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Flood Frequency Analysis supported by the largest historical flood

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Abstract

The use of non-systematic flood data for statistical purposes depends on reliability of assessment both flood magnitudes and their return period. The earliest known extreme flood year is usually the beginning of the historical record. Even if one properly assess the magnitudes of historic floods, the problem of their return periods remains unsolved. The matter in hand is that the only largest flood (XM) is known during whole historical period and its occurrence marks the beginning of the historical period and defines its length (L). It is the common practice of using the earliest known flood year as the beginning of the record. It means that the L value selected is an empirical estimate of the lower bound on the effective historical length M. The estimation of the return period of XM based on its occurrence (L), i.e. $\hat{M} = L$, gives the severe upward bias. Problem arises to estimate the time period (M) representative of the largest observed flood XM.

From the discrete uniform distribution with support $1, 2, \ldots, M$ of the probability of the L position of XM one gets $\hat{L} = M/2$. Therefore $\hat{M} = 2L$ has been taken as the return period of XM and as the effective historical record length as well this time. As in the systematic period (N) all its elements are smaller than XM, one can get $\hat{M} = 2(L + N)$.

The efficiency of using the largest historical flood (XM) for large quantile estimation (i.e. one with return period $T = 100$ yr) has been assessed using ML method with various length of systematic record (N) and various estimates of historical period length $\hat{M}$ comparing accuracy with the case when systematic records alone (N) are used only. The simulation procedure used for the purpose incorporates N systematic record and one largest historic flood (XM_i) in the period M which appeared in the L_i year backward from the end of historical period. The simulation result for selected distributions, values of their parameters, different N and M values are presented in terms of bias and RMSE of the quantile of interest and widely discussed.

1 Introduction

The flood engineering usually deals with the determination of the flood of a given return period T years, i.e. the flood quantile X_T or the design flood. The problems with the assessment of these parameters result from a short time series ($N < T$), unknown probability distribution function of annual peaks, error corrupted data, the simplifying assumptions as of identical independently distributed (i.i.d.) data and, in particular, the assumption of the stationarity of relatively long data series. All these account for high uncertainty of upper quantile estimate. The effect of a sample size is widely documented for various distribution models and estimation methods, thus now, it is obvious that due to a short sample the confidence interval of the design flood estimate is already very broad. Addition to Flood Frequency Analysis (FFA) other sources of error would result in increasing yet substantial uncertainty of design flood estimate. This feature is not appreciated by the designers as they want to have only one value for designing flood for related structures. Conversely, the efforts to improve the accuracy of estimates of the hydrologic design value by specifying the various sources of uncertainty and incorporating them in the analysis produce the opposite effect from the one intended.

To improve the accuracy of estimates of upper quantiles all possible sources of additional information and "statistical tricks" are used, such as: independent peaks above the threshold, seasonal approach, regional analysis, record augmentation by correlation with longer nearby records and, finally, augmentation of the systematic records by historical and paleo-flood data.

Frequency analysis of flood data arising from systematic, historical, and paleo-flood records has been proposed by several investigators (a review Stedinger and Baker, 1987; Frances et al., 1994; MacDonald, 2013). The use of non-systematic flood data for statistical purposes depends on reliability of assessment both flood magnitudes and their return period. If the historical record is available, the information about the floods larger than prevailing majority of floods reported in the systematic record can be introduced to the datasets and, if we are lucky, the unique information about the largest floods of all reported floods. Serious difficulties are related to the (un)availability and (not-) exhaustiveness of historical information, the (low) quality and (in)accuracy of historical sources. As if it was not enough, depending on the number of parameters and their method of estimation, the estimates of high quantiles are more or less sensitive to the largest observed floods.

The earliest and simplest procedures for employing historical and paleo-flood data were based on plotting positions and graphical concepts (Zhang, 1982, 1985; Bernieur et al., 1986; Wang and Adams, 1984; Hirsch, 1987; Cohn, 1986). The PWM method and *L*-moment method were introduced by Ding and Yang (1988), Wang (1990, 1996) and Hosking (1995). To deal with historical and paleo-floods Hosking and Wallis (1986a, b) applied the maximum likelihood (ML) as the estimation method. Recently the Bayesian estimation paradigm has been incorporated for the purpose (Vigilione et al., 2013; Parent and Bernier, 2003; Reis and Stedinger, 2005). It enables to take into account that the historical floods are known with uncertainty, for instance with lower and upper bounds (in fact the effect of corrupted historical flood magnitudes was investigated by Hosking and Wallis via MLE mentioned as early as in 1986a, b) The subject of historical floods currently constitutes one of the main scientific threads in flood frequency analysis (MacDonald, 2013; Payrastre et al., 2011, 2013). The log Gumbel, Weibull and Gamma distributions together with maximum likelihood method were considered by Frances et al. (1994) to tackle systematic and historical or paleo-flood data in FFA. To assess the potential statistical gain from historical information the asymptotic variances of the quantile estimates got from the systematic records alone and the combined time-series were compared by means of computer simulation experiments. The study performed to define the length (M) of historical period indicate that value of historical data for estimating flood quantiles can vary depending on only three factors: the relative magnitudes of the length of the systematic record (N) and the length of the historical period (M); the return period (T) of the flood quantile of interest; and the probability threshold defining the historical floods.

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Most often it is the first historical large flood that is the most remembered (and described in historical sources) and, therefore, it is usually not considered as important (or simply not known) what had happened before (Girguś and Strupczewski, 1965). Then the date of the first recorded historical flood is taken as the historical memory length L, i.e. L becomes the duration of non-systematic period commencing on the large flood. Even if one properly assess the magnitudes of historic floods, the problem of their return periods remains unsolved. In most literature examples (specially Benson, 1950; Dalrymple, 1960; IACWD, 1982; Zhang, 1982 and NERC, 1975, p. 177) one reads that effective length of historical record M used for frequency analysis is always taken to be the period from the first extraordinary flood to the beginning of the systematic record, i.e. L.

The matter in hand is that the only largest flood (XM) is known during whole historical period and its occurrence marks the beginning of the historical period and defines its length (L) (Fig. 1). That is because the beginning of the historical period was somehow forced by the appearance of the largest flood (XM) but in fact its unusual magnitude corresponds rather to a longer return period than L (or, if in systematic record all observations are smaller than XM, to $(L+N)$-period). Consequently, we can expect the upward bias of the upper quantile estimates if the historical period of length L is taken in FFA as the non-systematic observation period, or, in other words: the error comes from an underestimation of the return period ($\hat{M} = L$) of XM value.

In consequence, the attempts to eliminate or lessen this error lead us to the estimation the time period (M) representative of the largest observed flood XM as accurately as possible. In order to do so, we will carry out the evaluation of the efficiency of using the largest historical flood (XM) for large quantile estimation and its comparison with the case when systematic records alone (N) are used only. To keep and preserve the unspoiled genuine information contained in the observation (XM, L), the return period ($\hat{M}$) of the largest observed historical flood (XM) should be assessed without data larger than the XM value from the systematic record.

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It is obvious that the return period of the historical flood assessed on the base of the year of occurrence (*L*) represents just the lower limit of its real empirical return period (*M*). Of course, there is an upper limit as well, which however, can not be estimated unambiguously. This is so because, if the occurrence of a large flood was reported in a given year, for sure a similar or more serious flood a year before would have been also noted and commented in historical sources (Hirsch and Stedinger, 1987). The same can be stated for horizon of two, three, four, etc. years. If we could identify this time span, we would have determined the upper limit of the empirical return period.

The estimation of *M* based on the date of the first extraordinary flood occurrence exacerbates an already severe imprecision. By defining as historical floods all floods during the *M* period above a given threshold and taking four different plotting position formulas, Hirsch and Stedinger (1987) calculated (with the use of Monte Carlo experiment) the magnitude of the upward bias of the plotting position of the largest sample elements occurring when *L* is taken as the beginning of the historical record. Doing so they noticed that *L* is a random variable dependent on the flood-producing process itself; this would be a violation of the assumption of the plotting position formulas.

Similarly, Hosking and Wallis (1986a, b) use Monte Carlo (MC) computer simulation to assess whether a single paleo-flood estimate, when included in a single-site Maximum Likelihood (ML) flood frequency analysis procedures, gives a worthwhile increase in the accuracy of estimates of extreme floods. They found that the main factors affecting the utility of this kind of paleological information are the specification of the fitted flood frequency (whether it has two or three unknown parameters) and the size of the measurement error of paleo-discharge estimates. Errors in estimating the date of the paleo-flood is considered as to be of minor importance. For distributions with higher CV or skewness the difference between the effects of the errors of the magnitude of paleo-flood and its return period is smaller.

Note that the randomness of the systematic records time series of i.i.d. variable can also be sometimes questioned and undermined, e.g. when the largest value XM of a time series intentionally terminates the N-elements' systematic record. Then the XM is the last element of the N-element time-series. Such a case may arise when a water gauge was swept by a heavy flood (XM) and later not restored or intentionally being the consequence of the hydrological moving network design focused on the assessment of the variability range of annual peak flows. As before, the use of such a series in the FFA with $\hat{M} = N$ will lead to an overestimation of large quantiles.

2 Problem formulation

The object of the paper is to assess by means the maximum likelihood (ML) method whether there is any use of the largest flood terminating the time series assuming its magnitude (XM) is known. Therefore, the case of data with the largest flood terminating observation period is related to records without it. These two variants are examined by comparing the bias (B) and the root mean square error (RMSE) of flood quantiles. The two two-parameter distributions, namely Gumbel and Weibull were used while applying the simulation experiments. The emphasis is put on the effect of misspecification of the return period (M) of the largest historical (paleo-)flood (XM) and on the proper assessment of the M estimate on the basis of XM occurrence (L). So far, the results of such research has not been presented in the hydrological literature.

The theoretical framework of our research is based on Maximum Likelihood estimation which has been generally found to have desirable properties for combine systematic and historical information (Frances et al., 1994; Stedinger and Cohn, 1986; Naulet et al., 2005). It is assumed that the annual maximum floods are independent and identically distributed.

2.1 Assessment of the return period *M* of the XM flood

Dealing with the plotting positions Hirsch and Stedinger (1987) considered that the time of occurrence of the earliest documented historical flood L is the random variable

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defining a lower bound of the sample size used for computation of plotting positions. The position L of the largest in M period element (XM) (Fig. 1) is the random variable being discretely uniformly distributed in the M period, i.e. $p_t = 1/M$ for $t = 1, 2, \ldots, M$. Obviously the magnitude of the largest element (XM) is also a random variable. It can correspond in the population to a smaller or larger value of the exceedance probability than $1/M$ defining the effective return period (M_R) of XM, Therefore the difference ($M_R - L$) is not restricted in sign.

Assume that the return interval (M) of XM is known. As L is uniformly distributed variable in the M length time series with support $L \in [0, 1, \ldots, M]$, one gets $E(L) = M/2$ and $V(L) = M^2/12$. In reality M is not known and its assessment is our goal. Taking the observed L value as the estimate of the expecting value, i.e. $L = E(L)$ we get the M estimate equal $\hat{M} = 2L$. Because regardless of the estimation method the quantile estimators are not in general linear function of $\hat{M}$, the minimum bias of quantile $B(\hat{x}_p) = E[\hat{x}_p(\hat{M}) - x_p]$ does not necessarily correspond to the zero-bias of $\hat{M}$, i.e. to $\hat{M} = 2L$. If in the systematic period (N) all its elements are smaller than XM, one can get $\hat{M} = 2(L + N)$. Note that usually $N \ll L$.

3 Simulation procedure

The simulation procedure incorporates N systematic record and one largest historic flood (XM) in the period M which appeared in the L year backward from the end of historical period (Fig. 1). Obviously, the systematic record and both magnitude (XM) and year of occurrence (L) randomly vary from simulation to simulation. As an estimate of the length of the historical period shall be successively $\hat{M} = L, 2L$ and the actual value $\hat{M} = M$, i.e. the length of the period M in simulation experiment.

First, generate a gauged record x_1, $x_2, \ldots, x_N$ of independent random variates from the assumed (two-parameter) flood-like distribution $[F(x)]$ with parameters chosen to give specified values of CV. Then generate historical series of the same distribution of the length M, i.e. y_1, $y_2, \ldots, y_M$, and find the maximum event (XM) of the historical

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series denoting the time (L) of its occurrence. Since the random variables (XM) and L are mutually independent the XM can be generated from the distribution of the largest element in a M-element series, i.e. $F(M) = F_{1,M}(y) = F^M(y)$, while the corresponding time of its occurrence (L) from the discrete uniform distribution with support $\{1, 2, \ldots, M\}$.

Fit a flood frequency distribution by the method of maximum likelihood. If the fitted distribution has a distribution function $F(x, \boldsymbol{\theta})$ and a density function $f(x, \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of unknown parameters, then the likelihood function (L) is taken to be

$$L(\boldsymbol{\theta}; x; y) = F_x^{\hat{M}-1}(y = \mathrm{XM}; \boldsymbol{\theta}) \cdot f_x(y = \mathrm{XM}; \boldsymbol{\theta}) \cdot \left\{ \prod_{i=1}^{N} f_x(x_i; \boldsymbol{\theta}) \right\}, \tag{1}$$

i.e., the use of incomplete data likelihood, where $\hat{M} = L, 2L$ and M, and for systematic record only

$$L(\boldsymbol{\theta}; x) = \prod_{i=1}^{N} f_x(x_i; \boldsymbol{\theta}). \tag{2}$$

Calculate quantile estimates $\hat{X}_T = F^{-1}(1 - 1/T, \hat{\boldsymbol{\theta}})$ for $\hat{M} = L, 2L$ and M and the systematic record (N) only (i.e. when $\hat{M} = 0$), where F^{-1} is the inverse distribution function of the fitted flood frequency distribution, $\hat{\boldsymbol{\theta}}$ is the maximum likelihood estimate of $\boldsymbol{\theta}$, and T is the return period of interest.

Repeat the above steps a large number of times (i) and calculate the mean and variance of $\hat{X}_T$, and hence the relative bias RB and relative RMSE of $\hat{X}_T$ taking $\hat{M}_i = L_i$, $2L_i$ and M and the systematic record (N) only ($\hat{M} = 0$), considered as an estimator of the true quantile $X_T = F^{-1}(1 - 1/T; \boldsymbol{\theta})$. If in a generated series one gets $\max(x_1, x_2, \ldots, x_N) \geq \mathrm{XM}$ such simulation is ignored which allows us to assume $\hat{M} = 2L$.

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4 Simulation results

The concise frame of this paper made us to limit the number of models we took into consideration in our calculations. In order to lessen the number of the figures for all the combinations of CS and CV values we resigned from three-parameter distributions such as generalised extreme value (GEV) and turned into its two-parameter special forms, namely Gumbel (Gu) and Weibull (We). Another cause was also that, however theoretically sound, the GEV working perfectly for large samples often fails in far-from-asymptotic samples which we examine in this study. We scrutinised a number of two- and three-parameter distribution functions in terms of their best fit to hydrological annual and seasonal peak flows in Poland and it turned out that despite the regime of the river other models were preferred rather than GEV (Strupczewski et al., 2012; Kochanek et al., 2012). However, the crucial argument after the choice of the parent distribution was the pioneering works of Frances et al. (1994) that we wanted to continue and develop. Results of simulation experiments are shown for Gu and We distributions with four values of the coefficient of variation CV = 0.25, 0.5, 0.75, 1.0, two length of systematic records $N = 15$, 50 and the length of effective historical period $M = N\exp(a)$ where $a \in [0,3]$. Due to the limited capacity of this paper without the loss of generality, only the selected results were presented in Figs. 2–5, namely for CV = 0.25 and 1.0; the results for CV = 0.5 and 0.75 locate themselves between those presented in the figures. Results got for the correct value of the return period ($\hat{M} = M$) are compared with those got for $\hat{M} = L_i, 2L_i$. For completion the results for the systematic record only (i.e. $\hat{M} = 0$) were presented in all figures (solid line). Of course, for this case the results does not depend on M and in consequence on $\log(M/N)$.

5 Discussion of the results

– The shorter the gauged record (N) is, the more useful is the historical information.

– Using as the estimate of the true return period of largest historical flood (XM) the historical memory length (L) results in considerable upward bias RB of 1 % quantile far exceeding the bias for the systematic record only. Its value is growing with CV (and CS) and with the M/N ratio.

– Using in ML estimation the $\hat{M} = 2L$ instead of $\hat{M} = L$ considerable reduces the bias and further reduction is obtained for the $\hat{M} = M$, i.e. for the return period (M) of the largest historical flood XM.

– Although the use of $\hat{M} = 2L$ instead of $\hat{M} = L$ reduces the bias more than twice, it is still circa 40 % larger than the bias of a known return period M of XM, and comparable or lower than the bias from systematic record (N).

– As far as the relative root mean square error (RRMSE) of 1 % quantile is concerned, for both Gumbel and Weibull models one can notice a considerable reduction in its values when one uses L, $2L$ or M return periods in comparison to the systematic sample. The worst reduction of RRMSE one gets for L, better for $2L$ and the best for M which means that it is worth, first of all, employing the historical measurement XM in upper quantile estimation and then set the return period of XM to $2L$ rather than L if we do not know M.

– The reduction in RMSE for both models (Gumbel and Weibull) rises generally with M/N ratio. In other words: the bigger M (compared to N), the higher distance between RRMSE values got for the sample with additional historical information and the systematic series. It goes without saying, that for $N = 15$ one gets better reduction than for $N = 50$.

– For the Gumbel model, regardless the sample return period, L, $2L$ or M, the relative reduction in RRMSE compared to systematic samples does not depend on CV. It does not hold for Weibull where the reduction decreases with CV, e.g. between $C_V = 0.25$ and 1.0 there is usually a few-percent difference which is minimal (almost marginal) for $\hat{M} = M$.

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- For Gumbel model reduction in comparison to systematic sample for $\log(M/N) = 3$ and $N = 15$ the reduction gets up even to 19, 32 and 46 % for L, $2L$ and M respectively. For $N = 50$ the numbers drop roughly by half.
- For Weibull the gain in RRMSE is even more spectacular and for $M = N = 15$ and CV = 0.25 equals to 44, 53 and 64 % (!) for L, $2L$ and M respectively (when CV = 1.0 the gain is slightly lower). For $N = 50$ the general trend for Weibull remains the same as for $N = 15$ but the reduction of RRMSE is slightly smaller.
- To sum up the RRMSE issues, the inclusion of the largest historical flood in FFA with $\hat{M} = 2L$ (i.e. the effective historical record length) gives the substantial reduction in RRMSE of extreme flood estimates, however it is circa 40 % lower than if the length of simulation period M is taken, which is not available in reality and one is doomed to use $2L$ instead.
- Therefore, to benefit from the largest historical observation every effort should be made to establish M accurately.
- In the absence of any information about the period preceding the occurrence of XM one should put $\hat{M}$ equal $2L$ or $2(L+N)$.
- The benefit from including the largest historical flood is measured by the reduction of RRMSE. It depends on:
  i. the length of systematic record (N),
  ii. the ratio of the true return period of XM, i.e. M to N,
  iii. the ratio of N to the return period of quantile of interest,
  iv. the CV and skewness of the parent distribution.

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6 Conclusions

Errors in historical data reduce, of course, the utility of the data for improvement the estimate of the flood magnitude at the given return period. In the simulations (Figs. 2–5) it was assumed that the magnitude of largest historical flood (XM) was measured without error and the same was assumed for systematic record. It is realistic to suppose that the XM flood was measured much less accurate than the gauged record. Error in estimating the largest historical magnitude (XM) is much more important than error in estimating the date of its occurrence (e.g. Hosking and Wallis, 1986a, b). It is significant that inspired by the practice of efforts to improve the accuracy of estimates of flood quantiles through more realistic assumptions and a fuller use of the information they give just the opposite effect leading to increased uncertainty of flood estimates.

Next step should be to refer to the general problem of historical information when the applied distribution model is false, what is always the case (Strupczewski et al., 2002). On the other hand, the uncertainty of the paleo-historical floods (both in terms of their magnitude and return period) combined with considerable increase of the complication of the problem (when compared to analysis of systematic data only) provoke a fundamental question whether the whole operation is worth a candle. Therefore, whether to include the paleo-historical information or turn a blind eye to it, is a matter of conscience.

All these generate two important practical problems which we leave for further study, namely:

1. What is the upper limit of accuracy of high quantile estimation when the theoretical value (i.e. taken from the parent distribution) of return period for XM is known?

2. Here in our simulation experiment we assumed the knowledge of the true (parent) distribution function. The role of historical information when the assumed distribution serves as the model of the true distribution remains, for the time being, unknown.

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Only the solutions to these two problems completed by the consideration of the observation errors in FFA brings us closer to the answer to the fundamental question stated above.

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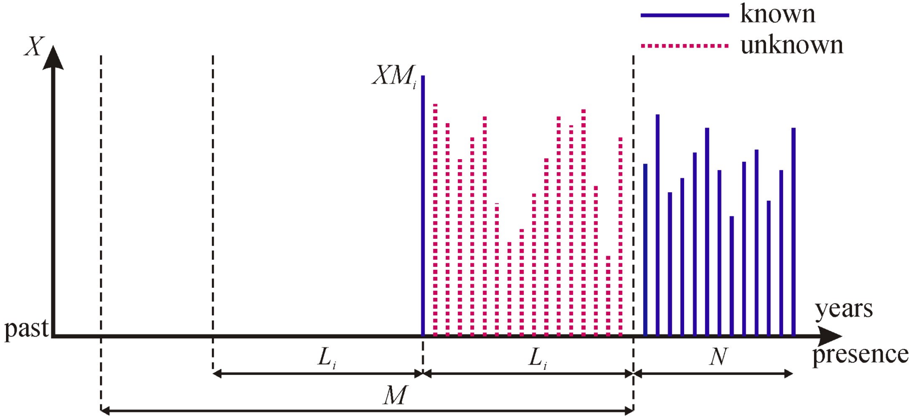

Fig. 1. The case of *N* systematic and one largest flood in the beginning of historical period.

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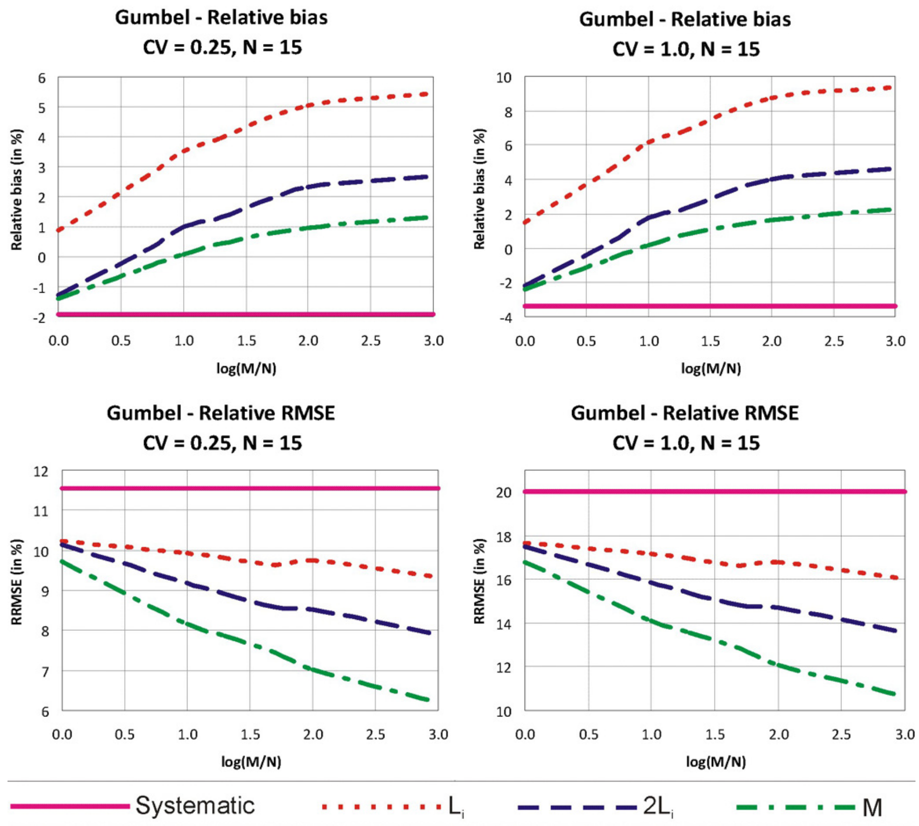

Fig. 2. Relative bias (RB) and relative root mean square error (RRMSE) of $\hat{X}_{T=100}$ as a function of gauge record length N and historic period M for $\hat{M}_i = 0, L_i, 2L_i, M$. Parent distribution Gumbel with CV equal: 0.25 and 1.0 and $N = 15$. Fitted distribution Gumbel.

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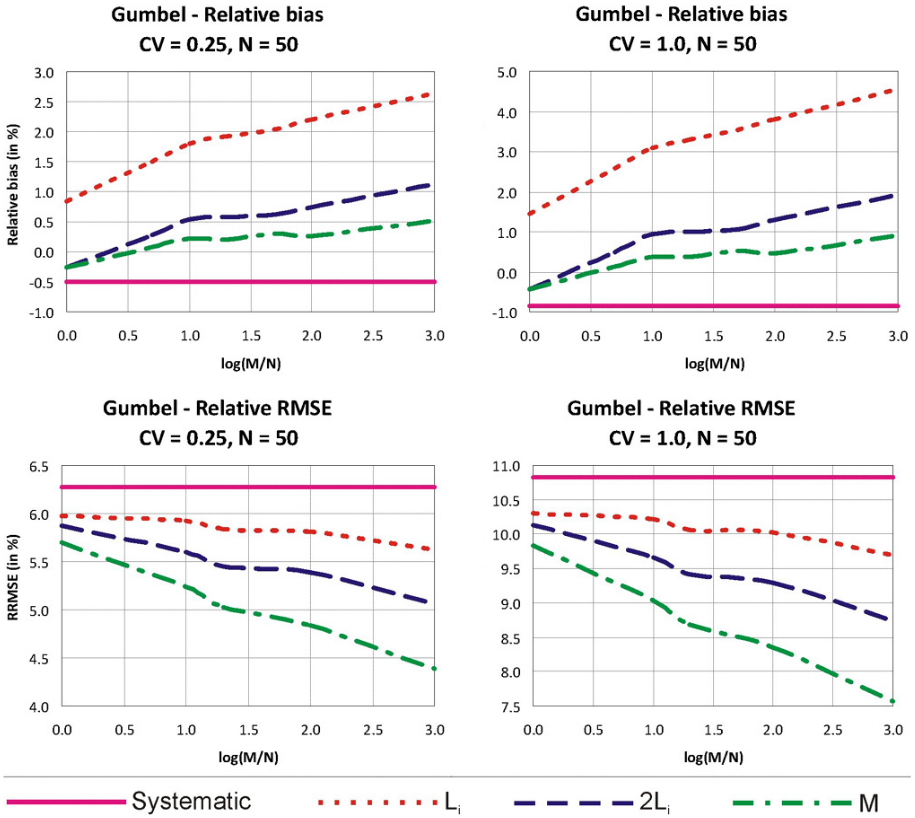

Fig. 3. RB and RRMSE of $\hat{X}_{T=100}$ as a function of gauge record length N and historic period M for $\hat{M}_i = 0, L_i, 2L_i, M$. Parent distribution Gumbel with CV equal 0.25 and 1.0 and $N = 50$. Fitted distribution Gumbel.

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Flood Frequency Analysis supported by the largest historical flood

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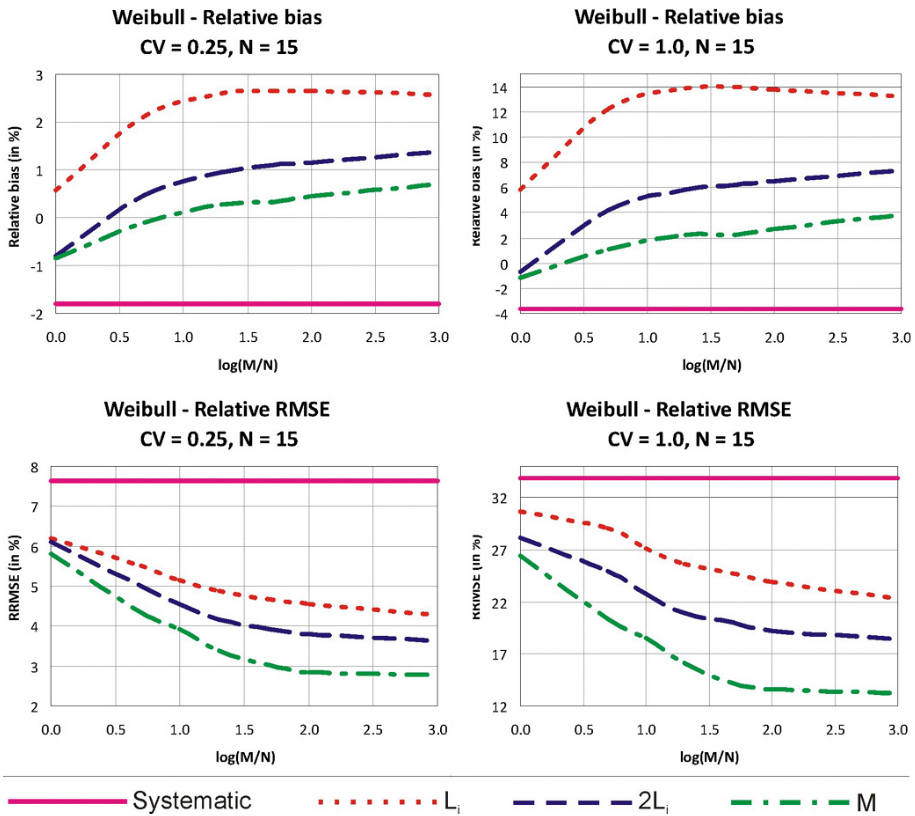

Fig. 4. RB and RRMSE of $\hat{X}_{T=100}$ as a function of gauge record length N and historic period M for $\hat{M}_i = 0, L_i, 2L_i, M$. Parent distribution Weibull with CV equal 0.25 and 1.0 and $N = 15$. Fitted distribution Weibull.

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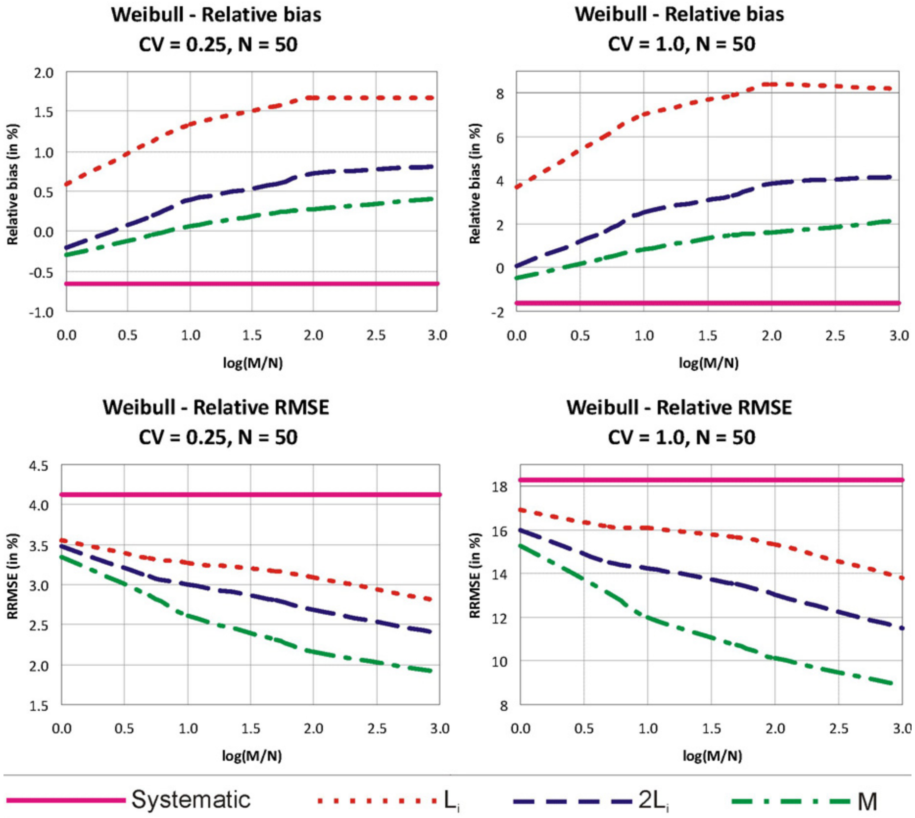

Fig. 5. RB and RRMSE of $\hat{X}_{T=100}$ as a function of gauge record length N and historic period M for $\hat{M}_i = 0, L_i, 2L_i, M$. Parent distribution Weibull with CV equal 0.25 and 1.0 and $N = 50$. Fitted distribution Weibull.