



A general probabilistic framework for prediction of extreme flow events at river confluences

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Abstract.

River confluences are critical nodes within river systems and are often exposed to increased flood risk, as the co-occurrence of peak streamflows and thus the superposition of flood waves from two or more tributaries may amplify their magnitudes, leading to compound extreme flow events. However, a systematic and holistic framework to analyse and predict extreme streamflows downstream of river confluences remains largely absent from the literature. This study investigates the interaction between upstream and downstream streamflows during extreme events at river confluences and provides a computationally efficient probabilistic framework for estimating extreme downstream flows based on combinations of upstream conditions from individual tributaries. In this work, a confluence is defined as the junction of two upstream river branches that merge into a downstream channel. We introduce a novel probabilistic-based methodology to describe and predict concurrent streamflows, including uncertainty quantification across the three branches when an extreme event occurs in at least one of them. Building on this, a copula-based probabilistic model is developed with a twofold objective: (i) to predict downstream flow given different combinations of upstream conditions, and (ii) to determine combinations of upstream flows associated with downstream flows exceeding specified safety thresholds. The proposed framework is demonstrated and tested using three contrasting river confluences: two confluences in the Rhine river system in Germany i.e., Rhine–Nahe at Bingen and Rhine–Main at Mainz, and the Mississippi–Missouri confluence at St. Louis in the United States. The results demonstrate that confluences sharing the same main river can behave fundamentally differently under extreme conditions. In the Rhine–Nahe system the influence of Nahe to the downstream streamflow is limited due to its smaller size compared to the Rhine. On the other hand, for the Rhine–Main confluence which is characterized by an intermediate difference between the magnitudes of the two contributing river branches, the results show that the superimposition of the flood waves remains a major control of downstream extreme floods. In contrast, for the Mississippi–Missouri confluence, where upstream streamflows of the two contributing river branches are of comparable magnitude, the simultaneous occurrence of moderate peaks is a primary driver of downstream extreme streamflows. In other words, under such conditions, the superimposition of individual flood waves is not the only dominant control on downstream extreme floods, but has the potential to lead to extreme flow events that may have catastrophic consequences. The probabilistic model developed here demonstrates high predictive skill in reproducing downstream streamflows from upstream observations with Nash–Sutcliffe Efficiency, $NSE > 0.97$ in all cases, despite the contrasting mechanisms underlying the generation of flood



waves at the three study confluences, indicating its generalizability and robustness for estimating and predicting upstream flow combinations that may lead to downstream streamflows beyond safety thresholds.

1 Introduction

30 Confluences are junctions in river networks where two or more tributaries merge to form a downstream river. The generated streamflow downstream of confluences is some non-linear combination of upstream streamflows, and can be understood as a compound event (Leonard et al., 2014; Zscheischler and Seneviratne, 2017) where the upstream flows are dependent or independent physical drivers. Flood frequency analysis considering univariate statistics can describe individual upstream and downstream conditions (Koutsoyiannis, 2021; Zaerpour et al., 2024; Villarini et al., 2011; Papoulakos et al., 2025), without
35 capturing their dependence structures. This can lead to an underestimation of the flood hazard at the downstream of the confluence (Jiang et al., 2024). Therefore, the type of modelling framework to predict extreme downstream flows from different plausible combinations of upstream streamflows has a direct implication for the design of flood mitigation measures on river confluences (Fischer and Schumann, 2021).

The investigation of the confluence behaviour under extreme conditions frequently relies on process-based or data-driven
40 hydrological models (Hrachowitz and Clark, 2017). Using these models we can quantify the upstream flows that could lead to extreme downstream flows. The first model type explicitly represents streamflow generation processes at the catchment scale while the latter relies on relationships between one or multiple environmental variables without further assumptions on the underlying physical mechanisms (Ragno et al., 2022). The data-driven models are often characterized by speed, ease of use, and comparable skill to process based models when there are sufficient observations (Slater et al., 2023). A variety of
45 different models types falls into this category, including multilinear regression functions (Barbarossa et al., 2017), long-short term memory networks (Kratzert et al., 2018), deep neural networks (Kabir et al., 2020) and graphical probabilistic tools, such as copulas (Renard and Lang, 2007). Copulas are flexible tools to model the dependence structure between two or more variables and as a result they have gained popularity in hydrology and coastal applications (Diakomopoulos et al., 2024; Ragno et al., 2023; Salvadori and De Michele, 2004; Volpi and Fiori, 2012; Rongen et al., 2024; Paprotny et al., 2024) among other
50 fields. In the specific application of river confluences such multivariate probabilistic frameworks are promising as they allow to account for the inherent interactions between upstream and downstream flows, while also providing explicit uncertainty quantification.

The reliability of probabilistic data-driven models depends strongly on the type, quantity, and quality of the available data, which becomes particularly critical when modelling rare and extreme streamflow events. In the case of river confluences,
55 the existing literature on data-driven models for extreme flows can be broadly classified according to how extreme events are defined. Some studies investigate the simultaneous occurrence of Annual Maxima streamflows (AMQ) in upstream river



branches (Gilja et al., 2018; Bačová Mitková et al., 2023; Kao and Chang, 2012; Wang et al., 2009). Gilja et al. (2018) study the confluence of Sava and Kupa in Croatia and the Sava-Una confluence on the border of Croatia with Bosnia and Herzegovina, estimating flood peaks using bivariate copulas assuming that the timing of AMQ in the larger main river and the smaller tributary, respectively, coincide. Similar research is conducted also for the Danube river in Slovakia (Bačová Mitková et al., 2023). Kao and Chang (2012) as well as Wang et al. (2009) propose the use of bivariate copulas to generate upstream streamflow pairs. They combined these pairs with linear models to estimate downstream streamflows at a confluence. However, these approaches can only be applied at the specific locations they have been developed for and where the climatic differences between upstream and downstream catchments are minor, or human interventions (e.g., regulation works between upstream and downstream stations) can be assumed negligible. In contrast, other studies do not assume AMQ co-occurrence in the upstream river branches of a confluence (Bender et al., 2016; Fischer and Schumann, 2021). Bender et al. (2016) analyse the Rhine–Sieg confluence and select AMQ in one of the upstream branches with the simultaneously occurring streamflows in the other, depending on its catchment size. This study using a bivariate probabilistic framework shows that extreme flooding events can occur even when AMQ in the large main river branch and the smaller tributary do not temporarily coincide. Therefore, assuming their simultaneous occurrence may lead to costly overdesign, highlighting the limited applicability of this a priori assumption. Following this asynchronous data selection approach, Fischer and Schumann (2021) investigated the Danube-Inn and the Rhine-Moselle confluences and the interaction between upstream and downstream flood types using a vine-copula based model. They selected as extreme events those above a threshold equal to the mean of all 3-days variances of the daily streamflows, plus 25% of the standard deviation of all 3-days variances.

Building upon the current literature, we here develop a general and fully probabilistic, copula-based model framework to quantify extreme conditions at river confluences. The framework enables the prediction of downstream flows under different combinations of upstream conditions and the identification of upstream flow combinations that may lead to downstream flows exceeding a given return period as safety threshold. In contrast to previous studies, we identify, in a first step, extreme streamflow conditions at a single confluence when at least one of the branches (upstream or downstream) is above its individual safety level. For each extreme condition, the corresponding respective streamflow levels in the other two branches within a specific window are determined and used in the subsequent analysis of time to capture the full extreme state of the confluence. The time window accounts for the propagation of the flood waves and thus their traveling time between the individual upstream and downstream gauging stations of a specific confluence, the geometries of the main river and the tributaries as well as the geomorphological properties of the upstream catchments. In a subsequent second step, a 3d vine copula is fitted to this dataset of extreme events, in which each event is defined by the above triplet of flows. The copula captures the dependence structure linking the three branches of each confluence and can be used to describe and eventually generate plausible combinations of streamflows around the confluences. The vine-copula inherently provides a quantification of the uncertainty in the generation of streamflows since each streamflow is treated as a random variable. Furthermore it is computationally efficient, and requires only streamflow data, making it transferable to other confluences worldwide. These specific novelties of this study are, firstly, the treatment of a river confluence as a single entity within the river network, rather than considering the individual branches separately. This approach jointly accounts for the streamflows in the three branches surrounding the confluence, two upstream

and one downstream, to characterize extreme events occurring at the confluence. Indeed, an extreme event is defined as an event during which at least one of the three streamflow gauges records a flow exceeding a predefined safety level. The second novelty is the ability of the developed probabilistic model framework to identify a range of different possible combinations of upstream streamflows and quantify their likelihood of generating an extreme event downstream. As proof-of-concept, the framework is tested on three contrasting confluences: Rhine-Nahe, Rhine-Main (Germany) and Mississippi-Missouri (USA) to assess the potential and limitation of the methodology proposed.

2 Data and study confluences

In this study, the proposed modelling approach for extreme events at confluences is implemented and tested at three contrasting river confluences. The three confluences of this study, (1) Rhine - Nahe at Bingen, (2) Rhine - Main at Mainz and (3) Mississippi - Missouri differ in the magnitudes of average annual flow of the smaller upstream river branch relative to the larger branch. In other words, the Nahe, at the first confluence, is a rather small tributary to the much larger main branch of the Rhine (Table 1, Figure 1 a) with average flow that reaches 2% of the flow in the larger main branch (Figure 1 d). The Main, the smaller upstream branch at the second confluence is already larger, although still smaller than the larger upstream branch of the Rhine (Table 1, Figure 1 b), with 13% of the average flow in the larger branch (Figure 1 e). Finally, the Missouri at the third confluence (Table 1, Figure 1 c) is characterized by an average flow of 68% of the average flow in the Mississippi (Figure 1 f). The choice of these three, structurally different types of confluences allows to assess the potential relevance of flood wave superposition for occurrence of extreme flows at confluences with different types of tributaries. The period of observations for the Rhine–Nahe confluence 1935–2016 (82 years), for the Rhine–Main confluence is 1963–2022 (60 years) and for the Mississippi–Missouri confluence 2000–2023 (24 years), depending on overlapping years of observations of the three stations.

Table 1: Characteristics of the confluences in this study. R_Q denotes the ratio of the mean streamflow of Up2 to that of Up1, while R_A denotes the ratio of the catchment area of Up2 to that of Up1.

Confluence Rhine-Nahe						
Station	Lat [°]	Lon [°]	Area [km ²]	Observation Period	R_Q	R_A
Up1-Rhine ^a	50.0040	8.2753	98000	1930-2022		
Up2-Mainz	49.9116	8.9108	4000	1935-2016	0.02	0.004
Down-Rhine	50.0854	7.7650	103000	1930–2022		
Confluence Rhine-Main						
Up1-Rhine	49.6411	8.3760	69000	1930-2022		
Up2-Main	50.1058	8.7150	25000	1963-2023	0.13	0.36
Down-Rhine ^a	50.0040	8.2753	98000	1930-2022		
Confluence Mississippi-Missouri						
Up1-Mississippi	38.9680	-90.4290	440000	1933-2023		



Up2-Missouri	38.7872	-90.4718	1300000	2000-2023	0.68	2.95
Down-Mississippi	38.6290	-90.1798	1800000	1861-2023		

^a The station Down-Rhine at the Rhine–Main confluence and Up1-Rhine at the Rhine–Nahe confluence refer to the same gauging station.

We used daily streamflow data from the Global Runoff Data Center (GRDC) available for the stations at the Rhine-Main and the upstream stations at the Rhine-Nahe confluences. For the downstream station of the Rhine-Nahe confluence, EStreams daily streamflow data were used (do Nascimento et al., 2024) and for the Mississippi-Missouri confluence the daily streamflow time series are from the US Geological Survey (USGS) National Water Information System (NWIS, 2021).

Note that the catchment areas of the individual upstream branches are broadly consistent with the magnitudes of their respective average streamflow at the Rhine-Nahe and Rhine-Main confluences (Table 1, Figure 1 a-b, d-e), due to largely comparable climate characteristics throughout the Rhine basin. This is in contrast to the Mississippi-Missouri confluence, where the much smaller Upper Mississippi branch is characterized by significantly wetter climate than the larger Missouri branch (Ziegler et al., 2005). As a consequence, average flow of the Mississippi exceeds that of the Missouri (Table 1, Figure 1 c,f; (Olsen et al., 1999; Umar et al., 2018)).

3 Methods

3.1 Definition of confluence

In this study a confluence is considered as a single entity in a river network described by three river gauges, two upstream, whereby the one with the higher average annual maximum streamflows (AMQ) is labelled as Up1 and the one with lower AMQ as Up2, and one downstream gauge labelled as Down, with corresponding streamflows Q_{Up1} , Q_{Up2} and Q_D . These values naturally align inversely with the Strahler stream order. At the Rhine-Nahe confluence, the Up1 and Down river branches share an order of 6, whereas the Up2 (Nahe) which is much smaller than the Up1 river, exhibits an order of 4. At the Rhine-Main confluence, the Up1 and the Down river branches both share a Strahler order of 6, while the incoming tributary (Up2) is of order 5. In contrast, for the Mississippi-Missouri confluence, both upstream branches are already order 7 rivers, merging to generate a Down river with a Strahler order of 8. The confluence point identifies the merging point between the two upstream rivers forming the downstream streamflow. A visual representation of a confluence can be found in Figure 1.

3.2 Sampling Annual Maxima at individual gauges

Before identifying the Annual Maxima streamflows (AMQ), stationarity of the used data needs to be ensured. Hence any trend in the observed data has been removed and the data has been homogenized as it is described in the Section "Methods" in the Supplementary Material.

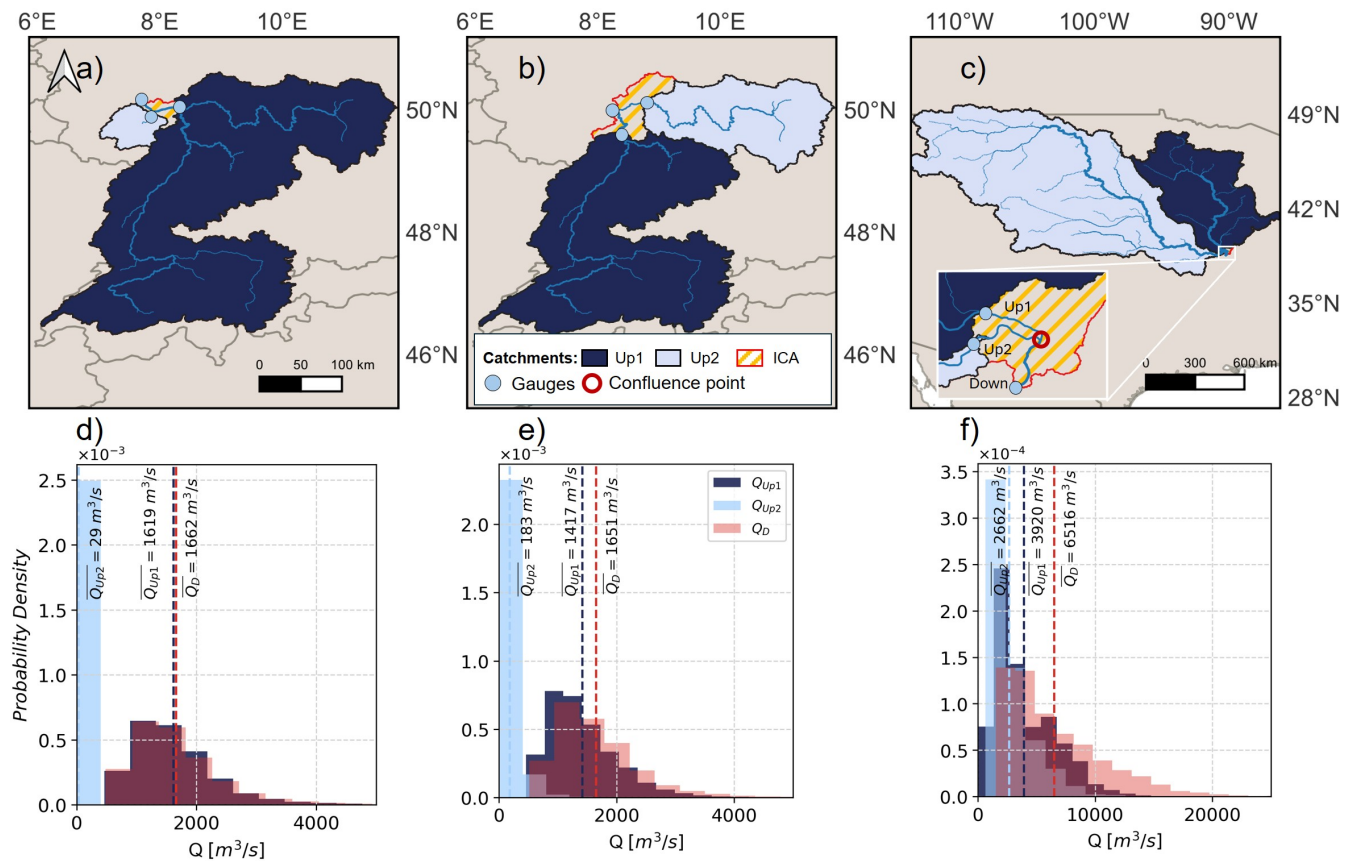


Figure 1. Location of the three confluences that are studied, (a) Rhine-Nahe, (b) Rhine-Main and (c) Mississippi-Missouri. The dark blue shades represent the catchment of the larger upstream river branch (Up1), the light blue shades the catchment of the smaller upstream river branch (Up2) and the orange hatched areas indicate the catchment area between the upstream and the downstream gauges, here referred to as Incremental Catchment Area (ICA). Panels (d), (e), (f) show histograms of the daily streamflow observations Q_{Up1} , Q_{Up2} , Q_D , while the dashed lines represent their mean values per station.



For the evaluation of extreme streamflow events at a confluence, we sample AMQ at each gauge station. To handle missing data in the detrended timeseries we adopt the method proposed by Papalexiou and Koutsoyiannis (2013) to select AMQ. First, the AMQ is calculated from the available data regardless of the number of missing values. Subsequently, two filter criteria are applied, and any AMQ matching one of them is discarded. The two criteria were established to identify potentially unreliable AMQ resulting from missing data and unusually low observed maxima. The first criterion is that the AMQ belongs to the 40% of the lowest values over the entire timeseries, and the second that the fraction of missing values within a year is $\geq 1/3$. These criteria provide flexibility and sufficient justification for the selection of AMQ even in stations with non-zero percentage of missing values, as they take into account both the yearly number of observations and the magnitude of its selected AMQ.

3.3 Selection of extreme events in confluences

In this study, an extreme event at a river confluence is characterized by an AMQ either in one of the upstream rivers or downstream at the confluence point, along with the corresponding streamflow conditions in the other contributing branches. We thus constructed a dataset for each confluence, hereafter referred to as AMQ-conf, that contains for each year of the study period three different values of AMQ ("scenarios") - one for each gauge at that confluence - together with the associated flows at the other two gauges that co-occurred around the same time. For every scenario streamflows that co-occurred at the other two stations are determined given that AMQ was observed at the third station at that day (Keef et al., 2013). The procedure was implemented as follows: (1) Scenario 1 was generated by selecting the AMQ of the Up1 station ($Q_{Up1,AM}$) and the co-occurring Q_{Up2} , Q_D respectively. (2) Scenario 2 used AMQ of Up2 ($Q_{Up2,AM}$) and the co-occurring Q_{Up1} , Q_D and (3) Scenario 3 contained the AMQ of the Down station ($Q_{D,AM}$) together with the co-occurring Q_{Up1} , Q_{Up2} (Figure 2). Here *co-occurring* is defined as the streamflows that occur within a specific time window around the date of the selected AMQ. The flood waves peaks from the upstream stations do not necessarily arrive simultaneously at the confluence point as a result of the river characteristics and the distance between the stations and the confluence point. Hence, to capture the movement of an event across the confluence these time lags are taken into account by defining a time window. This time window was determined based on the size of the catchment, river width and length and the correlation between the streamflows. Detailed information is given in Section 3.3.1 hereafter.

The three scenarios were subsequently pooled into a single dataset of extreme events, AMQ-conf. It is therefore possible that the same event is captured in all three scenarios. In such a case, only one event is retained in the full dataset (see Figure 3). This pooled dataset AMQ-conf of observed past AMQ, is in the following used as an input for the copula-based model developed in this study.

3.3.1 Lag time between corresponding maxima across confluences

A flood wave travels across a confluence reaching the gauges at different times. To capture the effect of the same meteorological events in all three stations, we need to identify a time window of one or more days in which we look for corresponding peaks. For scenarios 1 and 2, the length of the time window is selected as the one that maximizes Kendall's rank correlation coefficient (τ) between upstream AMQ and downstream flows. In addition, it is necessary to determine whether the streamflow from the

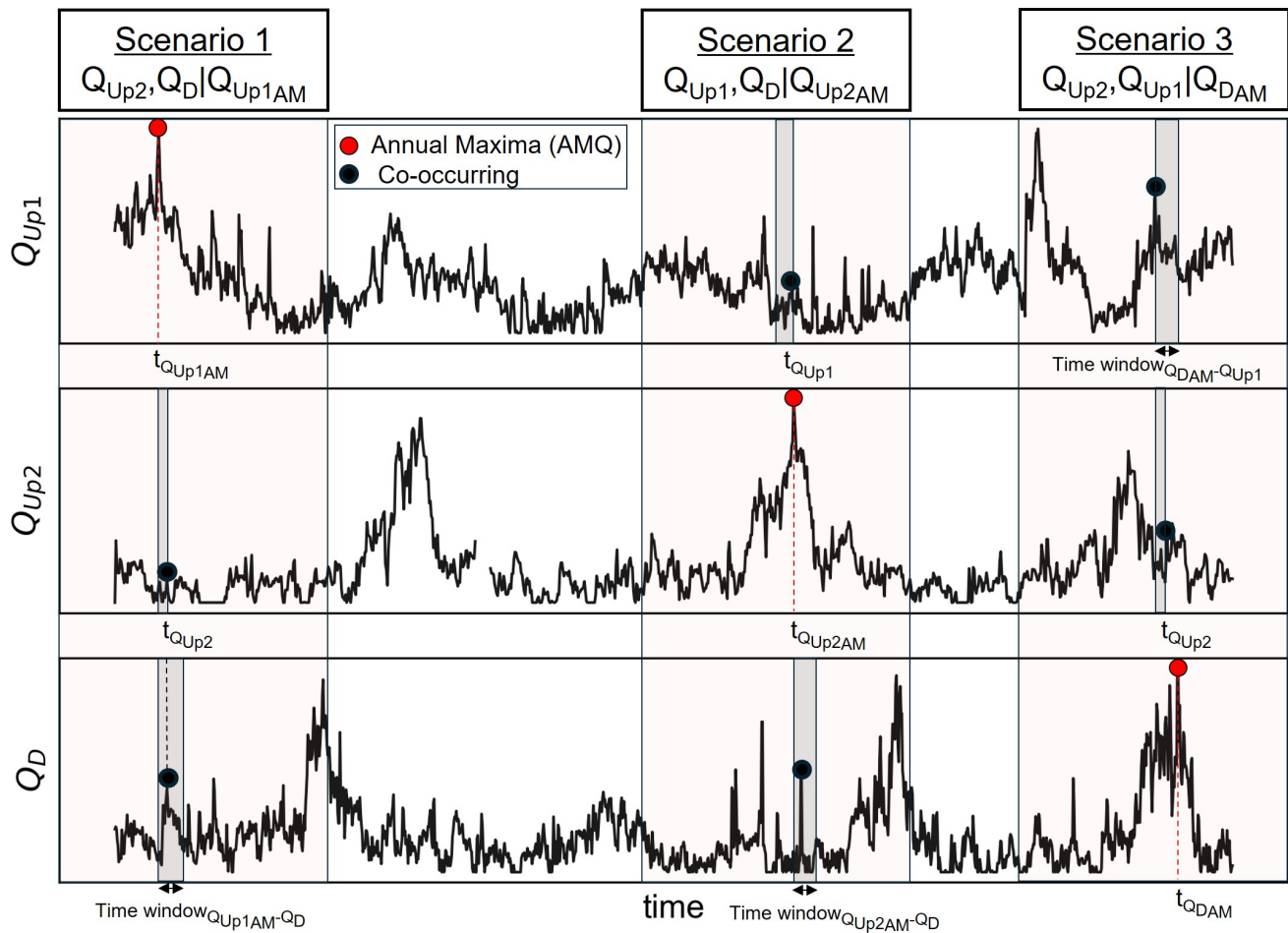


Figure 2. Scenarios of annual peaks AMQ and co-occurring flows. These three scenarios were combined to form the AMQ-conf dataset of extreme events in this study. In this typical example, the streamflow signal from the smaller river (Q_{Up2}) reaches the confluence point more quickly than that from the larger river (Q_{Up1}), and consequently, it occurs temporally between the peak dates of Q_{Up1} and Q_D . The time window between the AMQ and corresponding upstream or downstream station is calculated based on the ICA.

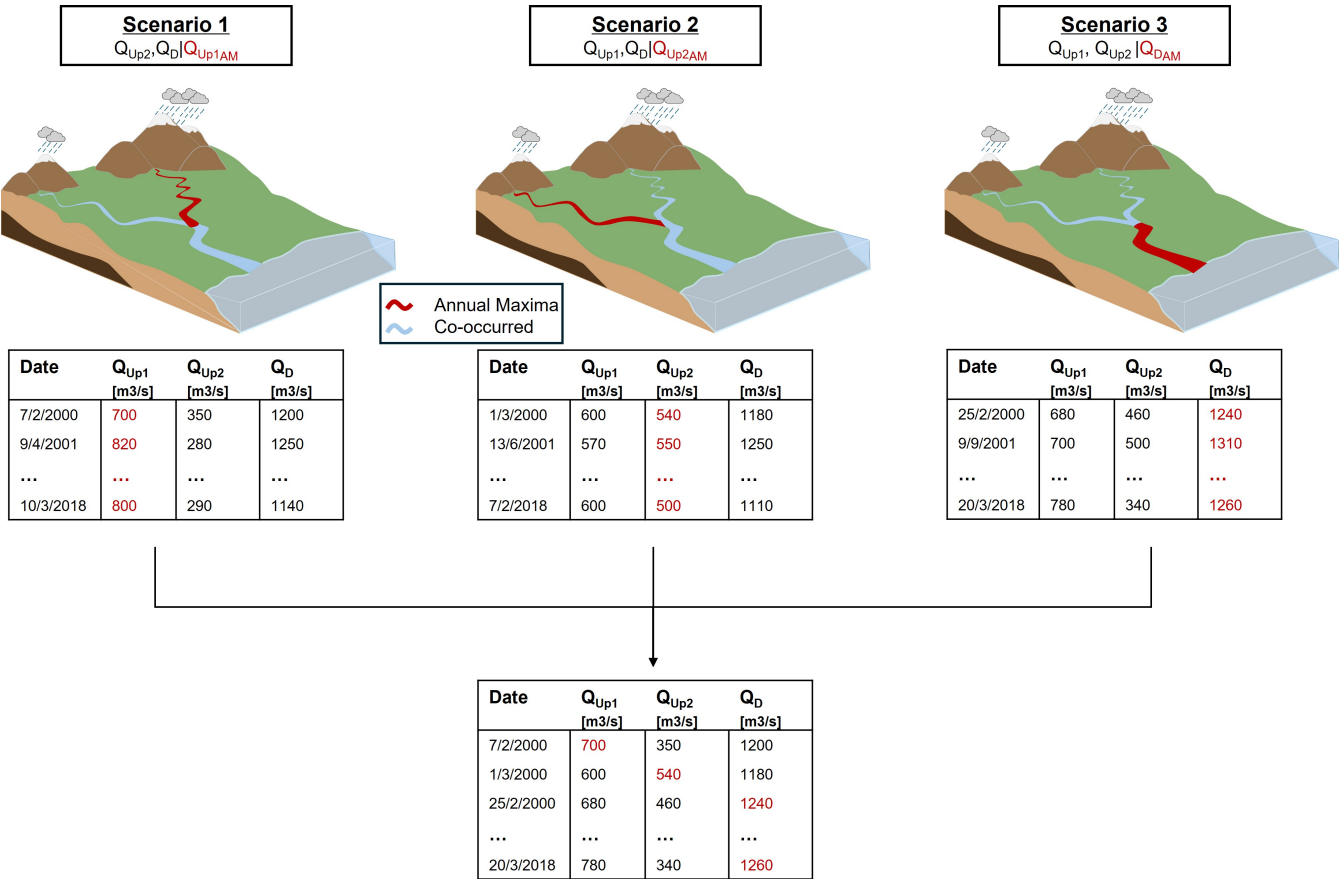


Figure 3. Schematic representation of the three scenarios considered in this study. The AMQ branch of the confluence is highlighted in red in each case. The three individual datasets (one for each scenario) are combined to generate the complete extreme event dataset used to capture extreme streamflows at each confluence.

other upstream river (Up2 for scenario 1 and Up1 for scenario 2) arrives at the downstream of the confluence before or after the AMQ event.

To define a suitable time window for each confluence, resulting in the selection of co-occurring events, we develop a stepwise procedure based on physical and statistical criteria. This procedure is applied for all three scenarios. The steps for Scenario 1 are described below:

Step 1. Identify extreme events upstream (Up1)

Identify the AMQ events at Up1 and record their dates of occurrence.

Step 2. Determine the time window for Up1 to arrive downstream (Down)



180 Determine the time window over which an extreme event at Up1 may be associated with an extreme event at the downstream station (Down).

1. Calculate the Incremental Catchment Area (ICA) between the upstream and downstream catchments as:

$$ICA = CA_{Down} - CA_{Up1} - CA_{Up2} \quad (1)$$

where CA denotes the catchment area of each station.

185 2. Use the ICA to define the maximum travelling time to get from Up1 to down based on the classification available in literature (Bender et al., 2016; Svensson et al., 2005):

- 1 day for $ICA \leq 5000 \text{ km}^2$
- 10 days for $5000 < ICA \leq 50,000 \text{ km}^2$
- 15 days for $50,000 < ICA \leq 100,000 \text{ km}^2$
- 190 – 25 days for $ICA > 100,000 \text{ km}^2$

This will determine the time window to be tested.

3. Test a series of candidate time windows within this range.

4. For each candidate time window, calculate Kendall's rank correlation coefficient (τ) between the AM streamflow at Up1 (Q_{Up1}) and the corresponding downstream streamflow (Q_D).

195 5. Select the time window that produces the highest τ

6. Select the corresponding Q_D and record the date of occurrence.

For example, for the Mississippi–Missouri confluence, where the ICA is $60,000 \text{ km}^2$, the maximum time window is 15 days based on literature. Hence, 15 candidate time windows, e.g., 1–15 days, are tested.

Step 3. Determine whether Up2 contributes within the selected time window

200 Assess whether an extreme event at Up2 can reach the confluence within the optimal time window identified in Step 2.

1. Estimate the river width (W) and depth (D) of Up2 using empirical power-law relationships with streamflow (Moody and Troutman, 2002):

$$W = 7.2 Q^{0.5} \quad (2)$$

205 $D = 0.27 Q^{0.39} \quad (3)$

where Q is the average AMQ.



2. Obtain the river slope (S) and channel length ($Length$) between the Up2 station and the confluence from elevation data and aerial imagery.
3. Estimate the flow velocity (V) using Manning's equation, assuming a rectangular channel cross-section and a Manning roughness coefficient representative for the Up2 and Up1 channels:

$$V = \frac{1}{n} \left(\frac{WD}{W + 2D} \right)^{2/3} S^{1/2} \quad (4)$$

where n is Manning's roughness coefficient and it is assumed similar for the $Up1$ and $Up2$ catchments.

4. Estimate the travel time of the flood wave from Up2 to Down.
5. Compare the travel times from Up1 and Up2 to Down and use their ratio to determine the corresponding occurrence dates of the Up2 events as follows:

$$R_t = \frac{Length_{Up1}/V_{Up1}}{Length_{Up2}/V_{Up2}} \quad (5)$$

6. Identify the Up2 events the date of occurrence of the Q_D and the selected time window between Q_{Up1} , Q_D . Then record the date of occurrence as follows:

$$Date_{Q_{Up2}} = Date_{Q_D} - TimeWindow_{(Q_{Up1_{AM}} - Q_D)} \cdot \frac{1}{R_t} \quad (6)$$

For Scenario 2, repeat Steps 1–3 with Up1 and Up2 interchanged; i.e., use Up2 as the reference upstream station and assess the contribution of Up1. For Scenario 3, follow Step 1 as Scenario 1, but start by identifying AM events at the downstream station (Down). Then the steps of scenario 1 or 2 are followed, depending on which of the CA_{Up1} or CA_{Up2} is larger.

3.3.2 Event Independence

The selected events from Scenarios 1, 2, and 3 are combined to construct the final extreme event dataset AMQ-conf. To ensure that the events in the pooled AMQ-conf dataset are independent, overlapping dates and events occurring within the same ICA-based time window are identified. When two events fall within the same time window, the event with the lower downstream discharge is removed. The remaining events are therefore considered independent.

3.4 Schematization of confluences via dependence models (3d Vine Copula)

We aim to model the joint distribution of streamflow at a confluence during an extreme event using vine copulas, as they explicitly describe and account for the dependencies between, in our case, the three streamflow variables. The joint distribution

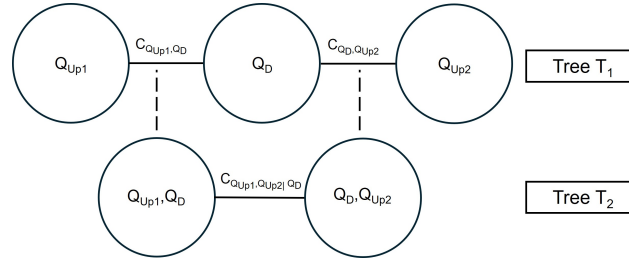


Figure 4. Example of the vine structure with 3 nodes of this study. The random variables represents river streamflows on a confluence.

will be used to generate plausible combinations of streamflows and to obtain upstream conditions given a specific event of interest downstream.

Vine copulas are graphical tools for constructing multivariate probability distributions using only bivariate copulas as building blocks (Czado and Nagler, 2022; Morales et al., 2008).

235 Given a d -dimensional random vector $Z = (Z_1, \dots, Z_d)$, a regular vine copula of dimension d is constructed as a sequence of linked trees $T_1, T_2, \dots, T_{d-1}$. A tree is made of nodes connected by edges. The first tree T_1 is a tree with d nodes corresponding to the marginal variables of the vector Z and $d-1$ edges. Each edge is quantified as the bivariate copula of the connected nodes (variables). Subsequent trees T_m , for $m \geq 2$, have nodes given by the edges of the previous tree, that is each tree T_i become the nodes of the subsequent tree T_{i+1} . The edges represent conditional bivariate copulas between variables conditioned on
 240 the node shared by the corresponding edges in the previous tree. This recursive structure continues until the tree T_{d-1} , which contains a single node.

In this study, a 3D regular vine copula is constructed for each confluence given the random vector $Q = (Q_{Up1}, Q_{Up2}, Q_D)$ defined by the above procedure. The structure of the vine is decided a priori, as shown in Figure 4. The choice of the vine structure stems from the physical configuration of a confluence in which the two upstream branches feed into the downstream flow.
 245 Accordingly, the downstream flow Q_D is selected as the central node, such that the dependence between each upstream flow and the downstream flow is explicitly represented in the first tree. Hence, for every confluence, the vine copula (multivariate distribution) is fitted to Q as follow:

1. Fitting the marginal distributions (univariate distribution) to the extreme streamflow data for each station independently;
2. Fitting the bivariate copulas (bivariate distribution) in the first tree to describe the dependence between each upstream
 250 streamflow and the downstream streamflow; and
3. Fitting the conditional copula (bivariate distribution) in the second tree to describe the dependence between the two upstream streamflows conditional on the downstream streamflow.



3.4.1 Marginal distributions

First, we fit univariate distribution to each to the AMQs for each gauge as identified in the AMQ-conf dataset (Q_{Up1} , Q_{Up2} and Q_D) independently. Theoretical distributions are preferred over empirical distributions for modelling extreme streamflow events because they allow extrapolation beyond the range of the observations.

The theoretical distributions considered for modelling the streamflows are the Log-Pearson III, Gamma, Weibull, and Generalized Gamma, which are described in detail in Supplementary Material Table S1.

The parameters of each candidate distribution are estimated using the Maximum Likelihood Estimation (MLE) method. The Kolmogorov–Smirnov (K–S) test is then used to assess how well each distribution represents the observations (Diakomopoulos et al., 2024) (Eq. 7):

$$D = \max |F_{obs}(x) - F_{est}(x)| \quad (7)$$

where D is the maximum distance between $F_{obs}(x)$, the empirical cumulative distribution function (CDF) of the random variable X, and $F_{est}(x)$, the theoretical CDF. A small value of D indicates a better agreement between the theoretical and empirical distributions. The distribution providing the best fit for each station is selected as the marginal distribution for the copula model.

3.4.2 Bivariate copulas and dependence

A bivariate copula is a function that couples univariate marginal distributions into a joint distribution. According to Sklar's theorem (Sklar, 1973), given two random variable (X,Y) any joint distribution $F_{X,Y}$ with continuous marginal distributions F_X and F_Y can be expressed as:

$$F_{X,Y} = C(F_X(x), F_Y(y)) \quad (8)$$

where C is the copula function, which is uniquely defined when the marginal distributions are continuous. The advantage of copulas resides in the dependence structure modelled separately from the marginal distributions so that different forms of dependence can be captured, including asymmetric dependence, such as stronger dependence during high-flow events than during low-flow events, or vice versa. This is a key advantage of copula families over conventional dependence measures such as Kendall's τ and Pearson's r which summarize the overall dependence between variables but do not capture potential simultaneous occurrence of the variables in the corner of the lower-left quadrant or upper-right quadrant of a bivariate distribution (Schmidt, 2005).



3.4.3 Goodness of fit measures

The best-fitting theoretical (conditional) copula is selected based on the Akaike Information Criterion (AIC) from the following candidate families: Gaussian, Student-t, Clayton, Gumbel, Frank, Joe, BB1, BB6, BB7, and BB8. If the dependence is not statistically significant at the 5% confidence level, the independence copula is selected. The fitting of the bivariate copulas in the vine structure is done using the pyvinecopulib toolbox in Python.

While the AIC provides a criterion for selecting the best-fitting copula among the candidate models, the ability of the fitted copula to adequately represent the dependence structure is further assessed using the non-parametric Kendall's rank correlation coefficient, τ (Kendall, 1938). Kendall's τ is used as a measure of dependence and allows comparison of the dependence observed in the data with that reproduced by the fitted copula model.

Given two variables X and Y, Kendall's τ can be expressed as:

$$\tau = \frac{N_{cp} - N_{dp}}{N_p} \quad (9)$$

where N_{cp} and N_{dp} are the numbers of concordant and discordant pairs, respectively, and $N_p = N_{cp} + N_{dp}$ is the total number of pairs. The coefficient ranges from -1, indicating perfect negative ordinal dependence, to +1, indicating perfect positive ordinal dependence, while a value of zero indicates no ordinal dependence.

3.5 Testing the ability of vine copulas to estimate streamflow

We further investigate the ability of the vine copula to simulate downstream flows given upstream conditions. This step is essential to obtain robust and reliable combinations of Q_{Up1} and Q_{Up2} that lead to extrapolated Q_D values corresponding to return periods (RP) greater than 30 and 50 years.

Hence, for each extreme event i observed, as available in the AMQ-conf dataset, a conditional realization of downstream streamflow is generated from the fitted vine copula given the corresponding observed upstream streamflows, and the resulting Q_D is compared with the observed downstream streamflow. It is worth noting that the vine copula conditioned on given upstream flows results in a distribution of possible downstream flows, providing a straightforward quantification of downstream flows and its uncertainty.

For each confluence, we obtain Q_D conditioned on Q_{up1} and Q_{up2} via a simulation-based empirical approach. First, a total of 100000 samples of $Q = (Q_{Up1}, Q_{Up2}, Q_D)$ are generated from the vine copula model. Second, For each observed extreme event i , from AMQ-conf simulated samples with upstream streamflows consistent with the observed upstream conditions are then identified. Specifically, a simulated sample is retained if:

$$0.97 * Q_{Up1,obs,i} \leq Q_{Up1,mod} \leq 1.03 * Q_{Up1,obs,i} \quad (10)$$

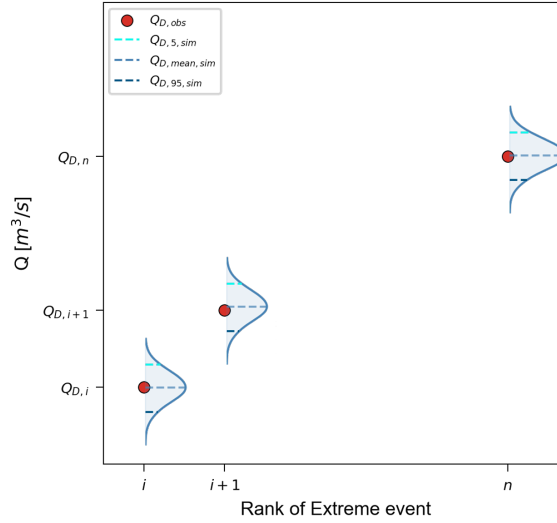


Figure 5. Representation of the sample of modelled values per i^{th} extreme event that is used for the calculation of statistics to evaluate the probabilistic model.

and

$$0.97 * Q_{Up2,obs,i} \leq Q_{Up2,mod} \leq 1.03 * Q_{Up2,obs,i} \quad (11)$$

This $\pm 3\%$ tolerance defines a plausible range around the observed upstream conditions and ensures that the modelled downstream flows are evaluated under upstream conditions that are comparable to those observed for the event. The Q_D values associated with the retained modelled samples are used to empirically approximate the conditional distribution of downstream streamflow for each observed event. We assume that the estimated Q_D corresponds to the mean of the modelled Q_D with confidence interval ranging between the 5th and 95th percentiles (Figure 5).

The quality of the estimated Q_D is quantified via the Nash Sutcliffe Efficiency (NSE) (Eq. 12):

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_i^{obs} - Q_i^{mod})^2}{\sum_{i=1}^n (Q_i^{obs} - \overline{Q^{obs}})^2} \quad (12)$$

where Q_i^{obs} is $Q_{D,obs,i}$ for the i^{th} extreme event and Q_i^{mod} is the mean of the modelled Q_D associated with that event.

3.5.1 Dependence vs independence assumption

To test the importance of explicitly accounting for the interdependence of streamflows around the confluence in the modeling framework, the vine copula obtained via the fitting procedure above is compared with the case in which the copulas $Q_{Up2}-Q_D$ and $Q_{Up1}|Q_D-Q_{Up2}|Q_D$ are equal to the independent copula. This independence assumption can be interpreted as a scenario



325 in which the contribution of the tributary to the downstream flood wave is neglected, such that Q_D is primarily governed by the main-river upstream flow, i.e., Q_{Up1} , regardless of the magnitude of the Q_{Up2} . In this sense, the independent-copula case represents a situation in which the interaction between the main river and the tributary is not explicitly accounted for. To quantify which of the two models performs better, in addition to the NSE, the Normalized Mean Square Error (NRMSE) is used (Eq. 13):

$$330 \quad NRMSE = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (Q_i^{\text{mod}} - Q_i^{\text{obs}})^2}}{\sigma_{\text{obs}}} \quad (13)$$

where Q_i^{obs} is $Q_{D, \text{obs}, i}$ for the i^{th} extreme event, Q_i^{mod} is the mean of the modelled Q_D associated with that event and σ_{obs} is the standard deviation of the observed Q_D .

4 Results

We implement and demonstrate the above general framework to the three confluences of this study, Rhine-Main, Rhine-Nahe
335 and Mississippi-Missouri to test the ability of the vine-copula model to reproduce the existing downstream streamflows for different confluence configurations.

4.1 Rhine-Nahe confluence

At the Rhine-Nahe confluence 113 individual extreme events have been detected and added to the AMQ-conf dataset in Supplementary Material Figure S1. The maximum $Q_D = 7160 \text{ m}^3/\text{s}$ is observed on 29/3/1988. On the same day, also the larger
340 upstream river branch reached its highest streamflow $Q_{Up1} = 6920 \text{ m}^3/\text{s}$ while the smaller tributary Up2, i.e. the Nahe river, reaches a maximum of $Q_{Up2} = 605 \text{ m}^3/\text{s}$ on 2/12/1952. We found that the suitable length of the time window between the AMQs and co-occurring streamflows within the extreme events AMQ-conf dataset is equal to one day, as the ICA is $\sim 1000 \text{ km}^2$. By analyzing separately the AMQ time series, we find that there is no year when AM $Q_{Up1, AM}$ and AM $Q_{Up2, AM}$ co-occur, so the assumption of the general simultaneous occurrence of AMQ upstream and downstream is not valid, and may
345 lead to overestimation of Q_D .

Assigning the observed streamflows of the extreme events AMQ-conf database at Rhine-Nahe to their corresponding RP from the best fitted distributions (Log Pearson III for all the stations see Supplementary Material Figure S1) it is shown in Figure 6a,d, the streamflow downstream of the confluence is almost exclusively controlled by Q_{Up1} , as the RPs of Q_D are identical with Q_{Up1} and independent of Q_{Up2} , which are almost negligible, in particular for the higher RP which are of
350 interest for this study. This finding was expected, as the CA of the Rhine river is approximately 25 times larger than that of the Nahe River and accounts for more than 95% of the total downstream CA.

Analysing the interaction between Q_{Up1} and Q_D during extreme events a strong positive correlation is observed, followed by symmetry (similar co-occurrence patterns for relatively lower and higher streamflow values) between the variables (Figure 7a). The best fitted copula is a symmetric student copula capturing both the symmetry and the strong positive dependence.



355 Kendall's τ of the modelled data from this copula replicates the observed value with $\tau_{obs} = \tau_{mod} = 0.9$ (Figure 7a). It can also
be seen that Q_{Up2} and Q_D are largely independent of each other with $\tau_{obs} = 0.02$ (Figure 7b), implying that the influence of
 Q_{Up2} on Q_D can be considered negligible. As a result an independent copula is fitted. Between Q_{Up1} and Q_{Up2} a weak not
statistically significant ($p_{value} = 0.3$) negative correlation is detected ($\tau_{obs} = -0.06$), as Q_{Up1} values with a RP of more than
ten years mainly co-occur with low values of Q_{Up2} (Figure 7c). Consequently, an independent copula is fitted.

360 The vine copula model reaches a high $NSE = 0.97$ showing that the model is able to reproduce the observed Q_D , from the
upstream streamflow combinations (Figure 8a). At the same all the observed extreme events $Q_{D,obs}$ are within the modelled
5 – 95th confidence interval, indicating the capability of the model to reproduce effectively the observed streamflow values. In
the Rhine-Nahe confluence almost all (88%) of the modelled Q_D with $RP > 30$ years are generated by Q_{Up1} with $RP > 30$
years, while the RP of Q_{Up2} during these events mainly remained < 10 years throughout. This illustrates the dominance of
365 Q_{Up1} as control on Q_D , largely independent of the streamflow contributions Q_{Up2} from the smaller upstream river branch
(Figure 9a).

4.2 Rhine-Main confluence

At the Rhine-Main confluence, 93 extreme events have been detected (see Supplementary Material Figure S2). The maxi-
mum $Q_D = 6920 \text{ m}^3/\text{s}$ is observed on 29/3/1988, while the larger river branch Up1 reaches its highest streamflow $Q_{Up1} =$
370 $5200 \text{ m}^3/\text{s}$ on 28/5/1983 and the smaller one Up2, i.e. the Main river, streamflow of $Q_{Up2} = 1780 \text{ m}^3/\text{s}$ on 29/1/1995, respec-
tively. Additionally we found that the most suitable length of the time window between AMQ and co-occurring streamflows
is one day, as the ICA is $\sim 4000 \text{ km}^2$. By separately analyzing the AMQ time series for the three individual stations, we find
that $Q_{Up1,AM}$ and $Q_{Up2,AM}$ occur on the same day only in 50% of the years, so the assumption of a general simultaneous
occurrence of AMQ upstream and downstream is not valid.

375 Ranking the AMQs of Q_D and the associated return periods RP as estimated from the best fitting distributions (Log Pearson
III for all three stations at this confluence; Supplementary Material Figure S2), together with the co-occurring Q_{Up1} and Q_{Up2} ,
it can be seen that the superposition of the upstream flows, with similar severity (RP levels) can cause Q_D of the same severity
(Figure 6e), in particular for RPs exceeding 10 years (Figure 6b).

For the Rhine-Main confluence we observe strong association between both lower values of Q_{Up1} and Q_D whereas the upper
380 quadrant exhibits greater variability between this two variables (Figure 7d) and a total value of the dependence coefficient
 $\tau = 0.77$ between the observed Q_{Up1} and Q_D . While a highly synchronized propagation of flood waves for lower AMQ
magnitudes, i.e. $RP < 10$ years can be observed, extreme high flow events are characterized by more divergence between Q_{Up1}
and Q_D , resulting in higher variance and weaker structural association. The best fitted copula is the 180-degree rotated Gumbel
(Survival Gumbel) copula, which is in accordance to the consideration above, as it is designed to model such asymmetric
385 dependence (stronger association of the lower values). The suitability of this copula is illustrated by the fact that it preserves
the observed dependence τ with $\tau_{obs} = \tau_{mod} = 0.77$ (Figure 7d). Between Q_{Up2} and Q_D the best fitted copula is the 180-
degree rotated Clayton (survival Clayton). The survival Clayton effectively models the strong association between the higher
values visible in the upper-right quadrant of the Figure 7e. This copula leads to a smaller value of AIC than the Gumbel copula



as there is a stronger dependence between simultaneously high values. The values of Kendall τ from the modelled data and the
390 observations are broadly consistent ($\tau_{obs} = 0.44$, $\tau_{mod} = 0.41$). Lastly, for the Q_{Up1} and Q_{Up2} dependence a Frank symmetric
copula is the best fit, and the modelled values result in a Kendall τ closely corresponds with the one from observations with
 $\tau_{obs} = 0.22$, and $\tau_{mod} = 0.19$, respectively (Figure 7f).

To quantify the ability of the 3d vine copula model to predict downstream flows Q_D from different upstream combinations,
it was evaluated how close the modelled Q_D are to the observed ones. Overall the model shows a strong performance with
395 $NSE = 0.99$ (Figure 8b), with the $Q_{D,mean,mod}$ closely corresponding to the observed $Q_{D,obs}$ (Figure 8e). For 93% of the
extreme events the $Q_{D,obs}$ is embedded inside the modelled 5 – 95th confidence interval, indicating the capability of the model
to effectively reproduce the observed streamflow values within limited margins of uncertainty.

Given the positive outcome of the validation procedure, we use the vine copula to assess the most likely combinations of
upstream flows generating downstream flow of magnitude greater than a 30 year event (Figure 9b). We see that 70% of the
400 modelled Q_D with a return period above 30 years are generated by Q_{Up1} and Q_{Up2} above exceed their respective 30-year event,
implying that the superposition of upstream flows Q_{Up1} and Q_{Up2} is an important factor for the generation and magnitude of
downstream extreme flows Q_D .

The results from flood waves and the simulations from the model highlight the difference between the Rhine-Nahe and
Rhine-Main confluences, underlining that even confluences with the same main river (Rhine-Nahe and Rhine-Main) may
405 behave completely different during extreme events. It is shown that in a confluence with a very small tributary compared to the
larger upstream river branch, i.e., Rhine-Nahe, Q_D is, as expected and unsurprisingly, controlled almost exclusively by Q_{Up1} ,
while in confluences with much larger Up2 tributaries (six times larger), although approximately eight times smaller than the
Up1, i.e., Rhine-Main, the simultaneous co-occurrence of Q_{Up1} and Q_{Up2} with $RP > 30$ years is the most likely combination,
which leads to Q_D with $RP > 30$ years.

410 4.3 Mississippi-Missouri confluence

For the Mississippi-Missouri confluence, 36 extreme events have been detected (Supplementary Material Figure S3). The
maximum $Q_D = 26363 \text{ m}^3/\text{s}$ is observed on 8/6/2019, followed by the maximum $Q_{Up1} = 14781 \text{ m}^3/\text{s}$ during the same event
(7/6/2019). The smaller upstream tributary with lower average flow, i.e. the Missouri, reaches a maximum streamflow of
 $Q_{Up2} = 14300 \text{ m}^3/\text{s}$ on 5/5/2017. Additionally, we found that all the extreme events occur in time windows varying from 1
415 to 11 days, with $ICA = 60000 \text{ km}^2$. By analyzing separately the AMQ time series, there is a 45% probability that Q_{Up1} and
 Q_{Up2} co-occur on the same day.

Assigning the observed streamflows of the extreme events database at the Mississippi-Missouri confluence to their corre-
sponding RP from the best fitted distributions (Log Pearson III for all the stations, see Supplement Figure S3), it is shown
in Figure 6c,f, that downstream of the confluence, extremes of Q_D can be dominated by extreme flows in either of the two
420 upstream river branches. However, a co-occurrence and thus superposition of extremes with similar severity ($RP \geq 30 \text{ years}$)
in both upstream tributaries has so far not been observed. In spite of the very low probability, such events emerging from



the superposition of upstream extremes can clearly not be ruled out and have the potential for catastrophic consequences as extremes in one of the upstream branches can already lead to widespread flooding.

Analysing the interaction between Q_{Up1} and Q_D during extreme events, a strong positive correlation and symmetry between
425 the variables is observed (Figure 7g). The best fitted symmetric Frank copula captures both the symmetry and the positive dependence. Kendall's τ of the modelled data, from this copula is close to the one from the observed data with $\tau_{obs} = 0.72$ and $\tau_{mod} = 0.68$, respectively (Figure 7g). In contrast to the other two confluences, also a strong positive dependence between Q_{Up2} and Q_D is observed. Frank symmetric copula leads to best AIC score and is selected. The Kendall's tau from the modelled data is almost equal to the one from observations with $\tau_{obs} = 0.7$ and $\tau_{mod} = 0.69$, respectively (Figure 7h). Between observed
430 Q_{Up1} and Q_{Up2} a positive dependence leading to $\tau_{obs} = 0.43$, is captured. Thus, also here a Frank copula is the best fit resulting in a value of $\tau_{mod} = 0.4$, close to the observed one.

The vine copula model reaches a high $NSE = 0.97$, showing the model's capability to reproduce the observed Q_D , from the upstream streamflow combinations. For 94% of the extreme events $Q_{D,obs}$ is embedded inside the modelled 5 – 95th confidence interval, indicating the capability of the model to reproduce effectively the observed streamflow values. At the same
435 time the $Q_{D,mean,mod}$ closely corresponds with the observed $Q_{D,obs}$ (Figure 8f). At the Mississippi-Missouri confluence the majority of the modelled Q_D with $RP > 30$ years (around 60%) are generated by a superposition of less extreme Q_{Up1} and Q_{Up2} , $RP < 30$ years. Furthermore, there is a 12% probability of generating Q_D with $RP > 30$ when the RP of both upstream flows < 10 years, showing that the superposition of moderate events may lead to extreme downstream streamflows (Figure 9c). Conversely, Q_D with $RP > 30$ years may also result from a highly extreme event in only one upstream river, with either Q_{Up1}
440 having $RP > 30$ years and Q_{Up2} having $RP < 10$ years, or vice versa, each occurring with a probability of approximately 19%. A co-occurrence and thus superposition of extremes with similar severity ($RP > 30$ years) in both upstream tributaries has so far not been observed. In spite of the very low probability, as also illustrated by the absence of such events in the modeled Q_D , based on 100000 realizations (Figure 9c), such events emerging from the superposition of upstream extremes can clearly not be ruled out and have the potential for catastrophic consequences as extremes in one of the upstream branches can already lead
445 to widespread flooding.

4.4 Comparison between the confluences

As shown in Figures 6 and 9, even confluences sharing the same main river (Rhine-Nahe and Rhine-Main) may exhibit divergent behaviors during extreme events, as the influence of the tributary varies. At the Rhine-Nahe confluence the downstream flows are controlled almost exclusively by the Rhine's upstream contribution, due to the much smaller CA and thus flow mag-
450 nitudes of the Nahe river compared to the Rhine. Conversely, at the Rhine-Main confluence, the superposition of extreme flood waves is the most likely driver of a 30 year flow event downstream. For the Mississippi-Missouri (Figures 6c,f and 9c), the most likely causes for downstream extremes are either a superposition of moderate upstream flows or a scenario where a single upstream river surpasses the 30-year RP threshold. However, a co-occurrence and thus superposition of extremes in both upstream tributaries which has so far not been observed has to be expected to have potentially catastrophic effects.

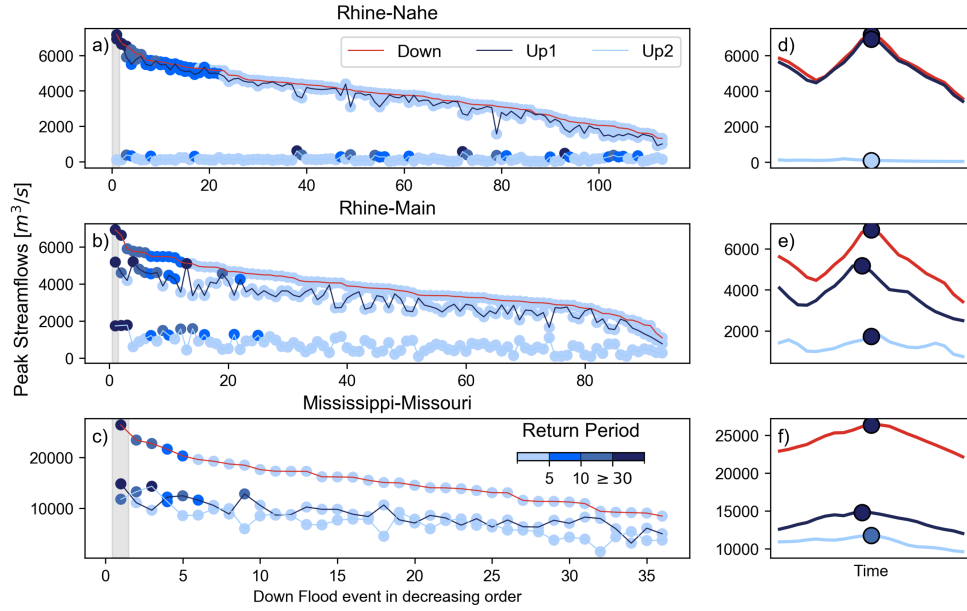


Figure 6. Downstream annual peak streamflows (Q_D) of extreme events in decreasing order (red line) and corresponding upstream peak streamflows (blue lines/dots) for the three river confluences of this study (a-c). The shading of the circle symbols indicates the return period of the streamflow in the individual river branches. Panels (d), (e), and (f) show the temporal hydrographs for the single most extreme downstream event, indicated by the gray shaded area in the corresponding left panels.

455 These results illustrate the capability of the model to provide reliable predictions of Q_D for structurally distinct types of confluences, demonstrating that it can be used both for confluences largely controlled by the main river branch with only minor effects of smaller tributaries and for confluences where the upstream river branches are similar in terms of streamflow magnitude.

The multivariate dependence model outperforms the model with the assumption of systematic independence between $Q_{Up2} -$
 460 Q_D and $Q_{Up1}|Q_D - Q_{Up2}|Q_D$, leading to higher values of NSE and lower of RMSE for modelled Q_D , for river confluences at which both of the upstream branches streamflow significantly contributes downstream (Figure 8b,c). More specifically, at the Rhine-Main confluence while the predicted Q_D from the model that explicitly accounts for the dependence structure leads to $NSE_{mod} = 0.99$ the predicted Q_D from the independent model leads to a lower value of $NSE_{ind} = 0.87$. At the same time the NRSME of the independent model is almost two times higher than our multivariate dependence model, $NRMSE_{ind} =$
 465 0.13 and $NRMSE_{mod} = 0.07$, respectively (Figure 8b). Similar behaviour is illustrated in Figure 8c for the Mississippi-Missouri confluence at which from the model that explicitly accounts for the dependence structure achieves $NSE_{mod} = 0.97$ and $NRMSE_{mod} = 0.13$ compared to $NSE_{ind} = 0.75$ and $NRMSE_{ind} = 0.23$ of the independent model. On the other hand for the Rhine-Nahe confluence as the Q_{Up1} and Q_D are independent of the Q_{Up2} the multivariate dependence model

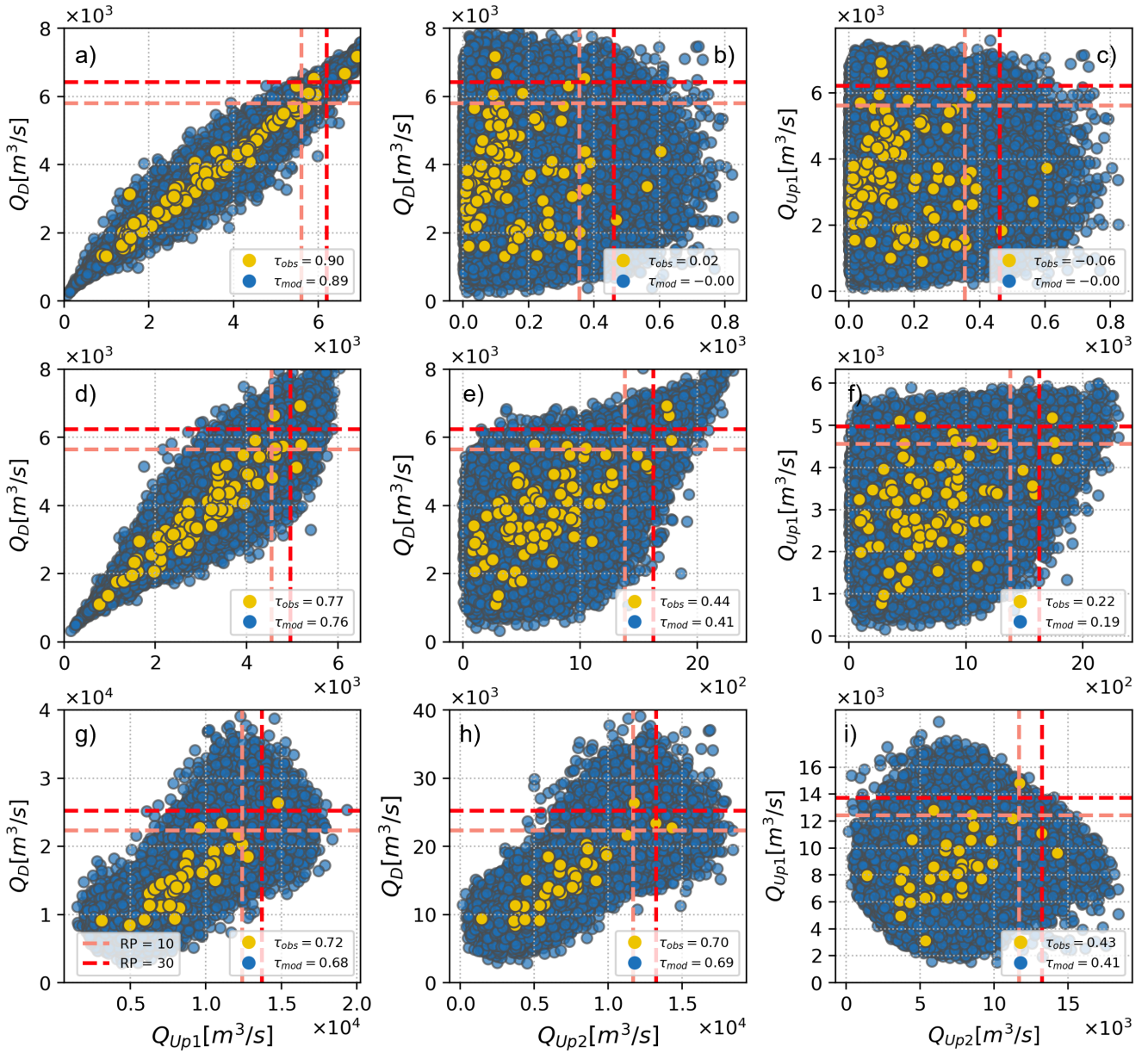


Figure 7. Panels (a-c). The observed and modelled pairs of Q_{Up1} , Q_{Up2} and Q_D for the Rhine-Nahe confluence. Panels (d-f). The observed and modelled pairs of Q_{Up1} , Q_{Up2} and Q_D for the Rhine-Main confluence. Panels (g-i). The observed and modelled pairs of Q_{Up1} , Q_{Up2} and Q_D for the Mississippi-Missouri confluence. The Kendall's rank correlation coefficient (τ) calculated from the observed and simulated values is added, as well as the dashed lines which represent the Return Periods of 10 and 30 years.

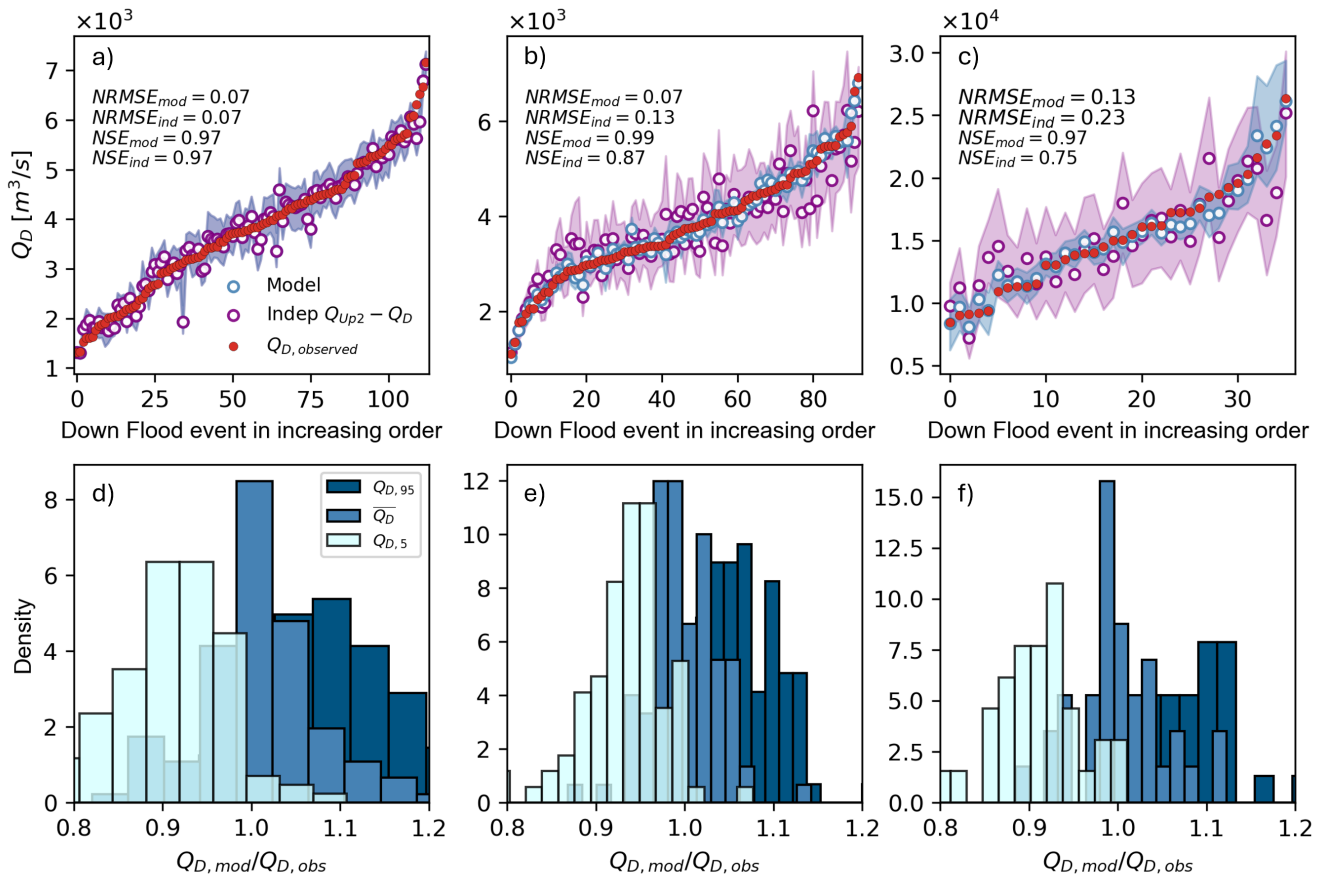


Figure 8. Panels (a),(b),(c). Comparison between modelled Q_D generated by the 3d vine copulas dependence modelling, Q_D generated by the independence model and the observed ones. The blue dots represent the results of the independence model (the model that explicitly accounts for the dependence structure), while the purple dots are the results from the assumption that Q_{YUp2} is independent of the other two streamflows. Panels (d),(e),(f) present the histograms for the ratios between the modelled mean of Q_D from the dependence model, per event with the observed values, and the corresponding 5th and 95th percentiles. Panels a,d correspond to the Rhine-Nahe confluence while b,e and c,f correspond to the Rhine-Main and Mississippi-Missouri confluences, respectively.

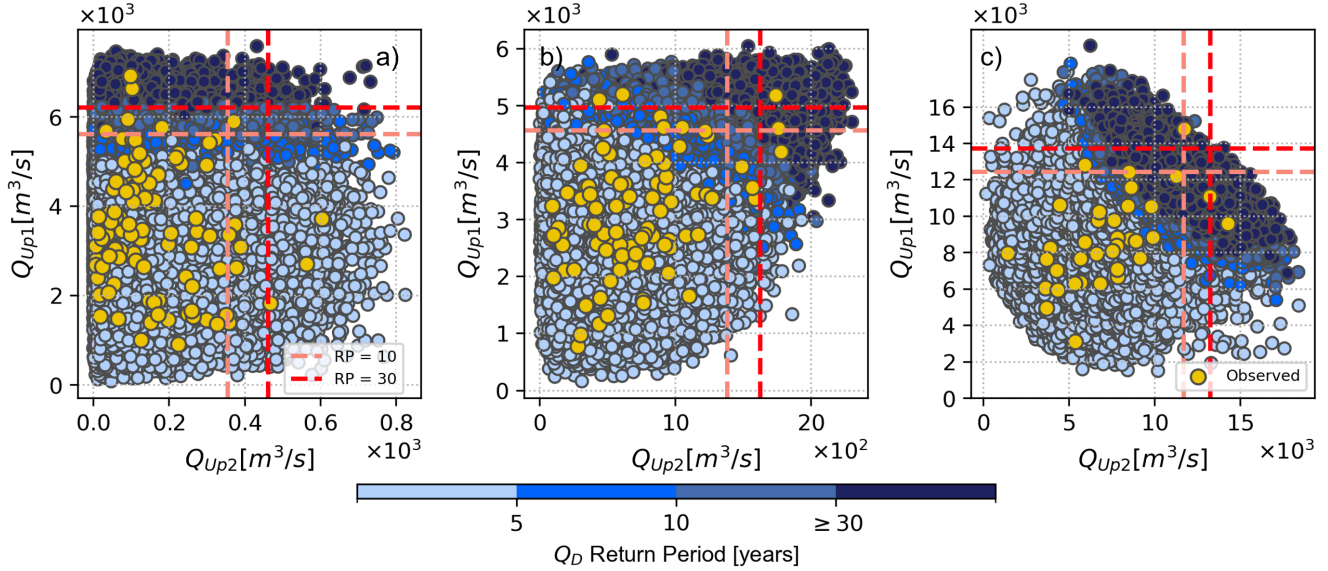


Figure 9. Observed (yellow dots) and modelled (blue dots) pairs of Q_{Up1} and Q_{Up2} . Panel (a) represents the Rhine-Nahe confluence, (b) the Rhine-Main and (c) the Mississippi-Missouri confluence. The blue dots indicate the generated from the model pairs of Q and their shades correspond to the RP of the Q_D of each pair. The red dashed lines represent the RP of 10 and 30 years as they have been calculated by the corresponding marginal distributions of Q_{Up1} and Q_{Up2} .

becomes equivalent with the independent model and there results are similar ($NSE_{mod} = NSE_{ind} = 0.97$ and $NRMSE_{mod} =$
 470 $NRMSE_{ind} = 0.07$ respectively).

5 Discussion

The objective of this study was to develop, implement and test a fully probabilistic, copula-based model framework that allows the identification of combinations of upstream flows that can potentially lead to unsafe flow conditions downstream via a fully probabilistic model (copula-based). The suitability and potential of the model were demonstrated above, however, some
 475 considerations are needed specifically on the assumptions of dependence between observations, extreme selection, data quality and quantity.

Interdependence assumption. The performance of the multivariate copula model indicates that the interdependence between the streamflow variables at river confluences should be explicitly modelled to better describe and predict the upstream combinations that lead to extreme downstream flows. Comparing the interdependence approach (taking into account all the correlations
 480 between the three stations at a confluence) with the assumptions of independence between $Q_{Up2} - Q_D$ and $Q_{Up1} - Q_{Up2}$ we observe that while in specific cases, e.g. when the second tributary is rather small, these assumptions could work, in general they fail to reliably estimate the extreme Q_D . To be more precise with the independence assumption between $Q_{Up2} - Q_D$ the



models reproduce well the observed extreme Q_D , similar to our interdependence model (Figure 8a) in the Rhine-Nahe confluence, as it behaves almost as a single channel system. However, assuming independence, extremes Q_D are systematically underestimated and considerably inflated prediction uncertainties can be observed at the other two confluences, with larger relative contributions from the smaller tributaries (Figure 8b,c).

Multivariate dependence modelling and flood risk. One of the most difficult conditions to predict at river confluences is whether extreme downstream flow can result from only moderate upstream conditions. Guse et al. (2020) analysed historical data from 37 confluences in Germany and showed that extreme flood wave superposition upstream (simultaneous co-occurrence of extreme peak streamflows in the two upstream branches) does not appear to play a major role in generating large floods downstream. Similarly, in our study of the Mississippi–Missouri confluence, extreme downstream flows can result from a combination of upstream flows with much lower Return Periods (RP). The advantage of our model lies in its ability to predict conditions such as this, by providing robust estimates of the upstream flow combinations that may lead to extreme downstream flows, along with their associated uncertainties. Furthermore, we can identify which branch is under stressed conditions, which can inform confluence management strategies aimed at reducing flow peaks before they propagate further into the river network.

Data quantity and quality. The primary uncertainties related to the copula selection for copula-based models, as with all process-agnostic models, is their reliance on high-quality data in sufficient quantities (Brunner et al., 2018). Specifically, our model treats streamflow data from three stations per confluence as random variables. Probability distribution functions are then fitted to this data to estimate extrapolated values for higher return period. Consequently, the modelling process is highly sensitive to measurement errors and the inherent scarcity of the extreme values that are central to our study. To mitigate this issue, we introduced the concept of the "selection of extreme events", to combine all the asynchronous extremes between the confluence stations, to extend the datasets available for distribution fitting. However, because the most extreme values and their interactions determine the asymmetries within the copula model, the quality and quantity of these data points remain critical to the model's accuracy.

Simultaneous co-occurrence of AM streamflows. Previous studies of extreme streamflows at river confluences have often assumed the simultaneous occurrence of AMQ in upstream tributaries (Gilja et al., 2018; Bačová Mitková et al., 2023). While this simplification may apply to specific cases, it must be rigorously tested when proposing a generalized framework. By analyzing the annual maxima streamflows independently in each branch for the three confluences in this analysis, we find that annual maxima streamflow upstreams (Q_{Up1} , Q_{Up2}) ($Q_{Up1,AM}$ and $Q_{Up2,AM}$) occur on the same day with a 50% probability at the Rhine-Main confluence and a 45% probability at the Mississippi-Missouri confluence. Notably, at the Rhine-Nahe confluence, there were no instances of same-day co-occurrence. These results suggest that the assumption of generally synchronized upstream AMQ events lacks physical justification and may lead to a systematic overestimation of downstream discharge (Q_D). Additional details are provided in the "Methods" section of the Supplementary Material and in Supplementary Material Figure S4.

Copula family selection. The advantage of multivariate copula based models is in the generation of larger samples. The selection of the copula family directly affects the dependence between the modelled variables. As a results the choice of the copula model requires attention beyond the traditional goodness of fit metrics (AIC in our study), especially when samples



beyond the range of observations are of interest (Ragno et al., 2023). Hence, here we critically assess the best fitted copulas with our understanding of the underlying relationship between streamflows and overall expected correlation (τ).

520 6 Conclusions

River confluences are critical nodes for flood risk management along river networks as they are characterized by the simultaneous contribution of two or more upstream branches to generate downstream flow. In this study, we showed that the proposed fully probabilistic vine-copula based model is able to describe and model upstream and downstream flows together with their respective dependencies at confluences while quantifying their uncertainty. Additionally, this model framework enables the estimation of the likelihood of specific upstream flow combinations that could may lead to downstream flows exceeding safety thresholds. This approach is computationally efficient, easily implemented, and applicable even to systems with non-linear upstream-downstream relationships.

Consequently this framework improves the characterization of extreme streamflows and the complex interactions that lead to flooding at river confluences. As such, it serves as a robust tool for decision-makers, scientists, and risk analysts seeking to define and analyze extreme events. By predicting upstream combinations that exceed downstream safety thresholds, the methodology is globally applicable.

Data availability. GRDC data are available from <https://portal.grdc.bafg.de/>, EStreams data are available from <https://www.estreams.eawag.ch/> (do Nascimento et al., 2024), US Geological Survey (USGS) data are available from the National Water Information System <https://waterdata.usgs.gov/explore/>

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540 *Competing interests.* At least one of the (co-)authors is a member of the editorial board of Hydrology and Earth System Sciences. The authors have no other competing interests to declare.

Author contributions. FD: conceptualization, data curation, formal analysis, investigation, methodology, conceptualization, validation, visualization, writing. ER: writing (review and editing), visualization, supervision, methodology, conceptualization, funding acquisition. LMS:

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writing (review and editing), methodology, supervision, conceptualization. MH: writing – review and editing, methodology, supervision, methodology, conceptualization.



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