Technical note: Statistical generation of climate-perturbed flow duration curves

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Abstract.

Assessing the robustness of a water resource system's performance under climate change involves exploring a wide range of streamflow conditions. This is often achieved through rainfall-runoff models, but these are commonly validated under historical conditions with no guarantee that calibrated parameters would still be valid in a different climate. In this note, we introduce a new statistical generation method to produce a range of plausible streamflow futures that are coherent across the full range of hydrological conditions. It relies on a three-parameter analytical representation of the flow duration curve (FDC) that has been proved to perform well across a range of basins in different climates. We rigorously prove that for common sets of streamflow statistics mirroring average behavior, variability, and low flows, the parameterisation of the FDC under this representation is unique. We also show that conditions on these statistics for a solution to exist are commonly met in practice. These analytical results imply that streamflow futures can be explored by sampling wide ranges of three key flow statistics, and by deriving the corresponding FDC to model basin response across the full spectrum of flow conditions. We illustrate this method by exploring in which hydro-climatic futures a proposed run-of-river hydropower plant in eastern Turkey is financially viable. Results show that contrary to approaches that modify streamflow statistics using multipliers applied uniformly throughout a time series, our approach seamlessly represents a large range of futures with increased frequencies of both high and low flows. This matches expected impacts of climate change in the region, and supports analyses of the financial robustness of the proposed infrastructure to climate change. We conclude by highlighting how refinements to the approach could further support rigorous explorations of hydro-climatic futures without the help of rainfall-runoff models.

1 Introduction

Projections of climate change and its impact on water resources are inherently uncertain, and this is likely to increase as a result of climatic, technological, economic and sociopolitical changes (Maier et al., 2016; McPhail et al., 2018). Water resource planners and decision makers are rightly concerned about the potential effects of future uncertainties, with the upfront cost of action to be weighed against the high potential social and environmental costs of inaction over time (Singh, 2018; Ray et al., 2018). Conventional engineering approaches to water systems planning have been summarised as "predict-then-act" (Lempert et al., 2013), with optimisation of a design objective under the assumption of a best-estimate (i.e., most likely) prediction of

25   the future suggesting the "best" course of action. To produce future streamflow in this framework, rainfall-runoff models are routinely forced by rainfall and temperature projections of dynamically downscaled global climate models (GCMs; Peel and Blöschl, 2011; Chen et al., 2019). There are, however, two categories of issues with this type of approach.

First, "predict-then-act" is not compatible with hard-to-quantify uncertainties, as it works best when a known single probability density function is available for each key parameter (Singh et al., 2015). If the future turns out to be different from the
30   hypothesized projection(s), the optimal solution could fail, sometimes catastrophically (Haasnoot et al., 2013; Hamarat et al., 2013). To avoid this, several emerging decision-making frameworks (Lempert, 2002; Bryant and Lempert, 2010; Brown et al., 2012; Haasnoot et al., 2013; Kasprzyk et al., 2013) strive to find adaptation solutions that are robust to uncertain and changing conditions. In the climate adaptation context, a robust alternative maintains satisfactory expected performance under a range of plausible futures (Maier et al., 2016; McPhail et al., 2018; Marchau et al., 2019), instead of being "optimal" in a single future.
35   Therefore, to identify robust alternatives, uncertainties have to be described with the aid of scenarios that represent coherent future pathways based on different sets of assumptions (Maier et al., 2016). In water resource applications, this entails defining specific ranges for future streamflow, then sampling them to generate an ensemble of plausible future conditions.

The second category of issues is with the use of rainfall-runoff models to generate future flow conditions. Indeed, these models have generally been calibrated and validated under historical conditions, with no assurance that these parameters would
40   still be valid under different hydro-climatic conditions (Peel and Blöschl, 2011). There is evidence that rainfall-runoff models' predictive skill decreases with changed climatic conditions (Saft et al., 2016; Seibert et al., 2016; Fowler et al., 2020). In fact, a study of the Rhine-Meuse basin from 1901 to 2010 shows that optimal calibration evolves with climate variability, and land use and river structure changes (Ruijsch et al., 2021). To compound these calibration issues, the significant resources and modelling skill needed for calibration and validation mean that is costly for water resource assessments based on rainfall-runoff models
45   to explore the full uncertainty space associated with climate change, with far-reaching consequences for planning.

For these reasons, approaches aimed at finding climate-robust adaptation solutions have often relied on multipliers applied uniformly along a time series also known as the "delta change" approach (Brown et al., 2012). Examples of this affect streamflow either directly through multiplication (e.g., Herman et al., 2014, 2015) or indirectly by applying to climate variables such as temperature and precipitation, before using regression to deduce annual runoff (e.g. Ray et al., 2018). More sophisticated
50   versions of this exist, e.g., Quinn et al. (2018) distinguished several multipliers to isolate changes to the mean, to variance, and to monsoonal dynamics in the Red River basin in Vietnam. However, to our knowledge there is no approach that seeks to describe catchment response under changing climate in a coherent way across the full range of hydrological conditions.

As the representation of the empirical cumulative distribution function (CDF) of streamflow (Vogel and Fennessey, 1994), a flow duration curve (FDC) precisely represents the full range of hydrological conditions. The FDC is unique to each catchment,
55   and it is influenced by various factors including climate, topography, physiography, vegetation cover, land use (Castellarin et al., 2013; Brown et al., 2013; Sadegh et al., 2016). It has become a popular tool used in modern hydrology for various water resources applications (Leong and Yokoo, 2021), since it provides concise and valuable information about river streamflow variability and catchment response (Blöschl et al., 2013; Boscarello et al., 2016). For example, slope steepness in the middle part of a FDC is characteristic of a catchment's precipitation retention properties (Yilmaz et al., 2008). This remark has led

60   Sadegh et al. (2016) to adapt a set of soil retention functions such as those proposed by van Genuchten (Van Genuchten, 1980) and Kosugi (Kosugi, 1996) to mimic the empirical FDCs of catchments. This analogy was proposed because both watersheds and soils are governed by similar hydroclimatologic forcing, and are able to store and dispel precipitation in response to similar gradients (Vrugt and Sadegh, 2013; Sadegh et al., 2016). Fitting FDCs to a set of 430 catchments of the MOPEX dataset (Duan et al., 2006), Sadegh et al. (2016) found that the three-parameter Kosugi model they proposed offered the best quality of fit

65   across a broad range of climate zones, under a goodness-of-fit criterion that weighs high and low flows equally.

This paper leverages the existence of high-performing parameterisations of the FDC across a range of climates to statistically generate plausible streamflow futures. We directly link parameter triplets of the Kosugi model with three streamflow statistics that are relevant to the management of water resources: central tendency, variability, and low-flow indicator. This one-on-one correspondence enables us to (1) sample hydro-climatic futures according to plausible ranges for streamflows statistics, and

70   (2) convert these into ensembles of FDCs that represent of the differentiated impacts of climate change across flow quantiles. The latter is consistent with studies of historically observed streamflow change (e.g. Pumo et al., 2016).

2   Methodology

This section demonstrates the technique that is the core of this paper, and introduces its workflow. First, Section 2.1 will introduce the Kosugi model of the flow duration curve (FDC). Then Section 2.2 will give results on how to parameterise the

75   FDC with the Kosugi model to reproduce desired streamflow statistics. These are the key results that enable us to build the methodological workflow to produce an ensemble of climate-perturbed flow duration curves, which we present in Section 2.3.

2.1   Kosugi model of the flow duration curve

The flow duration curve (FDC) is a cumulative frequency curve that ranks the observed record of n discharge values in descending order $\{q_1, q_2, \ldots, q_n\}$. The ranking of each value directly gives its empirical probability of exceedance u. In this work,

80   we represent the FDC with the three-parameter Kosugi model, which has been shown to provide an excellent approximation to FDCs under a wide range of climates (Sadegh et al., 2016), and is given by:

$$q(u) = c + (a - c)\, z(u)^b, \text{ with } z(u) = \exp\left[\sqrt{2}\, \mathrm{erfc}^{-1}\left(2\, u\right)\right] \tag{1}$$

where q is the streamflow value for a given value of the exceedance probability $u \in [0, 1]$, and (a, b, c) are the three coefficients of the Kosugi model. Given a discharge record, the Kosugi model is fitted by minimising the root mean square srror (RMSE).

85   Minimising the RMSE on $q(u)$ would lead to weigh errors in the high flows more than those on the low flows. For this reason, we minimise the RMSE in the exceedance probability space, i.e., the error on $\mathcal{U}$, the inverse of the $q(u)$ function defined in equation (1):

$$RMSE(x) = \left[\frac{1}{n}\sum_{i=1}^{n}\left[u_i - \mathcal{U}(q_i | a, b, c)\right]^2\right]^{0.5} \text{ where } \quad \mathcal{U}(q | a, b, c) = \frac{1}{2}\,\mathrm{erfc}\left[\frac{1}{\sqrt{2}\, b}\ln\left(\frac{q - c}{a - c}\right)\right] \tag{2}$$

2.2 Correspondence between common flow statistics and the Kosugi model

90 In this paragraph, we directly relate the three parameters of the Kosugi FDC model with sets of three streamflow statistics that are of interest to water resource management. This is key to relating a hydro-climatic future (described with different flow statistics) to a well-defined FDC. The central tendency, and the spread or the degree of variation are the two key aspects to describing a distribution (Weisberg and Weisberg, 1992; McCluskey and Lalkhen, 2007). Low flows are also of interests where water scarcity and availability are issues. With this we construct a triplet of streamflow statistics (M, V, L) where M is the

95 central tendency (mean or median), V is variability (standard deviation or coefficient of variation), and L can be given by a low flow quantile (first or fifth percentile of flow distribution).

We can entirely define the flow distribution associated to a hydro-climatic future defined by (M, V, L), if we can find a relationship relating it to parameters (a, b, c) of the Kosugi model defined in equation (1):

$$(a, b, c) = \mathcal{F}(M, V, L) \tag{3}$$

100 This correspondence needs to be unique: if there is more than one (a, b, c) for a future defined by (M, V, L), a method based on the Kosugi model cannot define future flows unambiguously. In this paper we focus on two sets of (M, V, L). On the one hand, using M as the mean, V as the standard deviation and L as a low flow percentile corresponds to a very common statistical description of a flow distribution. We will refer to this as the "mean" case hereafter. On the other hand, there are cases where using the median, coefficient of variation and low flow quantile as (M, V, L) is of interest. This is the case e.g., in appraisals of

105 run-of-river hydropower, see Section 3. We will refer to this as the "median" case hereafter.

Step by step derivation of these equations, along with proof of the uniqueness of a parameterisation, and conditions on the existence of solutions are provided in the Supplementary Information (SI) to this paper. In this section, we provide the main results for both the "mean" and "median" cases.

2.2.1 "Mean" case

110 In the "mean case", we know $(M, V, L) = (\mu, \sigma, q_{low})$ where where μ is the mean, σ is the standard deviation and q_{low} is the 1st or 5th percentile of flow. To parameterise the Kosugi equation in this case, one needs to first find b that is solution of:

$$\frac{\sigma}{\mu - q_{low}} = \frac{\sqrt{e^{b^2} - 1}}{1 - e^{-b^2/2} \varepsilon^b} \tag{4}$$

where ε is the value of $z(u)$ at q_{low}. For instance $\varepsilon = z(0.99) \approx 0.0976$ if q_{low} is the first percentile, and $\varepsilon = z(0.95) \approx 0.1930$ if q_{low} is the fifth percentile. There is at most one solution to this equation, and it exists if:

115 $$\frac{\sigma}{\mu - q_{low}} > \frac{-1}{\ln(\varepsilon)} \tag{5}$$

where $\varepsilon < 1$ so $\ln(\varepsilon) < 0$ and $-1/\ln(\varepsilon) \approx 0.43$ if q_{low} is the first percentile; 0.61 if q_{low} is the fifth percentile. Then one can deduce a and c using the following equations:

$$
\begin{cases}
a = \dfrac{q_{low}\left(1 - e^{-b^2/2}\right) + \mu\, e^{-b^2/2}(1 - \varepsilon^b)}{1 - e^{-b^2/2}\varepsilon^b} \\[3mm]
c = \dfrac{q_{low} - \mu\, e^{-b^2/2}\, \varepsilon^b}{1 - e^{-b^2/2}\varepsilon^b}
\end{cases}
\tag{6}
$$

2.2.2 "Median" case

120 In the "median" case, we know $(M, V, L) = (m, CV, q_{low})$, where m is the median, $CV = \mu/\sigma$ is the coefficient of variation, and q_{low} continues being a low flow percentile. One parameter of the Kosugi equation is easy to obtain:

$$
a = m
\tag{7}
$$

To find the other parameters it is necessary to find the b that is the solution of:

$$
CV = (1 - R)\frac{\sqrt{e^{b^2} - 1}}{1 - R + (R - \varepsilon^b)e^{-b^2/2}}
\tag{8}
$$

125 where $R = q_{low}/m$. b is unique, and exists provided a similar existence condition as in the "mean" case:

$$
\frac{CV}{1 - R} > \frac{-1}{\ln(\varepsilon)}
\tag{9}
$$

Then the final parameter c is obtained through:

$$
c = \frac{q_{low} - m\varepsilon^b}{1 - \varepsilon^b}
\tag{10}
$$

2.3 Producing an ensemble of climate-perturbed flow duration curves

130 Figure 1 illustrates our four-step methodology. In step (1), we fit the Kosugi FDC model to the available discharge record by finding the parameters (a_h, b_h, c_h) for the historical record, using equation (3) and the chosen historical flow statistics (M_h, V_h, L_h). We need to verify that this fit is close in performance to the best-fit model (a^*, b^*, c^*) obtained through RMSE minimisation as described by equation (2). We then check the method by deriving the FDC parameters based on three key statistics of historical flow. The method can be used if both curves adequately fit the functional shape of the empirical FDC.

135 To generate future flows, one needs to sample a set of futures in step (2). This corresponds to sampling the chosen parameters (M, V, L) to construct an ensemble $\{(M_i, V_i, L_i)_{1 \leq i \leq N}\}$ of N alternative futures, reflecting a broad range of plausible future conditions. Then in step (3), we find the unique set of parameters (a_i, b_i, c_i) for each triplet (M_i, V_i, L_i) and construct the corresponding FDC. Finally in step (4), we use the resulting ensemble of FDCs to support robustness assessments in a changing climate, by evaluating the performance of a decision adaptation(s) across future scenarios.

140 Note that the first three steps of this workflow can be replicated for any site using the Zenedo repository (Yildiz et al., 2022b) that accompanies this paper. The fourth step depends on the specificities of each robustness assessment, e.g., what infrastructure is considered, what performance measures, etc.
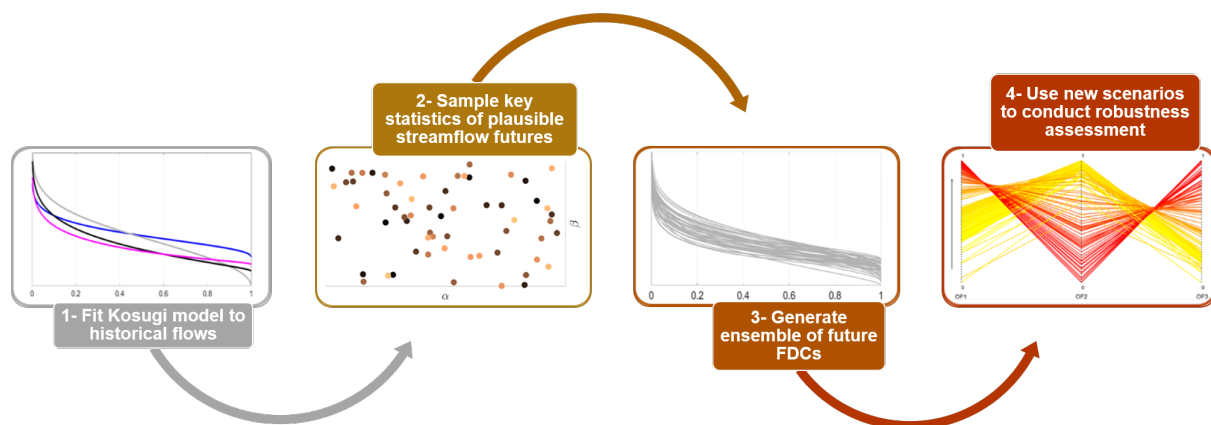
Figure 1. Flowchart of the approach. Steps are described in order through Section 2.

3 Case study

This section demonstrates the fitness of our method for robustness assessments.

3.1 Site description

The case study involves the climate change impact analysis of a proposed RoR hydropower plant at the Besik site on the Mukus River in Van province located in the Eastern Anatolia region of Turkey (Lat: 38.15°N; Lon: 42.80°E). Summers are dry and hot with temperatures above 30 °C. Spring and autumn are generally mild, but during both seasons sudden hot and cold spells frequently occur. 27 years of daily discharge observation are available. The discharge fluctuates considerably between values of 2 and 38 m³/s, with median flow of 4.79 m³/s, first percentile flow of 2.23 m³/s and coefficient of variation of 0.60. The design of the run-of-river hydropower project was optimised using the HYPER toolbox (Yildiz and Vrugt, 2019). The resulting design has an installed capacity of 8.73 MW, a penstock length of 208 m with a diameter of 1.60 m, and two side-by-side Francis turbines whose design discharge are 4.80 and 2.87 m³/s respectively.

3.2 Generation of climate-perturbed flow duration curves

Contrary to reservoir-based hydropower plants, RoR schemes have virtually no storage, so they are vulnerable to changes in flow as they cannot modulate flows and only operate in a predefined range. Extreme low flows are insufficient to activate the turbines, and equally, flows above the design discharge do not produce energy. Because of this focus on the mid-range flows, the median is a more important indicator of performance than the mean flow, which can be skewed by high discharges. For this reason, this application will relate median, standard deviation and first percentile flows to Kosugi parameters (the "median" case).

In step (1) of our approach, we fit the three-parameter Kosugi model to the daily discharge data. Figure 2 shows the historical records (red circles), the fitted Kosugi Model (black line) and the derived FDC based on the three statistical parameters of historical records (FDC from (M_h, V_h, L_h)). Both fitted curves offer close fits across the entire spectrum of flow conditions described by the FDC of historical records. In particular, the quality of the fit for middle and low flows shows the consistency

165   of the proposed approach, as their estimation is vital in assessing and managing water resources such as hydropower plants.
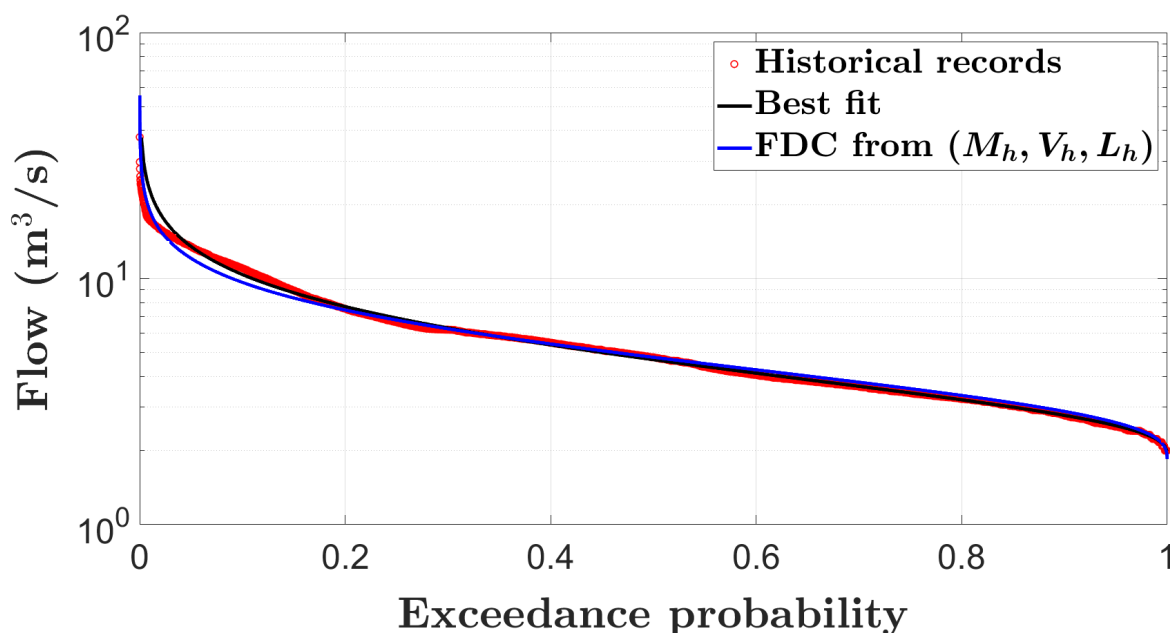
Figure 2. Plot of the daily flow duration curves (FDC) used in the case study (red circles). Black line represents the fitted Kosugi model and the blue line is the FDC deduced from (M_h, V_h, L_h): historical median, CV and first percentile.

In step (2), we determine plausible ranges for the three statistical parameters over the operational life of the proposed plant. In Turkey, hydropower projects are licensed to generate electricity for a period of 49 years. Several climate projections indicate a decrease in the mean discharge values that could reach up to 60% (SYGM, 2016 (accessed December 19, 2022). An increasing intensity of drought conditions is expected for the period of 2040 - 2071 in the region of the presented case study (Demircan

170   et al., 2017; Turkes et al., 2020; Yildiz et al., 2022a). In parallel, precipitation variability is widely forecast to increase (GCMs; Pendergrass et al., 2017), with the coefficient of variation of precipitation is projected to almost double by 2060 in various neighboring regions such as the Mediterranean (Giorgi and Lionello, 2008) or Iran (Zarrin and Dadashi-Roudbari, 2021). To reflect these various results while reflecting the uncertainties that surround them, we chose wide ranges for the scaling factors of our three parameters. These sampling ranges are summarised in Table 1 and reflect the concurrent tendencies for severe

175   drying and an increase in variability. Recall these ranges represent plausible rather than probable values. We then sampled $N = 500$ alternative future streamflow conditions using latin hypercube sampling.

Table 1. Sampling ranges for multipliers of statistical parameters, where 1 corresponds to the values for the historical time series.

Sampling Parameter	Lower Bound Multiplier	Upper Bound Multiplier
Median, m	0.3	1
Coefficient of Variation, CV	1	2
1st percentile, q_{low}	0.3	1

Next, in step (3), we primarily check if the the samples satisfy the condition for existence; the smallest and largest measured value of $\frac{CV}{1-R}$ across the sample are 0.75 and 5.15 respectively. All values are significantly larger than the existence condition for the parameterisation ($-1/\ln(\varepsilon) \approx 0.43$, see equation 9). Therefore we can derive the distribution parameters of Kosugi model by using equations (7) to (10) for each sampled future. Thereafter, we generate future scenarios by using these distribution parameters. Figure 3 displays the full FDC sample (gray lines), with drier and more variable flows compared with the historical record (dashed blue line) and the wide range of flow conditions considered. Clearly, our method can provide a suitable range of hydroclimatic conditions, with increased frequency of high flows and low flows, in accordance with likely impacts of climate change in the region. This versatility can be compared to the lack of flexibility offered by a uniform multiplier across the FDC of historical flows, also shown on Figure 3 with the examples of $\pm20\%$ across the flow distribution (dotted red and black lines).
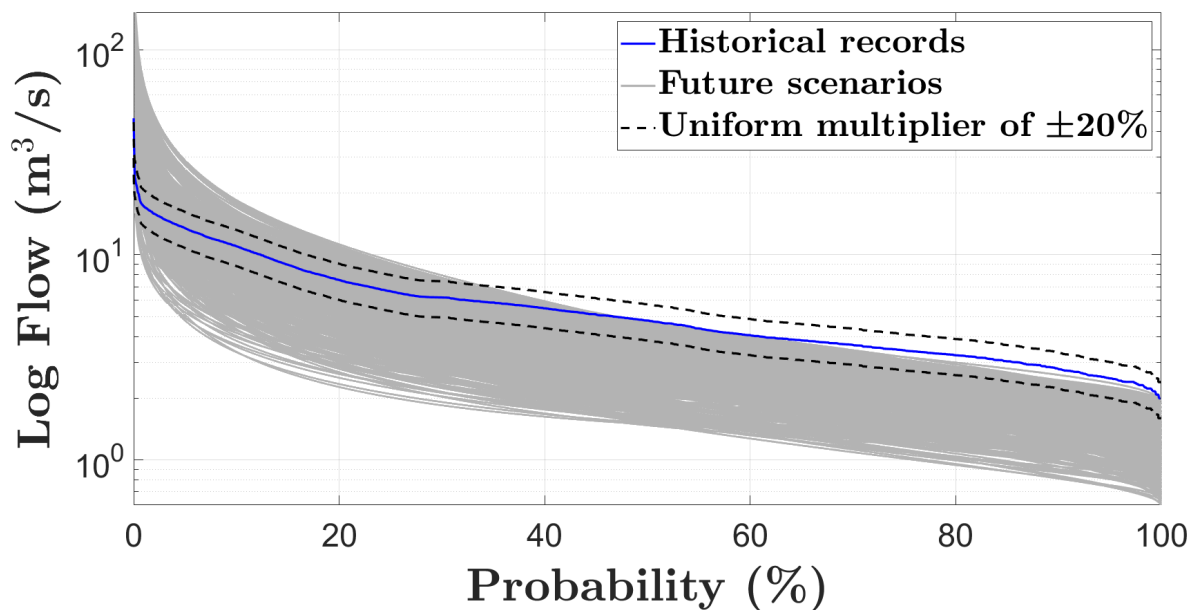
Figure 3. Plot of the flow duration curves (FDC) of the fitted Kosugi model (blue line) and sampled flow duration curves (gray lines) constructed by deriving the FDC parameters for Kosugi Model shown in Table 1.

3.3 Application to infrastructure robustness

Finally, in step (4), we evaluate the performance of a design under generated future flows. We input each ensemble member into state-of-the-art software to compute technical performance, energy production and economic profit of a design at a given site characteristics (HYPER; Yildiz and Vrugt, 2019). This enables us to quantify the Net Present Value (NPV) of the optimal

190   design of the run-of-river hydropower project under a range of changing climate conditions. Recall that the NPV is the value of projected cash flows, discounted to the present. We assess that the investment is robust to a future climate if NPV is greater than zero. Future FDCs with their respective robustness measure are presented in Figure 4. The Figure shows that although the NPV of current design based on historical records (blue line) is around 10 M\$, it decreases dramatically and even becomes negative (gray lines) under dry futures characterised in particular by a median m under 2.3 m^3/s; or a m under 2.6 m^3/s

195   accompanied by q_{low} under 1.10 m^3/s and CV below 0.8. The project is unfeasible under such conditions.
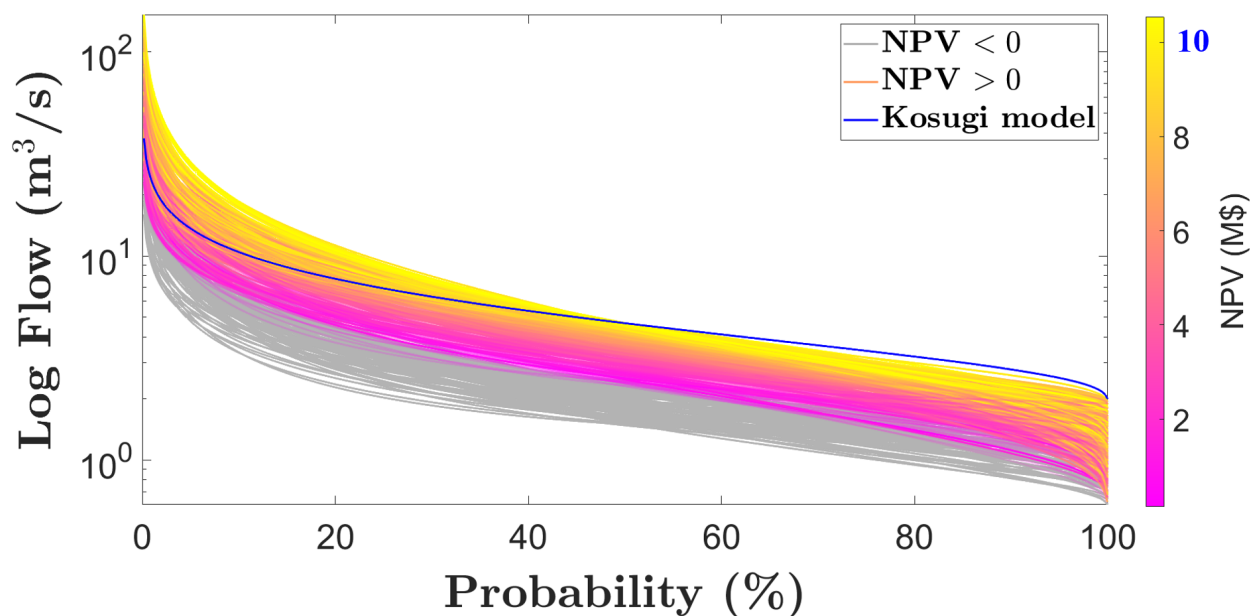
Figure 4. Plot of generated flow duration curves (FDCs), with each solution colored by its Net Present Value (NPV). Gray colored lines signifies SOWs in which NPV is negative. NPV of the optimal design based on observed discharge (blue line) is 10 M\$

4   Discussion and conclusion

In this technical note, we present an effective, practical and novel approach based on a near-universal parameterisation of flow duration curves (FDCs), and perturbation of these parameters to simulate a range of futures in a way that is hydrologically consistent across the spectrum of hydrological conditions. Our application to a run-of-river hydropower project in Eastern Turkey

200   showcases the ability of our method to provide a large range of climate-modified catchment responses, including increased frequency of both high flows and low flows to mimic the future projections for the area (i.e. more arid conditions with increased trend of extreme hydrological events). It compares favorably with existing statistical methods to perturb flows such as the delta change approach. This then supports robustness analyses for rivers for which no detailed hydrological model is available: applied here to assess the financial viability of run-of-river hydropower design in a changing climate. The ease of application

205   of the method illustrates its wide applicability in support of robustness assessments of infrastructure for which streamflow variability impacts performance. We now conclude with some remarks on how this novel approach could be extended to further support such assessments.

    Even though the three-parameter Kosugi model has been shown to fit FDCs well across a wide range of catchment characteristics (Sadegh et al., 2016), this does not a guarantee that it would be a good fit in all cases. Crucially, Sadegh et al.

210   (2016) proposed other functional forms for the FDC that could also be perturbed to generate future flows. One would need to re-establish conditions for the existence and unicity of the FDC parameterisation given streamflow statistics.

    We also identified two current limitations to this method that we believe can be addressed by future developments. First, recent studies reveal that there is an increasing trend of the number of zero-flow days in many regions such as the Mediterranean (e.g., Tramblay et al., 2021). Yet, the number of zero-flow days remains constant in this approach. Preliminary results show

215   that our proposed method supports time series with a large number of zero-flow days, by keeping the number of no-flow days constant and perturbing the FDC when flows are positive. Admittedly, this approximation ignores the fact that a change in climate regime could affect the number of no-flow days. Future work needs to examine the possibility of using the proportion of no-flow days as the low-flow indicator L, instead of a low flow quantile. Derivations for the existence and unicity of a parameterisation should then also be extended to that case.

220   Second, our approach only considers the FDC, and says nothing of the frequency and duration of dry and wet spells. There is mounting evidence that climate change is bound to cause hydrological intensification, i.e., it will make dry periods longer and more severe and wet periods more intense (Ficklin et al., 2022). We are not aware of a method that is currently able to simulate hydrological intensification without the help of rainfall-runoff models. One possibility going forward would be to combine hydrological model simulations with statistical generation of FDCs, as the latter could correct outputs from the former, if they

225   were obtained with a calibration that only reflects historical conditions.

Code and data availability. The climate-perturbed FDC generation model has been developed in Python 3.10.4. and is provided with an environment file. It is accessible from the Zenodo open-access repository at https://doi.org/10.5281/zenodo.7423056, with a link to the GitHub source codes of the latest release, including a detailed "run guide" and input files to statistically generate plausible streamflow futures.

230 *Author contributions.* VY: Conceptualization, Methodology, Writing - original draft, Formal analysis, Software, Investigation. CR: Supervision, Conceptualization, Methodology, Formal analysis, Writing - review & editing, Investigation. RM: Investigation. SB: Conceptualization, Investigation, Supervision. All authors have read and agreed to the published version of the manuscript.

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