

Supplementary Information for:

# A general framework for prediction of extreme events at river confluences

by Diakomopoulos et al. (2026)

## Supplementary Figures

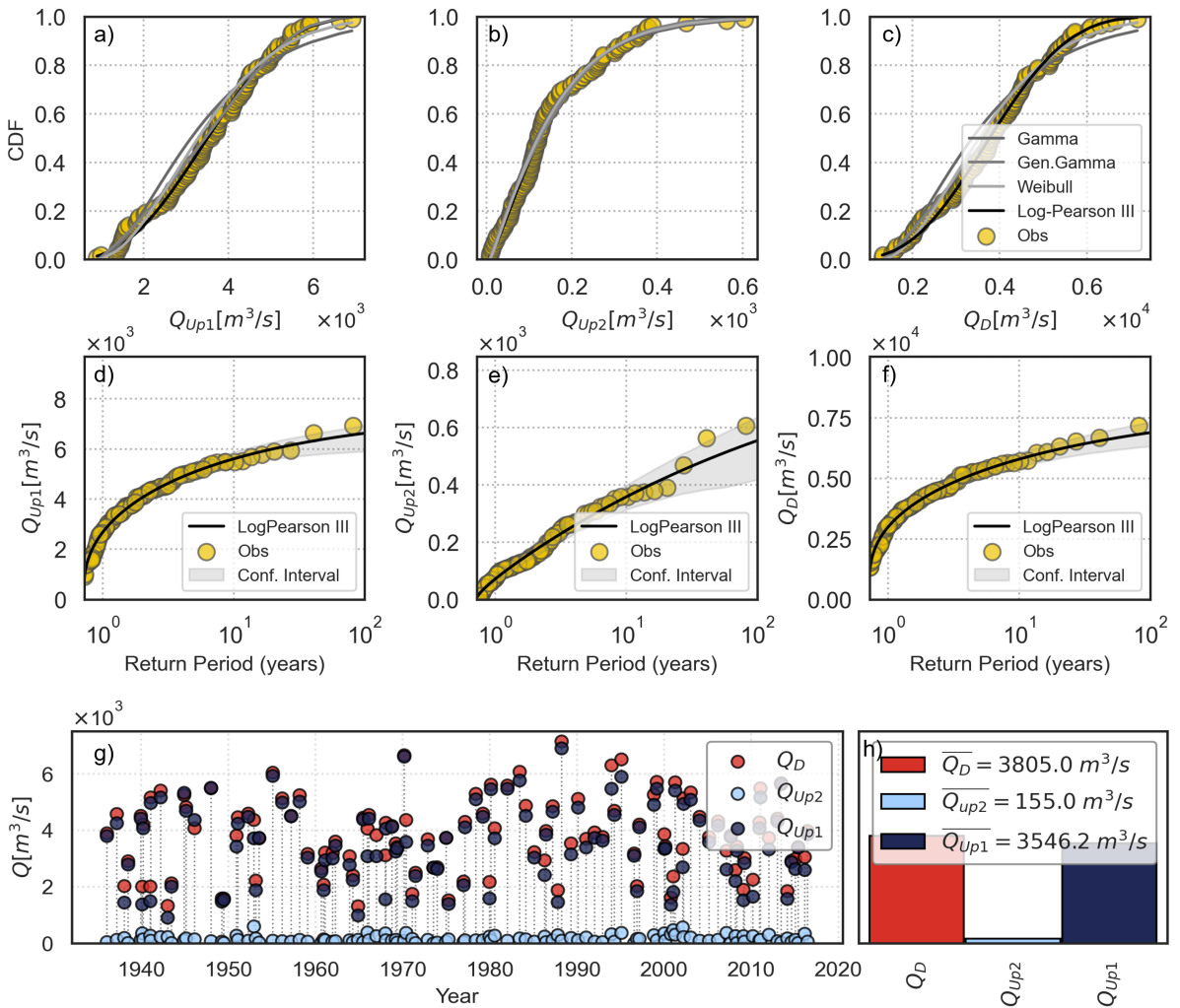


**Figure S1.** Panels (a), (b), (c) show theoretical distributions for the Rhine-Nahe confluence. Panels (d), (e), (f) show the distribution that leads to the highest value of Kolmogorov-Smirnov (KS) test and will be used as marginal distributions for the vine copula model (Log Pearson III). Panels (g), (h) illustrate extreme events for the Rhine-Main confluence, showing all the events of  $Q_{up1}$ ,  $Q_{up2}$  and  $Q_D$ , while on the right panel the average streamflows are shown.

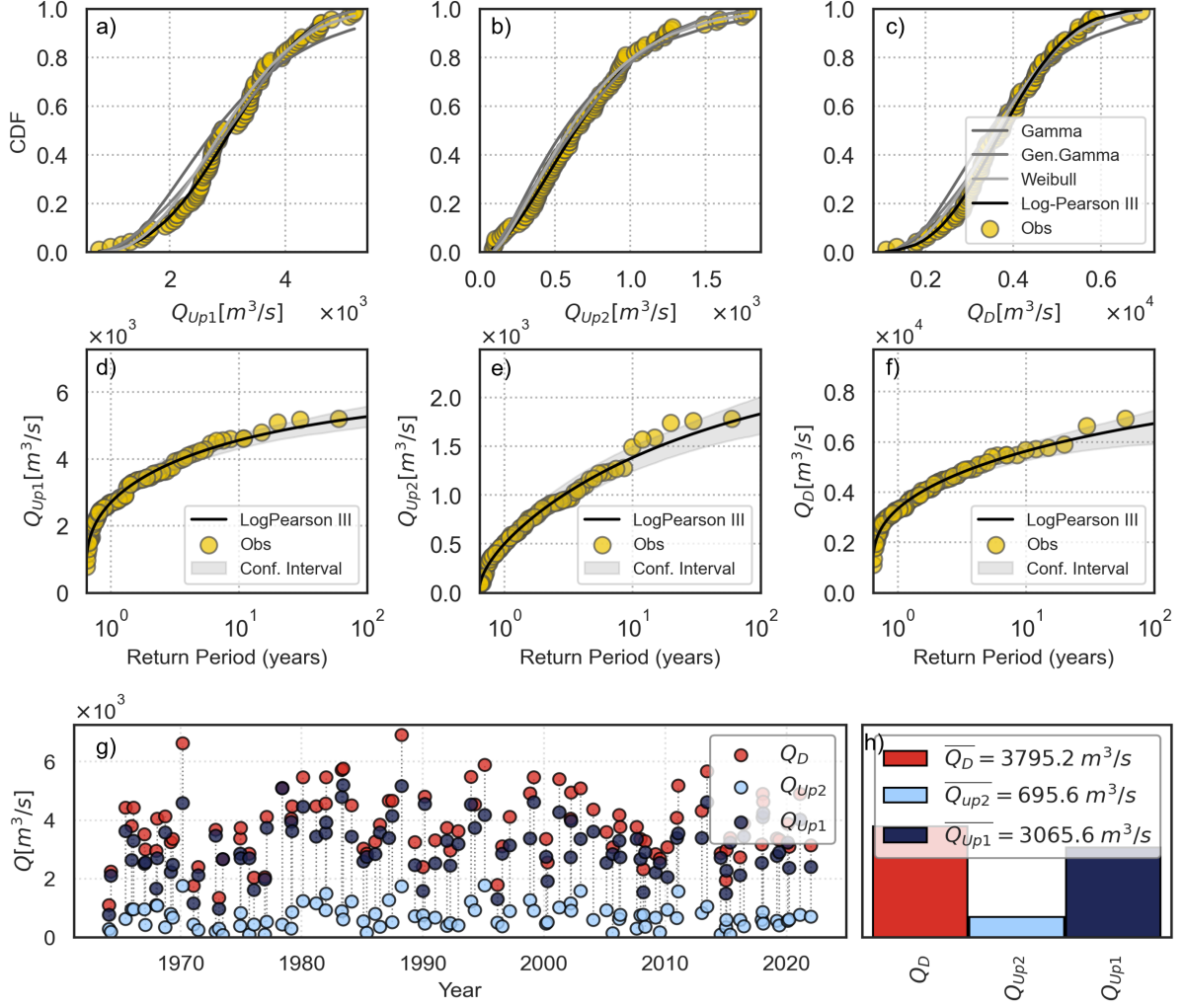


**Figure S2.** Panels (a), (b), (c) show theoretical distributions for the Rhine-Main confluence. Panels (d), (e), (f) show the distribution that leads to the highest value of Kolmogorov-Smirnov (KS) test and will be used as marginal distributions for the vine copula model (Log Pearson III). Panels (g), (h) illustrate extreme events for the Rhine-Main confluence, showing all the events of  $Q_{Up1}$ ,  $Q_{Up2}$  and  $Q_D$ , while on the right panel the average streamflows are shown.

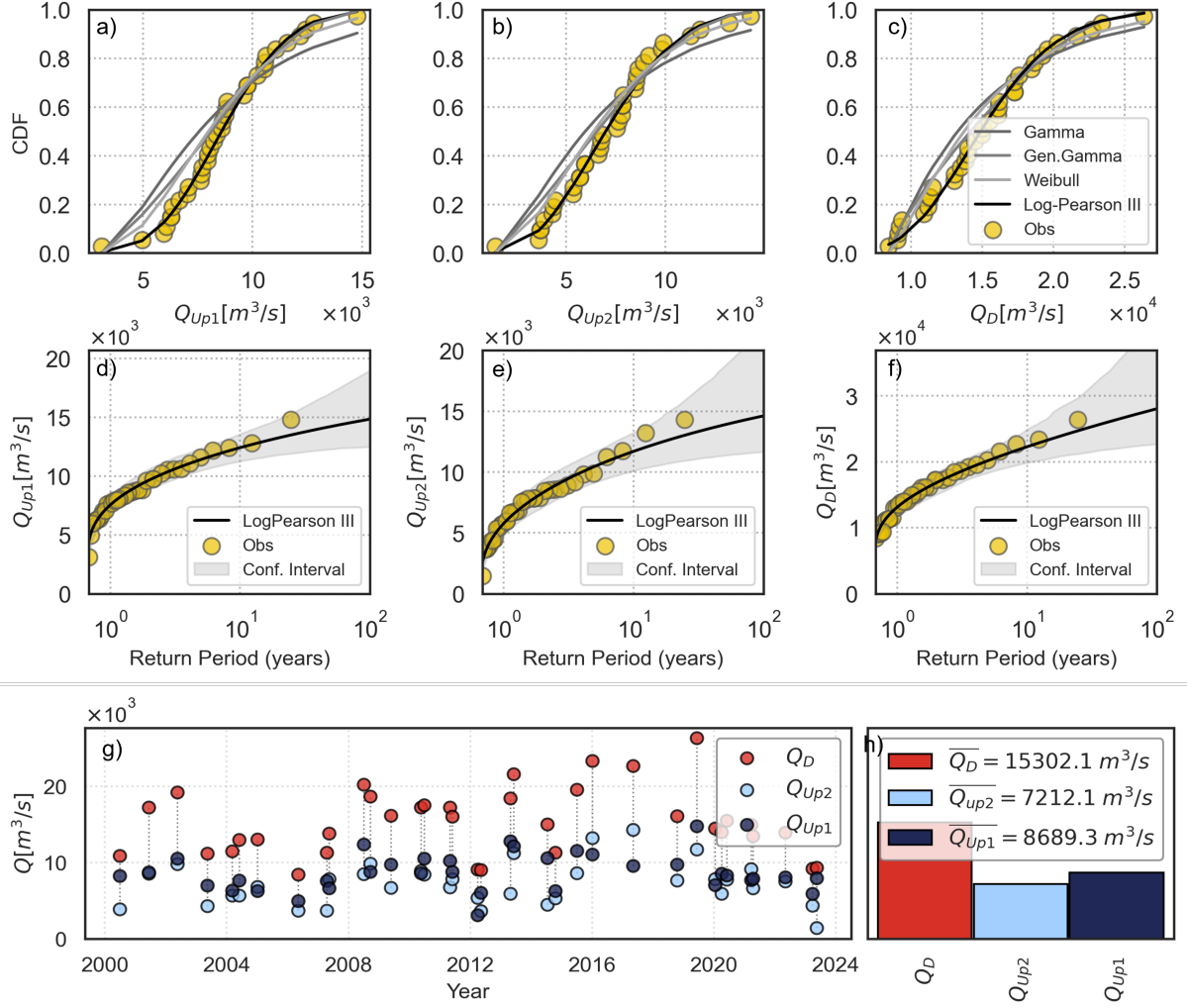


**Figure S3.** Panels (a), (b), (c) show theoretical distributions for the Mississippi-Missouri confluence. Panels (d), (e), (f) show the distribution that leads to the highest value of Kolmogorov-Smirnov (KS) test and will be used as marginal distributions for the vine copula model (Log Pearson III). Panels (g), (h) illustrate extreme events for the Rhine-Main confluence, showing all the events of  $Q_{Up1}$ ,  $Q_{Up2}$  and  $Q_D$ , while on the right panel the average streamflows are shown.

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## Supplement Methods

### Streamflows trends removal steps

Geomorphological changes, antropogenic interventions (dams, weirs) and climate change could affect the streamflows leading to non-stationary datasets . The data homogenization procedure can be described as follows: (i) the yearly average of the daily observations was calculated for each station, (ii) the presence of a trend was tested using the Mann–Kendall test at a significance level of  $\alpha = 0.05$ , (iii) if a trend was detected, the characteristic Sen’s slope was calculated, (iv) to adjust the data to the final year of each time series, the difference between the trend-line value of the final year and that of every other year was computed, and (v) this difference was added to the initial yearly average of the daily streamflow measurements to produce homogenized, corrected values.

### Simultaneous co-occurrence of upstream streamflows

The upper bound of the time windows for scenarios 1,2 and 3 for the Rhine-Nahe confluence is equal to 1 day according to the size of the ICA. At this confluence the influence of the  $Q_{Up2}$  compared to the  $Q_{Up1}$  is extremely lower as its average streamflow is 0.02 times the streamflow of  $Q_{Up1}$ . Even if the median time difference between  $Q_{Up1,AM}$  and  $Q_{Up2,AM}$  is 18 days, and as a result lower than the corresponding value of the Rhine-Main confluence, there is a 0% probability of simultaneous occurrence between  $Q_{Up1,AM}$  and  $Q_{Up2,AM}$  (see Figure S5e). In this case the assumption of independence doesn’t affect the results, as the tributary streamflow is almost negligible compared to the main river. The probability of the simultaneous occurrence between  $Q_{Up1,AM}$  and  $Q_{D,AM}$  is 86% as it is shown also in the Figure S5b, where their spider plots closely correspond.

For the Rhine-Main confluence a similar upper bound of 1 day for the time window for all of the three scenarios is observed. Analysis of the event dates in the flood event dataset indicates that 50% of the events occur on the same day for  $Q_{Up1}$  and  $Q_{Up2}$ , while in 34% of the events  $Q_{Up1}$  precedes  $Q_{Up2}$  by one day, and in the remaining 16% of the cases  $Q_{Up2}$  precedes  $Q_{Up1}$  by one day. The analysis of simultaneous AM streamflows at the upstream stations indicates that in almost 1 out of 4 years the AM co-occur (22%), while the median time lag between upstream AM streamflows is 31 days (see Figure S5a,d). A similar probability of 22% is observed for the co-occurrence of  $Q_{Up2,AM}$  and  $Q_{D,AM}$ . On the other hand, there is a 70% probability of co-occurrence of the  $Q_{Up1,AM}$  and  $Q_{D,AM}$  (see Figure S5a), showing a higher contribution of the  $Q_{Up1,AM}$  in the  $Q_{D,AM}$ , but also the influence of the  $Q_{Up2,AM}$ .

In the Mississippi-Missouri confluence where the average upstream streamflows are identical and the ICA is much bigger than the previous cases the upper bounds of time windows vary per scenario. For Scenario 1, the time lag is 1 day, for Scenario 2, it is 2 days, and for Scenario 3, it is 11 days. Analysis of the event dates in the flood-event dataset indicates that 45% of the events occur on the same day for  $Q_{Up1}$  and  $Q_{Up2}$ , while there is a 87% probability that  $Q_{Up1}$  and  $Q_{Up2}$  occur within a time window of  $\pm 1$  day. The median time difference between the upstream streamflows is 18 days (see Figure S5f). In 17% of the annual flood events,  $Q_{Up1,AM}$  and  $Q_{Up2,AM}$  occur simultaneously.  $Q_{Up1,AM}$  and  $Q_{D,AM}$  occur simultaneously in 38% of the observational years, and a similar percentage is observed for the co-occurrence of  $Q_{Up2,AM}$  and  $Q_{D,AM}$ . These results highlight the influence of both upstream streamflows on the downstream streamflow, in contrast to the other two confluences.

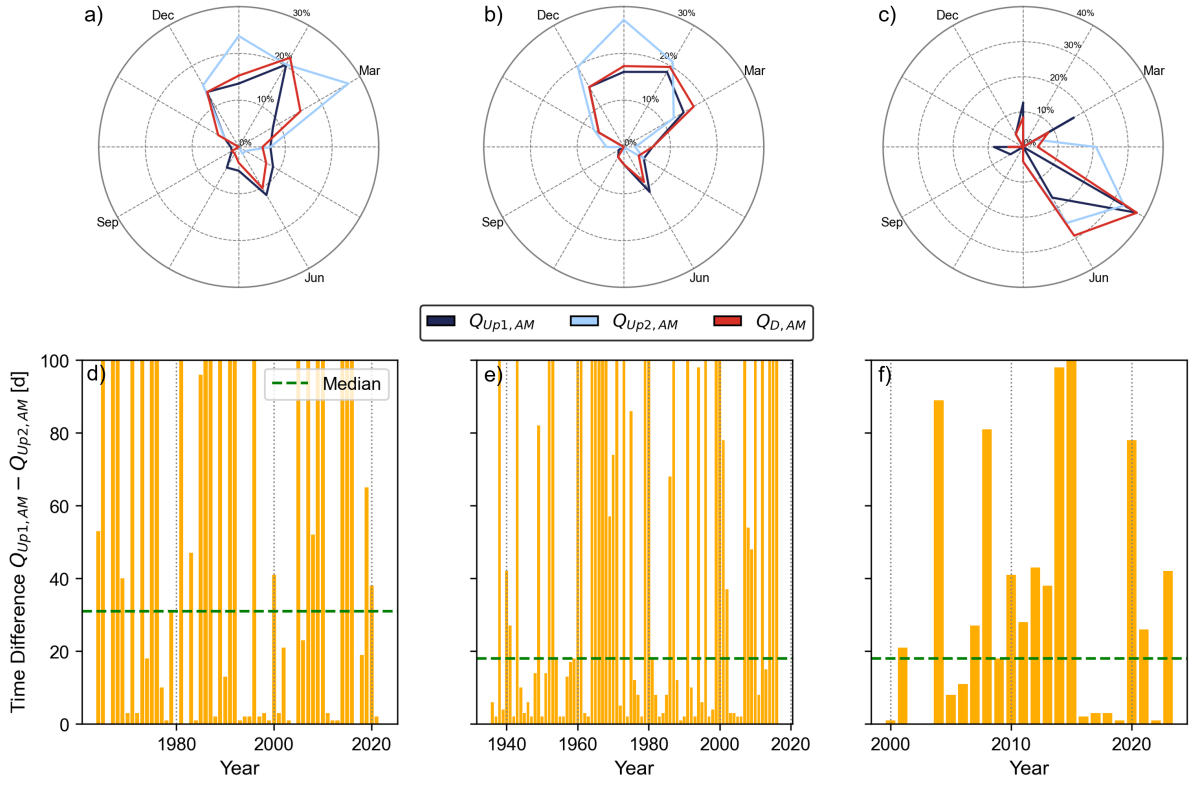


**Figure S4.** Panels a,b,c show the spider plot of how the AM are distributed during the months of the years for upstream and downstream streamflows. Panels d,e,f show the time difference in days between the dates of the Annual Maxima streamflows. Panel a,d represents the Rhine-Main confluence, while b,e and c,f the Rhine-Nahe and Mississippi-Missouri confluences, respectively.

## Theoretical distributions

**Table S1.** Tested Distributions.  $f(x)$  indicates the probability density function (pdf);  $x$  the streamflows from the extreme events dataset.

| Name              | Mathematical Description                                                                    | Parameters                                                                                                                                                    |
|-------------------|---------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Log-Pearson III   | $f(y) = \frac{ \beta }{\Gamma(a)} (\beta(y - \zeta))^{\alpha-1} \exp(-(\beta(y - \zeta)))$  | $y = \log(\frac{x}{\sigma})$<br>$x > 0$<br>$\beta = \frac{2}{\kappa}$<br>$\beta = \frac{4}{\kappa^2}$<br>$\zeta = -\beta$<br>$\kappa$ shape<br>$\sigma$ scale |
| Gamma             | $f(x) = \frac{(\frac{x}{\sigma})^{a-1} \exp(-(\frac{x}{\sigma}))}{\Gamma(a)}$               | $x \geq 0$<br>$\sigma$ scale<br>$a$ shape                                                                                                                     |
| Weibull           | $f(x) = c(\frac{x}{\sigma})^{c-1} \exp(-(\frac{x}{\sigma})^c)$                              | $a > 0$<br>$x \geq 0$<br>$\sigma$ scale<br>$c$ shape<br>$c > 0$                                                                                               |
| Generalized Gamma | $f(x) = \frac{k(\frac{x}{\sigma})^{k\alpha-1} \exp(-(\frac{x}{\sigma})^k)}{\Gamma(\alpha)}$ | $x \geq 0$<br>$\sigma$ scale<br>$k, \alpha$ shape<br>$k, \alpha > 0$                                                                                          |