



Assessing compound flooding potential with multivariate statistical models in a complex estuarine system under data constraints

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Abstract

Compound flooding may result from the interaction of two or more contributing processes, which may not be extreme themselves, but in combination lead to extreme impacts. Here, we use statistical methods to assess compounding effects from storm surge and multiple riverine discharges in Sabine Lake, TX. We employ several trivariate statistical models, including vine-copulas and a conditional extreme value model, to examine the sensitivity of results to the choice of data pre-processing steps, statistical model setup, and outliers. We define a response function that represents water levels resulting from the interaction between discharge and surge processes inside Sabine Lake and explore how it is affected by including or ignoring dependencies between the contributing flooding drivers. Our results show that accounting for dependencies leads to water levels that are up to 30 cm higher for a 2% annual exceedance probability (AEP) event and up to 35 cm higher for a 1% AEP event, compared to assuming independence. We also find notable variations in the results across different sampling schemes, multivariate model configurations, and sensitivity to outlier removal. Under data constraints, this highlights the need for testing various statistical modelling approaches, while the choice of an optimal approach remains subjective.

KEYWORDS

compound flooding, coastal flood risk, copulas, extreme value analysis, multivariate statistical modelling, regression, sensitivity analysis

1 | INTRODUCTION

Flooding is one of the deadliest and costliest natural disasters, particularly in coastal areas with a relatively higher concentration of exposed populations and assets (Hallegatte et al., 2013; Hinkel et al., 2014; Wahl

et al., 2017). Depending on the location, both extra-tropical and tropical storms can result in flooding events with a wide range of socio-economic consequences. In coastal areas, flooding can result from the interaction between freshwater fluxes (high rainfall or high discharge) and high coastal water levels (tide + surge +

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waves, or combinations thereof), when two or more flood drivers exceed high thresholds simultaneously or in close succession (Raymond et al., 2020; Zscheischler et al., 2020). For instance, the unusual series of winter storms in the United Kingdom in 2013/2014 led to widespread flooding and damage of coastal defences due to the joint action of extreme sea levels and waves (Haigh et al., 2016; Santos et al., 2017). In 2017, Hurricanes Harvey and Irma were categorised among the costliest disasters in the US history (Amadeo, 2018), leading to significant damages and loss of lives caused by extreme rainfall and storm surge (Dilling et al., 2017; Sebastian et al., 2017; Wahl et al., 2018). Despite the important implications for coastal flood risk management, dependence between flooding drivers is often ignored and can lead to a misinterpretation of flood risk (e.g., Moftakhari et al., 2017; van den Hurk et al., 2015; Wahl et al., 2015; Zscheischler & Seneviratne, 2017). To address this issue, a detailed understanding of potential compounding effects is necessary when building/upgrading flood risk reduction measures or performing risk analyses to improve resilience against these high-impact compound coastal and riverine flooding events.

Global and regional assessments provide insights into compound flooding potential over larger spatial scales (Couasnon et al., 2020; Eilander et al., 2020; Hendry et al., 2019; Kelln et al., 2020; Marcos et al., 2019; Ward et al., 2018), sometimes also analysing past trends (Wahl et al., 2015), or predicting future variability (Bevacqua et al., 2019; Moftakhari et al., 2017). However, every estuarine system is unique and local assessments of the interaction between flooding drivers provide a deeper understanding of the underlying processes driving compounding effects at a specific location (e.g., Bender et al., 2016; Bevacqua et al., 2017; Couasnon et al., 2018; Jane et al., 2020; Moftakhari et al., 2019; Serafin et al., 2019). Insights from such local studies can aid engineers and risk management officials in performing more robust flood risk assessments that consider compounding effects in the planning, design, and operation of flood risk reduction measures. Approaches for assessing compound flooding include the implementation of hydrodynamic and/or hydrologic models (e.g., Gori et al., 2020; Leijnse et al., 2021; Santiago-Collazo et al., 2019), application of statistical models capable of modelling dependence structures between flooding drivers (Heffernan & Tawn, 2004; Sklar, 1959), or a combination of both (e.g., Moftakhari et al., 2019; Muñoz et al., 2020; Serafin et al., 2019; van den Hurk et al., 2015).

Given their low computational cost and relatively easy implementation, statistical models provide an ideal way for an initial screening to assess whether, and to what extent, compounding effects are relevant. The

statistical appraisal of compound events usually requires implementing event sampling techniques to ensure observations are independent and identically distributed (IID). Thus, studying extreme co-occurring events in a robust statistical framework requires long overlapping records from which a sufficiently large number of events can be derived to capture the dependence structure between drivers. Yet, in many cases only relatively short observational records are available that are unlikely to be representative of the full range of environmental forcing conditions. For instance, Ward et al. (2018) highlight that on a global scale, overlapping discharge and sea-level records are usually shorter than 50 years. Overlapping data duration is especially crucial along hurricane-prone estuarine settings, where observational records may not contain sufficient events associated with tropical cyclone activity due to the rarity of such events, which may result in an underestimation of compounding effects and flooding risk. Despite advances in numerical modelling capabilities leading to longer and more consistent hydrological forcing records, data scarcity is an acute issue in studies of this nature. In particular, there is a need for a network to record all relevant variables concurrently, and ideally also provide information about the total water level response when combined. The uncertainty introduced by scarce data can lead to consequential uncertainties in assessing flood risk (e.g., Santos et al., 2021). These uncertainties can stem from the approaches utilised to sample events from the raw data (e.g., block maxima (BM) or peaks-over-threshold (POT)), how combinations of flooding drivers are defined (e.g., one-way or two-way sampling), and the statistical model of choice.

The main aim of the present study is to identify the strengths and weaknesses of different commonly used event sampling techniques and state-of-the-art statistical models when assessing compound flooding from river discharge and storm surge in a complex estuarine system with limited data. We focus our analysis on Sabine Lake, TX, where existing coastal storm risk management (CSRM) projects are being upgraded and new CSRM systems are proposed, and where compound flooding effects from riverine discharges and coastal storm surge processes may be relevant (Couasnon et al., 2020; Ward et al., 2018). The following objectives are addressed:

1. Develop a response (or impact) function that relates compound flooding drivers (storm surge and riverine discharge) with water levels inside Sabine Lake.
2. Assess the sensitivity of estimated total water levels to different types of multivariate statistical models.
3. Assess the sensitivity of estimated total water levels to different event sampling techniques.

4. Assess the sensitivity of estimated total water levels to removal of outliers from observational data.

2 | STUDY AREA DESCRIPTION

Sabine Lake is located at the border of Texas and Louisiana (Figure 1) and connected to the northern Gulf of Mexico through the Sabine Pass inlet. Port Arthur is the largest town bordering Sabine Lake, with over 50,000 residents (2010 census). Port Arthur, Beaumont, and Orange are together known as the ‘Golden Triangle’ and are home to a wide range of nationally critical petrochemical and industrial assets. Two main rivers flow into Sabine Lake, the Neches and Sabine Rivers. Both rivers are similar in length and catchment size (Figure 1b). The Neches River has a basin size of 10,011 mi² and a length of 416 miles, whereas the Sabine River has a catchment size of 9,756 mi² and is 510 miles long. Historic events, including most recently hurricane Laura, demonstrate that the study area is prone to flooding by both extra-tropical and tropical storms. For instance, record rainfalls during the first week of March in 2016 in the Sabine River basin resulted in Deweyville, TX, being only accessible by air or boat (Breaker et al., 2016; McIntosh & Lander, 2016). In 2017, Port Arthur suffered severe flooding during Hurricane Harvey. Although primarily driven by extreme rainfall and river discharge, flooding was likely exacerbated by a moderate storm-driven surge which hindered water drainage from Sabine Lake into the Gulf of Mexico over several days (Jonkman et al., 2018; Sebastian et al., 2017; Valle-Levinson et al., 2020).

3 | DATA

Our main focus is to assess the interaction between discharge, provided by the Neches and Sabine rivers flowing into Sabine Lake, and storm surge (or non-tidal residual; NTR). Other processes and/or inflows that may affect the water levels inside the lake include locally generated waves, discharge from smaller streams like Taylor Bayou, direct precipitation onto the lake, and overland flow. However, their contribution is small compared to the discharge from Sabine and Neches rivers entering the lake (TWDB, 1981). Depending on the hydrodynamic characteristics of the system, tides can also influence flooding consequences during compound events. However, the tidal amplitude at our study site is relatively small compared to extreme NTR events and tide-surge interaction is relatively minor. It is noted that Sabine Pass often makes the list as one of the locations with the highest number of days of ‘chronic nuisance flooding’ within the continental United States (Sweet et al., 2020). We focus here on analysing the dependence and associated compounding effects stemming from the meteorologically driven components of surge and discharge.

We use river discharge because it represents near-term runoff from a storm event that contributes to the riverine water levels at the confluence with Sabine Lake, where it interacts with coastal water levels. Discharge data are obtained from the U.S. Geological Survey Stream Gauge (SG) network (<https://waterdata.usgs.gov/nwis/rt>). SGs located near the mouths of the Neches and Sabine rivers and associated tributaries are shown in

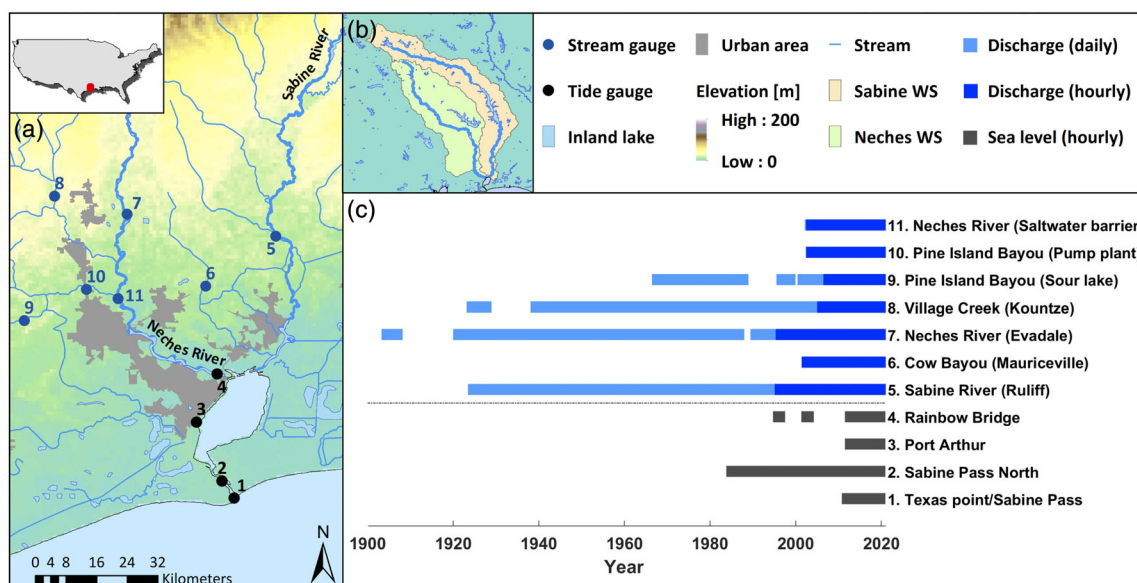


FIGURE 1 Overview of the study area, including locations of tide and stream gauges (a), schematic of the Sabine and Neches river watersheds (WS) (b), and length of available data records in the area (c)

Figure 1a. Discharge is available in hourly and daily time steps, but the record of the latter is significantly longer for most SGs (Figure 1c) and hence used in the analysis.

Coastal water levels are obtained from hourly sea-level data reported at National Oceanographic and Atmospheric Administration (NOAA) tide gauges (TGs) (<https://tidesandcurrents.noaa.gov/>) located in and around Sabine Lake (Figure 1a). TGs measure the total still water level, which includes mean sea level (MSL), tides, and NTR including effects of wave setup, currents, atmospheric pressure, winds, precipitation, and runoff processes. As we are interested in assessing the interaction between discharge and coastal NTR, we remove trends (due to sea-level rise), MSL seasonality, and the tidal signal from the observed water levels. To detrend the data for sea-level rise impacts we use a linear fit. Seasonal MSL is removed by subtracting a running monthly mean. Tidal effects were removed using the NOAA tidal predicted water level values in order to derive hourly NTR values. From the latter we derive the maximum daily NTR which can be directly paired with daily discharge data.

To assess compounding effects, we quantify how the interaction between flooding drivers can lead to, or can exacerbate, a response (or impact) variable of interest. In our case study, the flooding drivers are coastal NTR and discharge from both Sabine and Neches rivers, whereas the response variable is the NTR inside Sabine Lake, which is affected by the interaction between both the coastal and riverine components. We use NTR data from the tide gauge Sabine Pass North (TG 2 in Figure 1a) to represent the coastal hydrological forcing, as it provides the longest record in the direct vicinity of the study site. Discharge is taken from stream gauges at Evadale (SG 5 in Figure 1a) and Ruliff (SG 7 in Figure 1a) to represent inflows coming from the Sabine and Neches rivers (hereinafter referred to as D_S and D_N , respectively). Inside Sabine Lake, the tide gauge at Port Arthur (TG 3 in Figure 1a) measures the NTR generated by the interaction between both flooding drivers, which is considered here as the response variable (hereinafter referred to as WL). The WL across a lake can be affected by local wind forcing, thus in a perfect scenario the WL inside the lake would be represented by the average of measurements taken at different locations around the lake. To explore the variation, we examined the differences in WLs from two TGs located in the lake: TG3 located in east of the lake and TG4 located in the northeast of the lake, close to the mouth of the Neches River (Figure 1). Given where they are located in the lake, winds blowing latitudinally or diagonally might affect them differently, while longitudinal winds would induce the same effect on both. For the extreme events identified in overlapping records (see

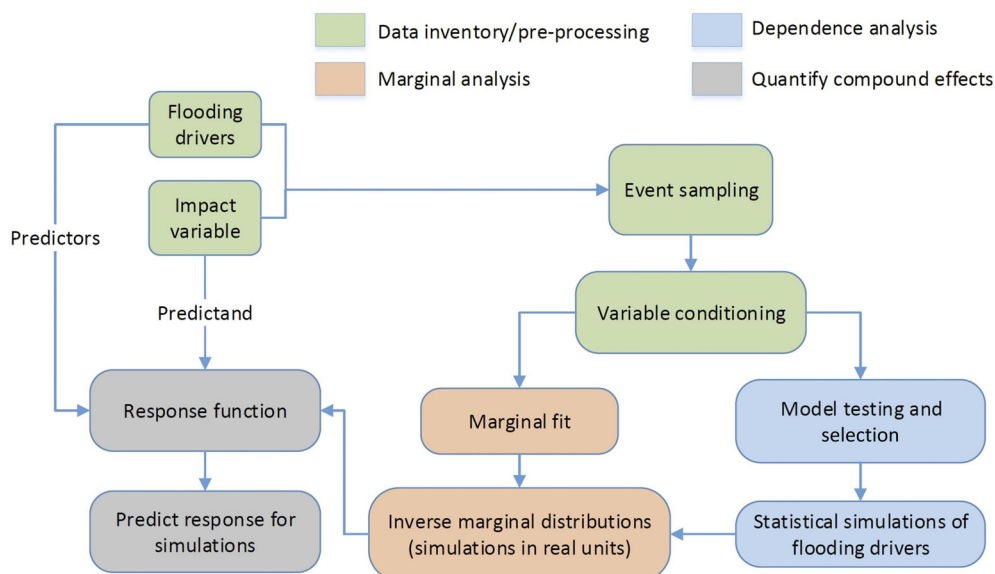
Section 4.1 for more details about sampling techniques), a root-mean-square error (RMSE) of 0.05 m was found between the extreme WL events at the two gauges leading us to conclude that local wind effects are negligible for the particular focus of our analysis. We use TG3 to define the response variable in our analysis, as TG4 records are likely more influenced by discharge due to its proximity to the mouth of the Neches River.

4 | METHODOLOGY

There are different choices one must consider when assessing compound flooding using multivariate statistical models, starting with the selection of the model to capture correlations between drivers. Here, we compare two different multivariate statistical models that are commonly used: copulas (Sklar, 1959) and the Heffernan and Tawn (2004) model (hereafter HT04). Another important choice is the methodology employed to sample a set of events from the raw data, from which dependence will be modelled. While some models require a specific approach to sampling (i.e., HT04 utilises declustered exceedances over a threshold), the choice of sampling is subjective when using copulas. For copula models, we test two different sampling techniques, namely POT and BM (see Section 4.1).

The framework followed to assess compound flooding using either approach (copula or HT04 modelling) is similar in implementation and outlined in Figure 2. The framework is divided into four main steps. First, extreme events are sampled from the time series ensuring they are IID and by conditioning on each variable in turn (green colour in Figure 2). Second, the sampled events are used to train a response function that links flooding drivers (used as predictors) and the associated response variable (the predictand; here WL in Sabine Lake) (grey colour in Figure 2). For simplicity and to ease comparison between the different sampling approaches considered here we use multiple linear regression models (Seber & Lee, 2012) for this purpose. Third, suitable marginal distributions are derived for the IID flooding driver events (i.e., surge and discharge) (orange colour in Figure 2). We test a wide range of probability distributions commonly used in hydrologic analysis and select the best fitting according to the Aikake information criterion (AIC) (Sakamoto et al., 1986). The declustered exceedances are fitted to a generalised Pareto distribution (GPD) (Coles et al., 2001). Fourth, different multivariate statistical models are tested and used to capture dependence between flooding drivers. Once an appropriate model has been selected, it is used to create a large set of synthetic events; first in probability space and then

FIGURE 2 Steps involved in data pre-processing (green), marginal analysis (orange), dependence modelling (blue), and developing a response function (grey)



transforming all variables into real units via the previously identified marginal distributions (blue colour in Figure 2).

After completing these analysis steps, we use the synthetic surge-discharge combinations along with the response function (from step 1) to predict the response variable WL; this is shown by the connection between orange and grey boxes in Figure 2. Compounding effects are assessed by repeating this procedure for two scenarios, one accounting for existing dependences between flooding drivers and another one assuming independence between flooding drivers. Comparing the results from these two approaches allows quantification of the compounding effects for a range of relevant annual exceedance probabilities (AEPs).

In the following two subsections we provide an overview of both statistical models, highlighting the different pre-processing steps. The analysis is performed using a trivariate statistical modelling approach (considering NTR, D_N , and D_S). We also tested a simplified bivariate approach where both river inflow time series are additively combined; we only show the final results for this analysis to compare against the trivariate approach.

4.1 | Sampling and dependence modelling with copulas

Data pre-processing for the application of copula models in the context of our analysis requires defining appropriate variable combinations that optimally explain the behaviour of the response variable. Sampled events from the time series should be IID and contain information of the memory of the system when significant lags between

flooding drivers and the response variable exist. We employ the two most frequently used methods (Ferreira & de Haan, 2015) to identify extremes: BM (Gumbel, 1958) and POT (Pickands III, 1975). The BM approach consists of dividing the time series of a given variable into non-overlapping periods of equal size (blocks) from which the maximum observation in each period is computed. As data are limited for our case study, blocks are defined on a monthly basis (e.g., Menéndez & Woodworth, 2010) instead of using annual maxima. BM ensures events are IID, but information about multiple extreme events happening in the same period is lost. The POT approach addresses this issue by selecting exceedances above a threshold. The threshold should be high enough so that selected events can be considered extremes (to not violate the asymptotic justification of the extreme value model) while also obtaining enough events to derive robust distribution parameters to reduce variance. Previous studies used thresholds resulting in approximately 3–5 events per year (e.g., Cao et al., 2020; Serafin & Ruggiero, 2014). POT exceedances must be declustered to ensure that the selected events abide by the IID rule (Davison & Smith, 1990). Declustering approaches may differ depending on the variable in question and its behaviour at a specific site. Here, we use the meteorological independence criterion (Ciavola & Coco, 2017) to decluster events, using a 3-day window for surge (e.g., Haigh et al., 2016). The appropriate declustering window for discharge is highly site specific and depends largely on the catchment characteristics. After applying a range of high thresholds and assessing the average duration of the exceedances, a 7-day window was used to decluster discharge series as events rarely lasted longer than a week. For a few events, these declustering windows were inappropriate, and in

these instances, exceedances were declustered manually by taking the maximum value from the observations exceeding a high threshold during a given event. For example, Hurricane Harvey's surge and extreme discharge lasted longer than 3 and 7 days, respectively.

In coastal regions, the complex interplay between storm surge and discharge can lead to compounding effects through multiple processes, which can be classified into three main mechanisms (Wahl et al., 2015; Zscheischler et al., 2020); in case (1) both drivers are extreme and in cases (2) and (3) only one is extreme but the other one still contributes to cause or increase impacts:

(1) The joint occurrence of extreme freshwater drivers and extreme NTR may elevate WLs to a point where flooding occurs and/or impacts are exacerbated;

(2) An extreme storm surge causes widespread flooding and impacts are aggravated by moderate rainfall and/or discharge; and

(3) The impacts of an extreme discharge or precipitation event are amplified through the interaction with a moderate storm surge which blocks or slows down drainage.

Two distinct approaches have been used in the past when selecting extreme event combinations that cover all the above-mentioned mechanisms: the impact-based approach (e.g., Bevacqua et al., 2017) and the n -way sampling approach (e.g., Wahl et al., 2015; Ward et al., 2018), where n indicates the number of flooding driver variables considered. The impact-based approach takes IID extreme events from the response variable (in our case WL inside Sabine Lake) and identifies coincident (or near-coincident) values of the flooding drivers (here NTR, D_N , and D_S). The n -way sampling approach is similar in implementation but is applied to all flooding drivers and carried out n times, conditioning on one variable at a time. For instance, if NTR is the conditioning variable, we first identify IID extreme NTR events and then match them with (near-)coincident observations of the other (conditioned) flooding drivers. In this study, the n -way sampling approach is utilised as the available data length for the impact variable is shorter (~6 years; TG 3 in Figure 1c) compared to the overlapping records of flooding drivers (~34 years; TG 2, SG 5, and SG 7 in Figure 1c). Moreover, we found that NTR peaks (at the coast) usually coincide with WL peaks (inside Sabine Lake), which means that the impact-based approach would likely lead to a very similar set of events compared to the n -way sampling approach when conditioning on NTR.

When matching the conditioning variable with the conditioned variables we use the following approach. When NTR is the conditioning variable we pair

declustered maximum daily NTR with the coincident river discharges (D_S and D_N , respectively). When discharge is the conditioning variable, we first find the highest NTR within a 10-day window of the discharge peak(s) and then select the discharge values that coincide with the identified NTR. As outlined in the previous paragraph, NTR was identified as the main driver for WL inside Sabine Lake and hence by following this approach we identify the flooding driver combinations which most likely resulted in the highest WL.

Once the multivariate samples of the flooding drivers have been identified, copulas can be used to model their dependence structure. Copulas are attractive for this kind of analysis as they enable the dependence structure between the contributing variables and their marginal characteristics to be modelled separately (Nelsen, 2007). Sklar, 1959 describes the connection between a copula C and a bivariate cumulative distribution function (CDF) $F_{XY}(x,y)$ of any pair of variables (X,Y) as follows:

$$F_{XY}(x,y) = C[F_X(X), F_Y(Y),],$$

where $F_X(x)$ and $F_Y(y)$ are the univariate marginal distributions. The bivariate probability density function (PDF) has the following form:

$$f_{XY}(x,y) = c[F_X(x), F_Y(y)]f_X(x)f_Y(y),$$

where $f_X(x)$ and $f_Y(y)$ represent the marginal PDF's. To simulate a realisation (x,y) from (X,Y) , first simulate a u variate on $[0,1]$.

The following conditional distribution of $\{V \text{ given } u\}$:

$$c_u(v) = \mathbb{P}\{V \leq v | U = u\} = \frac{\partial}{\partial u} C(u,v)$$

is exploited to obtain v by setting $v = c_u^{[-1]}(u)$. Subsequently, (u,v) are transformed to (x,y) using the probability integral transform:

$$\begin{cases} x = F_X^{[-1]}(u) \\ y = F_Y^{[-1]}(v) \end{cases}.$$

More details about simulations using copulas and sampling algorithms are described by Salvadori et al. (2007).

For the copula analysis we use rank order statistics to convert combinations of NTR and discharge events to the unit hyper-square (for bivariate analysis) or unit hypercube (for trivariate analysis). Then we derive copula parameters for a set of 40 different copulas (using the VineCopula R package version 2.3.0; Schepsmeier et al., 2015) using the maximum pseudo-likelihood

estimator (Kojadinovic & Yan, 2010). The best-fit copula model is selected by comparing the dependence structures of observations and simulations through AIC, and employing a goodness-of-fit test (Genest et al., 2009) to assess whether the selected copula model is appropriate.

The equations and explanation above refer to the bivariate case, which is considered here only for comparison purposes (and only final results are shown in Figure 10) by combining discharge time series from the Neches and Sabine rivers. For our main analysis we consider NTR and discharge from both rivers separately; this trivariate approach is implemented using vine copulas (Aas et al., 2009). Vine copulas are a type of pair-copula construction which allow a multivariate probability density to be represented as the product of a cascade of pair-copulas and marginal densities. This hierarchical construction provides more flexibility compared to the limited set of higher-dimensional copulas, as the bivariate copulas can be selected from a wide range of copula families. The regular vine (Bedford & Cooke, 2001) is a graphical model organising the many possible pair copula decompositions, which quickly becomes large as the number of dimensions increases. In the model, the dependence structure is determined by the bivariate copulas and a nested set of trees. The canonical (or C-) vine and D-vine are two special cases of regular vines, each providing a specific recipe for decomposing the multivariate probability density. Each of the three possible decompositions of a three-dimensional copula density are simultaneously a C- and a D-vine (e.g., Jane et al., 2020). There are three possible regular vine models on three variables depending on the ordering of the variables. The VineCopula R package implements the sequential method in Dissmann et al. (2013) to select among the regular vine structures. The method selects the arrangement yielding spanning trees which maximise the sum of absolute the empirical Kendall's rank correlation coefficient (τ ; Kendall, 1938) between the variable pairs at each step. The best fitting bivariate copula family between each variable pair is then determined by the AIC. For more information on fitting and simulating from vine copulas consult Aas et al. (2009).

4.2 | Sampling and dependence modelling with the HT04 model

We employ the HT04 model as an alternative way to capture marginal and dependence characteristics of the relevant flooding drivers when at least one is extreme. The HT04 model fits multivariate regression models to the conditional samples, capturing the dependence through the regression parameters and associated residuals rather

than prescribing a parametric distribution. In common with the copula approaches, the marginal and dependence modelling are carried out independently. Let $X_t = (X_i, \dots, X_j)_t$ be a time series of a set of flooding drivers. The marginal behaviour of each flooding driver is analysed individually by applying the POT method to define declustered extremes and fitting a GPD to the excesses above a sufficiently high threshold u_i . The empirical distribution \tilde{F}_i of X_i is combined with the GPD above the threshold (u_i), resulting in the following semiparametric function (Coles & Tawn, 1991):

$$\hat{F}_i(x) = \begin{cases} \tilde{F}_i(x) & x \leq u_i \\ 1 - \left(1 - \tilde{F}_i(u_i)\right) \left[1 + \xi_i \frac{(x - u_i)}{\beta_i}\right]^{-1/\xi_i} & x > u_i \end{cases}$$

where i denotes a given flooding driver, $\beta_i > 0$ and $\xi_i \in \mathbb{R}$ are the GPD parameters. In the dependence analysis, the variables are converted to common scales to remove the marginal information and ensure only information regarding the dependence structure remains. When implementing the HT04 approach, the variables are typically converted to standard Gumbel marginal distributions obtained by setting $Y_i = -\log(-\log[\hat{F}_i(X_i)])$. Letting Y_{-i} be the vector of all drivers except Y_i on the transformed scale, the HT04 model is generally implemented utilising the multivariate nonlinear regression model:

$$Y_{-i} | Y_i = aY_i + Y_i^b Z \text{ for } Y_i > v,$$

where v is a high threshold on Y_i , $a \in [0, 1]$ and $b < 1$ are parameters, and Z is a vector of residuals. Parameter estimation is carried out using maximum-likelihood estimation under the temporality assumption that Z follows a normal distribution with unknown mean and variance. Asymptotically, $Y_i > v$ is statistically independent of Z , thus v should be large enough for this condition to hold. A detailed description of the rejection sampling methodology involving conditioning a variable to exceed v and independently sampling joint residuals to simulate extreme events is given in Wyncoll and Gouldby (2015), among others. The HT04 model is only applied for the trivariate analysis, not in the simplified bivariate approach outlined above.

5 | RESULTS

The results section is structured as follows. The first subsection shows the performance of the response function that relates the flooding drivers to the response variable.

The second subsection summarises the results from the copula analysis for both BM and POT sampling methods as well as when removing outliers. The third subsection shows results from the HT04 model (including sensitivity to outlier removal) and concludes with a comparison of the compounding effects derived by all the different approaches.

5.1 | Response function

A response function that relates the three flooding drivers (NTR , D_N , and D_S) to the response variable (WL) requires overlapping data for all four variables. This overlapping data duration is ~6 years in our case. We use the impact-based sampling approach to identify high WL values and coincident flooding drivers. Simple (in the bivariate cases) and multiple (in the trivariate cases) regression models are used here. Results of the model performance from a 10-fold cross validation are shown in Figure 3 for the different cases considered in the analysis. Overall, the monthly BM approach (Figure 3a,c) leads to better results compared to the POT sampling approach. This is due to the BM approach ignoring some extreme events, that is, when two extremes happened in the same month only the most extreme is sampled and conversely it includes

more moderate events when no extreme occurred in a given month. The latter are better captured by the regression model implemented here for the response function. On the contrary, the POT sampling results in an underestimation of the most extreme WL events in the lake; the notable outlier (circled in red) in Figure 3b,d denotes hurricane Harvey.

5.2 | Copula analysis to assess compounding effects

First, we present the results for the BM approach (Figures 4 and 5). As we are using an n -way sampling procedure that leads to three distinct samples, we only show results for the conditioning case that captures the strongest compounding effects; for the BM approach this happens when we condition on D_S . Other cases are also analysed and included in the comparison Figure 10 but detailed results are not shown. We identify 406 discharge-surge pairs and their Kendall's τ reaches values of 0.17, 0.18, and 0.49 for the $NTR-D_N$, $NTR-D_S$, and D_S-D_N pairs, respectively; all statistically significant at the 95% confidence level. Figure 4a–c shows the marginal distributions that are selected for the individual flooding drivers; results are shown for all selected events (black)

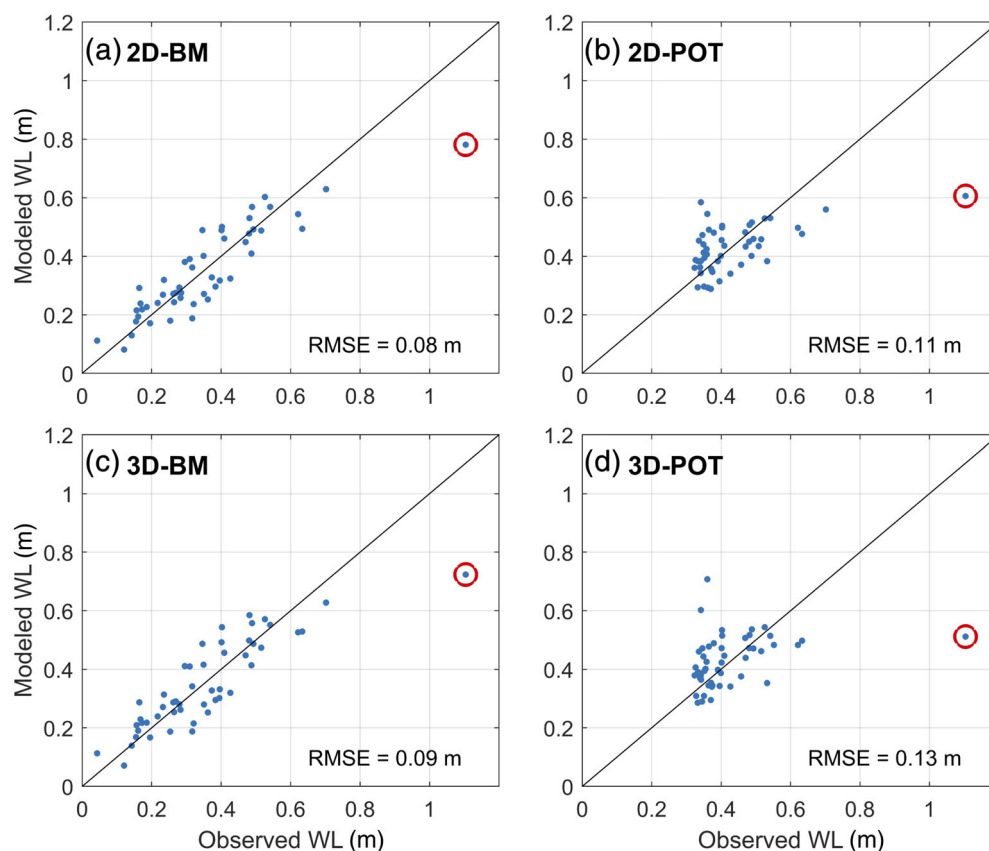


FIGURE 3 Performance of the response functions assessed by a 10-fold cross validation for the bivariate BM (a) and POT (b) sampling, and the trivariate BM (c) and POT (d) sampling. For POT, we chose a threshold leading to between three and five events per year on average, which translates to approximately the 97th percentile threshold applied to the response variable WL. BM, block maxima; POT, peaks-over-threshold

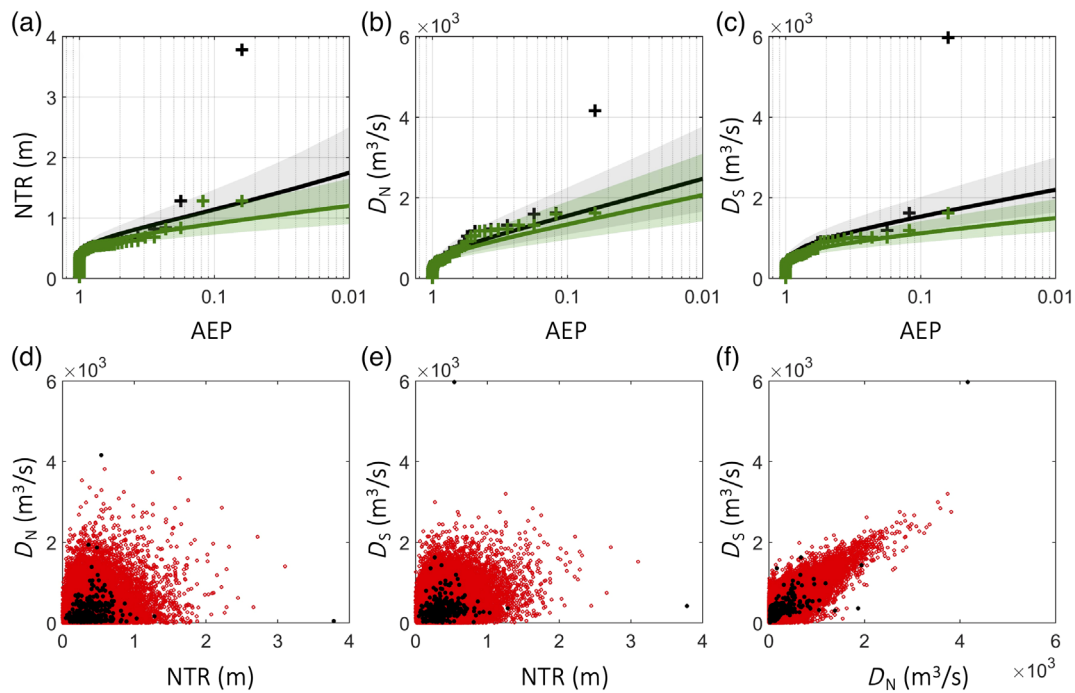


FIGURE 4 (a–c) Plotting positions (crosses) and the theoretical distributions selected as marginal distributions with 95% confidence levels (green: all events; black: outliers removed). (d–f) Observed data pairs (black) and 48,000 simulated (equivalent to 4000 years of data) pairs (red) from the fitted vine copula in the probability space

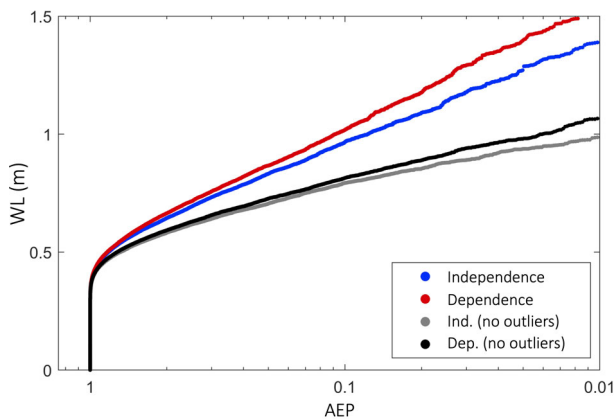


FIGURE 5 WL AEP curve for the n -way BM sampling approach when conditioning on D_S and modelling dependence with vine copulas. The response variable WL derived with multiple regression models using triplets of the flooding drivers as predictors when assuming independence (blue when all data are used; grey when outliers are removed) and when preserving dependence through the vine copula (red when all data are used; black when outliers are removed). AEP, annual exceedance probability; BM, block maxima

and when removing outliers (green; hurricanes Ike and Harvey removed). Removing the outliers leads to better marginal fits but AEP WLs decrease. Based on the AIC we select the generalised extreme value (GEV) distribution for NTR (Figure 4a) and Weibull distribution for

river discharges (Figure 4b,c). Figure 4d–f shows scatter plots of the observed and modelled (via vine copulas) variable pairs highlighting that the selected copula models can reproduce the observed dependence structures. The vine-copula structure which best describes the dependence between drivers contains two Frank copulas and the Joe copula.

Using the simulated pairs of flooding drivers (red dots in Figure 4d–f) we derive the response variable WL with the response function outlined in Section 5.1, and repeat the analysis under the assumption of independence. Figure 5 shows that the WL AEP curves accounting for dependence and using all data (red) are higher than when assuming independence (blue), indicating the existence of compounding effects. For the 1% AEP event, the WL derived with the dependence case is 15 cm higher than the one derived under the independence assumption. To assess the sensitivity of the results to outliers the analysis was repeated with outliers removed. More specifically, we are interested in removing the effect of extreme tropical cyclones in the records (Hurricanes Ike and Harvey), as these events belong to a different population for which available records do not provide a robust enough sample to identify an appropriate theoretical distribution. We have identified these on the basis of boxplots of the univariate data sets (not shown), where an outlier is defined as any observation further than three standard deviations from the mean. The differences across the

modelling approaches with dependence included or ignored persist when outliers are removed but become smaller, demonstrating the sensitivity of the AEP to individual extreme events in both the marginal distributions (Figure 4) and response variable (Figure 5) when short data records are used.

In the remainder of this subsection, we show the results for the POT approach (Figures 6 and 7). The application of POT to define events requires the selection of a relevant threshold by which exceedances are determined and declustered. We chose this threshold in such a way that approximately three events per year are selected on average. Similar to the monthly maxima approach, we show detailed results when D_S is the conditioning variable, as this conditioning case captures the strongest compounding effects. The 80th percentile was applied to derived declustered events, resulting in 96 events. This relatively low threshold is explained by the need to use a large storm window to decluster discharge events, which lowers the length of data that can be utilised to sample events. Kendall's τ reaches values of 0.03, 0.08, and 0.43 for NTR- D_N , NTR- D_S , and D_S - D_N pairs, respectively; only the correlation between the two discharges is significant at the 95% confidence level. Despite the rank correlation values being different, the overall picture in terms of the strength of dependence between different drivers is the same as in the monthly maxima approach. Based on the AIC we select the Log-normal

distribution as the marginal distribution for NTR (Figure 6a) and Weibull distributions for the river discharges (Figure 6b,c). The vine-copula structure that best describes the dependence between drivers again contains two Frank copulas and the Joe copula. The simulations provided by the copula models (Figures 4d-f and 6d-f) rarely exceed the highest observations despite synthetic records being significantly longer. In the copula models shown here, the outliers show there could be underestimation especially in the tail of the distributions: data shortness leads to few extremes, which affects the robustness of the marginal fit. Differences in the WL return levels from using simulated triplets under the dependence and independence assumptions are similar to those derived with the monthly maxima approach (i.e., approximately 15 cm for the 1% AEP event) (Figure 7). The effect of outlier removal is also evident here, but smaller as compared to the monthly maxima case (Figures 6a-c and 7).

Overall, both the BM and POT approaches lead to similar conclusions in terms of the existence and strength of compounding effects. However, differences exist in the strength of dependence between the flooding driver pairs, where lower rank correlation coefficients are found in the POT approach. The fact that significant dependence only exists between the river discharges, yet both approaches indicate similar compounding effects, highlights that co-occurrences of extreme discharges in the

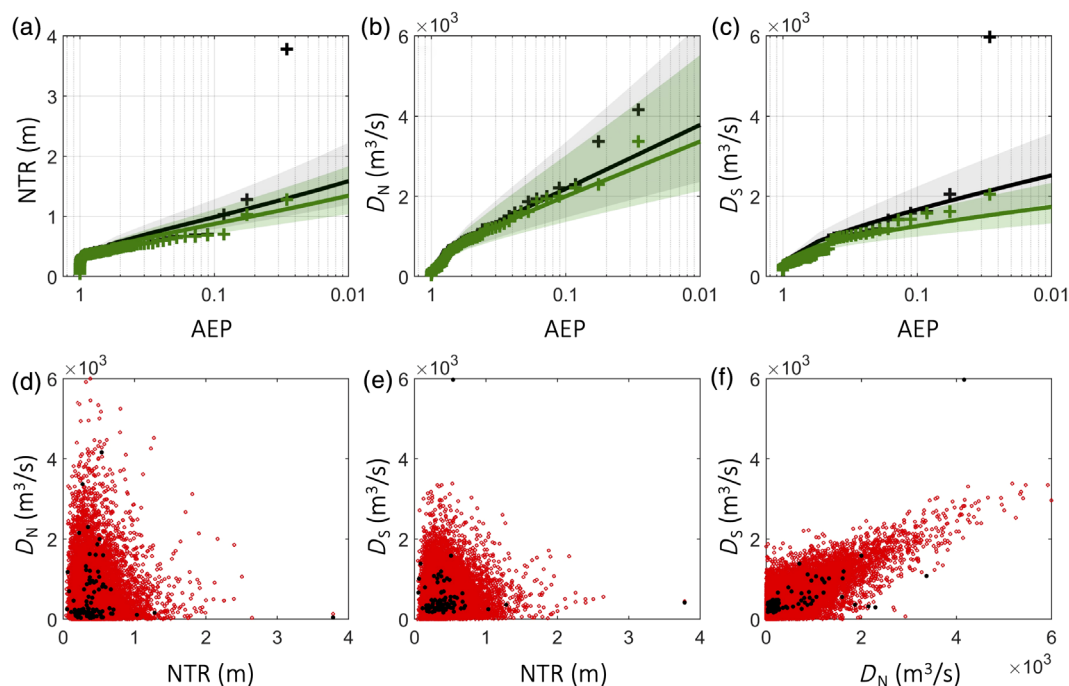


FIGURE 6 (a–c) Plotting positions (crosses) and the theoretical distributions selected as marginal distributions with 95% confidence levels (green: all events; black: outliers removed). (d–f) Observed data pairs (black) and 12,000 simulated (equivalent to 4000 years of data) pairs (red) from the fitted vine copula in the probability space

two rivers play an important role in generating these compounding effects. Although the correlation with NTR is low in the POT approach, the concurrent NTR values are often moderately high, hindering efficient conveyance of the high river discharge into the Gulf of Mexico.

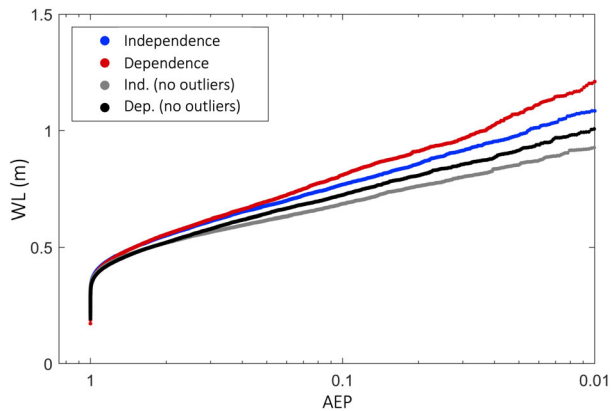


FIGURE 7 WL AEP curve for the n -way POT sampling approach when conditioning on D_S and modelling dependence with vine copulas. The response variable WL derived with multiple regression models using triplets of the flooding drivers as predictors when assuming independence (blue when all data are used; grey when outliers are removed) and when preserving dependence through the vine copula (red when all data are used; black when outliers are removed). AEP, annual exceedance probability; POT, peaks-over-threshold

5.3 | HT04 analysis to assess compounding effects

Lastly, we apply the HT04 model to confirm the existence and quantify potential compounding effects between flooding drivers including an assessment of the sensitivity of the results to outlier removal. Results from the HT04 model are shown in Figures 8 and 9. The response function used to transform HT04-derived simulations into real units is the 3D function leading to the highest performance (3D-BM in Figure 3). The marginal distributions are GPD for all flooding drivers (Figure 8a–c), as events are defined based on declustered POT exceedances following the sampling technique that is specific to the HT04 model; results are again shown for all data (black) and when outliers are removed (green). The comparison between observed and modelled pairs (black and red dots in Figure 8d–f) shows that the dependence structures between variable pairs are captured. In contrast with the previously shown copula models, various simulations exceed the highest discharge/NTR observations, indicating this model, which uses GPDs as marginals, may be more appropriate in the face of short records. Figure 9 shows notable differences in the AEP WLs of the response variable between the dependence (red) and independence (blue) assumptions when using all data. Compounding effects are stronger compared to those identified with the copula modelling approaches, leading

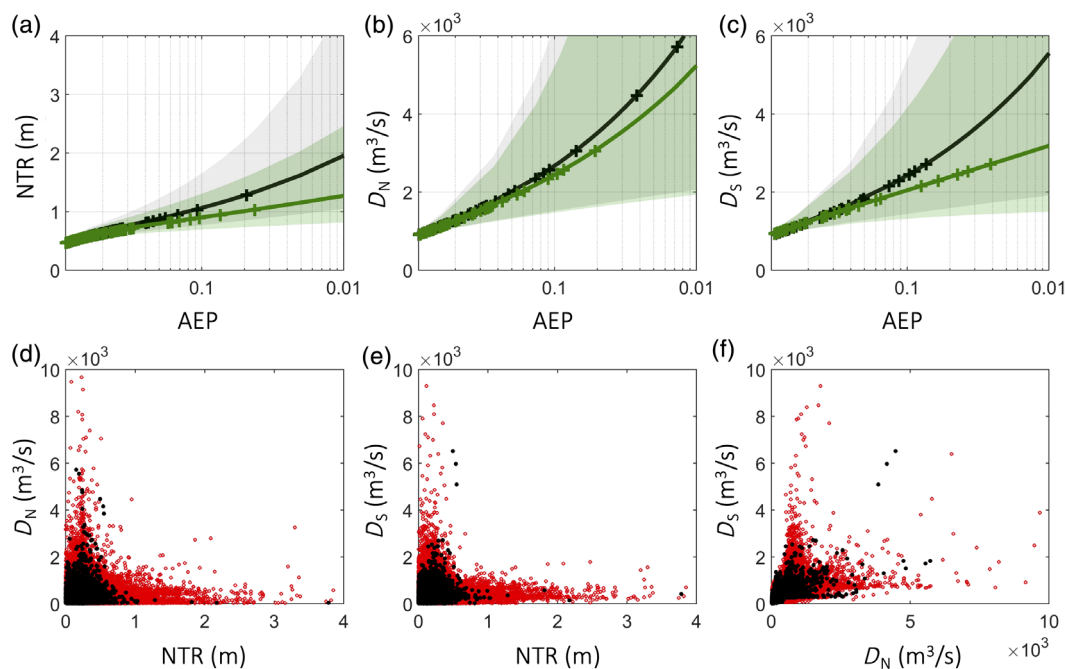


FIGURE 8 (a–c) Plotting positions (crosses) and the theoretical (GPD) distributions selected as marginal distributions with 95% confidence levels (green: all events; black: outliers removed). (d–f) Observed data pairs (black) and simulated (equivalent to 2000 years of data) pairs from the fitted HT04 model in the probability space. GPD, generalised Pareto distribution

to differences between dependence and independence cases of approximately 35 cm for the 1% AEP event (Figure 10). However, the response function changes notably, and compounding effects disappear when hurricanes Ike and Harvey are removed, indicating higher sensitivity of the HT04 approach to outlier removal.

Figure 10 shows the comparison of the compounding effects derived when subtracting the response function obtained under the independence assumption (WL_i ; blue curves in Figures 5, 7, and 9) from the one obtained when modelling the dependence (WL_d ; red curves in Figures 5, 7, and 9). We refer to the resulting curves as ‘delta curves’ and note that our main focus is on these differences that represent compounding effects, as opposed to the absolute WL values derived in either case. For each of

the copula modelling approaches we combine the delta curves for the different conditioning cases (including the ones not shown in detail above) by identifying for each AEP the highest value along the different delta curves, that is, delta curves are merged using an envelope that follows the highest values. In Figure 10 (the ‘2D’ curves), we also show the results for the simplified bivariate analysis where river discharge time series are combined. It is evident that this simplification does not appropriately capture the compounding effects that are otherwise evident, when both river discharge time series are treated separately.

6 | CONCLUSIONS

Here we develop and implement a framework that includes a range of different modelling approaches to explore compound flooding potential from riverine discharge and storm surge (or NTR) in Sabine Lake, TX. Sabine Lake is part of a complex estuarine system that receives discharge from two main rivers, the Neches and Sabine, and is connected to the Gulf of Mexico. Data constraints with short discharge and sea-level records make a reliable statistical assessment challenging. This led us to explore the sensitivity of the results to different multivariate models, sampling techniques, and removal of outliers.

In terms of multivariate statistical models, we employ (vine) copulas and the HT04 model, which are able to sufficiently capture the dependence structures between different flooding drivers when at least one can be considered extreme. For copulas, we use two approaches to sample extreme events, BM and POT, conditioning the flooding drivers using an n -way approach that samples from one variable at a time and ensures the longest records available in the study area are used. BM (here

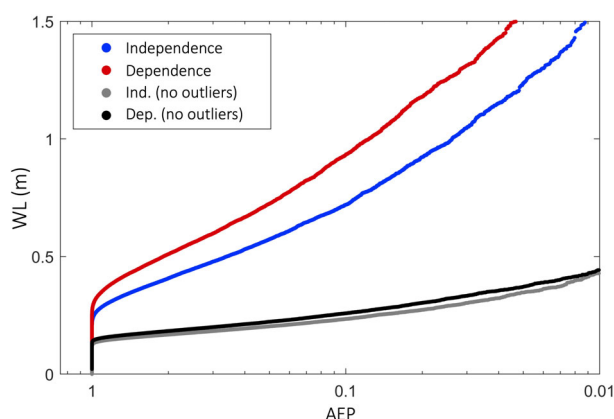


FIGURE 9 WL AEP curve for the HT04 approach. The response variable WL derived with multiple linear regression models using simulated triplets of the flooding drivers as predictors when assuming independence (blue when all data are used; grey when outliers are removed) and when preserving dependence through the HT04 model (red when all data are used; black when outliers are removed). AEP, annual exceedance probability; HT04, Heffernan and Tawn (2004)

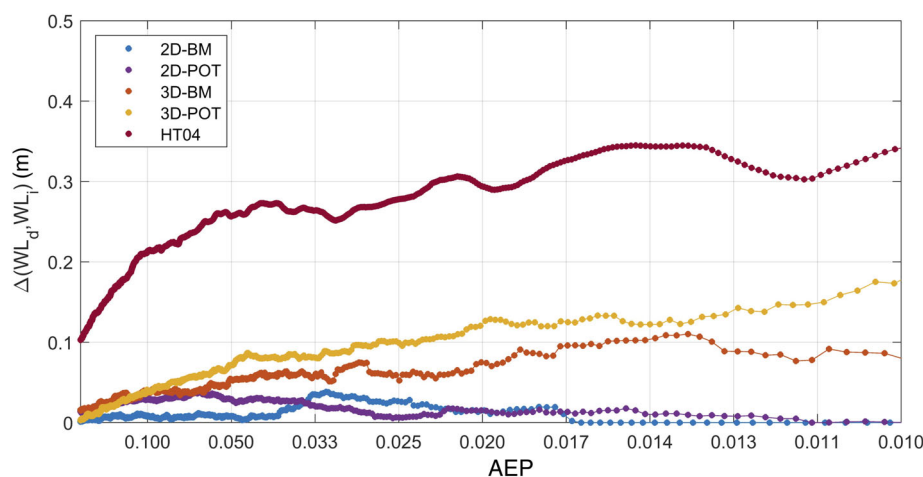


FIGURE 10 Difference between dependence and independence WL curves (delta curves) for all statistical models considered in the analysis. Delta curves derived from approaches that use the n -way sampling approach are obtained by taking the highest difference for a given AEP across the three conditioning cases. AEP, annual exceedance probability

monthly maxima) offers the advantage of selecting a more balanced set of events that increases the performance of a response function relating flooding drivers and the response variable (WL). However, some extreme events are lost in the sampling process, which may contain relevant information on potential compounding effects. The POT approach only selects the most extreme events which are of most interest from a flooding perspective but also the hardest to model; consequently, it is outperformed by the BM approach in the response function modelling.

Both BM and POT approaches point to the existence of compounding effects at the site of similar magnitude; for example, differences of ~15 cm in the 1% AEP WL of the response variable when comparing results from the dependence and independence assumptions. Results indicate that the co-occurrence of extreme discharge events from both rivers play an important role in generating compounding effects, in combination with moderate storm surges. Hence, a simplified bivariate analysis does not capture compounding effects in the same manner as the trivariate approaches used here. The disadvantage of the n -way sampling approach lies in the more complicated aggregation of results, as the methodology has to be implemented separately for each flooding driver. Such aggregation is straightforward when using the HT04 model. The latter provides an improved representation of the most extreme events and leads to larger differences of ~35 cm between dependence and independence return level curves for a 1% AEP event. However, the HT04 model is more sensitive to the removal of outliers in terms of compounding effects being detected compared to the copula approaches. The simulation procedure for the HT04 method involves resampling observed residuals (from the regression) rather than sampling from a fitted distribution and therefore it is expected that the results are more sensitive to the removal of the two largest events on record. Overall, large uncertainties in all considered approaches are associated with data scarcity and the presence of outliers caused by tropical cyclones. Taking a conservative approach, we identify the HT04 to be the best candidate, as it provides a good marginal fit and representation of the most extreme events in the dependence modelling.

The framework implemented here is generic and can be transferred to other locations with appropriate observational data or model hindcasts of the different flooding drivers. The analysis is particularly useful for initial assessments regarding the existence and importance of compounding effects, and can also help guide more complex process-based numerical modelling studies, for example, by identifying the dominant driver(s) of compounding effects and choosing combinations of process-

based models accordingly. An avenue for future research is the inclusion of volumetric flow rate in the modelling framework by accounting for the duration of the events. Although the incorporation of additional variables would significantly increase the complexity of the multivariate statistical model, the consideration of volume is noticeably relevant for gate operations and the appraisal of compound flooding potential.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available at https://github.com/victor-malagon/Sabine_Lake_data. These data were derived from the following resources available in the public domain: <https://waterdata.usgs.gov/nwis/rt> and <https://tidesandcurrents.noaa.gov/>.

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