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A Framework for Investigating the Diagnostic Trend in Stationary and Nonstationary Flood Frequency Analyses Under Changing Climate

Jitendra Singh[1], H. Vittal[1], Tarkeshwar Singh[2], Subhankar Karmakar[1,3,4]* and Subimal Ghosh[3,4,5]

[1]Centre for Environmental Science and Engineering, Indian Institute of Technology Bombay (IIT-B) Mumbai 400 076, India
[2]Applied Statistics and Informatics, IIT-B, Mumbai 400 076, India
[3]Interdisciplinary Programme in Climate Studies, IIT-B, Mumbai 400 076, India
[4]Centre for Urban Science and Engineering, IIT-B, Mumbai 400 076, India
[5]Department of Civil Engineering, IIT-B, Mumbai 400 076, India
✉ skarmakar@iitb.ac.in

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Abstract: The Nonstationary analysis drew formidable attention to the flood frequency analysis (FFA) research community due to analytically perceivable impacts of climate change, urbanisation and concomitant land use pattern on the flood event series. Albeit, the inclusion of nonstationarity in FFA significantly enhanced the accurate estimation of the return period, however, its application is questionable when the flood variables (FV) are not having persisting significant nonstationarity. In such cases, the assumption of stationarity is still valid and will direct to accurate estimation of the flood quantiles. Hence, prior to conducting the comprehensive FFA, it is vital to inspect the existence of stationarity/nonstationarity in the FV. This can be accomplished by a comprehensive trend analysis. The aim of present study is to emphasize the importance of a comprehensive trend analysis during FFA by proposing a framework to conduct the same. Further, the proposed framework has been demonstrated on unregulated daily streamflow series of two gauging stations, at the Kanawha Fall of Kanawha River, West Virginia, USA, and at the Baltara gauging station of Kosi River, Bihar, India.

The results show that the annual maxima (AM) delineated flood peak series has a significant trend in both the gauging stations, providing sufficient evidence of nonstationarity, which is modelled by first- and second-order nonstationary analyses. A comparison between first-order and second-order nonstationarity analyses has also been performed, which suggests higher order nonstationary analysis might give more accurate information on the occurrence of flood extremes. Overall, our study highlights that the proposed framework is an important initial step before initiating FFA to avoid the ambiguity between the selection of stationary and nonstationary analysis.

Keywords: Climatic variability; Frequency analysis; Nonstationary; Nonparametric; Return period; Trend analysis; Urbanisation.

Introduction

Flooding is a destructive natural hazard, which can cause loss of lives and livelihoods at a massive scale and requires various mitigative measures; such as construction of adequate downstream flood defences, efficient forecasting and proper land-use management (Kidson and Richards, 2005). All these mitigative

*Corresponding Author

measures require some information regarding hazard component of flood risk through a comprehensive and accurate flood frequency analysis (FFA). FFA defines the severity of a flood event by summarising the flood variables/characteristics, i.e., Peak (*P*), Volume (*V*), Duration (*D*) and Average Intensity (*I*) and by estimating their mutual dependence structure. It is often required for planning (Stedinger and Griffis, 2008), designing (Haddad and Rahman, 2012; Hirsch and Stedinger, 1987), operation of hydraulic structures (De-Michele et al., 2005), and also to spatially map flood risk combined with vulnerability and exposure for urban or riverine flood management (Karmakar et al., 2010). Recently, there are many studies (Choulakian et al., 1990; Karmakar and Simonovic, 2008, 2009; Yue, 2001; Yue and Rasmussen, 2002; Yue and Wang, 2004; Zhang and Singh, 2006, 2007) indicating the advancements in FFA to obtain more robust return periods; however, in all these advancements, the basic assumption were stationarity in the flood event/time series.

The assumption of stationarity has been challenged due to analytically-perceivable impacts of climate change, urbanisation and concomitant land use pattern (Gilroy and McCuen, 2012; Khaliq et al., 2006; Strupczewski et al., 2001; Strupczewski et al., 2009; Villarini et al., 2009; Villarini et al., 2010; Salas et al., 2012). The response of hydrologic extremes to change in climate and land use is noticeable in recent decades with significant impact on water resources planning and management (Mango et al., 2012). Remarkably, Milly et al. (2008) stated that 'stationary is dead', and invalidated the assumption of stationarity in hydrologic modelling in changing climate. Therefore, a provision should be made to conduct nonstationary FFA along with stationary FFA, specifically where the influences of climate change and land use pattern are significant in changing the hydrological characteristics of a water resources system.

Although many researches emphasised on the inclusion of nonstationarity in FFA (Khaliq et al., 2006; Milly et al., 2008; Strupczewski et al., 2001, 2009), its application is questionable when the characteristics of flood variables are not significantly altered. In such case, the assumption of stationarity will suffice in accurate estimation of the flood return periods. Therefore, prior to performing FFA, some initiative approach, which explains the behaviour of the flood variables, must be conducted. To ascertain this, several researchers have performed trend analysis to assess the change in statistical moments of the extreme hydrologic time series (Cunderlik and Ouarda, 2009; Petrow and Merz, 2009; Strupczewski et al., 2001). In hydrological modelling, different approaches of trend analysis have been adopted in the past studies; these include parametric and non-parametric trend analysis with their different circumstances and assumptions (Bates, 2010; Cunderlik and Burn, 2003; Kahya and Kalayci, 2004; Lacruz-Lorenzo et al., 2012; Petrow and Merz, 2009; Tao et al., 2011; Vogel et al., 2011). Under these circumstances, researchers need detailed information and a comprehensive framework in initiating the nonstationary FFA. The present study is an attempt to prepare such a framework and also to collate detailed information regarding the comprehensive trend analysis, including parametric and nonparametric trend methods with their strengths and weaknesses to assess the presence of nonstationarity.

Frequency analysis of nonstationary time series requires a different procedure than the conventional stationary approach because the probability density function changes with time (Villarini et al., 2009). The review of vast literature thus far (Figure 1) reveals different approaches implemented by the past researches in addressing nonstationary FFA, wherein the moments of statistical distribution are considered to be a function of time. Most of the past efforts on frequency analysis were considered either first-order (Vogel et al., 2011) or second-order nonstationarity (Cunderlik and Burn, 2003; Gilroy and McCuen, 2012; Strupczewski et al., 2001). Vogel et al. (2011) conducted first-order nonstationary FFA for several gauging stations throughout USA considering location parameter of the lognormal distribution as a function of time. Further, they introduced a recurrence reduction (RR) factor using a quantile function of a probability distribution to consider the observed trend and its consequences during the estimation of RPs. Although first-order nonstationary analysis can capture the effect of nonstationarity in the estimation of flood quantile, a second-order nonstationary FFA is reportedly more accurate (Cunderlik and Burn, 2003; Gilroy and McCuen, 2012; Strupczewski et al., 2001; , Villarini et al., 2009; Villarini et al., 2010). In view of that, many researchers performed second-order nonstationary FFA (Cunderlik and Burn, 2003; Gilroy and McCuen, 2012; Strupczewski et al., 2009) and mentioned subsequent increase in the accuracy of the RP estimation.

The aim of the present study is to emphasize the importance of initiative approaches in FFA by deriving a comprehensive framework. Such framework is required in FFA, to systematically perform all possible stationary and nonstationary frequency analyses. The proposed

Nonstationary FFA: In FFA, stationary is the heroic assumption. However, due to perceivable impact of climate change, land use pattern and urbanization, these assumptions would no longer valid, hence resulting nonstationarity in time series. A process has characteristics that distribution parameters (statistical moments) change through time.

Representative literature: Strupczewski *et al.,* 2001; Cunderlik and Burn, 2003**;** Khaliq *et al.,* 2006; Milly *et al.,* 2008; Strupczewski *et al.,* 2009; Villarini *et al.,* 2009; Bates *et al.,* 2010; Kundzewicz *et al.,* 2011; Ouarda and El-Adlouni, 2011; Vogel *et al.,* 2011; Gilroy *et al.,* 2012; Salas *et al.,* 2012.

First order approach to NFFA: A technique in which considered nonstationarity only in first moments of the probability distribution fitted to the flood variables series.

Representative literature: Vogel *et al.,* 2011.

Second order approach to NFFA: A technique in which considered non-stationarity in first and second moments of the probability distribution fitted to the flood variables series.

Representative literature: Strupczewski *et al.,* 2001; Cunderlik and Burn, 2003; Gilroy and McCuen, 2012.

Bayesian approach to NFFA: An approach in which, prior distribution define through the prior information of available data. This prior distribution updates with the observations to obtain the posterior distribution.

Representative literature: Ouarda and El-Adlouni, 2011.

Generalized Additive Models for Location, Scale and Shape parameters (GAMLSS) approach to NFFA: GAMLSS is an advance nonstationary tool which can be used to model the parameters of the probability distribution, as linear/non-linear or smooth functions of explanatory variables, may involve using non-parametric smoothing functions. It is semi-parametric regression type models and able to do first, second and even third order NFFA.

Representative literature: Villarini *et al.,* 2009, 2010.

Seasonal approach to NFFA: Nonstationary FFA estimated for winter and summer separately. Seasonal approach is more effective to annual series in terms of trend analysis and distribution in time. If contribution of both seasonal peaks is similar then accuracy will be increase than AM. This approach can be implementing for all above nonstationary approaches.

Representative literature: Strupczewski *et al.,* 2009.

Figure 1: Summary of past studies employing different methodologies for nonstationary FFA.

framework was then applied to the daily streamflow series at gauging station 03193000 of the Kanawha River basin (West Virginia, USA) for the period of 1879-2009. This gauging station dataset is well-accepted by the research community and was used by Grimaldi and Serinaldi (2006) for the period of 1877-2003 and Karmakar et al. (2012) for the period of 1879-2009 to conduct stationary FFA. However, both the studies did not validate the assumption of stationarity in the flood variables. Additionally, data for the period of 1972 – 2011 of the Baltara gauging station of the Kosi River (Bihar, India), has been considered as the second case study, which presents a challenge in terms of long and recurring severe flood hazards. The Kosi River flows through semi-urban areas and may show nonstationarity due to the significant impact of urbanisation and climatic variability.

Description of Stream Flow Datasets from the Two Study Areas

Kanawha River is a major river of the Kanawha County, West Virginia, which originates at the Town of Gauley Bridge in north-western Fayette County. Present study used streamflow data of the Kanawha Falls site (USGS gauging station: 03193000), which lies within Latitude 38°08′17″ N Longitude 81°12′52″ W, and has a drainage area of 8371 square miles. Kanawha River basin reportedly underwent rapid industrialisation with the development of coal and chemical companies in the past century (Hubacher and Wintz, 2003), which is likely to result in local climatic variability and consequent nonstationarity in the streamflow discharges. The past efforts made with the dataset of Kanawha Falls to demonstrate various approaches of FFA were with the assumption of stationarity (Grimaldi and Serinaldi, 2006; Karmakar et al., 2012). Therefore, present study compares both the stationary and nonstationary models for FFA and identifies whether the above-mentioned factors caused substantial nonstationarity.

In addition to the Kanawha falls, the developed framework is applied to the Kosi River (Baltara gauging station) of Bihar. The Kosi River originates in the Himalaya and drains 29,400 km^2 in China, 30,700 km^2 in Nepal and only 9,200 km^2 in India (Arogyaswamy, 1971). The Baltara gauging station lies in the southwest region of Bihar, India. Bihar is one of the developing states of India and has evidenced rapid urbanisation during the past few decades. These developments are likely to cause drastic local climate variability thereby introducing nonstationarity in the stream flow discharges (Thomas, 1993). The Kosi River is referred as 'Curse of Bihar' (Agarwal and Bhoj, 1992), because of its frequent flooding. Astonishingly, for this gauging station, FFA has not been reported earlier. Therefore, the results from the present study will provide useful information for the local communities. The daily unregulated discharge data from 1972-2011 (40 years) were procured from the Central Water Commission (CWC), Lower Ganga basin, Regional Office, Patna (Bihar), India.

An Initiative Approach for Frequency Analysis

Initially, flood variables from the daily streamflow time series were delineated from the two most widely accepted methods, i.e., peak over threshold (POT), and annual maxima (AM) (Solari and Losada, 2012). Both these approaches have advantages and disadvantages. The AM approach can omit the largest peak in the year, which may be greater than many AM peak discharges of the other years, thus, causing fewer observations (Khaliq et al., 2006; Solari and Losada, 2012). On the other hand, the POT method requires minimum time interval between the occurrence of flood events, which exceeds the threshold to ensure the independence of the POT series and Poisson process of occurrences of extreme events (Ouarda et al., 2006; Solari and Losada, 2012).

Additionally, the selection of the optimum threshold value in the POT method plays a significant role in the delineation of flood variables, which is very subjective. Despite the importance of the threshold value in the POT method, most of the studies usually select a fixed quantile from 95 to 99.5 percentile corresponding to a low exceedance probability (Luceño et al., 2006; Smith, 1987). Hence, to strengthen the POT method, some graphical and numerical methods have been developed by past researchers (Coles, 2001; Dupuis, 1999; Solari and Losada, 2012) for selecting the optimum threshold value. A graphical method, Mean Residual Life Plot (MRLP), is employed in the present study to choose the appropriate threshold value. MRLP is the locus of the points (Coles, 2001; Solari and Losada, 2012),

$$\left\{\left(u, \frac{1}{n_u}\sum_{i=1}^{n_u}\left(x_{(i)}\right)-u\right): u < x_{\max}\right\} \tag{1}$$

where $x_{(1)}...x_{(n_u)}$ are the n_u observations that exceed u, and $x_{\max}$ is the largest x_i, is termed the mean residual life plot. For $u > u_0, u_0$ at which the generalised Pareto distribution provides a valid approximation to the excess distribution, the mean residual life plot should be approximately linear in u. Hereto, the flood variables P, *V*, *D* and *I* can be extracted from the daily streamflow time series using optimum threshold as per the POT method. The reader may refer Karmakar and Simonovic (2008 and 2009), for further details about extraction of flood variables. The *I* is calculated as the ratio of volume to duration, which exhibits the shape of the peak events (Serinaldi and Kilsby, 2013).

Trend analysis can be performed by parametric as well as nonparametric approaches. Interestingly, both techniques have provided evidence of nonstationarity, but do not provide insight into the causal mechanisms. Given the ambiguity in selecting the parametric/nonparametric trend analysis, the present study develops a conceptual framework (Figure 2), which includes both the approaches; and briefs the pros and cons of both the trend analysis. Few researches have argued in favour of the parametric trend test; however, some assumptions, like normality, constant pattern of variance and independency of dataset, are associated with these tests and tend to reduce its accuracy (Hamed, 2007; Hamed and Rao, 1998). Generally, hydro-climatological datasets do not satisfy the required assumptions for parametric trend test in the detection of trend (Huth and Pokorná, 2004; Kahya and Kalayci, 2004), hence the parametric trend test should be followed up by residual analysis to evaluate its performance (Montgomery et

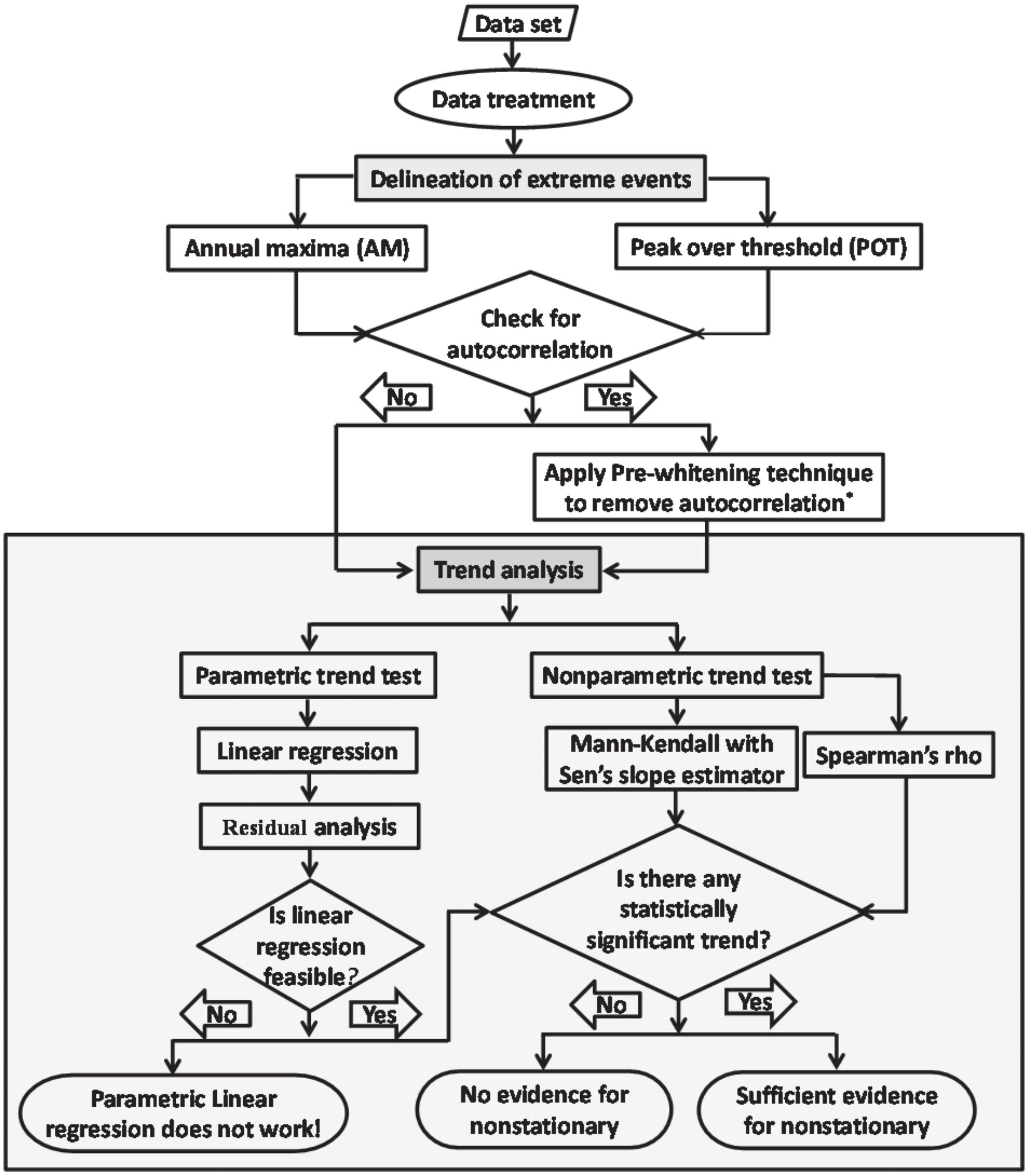

Figure 2: A proposed framework for comprehensive trend analysis required prior to FFA.

al., 2011). On the other hand, the nonparametric trend test provides higher statistical power in the case of non-normality, outliers and missing data, though it does require independency of dataset (Gemmer et al., 2011; Leclerc and Ouarda, 2007; Petrow and Merz, 2009; Wang et al., 2012; Xu et al., 2010; Xu et al., 2010). Therefore, it is always important to include non-parametric analysis to estimate the accurate trend in the time series, with minimal or none assumptions. There are two widely used nonparametric trend analysis, i.e. Mann-Kendall and Spearman's Rho tests**.** In the present study, both these tests are applied to have more assured results from the trend analysis. The next sections provide the brief discussion on the nonparametric trend tests.

Nonparametric Mann-Kendall Trend Test

Mann-Kendall (MK) is a robust nonparametric test, which was initially developed by Mann (1945) and subsequently Kendall (1975) derived the test statistics. Nonparametric Mann-Kendall test is widely accepted by the research community as an excellent tool for trend detection in hydrological variables (Birsan et al., 2005; Douglas et al., 2000; Hamed, 2007; Wang et al., 2012; Xu et al., 2010; Xu et al., 2010). However, the application of MK requires un-autocorrelated dataset in order to increase the strength of the test (Helsel and Hirsch, 1992; Xu et al., 2010; Xu et al., 2010). MK test may lead to overestimation/underestimation of the trend (Von-Storch and Navarra, 1995) or erroneous rejection of the null hypothesis, i.e., type I error (Yue et al., 2002) when dataset has statistically significant autocorrelation. The significant autocorrelation can be eliminated by a well-known pre-whitening technique (PWT) (Lacruz-Lorenzo et al., 2012; Von-Storch and Navarra, 1995). While applying PWT it should be noted that the magnitude of the existing trend should be preserved in the time series. Sometimes, the original trend may be disturbed during the elimination of autocorrelation from time series. The readers can refer Lacruz-Lorenzo et al. (2012) for detailed methodological framework on the MK trend analysis for the highly autocorrelated data set. Further the trend of the time series is estimated by the non-parametric Sen slope estimator developed by Sen (1968).

Nonparametric Spearman's Rho Trend Test

Spearman's rho test is a rank-based nonparametric test, which can be used to detect the trend in time series (Diermanse et al., 2010; Xiong and Guo, 2004; Yue and Rasmussen, 2002). The Spearman's rank correlations test is a quick and simple test to determine whether any significant correlation exists between two classifications of the series. In this test, a significant trend can only be found if the time steps and streamflow observations are significantly correlated (Kahya and Kalayci, 2004). The null hypothesis of the test states that no significant trend exists in time series while the alternative states vice versa. The detailed methodology can be obtained from Gupta and Kapoor (1970).

Apart from the nonparametric trend methods, the parametric linear regression technique has also been widely accepted by hydrologists worldwide (Cunderlik and Burn, 2003; Xu et al., 2010). Hence, the comprehensive trend analysis cannot be completed without implementation of parametric trend methods, which have been discussed in the next section.

Parametric Linear Regression

Linear regression is a parametric test that investigates the linear monotonic trend and is associated with some assumptions like normality, linearity and independence of dataset (Bates et al., 2010). Linear regression model is defined as:

$$Y = (\beta \times t) + \alpha + \varepsilon_t \tag{2}$$

where β and α are the estimated slope and intercept of the linear trend, respectively, and ε_t is the error term or residuals. Further, the statistical significance of the trend slope β can be examined using the Student's *t* test, and if statistically significant slope has been observed, the residuals analysis is conducted to quantify the performance of the parametric trend test. During the residuals analysis the normal plot can be constructed to examine the assumption of normality and residuals can be fitted against predicted values to inspect the pattern of variance. Montgomery et al. (2010) may be referred for more details about residual analysis.

Stationary and Nonstationary FFA

Parametric-nonparametric Stationary Approach

In the past studies, parametric distributions have been commonly used as higher depicters of the flood variables in FFA. However, the selection of the appropriate parametric distribution that may be acceptable in all conditions is not clear so far, which is a crucial problem in the field of hydrology (Karim and Chowdhury, 1995). Perhaps based on goodness-of-fit tests, certain distributions have often fitted well for the observed flood data despite the fact that each distribution tends to give different parametric estimates of the given quantile in the tail of the distribution (Karmakar and Simonovic, 2008). Nevertheless, in FFA, probability density functions (PDF) of flood variables are never known and must be assumed. Hence, nonparametric techniques have been introduced for better reproduction of the characteristics of the sample (Lall, 1995; Karmakar and Simonovic, 2008, 2009). Available literature on nonparametric FFA shows that kernel density estimates a flood variable more accurately and realistically. Hence, to avoid ambiguity between implementation of parametric and nonparametric distribution in the FFA, the present study incorporates a set of parametric (GEV, exponential, gamma, inverse Gaussian, lognormal, Weibull, extreme value) and nonparametric (Gaussian kernel, box kernel, triangular kernel, Epanechnikov kernel) distributions and further analysis will be carried out with the best fit distribution amongst them.

First-order Nonstationary Approach: Recurrence Reduction Factor Method

This technique is adopted from Vogel et al. (2011) and completely modified according to our conditions. Through this technique, a Recurrence reduction (RR) factor is developed that considers the observed trend and its consequences in the estimation of RPs. RR factor is calculated based on quantile function of two best fitted parametric GEV and lognormal distributions. Vogel et al. (2011) developed the RR factor only for lognormal distribution; however, the RR factor can be developed for other parametric distributions, as exemplified in this study. Note that during the estimation of the RR factor, first-order nonstationarity (considering only location parameter of the probability distribution as a function of time) was considered. Prior to applying the RR factor, the appropriate selection of distribution for a given dataset is also indispensable (Papalexiou and Koutsoyiannis, 2009). In the current study, six statistical techniques are performed over a set of selected parametric distributions and nonparametric kernel density estimators to obtain the best fit distribution for the AM peak discharge. For both the case studies, nonparametric Gaussian kernel estimator provided the best fit for AM peak discharge series while, in the case of parametric distributions, GEV and lognormal distributions are found to be best fit. However, Gaussian kernel distribution does not have a quantile function. Hence, RR factor is developed based on quantile function of GEV and lognormal distributions. Quantile function of GEV is given by Wilks (2011),

$$Y_p = \mu + \frac{\sigma}{\xi}\left\{(-\log(\mathrm{p}))^{-\xi} - 1\right\} \tag{3}$$

where μ is the location parameter, σ is the scale parameter, ξ is the shape parameter and p is exceedance probability. The linear trend is found to be prominent from a comprehensive trend analysis and is given as

$$X_t = \alpha + (\beta \times t) + \varepsilon_t \tag{4}$$

where t is time (year) and β, α and ε_t are slopes, intercept and residuals of the linear model, respectively. The mean of AM flood series through GEV distribution is defined by,

$$\text{Mean } (X_t) = \begin{cases} \mu + \sigma\left(\dfrac{\Gamma(1-\xi)-1}{\xi}\right) & \text{if } \xi \neq 0,\ \xi < 1 \\ \mu + (\sigma \times \gamma) & \text{if } \xi = 0 \\ \infty & \text{if } \xi \geq 1 \end{cases} \tag{5}$$

where γ is Euler's constant and Γ is a gamma function. The shape parameter (ξ) value was 0.105 and 0.059 for AM peak series of the Kanawha and Kosi rivers, respectively. Hence, the first case has been considered in Eq. (5). Combining the mean of $x_t = \alpha + \beta \times t$ and the ordinary least squares (OLS) estimate, the intercept term is given by $\hat{\alpha} = \bar{x} - \hat{\beta} \times \bar{t}$ Consequently, the location parameter of the GEV distribution has been obtained as function of time, using Eq. (5),

$$\mu(t) = \bar{x} + (\hat{\beta} \times (t - \bar{t})) - \left(\sigma \times \frac{\Gamma(1-\xi)-1}{\xi}\right) \tag{6}$$

where $\hat{\beta}$ is an ordinary least square estimate of β, and n is the number of years of observations. Substitution of nonstationary location parameter from Eq. (6) to Eq. (3), leads to the following nonstationary model:

$$Y_p(t) = \bar{x} + \left(\hat{\beta} \times (t - \bar{t})\right) - \left(\sigma \times \frac{\Gamma(1-\xi)-1}{\xi}\right) + \frac{\sigma}{\xi}\left\{(-\log(p))^{-\xi} - 1\right\} \tag{7}$$

From Vogel et al. (2011), RR is defined as the average time between floods in some future year t_f and some reference year t_0 with an average recurrence interval of T_0. If the average recurrence intervals of flood today and in some future year are T_0 and T_f, with exceedance probabilities $p_0 = 1/T_0$ and $p_f = 1/T_f$, respectively the average recurrence interval associated with the magnitude of the T_0 year flood will be in some future year t_f. Hence, RR is equal to the value of T_f, $= \dfrac{1}{p_f}$,

$$Y_{p_0}(t_0) = Y_{p_f}(t_f) \tag{8}$$

which requires the solution of the following expression for $T_f = \frac{1}{p_f}$,

$$\bar{x} + \left(\hat{\beta} \times \left(t_0 - \bar{t}\right)\right) - \left(\sigma \times \frac{\Gamma(1-\xi) - 1}{\xi}\right) + \frac{\sigma}{\xi}\left\{\left(-\log(p_0)\right)^{-\xi} - 1\right\}$$

$$= \bar{x} + \left(\hat{\beta} \times \left(t_f - \bar{t}\right)\right) - \left(\sigma \times \frac{\Gamma(1-\xi) - 1}{\xi}\right) + \frac{\sigma}{\xi}\left\{\left(-\log(p_f)\right)^{-\xi} - 1\right\} \tag{9}$$

which leads to,

$$p_f = \exp\left[-\left\{\left(\frac{\xi}{\sigma} \times \hat{\beta} \times \Delta t\right) + \left(-\log(p_0)\right)^{-\xi}\right\}^{-1/\xi}\right] \tag{10}$$

where $\Delta t = (t_f - t_0)$. Hence the RR factor is given as;

$$T_f = \frac{1}{p_f} \tag{11}$$

Similarly, the recurrence reduction factor has also been calculated using the quantile function of two parameter lognormal (LN2) probability distributions. Final model of RR factor based on quantile function of lognormal probability distribution is given by

$$T_f = \frac{1}{1 - \Phi(Z_{p_f})} \tag{12}$$

where the function ϕ is the cumulative density function of a standardised normal variable and represents the probability that a standardised normal variable is less than the value inside the parentheses. Also,

$$Z_{p_f} = Z_{p_0} + \frac{1}{\sigma_y}\log\left[\frac{\bar{x} - \hat{\beta}(t_0 - \bar{t})}{\bar{x} - \hat{\beta}(t_f - \bar{t})}\right] \tag{13}$$

where Z_{p_0} and Z_{p_f} are the inverse of standard normal random variable with exceedance probability p_0 and p_f, respectively, and t_0, t_f and $\bar{x}$ are the current year, future year (current year + interested future time horizon) and mean of those years in which flood observation occurs, respectively. Additionally to increase the strength of the nonstationary analysis in the present study, second-order nonstationry analysis also has been considered, which is described in the next section.

Second-order Nonstationary Approach

A very well-known technique, "moving time window," discussed by Kharin and Zwiers (2005) is performed to model the location and scale parameters of the best fitted parametric GEV distribution as a function of time. A 50-year moving time window was considered throughout the 131-year time series to estimate shape, scale and location parameter of GEV distribution using the method of maximum likelihood. The method of maximum likelihood is employed to estimate the distribution parameters as it provides more efficient estimation of distribution moments than the method of moments (Kendall and Stuart, 1973; Strupczewski et al., 2001). It is noted that the performance of the moving time window method depends on three aspects—the length of the series, the length of the window and the time step (Cunderlik and Burn, 2003; Gilroy and McCuen, 2012). Hence, the second-order nonstationary analysis could not be performed over Baltara gauging station due to the unavailability of requisite dataset. We obtain 82 points values for each of the three GEV parameters. The location and scale parameters are regressed over the moving time window. Quadratic and exponential trend models are found to be more prominent for the location and scale parameter of GEV distribution with a maximum value of R^2 (Figure 3). The equation of fitted quadratic and exponential models for location and scale parameter, respectively, are given below:

$$y = (0.0148 \times x^2)\ (2 \times x) + 225 \tag{14}$$

$$y = 119.29 \times e^{(-0.015 \times x)} \tag{15}$$

Gilroy and McCuen (2012) also reported an exponential trend in the scale parameter in their study. Coles (2001) and Gilroy and McCuen (2012) suggested that modelling of shape parameter as a function of time/explanatory variables may be unrealistic due to more sensitivity of higher moments (shape parameter). Hence, the shape parameter was held constant and the mean of 82 points was considered. Further, the trends of the location and scale parameters are extrapolated up to 131 points and substituted in cumulative distribution function of GEV distribution to obtain the nonstationary CDF values for AM flood peak discharges. Finally, nonstationary RP was calculated for the corresponding AM peak discharges.

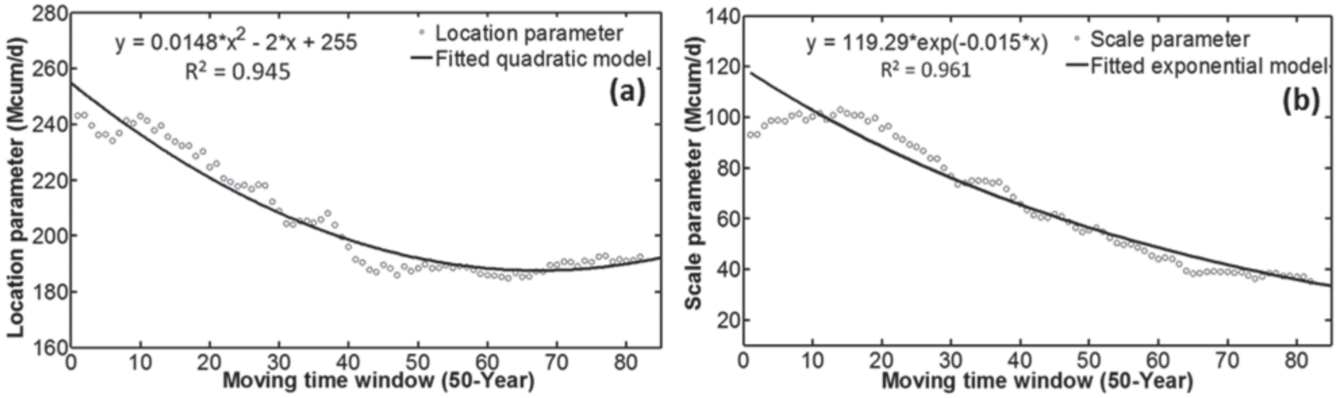

Figure 3: (a) Fitted quadratic trend model on GEV location parameter and (b) fitted exponential trend model on GEV scale parameter, over a 50-year moving time window for annual maximum peak at the Kanawha River.

Results and Discussion

From the mean residual life plot (Figure 4), the 95 percentile (94.66 Mcum/d) and 92 percentiles (533.599 Mcum/d) were found to be more appropriate threshold values for the POT method to extract the flood variables (*P*, *V*, *D* and *I*) for the Kanawha and Kosi River basins, respectively. Further, the same steps were followed for the comprehensive trend analysis, depicted in Figure 2.

Trend in Flood Variables

Parametric linear regression technique showed a significant negative trend in *P* and *I* while no statistically significant trend could be found in *V* and *D* delineated from the POT method, as shown in Table 1. However, the results from residual analysis depicted that parametric linear regression technique may not be a better choice. This is especially true in

Table 1: Test statistics of parametric linear regression test with trend slope for both the case studies

For the Kanawha River				
Methods	*Flood variables*	*Slope*	*P-value*	*Significant (Yes/No)*
Peak over threshold	Peak	**-0.043**	2.21×10^{-6}	**Yes**
	Volume	-0.047	0.0616	No
	Duration	0.0004	0.1302	No
	Avg. intensity	**-0.019**	$\mathbf{3.84\times10^{-6}}$	**Yes**
Annual mean of extreme events	Peak	**-0.23**	$\mathbf{9.26\times10^{-4}}$	**Yes**
	Volume	-0.19	0.375	No
	Duration	0.0038	0.123	No
	Avg. intensity	**-0.14**	$\mathbf{4.48\times10^{-4}}$	**Yes**
Annual maxima	Peak	**-1.11**	$\mathbf{1.41\times10^{-7}}$	**Yes**
For the Kosi River				
Peak over threshold	Peak	-0.514	0.45	No
	Volume	-4.3	0.846	No
	Duration	0.111	0.198	No
	Avg. intensity	-0.43	0.2124	No
Annual mean of extreme events	Peak	**-11.67**	**0.0025**	**Yes**
	Volume	-53.42	0.3728	No
	Duration	-0.13	0.5402	No
	Avg. intensity	**-2.72**	**0.0169**	**Yes**
Annual maxima	Peak	**-7.00**	**0.008**	**Yes**

Table 2: Trend results obtained from nonparametric tests for both the case studies

Methods	Flood variable	Mann-Kendall		Sen's slope estimator			Spearman's rho	
		Z_{stat}	Result	Slope	CI	Result	Z_{stat}	Result
For the Kanawha River								
Peak over threshold	Peak	-2.91	**Yes**	**-0.014**	[-0.025,-0.003]	**Yes**	2.92	**Yes**
	Volume	-1.44	No	-0.01	[-0.028,0.003]	No	1.46	No
	Duration	1.11	No	0	[0,0.0002]	No	1.37	No
	Avg. intensity	-3.31	**Yes**	**-0.01**	[-0.01,-0.0006]	**Yes**	3.33	**Yes**
Annual mean of extreme events	Peak	-3.74	**Yes**	**-0.23**	[-0.32,-0.15]	**Yes**	3.92	**Yes**
	Volume	1.93	No	-0.33	[-0.54,-0.08]	**Yes**	1.93	No
	Duration	1.28	No	0.002	[0,0.004]	No	1.28	No
	Avg. intensity	-3.62	**Yes**	**-0.14**	[-0.20,-0.09]	**Yes**	3.84	**Yes**
Annual maxima	Peak	-4.54	**Yes**	**-0.81**	[-1.19,0.46]	**Yes**	4.85	**Yes**
For the Kosi River								
Peak over threshold	Peak	-0.34	No	-0.89	[-0.56,0.31]	No	0.39	No
	Volume	0.456	No	0.47	[-1.20,2.93]	No	0.45	No
	Duration	1.37	No	0.045	[0,0.109]	No	1.36	No
	Avg. intensity	-0.76	No	-0.13	[-0.42,-0.11]	No	0.70	No
Annual mean of extreme events	Peak	-8.12	**Yes**	**-4.46**	[-5.86,-3.72]	**Yes**	2.57	**Yes**
	Volume	-2.17	**Yes**	**-17.73**	[-40.52,-2.87]	**Yes**	2.13	**Yes**
	Duration	-1.16	No	-0.12	[-0.3,0]	No	1.23	No
	Avg. intensity	-10.38	**Yes**	**-1.97**	[-2.35,-1.72]	**Yes**	3.04	**Yes**
Annual maxima	Peak	-2.66	**Yes**	**-6.49**	[-9.26,-2.79]	**Yes**	2.74	**Yes**

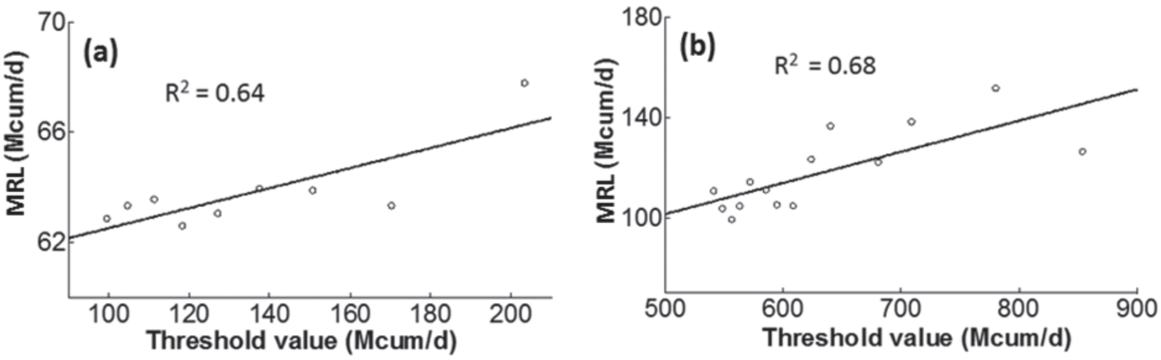

Figure 4: Mean residual life (MRL) plot for optimum threshold to delineate flood variables at (a) the Kanawha River basin and (b) the Kosi River basin. 95 percentile (94.6602 Mcum/d) and 92 percentile (533.59 Mcum/d) were found to be more appropriate threshold values to delineate flood variables for the Kanawha and Kosi River basins, respectively.

this case since the events series of flood variables did not satisfy the assumptions required for the parametric linear regression technique. On the other hand, results from nonparametric trend analysis revealed a negative trend in P and I with magnitude –0.014 and –0.01, respectively while no significant trend was found in V and D (Table 2). The flood variables extracted from the POT method are in the form of event series, not in time series; hence, due to the lack of the concept of time in flood variables extracted from POT, the parametric linear regression model did not perform well.

To overcome this limitation, the trend analysis was performed over the series extracted using annual mean of extreme events for all four flood variables. The parametric linear regression technique was performed over the series annual mean of extreme events (Figure

5). Again, the results exhibited a significant trend only in *P* and *I* (Table 1). The residuals analysis revealed that parametric test satisfied the assumption of normality for *P* and *I*, however, the assumption of constant pattern of variables had been violated (Figure 6). The significant negative trend was found in *P* and *I* while no significant trend could be detected in *V* and *D* from nonparametric test (Table 2). The method of annual mean of extreme events may be trivial because it lies between the POT and AM methods. However, it is apparent from Figure 6 that the residuals were found to be approximately normally distributed, which is the primary requirement of the parametric linear trend when considering the annual mean of extreme events.

In the case of AM peak discharge series, parametric and nonparametric tests showed a significant negative trend with slightly different magnitude of the slope calculated to be –1.11 and –0.81, respectively (Tables 1 and 2). The residual analysis indicated that the parametric test may be feasible for AM peak series. Hence, sufficient evidence for the existence of nonstationarity was found in the AM peak series through the trend analysis, which indicated the necessity to perform nonstationary FFA. Similar observations are made in the Kosi River case study. Remarkably, most of the extreme events (delineated through POT) are observed in the monsoon period because rains from June to September (monsoon period) months bring surplus water into the Kosi River. Further, a trend analysis was performed over all the flood variables using parametric and nonparametric trend methods. The test statistics of parametric linear regression techniques showed no statistically significant trend in any of the four flood variables delineated by the POT method. Additionally, the results from nonparametric trend methods also indicated that the trend slope is not statistically different from zero for POT-delineated flood variables.

Further trend analysis is performed for the series of the annual mean of extreme events (as done for the Kanawha Fall at the Kanawha River in the previous section), and a significant negative trend is found in *P* and *I* from the parametric test. However, here again the residuals analysis did not support the parametric linear regression model. From the nonparametric trend method, a significant negative trend was found in *P*, *V* and *I* with slope magnitude –4.46, –17.73 and –1.97, respectively while *D* exhibited no trend in particular (Table 2). In the case of AM peak discharge series, parametric and nonparametric tests showed a significant downward trend with slightly different magnitude of the slope –7.00 and –6.49, respectively (Tables 1 and 2). The residuals analysis confirmed the efficiency of the parametric test in detecting a trend in the AM peak series. Again, the trend analysis provided sufficient evidence for the presence of nonstationarity in AM peak at Baltara. Several studies have concluded that the magnitude of the slope based on Sen's slope estimator is more robust than that estimated by parametric linear regression (Lacruz-Lorenzo et al., 2012). We observe sufficient evidences on the presence of significant trends in AM series for both the case studies implying the presence of nonstationarity. Therefore, the AM series is utilized further to conduct nonstationary analysis.

Comparison of Stationary and Nonstationary Approaches

Six statistical tests [Kolmogorov-Smirnov (KS), Anderson-Darling (AD), Chi-Square, Root mean square error (RMSE), Akaike information criterion (AIC) and Bayesian information criterion (BIC)] are conducted to evaluate the performance of the selected set of parametric and nonparametric distributions. Nonparametric Gaussian kernel estimator is obtained as best fit with minimum values of RMSE, AIC and BIC. While, among the parametric distribution, we obtained GEV and lognormal as best fit distributions for both case studies (Tables 3 and 4). As an extension to this, a comparison of different probability distribution functions (Figure 7) depicted that the histogram of AM peak discharge for both the case studies is more accurately reproduced by the Gaussian kernel estimator. Other three types of the kernel estimator have not been portrayed in Figure 7 in the interest of greater clarity. Similar results were reported in Adamowski et al. (1998), who compared both parametric and nonparametric distributions for AM and partial duration (or POT) series, and considered only the peak as a flood variable. However, the results showed that the nonparametric kernel was more closely fitted to the observed peak than the parametric families of distribution, such as Gumbel, exponential, and GEV. Furthermore, these results indicated that the parametric distributions are sensitive to threshold level choice when applied to POT data. However, the nonparametric method was found to be less sensitive to the data type and the choice of threshold level.

The stationary RP was calculated with the best-fitted Gaussian kernel distribution while the RR factor was computed based on the quantile function of the parametric GEV and lognormal distribution to calculate nonstationary RP. For the RR factor, the 15-year and 10-year future time horizon was considered for the Kanawha and Kosi River basins, respectively. The

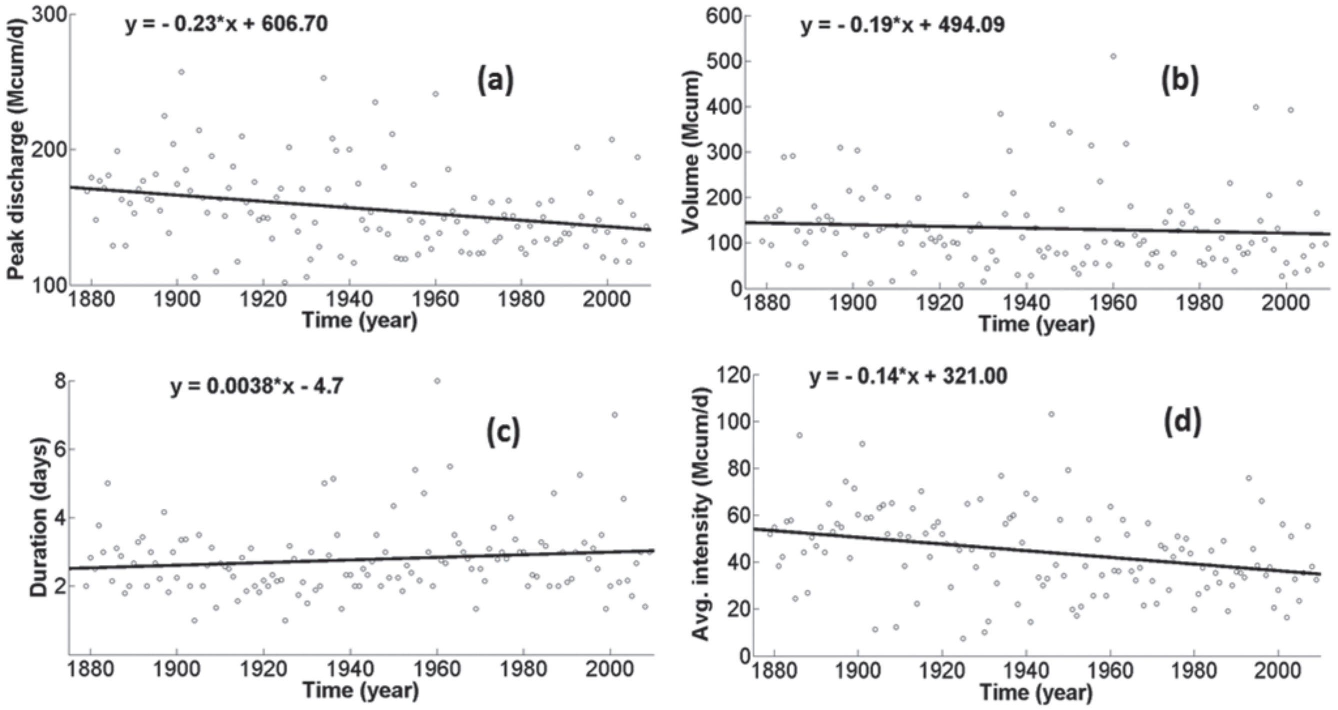

Figure 5: Parametric linear regression fitting on (a) peak discharge, (b) volume, (c) duration and (d) average intensity, delineated through annual mean of extreme events in the Kanawha River basin.

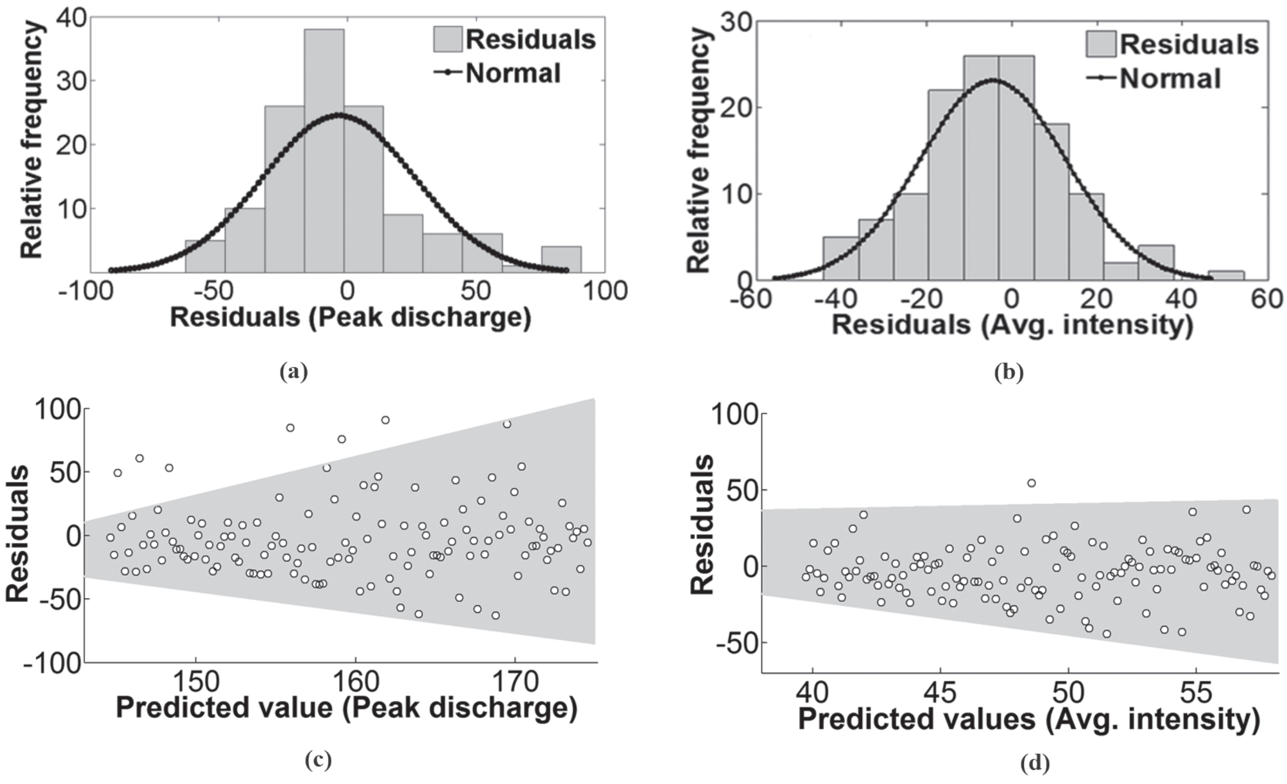

Figure 6: Normal probability fit on (a) residuals of peak discharge and (b) residuals of average intensity, delineated through annual mean of extreme events at the Kanawha River. The peak discharge and average intensity are satisfying the assumption of normality. Pattern of residuals against predicted values of (c) peak discharge and (d) average intensity. Figures (c) and (d) depict the diverge funnel, which indicates that the variance of peak discharge and average intensity are increasing with predicted values.

Table 3: Model selection criteria for a set of selected parametric and nonparametric distributions at the Kanawha River

Types of distribution	*Distributions*	*Kolmogorov-Smirnov*			*Anderson-Darling*		*Chi-Squared*			*RMSE*	*AIC*	*BIC*
		Statistics	*CV**	*p-value*	*Statistics*	*CV**	*Statistics*	*CV**	*p-value*			
Parametric	GEV	0.05	0.11	0.87	0.21	2.5	2.54	14.06	0.92	0.01	-894.02	-885.97
	Exponential	0.37	0.11	0	26.41	2.5	176.57	14.06	0	0.21	-329.61	-326.93
	Gamma	0.09	0.11	0.14	1.65	2.5	10.18	14.06	0.17	0.04	-690.19	-684.82
	Inv. Gaussian	0.07	0.11	0.38	0.81	2.5	7.11	14.06	0.41	0.03	-741.89	-736.52
	Lognormal	0.07	0.11	0.44	0.51	2.5	6.07	14.06	0.53	0.02	-783.31	-777.95
	Weibull	0.13	0.11	0.01	3.82	2.5	21.58	14.06	0.003	0.06	-579.21	-573.85
	Extreme value	0.20	0.11	0	5.23	2.5	45.08	14.06	0.001	0.12	-446.02	-440.66
Non-parametric	Gaussian kernel	-	-	-	-	-	-	-	-	**0.007#**	**-1058.62#**	**-1058.62#**
	Box kernel	-	-	-	-	-	-	-	-	0.025	-796.83	-796.83
	Triangle kernel	-	-	-	-	-	-	-	-	0.0394	-698.44	-698.44
	Epanechnikov kernel	-	-	-	-	-	-	-	-	0.0352	-723.19	-723.19

* – Critical Value; # – Shows Gaussian kernel is best in all respects; GEV – Generalised extreme value; RMSE – Root mean square error; AIC –Akaike information criterion; BIC – Bayesian information criterion.

Table 4: Model selection criteria for a set of selected parametric and nonparametric distributions at the Kosi River

Types of distribution	*Distributions*	*Kolmogorov-Smirnov*			*Anderson-Darling*		*Chi-Squared*			*RMSE*	*AIC*	*BIC*
		Statistics	*CV**	*p-value*	*Statistics*	*CV**	*Statistics*	*CV**	*p-value*			
Parametric	GEV	0.11	0.21	0.60	0.48	2.50	7.69	9.48	0.10	0.04	-246.46	-241.32
	Exponential	0.43	0.21	0	10.3	2.50	75.23	9.48	0	0.24	-113.51	-111.79
	Gamma	0.16	0.21	0.20	0.82	2.50	4.65	9.48	0.32	0.06	-216.27	-212.85
	Inv. Gaussian	0.14	0.21	0.30	0.65	2.50	6.51	9.48	0.16	0.05	-227.01	-223.58
	Lognormal	0.14	0.21	0.31	0.62	2.50	5.69	9.48	0.22	0.05	-227.95	-224.52
	Weibull	0.17	0.21	0.14	1.52	2.50	1.79	9.48	0.77	-0.08	-193.97	-190.54
	Extreme value	0.21	0.21	0.03	3.06	2.50	35.78	9.48	0	0.12	-167.59	-164.16
Non-parametric	Gaussian kernel	-	-	-	-	-	-	-	-	**0.018#**	**-326.78#**	**-326.78#**
	Box kernel	-	-	-	-	-	-	-	-	0.038	-252.73	-252.73
	Triangle kernel	-	-	-	-	-	-	-	-	0.048	-248.80	-248.80
	Epanechnikov kernel	-	-	-	-	-	-	-	-	0.045	-252.73	-252.73

* – Critical Value; # – Shows Gaussian kernel is best in all respect; GEV - Generalised extreme value; RMSE – Root mean square error; AIC – Akaike information criterion; BIC – Bayesian information criterion.

future time horizon was selected based on the change point analysis, which occurred at approximately 15 and 10-year time intervals in the Kanawha and Kosi River basins, respectively. The results show a remarkable difference in the RPs estimated by the stationary and nonstationary approaches in FFA. Figures 8a and 8b depict the comparison between stationary RP based on the Gaussian kernel estimator and nonstationary RP based on GEV and lognormal distribution, respectively, at the Kanawha River basin. Interestingly, the results from Figures 8a and 8b (enlarged version of Figure 8 in right-hand side) revealed insignificant difference in RP of smaller peak events while differences are found to get magnified for the extreme flood peak events at the Kanawha River. Additionally, the frequencies of extreme flood events decreased as per the nonstationary FFA because of the negative trend in streamflow.

A comparison between nonstationary RPs based on GEV and lognormal distributions has been exhibited in Figure 8c. It is shown that nonstationary RPs do not show significant difference for smaller peak events while considerable difference are found for extreme flood events at the Kanawha River. This may be so because extreme events lie in the tail of the distribution and the shape of the tail may be different for both the distributions. The selection criteria of distribution depends on the tail of the distribution while rest of the parts of both PDFs are same, resulting in almost the same AIC and BIC values for both distributions. Hence, the events lying in the tail of the distribution exhibit the variation in the return period values for different distributions. In some cases, the steep line of return period is also observed, which may be due to fewer numbers of extreme events (or rare/outlier events), affecting the smoothness of the pattern of return period. Similar results are obtained for AM peak discharge series at the Kosi River, as shown in Figures 9a, 9b and 9c.

The second-order nonstationary approach is performed only for the Kanawha River basin. Results from second-order nonstationary approach have been depicted in Figures 10a and 10b. The results exhibit a pattern similar to that obtained from RR factor-based nonstationary FFA, but the magnitudes of RPs corresponding to the extreme events are found to be slightly altered. Figure 10b exhibits the comparison in the RPs calculated based on the first-order (based on RR factor for 15-year future time horizon) and second-order nonstationary FFA; significant differences are found in the RPs of the extreme peak events.

Conclusions

Nonstationarity in hydrologic time series due to climate change and/or anthropogenic activities at local or global scales cannot be ignored in contemporary hydrological studies. Although nonstationarity analysis will produce a more accurate estimation of the return period, the question remains as to whether it is always necessary to incorporate nonstationarity (which may be computationally difficult) even though the hydrologic variables are not heavily influenced by the impacts noted above. In such a case, the assumption of stationarity is still valid, and the analysis may provide an accurate estimation of the flood quantiles. Hence, to address this issue, the assessment of nonstationarity in the

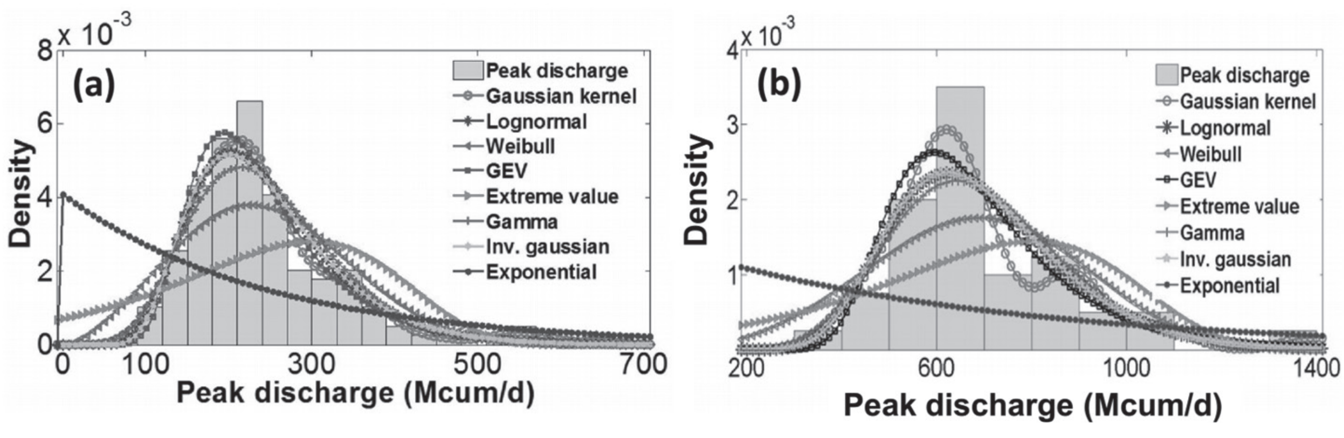

Figure 7: Comparison of different probability density functions for (a) AM peak discharge at the Kanawha Fall and (b) AM peak discharge at Baltara. The nonparametric Gaussian kernel estimator shows the best fit for both the case studies, followed by parametric GEV distribution.

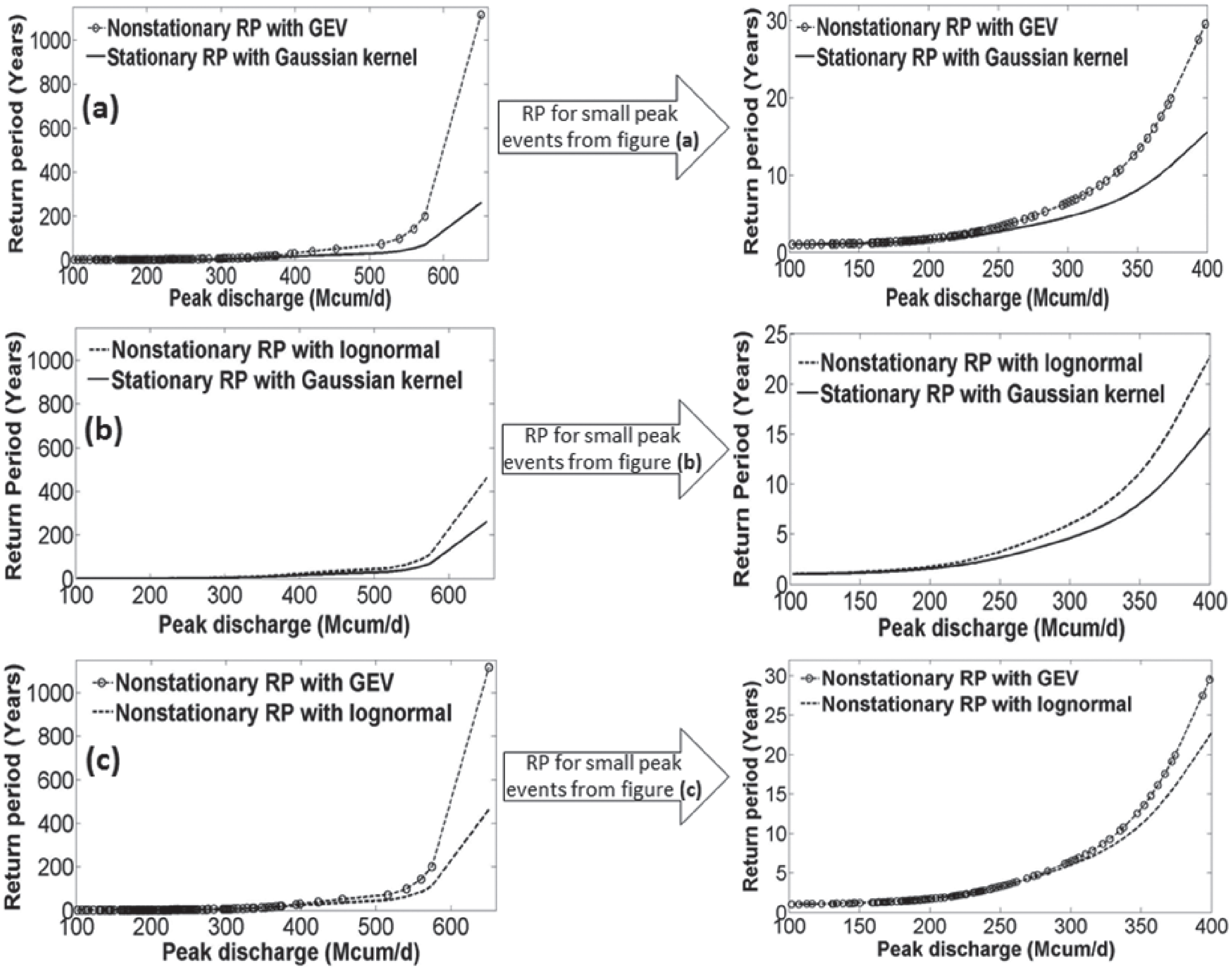

Figure 8: Comparison of stationary return period from Gaussian kernel estimator with (a) nonstationary return period from GEV distribution and (b) nonstationary return period from lognormal distribution. Figure (c) shows the comparison between nonstationary return period from GEV and lognormal distribution for AM peak discharge series at the Kanawha Fall.

event series is a necessary initial step, which can be achieved by comprehensive trend analysis. Therefore, the present study provides a framework for such a comprehensive trend analysis, which is appropriately needed to systematically perform the FFA.

Through this study, two nonstationary methods (RR factor and second-order nonstationary approaches) are performed in the context to capture the effects of nonstationarity in the estimation of return periods versus stream flows in two case studies. The results from the present study have clearly pointed out that it is not only important to identify nonstationarity, but also necessary to consider it in frequency estimation in order to obtain more accurate quantile estimation. The major findings obtained during this study are listed below:

1. A comprehensive trend analysis is performed to assess the presence of nonstationarity in flood variable series. Nonparametric trend methods are found to be more efficient in capturing the statistical trend as compared to parametric tests. Parametric trend method may lose their ability to capture the trend in time series due to their various assumptions.
2. A significant negative trend was evident in the AM peak discharge series at the Kanawha and Kosi rivers as per both the parametric and nonparametric trend tests. No significant trend could be detected in the POT-delineated series excluding the flood peak and average intensity series of the Kanawha River while all four flood variables showed no significant trend in the Kosi River basin. The residuals analysis

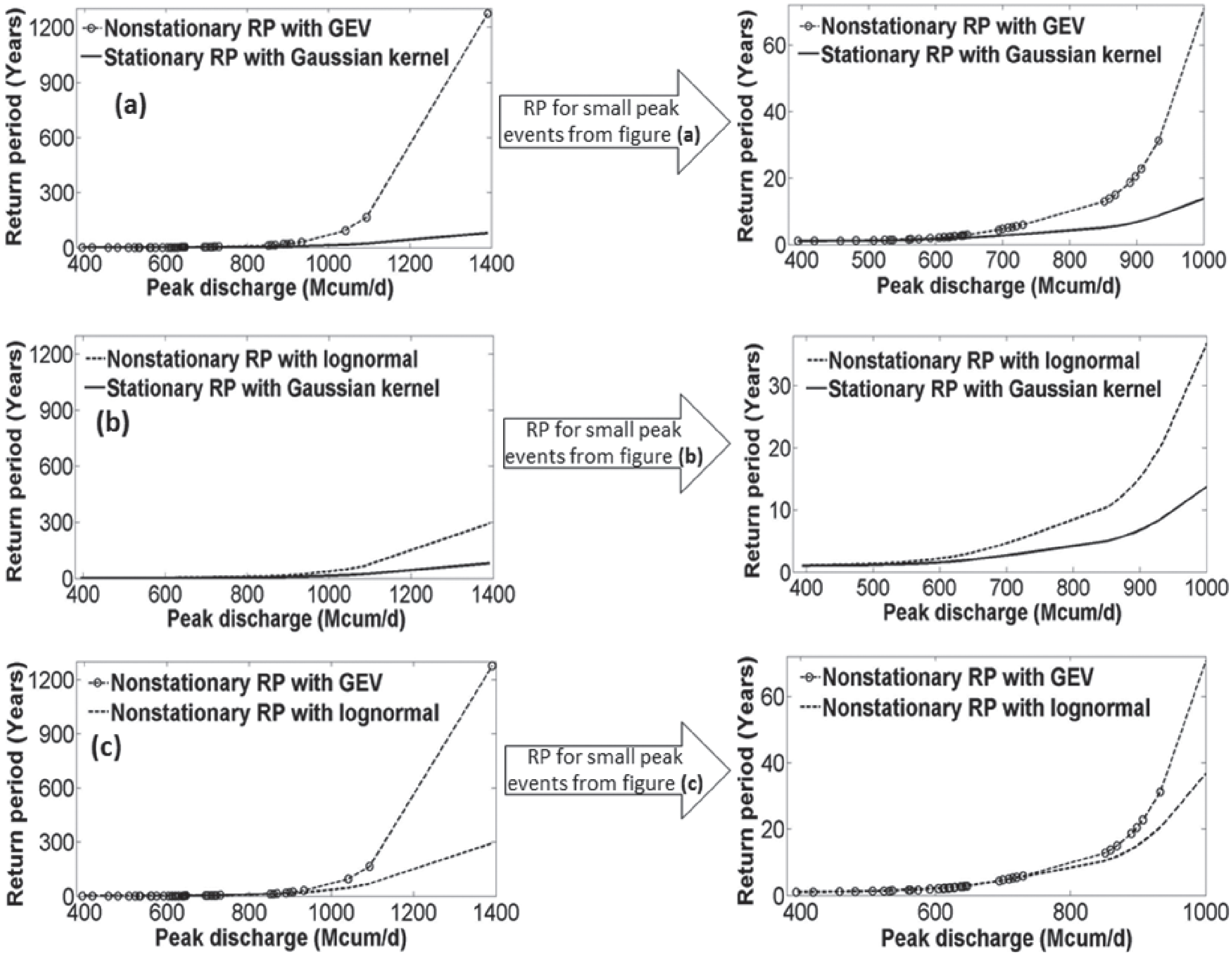

Figure 9: Comparison of stationary return period from Gaussian kernel estimator with (a) nonstationary return period from GEV distribution and (b) nonstationary return period from a lognormal distribution. Figure (c) shows the comparison between nonstationary return period from GEV and lognormal distribution for AM peak discharge series at Baltara.

underscored the unreliability of the parametric linear regression technique for the POT-delineated series on account of limitations related to parametric tests. Hence, it may be concluded that a trend analysis may not be completed without nonparametric trend methods and residuals analysis to quantify the accuracy of parametric test. The significant trends in the AM peak discharge indicate the presence of nonstationarity in the flood series.

Finally, the results underscored the significance of accounting the impact of nonstationarity during frequency estimation of extreme flood peak events. The results show significant differences in estimation of return periods considering stationarity and nonstationarity during frequency estimation of extreme flood peak events. Interestingly, the results obtained from stationary and nonstationary FFA showed almost the same return period for smaller peak events, whereas the difference got magnified for higher peak events. Also, the nonstationary FFA based on GEV and lognormal distribution showed significant variation in return period, which indicates that selection of distribution plays a major role in the estimation of return period. To improve the estimation of return period, second-order nonstationary approaches were implemented by using a 50-year moving window. Additionally, from a comparison of first- and second-order nonstationary FFA, it can be concluded that higher

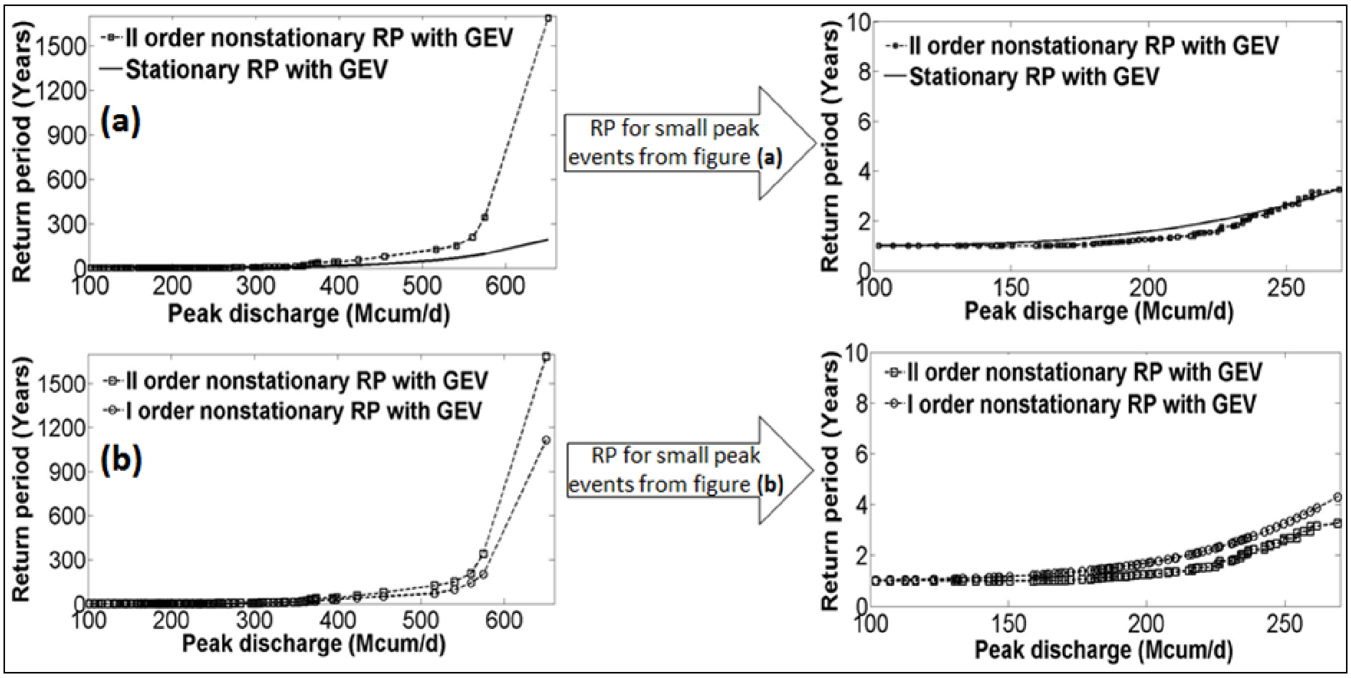

Figure 10: Comparison between return period calculated from second-order nonstationary modelling with GEV distribution and (a) stationary return period with GEV distribution and (b) first-order nonstationary return period estimated based on RR factor (for the quantile function of GEV distribution) for 15-year future time.

order nonstationary analysis provides more accurate return periods estimation.

The findings of the present study indicate that inclusion of nonstationarity during FFA, may direct to accurate estimation of the RPs. However, it is not always necessary to conduct nonstationarity, if the change in climate and land use patterns are not significantly influencing the characteristics of the flood variables. In such cases, a provision must be given to stationary FFA. To identify these pros and cons, trend analysis must be conducted to identify stationarity/nonstationarity in the event series.

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