The tumultuous relationship between flood frequency analysis and streamflow data uncertainty

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Abstract: Streamflow data is known to exhibit large uncertainty for high flow regimes. At the same time, high flows have a decisive influence on the fitting the probability distributions used in flood frequency analysis (FFA). Consequently, it seems critical to incorporate this type of uncertainty to ensure that design flood levels are consistent with the data used in their estimation. Few quantitative methods have been developed to do so. In this paper we use the method recommended in the Australian Rainfall and Runoff (AR&R) guidelines and apply it to 40 high quality stations across Australia. Our results suggest that incorporating streamflow uncertainty introduces systematic shift in FFA distributions if the data error is larger than 30%.

Keywords: *Flood frequency analysis, Bayesian calibration, streamflow uncertainty*

1. INTRODUCTION

Measuring streamflow during extreme floods is a perilous process associated with large uncertainty due to station by-pass, equipment failure, or change in hydraulic conditions compared to average flows. Consequently, most extreme streamflow measurements exhibit large uncertainty bounds that can reach values of 10 to 50%. At the same time, extreme flows have a decisive impact on the fitting of probability distributions used in flood frequency analysis, such as GEV or LogPearson3. This naturally leads to the idea that streamflow uncertainty should be incorporated in FFA. This paper reports the difficulty faced by the author in this process, and acts as a warning to flood modellers about this issue, which turned out to be far more complex than it appeared at first.

AR&R provides a comprehensive set of recommendations regarding the fitting of probability distributions for at-site peak flow frequency analysis. AR&R discusses the various issues related to inaccuracy in streamflow data, but the method to incorporate quantitatively this type of uncertainty in the fitting remains limited to the one proposed by Kuczera (1996). In this method, a multiplicative Gaussian error with a mean of 1 and chosen standard deviation is imposed on streamflow data above a given threshold, named "anchor", as follows:

$$\hat{q} = \begin{cases} q & if\ q < q_a \\ q_a + (q - q_a)\,\epsilon & otherwise \end{cases} \tag{1}$$

Where q is the "true" streamflow value, $\hat{q}$ is the observed value, q_a is the anchor, and ϵ is the error, which constitutes an additional parameter of the statistical model alongside the parameters of the chosen probability distribution (e.g. GEV). The prior distribution for the error ϵ is assumed to be a normal $N(1, \sigma_\epsilon)$, where σ_ϵ is a chosen hyper-parameter.

This model is conceptually simple, and straightforward to incorporate in a Bayesian FFA inference scheme. More advanced streamflow data uncertainty estimation methods are now available such as the BaRatin approach (Coz et al., 2014), but require a detailed knowledge of local hydraulic conditions, which is not necessarily available. Consequently, the multiplicative error proposed by Kuczera (1996) is retained in this work.

In the model of Equation (1), it is important to stress that only the prior probability of ϵ is $N(1, \sigma_\epsilon)$. Its posterior probability obtained after sampling is not necessarily normal, nor centred on the value $\epsilon = 1$ (i.e. no error).

2. METHOD AND RESULTS

The approach is tested on 40 high quality stations across Australia that possess streamflow records longer than 70 years, and, hence, allows testing of FFA methods in ideal conditions. Two alternative FFA inference schemes are compared. First, a reference Bayesian calibration of the GEV probability distribution is implemented with no account of streamflow data uncertainty. In this scheme, the data below the 30th percentile are censored to discard the influence of low outliers on the fitting. The method is implemented in the STAN and Python programming languages as described by Lerat and Vaze (2025). Second, the same inference scheme is applied in combination with the data error model of Equation (1). Multiple values of the anchor q_a and standard deviation σ_ϵ are tested.

The comparison between the two fitting exercises is shown in Figure 1 for the Russel River at Bucklands (111101). This figure reveals that streamflow data uncertainty can have a major impact on all design flood levels. In this figure the 1:100 AEP flood using the reference method is estimated to be 901 $m^3.s^{-1}$ (Figure 1.a), against 1214 $m^3.s^{-1}$ when taking data uncertainty in to account (Figure 1.b). Introducing data uncertainty shifts the whole FFA distribution upwards, which is difficult to justify given the long duration of the streamflow records at this station (74 years).

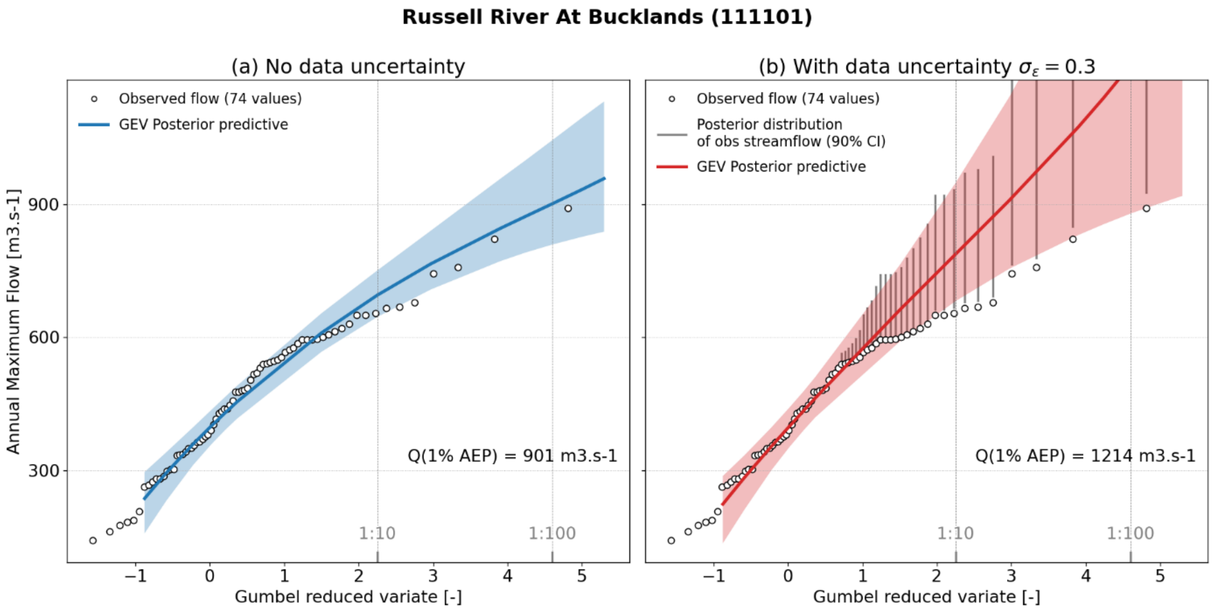

Figure 1: Impact of streamflow data uncertainty on the fitting of the GEV distribution for the Ovens River at Wangaratta (station ID 403200).

Similar comparisons undertaken for the 40 sites in our dataset (not shown) can be summarised as follows:

- Data uncertainty has negligible impact if the prior standard deviation σ_ϵ is lower than 0.3 (i.e. 30% error above anchor).
- Large values of σ_ϵ lead to a systematic underestimation of all design flood levels from 1:5 to 1:200 by approximately 10%. Credible intervals associated with design flood level widen with data uncertainty. The increase in width of these intervals is about 10%.

3. CONCLUSIONS AND WAY FORWARD

This work describes an attempt to incorporate data uncertainty into FFA. Initially considered as a logical step towards reconciling data uncertainty and design flood estimation, the exercise produced the unexpected result that FFA distributions can shift significantly away from observations, even when a large number of streamflow data points are available. This systematic shift was unexpected and led us to question the overall approach without finding a simple solution.

Our difficulties are probably the consequence of the paradox between wanting FFA distribution to fit observed data, while, at the same time, distrusting these data via an error model. In hindsight, it seems reasonable that the statistical model used here chose to distance itself from highly uncertain observations.

A way forward would be to expand the error model (1) to enforce a constraint on ϵ, so that its posterior remains centred around 1, and prevent a systematic shift of the FFA distribution.

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