Received: Added at production | Revised: Added at production | Accepted: Added at production

DOI: xxx/xxxx

HP RESEARCH ARTICLE

Hydrological modeling of streamflow approaching the new Hintze Ribeiro bridge

Abstract

The present work aims to provide reliable estimates of extreme discharge flows and their probability of occurrence. Such estimates are important for the assessment of the associated hydrological risk of hydraulic infrastructures, such as bridges and dams, in the design process as well as during their operations. The hydrological modeling herein developed was applied to estimate the design floods approaching the new Hintze Ribeiro bridge, in the north of Portugal. It proposes a statistical analysis of the maximum annual streamflow data by using a flood frequency analysis technique. The data series were subject to a reliability analysis and the specific modeling assumptions, required for the study, were appropriately given and tested. An extrapolation technique of the missing instantaneous discharge data was herein derived. Such technique was validated by two distinct methods. The estimations are accurate with a mean deviation of 7.2% relative to the observed data. A set of probabilistic models were considered and the models' performance verified by the goodness-of-fit tests and Q-Q plots. The model and the parameter uncertainties were taken into account. Model uncertainties were addressed by comparing the estimated design floods through selecting the best fitting probability model (MS) with the approach that considered the distribution functions which fit well the data (MM). On the other hand, the computed flow rates were estimated with 95% of confidence to reduce the inherent parameter uncertainties. An additional accuracy assessment of the parametric approaches was performed through a comparative analysis of such design floods with the ones retrieved by application of the non-parametric Kernel density estimate (KDE). The MM approach showed a lower discrepancy (18.5%) to KDE estimates, when compared with the MS results. A sensitivity analysis of the associated hydrological risks was also undertaken.

KEYWORDS:

design flood, flood frequency analysis, hydrological modeling, hydrological risk, new Hintze Ribeiro bridge, uncertainty analysis

1 | INTRODUCTION

Bridges, like other hydraulic infrastructures, play an important role in the economic development of a society. In recognition of their relevance, the assessment of the associated hydrological risk plays a vital role in the design process, as well as during their operation, namely when such bridges are founded on alluvial riverbeds (Simonović 2012). The risks associated with the likelihood of extreme events and their respective consequences call for the prediction, as accurate as possible, of the maximum annual flow discharges that approach the section of a bridge for different return periods (called design floods), as those may compromise its stability. According to Pizarro, Manfreda, and Tubaldi (2020), a deterministic approach is often employed, neglecting the natural and the epistemic sources of uncertainty that may affect the scour problem, and leading to a one-to-one relationship between the design flood discharge and the design scour depth (Arneson, Zevenbergen, Lagasse, & Clopper 2012; Highways Agency 2012; Melville & Coleman 2000).

The estimation of design floods approaching hydraulic structures requires the determination of instantaneous peak flows from the historical flood data since there may be significant stream flow fluctuations within hours or even minutes, especially for small watersheds (Dastorani, Koochi, Darani, Talebi, & Rahimian 2013). An interesting aspect concerns the process by which hydro-metereological agencies evaluate and make accessible the hydrological data. Most of the times, these agencies publish only the mean daily flow data, for which the consideration of the mean data in flood studies may cause underestimation of the design flood thus resulting the sizing of the hydraulic structure for a higher risk of collapse.

The extreme events and their occurrence rate depend, among other factors, on the physical characteristics of the river basin, the dominant runoff generation mechanisms (Robinson, Sivapalan, & Snell 1995), the magnitude and variability of the temporal distribution of rainfall (Kusumastuti, Struthers, Sivapalan, & Reynolds 2007), and the stream network geometry and river routing (Rogger, Kohl, et al. 2012; Rogger, Pirkl, et al. 2012). These factors may change along time as a result of the influence of climate change or socio-economic development aspects, so their estimation remains an area of continuous research interest. In the literature, several methods can be used, from which the statistical methods (flood frequency analysis) and hydro-meteorological methods stand out. Whilst both these methods have strengths and weaknesses (Calver, Stewart, & Goodsell 2009; Sordo-Ward, Bianucci, Garrote, & Granados 2014), the hydro-meteorological method requires a higher computational capacity.

Flood frequency analysis relates the magnitude of annual maximum flood events to the likely frequency of occurrence of natural events (Beven 2019; Moran 1957), by employing probability distribution models that describe the observed data. From the application of a set of different distributions, statistical tests are commonly used to select the model that best fits the given time series data from a number of candidate probabilistic distribution models. The selection of a single best distribution model (i.e. model selection, MS) represents an implicit assumption that the selected model can adequately describe the frequency of observed and future flood flow events (Okoli et al. 2018). Many hydrologists have pointed out ways to deal with the inherent uncertainties, always present in any mathematical evaluation such as from the parameter or model selection (Beven 2019; McMillan, Westerberg, & Krueger 2018).

The quantification of model uncertainty, in flood frequency analysis, can be tackled through the consideration of all candidate probability distribution models in the estimation of the design floods, where the final floods estimate is an average of all individual estimates, known as model averaging (Okoli, Mazzoleni, Breinl, & Baldassarre 2019). The model averaging can be performed either by taking the arithmetic mean of the design flood estimates (i.e. arithmetic model averaging, MM) or by attributing weights to the design floods of each individual candidate probability model (i.e. weighted model averaging, MA) depending on how best each model fits the time series data (Hoeting, Madigan, Raftery, & Volinsky 1999; Yan & Moradkhani 2014). According to Okoli et al. (2019), the selection of the best fitting probability distribution is associated with several outliers in comparison with multiple probability distributions, especially when facing short sample sizes (30 - 50 hydrological years).

Therefore, the present study proposes a hydrological modeling methodology for providing reliable estimates of extreme discharge flows and their occurrence probabilities, constituting thus a relevant input data for the assessment of the safety of new or existing hydraulic infrastructures. In order to demonstrate the hydrological modeling herein presented, the methodology was applied to estimate the flood events approaching the new Hintze Ribeiro bridge, built in 2002, over the Douro river, in Portugal. Various ways of accounting with the inherent uncertainties were also proposed herein.

Following this introduction, Section 2 of this paper presents and discusses the time series analysis techniques and properties, and describes the assessment of how to deal with the uncertainties inherent to a flood frequency application. In Section 3, the river basin defined by the case study bridge cross-section is described, and a set of hydrological plausible scenarios are defined. The application of the hydrological modeling to the new Hintze Ribeiro bridge is presented in Section 4. A sensitivity analysis of the hydrological risks was also undertaken. Finally, the main conclusions are provided and discussed in Section 5.

2 | HYDROLOGICAL MODELING METHODOLOGY

2.1 | Data reliability analysis

The applicability of any statistical method is preceded by a reliability analysis of the hydrological series under consideration. Such analysis consists on the verification of the consistency and the hypothesis of randomness of that series (Kite 2019; Naghettini & Pinto 2007, among others).

The conformity of data consistency refers to the detection and elimination of gross and/or systematic errors, for instance, using the usual double-mass technique, firstly developed by Searcy and Hardison (1960). A consistency check can reveal inconsistencies entailed by a variety of causes, including changes in land use (e.g. agricultural to forest), the construction of new control structures (e.g. dams) or modifications in the operation of these structures, changes in the amount of water diverted into or out of the watershed, the effect of large forest fires, alterations in agricultural practices, and changes to measurement methods or practices. Moreover, this consistency verification can reveal information regarding magnitude and timing of these aforementioned causes and determine whether the streamflow data need to be adjusted.

The randomness of an historical series is verified if it guarantees the assumptions of independence, homogeneity and stationarity (Kite 2019; Naghettini & Pinto 2007). Those assumptions are usually performed by using non-parametric tests (Hipólito & Vaz 2011; Lencastre, Franco, & Antunes 1984). The independence of the data series is usually assessed by the auto-correlation coefficient test whereas the homogeneity is verified by the application of the non-parametric test of Mann and Whitney (1947) or the local extremes number test. The Mann-Kendall trend test (Kendall 1975; Mann 1945) or the Spearman tests are typically used to identify trends on hydrological series. The Wald and Wolfowitz (1943) test is also used as a general verification of the randomness of a series. According to Hipólito and Vaz (2011) when the hypothesis of randomness is not rejected in more than two of the four tests, the hydrological series is assumed random and reliable for statistical analyses at a 95% confidence level.

2.2 | Statistical methods

2.2.1 | Flood frequency analysis

Given reliable historical streamflow records, the statistical method known as "flood frequency analysis" can be used to extend them and hence predict the likely frequency of occurrence of natural events, typically designated as "design floods" (Chow, Maidment, & Mays 1988). It often consists of fitting probability distribution functions to records of annual maximum flows that likely occur at a certain river location, namely at a bridge site for the current study. The accuracy of the estimated design floods, such as the 100-year flood (a flood with 1% annual frequency of exceedance), is essentially dependent on the record length, which should be longer than 30 hydrological years.

In flood frequency analysis it is common practice to employ probability distribution models that describe the observed data (Castellarin et al. 2012; Chow et al. 1988; Cunnane 1989; Hassan, Hayat, & Noreen 2019). In the present study, seven models were considered and their confidence intervals determined, namely for the following distributions: two- and three-parameter LogNormal ($2p$ and $3p$, respectively, being p the number of parameters), Gumbel, Generalized Extreme Value (GEV), Gamma, LogPearson III, and Weibull. For estimating the parameters of each probability distribution, the method of moments, the L-moments method and the method of maximum likelihood are the most advisable by hydrologists (Kite 2019).

2.2.2 | Goodness-of-fit tests and graphical methods

Once the probability distributions are adjusted, the performance of each model is usually assessed based on goodness-of-fit tests and accuracy measures (D'Agostino 1986; Naghettini & Pinto 2007). Generally speaking, goodness-of-fit tests describe how well a statistical model fits a set of observations, through the analysis of the discrepancy between observed and expected values under the probabilistic model in consideration.

Goodness-of-fit tests may be divided into qualitative and quantitative non-parametric tests. The former refers to the Kolmogorov-Smirnov (KS) test (Massey Jr. 1951), while the latter assigns the Chi-square (χ^2) test (Kenney & Keeping 1957). Other tests include the Filliben (Fi) test (Filliben 1975) and the Anderson-Darling (AD) test (Anderson & Darling 1954). The Anderson-Darling (AD) test constitutes a modification of the Kolmogorov-Smirnov (KS) test, giving more weight to the tails than the latter (KS test). Each of the goodness-of-fit tests has its own set of particularities, which inherently interferes with the rejection (or not) of a certain probabilistic model for the representation of the time series data under analysis (Maity 2018b; Naghettini & Pinto 2007).

A measure of accuracy given by the graphical method assessment obtained by the Quantile - Quantile plot (*Q-Q* plot) is also advised in the evaluation of those models' performance (D'Agostino 1986). The *Q-Q* plot checks the validity of a distributional assumption for a data set by computing the theoretically expected value for each data point based on the distribution in question. Whenever the data indeed follow the assumed distribution, the points on the *Q-Q* plot will fall approximately on a straight line. For determining the theoretical probability of non-exceedance of each data point, "plotting position" formulas are assigned and used depending on the type of distribution being fitted. The commonly used unbiased plotting positions comprise the formulas of Weibull, Blom, Cucane, Gringorten, Hazen, Chegodayev and Turkey (Naghettini & Pinto 2007; Stedinger 1993).

2.2.3 | Uncertainty and modeling approaches

Despite the wide practice of selecting a single best probability distribution (i.e. the model selection, MS) in the field of flood frequency analysis, the technique itself does not take into account the inherent uncertainties (Okoli et al. 2018). Moreover, any model faces uncertainty and its quantification is crucial for ensuring data quality and usability (Beven 2006; Kiang et al. 2018; McMillan et al. 2018). Besides the advances in the development of tools for quantitative uncertainty analyses, its quantification is not yet a standard practice in water resources planning, design, and operation (Beven 2019; Yen 2002).

The uncertainty in flood frequency analysis, as in any other area, can be divided into two distinct categories: natural uncertainty - irreducible uncertainty, and epistemic uncertainty - reducible uncertainty (Beven 2019; Huang, Kerenyi, & Shen 2018; Leandro et al. 2019; Yen 2002). While the first stems from variability of the underlying stochastic process, the second results from incomplete knowledge about the process under study. In the present investigation, the natural uncertainty refers to the variability that exists in the amount of annual flow discharge in consecutive hydrological years. The epistemic uncertainty is related to the ability of understanding and describing the system under analysis (Maity 2018a; Merz & Thieken 2005), namely model and parameter uncertainties.

In accordance with Okoli et al. (2019), model uncertainty can be reduced by using all candidate probability distributions for the design floods estimation, where the final estimate is a weighted average of all individual estimates. This procedure is known as model averaging (Bumham & Anderson 2002; Höge, Guthke, & Nowak 2019). The model averaging technique can be performed through two distinct ways: (i) by taking the arithmetic mean of the design flood estimates from the candidate probabilistic distributions (i.e. the arithmetic model averaging, MM) or (ii) by attributing different weights to the design floods of each candidate probability model (i.e. weighted model averaging, MA), depending on how best the probability function fits the data under analysis (Hoeting et al. 1999; Yan & Moradkhani 2014). Bayesian inference is one of the possibilities to estimate the weights assigned to a range of models considered for flood estimation purposes and Wood and Rodríguez-Iturbe (1975) showed, for the first time, an example of application in flood frequency analysis. A review on theoretical backgrounds of Bayesian model averaging (and selection) is provided in Höge et al. (2019).

In the present investigation, a modification of the MM approach (Okoli et al. 2019), is introduced, which consists in solely considering the distributions which ensure good performance on both goodness-of-fit tests and graphical methods. The comparative analysis between the widely applied MS approach and the modified MM approach presented herein will provide insights and consequently explain the importance of considering more than a single probability distribution for the representation of the time series data under analysis.

Parameter uncertainty, in turn, results from the inability to accurately quantify the model input parameters. The estimation of a random variable (x_T) for a particular return period (T), for each probabilistic distribution, is inherently dependent on the available sample size, which carries uncertainty to the system. In order to tackle such uncertainty, in the model selection approach (MS), the computed flow rates should be estimated with 95% of confidence interval for the full range of design floods (i.e. with lower and upper boundaries) as per best practice. This has been considered in the MS approach presented herein.

2.3 | Hydrological risk

Frequency analysis is of great relevance in the interpretation and assessment of flood flows, as well as in the evaluation of the flood occurrence risks for specific return periods. The hydrological risk is typically considered during the design process of any hydraulic infrastructure (Ojha, Berndtsson, & Bhunya 2008), such as a bridge or a dam, due to the aforementioned uncertainties (Subsection 2.2.3).

The designer is generally concerned with the return period for which the infrastructure should be designed. Based on the acceptable risk and on the design life (n) of an hydraulic infrastructure, the return period for which the structure should be designed can be ascertained.

Hydrological risk (R) is thus defined as the probability of occurrence of an event at least once $\left[P(X \geq x_T)\right]$ over a period of n successive years (see Equation 1).

$$\begin{aligned} R &= P(X \geq x_T) \\ &= 1 - \left(1 - \frac{1}{T}\right)^n \end{aligned} \tag{1}$$

3 | CASE STUDY AND DATABASE

3.1 | Case study framework

In Portugal, the persistence of discharge peaks exceeding 8,000 m^3s^{-1} in a three-months period have contributed to the collapse of the 19^{th} century Hintze Ribeiro bridge on the night of 4 March 2001, during the fifth flood event over the Douro river. This tragic accident has caused the death of 59 people who were crossing the bridge, in a bus and three cars, when one of its piers collapsed and the central sections plunged into the river.

The 19^{th} century Hintze Ribeiro bridge was built in 1885 and linked Castelo de Paiva and Entre-os-Rios. Following the disaster, preliminary studies were planned for the rehabilitation of the 19^{th} Hintze Ribeiro bridge, considering the importance of maintaining the crossing at the lower Douro level, particularly for those local populations. However, the underwater inspections undertaken promptly excluded that hypothesis and in April 2001 the Portuguese government announced the tendering procedure for the construction of the new bridge over the Douro river. The old bridge was, thus, replaced by the new Hintze Ribeiro bridge, inaugurated in May 2002, 7.5 m upstream of the old bridge's position (Figure 1).

The severe socio-economical impact of the collapse of the 19^{th} century Hintze Ribeiro bridge dictated its importance for the purposes of the current study, providing data and highlighting the importance for reliable estimates of extreme discharge flows and their occurrence probabilities at the new bridge's approach section.

3.2 | Hydrographic region characterization

The Portuguese region of the Douro watershed, representing 19.07% of its total area (97,477.66 km^2), is characterized by embedded valleys, strong riverbed slopes and overly narrow floodplains (APA 2019). As a result, the extraordinary floods of the Douro river are characterized by a strong water level rise, especially in the narrowest sections, with fast hydrological response and for a short duration of about 2 to 3 days (APA 2016). The highest flood peaks took place in the years of 1727, 1739, 1779, 1788, 1823, 1843, 1850, 1855, 1860, 1877, 1888, 1909 and 1962 (Silva & Oliveira 2002), all of which caused great damage to farms, long-distance ships, coastal, fishing vessels and river traffic, and loss of human lives. Since 1989, there have been no floods of a magnitude equal to or greater than 10,000 m^3s^{-1} (Rodrigues, Brandão, Costa, et al. 2003). The 1739 flood, with a recorded a value of 18,000 m^3s^{-1}, was not exceeded until now. The historical flood data collection and compilation, although mostly empirical, is an indispensable basis for establishing danger trends or flood-related disasters (Tato 1966; Vieira & Costa 2017), as occurred with the collapse of the 19^{th} century Hintze Ribeiro bridge in 2001.

The new Hintze Ribeiro bridge lies 500 m from the mouth of the Tâmega river (at the confluence with the Douro river), a right tributary of Douro river (Figure 2). The bridge section is located in the downstream reach of the Douro river, at the Crestuma-Lever dam reservoir (at a distance of 25.5 km). Upstream of the bridge section are the Torrão dam, on the Tâmega river, at a distance of 3.8 km, and the Carrapatelo dam, on the Douro river, at 16.7 km from the bridge. The Paiva river, a left tributary of Douro river, also contributes to the flow rates that approach the new Hintze Ribeiro bridge, through the records of "Fragas da Torre (EDP) (08H/02H)" gauging station (Figure 2).

3.3 | Hydrometric data collection

In the Douro river watershed, a real-time hydro-metereological network is operating since the beginning of the 20^{th} century (Tato 1966; Vieira & Costa 2017). Since 2012, its management is under the responsibility of the "Portuguese Environment Agency" (APA). The availability of streamflow data at gauging stations, located in the vicinity of the new Hintze Ribeiro bridge, represent indeed an important tool towards the assessment of the design floods that approach such bridge section. Those gauging stations are identified as follows:

(i) “Crestuma Dam (EDP) (07G/01A)”;

(ii) “Carrapatelo Dam (EDP) (07I/01A)”;

(iii) “Torrão Dam (EDP) (07H/01A)”;

(iv) “Fragas da Torre (EDP) (08H/02H)”.

The estimates of natural affluences to a reservoir, e.g. Crestuma-Lever reservoir, are subject to some uncertainties, mainly related to the estimate of water volumes flowing into the reservoir, either from fluvial flows or from direct precipitation, as well as the estimation of the effluent flows from the reservoir, corresponding to the supply, to evaporation losses, and other losses (Portela & da Silva 2014). In addition to such issues, the stream of the Douro river, which meanders along the 25.5 km separating the case study bridge and the Crestuma-Lever dam, is highly dependent of the discharges from the dams situated upstream of the bridge, Torrão and Carrapatelo dams, and the flow from the Paiva river (from records of item (iv)). Therefore, streamflow data from the “Crestuma Dam” (item (i)) gauging station was no longer considered.

Streamflow data, mean daily and instantaneous flow data, were taken from the “Water Resources Information System” (SNIRH, Portugal) platform and were made accessible by “Energias de Portugal” (EDP, Portugal), the Portuguese entity responsible for the management of the dams considered, respectively. Table 1 summarizes the data availability and the periods of required extrapolation.

3.4 | Hydrological modeling hypothesis

The resulting flow discharge approaching the new Hintze Ribeiro bridge was herein considered by combining the contributions of the three aforementioned gauging stations (items (ii) to (iv) mentioned in subsection 3.3). In light of the hydrographic location of the bridge, the resulting flow discharge approaching the new Hintze Ribeiro bridge was the direct sum of the flow discharges from the three gauging stations.

Following individual analyses to the preponderance that each gauging station plays on the approach flow discharges at the bridge section, the proposed direct sum hypothesis resulted in more conservative values. As such, this was selected as the modeling hypothesis. This combination assumes the temporal coincidence of flood peaks between the three gauging stations' records and simultaneously disregards the streamflow losses and gains between those stations and the bridge section. Figure 3 plots the maximum annual discharges from the mean daily values for the coincident recording years, i.e. from 1988/89 to 2018/19, comprising a total number of 31 hydrological years.

3.5 | Hydrological scenarios definition

By using the assumption of direct sum, four possible hydrological scenarios were considered to evaluate the maximum annual flow discharge approaching the new Hintze Ribeiro bridge (Q_{HR}) - Table 2.

The total flow rate was determined through the sum of the aforesaid records: $Q_{HR} = Q_C + Q_T + Q_{FT}$, where Q_C, Q_T and Q_{FT} stand for the streamflows extracted from the gauging stations “Carrapatelo Dam (EDP) (07I/01A)”, “Torrão Dam (EDP) (07H/01A)” and “Fragas da Torre (EDP) (08H/02H)”, respectively, either mean daily or instantaneous data. Table 2 summarizes how Q_{HR} was assessed, as well as the database under consideration.

Scenario 0 was promptly unconsidered due to the rejection of the hypothesis of homogeneity, since the hydrological time series of streamflow data, from the three gauging stations, do not follow the same statistical distribution.

Despite the rich vein of information available in the online platform SNIRH, often neither instantaneous data nor reliable records are available for a long period of time. Scenario 2, even though not as conservative as Scenario 1, seems to be a reasonable approximation of the reality. Since no account are taken of the streamflow losses and gains between the gauging stations, Scenario 2 may underestimate the approach flow to the new Hintze Ribeiro bridge.

Scenario 3, in turn, represents undoubtedly the more conservative scenario since it considers all exceptional flow rates occurred at the approach section of the new Hintze Ribeiro bridge.

4 | RESULTS AND DISCUSSION

4.1 | Data analysis and extrapolation

Some data gaps in the mean daily records from the three gauging stations were filled in order to guarantee data continuity (on the mean daily series) for Scenario 2. Such task was performed through application of a linear regression function for either one or two consecutive gap days. For three or more consecutive data gaps, a linear correlation was applied to the records of the station under study with its neighboring station records.

After analyzing the historical time series with regard to record length and quality of data, only records from the period between 1988/89 to 2018/19 were considered for further analysis, namely flood frequency analysis (ensuring the minimum required sample size of 30 years). As indicated in Table 1, from 1988/89 to 2008/09, the instantaneous streamflow data for "Carrapatelo Dam (EDP) (07I/01A)" and "Torrão Dam (EDP) (07H/01A)" were not available. For that period, an extrapolation of the missing instantaneous discharge data was needed.

Hence, the extrapolation of the missing instantaneous discharge data was derived by factoring the corresponding mean discharge in that year by a coefficient of proportionality (K). This coefficient was the result of averaging the yearly instantaneous discharge to mean discharge ratio ($Q_{instantaneous}/Q_{mean}$), for the available 10 hydrological years). Coefficients of proportionality of $K_C = 1.322 \pm 0.138$ ($\sigma = 0.222$) and $K_T = 1.568 \pm 0.190$ ($\sigma = 0.306$) were obtained for the hydrological time series of Q_C and Q_T, respectively. These coefficients were applied to the respective maximum annual mean daily discharges (Q_{mean}) to estimate the associated instantaneous data. For these cases, the adoption of different discharge classes for the estimation of K did not seem to influence the estimates. The limited size of the sample precludes its application, since what could be gained in differentiation would be lost in increased sample error, and consequent uncertainty. In order to validate the developed approach of estimating the instantaneous missing data, this technique was verified by two distinct methods (herein designated *Method A* and *Method B*). For that purpose, the resultant value for K_T was considered; a similar procedure can be performed for the Q_C case.

Method A - The magnitude of K_T was compared with the one obtained from the records of a neighboring station of "Torrão Dam", namely the gauging station of "Fridão (R.E.) (06I/03H)", for which both mean and instantaneous streamflow data were accessible.

Method B - The construction of the flow-duration curves, representative of the 10 years of available mean and instantaneous data, allowed for another estimate of K_T.

Regarding the application of *Method A*, the approach herein developed resulted in an coefficient of $K_F = 1.511 \pm 0.095$ ($\sigma = 0.270$) for the "Fridão (R.E.) (06I/03H)" gauging station. For this station, a total of 25 hydrological years of records was considered for the ratio $Q_{instantaneous}/Q_{mean}$ (Figure 4 - discharges were sorted in descending order based on the mean daily data). Also for this case, no classes were considered for the estimation of that coefficient due to the limited data sample size for an adequate statistical procedure. Besides the similar order of magnitude of the obtained proportional coefficients (K_T and K_F), the different sample sizes explain the lower sample error obtained for the "Fridão (R.E.) (06I/03H)" time series data.

In regard to *Method B*, the 10 years of available mean daily and instantaneous data for Q_T (indicated in Table 1) were used in obtaining the correspondent flow-duration curves (Figure 5). The flow-duration curve of the mean daily data presents an expected behavior. The same is not true for the instantaneous records, at least to some extent. If we revisit the function of these curves, their construction for instantaneous flow regimes is not usual. Such curves indicate the number of days in which a given flow discharge (Q_{mean} or $Q_{instantaneous}$) has been exceeded or equalized in that 10-year period of records.

A minimum mean daily discharge of 242.21 m^3s^{-1} was registered in the 2011/12 hydrological year, whereas a minimum instantaneous discharge of 322.66 m^3s^{-1} was attained in 1998/99. In order to cope with the strange behavior of the instantaneous flow-duration curve, the coefficient of proportionality (K_T) was considered for two separated instances: (i) the minimum mean daily discharge, and (ii) minimum instantaneous discharge. The former was reached and exceeded for 25 days, while the second was exceeded in 35 days of the year. Following these thresholds, the resultant coefficients of proportionality from the "Torrão Dam" gauging station data were: (i) $K_T = 1.474 \pm 0.018$ ($\sigma = 0.045$), and (ii) $K_T = 1.481 \pm 0.013$ ($\sigma = 0.040$). The flow-duration curves for the second limit (ii) are plotted in Figure 6. These curves do not represent annual duration. Rather, they correspond to 35 annual days from the 10 representative years, and present a sufficiently acceptable behavior to trust the estimated proportionality coefficients (very similar estimates for (i) and (ii)).

Another way to establish these limits is to impose the base flow for this watercourse, the Tâmega river. However, such information was not available on SNIRH's online platform. It is known that the base flow of Douro river is about 500 m^3s^{-1}, and that the affluence of Tâmega river represents 14.5% of the Douro river discharge in the bridge area. Therefore, it is reasonable to conclude that the base flow of Tâmega river is much lower, possibly in the order of the minimum mean daily discharge, as previously referred.

An additional verification was undertaken. The availability of mean daily and instantaneous Q_{FT} records for the same 10-year time period (from 2009/10 to 2018/19) allowed the quantification of the associated discrepancy, through the comparison of estimated and recorded instantaneous streamflow data. For that purpose, the coefficient of proportionality was estimated for the "Fragas da Torre" gauging station data, using the available sample of 66 hydrological years (Table 1). A value of $K_{FT} = 1.621 \pm 0.075$ ($\sigma = 0.316$) was obtained for Q_{FT} data. By imposing that coefficient to the mean daily data for the aforementioned 10-year period, new instantaneous discharge values were estimated, showing an average over-prediction of 7.2% when compared with the recorded data (Figure 7). Therefore, for the purposes of the current investigation, the estimated coefficients of proportionality for the Q_T and Q_C data were deemed to be conservative estimates of reasonable order of magnitude.

4.2 | Reliability analysis and scenario selection

Regarding the data reliability analysis, the verification of consistency and the hypothesis of randomness of the three hydrological time series were performed. The verification of consistency was not an issue, since there were neither changes in the location of the gauging stations nor the creation of obstacles nearby. The hypothesis of randomness was analyzed through the tests referred in subsection 2.1, following the procedures outlined in Hipólito and Vaz (2011). The hypothesis of randomness was thus satisfied for all the three scenarios, since the assumptions of independence and homogeneity were confirmed.

The hydrological scenarios, considered to evaluate the maximum annual flow discharge approaching the new Hintze Ribeiro bridge (Q_{HR}), are depicted in Figure 8 in the form of box-plots graphs, which include the median, and the lower and upper quantiles (defined as the 25^{th} and 75^{th} percentiles) for each of the scenarios. The long upper tails show the lack of symmetry in the data values for all of the scenarios. The red plus signs are outliers that should be investigated carefully. In the current study, they are all mild outliers and contain trustful information; for Scenario 3, for instance, the higher outlier corresponds to the 1989 flood, referenced in subsection 3.2, with a magnitude of 14,597.05 m^3s^{-1}.

It is relevant to note that, when compared with the Scenario 1, Scenario 2 leads to lower resultant discharge values (Q_{HR}). In practice this behavior have led us to the conclusion that flood peaks do not coincide in all rivers, namely Douro, Tâmega and Paiva rivers. Scenario 1 is more conservative, but less realistic. However, this difference is not significant, representing solely an over-prediction of 6.3% of the mean value (as indicated in Table 3). As expected and previously mentioned (Subsection 3.5), Scenario 3 is clearly the one which contains the higher discharge values. It over-predicts the Scenario 1 mean discharge value in a percentage of 26.8%. Further statistics for each scenario are given in Table 3.

Bearing in mind the main objective of the current study, providing a reliable estimate of extreme flow discharges at the bridge's approach section, the scenario that led to higher floods was desired and Scenario 3 was thus the one selected for the following analyses.

4.3 | Probabilistic models' performance

The frequency of flood events, considering the peak discharge and return period, was statistically analyzed by individually employing the seven parametric distributions referred in subsection 2.2.1. Seven different return periods were considered: $T = 2, 5, 10, 20, 50, 100, 500$ and 1000 years. The methods of moments and the L-moments were used to estimate the parameters of the aforementioned distributions. The performance of these probabilistic models was assessed by the goodness-of-fit tests (KS, χ^2, Fi and AD), as well as by the corresponding Q-Q plots.

The models with potential for the design floods estimation were the two- and three-parameter LogNormal distributions, the Gumbel distribution, and the Gamma distribution. The estimated design floods, computed with the free Matlab code developed by Benkaci (2019), are presented in Table 4. From the goodness-of-fit tests, only the qualitative χ^2 test did not give satisfying results for the Log-Normal ($3p$) distribution and the Gumbel distribution; however, these two were also accepted as potential representatives of the data time series under analysis (Scenario 3), since the remaining tests did not reject them. The graphical adjustments of those four probabilistic distributions of the maximum annual flow discharge approaching the new Hintze Ribeiro bridge (given by Q-Q plots) are shown in Figure 9. It should be noted that the design floods (Table 4) were estimated at a 95% confidence level, in which the upper and the lower boundaries are represented by dashed borderlines in Figure 9.

The Q-Q plots were built by using the empirical Weibull plotting position for all the distribution models, except for the Gumbel distribution, in which the Gringorten formula was selected. Figure 9 shows that the aforementioned four parametric distributions may produce satisfying results for Scenario 3 and that the Gamma distribution is the best fit for the available data (model selection, MS). The Gamma distribution not only passed the four goodness-of-fit tests, but also returned the highest correlation coefficient ($R = 0.979$). Despite the good performance of the Gamma distribution, the current study also considered an arithmetic average of the considered candidate models in order to reduce the model uncertainty, especially due to the available record length of only 31 hydrological years.

4.4 | Uncertainty and modeling approaches

In order to take model uncertainties into account and thus reduce some of the epistemic uncertainties (reducible uncertainty), the weighted averaging technique was also considered in the present study. For the purposes of this investigation, only the arithmetic model averaging (MM) approach was considered.

The design floods estimated by both approaches are given in Table 5. The MS design floods ranged from 3,986 m^3s^{-1} for $T = 2$ years of return period to 27,247 m^3s^{-1} for $T = 1{,}000$ years, whilst for the MM approach, the flood events varied between 3,925 m^3s^{-1} and 36,616 m^3s^{-1} for the same return periods, respectively. In spite of the record length of only 31 historical records, the obtained flood designs included the major floods registered in the Douro valley. The 1739 flood corresponded roughly to the design flood reached for $T = 50$ years in the MM approach. The first hydraulic infrastructure situated downstream of the case study bridge (Crestuma-Lever dam) was designed to withstand a discharge flow of 26,000 m^3s^{-1} for a correspondent return period of $T = 1{,}000$ years, in close proximity to MS estimate.

A "relative difference" between the MM and MS approaches was computed and it is indicated in Table 5. For return periods ranging from 20 to 1,000 years, the "relative difference" varied between 3.1% and 25.6%. For $T = 2$ to 10 years, the MM approach slightly underestimated the flood designs in comparison to the MS approach. Higher differences between the approaches, MS and MM, are expected for increasing return periods.

In other to get further insight the accuracy of the modeling approaches herein considered, both parametric representations (MS and MM), a non-parametric approach was also applied. A Kernel density estimate (KDE) is a non-parametric way of estimating the probability density function of a random variable (Apipattanavis, Rajagopalan, & Lall 2005; Lall, Moon, & Bosworth 1993), in this case, the maximum annual discharges that approach the new Hintze Ribeiro bridge. It constitutes a fundamental data smoothing problem where inferences about the hydrological series are made, based on a finite data sample size. Such estimates are closely related to histograms; the histogram of the Scenario 3 data time series is presented in Figure 10.

Figure 10 gives thus an idea of the frequency of the flood events, as well as their magnitudes, occurred at the bridge approach section along the 31 hydrological years (from 1988/89 to 2018/19). Regarding the standard deviation (σ) and the record length of the data series (n_s), estimates for the suitable Kernel bandwidth (h) can be computed through the rule-of-thumb formula (Silverman (1986), Equation 2), as well as by a variant in order to better fit tailed and skewed distributions of data (Equation 3).

$$h = \left[\frac{4\sigma^5}{3n_s}\right]^{-\frac{1}{5}} \tag{2}$$

$$h = 0.9 \min\left[\sigma; \frac{IQ}{1.34}\right] n_s^{-\frac{1}{5}} \tag{3}$$

Kernel bandwidths of 0.14 and 0.15 were obtained by equations 2 and 3, respectively, so a value of 0.15 was assumed for the Kernel optimal bandwidth, represented in Figure 11. The empirical cumulative distribution function (CDF) of the data series is also shown in Figure 11. The long stair-step, in Figure 11, ranging from the flow rate of 7,592 m^3s^{-1} to 11,559 m^3s^{-1} was due to the nonexistence of records within that interval. This situation is corroborated with the histogram of the Scenario 3 data time series, shown in Figure 10.

Figure 12 displays the cumulative density functions of the Scenario 3 data time series obtained by the parametric and non-parametric models from 2 to 1,000 years of return period. It is noticeable a general over-prediction of the parametric probabilistic models in relation to the Kernel density estimate, specially for the period ranging from $T = 5$ years to $T = 10$ years. The design flood values estimated by the parametric approaches, MS and MM, were compared with the correspondent values retrieved by the non-parametric approximation of Kernel density estimate (as previously performed in Table 5) and those relative differences are displayed in Figure 13 in the form of bar-graphs.

Figure 13 comprises a shorter range of return periods due to the available Kernel estimates (maximum return period of 23 years). Nevertheless, it can be concluded that all four probabilistic distributions exhibited a very similar design flood for $T = 10$

years, over-predicting the non-parametric approach at about 15.5%. For $T = 2$ years, the Gumbel distribution showed the highest percentage of relative difference (circa 26.5%). By neglecting the relative differences encountered for a return period of 10 years (which roughly corresponds to the magnitudes range with no records), the resulting MM approach prediction is -2.24%. This represents a reduction of 18.5% when compared to the MS approach prediction of -2.75%. The conclusion that can be drawn from the above information (Figures 12 and 13) is that for the range analyzed (until roughly $T = 20$ years of return period), the behaviors of the parametric approaches (individual and averaging models) were very similar and followed the non-parametric trend, justifying, this way, the validity of all four models in fitting the given data, i.e., through the MM approach. The exception arose for the aforementioned range, in which there were no records of flood events within the 31-hydrological years considered in this study. Nonetheless, all the parametric functions predicted the correspondent design floods on the safety side.

By assuming the typical 50 years for the expected design life of the new Hintze Ribeiro bridge, different return periods could be plausibly used, depending on the acceptance risks, through the application of Equation 1. Whereas a 100-year return period of the design flood event corresponds to a risk of 40%, the flood associated to 1000 years of return period presents a hydrological risk of 5%. It should be noted that the adopted return period as a design criterion, and associated design flood, also plays a significant role on the assessment of admissible scour risk (i.e., maximum scour depths at the bridge foundations level) for the bridge structural stability.

5 | CONCLUSIONS

A hydrological modeling methodology is herein presented that uses the flood frequency analysis technique allied to parametric and non-parametric approaches for providing reliable estimates of design floods that approach hydraulic infrastructures. The new Hintze Ribeiro bridge, over the Douro river, in Portugal, was selected as case study. The frequency analysis is also relevant for the assessment of the hydrological risk considered, or to be adopted, as a design criterion of those infrastructures.

The extrapolation of the missing instantaneous discharge data was herein derived by factoring the corresponding mean discharge in that year by a coefficient of proportionality (K). This procedure was key to satisfy the minimum required sample size for the application of the flood frequency analysis technique on hydrological time series data. Such extrapolation was performed to obtain the “Carrapatelo Dam” and “Torrão Dam” instantaneous data. Two validation methods verified the output, including the associated sample errors, and consequent uncertainties of their estimations. The associated discrepancy between estimated and recorded instantaneous data is an over-prediction of 7.2%. Thus, the estimated coefficients of proportionality for the Q_T and Q_C data were deemed to be conservative estimates of reasonable order of magnitude.

A variety of probabilistic models were considered in the assessment of the maximum annual flow discharges at the bridge approach section, and the models' performance verified by the goodness-of-fit tests and graphical methods (by the Q-Q plots). Besides the widely applied model selection approach (MS, Gamma distribution), in the present work, a modified approach of the arithmetic model averaging (MM) was also performed. In order to take into account the parameter uncertainties, all design floods were estimated at a 95% confidence interval. Contrarily to what performed by Okoli et al. (2019), herein the modified MM approach considered solely the contribution of the probability distributions that fitted well the Scenario 3 data, attributing equal contribution of the candidate probabilistic models on the estimation of the design flood events (four of the distribution models analyzed).

While slight differences were observed between the two approaches for lower return periods, for return periods higher than 20 years, the approaches become increasingly different. The proposed arithmetic model averaging (MM) approach was therefore entirely justified to cope with the model uncertainties. An additional analysis was performed by comparing both of the parametric representations (MS and MM) with a non-parametric approach, the Kernel density estimate (KDE). Unlike its parametric counterparts, no prior assumption of the underlying distribution was required, which makes it suitable for the assessment of the parametric approaches' accuracy. Despite the shorter range of validity of the Kernel estimates (maximum return period of 23 years), the behaviors of the parametric approaches (individual and averaging models) were very similar and followed the non-parametric trend, justifying the contribution of the all four models in fitting the data under study, through the MM approach. The relative difference between the non-parametric and the MS approach is reduced in 18.5% if the latter is replaced by MM approach results.

Based on the acceptable risk of flood occurrence in specific return periods (hydrological risk), and on the design life of a hydraulic infrastructure, the return period for which a structure should be designed can be ascertained. The selected return period and correspondent design flood also play a significant role on the assessment of admissible scour risk for any bridge structural stability, as for the new Hintze Ribeiro bridge.

ACKNOWLEDGMENTS

The first author thanks the Portuguese Foundation for Science and Technology (FCT) for financial support through the PhD scholarship (PD/BD/127798/2016). This manuscript is an outcome of the Doctoral Program INFRARISK - "Analysis and Mitigation of Risks in Infrastructures". This research was also supported by Centro Interdisciplinar de Investigação Marinha e Ambiental (CIIMAR) through the project with reference UID/Multi/04423/2019. Stream flow data was partly made accessible thanks to "Energias de Portugal (EDP)".

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Ana Margarida Bento orcid.org/0000-0002-8386-807X

References

Anderson, T. W., & Darling, D. A. (1954). A test of goodness of fit. *Journal of the American Statistical Association*, *49*(268), 765-769. doi: 10.1080/01621459.1954.10501232

APA. (2016). Plano de gestão dos riscos de inundações, região hidrográfica RH3 - Douro. Zonas Críticas: Régua, Porto/Vila Nova de Gaia e Chaves. Agência Portuguesa do Ambiente, I.P. *Departamento de Recursos Hídricos*, *PGRI*.

APA. (2019). Avaliação preliminar de risco de inundações, região hidrográfica RH3 - Douro. Agência Portuguesa do Ambiente, I.P. *Departamento de Recursos Hídricos*, *PGRI*.

Apipattanavis, S., Rajagopalan, B., & Lall, U. (2005). Local polynomial technique for flood frequency analysis. *Journal of Hydrology*.

Arneson, L., Zevenbergen, L., Lagasse, P., & Clopper, P. (2012). *Evaluating scour at bridges: Fifth edition (no. fhwa-hif-12-003)* (Tech. Rep.). United States. Federal Highway Administration.

Benkaci, T. (2019). *FFD 2.0.* Retrieved from `https://ch.mathworks.com/matlabcentral/fileexchange/67367-flood-frequency-distribution-ffd-2-0` Accessed: 2019-11-06.

Beven, K. (2006, March). A manifesto for the equifinality thesis. *Journal of Hydrology*, *320*(1-2), 18–36. Retrieved from `https://doi.org/10.1016/j.jhydrol.2005.07.007` doi: 10.1016/j.jhydrol.2005.07.007

Beven, K. (2019). How to make advances in hydrological modelling. *Hydrology Research*, *50*(6), 1481–1494. Retrieved from `https://doi.org/10.2166/nh.2019.134` doi: 10.2166/nh.2019.134

Bumham, K. P., & Anderson, D. R. (2002). *Model selection and multimodel inference: A practical information - theoretic approach*. Springer. Retrieved from `https://www.xarg.org/ref/a/B000QCQT0C/`

Calver, A., Stewart, E., & Goodsell, G. (2009, March). Comparative analysis of statistical and catchment modelling approaches to river flood frequency estimation. *Journal of Flood Risk Management*, *2*(1), 24–31. Retrieved from `https://doi.org/10.1111/j.1753-318x.2009.01018.x` doi: 10.1111/j.1753-318x.2009.01018.x

Castellarin, A., Kohnová, S., Gaál, L., Fleig, A., Salinas, J., Toumazis, A., ... Macdonald, N. (2012). Review of applied-statistical methods for flood-frequency analysis in Europe. *NERC/Centre for Ecology & Hydrology*, *122pp (ESSEM COST Action ES0901)*.

Chow, V. T., Maidment, D. R., & Mays, L. W. (1988). *Applied hydrology*. McGraw-Hill. Retrieved from `https://books.google.pt/books?id=rY_yMgEACAAJ`

Cunnane, C. (1989). *Statistical distributions for flood frequency analysis*. Secretariat of the World Meteorological Organization. Retrieved from https://books.google.pt/books?id=MbcPAQAAIAAJ

D'Agostino, R. B. (1986). *Goodness-of-fit-techniques* (Vol. 68). CRC press.

Dastorani, M. T., Koochi, J. S., Darani, H. S., Talebi, A., & Rahimian, M. (2013). River instantaneous peak flow estimation using daily flow data and machine-learning-based models. *Journal of Hydroinformatics*, *15*(4), 1089–1098.

Filliben, J. J. (1975). The probability plot correlation coefficient test for normality. *Technometrics*, *17*(1), 111–117.

Google Earth. (n.d.). *Google Earth.* https://earth.google.com/web/@41.03823572,-8.2749551,197.80672835a,19361.80108811d,35y,46.03798904h,45.11819578t,0r. Accessed: 2019-12-06.

Hassan, M. U., Hayat, O., & Noreen, Z. (2019, November). Selecting the best probability distribution for at-site flood frequency analysis a study of Torne river. *SN Applied Sciences*, *1(12)*(12). Retrieved from https://doi.org/10.1007/s42452-019-1584-z doi: 10.1007/s42452-019-1584-z

Highways Agency. (2012). *The assessment of scour and other hydraulic actions at highway structures* (Vol. 3(4).; Tech. Rep. No. 3(4).) The Stationery Office London, UK. Retrieved from http://www.standardsforhighways.co.uk/ha/standards/dmrb/vol3/section4/bd9712.pdf

Hipólito, J. R., & Vaz, A. (2011). *Hidrologia e recursos hídricos* (Editora Universitaria do Instituto Superior Tecnico, Lisboa ed.).

Hoeting, J. A., Madigan, D., Raftery, A. E., & Volinsky, C. T. (1999). Bayesian model averaging: A tutorial. *Statistical Science*, *14*(4), 382–401. Retrieved from http://www.jstor.org/stable/2676803

Höge, M., Guthke, A., & Nowak, W. (2019, May). The hydrologist's guide to Bayesian model selection, averaging and combination. *Journal of Hydrology*, *572*, 96–107. Retrieved from https://doi.org/10.1016/j.jhydrol.2019.01.072 doi: 10.1016/j.jhydrol.2019.01.072

Huang, C., Kerenyi, K., & Shen, J. (2018). Incorporation of scour uncertainty to current AASHTO LRFD bridge design specifications. In *Scour and erosion ix: Proceedings of the 9th international conference on scour and erosion (ICSE 2018), november 5-8, 2018, Taipei, Taiwan* (p. 375).

Kendall, M. (1975). *Rank correlation methods, Griffin, London.*

Kenney, J. F., & Keeping, E. S. (1957). *Mathematics of statistics* (Vol. 2). Van Nostrand.

Kiang, J. E., Gazoorian, C., McMillan, H., Coxon, G., Coz, J. L., Westerberg, I. K., … Mason, R. (2018, October). A comparison of methods for streamflow uncertainty estimation. *Water Resources Research*, *54*(10), 7149–7176. Retrieved from https://doi.org/10.1029/2018wr022708 doi: 10.1029/2018wr022708

Kite, G. (2019). *Frequency and risk analyses in hydrology*. Water Resources Publications, LLC. Retrieved from https://books.google.se/books?id=b9OKxAEACAAJ

Kusumastuti, D. I., Struthers, I., Sivapalan, M., & Reynolds, D. A. (2007, August). Threshold effects in catchment storm response and the occurrence and magnitude of flood events: implications for flood frequency. *Hydrology and Earth System Sciences*, *11*(4), 1515–1528. Retrieved from https://doi.org/10.5194/hess-11-1515-2007 doi: 10.5194/hess-11-1515-2007

Lall, U., Moon, Y.-i., & Bosworth, K. (1993). Kernel flood frequency estimators: Bandwidth selection and kernel choice. *Water Resources Research*, *29*(4), 1003–1015.

Leandro, J., Gander, A., Beg, M., Bhola, P., Konnerth, I., Willems, W., … Disse, M. (2019). Forecasting upper and lower uncertainty bands of river flood discharges with high predictive skill. *Journal of Hydrology*.

Lencastre, A. C., Franco, F. M., & Antunes, M. T. (1984). *Lições de hidrologia* (Editora Universitária da Faculdade de Ciências e Tecnologia ed., Vol. Monte da Caparica).

Maity, R. (2018a). Frequency analysis, risk, and uncertainty in hydroclimatic analysis. In *Statistical methods in hydrology and hydroclimatology* (pp. 145–189). Springer Singapore. Retrieved from https://doi.org/10.1007/978-981-10-8779-0{_}5 doi: 10.1007/978-981-10-8779-0_5

Maity, R. (2018b). Hypothesis testing and nonparametric test. In *Statistical methods in hydrology and hydroclimatology* (pp. 191–227). Springer Singapore. Retrieved from https://doi.org/10.1007/978-981-10-8779-0{_}6 doi: 10.1007/978-981-10-8779-0_6

Mann, H. B. (1945). Nonparametric tests against trend. *Econometrica: Journal of the Econometric Society*, 245–259.

Mann, H. B., & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *The annals of mathematical statistics*, 50–60.

Massey Jr., F. J. (1951). The kolmogorov-smirnov test for goodness of fit. *Journal of the American Statistical Association*, *46*(253), 68-78. doi: 10.1080/01621459.1951.10500769

McMillan, H. K., Westerberg, I. K., & Krueger, T. (2018). Hydrological data uncertainty and its implications. *Wiley Interdisciplinary Reviews: Water*, *5(6)*(6). Retrieved from `https://doi.org/10.1002/wat2.1319` doi: 10.1002/wat2.1319

Melville, B. W., & Coleman, S. E. (2000). *Bridge scour*. Highlands Ranch, Colorado: Water Resources Publications. Retrieved from `http://trove.nla.gov.au/work/33270845`

Merz, B., & Thieken, A. H. (2005). Separating natural and epistemic uncertainty in flood frequency analysis. *Journal of Hydrology*, *309*(1-4), 114–132.

Moran, P. A. P. (1957). The statistical treatment of flood flows. *Transactions, American Geophysical Union*, *38(4)*(4), 519. Retrieved from `https://doi.org/10.1029/tr038i004p00519` doi: 10.1029/tr038i004p00519

Naghettini, M., & Pinto, É. J. d. A. (2007). *Hidrologia estatística*. CPRM.

Ojha, C., Berndtsson, R., & Bhunya, P. (2008). *Engineering hydrology*. Oxford university press.

Okoli, K., Breinl, K., Brandimarte, L., Botto, A., Volpi, E., & Baldassarre, G. D. (2018, October). Model averaging versus model selection: estimating design floods with uncertain river flow data. *Hydrological Sciences Journal*, *63 (13-14)*(13-14), 1913–1926. Retrieved from `https://doi.org/10.1080/02626667.2018.1546389` doi: 10.1080/02626667.2018.1546389

Okoli, K., Mazzoleni, M., Breinl, K., & Baldassarre, G. D. (2019). A systematic comparison of statistical and hydrological methods for design flood estimation. *Hydrology Research*. Retrieved from `https://doi.org/10.2166/nh.2019.188` doi: 10.2166/nh.2019.188

Pizarro, A., Manfreda, S., & Tubaldi, E. (2020, January). The science behind scour at bridge foundations: A review. *Water*, *12*(2), 374. Retrieved from `https://doi.org/10.3390/w12020374` doi: 10.3390/w12020374

Portela, M. M., & da Silva, C. d. S. R. (2014). Da regionalização de informação hidrométrica ao dimensionamento de albufeiras de regularização e a análise de incertezas.

Robinson, J. S., Sivapalan, M., & Snell, J. D. (1995, December). On the relative roles of hillslope processes, channel routing, and network geomorphology in the hydrologic response of natural catchments. *Water Resources Research*, *31*(12), 3089–3101. Retrieved from `https://doi.org/10.1029/95wr01948` doi: 10.1029/95wr01948

Rodrigues, R., Brandão, C., Costa, J., et al. (2003). As cheias no douro ontem, hoje e amanhã. *SNIRH, Instituto da Água, Lisboa*.

Rogger, M., Kohl, B., Pirkl, H., Viglione, A., Komma, J., Kirnbauer, R., … Blöschl, G. (2012, August). Runoff models and flood frequency statistics for design flood estimation in Austria – do they tell a consistent story? *Journal of Hydrology*, *456-457*, 30–43. Retrieved from `https://doi.org/10.1016/j.jhydrol.2012.05.068` doi: 10.1016/j.jhydrol.2012.05.068

Rogger, M., Pirkl, H., Viglione, A., Komma, J., Kohl, B., Kirnbauer, R., … Blöschl, G. (2012, May). Step changes in the flood frequency curve: Process controls. *Water Resources Research*, *48*(5). Retrieved from `https://doi.org/10.1029/2011wr011187` doi: 10.1029/2011wr011187

Searcy, J., & Hardison, C. (1960). Double-mass curves. manual of hydrology: Part I, General surface water techniques. *US Geological Survey Water-Supply Paper*, *1541*.

Silva, J., & Oliveira, M. (2002). As cheias na parte portuguesa da bacia hidrográfica do rio douro..

Silverman, B. W. (1986). *Density estimation for statistics and data analysis* (Vol. 26). CRC press.

Simonović, S. P. (2012). *Floods in a changing climate: risk management*. Cambridge University Press.

Sordo-Ward, Á., Bianucci, P., Garrote, L., & Granados, A. (2014, December). How safe is hydrologic infrastructure design? analysis of factors affecting extreme flood estimation. *Journal of Hydrologic Engineering*, *19*(12), 04014028. Retrieved from `https://doi.org/10.1061/(asce)he.1943-5584.0000981` doi: 10.1061/(asce)he.1943-5584.0000981

Stedinger, J. R. (1993). Frequency analysis of extreme events. *in Handbook of Hydrology*.

Tato, J. F. (1966). *As cheias do rio Douro.*

Vieira, A., & Costa, F. d. S. (2017). As inundações do rio Douro em 1909: um contributo para o seu estudo a partir dos arquivos históricos da Agência Portuguesa do Ambiente. *Investigaciones Geográficas*, *53*, 77–92.

Wald, A., & Wolfowitz, J. (1943). An exact test for randomness in the non-parametric case based on serial correlation. *The Annals of Mathematical Statistics*, *14*(4), 378–388.

Wood, E. F., & Rodríguez-Iturbe, I. (1975, December). A bayesian approach to analyzing uncertainty among flood frequency models. *Water Resources Research*, *11*(6), 839–843. Retrieved from `https://doi.org/10.1029/wr011i006p00839` doi: 10.1029/wr011i006p00839

Yan, H., & Moradkhani, H. (2014). Bayesian model averaging for flood frequency analysis. In *World environmental and water resources congress 2014*. American Society of Civil Engineers. Retrieved from `https://doi.org/10.1061/`

9780784413548.189 doi: 10.1061/9780784413548.189

Yen, B. C. (2002, January). System and component uncertainties in water resources. In *Risk, reliability, uncertainty, and robustness of water resource systems* (pp. 133–142). Cambridge University Press. Retrieved from https://doi.org/10.1017/cbo9780511546006.015 doi: 10.1017/cbo9780511546006.015

FIGURE 1 Photograph of the new Hintze Ribeiro bridge (upstream view).

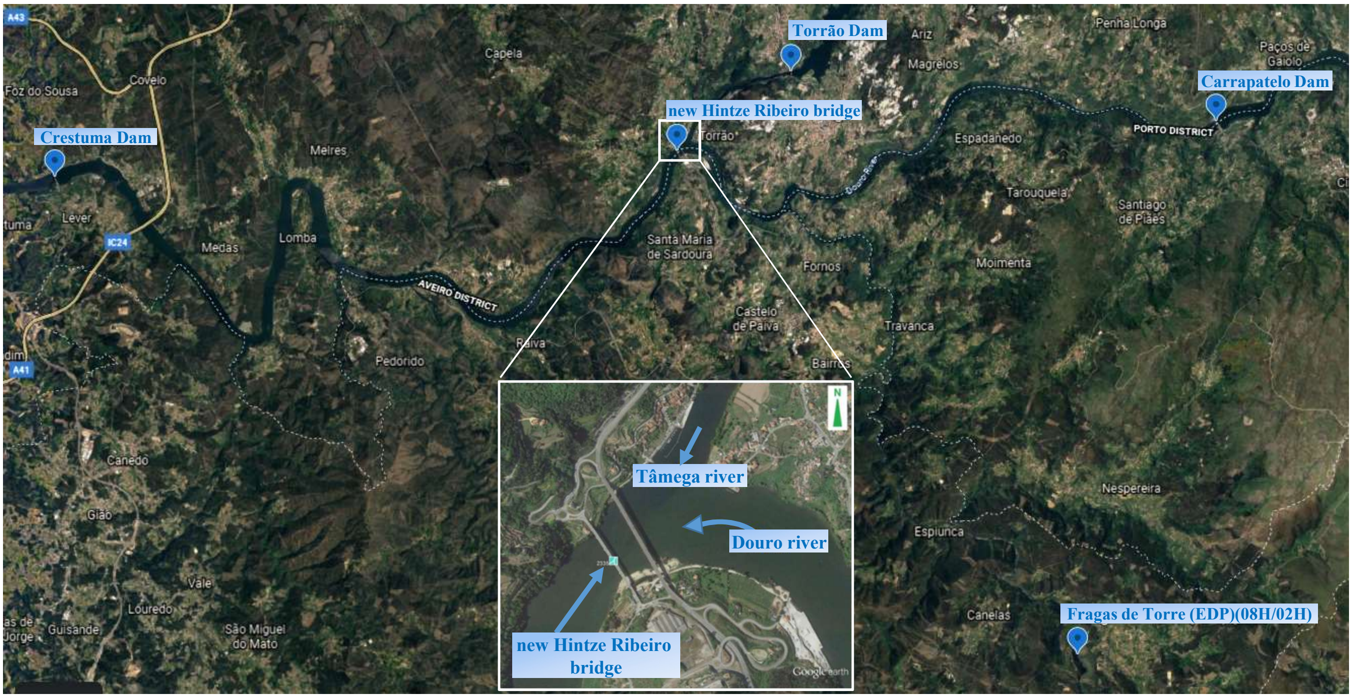


FIGURE 2 Map of the vicinity of the new Hintze Ribeiro bridge, over the Douro river (Google Earth n.d.).

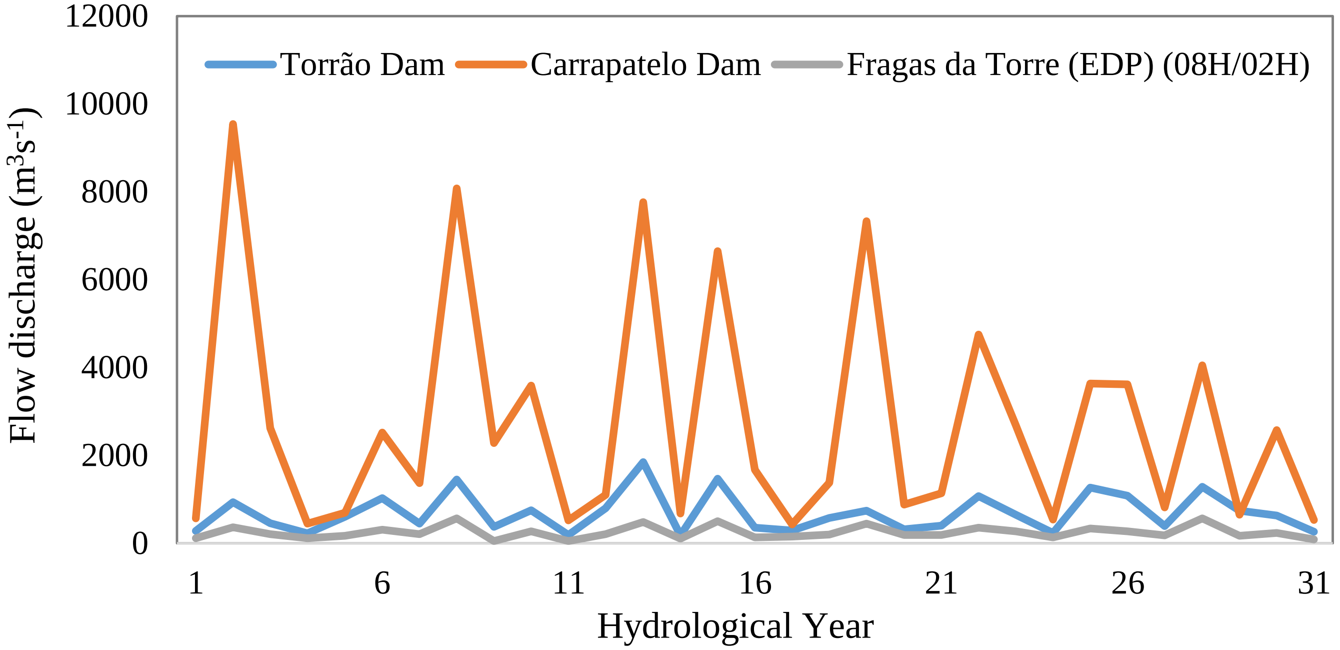


FIGURE 3 Maximum annual flow discharges from the mean daily values for the three gauging stations.

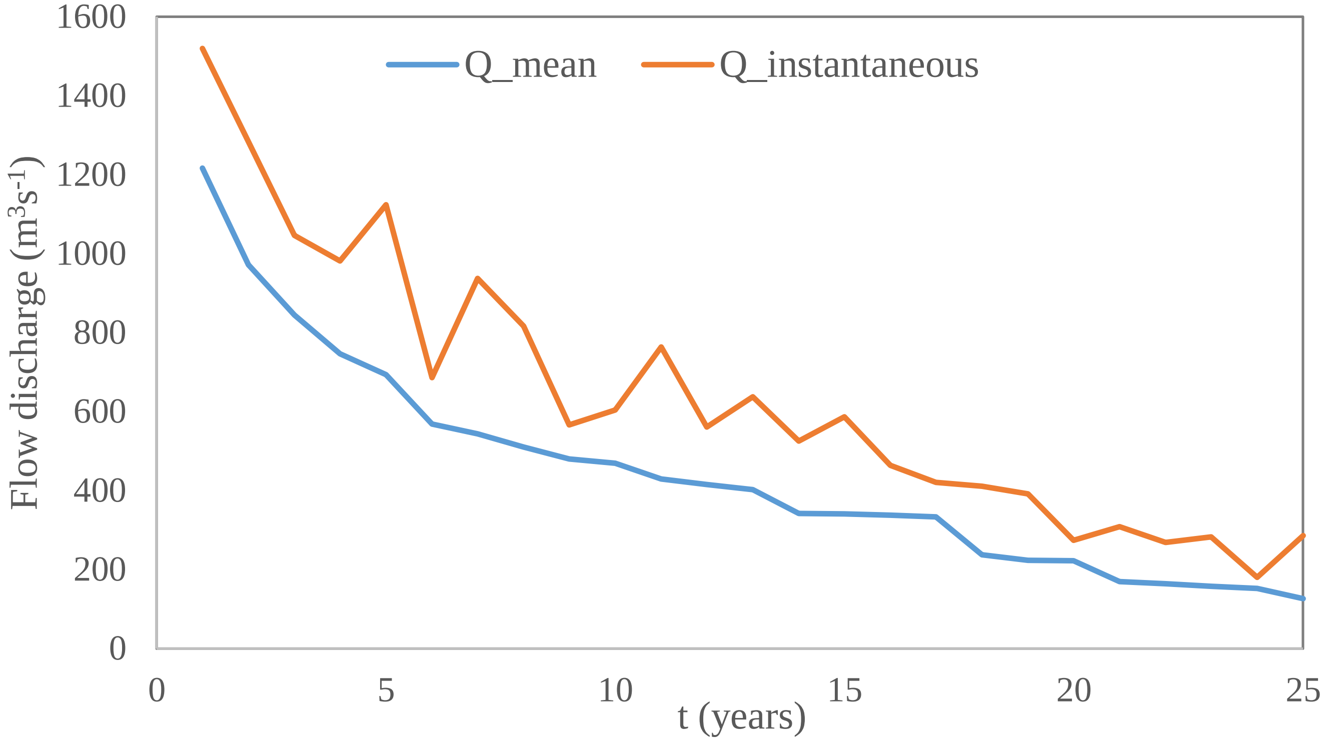


FIGURE 4 Maximum annual mean daily and instantaneous discharges of "Fridão (R.E.) (06I/03H)" gauging station.

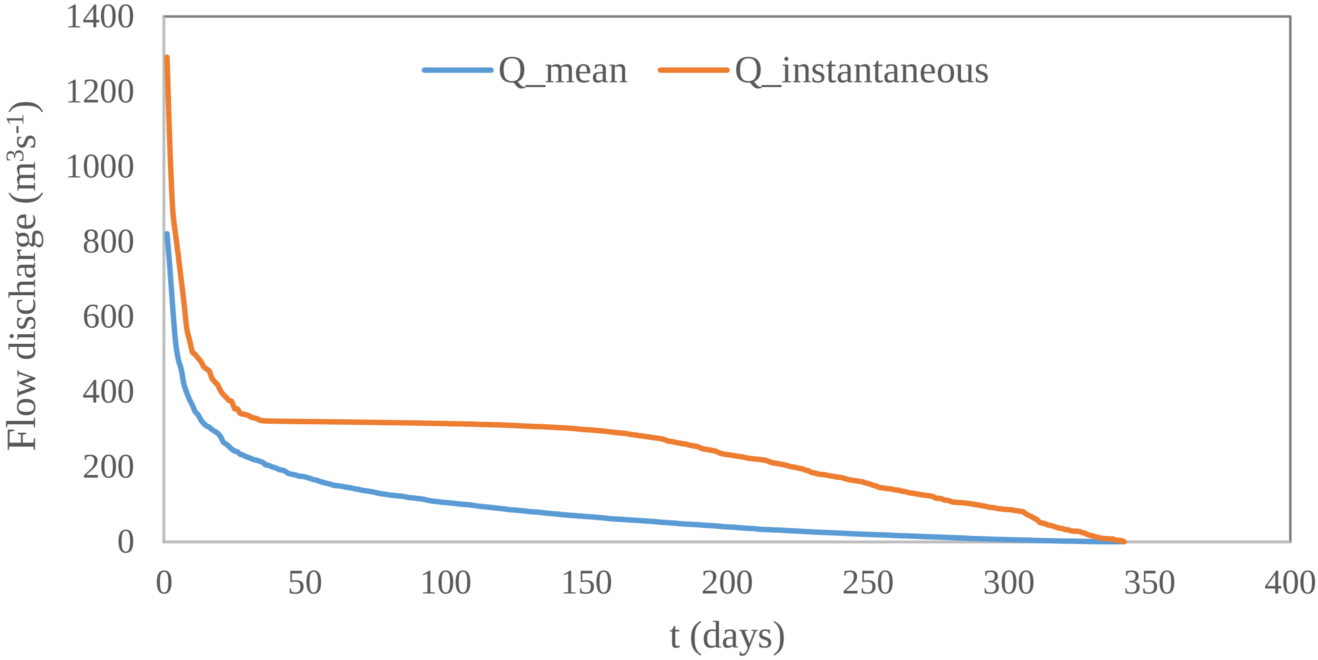


FIGURE 5 Flow-duration curves of mean daily and instantaneous data of Torrão dam gauging station.

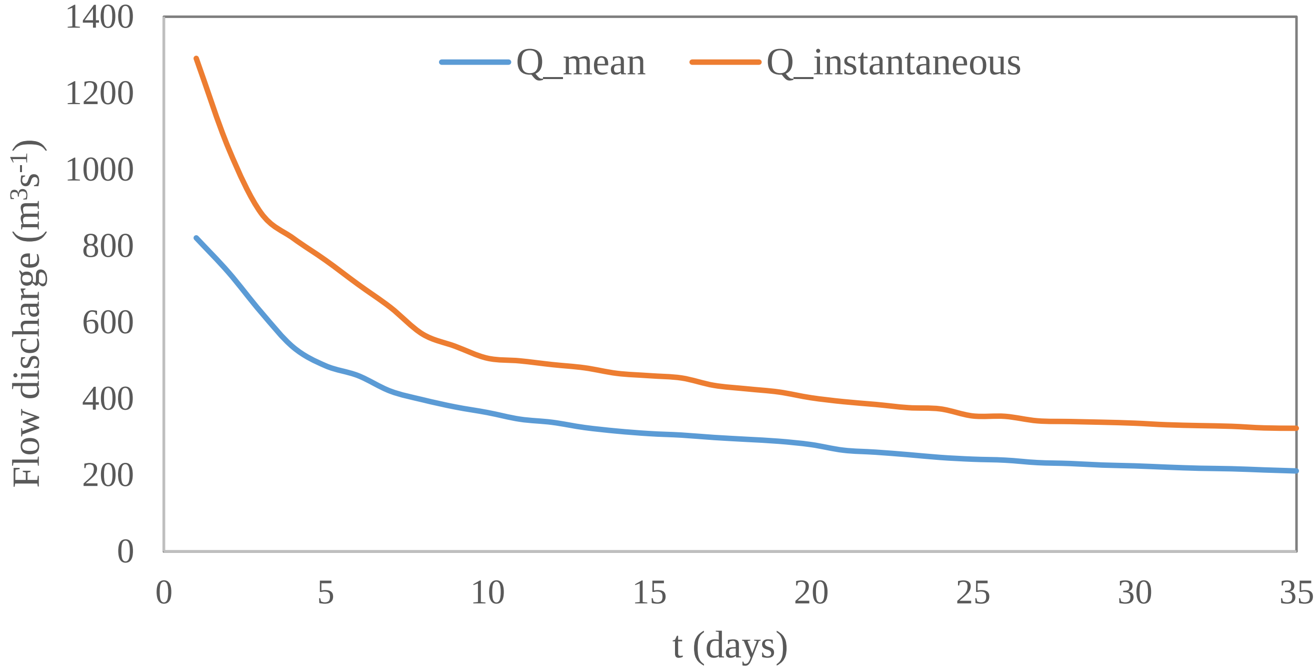


FIGURE 6 Flow-duration curves data considered in the estimation of K_T.

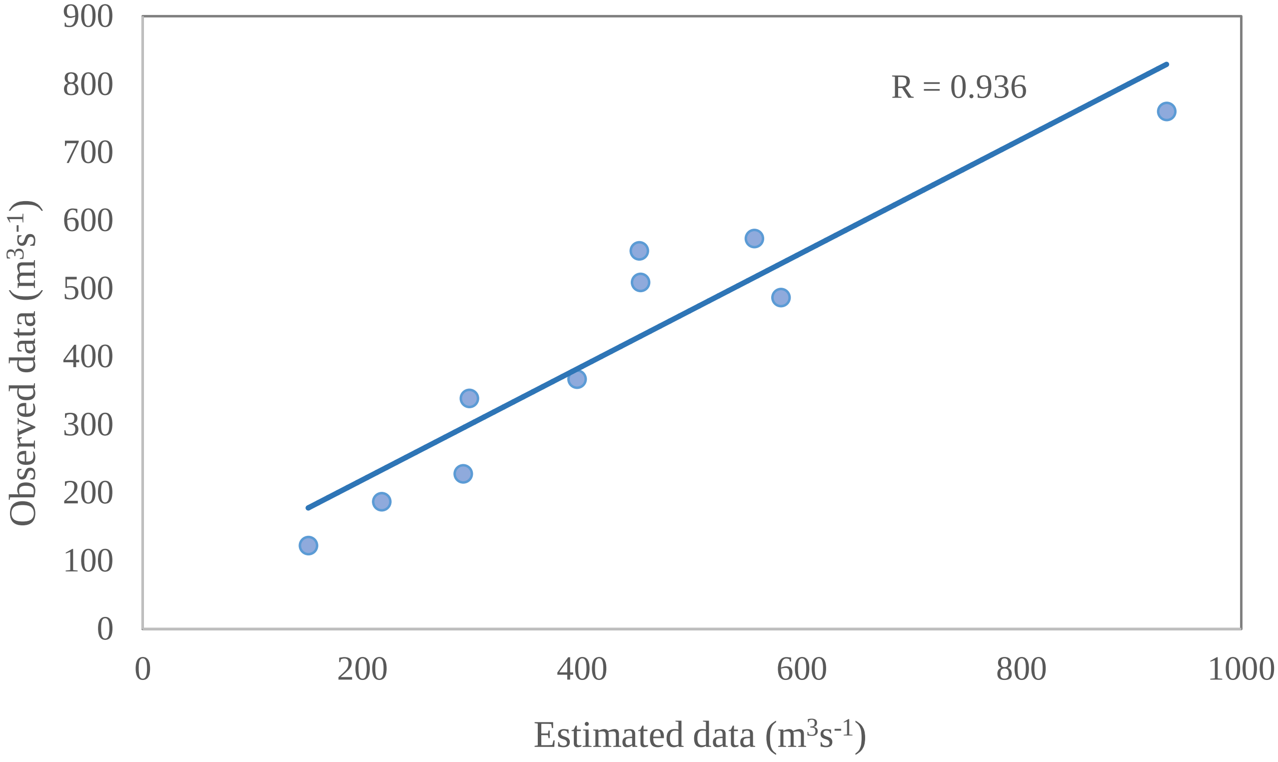


FIGURE 7 Correlation between observed and estimated instantaneous discharge values for Fragas da Torre gauging station.

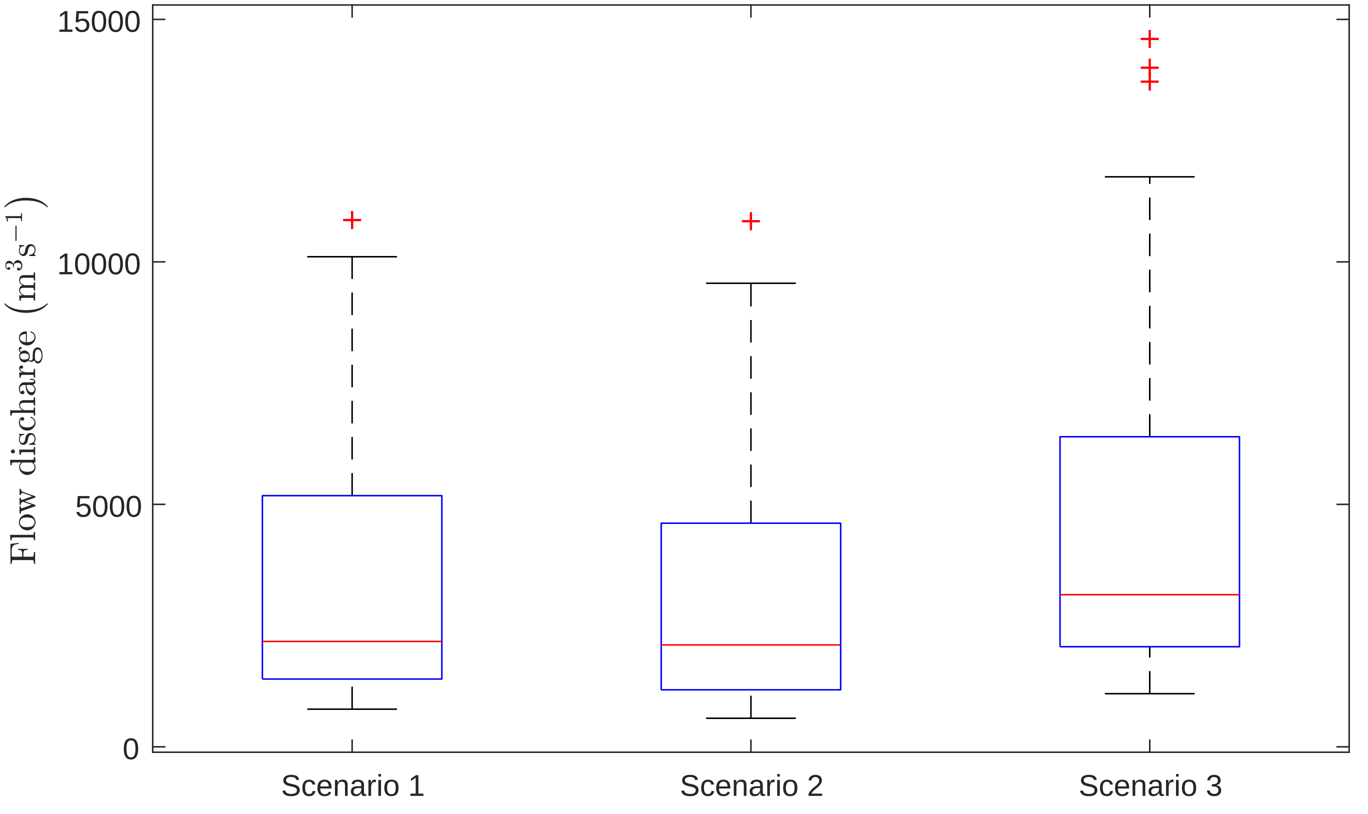
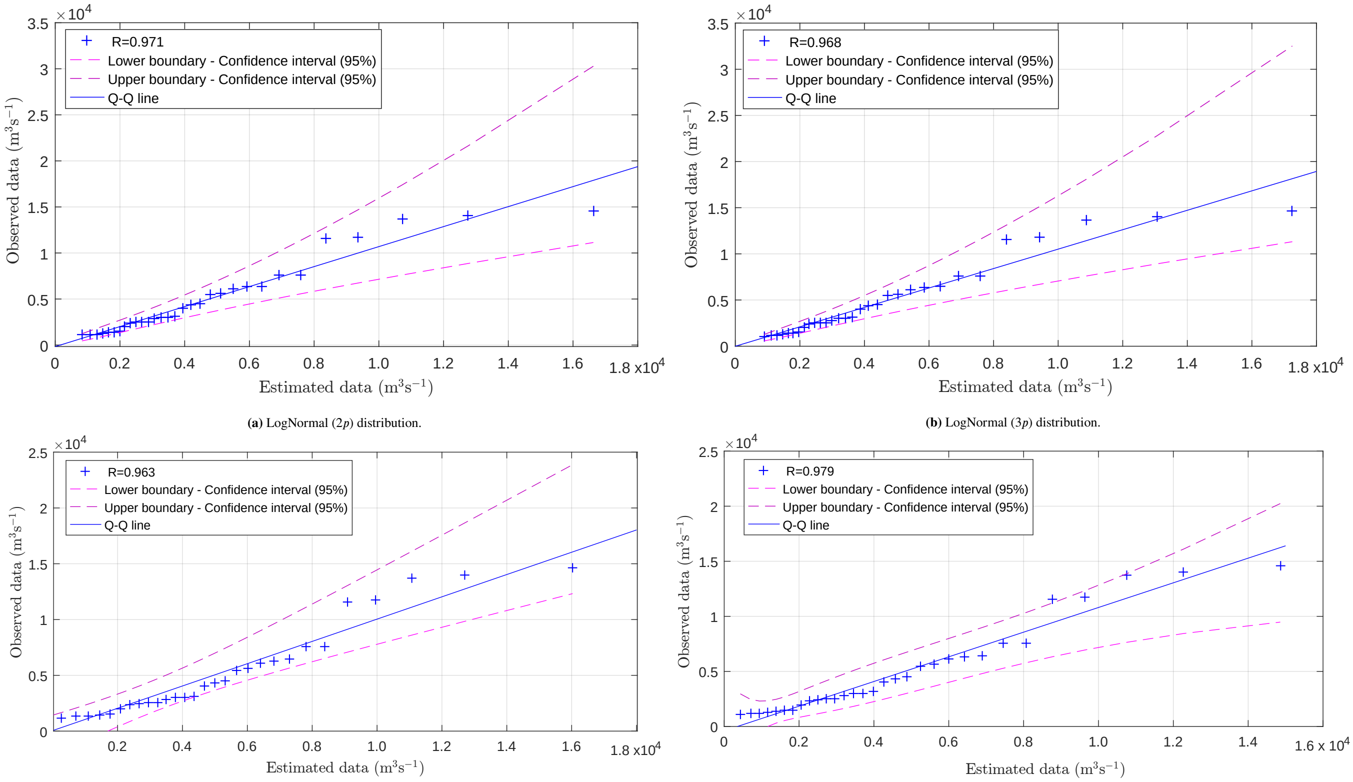


FIGURE 8 Box-plot graphs of Q_{HR} for the hydrological scenarios under consideration.



(a) LogNormal (2*p*) distribution.

(b) LogNormal (3*p*) distribution.

(c) Gumbel distribution.

(d) Gamma distribution.

FIGURE 9 Graphical adjustments (*Q*-*Q* plots) of the four probabilistic distributions to the Scenario 3 data time series.

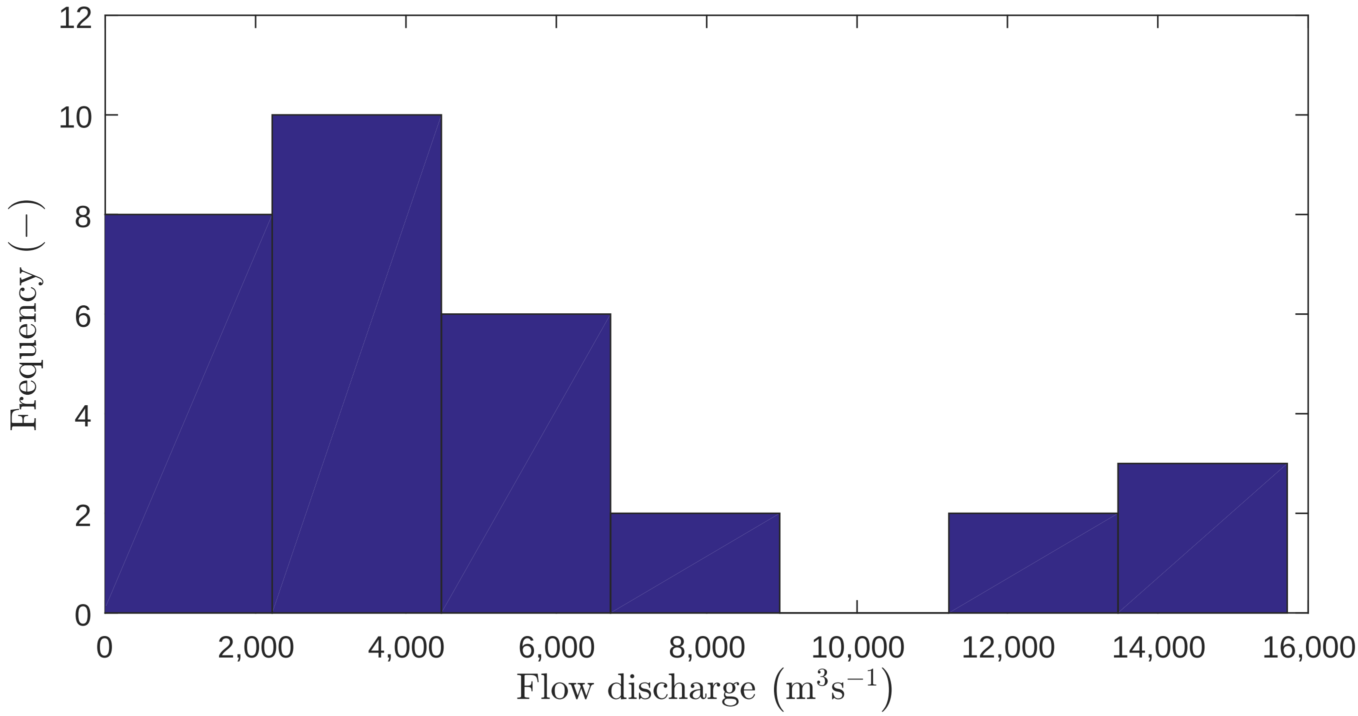


FIGURE 10 Histogram of the Scenario 3 data time series.

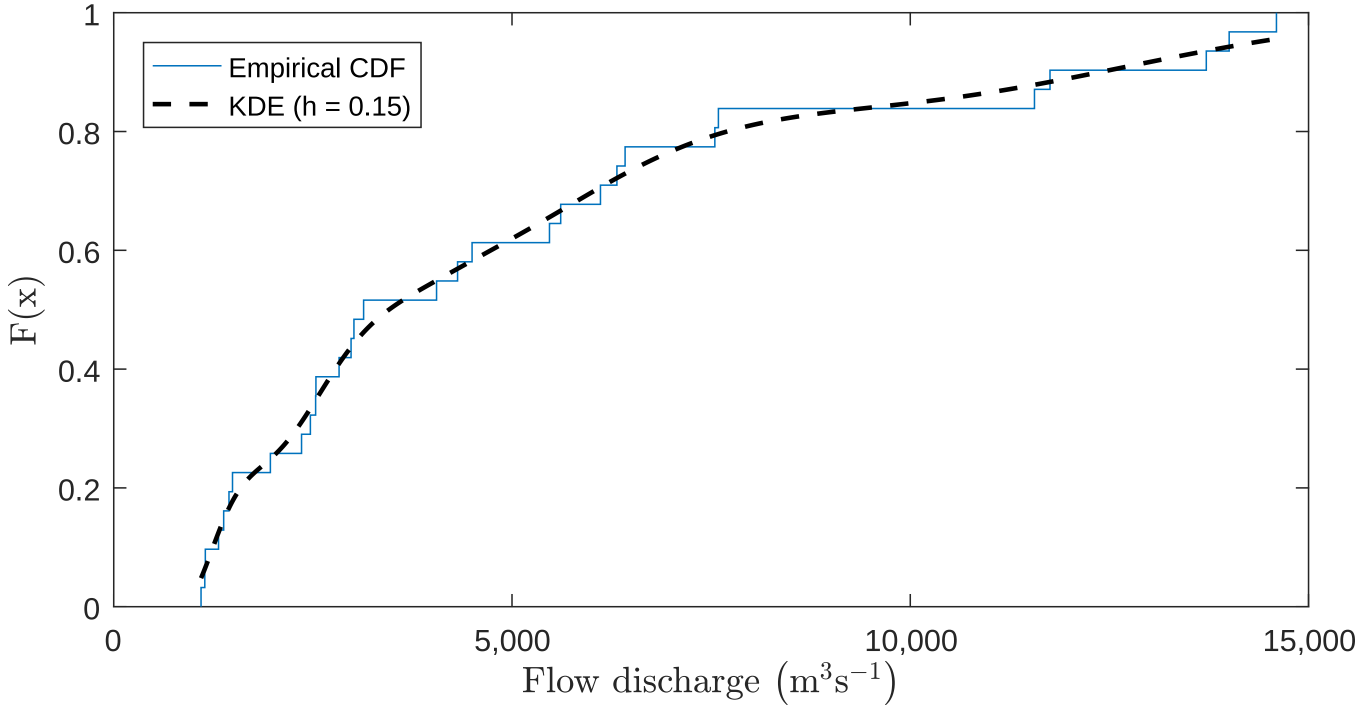


FIGURE 11 Kernel density estimated applied to the Scenario 3 data time series.

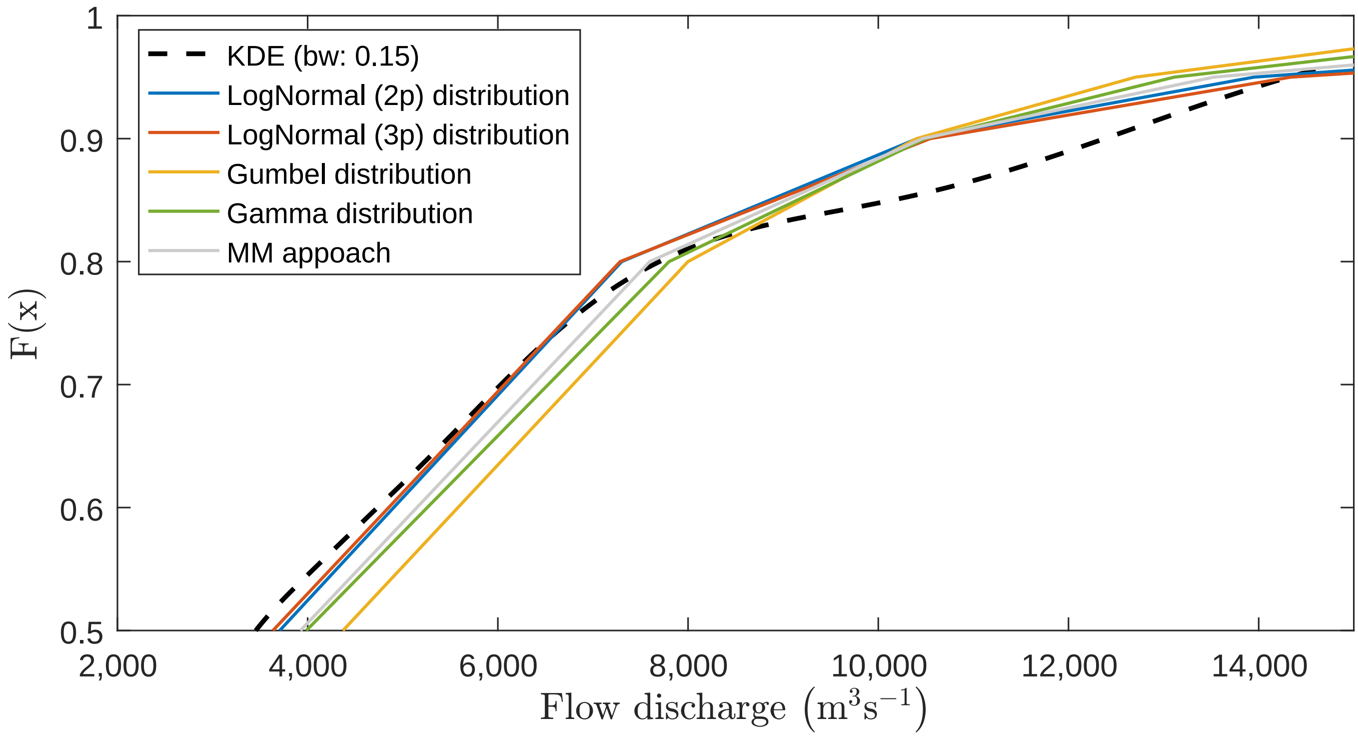


FIGURE 12 Cumulative density functions ($F(x)$) obtained by the parametric and the non-parametric distributions.

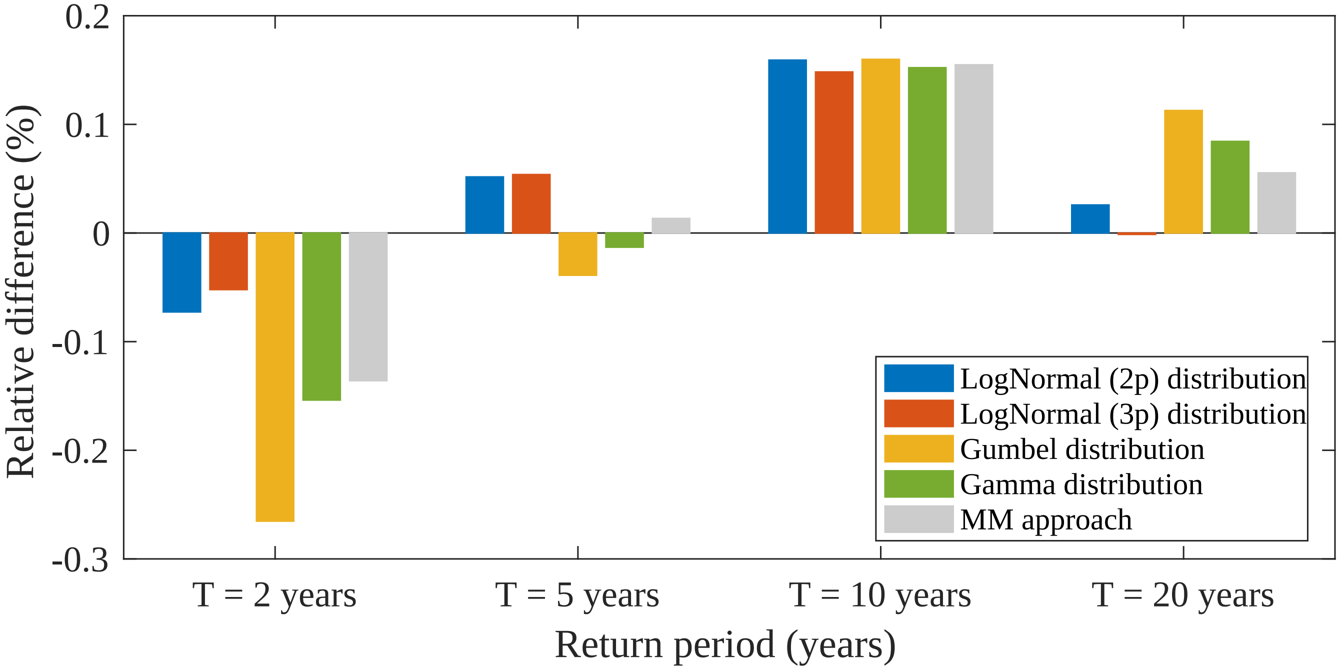


FIGURE 13 Relative differences of the design floods normalized by the respective non-parametric estimates.

TABLE 1 Time series and database available. Periods that require extrapolation of streamflow data.

Gauging stations	Mean daily data		Instantaneous data	
	N.º of annual records	Records period	N.º of annual records	Records period
Carrapatelo Dam (EDP) (07I/01A)	47	1972/73 to 2018/19	10	2009/10 to 2018/19
Torrão Dam (EDP) (07H/01A)	31	1988/89 to 2018/19	10	2009/10 to 2018/19
Fragas da Torre (EDP) (08H/02H)	68	1946/47 to 2018/19	66	1948/49 to 2018/19
Periods of required extrapolation				
Carrapatelo Dam (EDP) (07I/01A)	-	-	21	1988/89 to 2008/09
Torrão Dam (EDP) (07H/01A)	-	-	21	1988/89 to 2008/09

TABLE 2 Hydrological scenarios considered for Q_{HR} estimation.

Database	Description	Scenarios
Mean daily	Sum of the design floods obtained independently for each gauging station	0
	Sum of the maximum annual discharges of the three gauging stations	1
	Sum of the discharges from the three gauging stations and calculation of the maximum annual values	2
Instantaneous	Sum of the maximum annual discharges of the three gauging stations	3

TABLE 3 Statistics of Q_{HR} for the hydrological scenarios under consideration ($m^3 s^{-1}$).

Variables	Scenario 1	Scenario 2	Scenario 3
Mean	3,691.80	3,460.40	5,045.60
Minimum	776.80	589.10	1,096.00
Median	2,173.40	2,101.10	3,137.00
Maximum	10,862.00	10,839.00	14,597.10
Standard Deviation	3,095.30	2,976.90	4,105.30
Coef. of Skewness	0.13	1.16	1.21
Coef. of Kurtosis	0.14	0.32	0.41
Coef. of Variation	0.84	0.86	0.81

TABLE 4 Design floods of Scenario 3 estimated by the four probabilistic models (m^3s^{-1}).

T (years)	LogNormal (2p)	LogNormal (3p)	Gumbel	Gamma
2	3,706	3,635	4,371	3,986
5	7,302	7,286	7,999	7,801
10	10,410	10,545	10,401	10,496
20	13,950	14,338	12,705	13,113
50	19,395	20,296	15,688	16,497
100	24,160	25,604	17,923	19,018
500	37,689	41,029	23,087	24,788
1,000	44,713	49,196	25,307	27,247

TABLE 5 Design floods of the flow approaching the new Hintze Ribeiro bridge (Q_{HR}).

T (years)	Q_{HR} (m^3s^{-1})		relative difference (%)
	MS	MM	$(MM - MS)/MM$
2	3,986	3,925	-1.6
5	7,801	7,597	-2.7
10	10,496	10,463	-0.3
20	13,113	13,527	3.1
50	16,497	17,969	8.2
100	19,018	21,676	12.3
500	24,788	31,648	21.7
1,000	27,247	36,616	25.6