminish.

The procedure proposed in this study has been demonstrated to be useful for the trend and attribution analysis of flood series. The findings of this study can advance our understanding of interactions between flood behavior and the drivers, thereby improving flood management in urbanized basins.

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