

Response to Reviewers

Title: Understanding the Compound Flood Risk along the Coast of the Contiguous United States

Author Response 1st revision

Reviewer 1

Reviewer Comments:

In this manuscript, the authors apply a compound flood risk assessment (CFRA) to the coastal regions of the contiguous United States. In contrast to several previous studies, they do not only perform a bivariate extremes analysis between storm surge and river streamflow (referred to in their manuscript as data-based CFRA), but they couple their statistical analysis to a large-scale river-routing model and population exposure information (referred to in their manuscript as physics-based CFRA). Their main finding appears to be that their metrics, such as the marginal and joint exceedance probabilities and Kendall's rank correlation, differ substantially depending on the type of CFRA. The authors use their results to argue that 'data-based' CFRA alone does not provide a holistic view of CFRA and provides a biased view, hence different types of CFRA need to be considered. Although my experience in this field is limited, I think that this contribution is welcome and useful, and I also found it well written. I do have several comments, though, that I hope will help to improve the manuscript.

Author Response:

We appreciate the reviewer for the insightful comments and suggestions. In the following we address your comments point by point. Our responses and all changes in the revised paper are marked in blue. If you have further questions or concerns, please let us know. Although HESS does not allow us to share our revised manuscript at this stage of the review process, we provide excerpts throughout the response to help illustrate the changes. We will provide the revised manuscript when invited.

R1C1:

'Data-based CFRA': I am not sure if this is a commonly used term, but it is ambiguous to me because 'physics-based CFRA' is also based on data. Would it be possible to find terminology that more clearly distinguished the two types of CFRA? Perhaps 'statistics-based' and 'dynamics-based' or so?

Author Response:

We appreciate the reviewer's suggestion and agree that "statistics-based" and "dynamics-based" are better terminology for the two types of CFRAs.

This is the first comprehensive study to distinguish CFRA into two different types, so there is no adopted definition yet in the existing literature. According to the reviewer's suggestion, we found that "statistics-based" CFRA properly pertains to approaches that rely on the statistical analysis and data interpretation to understand the CF risk, where data can be either from observations or numerical models. "Dynamics-based" refers to the methodology that focuses on the study of how systems change over time and how various factors interact to determine the risk patterns, which would be a more appropriate terminology than "physics-based".

We have changed “data-based” to “statistics-based” and “physics-based” to “dynamics-based” throughout the revised manuscript.

R1C2:

Figures: for the maps, color schemes are used that I doubt are color-blind friendly/perceptually uniform. Could the authors please check and modify their figures where necessary?

Author Response:

Thanks for the comments. The color scheme is changed to ‘viridis’ and ‘spectral’ in all spatial maps of the revised manuscript (Figure 3, 5, 6 and 8~13) to ensure color-blind accessibility.

R1C3:

L64-L92: I am missing an introduction of existing large-scale compound flood risk studies with similar aims, such as <https://nhess.copernicus.org/articles/23/823/2023/>. I would encourage the authors to include a paragraph on such studies and explain the similarities and differences with their own manuscript. The same comment applies to the Discussion section.

Author Response:

We appreciate the helpful comment to improve our manuscript.

This work is not only inspired by and but also builds upon many previous studies using either statistical approaches or numerical simulations to quantify the CF risk. Although these studies have already been acknowledged in our literature review, we agree with the reviewer that more thorough discussions should be provided in the introduction to compare the existing studies and in the discussion to better explain the difference of the resulting CF risks when using different approaches.

In the introduction of the revised manuscript, we first elaborated on the literature review of the statistical approaches with a brief comparison of the listed studies:

“At regional and global scales, statistics-based CFRAs consider the CF hazard as statistical dependence or co-occurrence rate of multiple flood drivers including discharge and surge (Moftakhari et al., 2017; Sadegh et al., 2018; Muñoz et al., 2020), precipitation and surge (Bevacqua et al., 2019), discharge, surge, and wave (Camus et al., 2021), etc. Statistics-based CFRAs perform statistical analysis using long-term data at paired gauges near the land-ocean interface. The data can be obtained either from large-scale numerical simulations (Eilander et al., 2020; Nasr et al., 2021) or gauge observations (Ward et al., 2018; Paprotny et al., 2020). Bivariate or multivariate analyses are performed to measure the CF hazard in terms of the joint occurrence of event extremes (Salvadori et al., 2007; Zscheischler et al., 2020). The CF hazard is determined either using the extreme dependence among multiple CF drivers or the likelihood of their joint occurrence. The dependence structure can be assessed from correlation and/or tail dependence coefficients (Wahl et al., 2015; Nasr et al., 2021). The co-occurrence rate may be calculated as the joint exceedance probability when a single or multiple drivers are above their predefined thresholds

(Moftakhari et al., 2017), e.g., 95th or 99th percentile (Kew et al., 2013), which are defined as “OR” and “AND” hazard scenarios by Salvadori et al., 2016.”

We elaborated on the existing studies of large-scale models and acknowledged a particular contribution from the large-scale coupled river-coastal models.

“Such models offer the capability to evaluate spatiotemporally varied CF drivers, flood extent and population exposure to CF events from basin to global scales over multiple decades (Ikeuchi et al., 2017; Eilander et al., 2020; Eilander et al., 2023).”

The existing CFRA studies in the CONUS domain was briefly discussed in the last paragraph of the introduction. We expanded this part with more details added.

“The contiguous United States (CONUS) (Fig. 1) consists of 48 states, with coastal counties occupying about 10% of the total area. There are 17 major port cities, and ~40% of the US population residing in coastal counties are subject to high coastal flooding risks (Hanson et al., 2011). A high-resolution analysis study including pluvial, fluvial, and coastal flooding, projected a significant changing pattern of the flood risk in CONUS under future climate scenarios (Bates et al., 2021). Particularly, the CF risk was previously evaluated for the CONUS coastline or major US coastal cities using statistics-based CFRAs in terms of the dependence between storm surge and precipitation (Wahl et al., 2015), seasonable dependence among multiple CF drivers (Nasr et al., 2021), and the joint probability in “OR” hazard scenarios in response to sea level rise (Moftakhari et al., 2017).”

Finally in the result discussion (the end of Section 3.2.1), we provided a comparison of the risk assessments between ours and other statistics-based CFRAs. We highlighted that the CF risk could vary significantly when considering different CF drivers or using different statistical approaches.

“The CF hazard computed in this study shows both similarities and notable differences compared with previous statistics-based CFRAs (Eilander et al., 2020; Nasr et al., 2021; Wahl et al., 2015). For example, our analysis reveals several localized hotspots of the CF hazard characterized by a strong dependence between Q and SS in the Northwest and Gulf coasts (Fig. 12), as indicated by Eilander et al. (2020). However, the calculated τ values in our study are generally lower than those computed using annual maxima sampled from Q and SS observations in the East coast (Nasr et al., 2021). Also, our τ values are higher than that derived from the dependence of Q and precipitation along the West coast, and a previous study also demonstrated substantial variations in τ at specific locations when using different sampling approaches for the two CF drivers (Wahl et al., 2015). These differences result from variations in the sampling of extreme events, the specific CF drivers considered, the statistical methods employed, as well as other uncertainty sources discussed in Section 2.2.1. Despite the variations observed among different frameworks, each study provides unique insights into the understanding and addresses the complexities associated with CF risks. The choice of a specific CFRA depends on the local characteristics of the study area and the specific requirements of local flood planning and management.”

R1C4:

L144: Kendall’s rank correlation is computed, but it is not clear to me if/what lag is allowed between the two variables. Could the authors please also discuss how the samples for which the rank correlation is

computed are conditioned, i.e., are cases in which one of the variates but not necessarily both variables are extreme (two-sided) also considered or not, and why (not)?

Author Response:

We apologize for the typo and the missing information regarding this comment.

The first step in calculating the CF hazard should be referred as “CF event selection” instead of “storm surge event selection”. In sampling the CF events, we first extracted *SS* events using the event selection scheme proposed in Feng et al., 2022. This scheme uses a peak detection algorithm to filter independent *SS* events. For each selected *SS* event, a CF event is identified if Q during the event is over the predefined threshold of 95th percentile. The advantage of this method is that it allows a more realistic representation of a *SS* event than defining a time window around the peak, as *SS* may last longer than a few days. We acknowledge that the duration of a fluvial flood event may not precisely align with the duration of *SS* during a CF event. It is possible there is only a small overlap between the two events. But we don’t allow any time lag between Q and *SS* because the CF exposure is measured by the extent of backwater. Such effects are dominated by *SS* and will only be significant during the selected *SS* events.

The description of step (a) in the CF hazard calculation has been elaborated more clearly.

“(a) CF event selection: use a *SS* event selection scheme (Feng et al., 2022) to extract all *SS* events with the *SS* level over 95th percentile and then in the selected *SS* events identify them as CF events if river discharge of the corresponding station during these events is also over 95th percentile;”

“As the first step, our event selection scheme samples independent *SS* events from the time series data, which avoids dependence in the extremes and eliminates the need for declustering. We assume that the Q extreme within each *SS* event is independent as both frequency and duration of *SS* are generally much smaller than that of fluvial flooding. While it is possible that the duration of a fluvial flood event does not precisely align with a *SS* event, we don’t include time lag between Q and *SS* in the consideration as this study specifically quantifies the CF impact based on the *SS*-driven backwater effects.”

While recognizing that a CF event does not necessarily require all flood drivers to exceed their individual thresholds (Zscheischler et al., 2020), we don’t consider the case when only one of the drivers is significant because it will otherwise be difficult to identify the CF events in a large-scale analysis. We appreciate the reviewer’s remark. This limitation is discussed in Section 4.2 of the revised manuscript.

“Second, we quantify the CF impacts using the *SS*-induced backwater effects without considering the complex interactions between the two flood drivers or the possibility when a CF event is induced by an individual extreme driver. CF does not necessarily require all drivers to exceed their corresponding thresholds (Zscheischler et al., 2020).”

R1C5:

Section 2.1: information about declustering of the peak events seems to be missing, although declustering is necessary to avoid dependence in the extremes. Could the authors please explain if/how their data was declustered?

Author Response:

Thanks for the comment. According to R1C4, we applied a new event selection scheme to extract all *SS* events. This method ensures that the selected *SS* events are independent as the sign of water level is always changed even between two adjacent events. While this method does not ensure the independence of *Q*, the duration and frequency of a *SS* event are generally much shorter than that of fluvial flooding. We added the explanation to the revision:

“As the first step, our event selection scheme samples independent *SS* events from the time series data, which avoids dependence in the extremes and eliminates the need for declustering. We assume that the *Q* extreme within each *SS* event is independent as both frequency and duration of *SS* are generally much smaller than that of fluvial flooding. While it is possible that the duration of a fluvial flood event does not precisely align with a *SS* event, we don’t include time lag between *Q* and *SS* in the consideration as this study specifically quantifies the CF impact based on the *SS*-driven backwater effects.”

R1C6:

L318-332: this paragraph discusses figures that are not part of the main manuscript. I would either include both the discussion and those figures in the manuscript or put both in the supplements, and only briefly refer to them. Its current form is inconvenient to read in my opinion.

Author Response:

Thanks for the suggestion. The discussion associated with the figures is moved to the supplement and is briefly referred as

“The model-data comparison is provided for a few example basins to demonstrate the various types of uncertainties (see Supplement for further details).”

R1C7:

Section 3.2.1: A comparison with the results of previous (‘data-based’) studies in this region (e.g., Wahl et al., 2015; Nasr et al., 2021) would provide useful context, but is missing. Could this be added?

Author Response:

Thanks for your comment. We added an additional paragraph at the end of Section 3.2.1 to discuss the comparison with previous studies. Please see the response to R1C3 for more details.

R1C8:

L400-402: while I appreciate this remark, data that covers a longer period cannot simply be obtained. Could the authors please explain/discuss how they imagine a dataset such as the GTSM reanalysis being extended back in time with reasonable confidence? In the absence of such data, how can we get a sense of how uncertain the results of the present study are given the relatively short period used? This seems

especially relevant given the underrepresentation of tropical cyclones in the observations/reanalysis data. And what about the influence of temporal variability on the dependence between the two variates examined? (e.g., Wahl et al., 2015)

Author Response:

We agree with the reviewer that the atmospheric reanalysis forcing usually covers a shorter period (e.g., from 1979 to 2018) and this causes epistemic uncertainty. This uncertainty is elaborated in the revision:

“The reanalysis forcing typically covers a shorter period (e.g. from 1979 to 2018) and thus may underestimate extreme events, such as TCs. While it remains challenging to determine the sufficient data length, such uncertainty likely depends on the region-specific exceedance probability, particularly when lower probabilities correspond to longer return periods.”

The climate simulations and data used for climate research and assessments, including those from the Coupled Model Intercomparison Project Phase 6 (CMIP6), have uncertainties in representing extreme events. Despite substantial efforts, uncertainty quantification of the climate simulations remains challenging, which is beyond the scope of this study. We focused on the framework that assesses both CF hazard and exposure and highlight the uncertainties in the CF risk assessment. However, in the revision, we provide a promising path on how this uncertainty may be addressed in more advanced Earth system models. We briefly mentioned the new coupling capabilities developed within E3SM in Section 4.2:

“Such interactions contribute to another layer of complexity and uncertainty at the terrestrial and aquatic interface and should be simulated using ESMs with fully coupled land, river and ocean modeling components. Interactive coupling has been developed within the Energy Exascale Earth System Model (E3SM) (Feng et al., 2022; D. Xu et al., 2022) for further CFRA developments.”

And in the revision, we provide other features that could contribute to more accurate climate simulations of extreme events:

“Moreover, the limited representation of extreme events may be addressed by more advanced ESMs. The ability to better represent the complex processes at the terrestrial and aquatic interface, could also increase the simulation accuracy for extreme events. For example, several related new capabilities have recently been developed for Energy Exascale Earth System Model (E3SM) (Golaz et al., 2022), such as the multi-scale variable-resolution meshes and state-of-the-art techniques developed in E3SM land and ocean models (Lilly et al., 2023; Pal et al., 2023). These advancements have shown the potential to improve the representation of climate extremes, which is important for the CF risk assessment.”

We added a new paragraph to demonstrate the influence of climate variability:

“The broader definition of CF can be expanded to include the interaction between CF drivers and climate drivers (Zscheischler et al., 2020). Global warming will likely increase the frequency of extreme precipitation (Alfieri et al., 2016), the intensity of river discharge (Bermúdez et al., 2021) and storm surge (Camelo et al., 2020), and the duration of the fluvial and coastal flooding (Feng et al., 2022). All these factors contribute to the exacerbation of CF risks, as both marginal and joint exceedance probabilities will increase. Moreover, climate change has the potential to alter the characteristics or distributions of CF drivers. For instance, the dependence between storm surge and precipitation is enhanced by climate warming, which increases the CF hazard (Wahl et al., 2015). The elevated sea level will move the

backwater extent further upstream, increasing the CF exposure (Kulp and Strauss, 2019). Given the uncertainty of climate change, Earth System Models (ESMs) should be increasingly used to understand the potential impacts of different socioeconomic pathways on the CF risk.”

R1C9:

L440-445: The open access to the code used for the paper is commendable. I strongly recommend doing the same for the output data instead of sharing it ‘upon request’.

Author Response:

We apologize for the confusion. The MOSART simulation output and the statistical analysis results are already provided in this repository under the directory: [statistical_analysis/files/](#). Because the size of the full MOSART simulation (including other variables in the whole CONUS domain) is too large, we saved the MOSART simulated streamflow for all coastal cells in the file below:

[statistical_analysis/files/MOSART_discharge_GTSM_spatial.nc](#)

We have revised the statement of the Code and data availability to ensure clarity:

“The MOSART source code, the statistical analysis code of the compound flood risk assessment, the MOSART simulation output and the statistical analysis results are available on Zenodo (<https://doi.org/10.5281/zenodo.7588256>, Feng, 2023).”

Minor issues:

R1C10:

L55: ‘across rivers and estuaries’: I suggest changing this to ‘different rivers and estuaries’, unless variation within a river or estuary is meant.

Author Response:

We have revised it as suggested.

R1C11:

L103 could the authors please comment on using a river routing model v.s. using a hydrological model that also includes groundwater? I am not an expert, but I can imagine that changes in groundwater also affect the propagation time between upstream and the coastal interface?

Author Response:

Thanks. The runoff used as input for MOSART is from a well validated hydrological model with groundwater processes (Yang et al., 2021). We agree with the reviewer that the impacts of groundwater and other river-land interactive processes contribute to more river dynamics. In response to this comment, we added more discussion on groundwater to Section 4.2:

“For example, the interaction between flooded water and channel flow, groundwater and surface water, river discharge and upstream propagation of ocean tides and storm surge will likely attenuate the hydrograph, intensify inland flooding or affect the backwater propagation, particularly in low-lying watersheds. Such interactions contribute to another layer of complexity and uncertainty at the terrestrial and aquatic interface and should be simulated using ESMs with fully coupled land, river and ocean modeling components.”

R1C12:

L114: It only becomes clear later why the 2nd boundary condition is used (i.e., in eq. 6). It would be helpful to briefly motivate the 2nd boundary condition here already. Besides, it is not clear where this fixed level is derived from – is it the mean level in GTSM?

Author Response:

Thanks for the suggestion. We added a brief description to explain the use of simulations with the two BCs. Yes. The mean sea level is from GTSM. This sentence is rewritten to improve clarity:

“We apply two types of boundary condition (BC): (1) time-varying storm surge (*SS*) level and (2) fixed mean sea level. Both are obtained from the third-generation Global Tide and Surge Model (GTSM) (Muis et al., 2022). The *SS*-induced backwater effects in this study are quantified by comparing the two simulations which use the first and second BCs, respectively (Feng et al., 2022).”

R1C13:

L119: ‘statistical model’ please specify what this refers to.

Author Response:

We apologize for the confusion. We meant that the modeled streamflow used in the statistical analysis is from the MOSART simulation forced by the dynamic GTSM BC rather than the static MSL. In the revision, we have rewritten this sentence as below:

“The modeled streamflow used in the statistical analysis is from the MOSART simulation forced by the dynamic GTSM BC.”

R1C14:

L175: ‘using an R-package’ please specify which package.

Author Response:

We use the R-package “copula” (Kojadinovic & Yan, 2010), which is now specified in the revised manuscript.

R1C15:

L192: is this necessary? Can the authors not just change the scale of the relevant plots?

Author Response:

The original intention of including this scaling factor is (a) to scale the risk index to 1~10, and (b) to increase the visibility of small values in the upstream regions. But as we plot *CFRI* on the logarithmic scale using a base of 10, it is no longer necessary to upscale *CFRI* using a factor. According to the reviewer's suggestion, we slightly changed the definition of *CFRI* by excluding the factor of 10. We recomputed *CFRI* and updated Figure 13 (original Figure 10).

$$CFRI = CFHI \times CFEI, \tag{7}$$

where the CF hazard index (*CFHI*) and the CF exposure index (*CFEI*) are calculated by normalizing $P_{Q,SS}$ and W_p with their corresponding 95th percentile values."

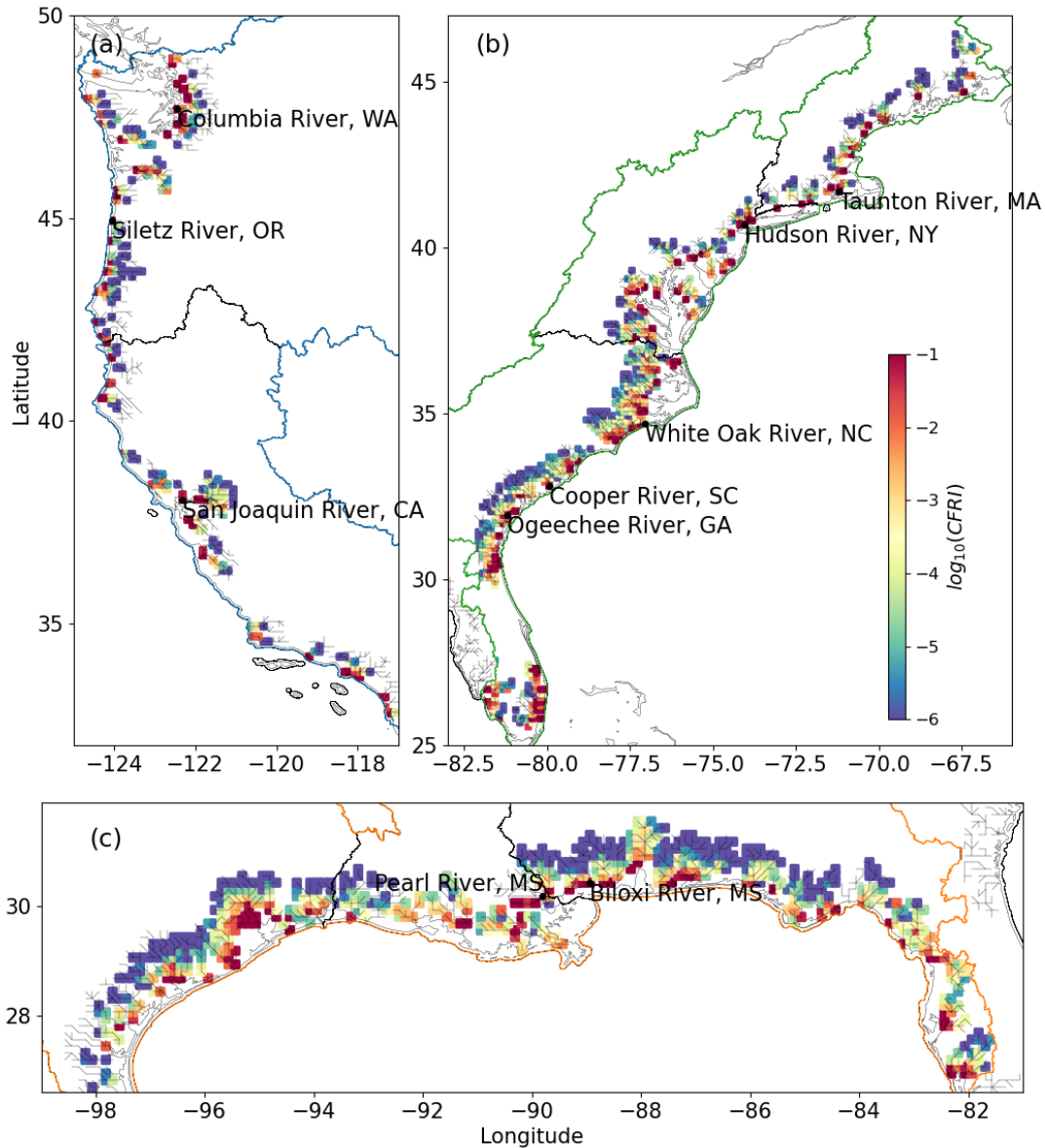


Figure 13: The *CFRI* represented on a logarithmic scale using a base of 10 along the (a) West coast, (b) East coast and (c) Gulf coast.

R1C16:

L200: to avoid confusing this section for a results section, I suggest replacing ‘investigate’ with ‘review’ or ‘discuss’. Additionally, I found this section not as well connected to the rest of the manuscript. Perhaps some sentences could be added as to why these uncertainty sources are introduced here.

Author Response:

Thanks for the comment. In the revision, we replaced “investigate” with “review” and added sentences to elaborate on the importance of uncertainty analysis and how such analysis is connected to CFRA.

“In this section, we review the uncertainty sources in the large-scale CFRAs. The uncertainty analysis is critical for a robust CFRA. Given that uncertainty can arise from diverse sources in both statistical and numerical models, an improved understanding of the uncertainty sources will provide valuable guidance for the future enhancement of the CFRA framework. We first examine the spatial variability in streamflow and storm surge and the relative impacts of riverbed elevations on the dynamics-based CFRA, as neglecting these physical factors leads to uncertainties in the statistics-based CFRA.”

R1C17:

L206-207: would be more consistent to define the different types of uncertainty in the same order as they are introduced.

Author Response:

Thanks. This is corrected as suggested. “The uncertainty in CFRA can generally be classified into two categories: aleatory uncertainty and epistemic uncertainty.”

R1C18:

L252: ‘shift’ is this the same as ‘lag’? If so, I think that would be a clearer term.

Author Response:

We agree with the reviewer on this point and used the term “lag” when referring to the shift in streamflow peaks between an upstream USGS gauge and the river outlet.

“The lag in streamflow peaks between an upstream location and the river outlet will cause biases in the CFRA if the upstream Q measurements are used in the CF risk analysis.”

“A longer flow time typically implies a larger time lag in streamflow peaks. In this study, the calculated flow time of each grid cell is averaged over the simulation period.”

“The averaged time lag in the Q peaks varies from 1 to 5 days, depending on the local topology, basin characteristics and hydrological response to coastal backwaters.”

R1C19:

L258: I suggest to change +/- 5 days to: a window of 10 days around the extreme, if this is indeed the intended meaning.

Author Response:

Thanks. This is revised as suggested: “we then identify the peak date of each extreme event and define a time window of 10 days around the extreme”.

R1C20:

Section 2.2.4: please consider putting this in a table, for a clearer overview.

Author Response:

Thanks. Table 2 is added for clarity: “We consider three combinations of Q and SS (Table 2):”

Table 2: Three combinations of Q and SS for model-data comparison.

	Q	SS
a	MOSART modeled value at the river outlet	GTSM modeled value at the river outlet
b	MOSART modeled value at the USGS gauge	GTSM modeled value at the NOAA gauge
c	USGS measurement	NOAA measurement

R1C21:

L279: ‘elevation gradient’ – would it be worth plotting the gradient instead of the elevation itself in figure?

Author Response:

We apologize for the confusion and have replaced “elevation gradient” with “elevation” in the revision:

“In particular, the elevation effect dominates in the Northwest coast (Fig. 3), where the large riverbed elevation impedes the propagation of coastal backwaters and the areas of high CF risks are thus restricted to the coastline (Fig. 4).”

Based on our previous study (Fig. 10a in Feng et al., 2022), the extent of the backwater propagation is determined by the riverbed elevation. As we think the elevation may be more representative of the CF drivers, it is used in the random forest model to calculate the relative importance.

R1C22:

L286-287: could use some more explanation, in my opinion.

Author Response:

Thanks. More explanations have been added to this point.

“The averaged time lag in the Q peaks varies from 1 to 5 days, depending on the local topology, basin characteristics and hydrological response to coastal backwaters.”

R1C23:

L298: I think this needs to be 'Section 2.2.4 at 24 river basins', correct?

Author Response:

Thanks. Corrected.

Bermúdez, M., Farfán, J., Willems, P., and Cea, L.: Assessing the effects of climate change on compound flooding in coastal river areas, *Water Resources Research*, 57, e2020WR029321, 10.1029/2020WR029321, 2021.

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