Response to Reviewers

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

Author Response 1st revision

Reviewer 3
Reviewer Comments:

The paper assesses compound flooding for CONUS based on a statistical analysis of compound flood drivers and an analysis of population exposed to flooding from coastal backwater. It also investigates the skill of the model to represent observed peak timing as well as the correlation between, and (joint) exceedance probabilities of surge and discharge. The paper potentially provides an interesting contribution to current literature. However, I have some major comments that I would like to see addressed before the paper is accepted for publication.

Author Response:

We would like to sincerely thank the reviewer for the valuable comments and recommendations. We have carefully addressed the reviewer's suggestions as follows. Excerpts of the revised manuscript are provided to explain our responses to the review comments, as HESS does not allow us to share our revised manuscript at this stage of the review process.

R3C1:

The paper would really benefit from a comparison, both in the introduction and discussion on results, with other large-scale coupled river-coast models (e.g. Ikeuchi et al., 2017 and Eilander et al., 2020), CONUS flood risk models (e.g. Bates et al., 2021) and statistical CF analysis (e.g. Wahl et al., 2015 and Nasr et al., 2021).

Author Response:

We appreciate the valuable comment and references. This work is not only inspired by and but also builds upon these studies that either proposed the statistical approaches or performed large-scale simulations to quantify the CF risk from basin to global scales. 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 respectively as "OR" and "AND" hazard scenarios by Salvadori et al., 2016."

We elaborated the existing studies of large-scale models and acknowledged a particular contribution from the large-scale coupled river-coast 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 elaborated this part with more details added. in the discussion.

"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 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, which study also demonstrates 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 addressing 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."

R3C2:

The difference between "data-based CFRA" (line 40) and "physics-based CFRA" (line 60) is not clear but essential to understand the introduction. It would help to start with defining both concepts before discussion pros and cons of both approaches. My first guess was that physics-based would refer to numerical models and data-based to observations, but models are also mentioned under data-based CFRAs (line 45) and observations under the physics-based approach (line 61). Also, the approach of Ikeuchi et al. 2017 and Eilander et al. 2020 are basically similar (analysis of simulated estuarine water levels in a coupled CaMa-Flood and GTSM model) but here mentioned as different approaches.

Author Response:

Thanks for the comment.

According to the suggestion from another reviewer, we changed the classification of CFRAs from "data-based" and "physics-based" to "statistics-based" and "dynamics-based" throughout the revised manuscript. As "statistics-based" CFRA better pertains to the 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 CFRA that, as the reviewer pointed out, is based on numerical simulations that could represent how systems change over time and how various factors interact to determine the risk patterns.

As suggested by this comment, we have clearly defined both concepts before discussing the details of the two approaches:

"CFRA can be classified into statistics-based and dynamics-based approaches. Statistics-based CFRAs rely on statistical modeling and define the CF hazard as the frequency of a CF event. Dynamics-based CFRAs use numerical simulations that can represent the spatiotemporal variabilities of CF drivers and how various CF drivers interact."

Yes. Ikeuchi et al. 2017 and Eilander et al. 2020 used similar modeling approaches as we introduced in this work. This study is inspired by their great work. We classify Ikeuchi et al. 2017 into dynamics-based CFRAs as their work mainly focuses on the dynamics of inundation simulated using the coupled numerical models. And we consider Eilander et al. 2020 as a key reference in which data used in statistical analysis can be sourced from large-scale numerical simulations, as in their work the dependence among CF drivers is assessed using the modeled variables.

R3C3:

The terms "hazard risk" and "exposure risk" (line 73) are confusing in my opinion as risk is usually referred to as the combination of hazard, exposure and vulnerability. "hazard risk" seems to only consider the hazard and seems similar to what Couasnon et al. (2020) call "compound flood potential". In short, I think usage of the term "risk" here is confusing and the term "comprehensive risk" (line 98) is even a bit misleading.

Author Response:

We appreciate the reviewer comment. Our intention of categorizing the CF risk into the hazard risk and exposure risk was because previous studies only focused on one particular type of the risk and we were trying to distinguish the two categories and propose the idea of integrating them into a single measure. Although flood exposure risk and flood hazard risk are defined elsewhere in the literature, we agree with the reviewer that such terminology is used less frequently than simply “flood exposure” and “flood hazard”. Similar to flood potential, flood hazard is commonly used to define the risk associated with the frequency of a flood event.

As the reviewer mentioned, flood risk usually refers to the combination of hazard, exposure and vulnerability. However, it is sometimes challenging to quantify vulnerability as it subjectively depends on a few factors (e.g. exposure, sensitivity, adaptive capacity and resilience) and the availability of such data is usually limited in large-scale domains. Thus, we consider the CF risk as a combination of hazard and exposure, similar to the risk defined as flood exceedance probability and damage in Judi et al., 2018 and Kalyanapu et al., 2015.

In response to this comment, we replaced “CF hazard risk” and “CF exposure risk” with “CF hazard” and “CF exposure” throughout the revised context. “CF comprehensive risk” is changed to “CF risk”.

R3C4:

The computation of the "risk" metrics is not entirely clear due several ambiguities in the methods section. Specifically for the sampling of events for the calculation of both metrics, see specific comments below.

Author Response:

We apologize for the confusion. Please see the responses to the following comments where we provided a clearer description of the methodology.

R3C5:

The Figures with maps and the overlying bars or dots are very difficult to read (Fig 3, 4 & 6).In Fig 6, 7 and 8 the color bars don't have a title or unit and there is no legend for the colors or x-axis label for the subplots.

Author Response:

We apologize for the unclear figures. The original intention of overlaying bars/dots on contour maps is to help readers visualize relevant information in a single figure. But we agree with the reviewer that condensing too much information in one figure will only make it harder to read.

In the revised manuscript, each of Figure 3, 4 and 6 is split into two separate figures. We also removed the subplot d (i.e., the overview of the CONUS domain) as this information is already presented in Figure 2. The original Figure 3 is divided into Figure 3 and 4. Figure 3 shows the spatial map of the riverbed elevation and Figure 4 shows the histogram of relative importance of the three CF drivers. The numbers representing river basins are marked in Figure S3 of the supplement. The original Figure 4 is divided into Figure 5 and 6. Figure 5 shows the spatially-varied flow time and Figure 6 shows the bars that represent the shifted days in Q and SS peaks. The numbers representing the observation gauges are marked in Figure S4 of the supplement. The original Figure 6 is divided into Figure 8 and 9. Figure 8 is the marginal exceedance probability $\boldsymbol{P_Q}$ computed for all MOSART coastal cells and Figure 9 is the marginal exceedance probability $\boldsymbol{P_{SS}}$ computed from the GTSM cells nearest to the corresponding outlets. The color scheme of the spatial maps is changed to a perceptually uniform one. State names are added to Figure 2, 3 and 5.

In Figures 8~11, we added labels to the color bars and x- and y- axis labels to the subplots, as well as more detailed description in the caption.

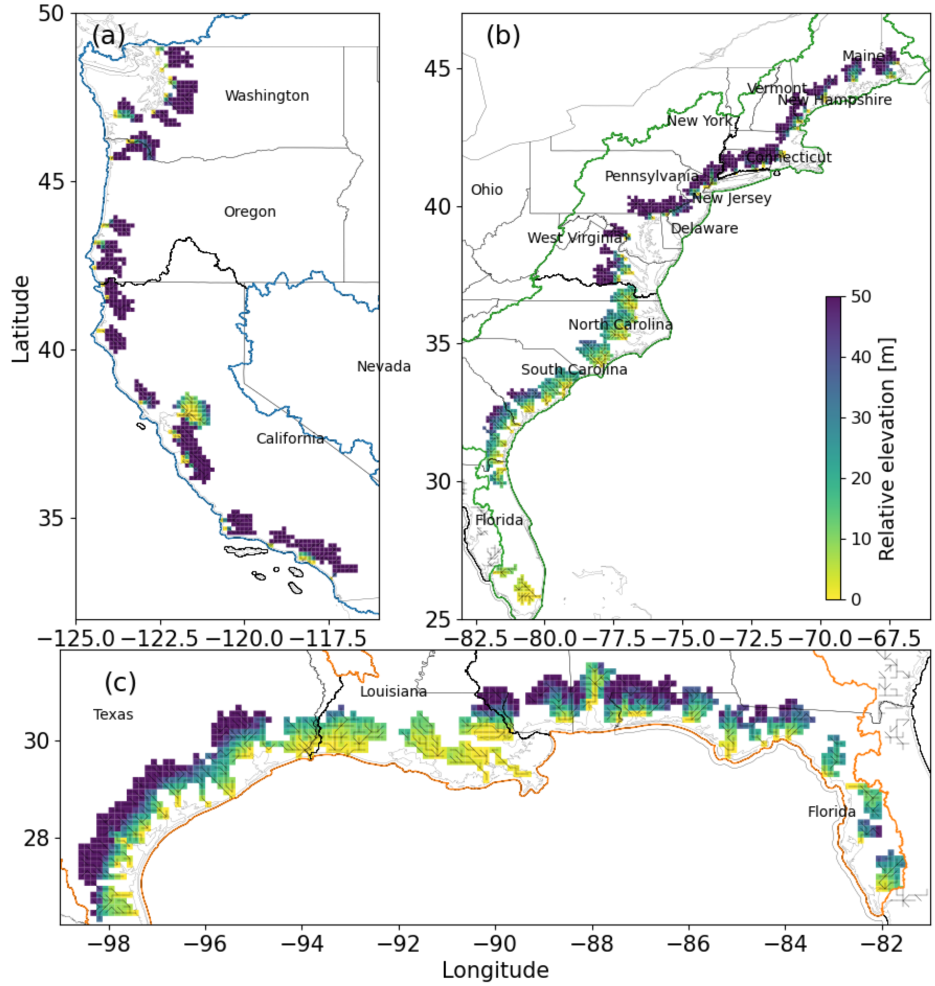

Figure 3: The relative riverbed elevation along the (a) West coast, (b) East coast and (c) Gulf coast. The river networks within the MOSART coastal cells are shown as black solid lines.

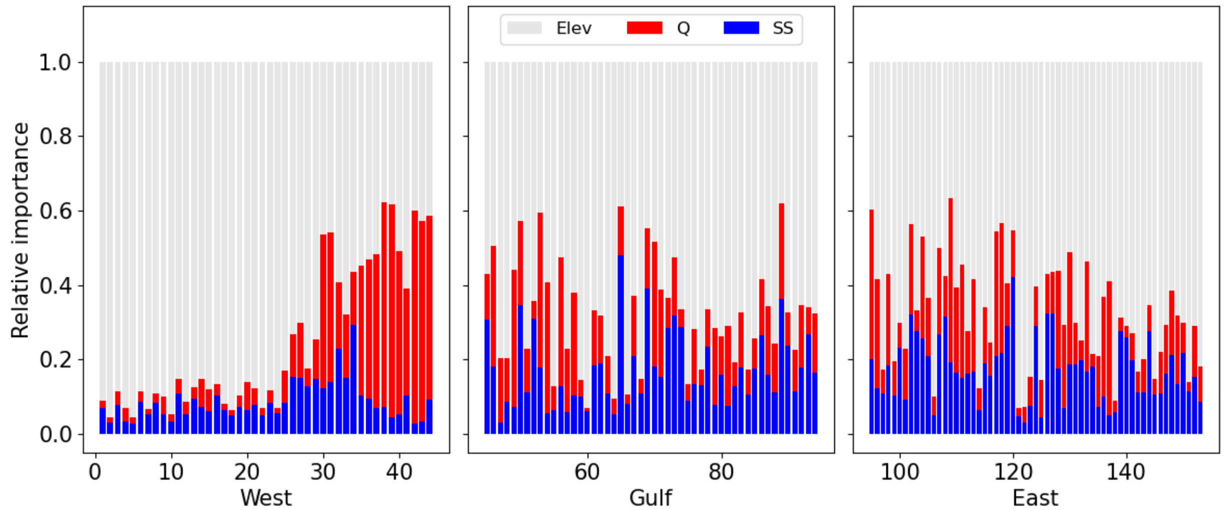

Figure 4: The relative importance of Q (red), SS (blue) and relative riverbed elevation (gray) provided in the counter-clockwise order of the river basins along the West, Gulf and East coastlines. The numbers representing individual river basins correspond to those in Figure S3.

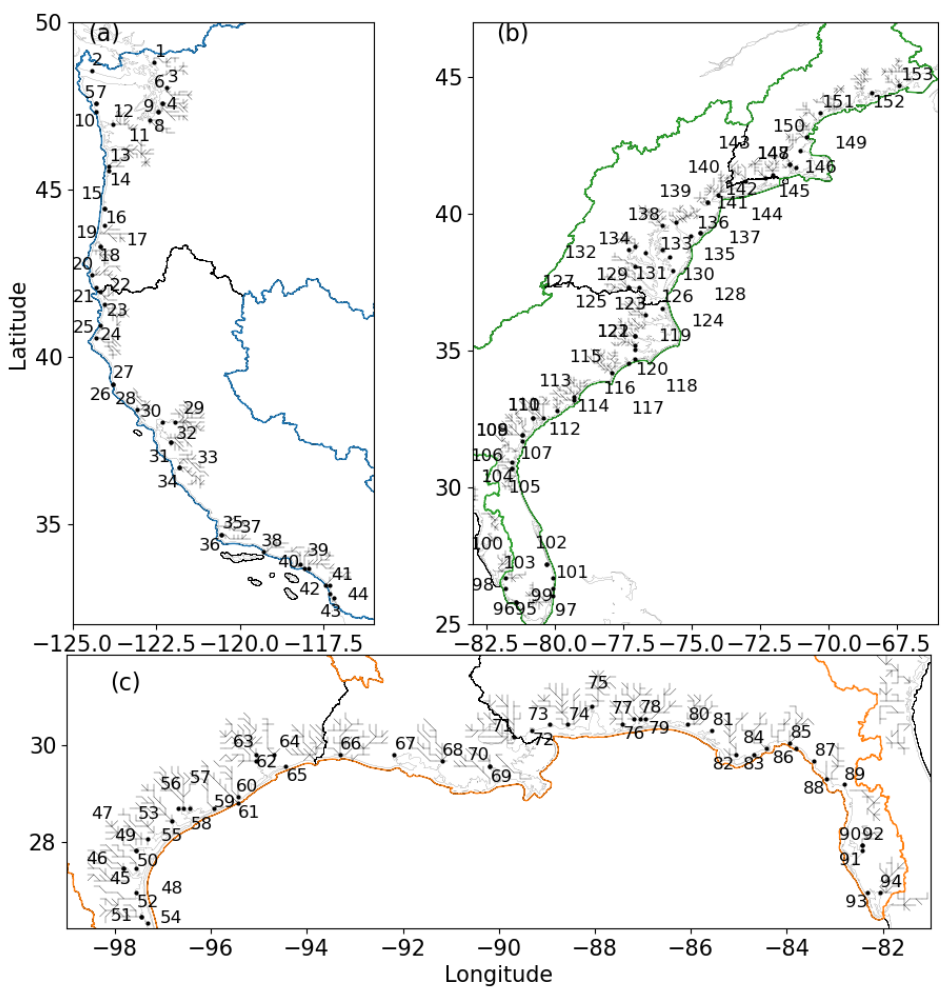

Figure S3. The numbers representing individual river basins corresponding to those in Figure 4.

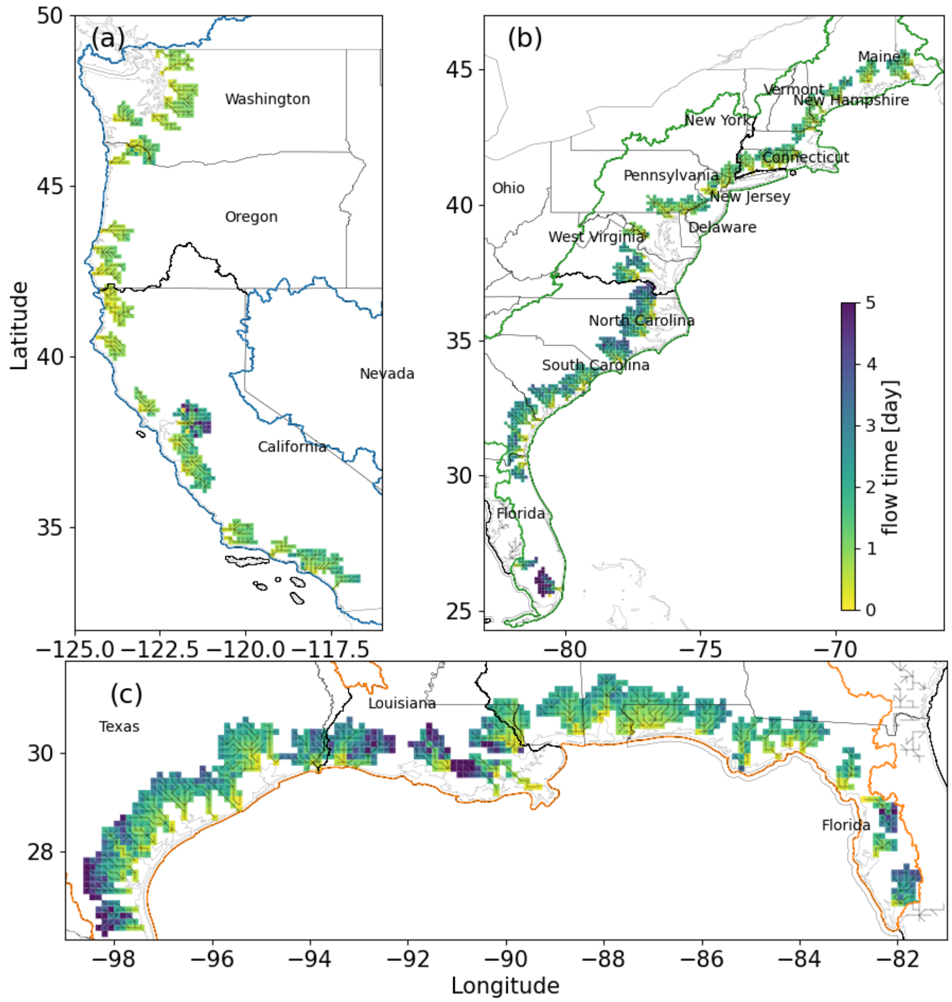

Figure 5: The flow time at the MOSART coastal cells along the (a) West coast, (b) East coast, and (c) Gulf coast.

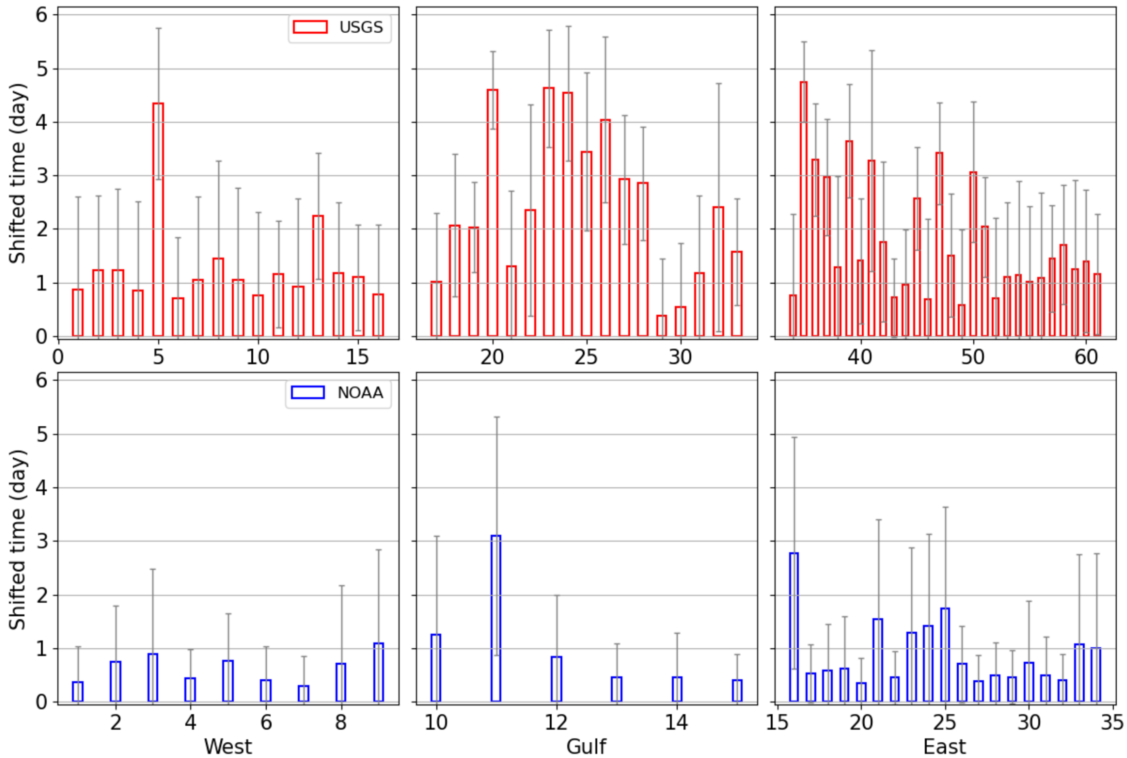

Figure 6: The shifted days in the *Q* and *SS* peaks between the observation gauges and the corresponding river outlets provided in the counter-clockwise order of gauges along the West, Gulf and East coastlines. The rectangular box represents the averaged shift over the simulation period and the error bar represents the standard deviation. The numbers representing observation gauges correspond to those in Figure S4.

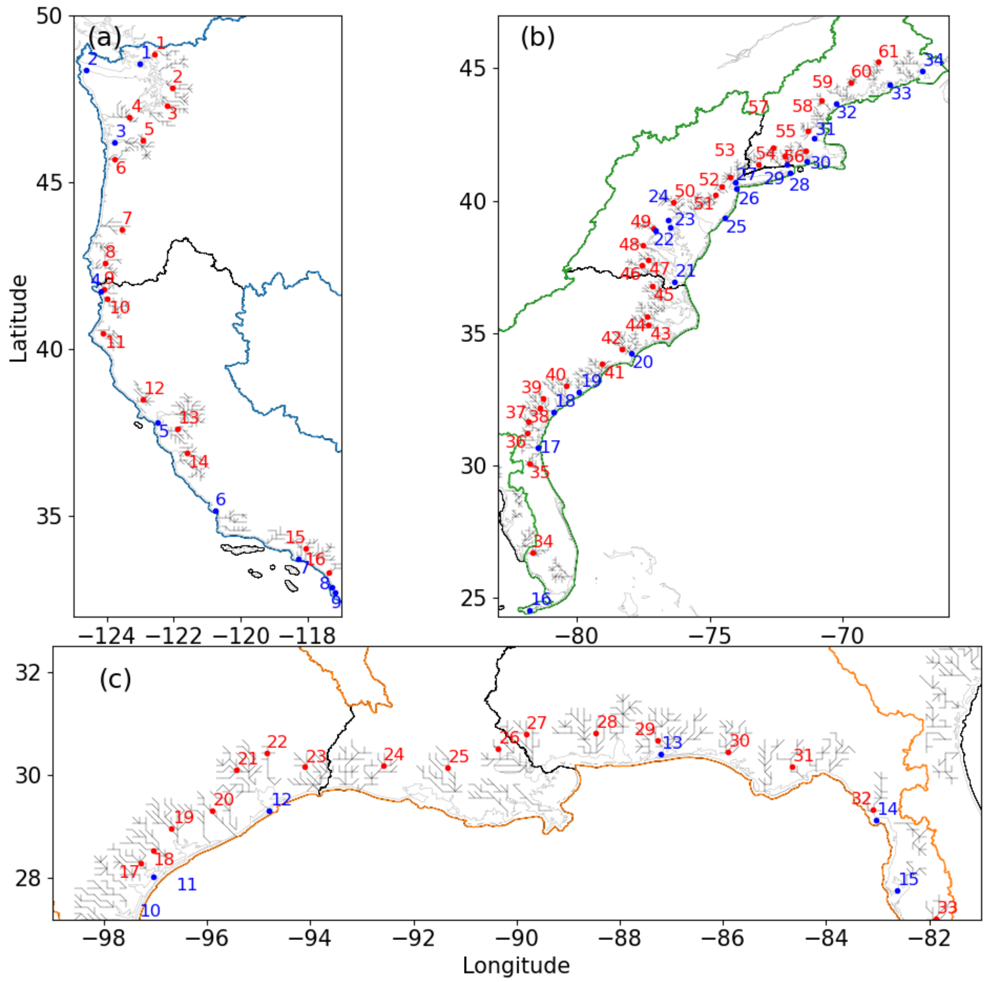

Figure S4. The numbers representing USGS gauges (red) and NOAA gauges (blue) corresponding to those in Figure 6.

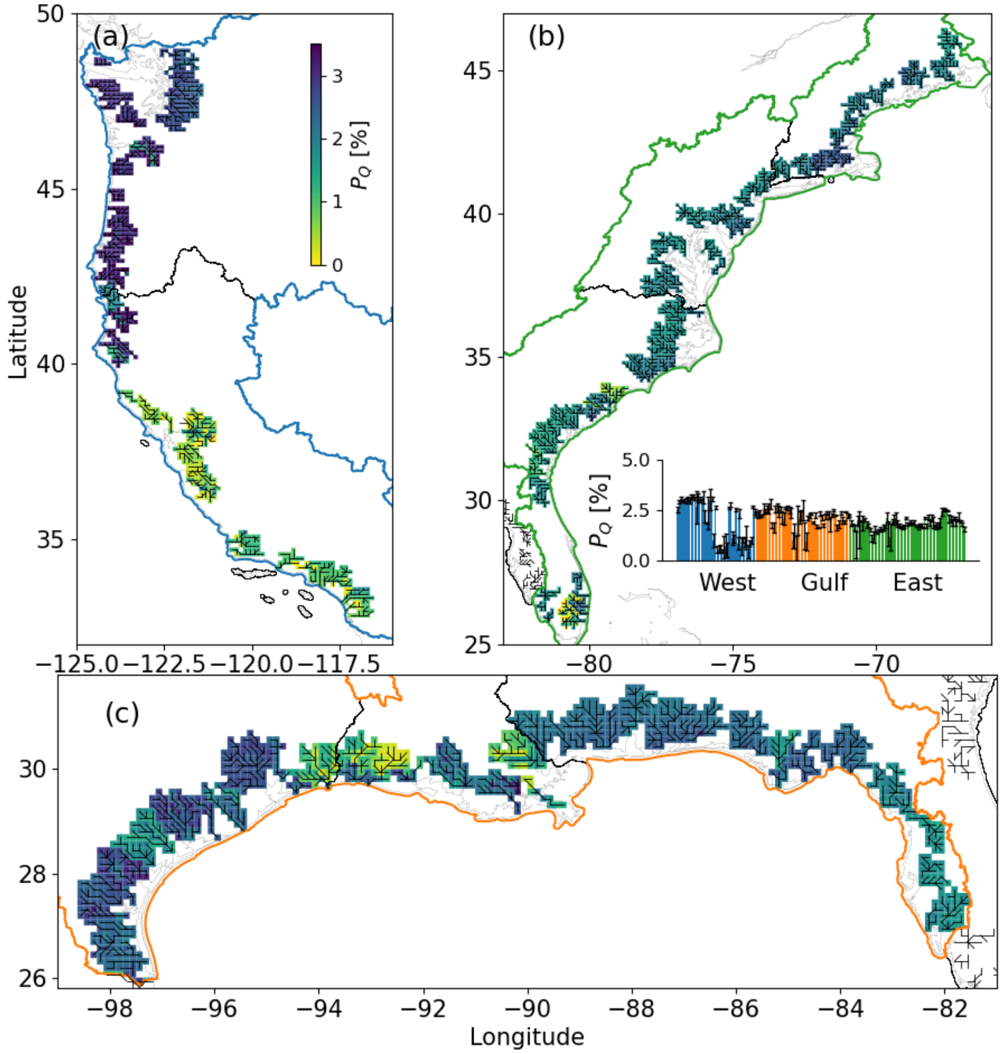

Figure 8: The marginal exceedance probability P_Q along the (a) West coast, (b) East coast and (c) Gulf coast. The basin-averaged P_Q is provided in the counter-clockwise order of the basins along the US coast in the lower left insert of subplot (b) where the error bars represent the corresponding standard deviation.

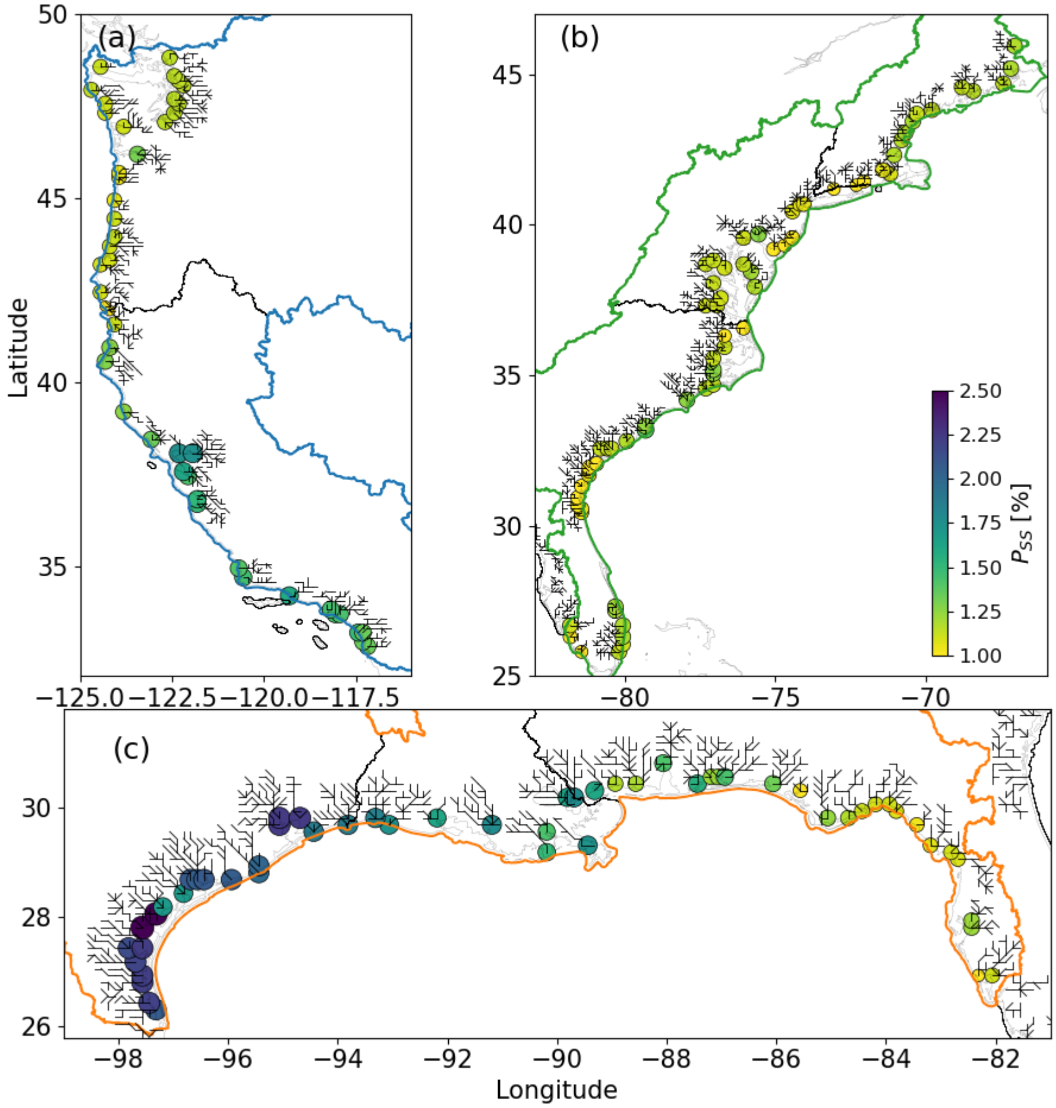

Figure 9: The marginal exceedance probability P_{SS} located at the GTSM cells nearest to the corresponding outlets.

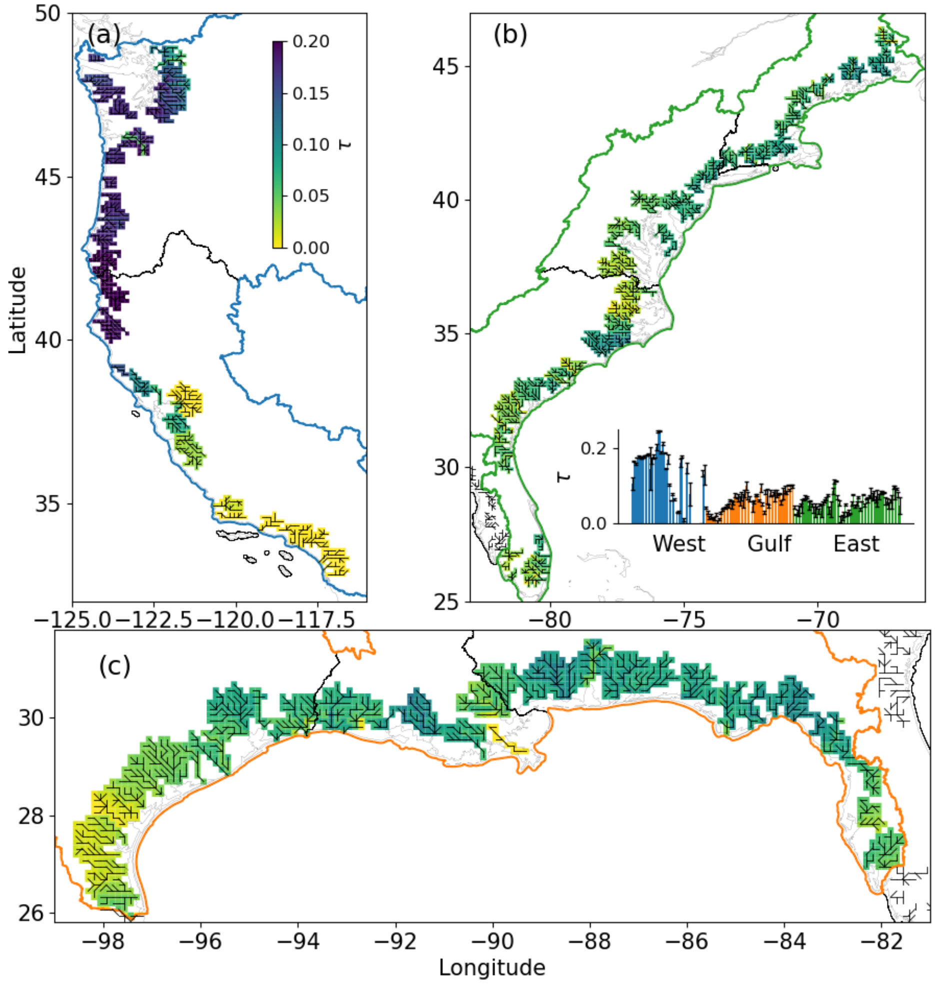

Figure 10: **The Kendall's correlation coefficient (τ) computed for each MOSART coastal cell using the corresponding Q and SS (Section 2.1). The insert in subplot (b) is the basin-averaged value of τ provided in the counter-clockwise order of the river basins along the West, Gulf and East coastlines with the error bars representing the corresponding standard deviation.**

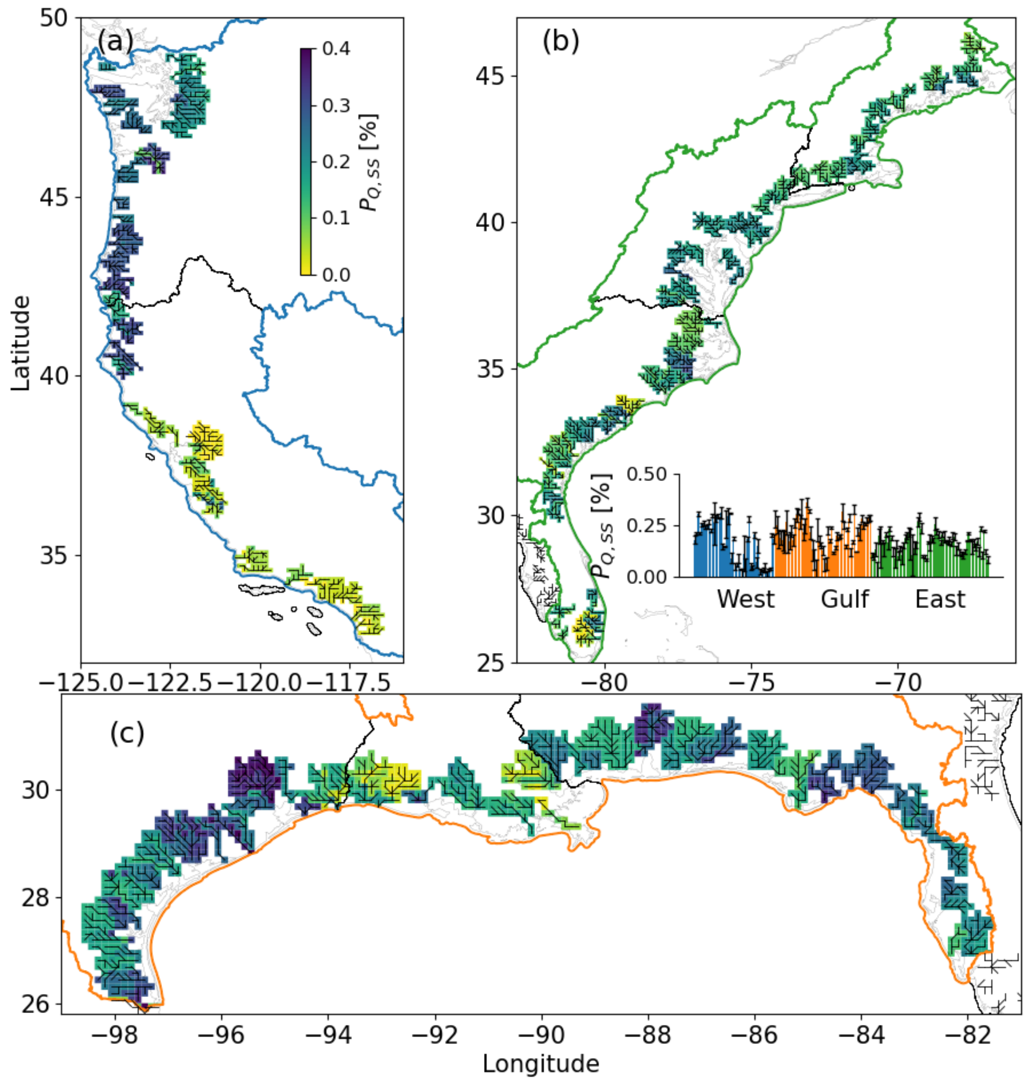

Figure 11: **The joint exceedance probability ($P_{Q,SS}$) computed for each MOSART coastal cell using Eq. 3 (Section 2.1). The insert in subplot (b) is the basin-averaged value of $P_{Q,SS}$ provided in the counter-clockwise order of the river basins along the West, Gulf and East coastlines with each error bar representing the corresponding standard deviation.**

Specific comments

R3C6:

line 28: "A CF event [...] occurs when the associated drivers exceed their respective thresholds (Zscheischler et al., 2020)." Zscheischler et al. (2020) actually argue that not all associated drivers need to exceed their respective thresholds to have large impact CF events. I suggest to rephrase this sentence.

Author Response:

We apologize for the confusion. We tried to express the same concept as explained by the reviewer. This sentence is now rephrased as: "It is possible that a compound flood (CF) event is not caused by extreme weather (Couasnon et al., 2020) but rather occurs when one or multiple flood drivers exceed their respective thresholds (Zscheischler et al., 2020)."

In our analysis, a CF event is identified when both drivers (i.e., Q and SS in our case) exceed their thresholds because it is otherwise difficult to identify the CF events in a large-scale analysis. We appreciate the reviewer's remark. To further acknowledge this limitation, more discussions have been added to Section 4.2.

"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 of a CF event induced by an individual extreme driver. CF does not necessarily require all drivers to exceed their corresponding thresholds (Zscheischler et al., 2020)."

R3C7:

line 78: Do you mean "A robust CFRA should provide a thorough understanding of the uncertainties related to the risk analysis such as uncertainties associated with flood frequency and possible flood damages" ? Would it be possible to make this more specific for *Compound Flood* Risk Analyses?

Author Response:

Thanks for the insightful suggestion. This sentence is rewritten to highlight uncertainty analysis for CFRA.

"A robust CFRA should consider the uncertainties associated with frequency and possible damages of compound flooding and provide a thorough understanding of the uncertainties related to the risk analysis (Apel et al., 2004). The uncertainty can stem from various sources in both statistics-based and dynamics-based CFRAs, such as measurement errors and approximations in numerical models. A comprehensive understanding of the uncertainty sources in CFRA is crucial for managing and predicting CF risks and will provide valuable insights for guiding future improvements."

R3C8:

line 89: Please clarify what is meant by "variability in the fluvial process".

Author Response:

By "variability in the fluvial process", we refer to the variations in the characteristics or behaviors of rivers over time and space. More specifically in this study, the variability is represented by the spatiotemporally varied streamflow.

Thanks for the suggestion. We elaborated this sentence to increase clarity.

"However, most existing studies rely on the flood driver measured/modeled at a single site and have not accounted for the dynamic change of river flow, such as the spatiotemporally varied streamflow, as well as river topology, coastal backwater effects and the associated uncertainties."

R3C9:

line 103-118 (CFRA model framework): could you provide some more details of the models. I.e. what is the temporal resolution of the MOSART and GTMS model outputs used here? How are the channel widths, depth and lengths defined? What equations are solved in the model (Full Saint-Venant, Local inertial, other)?

Author Response:

We appreciate the reviewer comment.

The statistical analysis uses daily streamflow from MOSART and daily maximum SS from GTSM. This is specified as: "The simulated daily streamflow (Q) at each selected cell is paired with the daily maximum storm surge (SS) level from the GTSM reanalysis dataset at the grid cell nearest to the outlet."

The temporal resolutions of MOSART and GTSM model outputs are daily and hourly, respectively. This information has been added to the revision:

"The model is run at an hourly time step from 1979 to 2018 and daily outputs are archived for analysis."

"Driven by the ERA5 atmospheric reanalysis dataset, the GTSM produces time series of hourly total water level and storm surge at global coasts from 1979 to 2018 (Muis et al., 2020),"

We agree with the reviewer that MOSART configuration and channel parameters are critical for the simulation. This study uses similar configuration in the same domain from a few previous studies and this information was specified as

"For more detailed descriptions of the model, please refer to Li et al., 2022."

We only described the specific changes in model configuration that are different from this reference, including the implementation of a macro-scale inundation scheme (Luo et al., 2017) and the updated river channel slope derived from a higher resolution DEM, and the downstream boundary conditions. We did not provide more details because we considered the focus of this study as risk assessment and uncertainty analysis.

In response to this comment, we added more details in model configuration and provide more references:

"MOSART is a physics-based river routing model at the basin to global scales. The model takes the total runoff generated by a land surface model and routes the surface runoff from hillslope to tributary subnetworks, which along with the subsurface runoff are discharged to river outlets through the main channels. In this study, kinematic wave method is used for overland flow routing, whereas diffusive wave method is applied in the river channels to represent the coastal backwater effects (Feng et al., 2022). The MOSART simulation is performed on the 1/8° resolution CONUS grid. The MOSART configuration on the same grid has been validated and applied to flow and sediment simulations (Li et al., 2015a; Li et al., 2022). The model parameters are available globally with more detailed descriptions in previous studies (Li et al., 2013; Li et al., 2015b). The model is run at an hourly time step from 1979 to 2018 and daily outputs are archived for analysis. The first-year simulation is excluded for analysis due to model spin-up. The floodplain inundation is represented using a macroscale inundation scheme (Luo et al., 2017)."

R3C10:

line 107: Is the slope of a 15 arcsec DEM (~25km) adequate to estimate the channel river slope?

Author Response:

We appreciate the reviewer's comment. We note the resolution of 15 arc-seconds is approximately 500 meters at the equator, which is adequate for resolving topology in the 1/8° MOSART grid.

R3C11:

line 133: Towner et al. (2019) study the skill of several GFMs (not including MOSART or GTSM) for peak flows in the Amazon, how does that relate to the skill of your model framework?

Author Response:

We apologize for any confusion.

We are aware that Towner's study is applied to a different domain using different GHMs. This study has performed a comprehensive skill assessment of various GHMs, providing reasonable guidance for evaluating the GHM performance in large-scale simulations. We used this reference to support that the MOSART performance is reasonable in the large-scale simulation as the skill metrics meet the standards proposed in Towner et al. 2019.

In the revision, this sentence is rewritten and the reference is deleted to avoid confusion:

"In the context of constructing a new CFRA framework within the CONUS domain and investigating the associated uncertainties, the performance of MOSART and GTSM models is deemed satisfactory in large-scale simulations."

R3C12:

line 139 (step a): The sampled events should be independent. How is this ensured?

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 the sampling CF events, we first extract 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. Within each selected SS event, a CF event is identified if Q 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.

This method also ensures that the selected SS events are independent as the sign of water level is always changed even between two adjacent events that are close to each other. While this method does not ensure the independence of Q, the frequency of a SS event is generally smaller than that of fluvial flooding.

In response to this comment and R3C13, we elaborated on the description of step (a) in the CF hazard calculation and explanations of independence to increase clarity.

"(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 does not require declustering. We assume that the Q extreme within each SS event is independent as both frequency and duration of SS are generally smaller than that of fluvial flooding."

R3C13:

line 142 (step b): How are Q events sampled? These are not mentioned under step a.

Author Response:

Please see the response to R3C12.

R3C14:

line 144 (step c): It is not clear how bivariate variables are defined. Is this based on AND or OR sampling of the variables? And do you allow for any time lag between the variables? Please clarify.

Author Response:

We appreciate this comment.

The bivariate variables are defined based on the "AND" hazard scenario (Salvadori et al., 2016). This may be implied by Equation 3. We have it clearly defined in the revised manuscript:

"(d) bivariate analysis: calculate the joint exceedance probability based on "AND" hazard scenario (Salvadori et al., 2016) that accounts for both marginal distributions and dependence structure."

We acknowledge that the duration of a fluvial flood event may not precisely align with the duration of SS during a compound flood (CF) event. It is possible there is small overlapping between a SS event and the corresponding fluvial flooding event. But we don't allow any lag for Q because the CF exposure is measured as the extent where SS-induced backwater matters. Such effects are dominated by SS and will only be significant during the selected SS events. This discussion is added to the revision.

“While it is possible that the duration of a fluvial flood event does not precisely align with a SS event, we don’t include any time lag between Q and SS in the consideration as this study specifically quantifies the CF impact based on the SS-driven backwater effects.”

R3C15:

line 179-184 (exposure risk): The exposure risk metric accounts not only for surge but also tide as the 'baseline' downstream boundary conditions is based on MSL only (and not MSL+tide). This has several consequences on the analysis in my opinion which are not included nor discussed. For instance, the tidal amplitude is in many locations probably an important predictor of backwater volumes (section 2.2.2) but not accounted for. It could also explain some of the differences between both CF metrics which is not discussed (section 3.2.2). And it should not be referred to as "surge-induced backwater effects" (line 405).

Author Response:

Thanks for the comment. Tide is excluded from our simulations. As defined in Section 2.1, at the downstream boundary of MOSART only the time series of storm surge are applied.

“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).”

We have not accounted for tide because: (a) the higher-frequency variability of tides compared to river discharge and storm surge poses challenges in quantifying tide as a CF driver along with the other two; (b) our sampling algorithm is only able to extract the low-frequency SS but not tides; and (c) we previously showed storm surge dominates the backwater effects in a low-lying river basins (Feng et al., 2022). Thus, this study only considers the SS-induced backwater effects. But we agree with the reviewer that tide and its nonlinear interaction with storm surge could be an important predictor in many locations. This limitation is now acknowledged in Section 4.2.

“The backwater effects are driven in MOSART by prescribing the SS time series at the downstream boundary. However, the actual CF is driven by the interactive processes between multiple drivers, including precipitation, land surface runoff and inundation, river discharge and coastal tide, storm surge and wave (Nasr et al., 2021), as well as their nonlinear interactions. 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.”

R3C16:

line 193: "the CF hazard index (CFHI) and the CF exposure index (CFEI) are obtained by normalizing Pq,ss and Wp with their corresponding 95th percentile values". How are the 95th percentile values calculated? If I understand correctly, both indicators are a single value per cell right?

Author Response:

Yes. The 95th percentile value is calculated from every grid cell. This is clarified in the revision:

"the CF hazard index ($CFHI$) and the CF exposure index ($CFEI$) are obtained by normalizing $P_{Q,SS}$ and W_p with their corresponding 95th percentile values at every grid cell."

R3C17:

line 196: "Our approach transforms the probability of occurrence into a direct measure of human exposure." Could you explain how?

Author Response:

This sentence is rephrased to:

"Our approach integrates measures of risks that consider both the probability of occurrence and human exposure."

R3C18:

line 239-250 (Impact of riverbed elevation): Is this analysis done per cell or per basin? And where does the riverbed elevation data come from? (see also earlier comment on the CFRA framework)

Author Response:

This analysis is performed for every cell. This is explained as "For each coastal grid cell, we use the MOSART simulated Q, the GTSM simulated SS at the river outlet, and the grid cell elevation."

The riverbed elevation is derived from the 15 arcsec digital elevation model (DEM) of the HydroSHEDS, which has been clarified:

"the channel slope and the riverbed elevation are derived from the 15 arcsec digital elevation model (DEM) of the HydroSHEDS and river vector data."

R3C19:

line 384: "In summary, CFRA should not rely on any single method; more comprehensive thinking is needed considering the different characteristics among the different risk types." How does the CF comprehensive risk metric compare to an actual risk analysis (i.e., combining the hazard and its potential consequences to derive e.g., annual expected losses or people exposed)

Author Response:

We appreciate the reviewer's insight. This study does not intend to critique any existing approaches. Rather, we build on their success and aim to demonstrate that more factors can be integrated to provide a comprehensive understanding of the CF risk.

This sentence is rephrased to: "to comprehensively understand the complex CF risk, it is critical for CFRAs to integrate multiple risk factors based on the available approaches."

Based on our experience, the actual flood risk analysis is a real-time or near real-time assessment in specific areas that updates risk factors based on the latest available data. Such analysis typically has a different focus from ours. While the goal of the actual risk analysis is to provide timely and accurate information to emergency responders, the framework proposed in this study aims to assess the risk at the continental scale to understand the spatial variability and uncertainty within different risk factors, and can help, e.g., "provide target regions where the computational mesh should be refined to improve model accuracy." Instead of delving into excessive details of comparing metrics, we acknowledge in Section 2.1 that "the combination of different types of risks, despite providing a comprehensive estimation of the CF risk, is subjective and may affect the risk assessment results."

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