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Fragility and ambiguity in design floods

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Abstract

Flood hazard assessment worldwide has relied for over a century on "design floods" — synthetic events tied to a fixed annual exceedance probability (AEP), typically 1:100 years. We argue that the practice of assuming a fixed, spatially homogeneous flood probability is both fragile and ambiguous, affecting flood zoning, the design of flood mitigation infrastructure, and flood insurance. Fragility stems from shifts in flood quantiles following an extreme event: in Australia's costliest flood, a single event raised the 1:100 quantile by 0.8 m at a station with a 56-year history. This estimator uncertainty is well known in theory but often unacknowledged in practice. Ambiguity arises because maintaining the same flood probability throughout a river system is mathematically impossible except under perfect tributary dependence, which never holds in practice. AEP on tributaries must therefore be implicitly "sacrificed". In the same example, a 1:100 AEP on the main river imposes a 1:25 AEP on the tributaries, averaged across equiprobable scenarios. We propose three mitigation strategies: (1) evaluate design flood uncertainty through statistical methods that use covariates and model spatial dependence; (2) acknowledge the AEP sacrifices at confluences; (3) consider historical scenarios as an alternative to probabilistic-based flood risk assessment to circumvent fragility.

1. Introduction

Flood is one of the most frequent and damaging natural hazards, with an estimated 1.65 billion people affected between 2000 and 2019¹. Scientific assessment of flood hazard was formalised in the early 20th century in the United States based on probability theory². This approach, referred to as "flood frequency analysis", became a cornerstone of hydrological sciences over the following decades, and extended beyond hydrology to become extreme value theory^{3,4}. These early developments focused on the estimation of flood hazard at a point, which is generally expressed in terms of the annual exceedance probability (AEP) of peak streamflow, often chosen as 1:100. Societal needs, such as flood insurance, later required an extension of point flood hazard estimation to cover river reaches, and, eventually, entire catchments. This process is now well established in many countries, supported by several national guidelines^{5–7}. However, we argue in this paper that catchment-scale flood hazard assessment suffers

33 from two fundamental issues that remain unresolved despite an extensive scientific literature. First, this
34 assessment is fragile due to the finite nature of hydro-climate data records and the large uncertainty
35 associated with extreme events. Second, catchment-scale flood hazard assessment based on a single AEP
36 across a catchment, as often presented in flood mapping, is ambiguous because it is mathematically
37 impossible due to the randomness of spatial hydroclimate patterns. The paper aims to clarify these two
38 issues and formulate recommendations to overcome them using the exceptional 2022 flood in Australia
39 as an illustrative example.

40 Both issues highlighted above are the topic of considerable research, which is summarised briefly here.
41 Regarding the first one, flood frequency analysis is a difficult statistical problem because it requires
42 estimating the probability of events that occur only a few times per century, when hydroclimate records
43 cover a few decades at best⁸. Consequently, the uncertainty associated with a streamflow value for a low
44 AEP such as 1:100 is large. The techniques to reduce this uncertainty include the development of
45 sophisticated statistical fitting methods^{9,10}, the combination of at-site data with regional information^{11–}
46 ¹³, and the use of paleo-^{14,15} and historical^{16,17} data. Alternatively, the limited duration of observed
47 streamflow records can be circumvented by using the design storm method¹⁸. In this approach, a flood
48 with a given AEP is simulated by a hydrological model¹⁹ fed with rainfall forcings derived from
49 Intensity-Duration-Frequency curves^{20,21}. However, this approach does not necessarily reduce
50 uncertainty²² compared to observation-based flood frequency analysis, due to the combined uncertainties
51 in rainfall data, Intensity-Duration-Frequency curves²³, model parameters²⁴, and structure²⁵. Regardless
52 of the modelling method adopted, the lack of knowledge about extreme floods has problematic
53 consequences when a record-breaking flood occurs: because each additional data point carries a large
54 amount of information in a small data sample, a record-breaking event often shifts the probability
55 distributions of annual maxima of streamflow and rainfall. This phenomenon generally increases flood
56 quantiles, such as the 1:100 AEP²⁶. As a result, the level of protection provided by flood mitigation
57 infrastructure decreases after an extreme event. In other words, flood hazard assessment based on a fixed
58 AEP is vulnerable to extremes, or fragile²⁷. Research on out-of-sample events has essentially focused on
59 the number of such extreme events, with applications in a changing climate^{28,29}. The impact of extreme
60 events on flood quantiles, and more generally on flood risk management, has received much less
61 attention³⁰. A study on 2790 gauges in the United States showed that excluding the largest annual
62 streamflow maxima reduces the 1:100 AEP flood by 10.5% on average compared to fitting to all
63 available data²⁶. A similar value was obtained based on a set of 1094 gauges in Australia³¹. To clarify
64 the fragile nature of flood frequency analysis with an example from a recent extreme flood in Australia
65 and to formulate potential strategies to address this issue is the first objective of this paper.

66 The second issue raised in our introductory paragraph concerns the ambiguity of a design flood event
67 associated with a single AEP across an entire catchment. Such a spatially homogeneous AEP is required
68 to maintain the equality of protection against flood risk that underpins integrated flood risk
69 management^{32,33}, and hence most flood risk management policies worldwide. In this context, the
70 standard approach to estimating flood hazard begins by assessing flood frequency for each sub-
71 catchment via at-site flood frequency analysis or through the design storm approach as indicated in the
72 previous section. This process leads to the definition of several upstream flow boundary conditions,
73 which are subsequently passed to a hydrodynamic model used to determine the flood extent
74 downstream³⁴. This approach is particularly challenging to apply in practice in the presence of
75 confluences, which always occur in natural catchments except if the study area is limited to a small river
76 reach. The difficulty lies in the fact that the sum of tributary inflows, each associated with the same
77 AEP α , does not have an AEP equal to α in general. It can be proved mathematically³⁵ that the sum of
78 quantiles corresponding to α for each inflow is always greater than the same quantile computed for the
79 flow sum. The equality holds only if all tributary inflows are comonotonic, i.e., perfectly correlated. In
80 other words, it is mathematically impossible to maintain a constant AEP across all inflows and outflows
81 of a confluence in a real-world catchment where natural randomness prevents comonotonicity. This fact
82 has two fundamental consequences on catchment-scale flood risk management. First, it means that a
83 physical model of an entire catchment, for example in the design storm approach, cannot generate a
84 flood event that maintains a fixed AEP throughout a catchment. This issue is recognised in certain
85 technical guidelines, for example in Australia³⁶. However, it is somewhat overshadowed by the goal of
86 achieving “probability neutrality”³⁷ in the design storm approach, where some guidelines suggest that
87 selecting an AEP for rainfall inputs could guarantee the same AEP for downstream simulations¹⁸. A
88 second, and more important, consequence arises for large-scale mapping of flood risk, for example in
89 the United States³⁸ or Europe³⁹. More precisely, let us assume that a confluence occurs between the main
90 river and a secondary tributary. If a flood map assumes the same AEP α upstream and downstream of
91 the confluence, it means that the AEP of the flood extent on the tributary must be lower than α . In other
92 words, a sacrifice is required in the assessment of flood hazard on the tributary. This can be corrected
93 by independently estimating flood hazard in the tributary, but this raises the issue of potential
94 discontinuity at the junction between the two systems. It also prevents examination of the impact of
95 flood mitigation activities undertaken on the tributary for the main river, and vice versa. Research on the
96 spatial dependence of flood processes is abundant and recognises the importance of correlation among
97 extreme floods across multiple sites through the development of multivariate flood frequency models^{40–}
98 ⁴³. Such multivariate models have been applied to confluences^{44–47}, leading to several extensions of the
99 concept of a univariate AEP^{48,49} to a multivariate setting. All this research provides the tools to articulate

100 catchment-scale flood hazard assessment in a well-established multivariate statistical framework.
101 However, it does not solve the ambiguity raised at the beginning of this paragraph, simply because it is
102 mathematically impossible to do so. Here again, this paper aims to provide an example of this issue
103 using a recent case study in Australia and to formulate recommendations for future development of
104 catchment-scale flood hazard assessment.

105 **2. Results**

106 The Richmond River catchment in eastern Australia experienced one of the most extreme floods in the
107 recent history of Australia in 2022³¹. This flood resulted in 24 deaths^{50,51} and is considered the costliest
108 flood event in Australia, with total insurance claims estimated at over AUD \$ 6 billion. Our analysis of
109 flood hazard focuses on three gauging stations located upstream of the city of Lismore, one of the worst-
110 affected areas during the 2022 flood. Figure 1.b shows the pairwise scatter plots of the annual streamflow
111 maxima series in our dataset. Despite the high correlation between the values, with Spearman rank
112 correlation ranging from 0.55 to 0.71, they are obviously not comonotonic, with substantial randomness
113 in the dependence between the variables as suggested by the scatter of the points in each plot.

114 Flood frequency is investigated using a multivariate statistical model that estimates the joint probability
115 of exceeding annual streamflow maxima at three study sites immediately upstream of Lismore. This
116 model is later used in the paper to estimate the gauged fraction of inflows reaching this city by summing
117 the flows at the three sites. The model combines a Generalised Extreme Value (GEV) distribution as the
118 marginal distribution for each site, and a Gaussian copula to represent the dependence between the
119 sites⁵². It also includes an additional variable generated from a continental-scale hydrological simulation
120 (AWRA-L^{53,54}), providing a 110-year reanalysis of the runoff for the Lismore catchment⁵⁵. The model
121 is fitted to observed data within a Bayesian inference framework, taking into account the fact that some
122 data might be missing (e.g. at the beginning of the last century when only AWRA-L data are available)
123 or below a low censoring threshold via an efficient approach relying on latent variables, as detailed in
124 the method section. As can be seen in Table 1, the statistics computed from the model outputs are close
125 to their observed counterpart when evaluating both univariate (through the LH skewness⁵⁶) and
126 multivariate (through the multivariate upper tail dependence coefficient⁵⁷) statistics. In addition to the
127 multivariate model, a univariate model that is more representative of standard flood frequency
128 practices^{6,58} is also applied to each of the three stations independently.

129

130

131 Table 1: Site characteristics and performance of the statistical model. Performance is measured by
 132 computing statistics from observed and simulated data generated from the statistical model. The two
 133 metrics are the univariate LH skewness and the multivariate upper tail dependence coefficient. For the
 134 simulated data, the table reports the mean and standard deviation of the values generated from the
 135 posterior predictive distribution.

ID	Name	Catchment	Record	LH Skewness		Multivariate upper tail dependence coefficient above 50% percentile	
		Area [km ²]	Length [years]	Observed [-]	Simulated [-]	Observed [-]	Simulated [-]
203010	Leycester	179	56	0.25	0.21		
	Creek at Rock Valley				±0.06		
203024	Coopers	148	27	0.15	0.20	0.5	0.57
	Creek at Ewing Bridge				±0.06		±0.06
203014	Wilsons	223	66	0.31	0.25		
	River at Eltham				±0.07		
AWRA-L	Lismore catchment	1390	110	0.28	0.30 ±0.07		

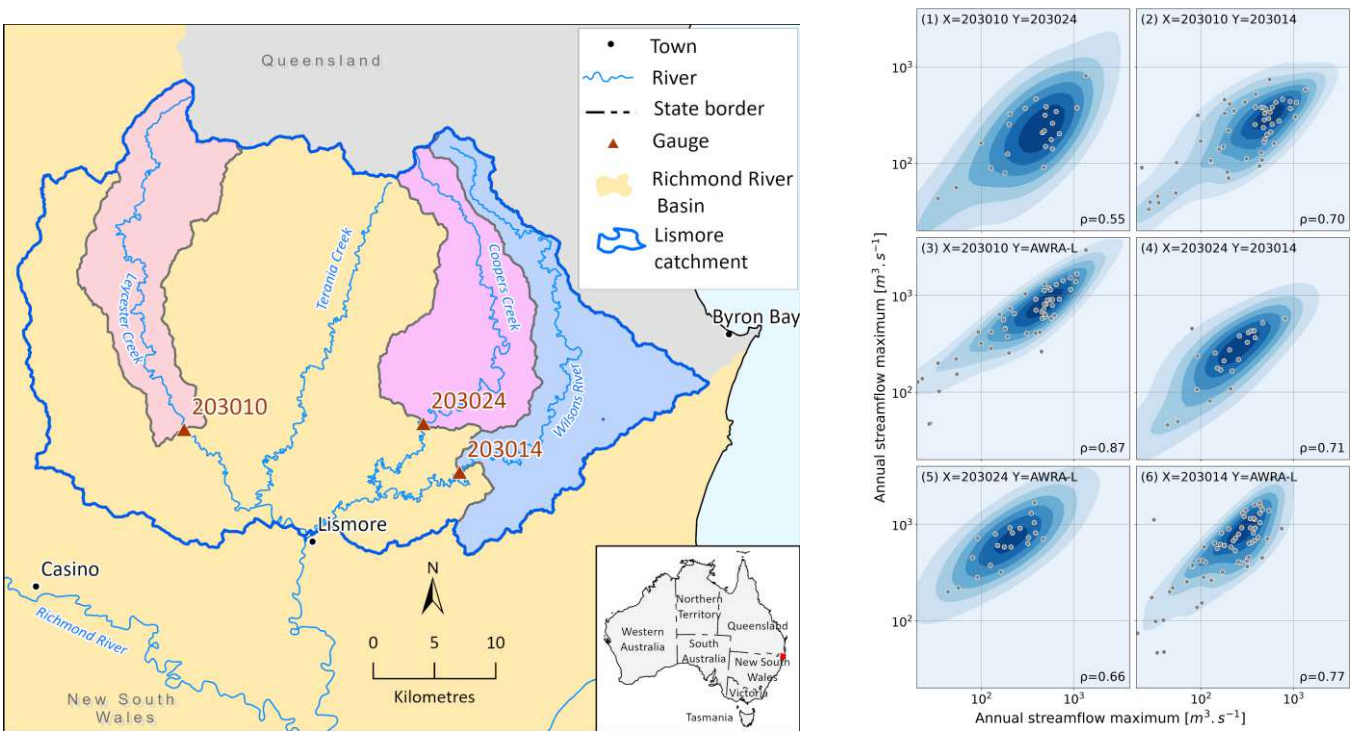
136

137 It is acknowledged that these statistical models are simpler than physically based models used in the
 138 design storm approach. Note that a fully distributed hydrological and hydrodynamic model of a large
 139 area encompassing the Wilsons catchment was also built in parallel to investigate flood mitigation
 140 scenarios⁵⁹. However, this model is much more computationally demanding than the statistical models
 141 introduced above and is not suitable for running the numerical experiments presented in this paper. The
 142 simpler statistical models were, thus, retained.

143 **2.1. Flood risk assessment relying on finite observed records is fragile**

144 Our introduction highlighted that estimating streamflow values for a given AEP is highly uncertain and
 145 sensitive to the most extreme values in historical streamflow records. Figure 2 illustrates this point by
 146 showing flood frequency curves estimated for the Leycester Creek at Rock Valley. This site has 56 years

147 of record (see Table 1), which is longer than most streamflow records in Australia and worldwide. It is,
 148 as such, a valuable reference for flood frequency analysis. Figure 2 shows four different flood frequency
 149 curves obtained by fitting two flood frequency models: the univariate model recommended by most
 150 national guidelines when long streamflow records are available^{6,58} is shown in the two plots on the left-
 151 hand side of the figure. The multivariate model is used on the right-hand side of the figure. The figure
 152 also compares curves obtained by fitting both models to all data points (second row) with a fit that
 153 excludes the 2022 flood (top row). For each plot, the value of the 1:100 AEP flow and its 90% credible
 154 interval, computed from the model posterior distribution, are given in the top-left corner, alongside the
 155 corresponding stage obtained by applying the rating curve to streamflow data.
 156



157 Figure 1: Site locations and pairwise scatter plots of annual streamflow maxima at the three study sites
 158 and against the AWRA-L simulation corresponding to the Wilsons River at Lismore catchment. The
 159 blue shades in the background of the scatter plots are the KDE density. The Spearman rank correlation
 160 between the two variables (ρ) is indicated in the bottom right corner of each scatter plot.
 161

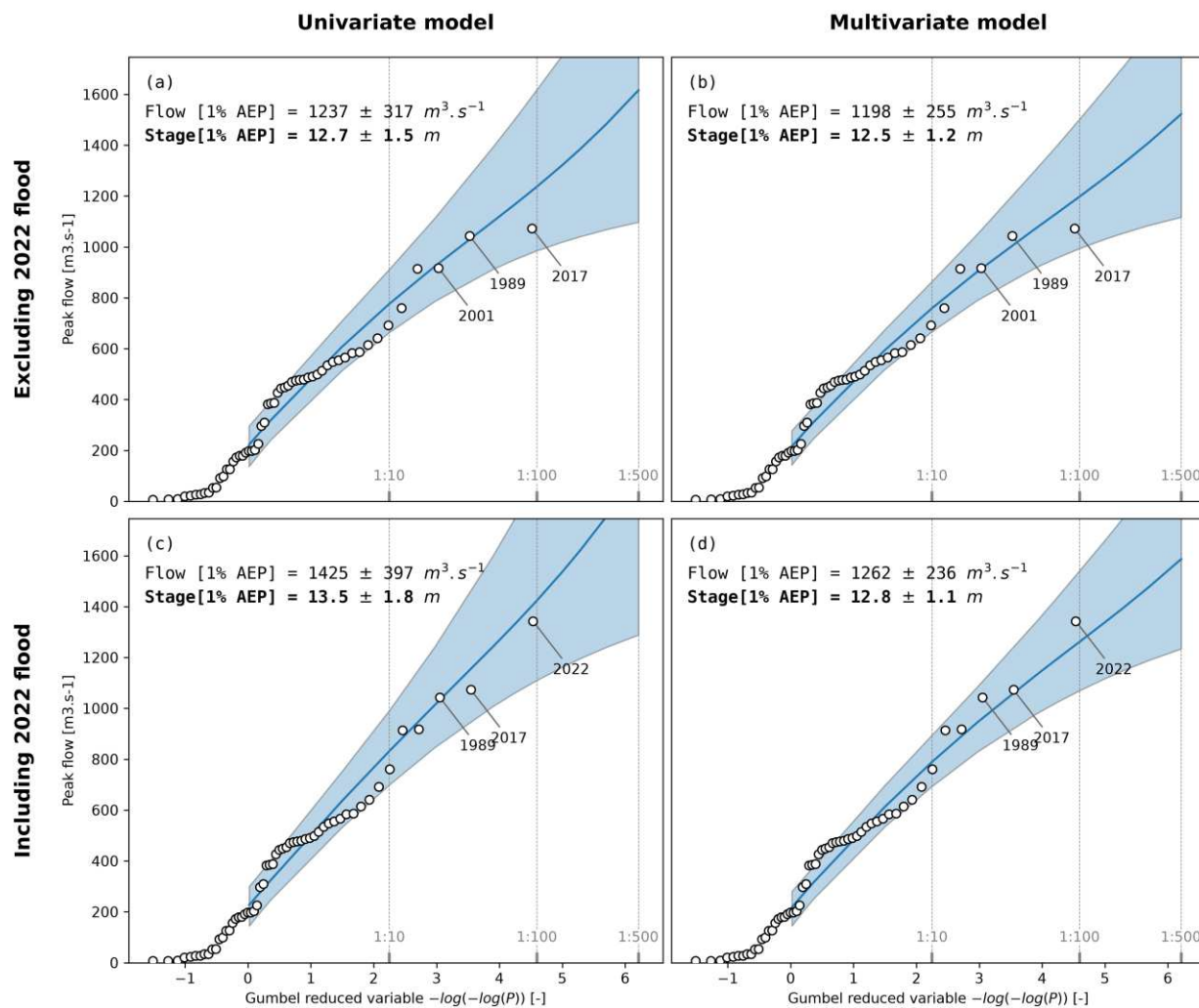


Figure 2: Flood frequency distribution for the Leicester Creek at Rock Valley estimated from data excluding (first row) and including (bottom row) the 2022 flood.

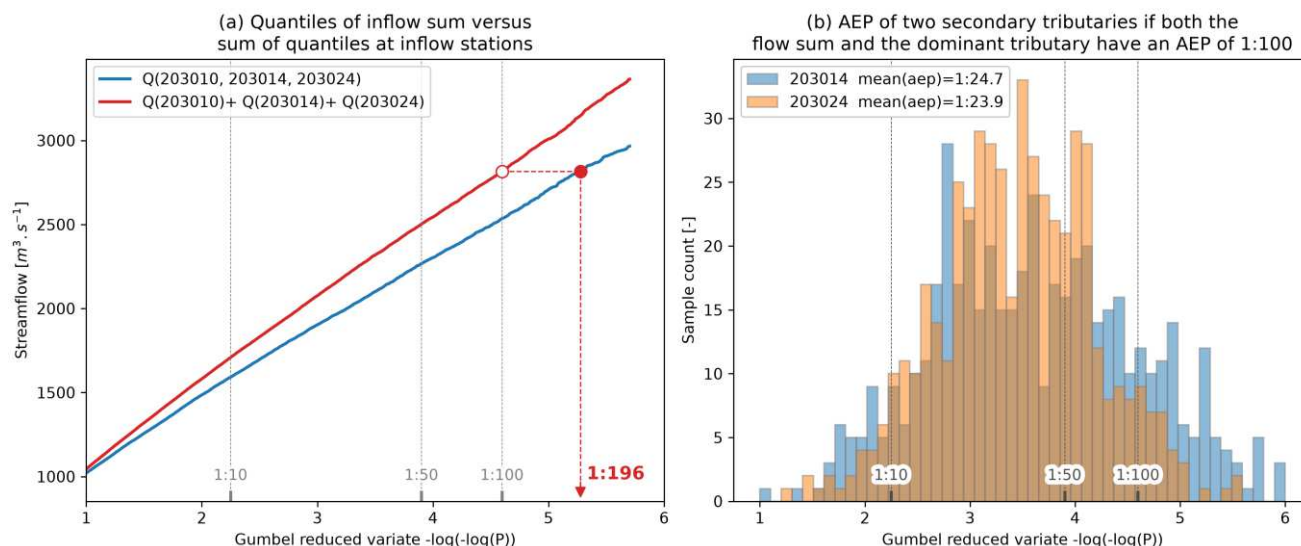
All the plots in Figure 2 highlight the large uncertainty associated with the 1:100 AEP. Regardless of the model used, this uncertainty is always larger than one meter, which suggests that considerable caution is warranted if this 1:100 AEP threshold is to be used in the design of flood mitigation infrastructure. We highlight that similar levels of uncertainty are likely to affect statistical models developed for rainfall data that underpin Intensity-Frequency-Duration curves²³ and hence the design storm approach, because most rainfall records are of a similar length to that of the Rock Valley station. One may argue that a more advanced statistical model, for example, combining local information with that from nearby gauges, could significantly reduce this uncertainty. Recent work comparing spatial hierarchical Bayesian models¹³ with the multivariate model presented in the previous section concluded that the latter is superior at reducing uncertainty bands for flood quantiles across a large number of sites in Australia⁵⁵. As a result, using a spatial model in this case is unlikely to tighten the uncertainty bands beyond what is shown in Figure 2.

177 Uncertainty per se does not make a process fragile: uncertainty can be incorporated into the decision-
178 making process, which has been shown to lead to more robust flood infrastructure design^{30,60,61}.
179 However, this is only possible if uncertainty estimation remains stationary, which is not the case when
180 an extreme flood occurs, as can be seen in Figure 2: using a univariate model (i.e. the standard approach)
181 prior to 2022, the 1:100 AEP flow is estimated to reach a level of $12.7m$ with a 90% credible interval
182 of $\pm 1.5m$ (Figure 2.a). This estimate shifts to $13.5m \pm 1.8m$ after 2022. The new estimate remains
183 within the bounds of the old one, but it has increased by 80cm, which could significantly alter the
184 estimated damage associated with the 1:100 AEP.

185 In this case, using a multivariate model reduces this fragility. A comparison between Figure 2.b and d
186 suggests that the estimation of the 1:100 AEP flood based on this model changes from $12.5m \pm 1.2m$
187 prior to 2022, to $12.8m \pm 1.1m$ after 2022. We also note that the uncertainty range is narrower than
188 with the univariate model. Consequently, it is possible to reduce fragility and the associated shifts in
189 flood-frequency estimates by using state-of-the-art multivariate statistical models. However, this will
190 require a significant investment by the flood modelling industry, which relies essentially on univariate
191 models^{6,58}. Nonetheless, it is noted that the limited duration of the observed records will remain a major
192 limitation in reducing uncertainty in flood quantiles, even when using advanced statistical models. A
193 way forward is discussed in Section 3.

194 **2.2. Catchment-scale flood hazard assessment is ambiguous**

195 The second issue raised in this paper relates to the mathematical impossibility of generating physically
196 realistic flood simulations with a constant AEP across a catchment. Figure 3.a illustrates this issue by
197 comparing two flood frequency curves for the Lismore gauged inflow. The first one (blue) is obtained
198 by generating 50,000 samples from our multivariate statistical model, then summing the three values for
199 the Rock Valley, Ewing Bridge, and Eltham stations (see Table 1), and finally computing their
200 cumulative distribution. The second curve (red) is obtained by computing the cumulative distribution of
201 the flow for each station independently, and subsequently summing the three quantiles. The red curve
202 consistently exceeds the blue one, thereby confirming that the sum of quantiles from correlated variables
203 exceeds the quantiles of their sum³⁵. Furthermore, the figure indicates that the sum of the three 1:100
204 AEP quantiles is approximately equal to a 1:200 AEP quantile for their sum. In plain language, summing
205 the three flood quantiles doubles the average return interval. This constitutes an important
206 overestimation of flood hazard assessment for the city of Lismore.



207

208 Figure 3: Figure (a) shows a comparison between the quantiles of the gauged inflows to Lismore (i.e.
 209 the sum of flows at stations 203010, 203014 and 203024) in blue with the sum of the quantiles at the
 210 same stations in red. Figure (b) shows the distribution of the AEP for the two stations of Eltham
 211 (203014) and Ewing Bridge (203024) if both the gauged inflow to Lismore and the flow at Rock
 212 Valley (203010, dominant tributary) are equal to their 1:100 AEP value.

213 Figure 3.b highlights a different problem related to confluences: let us assume that a 1:100 AEP flood
 214 map is being generated around Lismore, including the three upstream gauged tributaries where a 1:100
 215 AEP is imposed for the dominant tributary (i.e. Leicester Creek at Rock Valley, see Figure 1) and for
 216 the gauged flow downstream of the confluence (i.e. the sum of flow at the three stations of Rock Valley,
 217 Eltham and Ewing Bridge). Subsequently, we generate 500 samples from our multivariate flood
 218 frequency model, subject to these two constraints. Figure 3.b shows the distribution of the AEP on the
 219 two minor tributaries (i.e. Wilsons River at Eltham and Coopers Creek at Ewing Bridge) computed from
 220 these samples. As expected, the plot reveals that it is impossible to maintain a 1:100 AEP on the
 221 tributaries. The average AEP for both tributaries is approximately 1:25, as shown in the legend. This
 222 result highlights the extent of the sacrifice required on the tributaries to maintain a consistent AEP
 223 through a confluence. The figure also highlights the wide range of AEPs on the two minor tributaries
 224 that meet this constraint, with certain AEPs reaching values markedly below 1:10 or above 1:100. It is
 225 remarkable that some AEPs can be above 1:100 while the main tributary remains at 1:100 AEP above
 226 and below the confluence. This can be explained by the fact that a low AEP on one minor tributary can
 227 be compensated by a high AEP on another one. Consequently, imposing a fixed AEP on the main river
 228 above and below a confluence is not an effective constraint on multiple tributary flow. This result
 229 suggests that the sacrifices indicated above could be potentially much worse than the average value (1:25
 230 for fixed AEP of 1:100 on the main river).

231 3. Pathway forward and conclusion

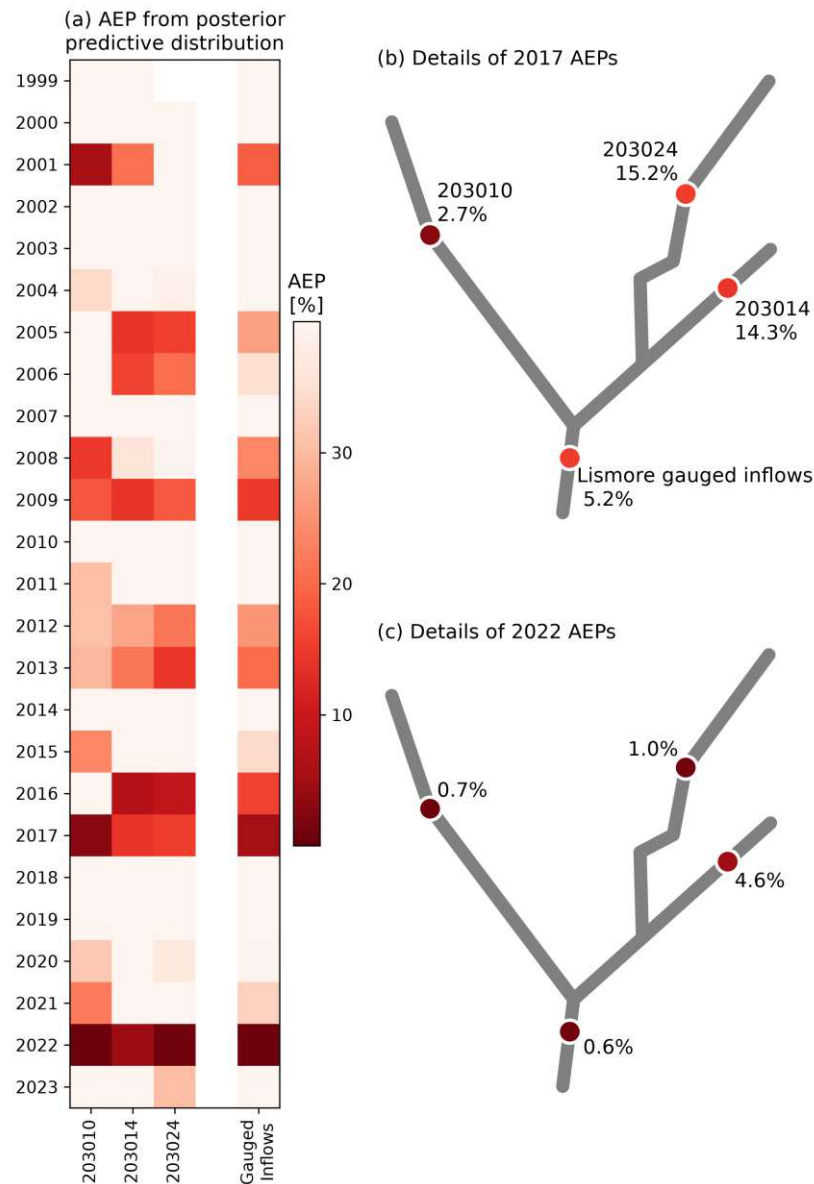
232 The previous sections highlighted the fundamental issues of fragility and ambiguity in catchment-scale
233 flood hazard assessment. Examples of problems related to these issues were provided using the Lismore
234 catchment as an example, which was affected by one of the most extreme floods in recent Australian
235 history. Three strategies can be proposed to mitigate these problems:

236 (1) **Evaluate uncertainty in flood quantiles through ensemble methods that enforce spatial**
237 **consistency:** The length of hydroclimate records in observation networks does not permit an
238 accurate estimation of rare flood quantiles, even for some of the longest streamflow records in
239 the world (500 years in the Danube⁶²) and even using state-of-the-art statistical models. This
240 limitation affects both at-site flood frequency analysis and the design storm approach via the
241 uncertainty in Intensity-Frequency-Duration curves. In our study catchment, uncertainty in the
242 1:100 AEP stage level for a station with a record of 56 years record was found to exceed 1 m.
243 Such a large uncertainty must be estimated and taken into account in the decision-making
244 process. In addition, the possibility that flood quantiles will change following a major event
245 must be explained. Flood quantiles based on streamflow records longer than 50 years are not
246 immune to such shifts, as shown in Section 2.1 where the 1:100 AEP increased by up to 0.8
247 meters after a single event when using a standard flood frequency analysis method. Bayesian
248 statistical models are useful in that regards because of their capability to incorporate parametric
249 uncertainty in the inference process while accounting for missing data and discarding low
250 outliers. These models can also incorporate a range of covariates, for example, a long re-analysis
251 of simulated streamflow, that adds information to the fitting process and reduces the sensitivity
252 of the flood quantiles to extreme events.

253 (2) **Acknowledge the sacrifices in flood hazard assessment at confluences:** it is mathematically
254 impossible to maintain the same AEP for all tributaries upstream and downstream of a confluence
255 in a natural catchment. This is a fundamental limitation of catchment-scale hazard assessment
256 that must be recognised in all flood risk management procedures. Consequently, maintaining the
257 same AEP on the main river through all confluences of the study area implies that the flow of all
258 secondary tributaries will be associated with a lower AEP, and may therefore not be protected at
259 the same risk level as the main river. This fact must be communicated to stakeholders explicitly.

260 (3) **Consider scenario-based modelling** as an alternative to frequency-based flood hazard
261 assessment. The two previous points stem from the fact that characterising flood hazard at the
262 catchment scale through probabilistic concepts remains a highly complex and uncertain
263 endeavour despite the vast amount of research available on the topic. These difficulties may be
264 deemed unacceptable in certain catchments where stakeholders expect a more pragmatic, albeit

less ambitious, approach. As a complement to frequency-based assessment, an alternative method that overcomes most issues raised above is to rely on scenarios that are not generated to match a specific flood quantile. A particularly simple solution lies in selecting some of the most extreme historical scenarios^{63,64}. Of course, this is only feasible in data-rich catchments where high-quality hydro-climate records exist and where significant flood events occurred. This approach is legislated in certain countries such as France⁶⁵, and was used in a recent study in the Lismore catchment where community consultations were organised to identify historical scenarios for consideration in a flood mitigation study⁵⁹. Most participants considered the 2017 event the most representative of damaging floods, while the 2022 event was judged beyond the scope of realistic flood mitigation measures. Such historical scenarios are, by definition, fixed and hence do not suffer from large uncertainty and shifting-quantile problems. They are also real flood events, which are more easily interpretable for local communities than artificial constructs based on probabilistic concepts⁶⁶. However, historical scenarios are spatially variable and therefore do not resolve the equity issue in flood hazard protection raised above related to AEP at confluences. This point is illustrated in Figure 4, which shows the AEP of recent historical floods at the three sites considered in Section 2 and of gauged inflows to Lismore. The figure confirms that it is impossible to observe homogeneous AEP, even in the case of the extreme flood of 2022 shown in Figure 4.c where one of the stations (Eltham, 203014) reached an AEP of 4.6%, which is significantly higher than for the other points. Despite this heterogeneity, the number of significant flood events remains limited in this case, as can be seen in Figure 4.a, leading to the choice made by the local communities during the aforementioned study. Overall, historical scenarios do not solve all problems related to catchment-scale flood hazard assessment, but they certainly deserve a more prominent place in the toolbox of flood engineers.



289

290 Figure 4: Annual exceedance probabilities of historical maxima computed from the predictive
 291 posterior distribution of our multivariate model. The marginal AEPs are given for each site and each
 292 event, including gauged inflows to Lismore, computed as the sum of the flows from the three stations
 293 of Rock Valley (203010), Eltham (203014), and Ewing Bridge (203024). Figures b and c show the
 294 details of the two events that occurred in 2017 and 2022.

295 4. Method

296 4.1. Univariate annual streamflow maxima model

297 The univariate model considers a single variable, the annual streamflow maxima referred to as X , which
 298 is assumed to be sampled from the Generalised Extreme Value distribution (GEV). The GEV density
 299 for a given value x is:

$$f_X(x|\theta) = \begin{cases} \frac{1}{\sigma} \left(1 - \kappa \frac{x - \mu}{\sigma}\right)^{\frac{1}{\kappa}-1} \exp \left[- \left(1 - \kappa \frac{x - \mu}{\sigma}\right)^{\frac{1}{\kappa}} \right] & \text{if } \kappa \neq 0 \\ \frac{1}{\sigma} \exp \left[-\frac{x - \mu}{\sigma} - \exp \left(-\frac{x - \mu}{\sigma} \right) \right] & \text{otherwise} \end{cases} \quad (1)$$

where μ , σ and κ are the GEV location, scale and shape parameters, respectively, denoted collectively as θ . The model is fitted within a Bayesian inference framework which estimates the posterior distribution of θ_X given observed data. Assuming independence between the years, this posterior is computed as:

$$\Pr(\theta_X | \tilde{x}) \propto \Pr(\tilde{\theta}) \prod_{t=1}^N L(x[t] | \theta_X) \quad (2)$$

where N is the number years in the data record, $\tilde{x} = \{x[t]\}_{t=1, \dots, N}$ are the observed streamflow values for the site, and $\Pr(\theta_X)$ is the prior distribution of the GEV parameters. The impact of low outliers⁶⁷ is eliminated via a censoring approach. This leads to the following expression of the likelihood function:

$$L(x|\theta) = \begin{cases} f_X(x|\theta) & \text{if } x > C \\ F_X(C|\theta) & \text{otherwise} \end{cases} \quad (3)$$

where C is the censoring threshold set to the 30th quantile of the observed data^{31,55} and F_X is the GEV cumulative density. The prior in Equation (2) is given by:

$$\Pr(\theta) = \Pr(\sigma) \Pr(\kappa) \quad (4)$$

This prior implicitly associate a flat prior to μ . The prior for σ and κ are:

$$\log(\sigma) \sim N_{-20,20}(0, 20) \quad (5)$$

$$\kappa \sim N_{-2,2}(0, 0.2) \quad (6)$$

where $N_{a,b}(m, s)$ denotes the truncated normal distribution over the interval $[a, b]$ with location m and scale s . These priors are selected to be as uninformative as possible, while ensuring that the parameters remain physically plausible⁶⁸.

The parameters of this model are sampled from the posterior distribution using the No-U-Turn Hamiltonian MCMC sampler implemented in the Stan statistical software⁶⁹. The sampler is wrapped in the Python programming language and made available as indicated in the Data and Code Availability section. This process leads to P parameters samples. In this paper, we sampled $P = 50,000$ parameters from 10 MCMC chains initialised with a warmup of 10,000 samples.

318 Based on the posterior distribution of parameters, the posterior predictive distribution of X presented in
 319 Figure 2 is computed as:

$$F_X^{-1*}(p) = \int_{\theta_X} F_X^{-1}(p|\theta_X) \Pr(\theta_X|\tilde{x}) d\theta_X \quad (7)$$

320 where F_X^{-1} is GEV quantile function.

321 **4.2. Multisite annual streamflow maxima model**

322 The multivariate model estimates the joint probability of four variables: the annual streamflow maxima
 323 at the three stations listed in Table 1 in addition and the annual runoff maxima of the AWRA-L
 324 simulation for the Lismore catchment. Using a multivariate setup increases the information that can be
 325 used to constrain the model parameters, but it also increases the chance of encountering missing data
 326 and undesirable low outliers⁶⁷. In our case, the AWRA-L simulations covers 110 years, out of which a
 327 fraction only is covered by observed records for the three gauging stations, which leads to a large number
 328 of missing data. This is a challenging problem for multivariate statistical models⁷⁰. The approach
 329 adopted here relies on an extension of the censoring approach presented in the previous section via latent
 330 variables⁷¹.

331 Let us assume that we collect data for the four variables described above over a period of N years. In
 332 this dataset, some of the data are missing for reasons assumed independent from the flood levels (i.e.
 333 missing at random⁷²), or fall below a censoring threshold defined similarly to the univariate model (see
 334 previous section). For a particular year t , let us denote a “complete” dataset of the $P = 4$ variables
 335 described above for a particular year t as $\tilde{x}[t] = \{x_i[t]\}_{i=1,\dots,P}$. In reality, only a fraction of these values
 336 is valid while others are either left-censored or missing. This information is recorded in a vector $I[t] \in$
 337 $\mathbb{N}^P$ where the status of each variable is marked as valid (=1), censored (=2) or missing (=3).

338 We assume that the complete dataset is characterised by a Gaussian copula with GEV marginals⁵².
 339 Formally, this means that the join distribution g of the components of $\tilde{x}[t]$ is given by

$$g(\tilde{x}[t]|\theta_1, \dots, \theta_P, R) = c_G[F(x_1[t]|\theta_1), \dots, F(x_P[t]|\theta_P)| R] \prod_{i=1}^P f(x_i[t]|\theta_i) \quad (8)$$

340 where f and F are GEV density and cumulative density, θ_i are the GEV parameters for variable i , R is
 341 a correlation matrix, and c_G is the density of the Gaussian copula⁵⁷:

$$c_G[u_1, \dots, u_P | R] = \frac{\phi_P(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_P) | R)}{\prod_i^P \phi(\Phi^{-1}(u_i))} \quad (9)$$

where ϕ is the standard normal density, Φ its cumulative density and ϕ_P is the P -multivariate normal density with correlation matrix R .

Our model estimates the posterior distribution of the parameters $\Theta = \{R, \theta_1, \dots, \theta_P\}$ given the valid data and the occurrence of valid, censored and missing data. Following the latent variable approach⁷¹, this posterior computation is expanded to include an estimation of the (unobserved) censored and missing values, both considered as inferred quantities. Without such expansion, the calculation of the posterior distribution requires the consideration of all possible combinations where each variable can be valid, missing or censored. This leads to computational difficulties because the number of such combinations can be large in high dimensions. Consequently, the posterior distribution of parameters Θ and latent variables is:

$$\Pr(\Theta, \{\tilde{x}_{I=2,3}[t]\}_{t=1\dots N} \mid \{\tilde{x}_{I=1}[t], I[t]\}_{t=1\dots N}) = \prod_{t=1}^N \Pr(\Theta, \tilde{x}_{I=2,3}[t] \mid \tilde{x}_{I=1}[t], I[t]) \quad (10)$$

where the notation $\tilde{x}_{I=k}$ refers to the subset of $\tilde{x}$ in which the status I is equal to k . In the above equation, the posterior can be factored across the years because we assumed that the data are independent between years, similarly to what was done for the univariate model. The posterior distribution for each year is further factored as a likelihood and prior distribution as follows, where we drop the reference to the year t to simplify notations:

$$\Pr(\Theta, \tilde{x}_{I=2,3} \mid \tilde{x}_{I=1}, I) \propto \Pr(\tilde{x}, I \mid \Theta) \Pr(\Theta) \quad (11)$$

where the prior $\Pr(\Theta)$ is detailed in the following section. Finally, the likelihood in the equation above is computed as:

$$\Pr(\tilde{x}, I \mid \Theta) = \Pr(\tilde{x} \mid \Theta) \Pr(I \mid \tilde{x}, \Theta) \quad (12)$$

The first term in the right-hand side of the previous equation is the joint distribution g in Equation (8). The second term is the probability of the variable status I given the complete data $\tilde{x}$ and the parameters. We note that the status “valid” (=1) has a certain probability of occurrence given the complete data $\tilde{x}$, which contains the observed data. Hence it does not contribute to $\Pr(I \mid \tilde{x}, \Theta)$. Similarly, the status “missing” (=3) is independent of the data and parameters by definition and does not contribute to $\Pr(I \mid \tilde{x}, \Theta)$. Overall, only the status “censored” affects $\Pr(I \mid \tilde{x}, \Theta)$, which leads to:

$$\Pr(I|\tilde{x}, \Theta) = \prod_{i \in \{k/ I_k=2\}} \mathbf{1}_{\tilde{x}_i < C_i} \quad (13)$$

where $\mathbf{1}_A$ is the indicator function of A and C_i is the censoring threshold for variable i .

4.3. Prior distribution of parameters in the multivariate model

The prior distribution $\Pr(\Theta)$ adopted here assumes the independence of the prior for each vector θ_i and R as follows:

$$\Pr(\Theta) = \Pr(R) \prod_{i=1}^P \Pr(\theta_i) = \Pr(R) \prod_{i=1}^P f_{\sigma}(\sigma_j) f_{\kappa}(\kappa_j) \quad (14)$$

where f_{σ} and f_{κ} are prior distributions identical to Equations (5) and (6), and $\Pr(R)$ is the modified inverse-Wishart density for four-dimensional correlation matrices⁷³:

$$\Pr(R) \propto |R|^{\frac{P(P-1)}{2}} \left(\prod_{j=1}^P R_{jj} \right)^{-\frac{(P+1)}{2}} \quad (15)$$

This prior density ensures that the marginal distribution of the correlation coefficients is uniform over $[-1,1]$, which allows the model to reach high correlation coefficients for some of the variables.

4.4. Performance assessment

The model's performance is measured by generating 50,000 replicates of the observed annual maxima dataset from the model's posterior distribution. For each of these replicates, two statistics are computed: (1) the LH skewness⁵⁶ which is the third shifted L moment, and (2) the upper tail dependence coefficient above the 50th percentile, computed as:

$$\tau_{50} = \frac{P(x_1 \geq q_1[50], \dots, x_P \geq q_P[50])}{0.5} \quad (16)$$

where $q_i[50]$ is the 50th percentile for the annual maxima at station i . Finally, the statistics computed from simulated data generated from our model posterior predictive distribution are compared with their observed counterpart as reported in Table 1.

5. Data availability

The annual streamflow maxima used in this research were computed from instantaneous streamflow time series downloaded from the WaterNSW website⁷⁴. The data is provided as part of the repository containing the code described in Section 6.

385 **6. Code availability**

386 All code and data used in this paper can be downloaded from the associated code repository⁷⁵.

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392

393 **Author contributions**

394 Julien Lerat contributed to the conception of the work, acquisition, analysis, and interpretation of data,
395 development of code used in the work, and drafted the initial version of the manuscript. Jai Vaze
396 contributed to the conception of the work and substantively revised the initial version of the manuscript.

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