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Impacts of historical records on extreme flood variations over the conterminous United States

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Abstract

Evaluation of flood variations over time, especially for floods with large return periods, is of great significance to flood risk assessment. 'Historical' data that have been recorded before the construction of a gauging station provide an effective way to analyse the temporal changes of extreme floods. Here, comparison of maximum likelihood method, L-moment method and Bayesian theory are made to calculate the Gumbel distribution parameters via Monte Carlo simulation experiment. The best option is applied to 37 unregulated rivers over the conterminous United States to analyse their 100-year flood variations. The Monte Carlo simulation results indicate that L-moment method is substantially better than the other two estimators for both systematic and unsystematic series. Over 70% of studied river catchments detect 100-year flood decrease when the historical data are considered. The impacts of historical records on 100-year flood variation estimations are closely related to censoring threshold and historical period length.

Introduction

Over the past century, a huge number of major floods occurred around the world, which indicates that floods may have undergone increases in both magnitude and frequency (Blöschl *et al.*, 2015). Estimation of flood variations, especially with low frequencies (less than 1%), is an important issue in river flood risk evaluation as well as hydraulic projects design. In practice, a possible flood magnitude corresponding to a given return period is obtained through statistical analysis of a number of observed flood data. Unfortunately, most rivers typically have a short length of gauged records, while river catchments with long records are usually affected by human activities. These data series cannot accurately reflect the extreme flood change under natural environment (Dai *et al.*, 2009; Xu *et al.*, 2010). Hence, there is a need for more undisturbed flood records to discern the flood variations over time.

Historical flood information has been recorded during the time prior to the construction of a gauging station and extends to the period of flood time series and thus provides a broader perspective for flood variation analysis. During the past decades, several studies have been carried out to take advantage of historical information in flood frequency analysis and concluded that historical information has great value in extreme flood assessments (Hosking and Wallis, 1986; Archer, 1987; Acreman and Horrocks, 1990; Guo, 1991; Jarrett and Tomlinson, 2000; Williams and Archer, 2002; Parent and Bernier, 2003; Benito *et al.*, 2004). One of the main problems to incorporate historical records into flood quantile estimation is how to deal with the censored data during the historical period. To overcome this problem, a number of moment-based methods were proposed, which represent the missing below-threshold historical values by the below-threshold systematic records in different terms (WRC (US Water Resources Council), 1982; Hosking and Wallis, 1997; Cohn *et al.*, 1997). At the same time, maximum likelihood framework was introduced to consider the historical information in flood frequency analysis (Stedinger and Cohn, 1986). More recently, the Bayesian probability theory was used to deal with historical floods by establishing conjugate informative priors that have similar form to posterior distribution for the parameters (Frances *et al.*, 1994; O'Connell *et al.*, 2002; Reis and Stedinger, 2005). In spite of extensive research of each method in hydrology, the former works mainly focused on the improvement of flood estimation precision by considering historical flood records, without applying the related results in practise to identify the changes in extreme floods over time. Clarification of the magnitudes of extreme floods change over time and the processes that cause flood changes are important for dealing with future flood risk (Blöschl *et al*., 2015).

Thus, the major objectives of this research include: 1) derive an advanced approach of flood quantile estimation when historical flood information is available; 2) apply the best option to a large number of river catchments in the United States to assess extreme flood variations; 3) discern possible extreme flood trends at national scale with reference to historical records and further investigate the impact factors.

Data collection and methods

In many sampling situations, complete information of all samples may not be obtained due to various reasons (i.e. human influence and objective factors). The appropriate way to consider all the available information is to make the premise that a censoring level exists, and that all excesses of this threshold level over a specified time interval have been recorded. Following Guo and Cunnane (1991) and England *et al*. (2003a), schematic description of historical data, systematic data and discharge threshold is given in Figure 1. Let N_h *and* N_s represent historical record length and systematic record length, respectively. The unsystematic record (total record) length N is equal to N_h plus N_s. Let T define discharge threshold. During the historical period, $N_h^>$ floods exceeded the threshold T and were recorded because they are unusually large. Analogously to the recorded historical flood peaks, there are $N_h^<$ unmeasured discharges with magnitudes less than T, being represented by shaded area. The historical period is followed by N_s years of systematic gauged records, during which $N_s^>$ floods exceed T and $N_s^<$ floods are below T.

Data collection

River systems with recorded historical floods are of particular importance to obtain better knowledge on extreme flood variations. The United States provides the most prominent examples of such kind of river catchments (Webb and Jarrett, 2002; England *et al*., 2003a).

Three main criteria are considered to select the river catchment in this paper. Firstly, the gauging station should be free from anthropogenic influences to ensure the data homogeneity. Secondly, the record coverage of systematic information is required to be longer than 30 years for a reliable statistical analysis (Madsen *et al*., 2013). Thirdly, the historical record length should be commensurate with or less than that of systematic records to reduce the uncertainty associated with the missing data over the historical period (Hosking and Wallis, 1997; Strupczewski *et al*., 2013). Thirty-seven river catchments that satisfy the above requirements make up the data base for this study (Figure 2). Characterisations of each river gauging station with location, elevation, drainage area, historical and systematic records information are given in Table A1. Initial review of the gauging stations shows that the 37 river catchments cover

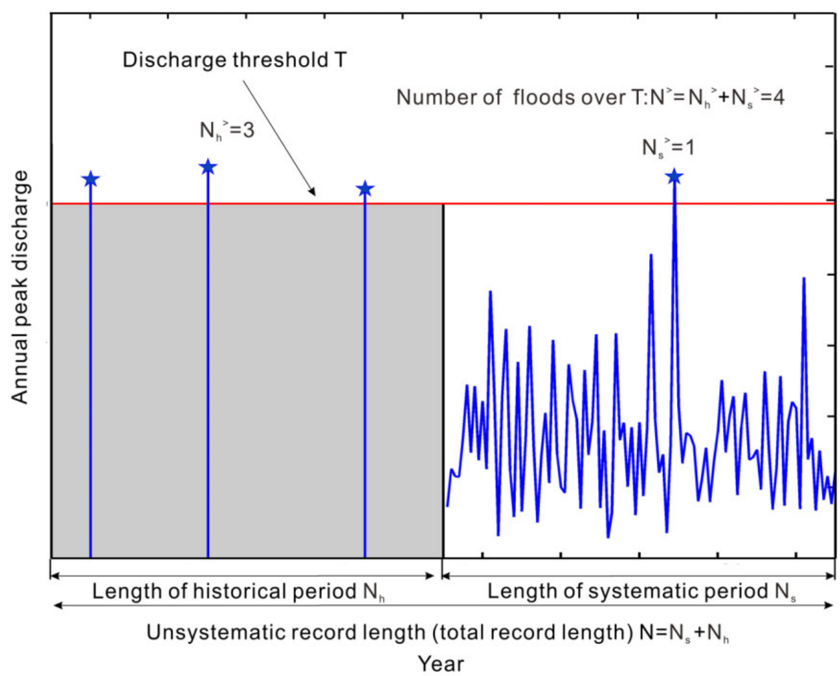

Figure 1 Schematic description of historical data, systematic data and discharge threshold. In the historical period, only floods exceed threshold are recorded while the unobserved floods with magnitude less than threshold are denoted by shaded area.

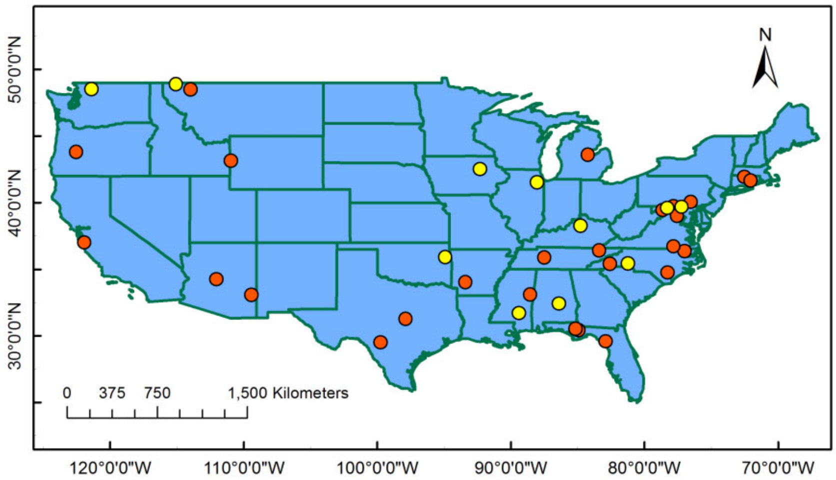

Figure 2 Location of the 37 studied river catchments in the United States (refer to Table A1). Red circle denotes 100-year flood estimation decrease when considering historical flood records, while yellow circle represents 100-year flood estimation increase when considering historical flood records.

23 states of the United States involve a wide range of hydrologic conditions and climate types, where the main reasons for extreme floods include several rainfall and excessive snowmelt. The drainage areas for the selected gauging stations range from 40 km^2 to 67,314 km^2. Most gauging stations started to work between the 1920s and 1950s while the historical floods are mainly recorded between the 1880s and 1910s. The annual peak discharge series and the historical flood information are collected from the U.S. Geological Survey (USGS) websites (Source: http://water.usgs.gov/waterwatch/).

Methods

Hydrological data for any flood frequency analysis should in theory be consistent, which can be statistically evaluated through a series of tests, including autocorrelation test, trend test and change point test. The first order autocorrelation coefficient is used to detect the existence of autocorrelation in each time series (Salas *et al*., 1980). Mann-Kendall test and standard normal homogeneity test are carried out respectively to examine the potential trend and abrupt change in the data set (Alexandersson and Moberg, 1997; Yue *et al*., 2002).

Gumbel distribution, one of the most frequently used models in hydrology, is adopted to compute flood quantile in this study. The probability density function and cumulative distribution function of the Gumbel distribution take the forms as

$$f(x) = \lambda \exp[-\lambda(x-\mu) - \exp(-\lambda(x-\mu))] \tag{1}$$

$$F(X<x) = \exp[-\exp(-\lambda(x-\mu))] \tag{2}$$

where X is the random variable, μ and λ are the location parameter and scale parameter, respectively.

In flood frequency analysis, one of the inquiries that have been frequently required is to evaluate the magnitude of flood with relatively large return period. The quantile function of the Gumbel distribution is given by

$$x_F = \mu - \frac{\ln(-\ln(F))}{\lambda} \tag{3}$$

In spite of the extensive use of the Gumbel distribution, no single method of estimating scale parameter λ and location parameter μ is standard. Here, the Maximum Likelihood Method (MLM), the L-moments Method (LMM) and the Bayesian framework, three common parameter estimation methods in hydrology field, are suggested to estimate the Gumbel parameters. Two scenarios, systematic records only and unsystematic records including both systematic and historical observations, are studied respectively.

Maximum Likelihood Method (MLM)

Suppose a sample consists of n points $x_1, x_2, \ldots x_n$. The likelihood function to draw n samples x_i from the Gumbel distribution with parameters λ and μ is (Lowery and Nash, 1970)

$$\begin{aligned} L(\lambda,\mu) &= P(x_1 \cdots x_n/\lambda,\mu) \\ &= \prod_{i=1}^{n} \lambda \exp[-\lambda(x_i-\mu) - \exp(-\lambda(x_i-\mu))] \end{aligned} \tag{4}$$

The log likelihood function is derived as

$$\log L(\lambda,\mu) = n\log\lambda - \sum_{i=1}^{n}\lambda(x_i-\mu) - \sum_{i=1}^{n}\exp(-\lambda(x_i-\mu)) \tag{5}$$

The partial first derivations can be get from $\log L(\lambda, \mu)$ in terms of

$$\frac{\partial \log L}{\partial \mu} = n\lambda - \lambda \sum_{i=1}^{n} \exp(-\lambda(x_i - \mu)) \tag{6}$$

$$\frac{\partial \log L}{\partial \lambda} = \frac{n}{\lambda} - \sum_{i=1}^{n}(x_i - \mu) + \sum_{i=1}^{n}(x_i - \mu)\exp(-\lambda(x_i - \mu)) \tag{7}$$

By setting the above two functions as 0, the maximum likelihood estimates for the parameters are derived as

$$\tilde{\mu} = -\frac{1}{\tilde{\lambda}} \log\left[\frac{1}{n}\sum_{i=1}^{n}\exp\left(-\tilde{\lambda}x_i\right)\right] \tag{8}$$

$$\frac{1}{\tilde{\lambda}} - \frac{1}{n}\sum_{i=1}^{n} x_i + \sum_{i=1}^{n} x_i \exp\left(-\tilde{\lambda}x_i\right) \Big/ \sum_{i=1}^{n} \exp\left(-\tilde{\lambda}x_i\right) = 0 \tag{9}$$

The Newton–Raphson algorithm is applied to find the estimators of the parameters in this study.

When the historical information is considered, the new data set is composed by systematic observations and the historical floods. The probability of a data set which includes N_s systematic gage records and $N_h^>$ historical floods are

$$\begin{aligned} L(\lambda, \mu) &= P\left(x_1 \cdots x_{N_s}, x_{N_s+1} \cdots x_{N_s+N_h^>} / \lambda, \mu\right) \\ &= \prod_{i=1}^{N_s+N_h^>} \lambda \exp[-\lambda(x_i - \mu) - \exp(-\lambda(x_i - \mu))] \\ &\quad (\exp[-\exp(-\lambda(T - \mu))])^{N_h^<} \end{aligned} \tag{10}$$

The related log likelihood function is

$$\begin{aligned} \log L(\lambda, \mu) = {} & (N_s + N_h^>)\log\lambda - N_h^< \exp(-\lambda(T - u)) \\ & - \sum_{i=1}^{N_s+N_h^>} \lambda(x_i - \mu) - \sum_{i=1}^{N_s+N_h^>} \exp(-\lambda(x_i - \mu)) \end{aligned} \tag{11}$$

Taking the partial derivation with respect to λ and μ, the above function gives

$$\begin{aligned} \frac{\partial \log L}{\partial \mu} = {} & \left(N_s + N_h^>\right)\lambda - N_h^< \lambda \exp(-\lambda(T - u)) \\ & - \lambda \sum_{i=1}^{N_s+N_h^>} \exp(-\lambda(x_i - \mu)) \end{aligned} \tag{12}$$

$$\begin{aligned} \frac{\partial \log L}{\partial \lambda} = {} & \frac{\left(N_s + N_h^>\right)}{\lambda} + N_h^<(T - \mu)\exp(-\lambda(T - \mu)) \\ & - \sum_{i=1}^{N_s+N_h^>}(x_i - \mu) + \sum_{i=1}^{N_s+N_h^>}(x_i - \mu)\exp(-\lambda(x_i - \mu)) \end{aligned} \tag{13}$$

By setting the above function as 0, the solutions of the parameters are

$$\tilde{u} = -\frac{1}{\tilde{\lambda}} \log\left[\frac{1}{N_s + N_h^>}\left(N_h^< \exp\left(-\tilde{\lambda}T\right) + \sum_{i=1}^{N_s+N_h^>} \exp\left(-\tilde{\lambda}x_i\right)\right)\right] \tag{14}$$

$$\begin{aligned} & \frac{1}{\tilde{\lambda}} - \frac{1}{N_s + N_h^>} \sum_{i=1}^{N_s+N_h^>} x_i \\ & + \frac{N_h^< T \exp\left(-\tilde{\lambda}T\right) + \sum_{i=1}^{N_s+N_h^>} x_i \exp\left(-\tilde{\lambda}x_i\right)}{N_h^< \exp\left(-\tilde{\lambda}T\right) + \sum_{i=1}^{N_s+N_h^>} \exp\left(-\tilde{\lambda}x_i\right)} = 0 \end{aligned} \tag{15}$$

L-Moment Method (LMM)

Let $x_{1:n} \le x_{2:n} \le \ldots \le x_{n:n}$ are n data values in increasing order (that have been recorded in systematic period); the sample probability can be expressed as

$$b_k = \frac{1}{n}\sum_{i=1}^{n} \frac{(i-1)(i-2)\cdots(i-k)}{(n-1)(n-2)\cdots(n-k)} x_{i:n} \tag{16}$$

By taking linear combinations of the order statistic expectations, the L-moments for an ordered sample are derived as (Hosking, 1990)

$$l_{r+1} = \sum_{k=0}^{r} (-1)^{r-k} \binom{r}{k}\binom{r+k}{k} b_k \tag{17}$$

For an ordered sample, the parameters for the Gumbel distribution can be estimated by the following functions

$$\tilde{\lambda} = \log 2 / l_2 \tag{18}$$

$$\tilde{u} = l_1 - r/\tilde{\lambda} \tag{19}$$

where r is Euler's constant, equal to 0.5772.

In order to establish linear relations for the records including historical information, the unsystematic data series over the study period N is assumed as a stationary set. As the river gauging stations in this research have relatively short historical periods, the unobserved below-threshold historical data can be represented by the below-threshold systematic records in terms of sample average and variability (Chen *et al.*, 2001, 2004).

$$b_0 = \frac{1}{N}\left[\frac{N^<}{N_s^<}\sum_{m=1}^{N_s^<} x_m + \sum_{m=N_s^<+1}^{N_s^<+N^>} x_m\right] \tag{20}$$

$$\begin{aligned} b_1 = \frac{1}{N}\Bigg[& \frac{N^<}{N_s^<}\sum_{m=1}^{N_s^<} \frac{(m-1)}{(N_s^< - 1)} \frac{(N^< - 1)}{(N - 1)} x_m \\ & + \sum_{m=N_s^<+1}^{N_s^<+N^>} \frac{(N - N_s^< - N^> + m - 1)}{(N - 1)} x_m \Bigg] \end{aligned} \tag{21}$$

where x_m is the unsystematic records in increasing order.

Bayesian framework

Differently from the classical statistical methods, the Bayesian scheme considers the information in the data set in forms of likelihood function with the prior information related to the parameters. Generally, the prior knowledge about the parameters can be gathered from other data sets or an expert's knowledge (Wood and Rodriguez-Iturbe, 1975; Bretthorst, 1990; Kuczera, 1999). Parameter estimation through Bayes Theorem is expressed in terms of posterior distribution

$$p(\lambda/x) = \frac{f(x/\lambda)\,p(\lambda)}{\int_0^\infty f(x/\lambda)\,p(\lambda)\,d\lambda} \tag{22}$$

where $p(\lambda/x)$ is the posterior distribution of the parameter λ, $f(x/\lambda)$ is the likelihood function, and $p(\lambda)$ is the prior distribution of the parameter.

In this paper, the likelihood model of the Bayesian framework is represented by the Gumbel distribution

$$\begin{aligned} f(x/\mu,\lambda) = \lambda \exp\left[-\lambda\left(\sum x_i - \mu\right)\right] \\ \exp\left[-\sum \exp(-\lambda(x_i-\mu))\right] \end{aligned} \tag{23}$$

The unknown parameters λ and μ are described by normal distribution with their own mean and standard deviation parameters

$$\begin{aligned} p(u,\lambda) = f(u)\times f(\lambda) = \frac{1}{\sqrt{2\pi}\sigma_u}\exp\left[-\frac{(x-u_u)^2}{2\sigma_u{}^2}\right] \\ \times \frac{1}{\sqrt{2\pi}\sigma_\lambda}\exp\left[-\frac{(x-u_\lambda)^2}{2\sigma_\lambda{}^2}\right] \end{aligned} \tag{24}$$

The posterior distribution is then derived as

$$\begin{aligned} p(u,\lambda/x) = Cp(u,\lambda)\lambda \exp\left[-\lambda\left(\sum x_i - \mu\right)\right] \\ \exp\left[-\sum \exp(-\lambda(x_i-\mu))\right] \end{aligned} \tag{25}$$

where C is the normalization constant to ensure $p(u, \lambda/x)$ integrates to 1.

The posterior predictive is expressed as

$$P(x<X) = \iint F(X/u,\lambda)\,p(u,\lambda/x)\,du\,d\lambda \tag{26}$$

If the historical flood data are available, they can be placed in the prior distribution to provide additional extent of certainty. Here, the parameters λ and μ are assumed to follow the bivariate normal distribution. The joint probability density function of λ and μ is

$$f_{\Lambda,\Delta}(\mu,\lambda) = c\exp(-q(\mu,\lambda)) \tag{27}$$

where the normalizing constant is defined as

$$c = \frac{1}{2\pi\sqrt{1-\rho^2}\sigma_\Lambda\sigma\Delta} \tag{28}$$

The exponent term $q(\mu/\lambda)$ is a quadratic function of λ and μ

$$q(\mu,\lambda) = \frac{\dfrac{\mu^2}{\sigma_\Lambda^2} - 2\rho\dfrac{\mu\lambda}{\sigma_\Lambda\sigma_\Delta} + \dfrac{\lambda^2}{\sigma_\Delta^2}}{2\left(1-\rho^2\right)} \tag{29}$$

By combining the prior bivariate normal distribution with the likelihood Gumbel model, a new posterior distribution that considers historical information can be generated.

Comparison methods

With the rapid development of computer technology in recent years, many tools for intense numerical calculation in statistical inference have been provided, such as Monte Carlo simulation method. In this paper, the performance of MLM, LMM and the Bayesian framework, for systematic samples only and unsystematic samples including both systematic series and historical floods above a certain threshold, are compared based on Monte Carlo simulation experiments.

Quantile estimation has been widely used in hydrology as a basis to compare the results of various estimation methods with empirical data (true value) (Stedinger and Cohn, 1986; Cohn *et al.*, 1997; England *et al.*, 2003b). Sample error, the difference between estimated flood discharge and the true value, is suggested as the comparison criterion in this paper. To test the unbiasedness and validity of each method in 100-year flood estimation, Error (E) and Squared Error (SE) of the sample are defined as

$$\begin{aligned} E\left(\hat{X}_{0.99}\right) &= \hat{X}_{0.99} - X_{0.99} \\ &= \ln\left(\hat{Q}_{0.99}\right) - \ln\left(Q_{0.99}\right) \end{aligned} \tag{30}$$

$$\begin{aligned} SE\left(\hat{X}_{0.99}\right) &= \left(\hat{X}_{0.99} - X_{0.99}\right)^2 \\ &= \left(\ln\left(\hat{Q}_{0.99}\right) - \ln\left(Q_{0.99}\right)^2\right) \end{aligned} \tag{31}$$

where $Q_{0.99}$ is the true 100-year flood, $\hat{Q}_{0.99}$ is the estimated 100-year flood, $X_{0.99}$ is the logarithm of $Q_{0.99}$ flood, $\hat{X}_{0.99}$ is the logarithm of $\hat{Q}_{0.99}$.

Results

Monte Carlo simulation experiment

A Gumbel distribution, with location parameter $\mu = 100$ and scale parameter $\lambda = 1/12$, is selected for the Monte Carlo experiments. The systematic record length is fixed as 50 years while two types of historical record lengths are simulated: 0

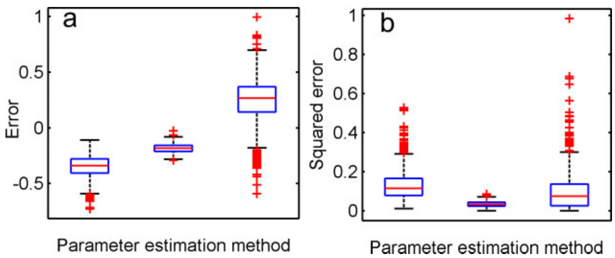

Figure 3 Performance of Maximum Likelihood Method, L-Moment Method and Bayesian method for systematic records. (a) Error results; and (b) squared error results.

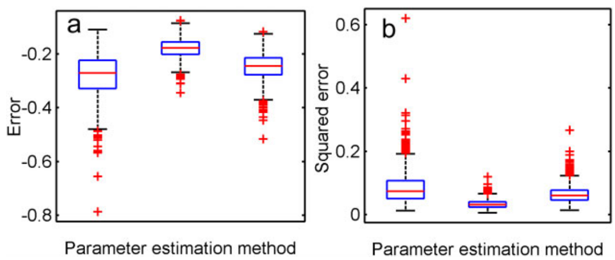

Figure 4 Performance of Maximum Likelihood Method, L-Moment Method and Bayesian method for unsystematic records. (a) Error results; and (b) squared error results.

year (systematic series) and 50 years (unsystematic series). For each set of combination, 1000 replicate samples are generated. Then, the E and SE results of each method are presented in terms of boxplot. Boxplot depicts groups of data sets in terms of quartiles. For each box, it goes from 25th percentile to 75th percentile, representing the middle 50% of the data with the central line indicating the median value. The whiskers extend from the box edges to the extreme points, while outliers are plotted as individual points.

Systematic series

When only considering the systematic records, 50 Gumbel random data are generated and served as input for the three estimation methods to calculate the Gumbel parameters. The sample E and SE for each set of parameters can be obtained by Eqns (30) and (31). Boxplots of 1000 E and SE for the three methods are illustrated in Figure 3. It seems that LMM provides the most accurate and stable estimators for the 100-year quantile, while MLM and Bayesian approaches present larger uncertainties in the estimations and suggest larger ranges of fluctuation among different samples.

Unsystematic series

In order to model the cases containing both systematic and historical data, a Gumbel series of length N ($N = N_s + N_h$, both N_s and N_h are defined as 50) is generated. The 90th percentile of the N data is set as threshold to remove the below-threshold data in the historical period and to create a new censored sample. Thereafter, the three estimation procedures are applied to the censored sample to generate three groups of Gumbel parameters and related E and SE values. The E and SE results for the 1000 replicate samples are shown in Figure 4. It is shown that LMM indicates the smallest E and SE, and reflects the most accurate empirical flood behaviour when calculating the 100-year event. As for the other two methods, MLM still has the problem of large variation among different samples while the Bayesian estimation depends too much on the informative historical records and leads to higher E and SE on average.

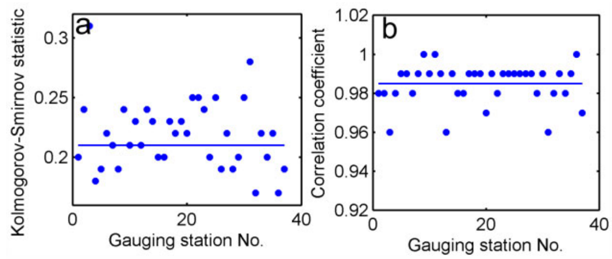

Figure 5 Goodness of fit of Gumbel distribution. (a) Kolmogorov-Smirnov statistic; and (b) correlation coefficient.

Case study

Consistency test

To ensure that the collected data for each river catchment belongs to the same statistical population, consistency check is carried out through a series of tests, including the first order autocorrelation coefficient test (autocorrelation test), Mann–Kendall test (trend test) and standard normal homogeneity test (change point test). It is shown that, at 5% significant level, no statistical significant autocorrelation, trend and change point is detected in the 37 groups of observed data series. Therefore, they satisfy the consistency assumption for further flood frequency analysis.

Goodness of fit

A number of probability distributions have been suggested to describe the extreme events of different magnitudes in hydrological research (Benson, 1968; Stedinger *et al.*, 1993; Rao and Hamed, 2000). Selection of an appropriate flood frequency distribution is an important step in flood frequency analysis (Haddad and Rahman, 2011). Therefore, it is necessary to describe how well the Gumbel distribution and the associated LMM estimation procedure fit the flow observations in the 37 river catchments. Figure 5 presents the discrepancy between theoretic frequency and expected frequency in terms of Kolmogorov–Smirnov statistic (KS)

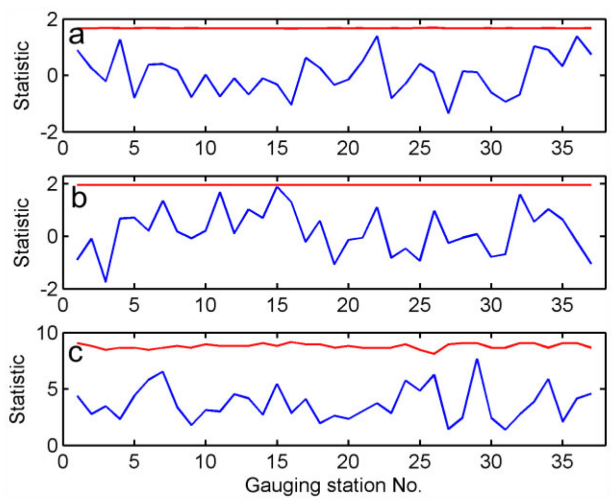

Figure 6 Consistence test results. (a) Autocorrelation coefficient test; (b) Mann-Kendall test; and (c) Standard normal homogeneity test. Red line in each figure denotes the critical value.

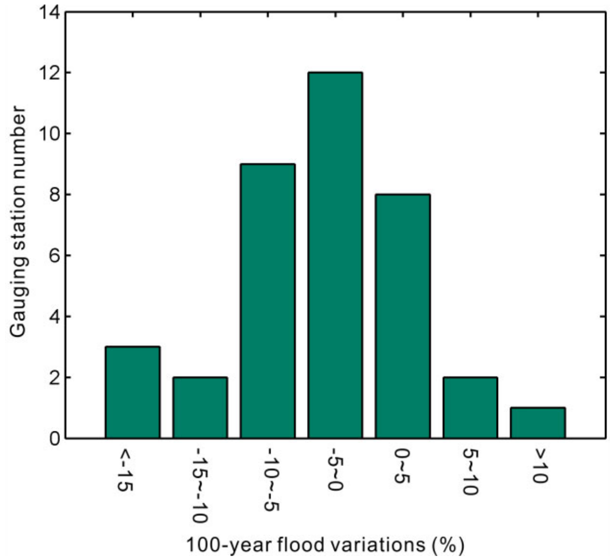

Figure 7 Consideration of historical records induced 100-year flood variations in the studied river catchments. The variation is expressed herein as a ratio of ($Q_{0.99\text{-}u}$-$Q_{0.99\text{-}s}$) to $Q_{0.99\text{-}s}$. $Q_{0.99\text{-}u}$ represents 100-year flood estimated from unsystematic records, while $Q_{0.99\text{-}s}$ denotes 100-year flood calculated from systematic records.

and correlation coefficient (R). It is shown that both KS and R statistic suggest high goodness of fit. Accordingly, Gumbel is an appropriate form of distribution to describe the flood characteristic in the studied river catchments.

Flood quantile analysis

For each study gauging station, two estimators are derived for 100-year flood, based on the systematic and unsystematic flow records, respectively. The smallest flood record during the historical period is set as peak discharge threshold in this study. The variation of 100-year flood is expressed herein as a ratio of ($Q_{0.99\text{-}u}$–$Q_{0.99\text{-}s}$) to $Q_{0.99\text{-}s}$. $Q_{0.99\text{-}u}$ represents 100-year flood estimated from unsystematic records, while $Q_{0.99\text{-}s}$ denotes 100-year flood calculated from systematic records. It is shown that the 37 river catchments over the United States suggest different degrees of change in 100-year flood when consider the past historical floods (Figure 6). A total of 26 gauging stations suggest decreases in 100-year flood quantile when introducing the historical information into flood frequency analysis, varying between 0.6% and 22.17% with a mean of 6.83%. The remaining 11 gauging stations indicate upward trends with the reference of historical floods and are located in the range of 0.71% to 13.63%. It is shown that the river catchments, indicating uptrend in 100-year flood, is mainly located in the east of the contiguous United States (Figure 2). Moreover, the 37 gauging stations are divided into 7 specialised groups according to their variation degrees in 100-year flood with a 5% interval (Figure 7). It is evident that the interval –5% to 0 accounts for the greatest proportion (12 in 37), being followed by the intervals of –10% to –5% and 0 to 5%.

Discussion

The magnitude of the threshold (T) and the time length of the historical record (N_h) are the most influential parameters of extreme flood change evaluations (Gaál *et al.*, 2010). Here, the responses of 100-year flood variations to the historical information are discussed. To ensure that the influence of threshold and historical record length on 100-year flood variation for the 31 river catchments is directly comparable to each other, the two parameters are expressed in term of dimensionless parameters. Specifically, the threshold is transferred to the percentile rank for threshold in ordered systematic records (Q_T). The historical record length is denoted by the ratio between historical record length and unsystematic record length (N_h/N).

Threshold

Q_T data for the 37 river catchments and their corresponding 100-year flood variations are shown in Figure 8. Around 90% of studied river catchments indicate high Q_T by exceeding 0.8 (33 in 37). The linear fitting between 100-year flood variations and Q_T suggests significant positively correlation at 0.01 significant level. It means that both large and small censoring thresholds are likely to lead to larger changes in extreme floods.

Historical record length

The N_h/N ratios for the 37 river gauging stations are ranging from 0.09 to 0.57 with a large part distributed between 0.1

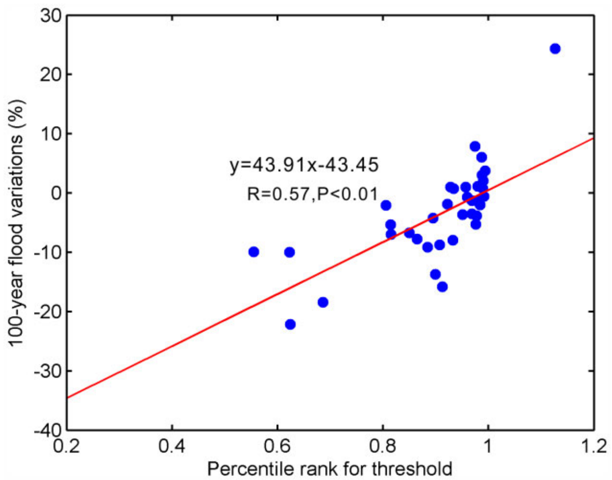

Figure 8 Relation between 100-year flood variation and threshold magnitude. The threshold is expressed by the percentile rank for threshold in ordered systematic records. R denotes the correlation coefficient. $P < 0.01$ indicates that the relation between data points and fitting line is statistical significant at 0.01 significant level.

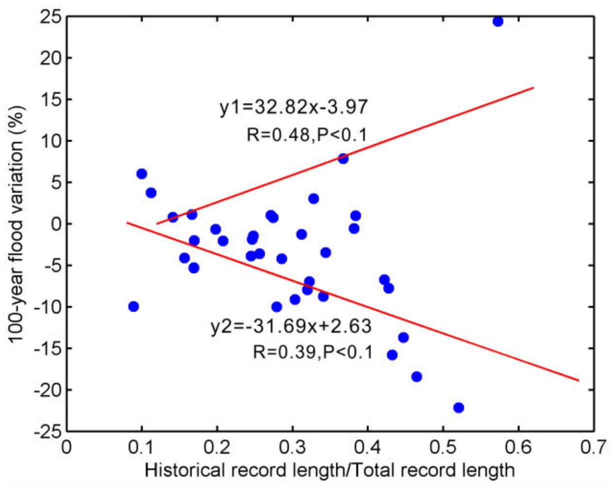

Figure 9 Relation between 100-year flood variation and historical record length. The historical record length is expressed as ratio between historical record length and unsystematic record length. R denotes the correlation coefficient. $P < 0.1$ indicates that the relation between data points and fitting line is statistical significant at 0.1 significant level.

and 0.4, suggesting that the length of historical records in most studied river catchments are shorter than that of systematic observations (Figure 9). As for the magnitudes of flood quantile change, both negative and positive data suggest larger variations when the historical record length increases. The two groups of linear fittings suggest significant correlations with $P < 0.1$.

Among the total 37 river catchments, 26 river catchments suggest decreases in 100-year flood quantile when introducing the historical information into flood frequency analysis, accounting for 70.3%. It is noteworthy that the decrease in 100-year flood quantile occurs when modern large floods surpass historical floods in magnitude. Therefore, over last century, the magnitudes of 100-year flood events have increased in most of the United States regions. With the rapid development of human society, a large number of hydraulic structures are underconstructed around the world, especially in the developing countries like China (Dai *et al.*, 2011). At the same time, high degrees of geographic vulnerabilities associated with flood risk were realised over recent decades (Brody *et al.*, 2007, 2008). It is recommend to consider the changes in extreme floods over time and take historical flood information into account when assess the extreme floods, such to provide more accurate suggestions in flood risk assessment and hydraulic project design in the future.

Conclusions

This paper investigates the change in extreme flood by taking advantage of historical information at national scale. Specifically, three types of parameter estimate methods, including maximum likelihood method, L-moment method and Bayesian estimation, that enable the incorporation of historical floods into flood quantile estimation, are reviewed and compared on the basis of Monte Carlo simulation experiments. Then, the suggested approach is applied to 37 river catchments over the United States, which cover a wide range of hydraulic conditions, to assess the 100-year flood variations over time. The main conclusions are drawn as following:

1. L-moment method presents better performance than maximum likelihood method and Bayesian theory when deriving 100-year quantile from the Gumbel random data, no matter the case of systematic records or unsystematic records.
2. The change rates of 100-year flood for the 37 river catchments over the United States are ranging from −22.17% to 13.63%, with mean level at −3.69%. Twenty-six river catchments indicate increases in 100-year flood quantile during the past century.
3. The changes of 100-year flood are sensitive to censoring threshold and historical record length. Both high and low censoring thresholds, and long historical record length, can result in larger variations in 100-year flood.

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Appendix

Characterization of river gauging stations with location, elevation, drainage area, historical and systematic records

Site No.	River station (State)	Location Lat.	Long.	Elevation (m)	Drainage area (km^2)	Historical record	Systematic record
1	Alabama River near Montgomery (AL)	32.41	86.41	29.85	39075	1886–1928	1928–2013
2	Eagle Creek near Morenci (AZ)	33.06	109.44	1119.97	1611	1916–1944	1944–2013
3	Verde River near Clarkdale (AZ)	34.25	112.07	1067.07	9073	1916–1967	1967–2013
4	Antoine River at Antoine (AR)	34.04	93.42	69.92	461	1905–1951	1951–2013
5	Soquel Creek at Soquel (CA)	36.99	121.95	6.52	104	1937–1950	1950–2013
6	Broad Brook at Broad Brook (CT)	41.91	72.55	14.09	40	1938–1962	1962–2012
7	Little River near Hanover (CT)	41.67	72.05	67.44	78	1936–1952	1952–2012
8	Suwannee River near Wilcox (FL)	29.59	82.94	–0.16	24967	1931–1944	1944–2013
9	Telogia Creek near Bristol (FL)	30.43	84.93	30.34	326	1903–1951	1951–2013
10	Chipola River near Altha (FL)	30.53	85.17	6.08	2023	1913–1922	1922–2013
11	Henderson Creek near Oquawka (IL)	41.00	90.85	165.00	278	1902–1945	1945–2013
12	Cedar River at Waterloo (IA)	42.50	92.33	251.26	13328	1929–1941	1941–2013
13	Elkhorn Creek near Frankfort (KY)	38.27	84.81	164.70	1225	1932–1940	1940–2011
14	Conococheague Creek at Fairview (MD)	39.72	77.82	119.47	1279	1889–1929	1929–2012
15	Monocacy River at Bridgeport (MD)	39.68	77.23	103.91	448	1933–1942	1942–2012
16	Tittabawassee River at Midland (MI)	43.60	84.24	176.85	6216	1876–1910	1910–2013
17	Noxubee River at Macon(MS)	33.10	88.56	41.71	1989	1892–1929	1929–2013
18	Leaf River near Collins(MS)	31.71	89.41	60.06	1924	1856–1939	1939–2013
19	Tobacco River near West Eureka (MT)	48.89	115.09	767.94	1084	1948–1959	1959–2013
20	MF Flathead River near West Glacier (MT)	48.50	114.01	953.88	2914	1916–1940	1940–2013
21	Potecasi Creek near Union (NC)	36.37	77.03	1.08	583	1929–1958	1958–2013
22	Black River near Tomahawk (NC)	34.76	78.29	7.50	1751	1928–1952	1952–2013
23	Indian Creek near Laboratory (NC)	35.42	81.27	226.32	179	1916–1952	1952–2013
24	Mills River near Mills River(NC)	35.40	82.60	636.73	173	1876–1935	1935–2013
25	Illinois River near Tahlequah(OK)	35.92	94.92	202.48	2460	1916–1935	1935–1985
26	MF Willamette River near Oakridge(OR)	43.80	122.56	284.99	2393	1890–1923	1923–1960
27	Susquehanna River at Marietta (PA)	40.05	76.53	61.15	67314	1889–1932	1932–2013
28	Clinch River above Tazewell(TN)	36.43	83.40	323.38	3818	1862–1920	1920–2013
29	Piney River at Vernon(TN)	35.87	87.50	140.77	500	1897–1926	1926–2013
30	Cowhousse Creek at Pidcoke(TX)	31.28	97.88	224.61	1178	1900–1951	1951–2013
31	Dry Frio River near Reagan Wells(TX)	29.50	99.78	407.07	326	1932–1953	1953–2013
32	Goose Creek near Leesburg (VA)	39.02	77.58	75.89	860	1889–1910	1910–2012
33	Meherrin River near Lawrenceville (VA)	36.72	77.83	41.63	1430	1889–1928	1928–2013
34	Cascade River at Marblemount (WA)	48.53	121.41	100.61	445	1815–1929	1929–2013
35	South Branch Potomac River near Springfield(WV)	39.45	78.65	171.35	3784	1877–1900	1900–2012
36	Cacapon River near Great Cacapon(WV)	39.58	78.31	139.40	1748	1889–1923	1923–2012
37	Greys River near Alpine (WY)	43.14	110.98	1746.65	1160	1918–1937	1937–2013

Note: Datum of elevation gage: National Geodetic Vertical Datum of 1929 (NGVD29).

