On the applicability of the expected waiting time method in nonstationary flood design

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Abstract

Given a changing environment, estimating a flood magnitude corresponding to a desired return period considering nonstationarity is crucial for hydrological engineering designs. Four nonstationary design methods, namely expected waiting time (EWT), expected number of exceedances (ENE), equivalent reliability (ER), and average design life level (ADLL) have already been proposed in recent years. Among them, the EWT method needs to estimate design flood magnitudes by solving numerically. In addition, EWT requires estimating design quantiles for infinite lifespan, or extrapolation time (t_{extra}), to guarantee the convergence of the EWT solution under certain conditions. However, few studies have systematically evaluated pros and cons of the EWT method as to how to determine the t_{extra} and what kinds of misunderstandings on the applicability of the EWT method exist. In this study, we aim to provide the first investigation of various factors that influence the value of t_{extra} in the EWT method, and provide comprehensive comparison of the four methods from the perspectives of t_{extra}, design values and associated uncertainties. The annual maximum flood series (AMFS) of 25 hydrological stations, with increasing and decreasing trends, in Pearl River and Weihe River were chosen for illustrations. The results indicate that: (1) the t_{extra} of EWT is considerably affected by the trend of AMFS and the choice of extreme distributions. In other words, the t_{extra} of stations with increasing trends was significantly smaller than that of stations with decreasing trends, and the t_{extra} was also larger for distributions with heavier tail; (2) EWT produced larger design values than ENE for increasing trends, and both EWT and ENE yielded larger design values than ER and ADLL for higher return periods, while complete opposite results were obtained for decreasing trends.

Keywords: Nonstationary hydrological design; Extrapolation time; Expected waiting time; Expected number of exceedances; Equivalent reliability; Average design life level

1. Introduction

The traditional flood frequency analysis (TFFA) has been a standard procedure to estimate flood magnitude with a given return period in the fields of engineering design and water resources management. A typical assumption in TFFA is stationarity, i.e., the statistical characteristics (e.g., mean and standard deviation) in flood sample series collected during a historical period are identical in the future. However, hydrological systems throughout the world have undergone substantial alterations caused by natural and anthropogenic changes, and the stationary assumption is untenable and questionable (Su and Chen 2019; Xiong et al. 2019; Li et al. 2018; Serago and Vogel 2018; Wang et al. 2018; Xie et al. 2018; Zhang et al. 2018a, b). Thus, TFFA should be revised and accommodated to take into account nonstationarity in flooding design, in particular a system vulnerable to changing environment.

The nonstationary flood frequency analysis (NFFA) approach appears at this moment and has been one of the research hotspots in hydrology. In NFFA, the time-varying probability distribution model (TVPD) constructed by time-varying moments method has been actively applied to describe the nonstationarity of flood series. In the TVPD model, the statistical parameters are modelled as a function of time or other physical covariates (Kang et al. 2019; Lu et al. 2019; Wang et al. 2019; Xu et al. 2018; Gu et al. 2017; Yan et al. 2017a; Prosdocimi et al. 2015). Thus, how to estimate the nonstationary design flood with a prescribed return period under nonstationary context is one of the core questions (Jiang et al. 2019; Yan et al. 2017a; Salas and Obeysekera 2014). If we still use the design methods under the stationary context, the annual design flood $z_t(m)$ associated with return period *m* varies with time. Obviously, such kind of time-varying annual design flood for the given return period would be impractical for many engineering design problems under changing environment, since the relationship between design flood and return period is no longer one-to-one.

Recently, many studies have suggested nonstationary approaches to address the aforementioned issue of flood estimation (Yan et al. 2017b, 2019; Acero et al. 2018; Hu et al. 2018; Salas and Obeysekera 2014; Cooley 2013; Rootzén and Katz 2013; Parey et al. 2010, 2007; Olsen et al. 1998). Among them, two return-period-based methods, i.e., expected waiting time (EWT) (Cooley 2013; Olsen et al. 1998) and expected number of exceedances (ENE) (Parey et al. 2010, 2007) have drawn considerable attention. Cooley (2013) presented a detailed review about the mathematical expressions of ENE and EWT methods under both stationary and nonstationary contexts. Salas and Obeysekera (2014) first introduced ENE and EWT methods to the field of hydrology and proposed a framework to estimate the return period and risk of hydrological events under nonstationary context. In NFFA, Gu et al. (2017) compared the differences between stationary and nonstationary flood return periods calculated by EWT method, and estimated the flood risk in Pearl River basin based on TVPD model that employs time as a covariate. Hu et al. (2017) conducted a comprehensive comparison between the EWT and ENE methods with regard to the impacts of parameter uncertainty in estimating nonstationary design flood. Besides, they also estimated the reliability of flood-control infrastructure based on the TVMD model.

However, there are two major challenges in applications of the return-period-based methods. The first challenge may occur, as pointed out by Read and Vogel (2015), in the extrapolation time (t_{extra}) of exceedance probabilities of EWT given annual flood series decreasing over time. In other words, the additional exceedance probabilities required for estimating design quantiles might be infinite with lognormal distribution (LN). With a hypothetical example where the data series decreased with time and also a real case of decreasing sea levels, Salas and Obeysekera (2014) found that EWT can be applied for cases of decreasing trend series with a generalized extreme distribution (GEV) distribution. Hu et al. (2017) also investigated a hypothetical experiment that the location parameter of a time-varying GEV distribution varied with time, and they found that the t_{extra} of EWT was pronounced larger than that of ENE. Besides, the t_{extra} from EWT for a decreasing case is tenfold larger than that for an increasing case. From literature, the choices of extreme distributions and the changing patterns (upward trend or downward trend) may play an important role in determining the textra of EWT. There are ambiguous cognitions about the applicability of EWT method, since some researchers reported t_{extra} of EWT is infinite for decreasing hydrological series, whereas others did not (Hu et al., 2017; Read and Vogel, 2015). However, to our knowledge few studies have provided a comprehensive assessment of the influencing factors on the t_{extra} of EWT.

The other challenge is that EWT and ENE methods have a limitation to consider the impacts of design lifespan of hydrological structures on design values (Read and Vogel 2015; Rootzén and Katz 2013). In recent years, various nonstationary design methods have been proposed to take into account a design life period of projects. Obeysekera and Salas (2016) suggested using the expected number of extreme events over a design life period (ENEDL) as an alternative measure for nonstationary hydrological design. Rootzén and Katz (2013) proposed a concept of design life level (DLL) to calculate the design value with a prescribed reliability during a design life period of a project. As the reliability-based method is designed to communicate the reliability of projects during their design lifetime, the reliability-based design criterion plays a crucial role in a nonstationary hydrological design. However, another challenge stems from the fact that how well reasonable reliability is determined to fully consider the risk that a hydrological structure will experience during its design life period (Hu et al., 2018). The concept of return period has been favorably accepted by engineers and decision-makers as it has served as basis of engineering design for decades. Therefore, Hu et al. (2018) moved forward and proposed a well-designed design method, called equivalent reliability (ER). In this method, the reliability during the design life period of a project under nonstationarity is set to be identical to the reliability under the stationary condition. Yan et al. (2017a) also proposed a return-period-based design method, average design life level (ADLL), which argued that the annual average reliability over a project's design life period under nonstationarity should be identical to that of yearly reliability 1-1/*m* corresponding to return period *m*. Yan et al. (2017a) also compared the design floods estimated by ENE, DLL, ER and ADLL methods to investigate the capability of different nonstationary hydrological design methods, and found that ENE, ER and ADLL can yield similar design results when they incorporate physical covariates. However, the EWT method has been left out of their selection for the inter-comparison study.

Overall, it is necessary to clarify misunderstandings on return-period-based nonstationary design methods and to highlight the significance of incorporating the project's design life period into return-period-based design methods in the nonstationary hydrological design. Therefore, the objectives of this study are: (i) to provide a comprehensive assessment of influencing factors on the t_{extra} of EWT, and (ii) to compare the design floods and uncertainties estimated by four different return-period-based design methods, namely EWT, ENE, ER and ADLL. For the purpose of fulfilling these objectives, annual maximum flood series (AMFS) of 16 stations in the Pearl River basin (PRB) and 9 stations in the Weihe River basin (WRB) were selected as the alternative demonstration cases. The flowchart of this study is shown in Fig. 1.

2. Methodology

2.1 Nonstationary hydrological design methods

2.1.1. Expected waiting time (EWT)

The EWT method was first proposed by Olsen et al. (1998), and then independently derived by Salas and Obeysekera (2014) using a geometric distribution with time-varying parameters. Under nonstationary conditions, the geometric distribution describing waiting time before the first occurrence of an event exceeding the design quantile z_q is

$$f(x) = P(X = x) = p_x \prod_{t=1}^{x-1} (1 - p_t) \quad x = 1, 2, \ldots, x_{\max} \tag{1}$$

Where variable X is the year of the first occurrence of an event exceeding the design quantile z_q, $p_t = 1 - G_{Z,t}(z_q \mid \boldsymbol{\theta}_t)$ is annual exceedance probability varying with time step t. $x_{\max}$ is the time where the annual exceedance probability p_t is equal to 1 for an upward-trend flood series or is equal to 0 for a downward-trend flood series. The return period m is the expected value of X, thus in the EWT method, the design value with an m-year return period, denoted by $z^{EWT}(m)$, is the solution to the equation:

$$m = E(X) = \sum_{x=1}^{x_{\max}} x f(x) = \sum_{x=1}^{x_{\max}} x(1 - G_{Z,x}(z^{EWT}(m) \mid \boldsymbol{\theta}_x)) \prod_{t=1}^{x-1} G_{Z,t}(z^{EWT}(m) \mid \boldsymbol{\theta}_t) \tag{2}$$

An equivalent expression simplified by Cooley (2013) is

$$m = E(X) = 1 + \sum_{x=1}^{x_{\max}} \prod_{t=1}^{x} G_{Z,t}(z^{EWT}(m) \mid \boldsymbol{\theta}_t) \tag{3}$$

For the reason that Eq. (3) cannot be written as a geometric pattern, $z^{EWT}(m)$ must be solved numerically.

2.1.2. Expected number of exceedances (ENE)

ENE method was first proposed by Parey et al. (2007, 2010). In this method, the number that hydrological variable z_t exceeds the design value z_q in m years is defined by N, then $N = \sum_{t=1}^{m} I(z_t > z_q)$ under nonstationary context. Thus, the expected value of N is defined by

$$E(N) = \sum_{t=1}^{m} E[I(z_t > z_q)] = \sum_{t=1}^{m} P(z_t > z_q) = \sum_{t=1}^{m} (1 - G_{Z,t}(z_q \mid \boldsymbol{\theta}_t)) \tag{4}$$

where $I(\cdot)$ is an indicator function. In the ENE method, the design value with an m-year return period is denoted by $z^{ENE}(m)$, for which the expected number of exceedances in the m-year equals to one. Thus $z^{ENE}(m)$ is the solution to the following equation:

$$1=\sum_{t=1}^{m}(1-G_{Z,t}(z^{ENE}(m)\,|\,\boldsymbol{\theta}_t)) \tag{5}$$

2.1.3. Equivalent reliability (ER)

The ER method was proposed by Hu et al. (2018). Under stationary conditions, for a given return period *m*, the reliability over the design life period T_1-T_2 of a project is denoted by $RE^{s}_{T_1-T_2}$, which is calculated by

$$RE^{s}_{T_1-T_2}=\left(1-\frac{1}{m}\right)^{T_2-T_1+1} \tag{6}$$

While under nonstationary conditions, the design reliability $RE^{ns}_{T_1-T_2}$ that no flood exceeds the design value z_q within design life period T_1-T_2 is given by

$$RE^{ns}_{T_1-T_2}=\prod_{t=T_1}^{T_2}G_{Z,t}(z_q\,|\,\boldsymbol{\theta}_t) \tag{7}$$

Assuming $RE^{s}_{T_1-T_2}=RE^{ns}_{T_1-T_2}$, the design value $z^{ER}_{T_1-T_2}(m)$ based on the ER method can be calculated by solving the following equation:

$$\prod_{t=T_1}^{T_2}G_{Z,t}(z^{ER}_{T_1-T_2}(m)\,|\,\boldsymbol{\theta}_t)=\left(1-\frac{1}{m}\right)^{T_2-T_1+1} \tag{8}$$

2.1.4. Average design life level (ADLL)

The ADLL method was proposed by Yan et al. (2017a). Under nonstationary condition, the annual average reliability is defined as (Read and Vogel 2015)

$$RE^{ave}_{T_1-T_2}=\frac{1}{T_2-T_1+1}\sum_{t=T_1}^{T_2}(1-p_t)=\frac{1}{T_2-T_1+1}\sum_{t=T_1}^{T_2}G_{Z,t}(z_q\,|\,\boldsymbol{\theta}_t) \tag{9}$$

The ADLL method assumes that for a project with design life period starting from T_1 to T_2, the annual average reliability for a design value z_q should be identical to the yearly reliability 1-1/*m*, i.e., $RE_{T_1-T_2}^{ave}=1-1/m$. Thus the *m*-year design value $z_{T_1-T_2}^{ADLL}(m)$ based on the ADLL method can be derived from the following equation:

$$\frac{1}{T_2-T_1+1}\sum_{t=T_1}^{T_2}G_{Z,t}(z_{T_1-T_2}^{ADLL}(m)|\theta_t)=1-1/m \tag{10}$$

2.2 Theoretical analysis of extrapolation time for different design methods

In the EWT method, design value $z^{EWT}(m)$ must be solved numerically. However, as pointed by Cooley (2013), we can provide the bounds of return period *m* based on Eq. (3). The right side of Eq. (3) can be divided into the following equation for any extrapolation time *L*:

$$m=1+\sum_{x=1}^{L}\prod_{t=1}^{x}G_{Z,t}(z^{EWT}(m)|\theta_t)+\sum_{x=L+1}^{x_{\max}}\prod_{t=1}^{x}G_{Z,t}(z^{EWT}(m)|\theta_t) \tag{11}$$

where *L* is positive integer, and thus the lower bound of *m* is determined as $m>1+\sum_{x=1}^{L}\prod_{t=1}^{x}G_{Z,t}(z^{EWT}(m)|\theta_t)$. Furthermore, the upper bound of *m* can be derived as

$$\begin{aligned} m&=1+\sum_{x=1}^{L}\prod_{t=1}^{x}G_{Z,t}(z^{EWT}(m)|\theta_t)+\prod_{t=1}^{L}G_{Z,t}(z^{EWT}(m)|\theta_t)\sum_{x=L+1}^{x_{\max}}\prod_{t=L+1}^{x}G_{Z,t}(z^{EWT}(m)|\theta_t)\\ m&\le 1+\sum_{x=1}^{L}\prod_{t=1}^{x}G_{Z,t}(z^{EWT}(m)|\theta_t)+\prod_{t=1}^{L}G_{Z,t}(z^{EWT}(m)|\theta_t)\sum_{x=L+1}^{x_{\max}}(G_{Z,t}(z^{EWT}(m)|\theta_t))^{x-L}\\ &=1+\sum_{x=1}^{L}\prod_{t=1}^{x}G_{Z,t}(z^{EWT}(m)|\theta_t)+\prod_{t=1}^{L}G_{Z,t}(z^{EWT}(m)|\theta_t)\frac{G_{Z,L+1}(z^{EWT}(m)|\theta_t)}{1-G_{Z,L+1}(z^{EWT}(m)|\theta_t)} \end{aligned} \tag{12}$$

where the above bounds of *m* are derived based on the fact that $G_{Z,L+1}\ge G_{Z,t}$ if $t>L+1$, i.e., $G_{Z,t}$ is monotonically decreasing as *t* increases to $x_{\max}$. That means the extreme events are getting more extreme in future, such as the increasing flood events or the decreasing low-flow events. Considering the bounds of *m*, one can achieve any width of *m* by setting *L* large enough in the numerical solution of $z^{EWT}(m)$. In this study, the tolerance range *m* is set to be ± 0.001. For EWT, the positive integer L that achieves the tolerance range of m is t_{extra}.

For the ENE method, based on Eq. (5), t_{extra} is equal to the length of return period m, while for the ER and ADLL methods, t_{extra} is equal to the design life of a project.

2.3 Flood frequency analysis under nonstationarity

Probability distributions in flood frequency analysis can be categorized into four groups: the normal family (e.g., normal, lognormal), the general extreme value (GEV) family (e.g., GEV, Gumbel, Weibull), the Pearson type Ⅲ family (e.g., gamma, Pearson type Ⅲ), and the generalized Pareto distribution. In this study, lognormal (LN), Gumbel (GU), GEV, and gamma (GA) are selected to represent normal, GEV and Pearson type Ⅲ families. Under nonstationary conditions, the time-varying moment method built in the framework of Generalized Additive Models in Location, Scale and Shape (GAMLSS) are used to account for nonstationarity of AMFS. See Rigby and Stasinopoulos (2005) for detailed description of time-varying moment method. In the analysis of extrapolation time, only time is employed as covariate since the length of physical covariates is often too short for EWT for higher return periods.

In this study, the Akaike Information Criterion (Akaike, 1974) is employed to determine the optimal nonstationary model. The lower the AIC score is, the better the performance of the model is. Besides, the worm plot, also known as the detrended Q-Q plot, and the centile curves plot are used to diagnose the fitting quality of the selected optimal models.

2.5 Uncertainty analysis of design flood

In this study, to give a comprehensive comparison of different design methods, i.e., EWT, ENE, ER and ADLL, the uncertainties of design floods are estimated using the nonstationary nonparametric bootstrap (NNB) method. See Yan et al. (2017a) for detailed information about the NNB method.

3. Study area and data

The AMFS of 25 hydrological stations in the Pearl River basin (PRB) and the Weihe River basin (WRB) were selected as study cases. The observed AMFS were collected from the Hydrological Bureaus of Shaanxi Province and Guangdong Province, respectively. The details related to these stations are presented in Fig. 2 and Table 1.

PRB located in southeast China is influenced by the subtropical climate while the WRB located in northern China is influenced by the typical temperate continental monsoon climate (Fig. 2). The Pearl River is the main source of water supply for the megacities within PRB, and nearly 80% of the water of Hong Kong is supplied by the East River, a tributary of the Pearl River. The Weihe River is the major source of water supply for the Guanzhong Plain, a key economic development zone. In recent decades, the nonstationarity of AMFS for both PRB and WRB has been reported in many publications as both PRB and WRB have suffered from intensive human activities and climate change. (Su and Chen 2019; Zhang et al. 2018a; Gu et al. 2017; Yan et al. 2017b). In this study, AMFS of 4 hydrological stations in PRB and 2 hydrological stations in WRB were selected for illustration purpose. Among them, significant upward trends in AMFS were detected at 3 stations by the Mann-Kendall test while downward trends at the other 3 stations (Table 1). The different trends (decreasing and increasing) of the selected 6 AMFS are beneficial for the comprehensive analysis of extrapolation time of return-period-based design methods (Fig. 3).

4. Results and discussions

4.1. Nonstationary frequency analysis of annual maximum flood series

For each of the selected 6 stations, the optimal model was selected based on the AIC value (Table 2). Fig. 4 presents the goodness-of-fit of the optimal nonstationary model that incorporates time covariate. For both stations, all scatter points in the worm plots are within the 95% confidence intervals (Figs. 4a, 4b), indicating that the nonstationary model shows good agreement with observations.

As for centile curves, for Huaxian station, the percentages of observation points below the 5th, 25th, 50th, 75th and 95th centile curves are 3.2%, 33.9%, 45.2%, 69.4% and 95.2% using time covariate (Fig. 4c). For Dahuangjiangkou station, the percentages of observation points below the 5th, 25th, 50th, 75th and 95th centile curves are 3.7%, 27.8%, 44.4%, 72.2% and 98.1% (Fig. 4d). These results indicate that the selected optimal models perform satisfactorily in modeling the variability of the observations.

4.2. Extrapolation time for different design methods

While the extrapolation time t_{extra} is determined based on Eqs. (5)-(10) for the ENE, ER and ADLL methods, respectively, the EWT method determines t_{extra} numerically by solving Eq. (3). Table 3 presents the t_{extra} of EWT method. It is found that t_{extra} is identical to the length of the return period for ENE, and t_{extra} is equal to the length of design life for ER and ADLL methods. However, the t_{extra} obtained from EWT is not straightforward but more complicated. Overall, the t_{extra} of EWT is larger than those of

ENE, ER and ADLL. Furthermore, the t_{extra} of EWT for the stations with the upward trend is significantly smaller than those of stations with a downward trend, in particular t_{extra} is larger than 1e7 in most cases (more than half of the cases) with the downward trend. These results are consistent with our analysis in Section 2.2, indicating that it is likely to be achieved by the numerical solution of EWT for cases with an increase in flood events.

In addition to the trends in AMFS, t_{extra} is also influenced by distribution types. The wildly used extreme distributions differ from each other with regard to the tail behaviour (El Adlouni et al., 2008). In this study, the t_{extra} of EWT calculated by lognormal distribution was larger than those calculated by gamma and Gumbel distributions (Table 3). As El Adlouni et al. (2008) provides a detailed discussion on the tail behaviour for extreme distributions widely used in flood designs, the tail of lognormal was thicker than gamma and Gumbel. This conclusion is consistent with the result of t_{extra} of EWT computed by different distributions. Consequently, it is concluded that the thicker the distribution is, the larger extrapolation time is required for the EWT method. To intuitively depict the influence of t_{extra} on the estimation of design flood using EWT method, Figs. 5 and 6 summarize design flood quantiles with different t_{extra} for stations with increasing and decreasing trends, respectively. It is prominent that the EWT method requires a larger t_{extra} to guarantee the convergence of design flood quantiles for cases with a downward trend.

4.3. Design floods and associated uncertainty of different design methods

Given an assumption that a hydrological structure is planned to be in service for

50 years from 2015 to 2064, the optimal nonstationary models with the time covariate for Huaxian station (a downward trend in AMFS) and Dahuangjiangkou station (an upward trend in AMFS) were employed to estimate the design floods using the EWT, ENE, ER and ADLL approaches. In addition, their associated bootstrapped 95% confidence intervals (CIs) were also estimated to provide a fair comparison among the different approaches as the work in Yan et al. (2017a).

Fig. 7 shows the design flood values for the Huaxian and Dahuangjiangkou stations estimated by the four design methods with the time covariate. For the Huaxian station with a downward trend, the design flood values estimated by the four nonstationary design methods were smaller than those estimated by the stationary methods. Among the four nonstationary design methods, the design flood values estimated by EWT were always smaller than those estimated by ENE while ER yielded similar design values as ADLL. Besides, EWT produced the smallest design flood values among the four methods for $m \in [10,100]$. Regarding uncertainties, ENE produced the largest CIs for higher return periods while the CIs generated by ER and ADLL were similar and slightly larger than those generated by EWT for $m \in [50,100]$. For Dahuangjiangkou station with increasing trend, ER and ADLL produced very similar design values while design floods estimated by EWT were larger than those estimated by ENE. In addition, the design floods estimated by EWT and ENE were larger than those estimated by ER and ADLL for $m \in [50,100]$. As for uncertainties, the CIs generated by EWT were larger than those generated by ENE for $m \in [2,100]$. The CIs generated by ER and ADLL were similar to each other while smaller than those yielded by EWT and ENE for $m \in [50,100]$.

It should be mentioned the methods and results of this study can also be applied to cases with mixed populations. If there exists nonstationarity in mixed flood populations, time-varying mixture distributions should be constructed (Yan et al. 2017b; Zeng et al. 2014; Khaliq et al. 2006). Thus, we can also obtain future exceedance probabilities, and then investigate the influencing factors of textra of EWT and compare the difference of design results based on time-varying mixture distributions.

5. Conclusions

The estimation of nonstationary design flood plays a key role in flood prevention and hazard reduction under changing environment. This study investigated the applicability of EWT by not only analyzing the factors that influence the t_{extra} but also comparing the design floods and associated uncertainties of EWT with other return-period-based design methods (EWT, ENE, ER and ADLL). Given different trends in AMFS and probability distributions, the extrapolation time t_{extra} was estimated by the four return-period-based nonstationary design methods. Subsequently, we compared the difference of design floods and associated uncertainties estimated by the four design methods. The main findings of this study are as follows:

(1) The t_{extra} for ENE was identical to the length of the return period while the t_{extra} for ER and ADLL was equal to the length of design life of a project. However, the t_{extra} for EWT was larger than those for ENE, ER and ADLL. We found that the t_{extra} of EWT is affected by both the trends of AMFS and probability distributions. More specifically, the t_{extra} of stations with upward trends was significantly smaller than

that of stations with downward trends. Besides, the thicker the tail of distribution was, the larger t_{extra} was required for the EWT method. This conclusion is consistent with the theoretical analysis suggested in this study.

(2) For Huaxian station with a downward trend, the nonstationary design floods were smaller than stationary design floods. As for the four nonstationary design methods, the EWT-based estimation of design floods were smaller than those estimated by ENE, whereas ER and ADLL estimated very similar design floods to each other. For higher return periods, the CI of ENE was the largest while the CIs of ER and ADLL were similar and slightly larger than those of EWT. For Dahuangjiangkou station with an upward trend, the EWT-based estimation of design floods were larger than those estimated by ENE while both EWT and ENE yielded larger design floods compared with those from ER and ADLL for larger return periods. With regard to the uncertainties of design floods, ER and ADLL produced similar Cis while EWT yielded a larger CI compared with ENE for $m \in [2,100]$. In addition, the CIs of EWT and ENE were larger than those of ER and ADLL for $m \in [50,100]$. These results indicate that the use of ER and ADLL design methods, reflecting the design life of a project, is recommended to estimate nonstationary flood values for hydrological designs. Furthermore, ER and ADLL are return-period-based methods that are widely accepted for engineers and decision-makers.

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