

Dear Reviewer 2,

Thank you for taking the time to prepare your constructive review, which has improved this paper. At the end of this letter is the revised manuscript draft, supplementary material, and tracked changes. We have made the following revisions based on your comments (line numbers refer to the revised manuscript draft):

General Comments

“The introduction needs to be revised to highlight the study’s novelty. While the authors provide limited background on defining compound flood and the various models used to model it, they do not address the literature gap this study seeks to bridge. Furthermore, the authors do not present a clear research question that the study will address, and this question is not supported by the literature. The introduction only summarizes the methods at the end (which is very confusing and needs to be better restructured); it is not clear how the study will advance the field, given the lack of research questions and the identified knowledge gap. As it is now, it only tells me that the study is comparing two flood models for compound floods, which is not novel. However, if the authors reshaped the introduction according to my suggestions, the novelty this study proposes would be clearer. Furthermore, the authors compare their proposed approach with another study, but fail to explain why their study differs. It is crucial for the reader to understand why the proposed study differs from the literature.”

We revised and restructured the introduction to clarify the study’s novelty, address the research gap, and pose research questions. We articulate the research gap near the end of the introduction (L64-75), and pose three research questions immediately after. We also clarify how our study differs from and expands upon Muñoz et al. (2022) (L83-85).

“Regarding the simplified approach for estimating compound flood (section 2.2.1), I have concerns about their proposed selection of the compound flood level based solely on the maximum flood levels between the coastal and pluvial/fluviol levels. In the introduction, the authors cited several studies indicating that, in a compound flood event, the flood drivers exhibit nonlinear interactions. This means that when combined, their compound flood level could be lower or higher than the sum of their superposed levels. Thus, by selecting the maximum value between these two drivers, you can under- or overestimate the real compound flood while ignoring the other flood driver that was not chosen.”

We revised Sec. 2.2.1 to remove the claim that our linear combinations yield a lower-bound estimate of compound flood depth, and clarify the purpose and tradeoffs of this simplified approach (L135-136). We also state in the discussion that “SCM-derived rating surfaces may under- or overestimate compound flood depth at individual locations” (L366-367).

“This approach could have benefited from using a nonlinear regression or a machine learning- based approach to estimate the true compound flood value, rather than taking the easy way out and selecting the maximum value as a conservative estimate.”

We consider nonlinear regression and ML-based approaches beyond the scope of this study, as our objective is to generate rating surfaces efficiently with simplified conceptual models (SCMs). We agree that SCMs do not capture nonlinear compound flooding effects,

which is why we include a comparison with SFINCS. SFINCS is a hydrodynamic compound flood model that is capable of representing more complex compound flood processes, and provides a benchmark against which we can compare the SCM results.

“Furthermore, the authors comment that the compound flood results from the simple model (L226) have a linear pattern without noise, contradicting previous studies that claim a nonlinear behavior between the flood drivers as their SFINCS results. If the authors plan to keep this, they need to do a better job of justifying this approach and limiting its implications. However, the manuscript lacks a limitations section, which is necessary for studies like this that propose a new flood modeling technique. I would require the authors to include a limitations section before the results or within the discussion that outlines all the simplifications and assumptions used by the authors.”

Thank you for this suggestion. We would like to clarify that the rating surfaces framework that we propose is model agnostic—we have updated the text to highlight this (L4, L270-271, L332-333, L400-402). We have added a limitations section (Sec. 4.4), where we clarify that SCMs should be interpreted as first-order approximations of compound flooding, not hydrodynamic simulations, and that compound flooding is a nonlinear process (L365-367). We also clarify in the introduction that SCMs “do not resolve hydrodynamics or nonlinear interactions among flood drivers” (L67). Additionally, we reference this limitations section in the methods for SCM-based compound flooding (L135).

“Similarly, the SFINCS model section is missing significant information on model building (see specific comments).”

We address all specific comments in the following “Specific Comments” section.

“Also, neither model (simple or SFINCS) was calibrated/validated against the various tropical cyclones that have impacted the area, limiting the reliability of the outcomes.”

We validate the rating surfaces by using the maximum forcings observed during Hurricane Harvey to extract the predicted maximum flood depth, and compare the results with Hurricane Harvey HWMs collected by USGS (L186-191, L310-322). We acknowledge the absence of a full validation of each component model (SCMs and SFINCS) in the new limitations section (L394-398).

“Also, it is not clear to me why the authors force the SFINCS and the simple model with two flood drivers at once (coastal with pluvial or coastal with fluvial), since they claimed in the introduction that compound floods can include all three flood drivers.”

Thank you for bringing up this concern. We have added this text to the limitations section: “We construct rating surfaces from pairwise combinations of flood drivers, varying two flood drivers while holding the third driver at a baseline value. In reality compound flood depth may depend on interactions between three or more flood drivers (Zscheischler et al., 2018). We depict maximum compound flood depth at POIs as two-dimensional rating

surfaces to facilitate interpretability and comparison between SCM and SFINCS results.” (L370-373).

“The Result section is poorly written with unnecessary content, such as a repetition of the methods (L230-235), and only set of figures that evaluate the same outcome. The interpretation of these results is very superficial (2-3 sentences per figure), and more content (from figures to text) is needed. However, the discussion has been framed as an extension of the results, as it provides a description and the physical meaning of the results. The discussion needs to connect the study results with the literature and the research gap, but without proper research questions, it is impossible for the authors to cite other studies.”

We have removed the redundant text from the results section. We have also expanded the results section by moving the content related to the physical meaning of the results from the discussion to the results (Sec. 3). We have rewritten the discussion section to address each of the new research questions we pose in the introduction, and to connect with the literature (Sec. 4).

“Overall, many of the paragraphs (section 2.2, some in the introduction, etc.) contain statements that were just thrown there without any connection/transition between topics, making it hard to read and follow the author’s point. Thus, I strongly suggest that the authors rephrase and strengthen the connection so they can tell a story with the publication rather than just a technical report. However, the approach selected to create the compound flood model using the simple approach may have substantial flaws within the literature, and without further modification of equations 1-3, the manuscript could be difficult to publish.”

We have reread the manuscript closely and revised to improve flow and transitions throughout, including in Section 2.2 and in the introduction. As discussed above, we have added context to equations 1-3, including clarifying that SCMs do not capture nonlinear compound flood interactions, and have expanded upon this in the new dedicated limitations section.

Specific Comments

“L25-26: rephrase the sentence since the “compound coastal flooding” is used incorrectly, since compound flood implies that coastal and hydraulic flooding are happening. You may want to say that you are focusing on compound flood in coastal areas rather than estuaries, but compound has to also occur in the coastal area, so it might be redundant. The same occurs on L27 and L30, so please fix throughout the manuscript and call it only compound flood and not compound coastal flood.”

We have removed all occurrences of “compound coastal flood” and replaced them with “compound flood.”

“L26-27: The sentence talking about compound events (broader than flooding) seems out of context. I would remove.”

We have shifted that sentence to the topic sentence position of paragraph 2 (L25), and have restructured for better flow.

“L24-38: This paragraph would benefit from improving the reading flow by enhancing the transitions and connections between sentences. Some statements look like they were just thrown there without any coherence. Please improve.”

Thank you for this suggestion. We have restructured paragraph 2 (L25-38) to improve transitions and flow.

“L39-52: Avoid having a small paragraph with 3 sentences or fewer. Try combining them with their appropriate transition, so your paragraphs are longer (5-8 sentences).”

We have merged that paragraph with the preceding one (L39-48).

“L46-47: Why are these models less applicable? Give a reasoning for your statement and cite some literature supporting your claim.”

We have added an explanation and references for this claim (L45-47).

“Figure 1: I will suggest adding the river location on panel b and even removing the grey background from this panel since it does not allow to visualize how this inland community could be affected by compound flood through the river. I will also highlight the river/coastline/bay on panels C and D, as it is important for your compound flood. Also, what is the vertical datum reference for the DEM elevation?”

“L85-85: I need to see these water features (river, lakes, and bay) commented in Figure 1.”

We have made these suggested changes and specified the vertical datum in the figure caption, which is NAVD88. We show the major rivers, Neches and Sabine, on panels B-D. We also show the catchments of NHDPlusV2 MR stream reaches on panels C and D. We do not show the stream reach centerlines themselves to avoid clutter on the study area figure. We show all NHDPlusV2 MR centerlines on Figure 2.

“L100-101: This statement needs support from the literature since it is a big assumption and limitation.”

We have added supporting literature (L117-119) and reference the limitations section, where we discuss this further (L380-389).

“L127-128: The claim that infiltration is not needed since the POI are in impervious regions is not 100% true, since water will travel from overland and accumulate. For example, if water upstream of the POI is traveling through grass, it should infiltrate some portion before reaching the POI, but in the assumed case, it would not, and more water would be there.”

We have removed this claim, and discuss the implications of not including infiltration in the limitations section (L380-389).

“Table 1: There is no justification or rationale for the values chosen on this table, nor its physical meaning. I am positive about the selected approach for creating the synthetic events. However, this needs to be grounded in the real conditions. For example, the authors have to comment on how realistic it is to have an X mm rainfall with a Y m coastal water level. Also, it is not clear if the rainfall being applied is uniform or not throughout the domain.”

We comment on our rationale for choosing the values in Table 1, as well as their physical meaning, in Sec. 2.5 (L193-203), and expand on the physical meaning of each forcing in the subsequent subsections (Sec 2.5.1, 2.5.2, and 2.5.3). We also clarify that high-magnitude forcings will have rare probabilities of occurrence, and that a multivariate statistical analysis to determine these probabilities is beyond the scope of this paper (L197-200). We expand upon this in the limitations section (L405-409).

“L174-176: The authors need to further justify how realistic it would be to have a relatively high coastal water level be applied uniformly this high for seven days. Why not add tidal conditions or recreate a storm surge hydrograph, which will raise the water level temporarily rather than for the whole 7 days?”

We apply this seven-day forcing to facilitate comparison with c-HAND, which estimates static maximum inundation extent and depth for a given coastal water level. We clarify our reasoning in the manuscript (L208-211). We expand upon this in the limitations section (L374-377).

“L195-200: Please add MKGE and NSE as a comparison metric. These metrics represent a better comparison with streamflow data.”

We have added mKGE and NSE as comparison metrics (L230-248, supplementary figure S1).

“L217: It is not clear why the authors selected the mentioned rainfall intensity. Also, what was the temporal distribution of the rainfall, as well as the spatial distribution?”

We revised the text to clarify how we select rainfall intensity (L255-266). For each pluvial depth scenario, we prescribe the total precipitation depth and ARI, and interpolate the corresponding storm duration from the NOAA DDF table. We then calculate rainfall intensity as the scenario's total depth divided by its interpolated duration. We also clarify that the precipitation forcing is applied as a spatially uniform rainfall field and as a temporally constant hyetograph over each scenario's duration, followed by zero rainfall for the remainder of the seven-day simulation.

“L238-239: This statement is not correct. For example, the results between the simple and the SFINCS model for the Silsbee POI 1-2 and HWM 1-2 are completely different, but the statement says depth are similar.”

Thank you for pointing this out. We revised this statement to avoid implying that SCM and SFINCS produce similar depth ranges at every POI/HWM (L287-290).

Rating Surfaces for Quantifying Compound Flooding at Points of Interest

Mark Wang¹, Paola Passalacqua^{2,3,1}, Hamed Moftakhari⁴, and Bailey Hardage¹

¹Fariborz Maseeh Department of Civil, Architectural, and Environmental Engineering, Center for Water and the Environment, University of Texas at Austin, Austin, USA

²Institute of Environmental Engineering, Department of Civil, Environmental and Geomatic Engineering, ETH Zürich, Zürich, CH

³Eawag, Swiss Federal Institute of Aquatic Science and Technology, Dübendorf, CH

⁴Department of Civil, Construction and Environmental Engineering, Center for Complex Hydrosystems Research, University of Alabama, Tuscaloosa, USA

Correspondence: Paola Passalacqua (ppassalacqua@ethz.ch)

Abstract. Compound flooding in low-relief coastal regions arises from interactions among coastal water levels, river discharge, and precipitation. Capturing these interactions typically requires coupled hydrodynamic models, which can be computationally expensive, limiting their use in high-resolution or large-ensemble analyses. In this study, we introduce the rating surface, a model-agnostic framework that transforms ensembles of flood inundation simulations into two-dimensional contours of compound flood depth at points of interest across pairs of potentially interacting flood drivers. Using Southeast Texas as a testbed, we generate synthetic inundation scenarios with both efficient terrain-based models (c-HAND, GeoFlood, and Fill-Spill-Merge) and the reduced-physics hydrodynamic model SFINCS. Sampling these scenarios at points of interest yields rating surfaces that characterize how precipitation, discharge, and coastal water level influence maximum compound flood depth. Across locations, simplified and hydrodynamic models produce similar depth patterns, but SFINCS captures finer-scale nonlinearities. The two approaches provide comparable depth estimates and their prediction envelope typically includes the observed high-water marks. Rating surfaces provide an efficient tool for scenario assessment and communicating compound flood hazards at points of interest.

Copyright statement. Author(s) 2026. This work is distributed under the Creative Commons Attribution 4.0 License.

1 Introduction

Flooding is the most frequent and widespread natural disaster, affecting over 2 billion people globally from 1998 to 2017 (Wallemacq et al., 2018) and costing the United States more than USD 180 billion annually (U.S. Congress, 2024). Over 50% of the U.S. population now lives in coastal watersheds (Crossett et al., 2013), and the global coastal population is projected to exceed 1 billion by 2060 (Neumann et al., 2015; Reimann et al., 2023). These populations are particularly vulnerable to tropical cyclones, which threaten coastal areas worldwide (Dullaart et al., 2021) and have caused over USD 1.425 trillion in damages

20 in the United States from 1980 to 2024, with an average cost of USD 22.3 billion per event (Smith, 2024). Recent tropical cyclones that produced severe flooding in the United States include Hurricane Harvey (2017), Tropical Storm Imelda (2019), Hurricanes Isaias and Laura (2020), Hurricane Ida (2021), and Hurricanes Helene and Milton (2024). As coastal populations grow and their exposure to flooding and tropical cyclones increases, understanding the interplay among multiple flood drivers is crucial.

25 Compound events are natural hazards that co-occur over time or space and threaten society and the environment (Zscheischler et al., 2020). In coastal settings, compound flooding often occurs when storm surge, riverine flooding, and heavy rainfall interact, amplifying flood impacts beyond those caused by any single driver (Bevacqua et al., 2020; Hao and Singh, 2020). These events pose considerable challenges for prediction and hazard assessment, especially in low-relief coastal regions where coastal residents are highly exposed. Compound flooding is often triggered by tropical cyclones, which can generate storm
30 surge, fluvial flooding, and pluvial flooding (Green et al., 2025). The primary drivers of compound flooding—coastal water levels, precipitation, and river flow—are interdependent and inherently correlated (Zheng et al., 2013; Wahl et al., 2015; Mof-takhari et al., 2017; Hendry et al., 2019). These drivers can act simultaneously or sequentially, producing dynamic interactions that amplify flood hazards. Predicting these interactions is particularly challenging in low-relief flood transition zones, where hydrologic and coastal flood processes interact nonlinearly (Shen et al., 2019; Bilskie et al., 2021; Santiago-Collazo et al.,
35 2024). For example, storm surge, driven by strong winds and low atmospheric pressure, raises coastal water levels and can impede river discharge, causing backwater effects and prolonged inland flooding (Lewis et al., 2013; Wijetunge and Neluwala, 2023). Similarly, heavy precipitation can saturate soils, reduce infiltration, and increase runoff, while high tides and waves can further elevate water levels (Bilskie and Hagen, 2018).

Accurate flood estimation is essential for flood management; however, no single approach is ideally suited to fully capture
40 compound flood events. Researchers and policymakers use three broad approaches to estimate flooding: empirical methods, hydrodynamic models, and simplified conceptual models (Teng et al., 2017). These flood estimation approaches help address challenges in planning, impact assessment, and emergency response (Bates, 2022), but each approach has strengths and limitations that influence its utility. Empirical methods provide direct observations of compound flooding, including remote sensing, sensor data, and crowdsourced information (Tellman et al., 2021; Hamidi et al., 2023; Silverman et al., 2022; Dasgupta et al.,
45 2022). While empirical methods are invaluable for planning and post-event assessments, observed inundation alone is less suited to predictive and scenario-based compound flood analysis, which requires representing interacting flood drivers such as coastal water level, rainfall, and riverine flow (Santiago-Collazo et al., 2019; Loveland et al., 2021). As a result, process-based and simplified modeling approaches are often needed to estimate flooding under current or hypothetical forcing conditions.

Hydrodynamic models estimate flow using the Navier-Stokes equations, and are widely adopted for flood simulations (Bates,
50 2022). To balance accuracy and efficiency, hydrodynamic modelers often simplify the Navier-Stokes equations using two-dimensional shallow-water or one-dimensional Saint-Venant formulations (Westerink et al., 1992; Horritt and Bates, 2002; USACE, 2025). Coupled hydrodynamic models have been developed to describe compound flood processes, with some tools optimized for computational efficiency (Leijnse et al., 2021; Lee et al., 2025). However, computational demands limit hydrodynamic models' applicability to real-time or high-resolution scenarios (Miura et al., 2021b).

55 Simplified conceptual models use physical principles, geographic information systems (GIS), and terrain analysis to estimate flood extent and depth efficiently (Teng et al., 2017; Bates, 2022). These models do not simulate flood dynamics, but instead can estimate static flood extent and depth by applying geomorphic and proximity-based approaches to topographic and hydrologic data. Early applications automated valley bottom detection to designate flood-prone areas (Williams et al., 2000; Gallant and Dowling, 2003). Some simplified conceptual models distribute water volume across terrain (Lhomme et al., 2009; Miura et al., 2021b; Shi et al., 2025), while others classify floodplains based on digital elevation models (Nardi et al., 2006; Manfreda et al., 2011; Samela et al., 2017). Simplified conceptual models enable large-scale, high-resolution flood hazard assessments and support rapid decision-making in emergency response scenarios (Murphy et al., 2025; Jafarzadegan et al., 2023; Preisser et al., 2023).

Although coupled hydrodynamic models can resolve compound flood processes, their computational cost limits systematic simulation of large-ensemble forcing scenarios at high spatial resolution (Santiago-Collazo et al., 2019; Miura et al., 2021a). Conversely, simplified conceptual models can efficiently estimate static inundation maps across many forcing scenarios, but they do not resolve hydrodynamics or nonlinear interactions among flood drivers (Teng et al., 2017). Beyond this modeling tradeoff, compound flood assessment also poses a communication challenge: flood managers need location-specific summaries of how flood driver combinations affect compound flood depth. Rating curves provide such summaries for riverine flooding by relating stage to discharge at a gage, but no comparable tool exists for compound flooding, where flood depth depends on multiple drivers. Together, these challenges leave a practical gap: a need for an efficient and interpretable tool that communicates how flood depth varies across combinations of coastal water level, river discharge, and precipitation at a given location. We address this gap by proposing rating surfaces, which extend the logic of rating curves from one-dimensional stage-discharge relationships to two-dimensional forcing spaces that represent maximum flood depth across pairs of flood forcings at points of interest.

Specifically, in this manuscript we address three research questions:

1. Can rating surfaces, constructed from a finite ensemble of flood inundation simulations, efficiently estimate maximum compound flood depth for any combination of two flood drivers at points of interest (POIs)?
2. What do rating surfaces reveal about the local influence of different flood drivers on maximum compound flood depth at POIs?
3. To what extent do rating surfaces constructed from simplified conceptual models agree with those constructed from SFINCS, a hydrodynamic model?

Our approach builds on the fluvial–coastal water level surfaces proposed by Muñoz et al. (2022), but differs by focusing on maximum compound flood depth at POIs, considering coastal–pluvial, fluvial–coastal, and fluvial–pluvial forcing pairs, and comparing surfaces derived from both simplified conceptual and hydrodynamic models. Using Southeast Texas as a testbed, we generate high-resolution (1 m) compound flood inundation scenarios using public datasets and open-source models, sample the resulting maximum depth grids at point locations to calculate rating surfaces, and compare rating surface-predicted depths with high-water marks observed during Hurricane Harvey.

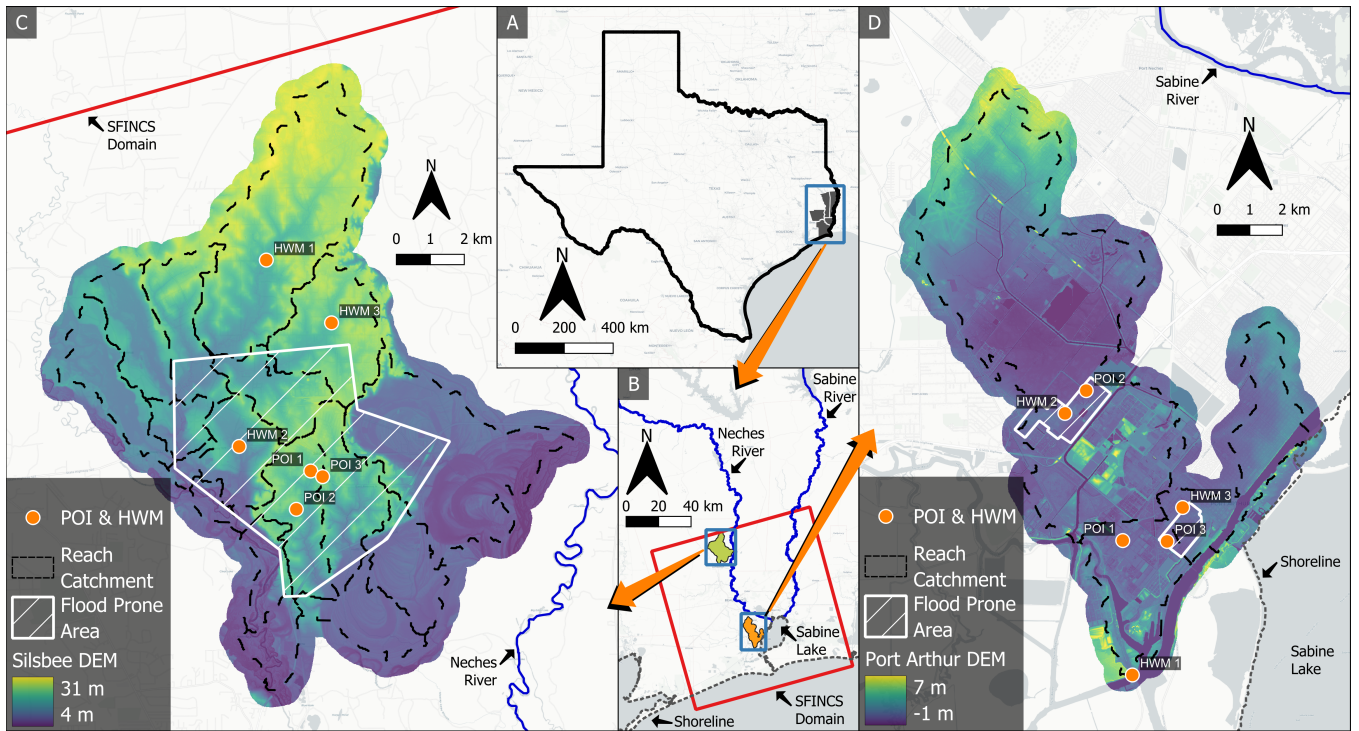


Figure 1. Location of (A) Southeast Texas within the state of Texas, (B) the Silsbee and Port Arthur study areas within Southeast Texas, as well as the SFINCS domain, (C) the Silsbee study area extent and datasets, and (D) the Port Arthur study area extent and datasets. The vertical datum of the DEMs is NAVD88. Basemap © OpenStreetMap contributors, © CARTO.

2 Methods

90 2.1 Study areas

Our study areas are the inland town of Silsbee and the coastal city of Port Arthur, both located in Southeast Texas on low-relief topography susceptible to compound flooding (Fig. 1). We choose POIs within regions designated as flood-prone by local stakeholders working with the Southeast Texas Urban Integrated Field Laboratory (SETx-UIFL, 2024). POIs in the study areas are situated near socially vulnerable populations and critical energy infrastructure. The Southeast Texas region encompasses the

95 Beaumont-Port Arthur metropolitan area, smaller towns like Silsbee, agricultural lands, forests, and swamps. Tropical cyclones including Beryl (2024), Imelda (2019), and Harvey (2017) have impacted the area. The region is drained by the Sabine and Neches Rivers and their tributaries. Terrain slopes gently toward the Gulf of Mexico, which is typical of the Texas Coastal Plains. The Sabine Lake is the major estuary in Southeast Texas.

2.2 Simplified conceptual models

100 We use three simplified conceptual models (SCMs) to separately estimate the coastal, fluvial, and pluvial components of compound flooding. Each model produces a maximum inundation depth grid corresponding to one flood driver using high-resolution terrain data, forcing conditions, and physical approximations. We combine these individual flood driver depth grids to estimate compound flood depth (Sec. 2.2.1).

c-HAND produces coastal flood inundation scenarios (Wang et al., 2024). c-HAND is a static method that uses high-
105 resolution elevation data and a coastal water level forecast to estimate coastal flood extent and depth. It is a modification of the HAND method and estimates coastal inundation by enforcing an ocean connectivity constraint. A c-HAND backcast of coastal inundation from Hurricane Ike showed reasonable agreement with an ADCIRC simulation (Wang et al., 2024). We force c-HAND with coastal water levels (Sec. 2.5.1).

We generate synthetic fluvial flood inundation scenarios with a modification of the GeoFlood workflow (Zheng et al., 2018).
110 GeoFlood estimates fluvial flood extent and depth from river discharge and terrain-analysis operations, and has been validated against observations from Hurricane Harvey (Zheng et al., 2022). We force GeoFlood with synthetic river discharge scenarios (Sec. 2.5.2) in the NHDPlusV2 MR stream reach catchments containing our POI/HWM.

We estimate pluvial flooding with Fill-Spill-Merge, a terrain depression flow routing algorithm that can be applied to a broad range of natural phenomena (Barnes et al., 2021). Fill-Spill-Merge has been used to map pluvial flooding in Texas (Preisser
115 et al., 2022, 2023). We force Fill-Spill-Merge with uniform precipitation depths (Sec. 2.5.3). Because Fill-Spill-Merge does not take drainage infrastructure or infiltration into account, we assume that soil is saturated and the drainage system is at capacity during large precipitation events. This assumption is consistent with soil moisture observations during recent tropical cyclones in Southeast Texas and local regulations that allow roadway ponding for severe events (Case et al., 2021; Jefferson County Drainage District No. 7, 2019). We will discuss the implications and limitations of this assumption (Sec. 4.4).

120 2.2.1 Compound flood depth with simplified conceptual models

We produce 1 m resolution coastal, fluvial, and pluvial maximum flood depth grids separately across the study area with SCMs (Sec. 2.2). To estimate compound flood depth from these single-forcing maximum flood depth grids, we combine pairs of forcing scenarios (Eq. 1–3). We analyze pairwise combinations of flood drivers to show how compound flood depth responds to variation in two drivers while the third driver remains constant (Sec. 2.6).

$$125 \quad h_{\text{fluvial-pluvial}} = h_{\text{pluvial}} + h_{\text{fluvial}} \quad (1)$$

$$h_{\text{coastal-pluvial}} = \max(h_{\text{coastal}}, h_{\text{pluvial}}) \quad (2)$$

$$h_{\text{fluvial-coastal}} = \max(h_{\text{coastal}}, h_{\text{fluvial}}) \quad (3)$$

where $h_{\text{fluvial-pluvial}}$ is the compound fluvial-pluvial flood depth, $h_{\text{coastal-pluvial}}$ is the compound coastal-pluvial flood depth, $h_{\text{fluvial-coastal}}$ is the compound fluvial-coastal flood depth, h_{fluvial} is the fluvial flood depth, h_{pluvial} is the pluvial flood depth, and h_{coastal} is the coastal flood depth.

We use the compound flood depths resulting from Eq. 1–3 to construct rating surfaces for pairs of forcings at each POI/HWM. We sum pluvial and fluvial inundation because fluvial inundation is calculated on a depression-removed DEM and pluvial inundation is calculated on a DEM including depressions. We take the maximum of coastal and either fluvial or pluvial inundation because coastal inundation acts as a downstream boundary condition that controls water surface elevations across low-lying terrain. These equations do not represent hydrodynamics or nonlinear interactions among flood drivers (Sec. 4.4). Rather, these equations provide an efficient approximation of maximum compound flood depth with SCMs. We evaluate SCM-derived compound flood depth against SFINCS, which couples coastal, fluvial, and pluvial forcings (Sec. 3).

2.3 SFINCS model setup

The SFINCS model domain spans 100×100 km and uses a 50×50 m regular grid with a 1×1 m subgrid scheme that resolves fine-scale topography (van Ormondt et al., 2025). We mosaic the topography and bathymetry datasets to cover the full SFINCS domain (Fig. 2). We apply outflow boundary conditions at domain edges intersecting land and constant water level boundary conditions at domain edges intersecting the ocean. We assign inflow boundary conditions where stream reaches intersect the model boundary and at headwaters within the domain. The subgrid tables include NHDPlusV2 MR stream reach centerline geometry, bankfull width and depth, and channel roughness, as well as land cover-based roughness outside of stream reaches. We disable infiltration in SFINCS to reduce systematic model bias and maintain consistency with the SCMs, which omit infiltration. We will discuss the implications and limitations of this assumption (Sec. 4.4). We run seven-day SFINCS simulations with coastal, pluvial, and fluvial forcing scenarios.

2.3.1 SFINCS compound scenario selection

We generate compound flooding scenarios by pairing coastal, fluvial, and pluvial forcings across their full ranges (Sec. 2.5.1–2.5.3). SFINCS receives each forcing combination as a seven-day simulation that shares a common domain, boundary setup, and subgrid configuration. The only difference among SFINCS scenario setups is the choice of forcing magnitudes.

For each pair of flood drivers, we construct a continuous two-dimensional forcing space, discretized with a deterministic Halton sequence (Halton, 1960). The Halton sequence distributes sample points uniformly across the forcing space. We hold the third driver at a constant low value so that maps are representative of the inundation resulting from two drivers, as with the SCMs (Table 1). We describe the physical basis for the forcing ranges we list in Table 1 (Sec. 2.5). Similar to the SCMs, we apply a uniform precipitation depth throughout the SFINCS domain. We set coastal water level to 0 m NAVD88 for fluvial-pluvial scenarios, which falls between mean low water (-0.07 m NAVD88) and mean sea level (0.07 m NAVD88) at the Port Arthur tide gage. We set discharge to baseflow for coastal-pluvial scenarios and set precipitation depth to 0 mm for fluvial-coastal scenarios.

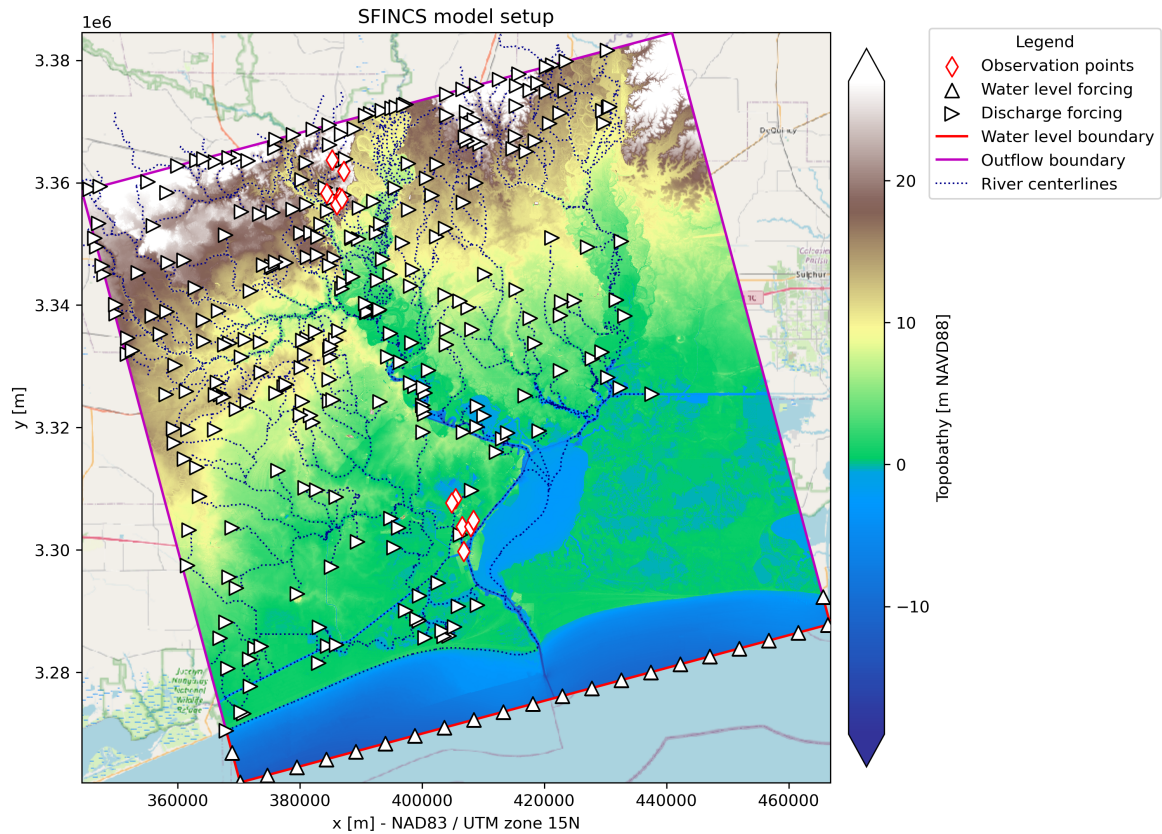


Figure 2. SFINCS model setup. Basemap © OpenStreetMap contributors.

Table 1. SFINCS compound scenario types and corresponding forcing ranges.

Scenario type	Forcings		
	Coastal [m NAVD88]	Fluvial ^a [m ³ s ⁻¹]	Pluvial [mm]
Fluvial–pluvial	0	25 to 20000	10 to 300
Coastal–pluvial	0.1 to 2.0	baseflow ^b	10 to 300
Fluvial–coastal	0.1 to 2.0	25 to 20000	0

^a Represents maximum discharge within the watershed.

^b Historical NWM baseflow condition (Sec. 2.5.2).

160 We generate 1000 forcing combinations across the three pairs of drivers. The three forcing grids (coastal–pluvial, fluvial–pluvial, and fluvial–coastal) span the full ranges of coastal water level, maximum discharge, and precipitation depth. The Halton-sampled points evenly fill each forcing space (Fig. 3). This approach provides broad coverage while keeping the total number of SFINCS simulations computationally feasible.

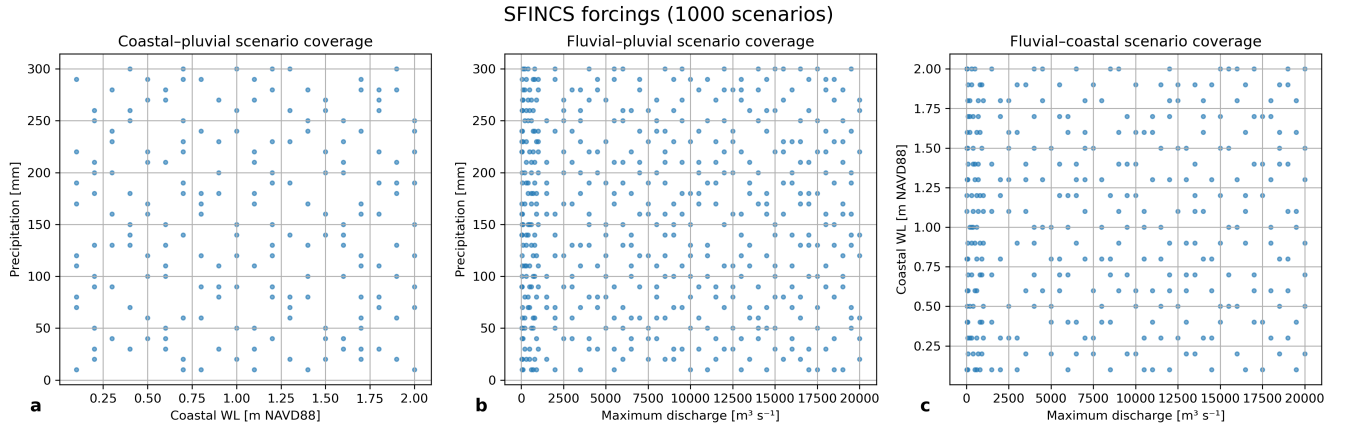


Figure 3. Halton-sequence coverage of compound forcing spaces used for SFINCS simulations. The three panels show 1000 forcing combinations across the three pairs of drivers: (A) coastal–pluvial, (B) fluvial–pluvial, and (C) fluvial–coastal. Apparent clustering near zero discharge reflects the non-uniform spacing of fluvial forcing magnitudes, where resolution at low flows is increased (Sec. 2.5.2).

Each SFINCS run produces a time series of water surface elevation on the 50 m grid. We compute the maximum value over the full seven-day period at every coarse grid cell and downscale the coarse maximum water surface grid to a 1 m depth grid. We sample the 1 m maximum depth grid at each POI/HWM. The sampled depths form the inputs for rating surface construction (Sec. 2.6).

2.4 Datasets

We obtain 1 m resolution bare-earth digital elevation models (DEM) from the USGS 3D Elevation Program for Silsbee and areas outside of Jefferson County (USGS, 2024) and from the TNRIS StratMap Program for Port Arthur and areas within Jefferson County (TNRIS, 2017) (Fig. 1). We obtain bathymetry with the finest available resolution of 4 m from NOAA BlueTopo (NOAA, 2025a). We delineate the coastline using U.S. Census TIGER/Line data (US Census Bureau, 2025). All geospatial datasets reference UTM Zone 15N coordinates (EPSG:26915) and the NAVD88 vertical datum (EPSG:5703).

Stream reaches, gage-adjusted mean annual flow for each stream reach, and stream reach catchments are from the National Hydrography Dataset Version 2 Medium Resolution (NHDPlusV2 MR) Dataset, which is maintained by the USGS (McKay et al., 2012). The National Water Model (NWM) provides historical flow rates (Cosgrove et al., 2024) and the USGS provides hydraulic geometry estimates including bankfull width and depth (Schwarz et al., 2018) for each NHDPlusV2 MR stream reach. We assign channel Manning’s n by stream order following GeoFlood’s current implementation, and where stream order is unavailable we assign n to 0.03. Outside of stream channels, we assign roughness based on the 2023 National Land Cover Database 30 m dataset (USGS, 2025) with recommended land cover class–Manning’s n mappings from the HEC-RAS manual (USACE, 2025).

Table 2. High-water mark (HWM) and point-of-interest (POI) information.

Site	Location	Type
Port Arthur POI 1 ^a	S Gulfway Dr & Valero Refinery Gates	Industrial
Port Arthur POI 2	Linkwood St & Austin Ave	Residential
Port Arthur POI 3	W 10th St & Herget Ave	Residential
Port Arthur HWM 1 ^a	Under West Port Arthur Bridge	Bridge crossing
Port Arthur HWM 2	Back of St John’s Catholic Church	Drainage swale
Port Arthur HWM 3	Across from Booker T. Washington Elementary	Drainage swale
Silsbee POI 1 ^a	Hwy 96 & FM 327	Downtown
Silsbee POI 2	Maxwell Dr & Lindsey	Residential
Silsbee POI 3	Watts Rd & FM 327	Highway underpass
Silsbee HWM 1	Upstream side of bridge on FM 1122	Bridge crossing
Silsbee HWM 2	Upstream of culvert on FM 327	Culvert crossing
Silsbee HWM 3 ^a	Downstream of bridge on FM 92	Bridge crossing

^a Located on or adjacent to a TxDOT-designated evacuation route.

We calculate rating surfaces at 12 point locations: three POIs and three HWMs in both Silsbee and Port Arthur (Table 2). We select POIs at locations where estimating compound flood depth for specific combinations of hydrological forcings is important for identifying management strategies. POIs are located in residential areas, along hurricane evacuation routes (TxDOT, 2025), and near critical infrastructure (Fig. 1). USGS collected the HWMs after Hurricane Harvey (USGS and Arctur, 2018).

To validate the rating surfaces, we use observed forcing magnitudes from Hurricane Harvey. Peak stream segment discharges were $6140 \text{ m}^3 \text{ s}^{-1}$ at Silsbee and $14440 \text{ m}^3 \text{ s}^{-1}$ at Port Arthur according to NWM retrospective data. Coastal water level at the Port Arthur tide gage reached 1.13 m NAVD88. The National Hurricane Center reported 173 mm of rainfall within one hour during Hurricane Harvey (Blake and Zelinsky, 2018). This depth corresponds to the 1000 yr, 1 h event at Beaumont (NOAA, 2025b), which we adopt as the representative precipitation depth for validation. These values are used as inputs to the rating surfaces to evaluate modeled flood depths against the observed high-water marks.

2.5 Compound flood forcings

We select coastal, fluvial, and pluvial forcing ranges to generate a broad set of synthetic forcing scenarios for which we simulate flooding and construct rating surfaces. The individual drivers in each scenario span a forcing envelope from baseline conditions to values above recently observed tropical cyclone flood conditions in Southeast Texas. We simulate these scenarios with both SCMs (Sec. 2.2) and SFINCS (Sec. 2.3). We design these scenarios to evaluate compound flood depth sensitivity across relevant conditions in Southeast Texas. Pairing high-magnitude compound flood forcings produces rare combinations; multivariate statistical methods are required to estimate the joint likelihood of these combinations (Jane et al., 2025; Zheng et al., 2014). This study is concerned with simulating physically relevant combinations to evaluate possible compound flood depth responses

200 at points of interest, rather than assigning probabilities to each joint occurrence. Coastal water levels span typical to extreme values at the Port Arthur tide gage (Sec. 2.5.1), discharge scenarios span below-baseflow to greater-than-Harvey conditions (Sec. 2.5.2), and precipitation depths span frequent to rare rainfall totals based on NOAA depth-duration-frequency (DDF) estimates for Beaumont (Sec. 2.5.3).

2.5.1 Coastal

205 We apply coastal water levels ranging from 0.1 m to 2.0 m by increments of 0.1 m. The maximum water surface elevation measured by the NOAA tide gage at Port Arthur (Station 8770475) is 1.13 m (record begins in 2004). c-HAND calculates a static maximum coastal inundation map for each coastal water level, while we force SFINCS with a constant coastal water level throughout each seven-day simulation and obtain the corresponding downscaled maximum inundation maps. We apply constant coastal water levels to the SFINCS hydrodynamic simulations for parity with c-HAND, which estimates static maximum inundation extent for a specified coastal water level. We apply this constant forcing to estimate maximum inundation conditional on a specified coastal water level.

2.5.2 Fluvial

We generate fluvial scenarios consisting of discharge ensembles. First we obtain gage-adjusted mean annual discharge from the NHDPlusV2 EROM dataset (US EPA, 2015). Then we assign discharge to each stream reach based on its mean annual discharge relative to the minimum and maximum in the study area, resulting in a vector of normalized discharges ranging from 0 to 1 (Eq. 4). We multiply this vector by a constant value to generate a corresponding synthetic discharge scenario (Eq. 5):

$$Q_{i,\text{norm}} = \frac{Q_i - Q_{\min}}{Q_{\max} - Q_{\min}} \quad \forall i \quad (4)$$

$$Q_{\text{scenario}} = C \times Q_{\text{norm}} \quad (5)$$

where $Q_{i,\text{norm}}$ is the normalized discharge at stream segment i , Q_i is mean annual discharge at stream segment i , $Q_{\min}$ is the minimum mean annual discharge of a stream segment in the study area, $Q_{\max}$ is the maximum mean annual discharge of a stream segment in the study area, Q_{scenario} is the vector of discharges corresponding to a synthetic discharge ensemble, C is the scaling factor corresponding to the maximum discharge ($\text{m}^3 \text{s}^{-1}$) for a given synthetic scenario, and Q_{norm} is a dimensionless vector of the normalized discharges at each stream segment. We force GeoFlood and SFINCS using fluvial scenarios defined by scaling factors C corresponding to maximum discharges ranging from $25 \text{ m}^3 \text{s}^{-1}$ to $20000 \text{ m}^3 \text{s}^{-1}$ (from less than baseflow to greater than Harvey)¹. GeoFlood produces a static maximum inundation map associated with each fluvial scenario, while

¹ $C [\text{m}^3 \text{s}^{-1}]$: 25, 50, 75, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500, 5000, 5500, 6000, 6500, 7000, 7500, 8000, 8500, 9000, 9500, 10000, 10500, 11000, 11500, 12000, 12500, 13000, 13500, 14000, 14500, 15000, 15500, 16000, 16500, 17000, 17500, 18000, 18500, 19000, 19500, 20000.

we force SFINCS with each constant fluvial scenario throughout each seven-day simulation and obtain the corresponding downscaled maximum inundation maps.

To validate the discharge scaling method, we compare scaled synthetic discharges with maximum NWM discharges from three major flood events in Southeast Texas—Hurricane Ike, Hurricane Harvey, and Tropical Storm Imelda—as well as baseflow conditions. We use the modified Kling-Gupta Efficiency (mKGE) and the Nash-Sutcliffe Efficiency (NSE) to evaluate agreement between scaled synthetic discharges and observed NWM peak discharges across stream reaches (Kling et al., 2012; Nash and Sutcliffe, 1970):

$$\text{NSE} = 1 - \frac{\sum_{i=1}^n (Q_{\text{obs},i} - Q_{\text{pred},i})^2}{\sum_{i=1}^n (Q_{\text{obs},i} - \bar{Q}_{\text{obs}})^2} \quad (6)$$

$$\text{mKGE} = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2} \quad (7)$$

$$\beta = \frac{\bar{Q}_{\text{pred}}}{\bar{Q}_{\text{obs}}} \quad (8)$$

$$\gamma = \frac{\text{CV}_{\text{pred}}}{\text{CV}_{\text{obs}}} = \frac{\sigma_{\text{pred}}/\bar{Q}_{\text{pred}}}{\sigma_{\text{obs}}/\bar{Q}_{\text{obs}}} \quad (9)$$

where $Q_{\text{pred},i}$ and $Q_{\text{obs},i}$ are the predicted synthetic and observed NWM peak discharges at stream segment i , respectively, n is the number of stream segments, and the terms $\bar{Q}$, CV, and σ are the mean, coefficient of variation, and standard deviation of peak discharge, respectively, across stream segments for a given site and event. The mKGE terms r , β , and γ represent the Pearson correlation coefficient, bias ratio, and variability ratio, respectively; all three terms are dimensionless. We report mKGE and NSE as dimensionless measures of model performance to compare events across different magnitudes and sites. Both the NSE and mKGE metrics range from $-\infty$ to an optimum value of 1. mKGE values closer to 1 indicate better agreement in the correlation, bias, and variability of predicted and observed peak discharges across stream segments. NSE values closer to 1 indicate better agreement between predicted and observed peak discharges; a value of 0 indicates that predicting the mean observed peak discharge for every stream segment performs as well as the predicted discharges. The mKGE values range from 0.5804 to 0.9893 (Fig. S1a), indicating that the discharge scaling method provides an efficient, approximate technique for systematic generation of multiple synthetic fluvial scenarios. The NSE values range from 0.9460 to 0.9998 (Fig. S1b), however, because we scale synthetic discharges by their corresponding NWM peak flows (Eq. 4–5), NSE values tend to be high.

2.5.3 Pluvial

We generate pluvial scenarios with total precipitation depths ranging from 10 mm to 300 mm, incremented by 10 mm. Fill-Spill-Merge calculates a static maximum inundation map for each depth, while we force SFINCS with precipitation time series corresponding to each depth. SFINCS requires a precipitation time series rather than a total depth. We derive these time series

using the NOAA precipitation DDF table for Beaumont (Station ID 41-0611), which is located near the geographic midpoint between Silsbee and Port Arthur (NOAA, 2025b).

255 To generate the SFINCS precipitation time series for each depth scenario, we assign an annual recurrence interval (ARI) ranging from 1 yr to 1000 yr, with larger ARI values assigned to larger depths (Fig. S2). We then enter the DDF table with the scenario's ARI and depth, using regular grid interpolation to extract the corresponding storm duration. We calculate the precipitation intensity as a constant rate that is a function of the scenario's assigned depth and interpolated duration: the intensity is the scenario depth divided by the interpolated duration. The resulting precipitation scenario is a hyetograph with a
260 spatially uniform and temporally constant intensity applied over the interpolated duration at the beginning of each seven-day simulation, followed by zero rainfall for the remainder of the simulation.

For example, we assign a 2 yr ARI to the 50 mm depth scenario. Interpolating the DDF table shows that this ARI and depth combination corresponds to a storm duration of 0.7 h at Beaumont. The constant intensity needed to apply 50 mm of precipitation over 0.7 h is 71.43 mm h^{-1} . The precipitation time series supplied to SFINCS for the 50 mm depth scenario
265 therefore consists of 71.43 mm h^{-1} for the first 0.7 h of the seven-day simulation, followed by 0 mm h^{-1} for the remainder of the simulation. We repeat this process for each pluvial scenario.

2.6 Rating surfaces

We define rating surfaces as contour plots of maximum compound flood depth across pairwise combinations of flood drivers. We first estimate flood inundation for a finite ensemble of forcing combinations and magnitudes with a compound flood model,
270 in this case SCMs or SFINCS. Any model that outputs maximum flood inundation depth grids given varying magnitudes of compound flood forcings may be used. Then we construct rating surfaces by sampling the resulting high-resolution maximum depth grids at POI/HWM and interpolating two-dimensional contours of compound flood depth. These contours illustrate the compound flood depth response to variation in two flood drivers at a fixed location while the third driver remains constant. Rating surfaces allow estimation of compound flood depth for forcing combinations that were not explicitly simulated, given
275 that the forcing combination of interest is within the simulated forcing range. Though we model up to three compound flood drivers at each POI, we plot rating surfaces as two-dimensional contours of compound flood depth to present multiple data sources simply and clearly. Representing compound flood depth as a function of three forcings is possible, but pairwise contours improve interpretability and clarify individual and joint effects. We apply Gaussian smoothing with $\sigma = 3$ to reduce small-scale noise in the interpolated SFINCS rating surfaces (Virtanen et al., 2020). SCM rating surfaces remain unsmoothed because they
280 exhibit linear patterns without noise.

3 Results

Coastal-pluvial rating surfaces show that maximum flood depth at Port Arthur increases primarily with coastal water level and more modestly with precipitation (Fig. 4a–l). SCM estimates at Port Arthur HWM 1 and 2 vary only with coastal water level (Fig. 4g,i). This result is expected given Port Arthur's low-relief topography and proximity to the coast. At inland Silsbee,

285 maximum flood depth varies mainly with precipitation and is largely insensitive to coastal water level, as coastal inundation does not reach these locations (Fig. 4m–x). Coastal–pluvial rating surfaces show the closest agreement between SCM and SFINCS among the three forcing pairs. The models produce similar overall response patterns and depth ranges at most Port Arthur POI/HWM locations and at Silsbee POI 3. However, SFINCS captures more localized variation across the forcing combinations. The largest differences occur at Silsbee POI 1–2 and HWM 1–2, where the SCM and SFINCS rating surfaces
290 predict different precipitation-driven responses (Fig. 4m–p,s–v).

Fluvial–coastal rating surfaces show that maximum flood depth at Port Arthur is controlled primarily by coastal water level, with river discharge exerting a minor influence (Fig. 5a–l). The exception is the SCM estimate at POI 1, which also varies with river discharge (Fig. 5a). At inland Silsbee, the pattern reverses, with maximum flood depth varying primarily with river discharge rather than coastal water level (Fig. 5m–x). Several Silsbee locations are not inundated under the fluvial–coastal
295 forcing combinations (Fig. 5n,p,q,r,u,v), suggesting that pluvial flooding is a more dominant regime at these locations. SCMs and SFINCS produce similar response patterns at most POI/HWM locations. However, SCMs predict substantially greater depths than SFINCS at Silsbee POI 1 and 2, with maximum differences of nearly 2 m and 7 m, respectively (Fig. 5m–p). We will discuss the cause of these discrepancies (Sec. 4).

Fluvial–pluvial rating surfaces show mixed agreement between SCM and SFINCS (Fig. 6). At Port Arthur, maximum flood
300 depth varies primarily with precipitation, with the exception of the SCM estimate at POI 1, which indicates river discharge as the dominant flood driver (Fig. 6a–l). Port Arthur POI 1 is located within a terrain depression that is filled by the SCM Fill-Spill-Merge after approximately 200 mm of precipitation, after which river discharge contributes to additional depth variation. Both SCMs and SFINCS predict zero or nearly zero inundation at Port Arthur HWM 1 and 2 under most fluvial–pluvial forcing combinations, indicating that coastal forcing is the primary cause of flooding at those locations (Fig. 6g–j). At Silsbee, SCM
305 rating surfaces show flood depth varying with both precipitation and river discharge, whereas SFINCS rating surfaces vary primarily with precipitation (Fig. 6m–x). The largest differences in depth range again occur at Silsbee POI 1 and 2, where SCMs predict depths more than 2 m and 7 m greater than SFINCS, respectively (Fig. 6m–p). Despite these differences in predicted forcing contributions, SCMs and SFINCS predict similar depths at the Silsbee HWM locations when evaluated using Hurricane Harvey forcings (Fig. 6s–x).

310 We validate the rating surfaces approach by comparing predicted flood depths against observed Hurricane Harvey HWMs in Port Arthur and Silsbee (Fig. 7). We select three HWMs collected during Hurricane Harvey for each study area and calculate rating surfaces at their locations (Figs. 4–6, panels s–x). We extract predicted maximum flood depths from each rating surface using the maximum fluvial, pluvial, and coastal forcings observed during Harvey (Sec. 2.4). At Port Arthur, depth errors range from -0.52 m to 0.56 m for both SCM and SFINCS. At Silsbee, depth errors range from -0.53 m to 2.26 m with SCMs and
315 -0.53 m to 1.99 m with SFINCS. With the exceptions of HWM 2 at Port Arthur and HWM 3 at Silsbee, observed HWMs lie within the envelope of depths predicted across the three forcing pairs. Across both study areas, SCM and SFINCS predictions given the Harvey forcing combination are broadly similar, even at sites where predicted and observed depths diverge. This result may indicate that SCMs capture dominant patterns of hydrodynamic simulations despite their approximations. The largest discrepancies occur at the inland Silsbee sites, where pluvial and fluvial contributions are more uncertain due to low-

Coastal-Pluvial Rating Surfaces (L: SCM, R: SFINCS)

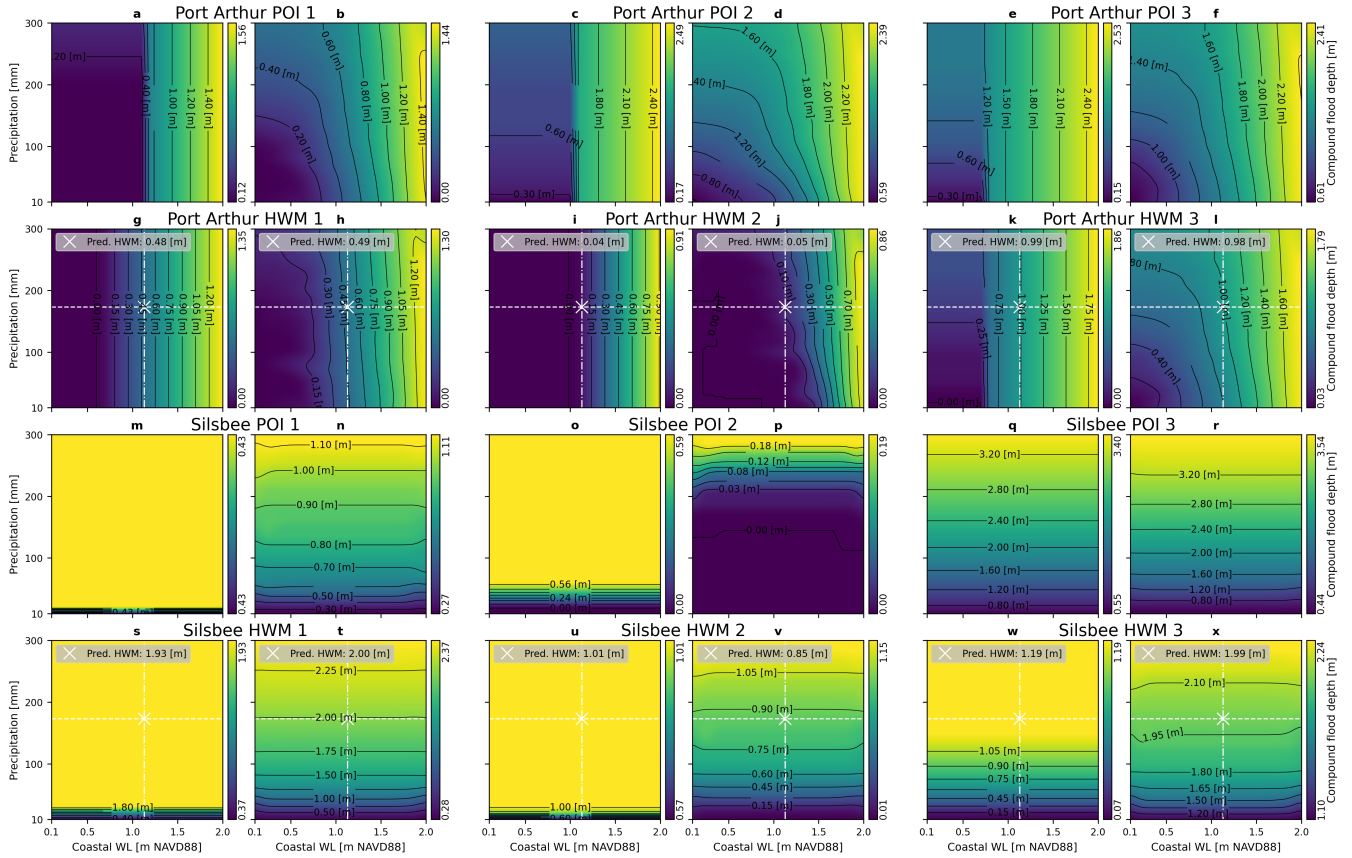


Figure 4. Coastal-pluvial rating surfaces derived from simplified conceptual models (SCMs; left columns) and SFINCS (right columns). Panels show compound flood depth as a function of coastal water level and precipitation across POI/HWM in both study areas.

320 relief topography and HWM collection near bridges and culverts. Uncertainties in the observed Hurricane Harvey forcings, including peak discharge reported by the NWM (Timilsina and Passalacqua, 2025) and extreme rainfall observations (Blake and Zelinsky, 2018), may also impact the accuracy of their corresponding rating surface-derived depths.

4 Discussion

Rating surfaces constructed from ensemble simulations allow maximum compound flood depth estimation across any pair
 325 of flood drivers within the modeled forcing range. The results reveal local variation in flood driver influence on maximum compound flood depth. Comparing rating surfaces constructed from different model classes helps to clarify where higher-fidelity hydrodynamic simulations improve estimates. In this section we revisit the research questions posed in the introduction, discuss limitations and uncertainties, and conclude.

Fluvial-Coastal Rating Surfaces (L: SCM, R: SFINCS)

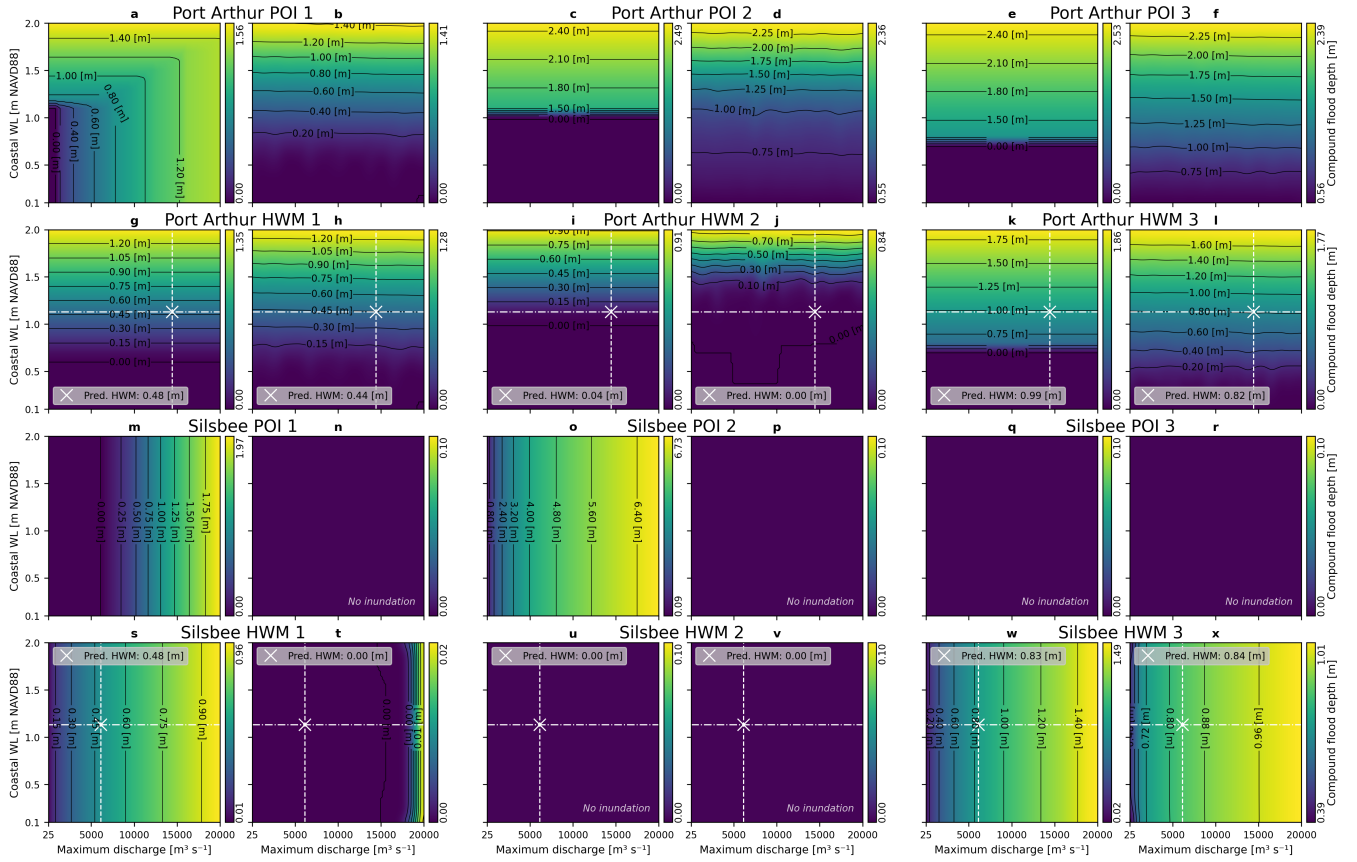


Figure 5. Fluvial-coastal rating surfaces derived from simplified conceptual models (SCMs; left columns) and SFINCS (right columns). Panels show compound flood depth as a function of maximum discharge and coastal water level across POI/HWM in both study areas.

4.1 RQ1: Estimating compound flood depth with rating surfaces

Rating surfaces convert ensembles of flood inundation simulations into location-specific relationships between maximum compound flood depth and pairs of forcing variables. Within the sampled forcing range, rating surfaces provide depth estimates for all forcing pairs, including pairs that were not explicitly simulated. We construct rating surfaces from both SCM and SFINCS simulations, demonstrating that the framework is independent of the underlying flood inundation model. Extending prior fluvial-coastal response surfaces for channel water levels (Muñoz et al., 2022), the rating surfaces we develop here represent maximum compound flood depth at POIs and HWMs across coastal-pluvial, fluvial-coastal, and fluvial-pluvial forcing pairs. This representation makes it possible to identify the relative influence of coastal water level, river discharge, and precipitation on maximum flood depth at nearby locations.

Fluvial-Pluvial Rating Surfaces (L: SCM, R: SFINCS)

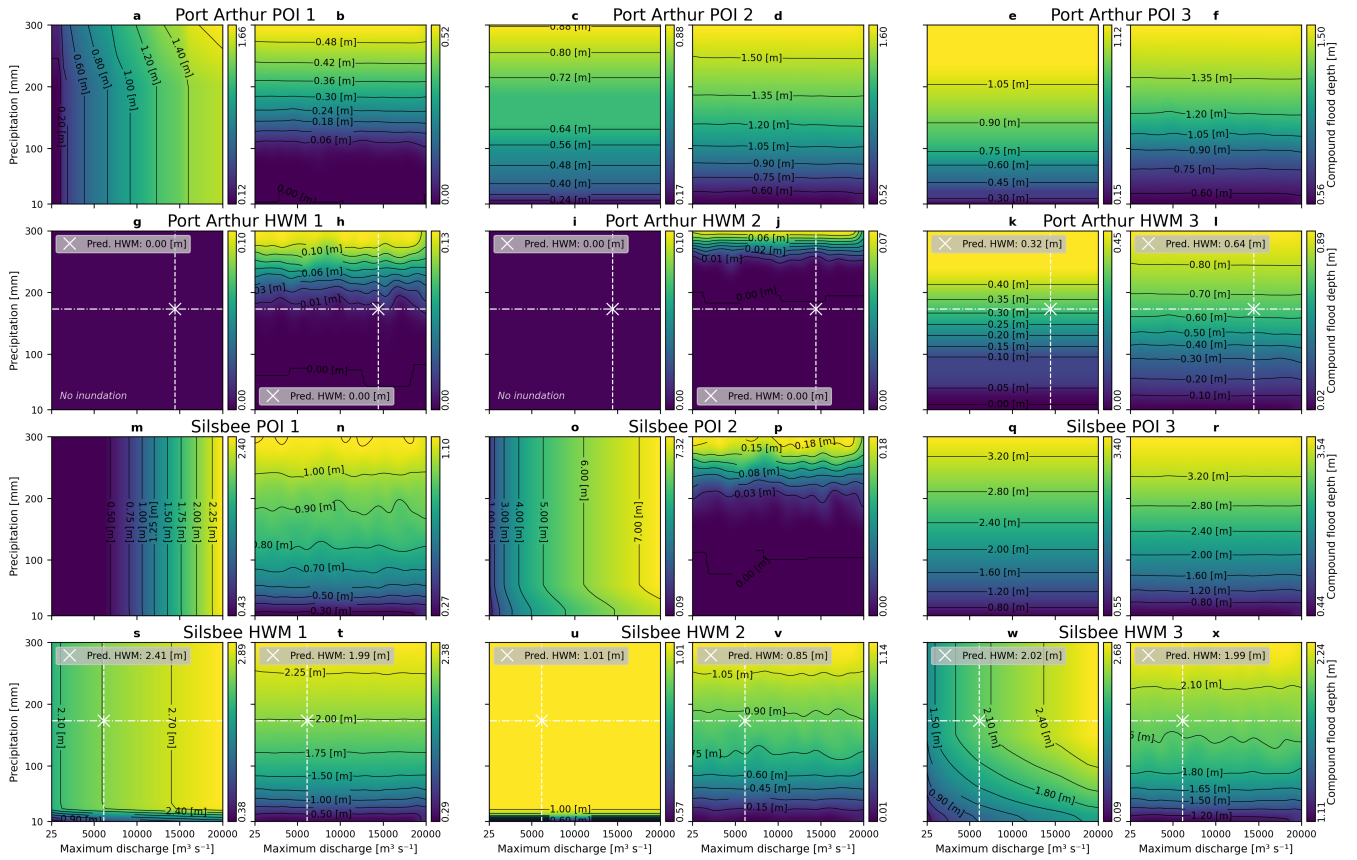


Figure 6. Fluvial–pluvial rating surfaces derived from simplified conceptual models (SCMs; left columns) and SFINCS (right columns). Panels show compound flood depth as a function of maximum discharge and precipitation across POI/HWM in the Port Arthur and Silsbee study areas.

4.2 RQ2: Local compound flood depth response

Rating surfaces reveal that the relative influence of flood drivers on maximum compound flood depth varies across POIs and HWMs. At Port Arthur, coastal–pluvial and fluvial–coastal rating surfaces vary strongly with coastal water level across most locations, while precipitation also modifies depth and river discharge has a less pronounced influence. In contrast, fluvial–pluvial rating surfaces at Port Arthur vary primarily with precipitation. These patterns are consistent with the low-lying coastal setting of Port Arthur, where coastal water levels strongly influence maximum inundation depth. The Silsbee rating surfaces exhibit greater spatial heterogeneity. Coastal water level has little influence on maximum compound flood depth at these inland sites; instead, precipitation, river discharge, or both account for the largest variation. This heterogeneity is particularly apparent in the fluvial–pluvial surfaces at Silsbee, where SCM estimates vary with both precipitation and river discharge, while SFINCS

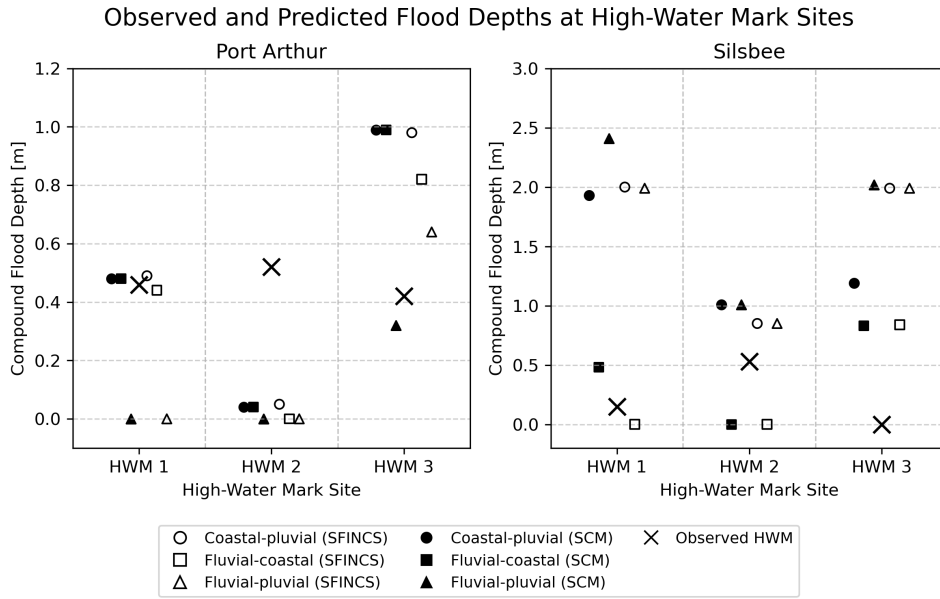


Figure 7. Observed and predicted high-water mark (HWM) flood depths at Port Arthur and Silsbee. Observed Harvey HWM depths are shown with predicted depths extracted from coastal–pluvial, fluvial–coastal, and fluvial–pluvial rating surfaces derived from SFINCS and simplified conceptual models (SCM).

estimates vary primarily with precipitation. This result shows that even among nearby inland locations, the relative importance of flood drivers can vary spatially and depend on the underlying flood model.

4.3 RQ3: Agreement between SCM- and SFINCS-derived rating surfaces

SCM-derived rating surfaces reproduce the first-order patterns of SFINCS-derived rating surfaces at many locations, particularly for coastal–pluvial scenarios in Port Arthur. Both approaches identify the same dominant flood driver in the majority of cases and produce comparable depth ranges at many POIs and HWMs. However, the agreement between SCMs and SFINCS is not uniform. Large discrepancies occur at Silsbee POI 1 and POI 2, where SCMs estimate greater fluvial contributions than SFINCS for both fluvial–coastal and fluvial–pluvial forcing pairs. These differences are due to a known limitation of HAND-based methods that causes increased inundation depth in isolated river segment catchments (Aristizabal et al., 2023). Because SFINCS is a hydrodynamic model, the SFINCS rating surfaces contain localized curvature and nonlinear patterns that SCMs do not reproduce with their simplified combination rules (Sec. 2.2.1).

4.4 Limitations and uncertainties

Rating surfaces inherit structural limitations from their underlying flood inundation mapping tools. In the case of SCM-based rating surfaces, we estimate inundation extent and depth with static topographic relationships, rather than solving a form of

the shallow-water equations. SCM-based estimates do not consider hydrodynamic processes such as flow routing, backwater effects, or drainage infrastructure. These limitations are particularly important on low-relief terrain, where static approaches like HAND and c-HAND may overestimate flood inundation (Johnson et al., 2019; Garousi-Nejad et al., 2019; Scriven et al., 2021; Wang et al., 2024). Depth estimates derived from SCMs should be interpreted as efficient, first-order approximations of maximum inundation scenarios, rather than event-specific hydrodynamic predictions. The interaction between coastal and inland flooding is nonlinear (Bilskie and Hagen, 2018); accordingly, SCM-derived rating surfaces may under- or overestimate compound flood depth at individual locations. We compare with SFINCS to identify where our SCM combination rules for compound flood depth (Eqs. 1–3) reproduce first-order depth patterns and where explicit hydrodynamic representation becomes important.

We construct rating surfaces from pairwise combinations of flood drivers, varying two flood drivers while holding the third driver at a baseline value. In reality compound flood depth may depend on interactions between three or more flood drivers (Zscheischler et al., 2018). We depict maximum compound flood depth at POIs as two-dimensional rating surfaces to facilitate interpretability and comparison between SCM and SFINCS results. In addition to limiting our analysis to two varying flood drivers, we simplify the spatial and temporal representation of the individual forcings within each scenario. The coastal simulations in this study apply a constant water level boundary rather than a tidal or storm-surge hydrograph. This choice supports comparison with static maximum coastal inundation estimates from c-HAND, but does not represent event-specific details including surge timing or tidal effects. Similarly, we apply spatially uniform precipitation with a simplified temporal distribution for the SFINCS simulations. Rating surfaces should therefore be interpreted as conditional maximum inundation approximations, rather than reconstructions of time-varying flood events.

We assume saturated soil and an at-capacity drainage system for both SCMs and SFINCS. Fill-Spill-Merge does not represent infiltration or drainage infrastructure; we neglect infiltration in SFINCS to impose a consistent saturated, drainage-limited condition across approaches. This choice avoids confounding the model comparison with differences in infiltration representation, allowing results to be interpreted more directly in terms of model structure. Soil moisture observations during Hurricane Harvey and Tropical Storm Imelda in Southeast Texas support the plausibility of saturated soil conditions during intense rainfall events, and local drainage regulations indicate that drainage systems may also be capacity-limited during those events (Case et al., 2021; Jefferson County Drainage District No. 7, 2019). However, representing infiltration does improve the accuracy of extreme flood simulations (Li et al., 2022). By neglecting infiltration, we may overestimate pluvial contributions to compound flood depth at POIs. So, maximum compound flood depths predicted by rating surfaces may be more applicable during intense events where saturated soil and capacity-limited drainage are more likely.

Rating surface accuracy also depends on the quality of input datasets, including elevation, hydrography, land cover, and forcings. Missing or inaccurate hydrography can affect fluvial inundation accuracy, for example, the absence of an NHDPlusV2 MR flowline along part of the Sabine–Neches Waterway may bias local fluvial depth estimates. Modeled flood depth is also sensitive to DEM quality, especially on low-relief terrain. Additionally, uncertainty in observed forcings during a given event affects the accuracy of maximum flood depths extracted from rating surfaces. Although prior studies have evaluated the models used in this study (other than Fill-Spill-Merge) against past events (Zheng et al., 2022; Wang et al., 2024; Sebastian et al.,

2021; Chowdhury et al., 2026), and we compare rating surface estimates of maximum compound flood depth with Hurricane Harvey high-water marks (Fig. 7), this study does not calibrate to or validate against other tropical cyclones that have impacted Southeast Texas.

4.5 Conclusions and future work

400 Independent of the underlying flood model, rating surfaces allow maximum compound flood depth to be estimated for any pair of forcings within the modeled range. This representation permits exploration of an arbitrary number of forcing scenarios without requiring additional model runs, despite modeling only a finite subset of scenarios. In this sense, rating surfaces extend the role of a stage-discharge rating curve to compound flooding by providing a compact, location-specific relationship between multiple flood drivers and maximum flood depth.

405 Rating surfaces do not characterize the frequency at which forcing combinations occur or the relative contributions of flood drivers to historical events, which can vary spatially and seasonally (Sohrabi et al., 2025). We select forcing combinations in this study that span physically relevant conditions in Southeast Texas, without addressing their probabilities of occurring jointly. In order to quantify the joint likelihood of paired coastal, fluvial, or pluvial forcings, multivariate statistical analysis is required (e.g., Jane et al., 2025; Moftakhari et al., 2019; Zheng et al., 2014). Future work could pair rating surfaces with
410 joint probability models of compound flood drivers, similar to some probabilistic flood hazard assessments that have been implemented in Dutch regulatory frameworks (Geerse et al., 2011; Duits, M. T., 2004).

This study introduces rating surfaces as a method to quantify and visualize compound flood depth as a function of two flood drivers at points of interest. We generate large ensembles of high-resolution inundation scenarios using both simplified conceptual models and a hydrodynamic model and sample these scenarios at POIs to construct rating surfaces. The resulting
415 surfaces provide an interpretable representation of how local flood depth responds to combinations of precipitation, discharge, and coastal water level. Rating surfaces from both simplified and hydrodynamic modeling approaches capture relatively consistent first-order patterns across the range of forcings that we investigate. However, the hydrodynamic model captures finer-scale nonlinearities and local differences in interactions among flood drivers that the simplified models do not represent. These differences suggest that simplified models may be well suited to rapid scenario exploration, but hydrodynamic modeling is
420 necessary when nonlinear interactions substantially affect local compound flood depth estimates. Validation against Hurricane Harvey high-water marks shows that rating surfaces reproduce event-scale magnitudes within the limits of underlying topography, hydrography, and historical forcing uncertainties. The spatial variability we observe across nearby POIs underscores the importance of neighborhood-scale analyses and high-resolution elevation data when assessing flood hazards in developed low-lying areas. Rating surfaces are a flexible tool for representing compound flooding at locations of interest across diverse
425 modeling environments.

Supplement. The supplement related to this article is available online at [x].

Code and data availability. All datasets used in this study are publicly available online from the USGS, TNRIS, NOAA, and the U. S. Census Bureau. pyGeoFlood (which implements GeoFlood, c-HAND, and Fill-Spill-Merge) and SFINCS are free and open-source software (<https://passah2o.github.io/pygeoflood/>, <https://sfincs.readthedocs.io/en/latest/>).

430 *Author contributions.* MW obtained the datasets, performed the analysis, and wrote the original draft. PP and HM contributed to this study's conceptualization and design. PP, HM, and MW edited the draft. PP provided research supervision and funding acquisition. BH assisted with data analysis.

Competing interests. The contact author has declared that none of the authors has any competing interests.

435 *Acknowledgements.* We are grateful to Wonhyun Lee and David Maidment for helpful conversations, as well as the Texas Advanced Computing Center (TACC) at UT Austin for providing computational resources that have contributed to the research results reported within this paper (URL: <http://www.tacc.utexas.edu>). We thank two anonymous reviewers for feedback that greatly improved this paper.

Financial support. This material is based upon work supported by the U.S. Department of Energy, Office of Science, Biological and Environmental Research Program under Award Number DE-SC0023216, the NOAA Adaptation Sciences Program (NOAA-OAR-CPO-2021-2006389), the Cockrell School of Engineering, and Planet Texas 2050, a research grand challenge at the University of Texas at Austin.

440 References

- Aristizabal, F., Salas, F., Petrochenkov, G., Grout, T., Avant, B., Bates, B., Spies, R., Chadwick, N., Wills, Z., and Judge, J.: Extending Height Above Nearest Drainage to Model Multiple Fluvial Sources in Flood Inundation Mapping Applications for the U.S. National Water Model, *Water Resources Research*, 59, e2022WR032039, <https://doi.org/10.1029/2022WR032039>, 2023.
- Barnes, R., Callaghan, K. L., and Wickert, A. D.: Computing water flow through complex landscapes - Part 3: Fill-Spill-Merge: Flow routing
445 in depression hierarchies, *Earth Surface Dynamics*, 9, 105–121, <https://doi.org/10.5194/esurf-9-105-2021>, 2021.
- Bates, P. D.: Flood Inundation Prediction, *Annual Review of Fluid Mechanics*, 54, 287–315, <https://doi.org/10.1146/annurev-fluid-030121-113138>, 2022.
- Bevacqua, E., Vousdoukas, M. I., Zappa, G., Hodges, K., Shepherd, T. G., Maraun, D., Mentaschi, L., and Feyen, L.: More meteorological events that drive compound coastal flooding are projected under climate change, *Communications Earth & Environment*, 1, 1–11,
450 <https://doi.org/10.1038/s43247-020-00044-z>, 2020.
- Bilskie, M. V. and Hagen, S. C.: Defining Flood Zone Transitions in Low-Gradient Coastal Regions, *Geophysical Research Letters*, 45, 2761–2770, <https://doi.org/10.1002/2018GL077524>, 2018.
- Bilskie, M. V., Zhao, H., Resio, D., Atkinson, J., Cobell, Z., and Hagen, S. C.: Enhancing Flood Hazard Assessments in Coastal Louisiana Through Coupled Hydrologic and Surge Processes, *Frontiers in Water*, 3, <https://doi.org/10.3389/frwa.2021.609231>, 2021.
- 455 Blake, E. S. and Zelinsky, D. A.: National Hurricane Center Tropical Cyclone Report: Hurricane Harvey, https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf, 2018.
- Case, J. L., Wood, L. T., Blaes, J. L., White, K. D., Hain, C. R., and Schultz, C. J.: Soil Moisture Responses Associated with Significant Tropical Cyclone Rainfall Events, *Journal of Operational Meteorology*, pp. 1–17, <https://doi.org/10.15191/nwajom.2021.0901>, 2021.
- Chowdhury, M. E., Lee, J.-W., and Lee, W.: Spatiotemporal quantification of relative contributions of compound flood drivers using Shapley
460 value-based approach, *Journal of Hydrology*, 677, 135–150, <https://doi.org/10.1016/j.jhydrol.2026.135808>, 2026.
- Cosgrove, B., Gochis, D., Flowers, T., Dugger, A., Ogden, F., Graziano, T., Clark, E., Cabell, R., Casiday, N., Cui, Z., Eicher, K., Fall, G., Feng, X., Fitzgerald, K., Frazier, N., George, C., Gibbs, R., Hernandez, L., Johnson, D., Jones, R., Karsten, L., Kefelegn, H., Kitzmiller, D., Lee, H., Liu, Y., Mashriqui, H., Mattern, D., McCluskey, A., McCreight, J. L., McDaniel, R., Midekisa, A., Newman, A., Pan, L., Pham, C., RafieeiNasab, A., Rasmussen, R., Read, L., Rezaeianzadeh, M., Salas, F., Sang, D., Sampson, K., Schneider, T., Shi, Q., Sood, G., Wood,
465 A., Wu, W., Yates, D., Yu, W., and Zhang, Y.: NOAA’s National Water Model: Advancing operational hydrology through continental-scale modeling, *JAWRA Journal of the American Water Resources Association*, 60, 247–272, <https://doi.org/10.1111/1752-1688.13184>, 2024.
- Crossett, K., Ache, B., Pacheco, P., and Haber, K.: National Coastal Population Report, <https://cdn.oceanservice.noaa.gov/oceanserviceprod/facts/coastal-population-report.pdf>, 2013.
- Dasgupta, A., Grimaldi, S., Ramsankaran, R., Pauwels, V. R. N., and Walker, J. P.: A simple framework for calibrating hydraulic flood
470 inundation models using Crowd-sourced water levels, *Journal of Hydrology*, 614, 128–147, <https://doi.org/10.1016/j.jhydrol.2022.128467>, 2022.
- Duits, M. T.: Handleiding Hydra-B – Geavanceerde gebruikers (versie 3.0), Rijkswaterstaat, 221559, <https://open.rijkswaterstaat.nl/@167823/handleiding-hydra-geavanceerde/>, 2004.
- Dullaart, J. C. M., Muis, S., Bloemendaal, N., Chertova, M. V., Couasnon, A., and Aerts, J. C. J. H.: Accounting for tropical cyclones
475 more than doubles the global population exposed to low-probability coastal flooding, *Communications Earth & Environment*, 2, 1–11, <https://doi.org/10.1038/s43247-021-00204-9>, 2021.

- Gallant, J. C. and Dowling, T. I.: A multiresolution index of valley bottom flatness for mapping depositional areas, *Water Resources Research*, 39, <https://doi.org/10.1029/2002WR001426>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2002WR001426>, 2003.
- Garousi-Nejad, I., Tarboton, D. G., Aboutaleb, M., and Torres-Rua, A. F.: Terrain Analysis Enhancements to the Height Above Nearest Drainage Flood Inundation Mapping Method, *Water Resources Research*, 55, 7983–8009, <https://doi.org/10.1029/2019WR024837>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2019WR024837>, 2019.
- Geerse, C., Slomp, R., and de Waal, H.: Hydra-Zoet for the fresh water systems in the Netherlands, *Rijkswaterstaat*, 501244, <https://open.rijkswaterstaat.nl/@171393/hydra-zoet-probabilistic-model-for-the/>, 2011.
- Green, J., Haigh, I. D., Quinn, N., Neal, J., Wahl, T., Wood, M., Eilander, D., de Ruiter, M., Ward, P., and Camus, P.: Review article: A comprehensive review of compound flooding literature with a focus on coastal and estuarine regions, *Natural Hazards and Earth System Sciences*, 25, 747–816, <https://doi.org/10.5194/nhess-25-747-2025>, 2025.
- Halton, J. H.: On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals, *Numerische Mathematik*, 2, 84–90, <https://doi.org/10.1007/BF01386213>, 1960.
- Hamidi, E., Peter, B. G., Muñoz, D. F., Moftakhari, H., and Moradkhani, H.: Fast Flood Extent Monitoring With SAR Change Detection Using Google Earth Engine, *IEEE Transactions on Geoscience and Remote Sensing*, 61, 1–19, <https://doi.org/10.1109/TGRS.2023.3240097>, conference Name: IEEE Transactions on Geoscience and Remote Sensing, 2023.
- Hao, Z. and Singh, V. P.: Compound Events under Global Warming: A Dependence Perspective, *Journal of Hydrologic Engineering*, 25, 03120001, [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0001991](https://doi.org/10.1061/(ASCE)HE.1943-5584.0001991), 2020.
- Hendry, A., Haigh, I. D., Nicholls, R. J., Winter, H., Neal, R., Wahl, T., Joly-Laugel, A., and Darby, S. E.: Assessing the characteristics and drivers of compound flooding events around the UK coast, *Hydrology and Earth System Sciences*, 23, 3117–3139, <https://doi.org/10.5194/hess-23-3117-2019>, 2019.
- Horritt, M. and Bates, P.: Evaluation of 1D and 2D numerical models for predicting river flood inundation, *Journal of hydrology*, 268, 87–99, 2002.
- Jafarzadegan, K., Moradkhani, H., Pappenberger, F., Moftakhari, H., Bates, P., Abbaszadeh, P., Marsooli, R., Ferreira, C., Cloke, H. L., Ogden, F., and Duan, Q.: Recent Advances and New Frontiers in Riverine and Coastal Flood Modeling, *Reviews of Geophysics*, 61, e2022RG000788, <https://doi.org/10.1029/2022RG000788>, 2023.
- Jane, R., Santiago-Collazo, F. L., Serafin, K. A., Gori, A., Peña, F., and Wahl, T.: Chapter 5 - Compound hazards during tropical cyclones, in: *Tropical Cyclones and Associated Impacts*, edited by Villarini, G., Vecchi, G. A., and Scoccimarro, E., pp. 95–119, Elsevier, ISBN 978-0-323-95390-0, <https://doi.org/10.1016/B978-0-323-95390-0.00005-4>, 2025.
- Jefferson County Drainage District No. 7: Drainage Criteria Manual, https://www.dd7.org/files/6d75b42a9/DD7+Drainage+Criteria+Manual+11-19-19-Final_1.pdf, 2019.
- Johnson, J. M., Munasinghe, D., Eyelade, D., and Cohen, S.: An integrated evaluation of the National Water Model (NWM)–Height Above Nearest Drainage (HAND) flood mapping methodology, *Natural Hazards and Earth System Sciences*, 19, 2405–2420, <https://doi.org/10.5194/nhess-19-2405-2019>, 2019.
- Kling, H., Fuchs, M., and Paulin, M.: Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios, *Journal of Hydrology*, 424–425, 264–277, <https://doi.org/10.1016/j.jhydrol.2012.01.011>, 2012.
- Lee, W., Sun, A. Y., and Scanlon, B. R.: Probabilistic storm surge and flood-inundation modeling of the Texas gulf coast using super-fast INundation of CoastS (SFINCS), *Coastal Engineering*, 198, 104721, <https://doi.org/10.1016/j.coastaleng.2025.104721>, 2025.

- Leijnse, T., van Ormondt, M., Nederhoff, K., and van Dongeren, A.: Modeling compound flooding in coastal systems using a computationally efficient reduced-physics solver: Including fluvial, pluvial, tidal, wind- and wave-driven processes, *Coastal Engineering*, 163, 103 796, <https://doi.org/10.1016/j.coastaleng.2020.103796>, 2021.
- Lewis, M., Bates, P., Horsburgh, K., Neal, J., and Schumann, G.: A storm surge inundation model of the northern Bay of Bengal using publicly available data, *Quarterly Journal of the Royal Meteorological Society*, 139, 358–369, <https://doi.org/10.1002/qj.2040>, <https://rsmets.onlinelibrary.wiley.com/doi/pdf/10.1002/qj.2040>, 2013.
- Lhomme, J., Sayers, P., Gouldby, B., Samuels, P., Wills, M., and Mulet-Marti, J.: Recent development and application of a rapid flood spreading method, in: *Flood Risk Management: Research and Practice*, pp. 15–24, Taylor & Francis Group, London, ISBN 978-0-415-48507-4, http://www.sayersandpartners.co.uk/uploads/6/2/0/9/6209349/2008_lhomme_sayers_et_al_-_recent_development_and_application_of_a_rapid_flood_spreading_method_floodrisk08.pdf, 2009.
- Li, Z., Chen, M., Gao, S., Wen, Y., Gourley, J. J., Yang, T., Kolar, R., and Hong, Y.: Can re-infiltration process be ignored for flood inundation mapping and prediction during extreme storms? A case study in Texas Gulf Coast region, *Environmental Modelling & Software*, 155, 105 450, <https://doi.org/10.1016/j.envsoft.2022.105450>, 2022.
- Loveland, M., Kiaghadi, A., Dawson, C. N., Rifai, H. S., Misra, S., Mosser, H., and Parola, A.: Developing a Modeling Framework to Simulate Compound Flooding: When Storm Surge Interacts With Riverine Flow, *Frontiers in Climate*, 2, <https://doi.org/10.3389/fclim.2020.609610>, 2021.
- Manfreda, S., Di Leo, M., and Sole, A.: Detection of Flood-Prone Areas Using Digital Elevation Models, *Journal of Hydrologic Engineering*, 16, 781–790, [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0000367](https://doi.org/10.1061/(ASCE)HE.1943-5584.0000367), 2011.
- McKay, L., Bondelid, T., Dewald, T., Johnston, J., Moore, R., and Rea, A.: NHDPlus Version 2: User Guide, https://www.epa.gov/system/files/documents/2023-04/NHDPlusV2_User_Guide.pdf, 2012.
- Miura, Y., Dinenis, P. C., Mandli, K. T., Deodatis, G., and Bienstock, D.: Optimization of Coastal Protections in the Presence of Climate Change, *Frontiers in Climate*, 3, <https://doi.org/10.3389/fclim.2021.613293>, 2021a.
- Miura, Y., Mandli, K. T., and Deodatis, G.: High-Speed GIS-Based Simulation of Storm Surge–Induced Flooding Accounting for Sea Level Rise, *Natural Hazards Review*, 22, 04021 018, [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000465](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000465), 2021b.
- Moftakhari, H., Schubert, J. E., AghaKouchak, A., Matthew, R. A., and Sanders, B. F.: Linking statistical and hydrodynamic modeling for compound flood hazard assessment in tidal channels and estuaries, *Advances in Water Resources*, 128, 28–38, <https://doi.org/10.1016/j.advwatres.2019.04.009>, 2019.
- Moftakhari, H. R., Salvadori, G., AghaKouchak, A., Sanders, B. F., and Matthew, R. A.: Compounding effects of sea level rise and fluvial flooding, *Proceedings of the National Academy of Sciences*, 114, 9785–9790, <https://doi.org/10.1073/pnas.1620325114>, 2017.
- Murphy, S., Wang, M., Cheng, C.-S., Passalacqua, P., and Leite, F.: Land-use analysis using infrastructure representations and high-resolution flood inundation mapping techniques, *International Journal of Disaster Risk Reduction*, 123, 105 518, <https://doi.org/10.1016/j.ijdr.2025.105518>, 2025.
- Muñoz, D. F., Moftakhari, H., Kumar, M., and Moradkhani, H.: Compound Effects of Flood Drivers, Sea Level Rise, and Dredging Protocols on Vessel Navigability and Wetland Inundation Dynamics, *Frontiers in Marine Science*, 9, <https://doi.org/10.3389/fmars.2022.906376>, 2022.
- Nardi, F., Vivoni, E. R., and Grimaldi, S.: Investigating a floodplain scaling relation using a hydrogeomorphic delineation method, *Water Resources Research*, 42, <https://doi.org/10.1029/2005WR004155>, 2006.

- Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models part I — A discussion of principles, *Journal of Hydrology*, 10, 282–290, [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6), 1970.
- Neumann, B., Vafeidis, A. T., Zimmermann, J., and Nicholls, R. J.: Future Coastal Population Growth and Exposure to Sea-Level Rise and Coastal Flooding - A Global Assessment, *PLOS ONE*, 10, e0118571, <https://doi.org/10.1371/journal.pone.0118571>, 2015.
- 555 NOAA: BlueTopo, <https://www.fisheries.noaa.gov/inport/item/75311>, 2025a.
- NOAA: NOAA Atlas 14 Point Precipitation Frequency Estimates: TX, https://hdsc.nws.noaa.gov/pfds/pfds_map_cont.html?bkmrk=tx, 2025b.
- Preisser, M., Passalacqua, P., Bixler, R. P., and Hofmann, J.: Intersecting near-real time fluvial and pluvial inundation estimates with sociodemographic vulnerability to quantify a household flood impact index, *Hydrology and Earth System Sciences*, 26, 3941–3964, <https://doi.org/10.5194/hess-26-3941-2022>, 2022.
- 560 Preisser, M., Passalacqua, P., Bixler, R. P., and Boyles, S.: A network-based analysis of critical resource accessibility during floods, *Frontiers in Water*, 5, <https://www.frontiersin.org/journals/water/articles/10.3389/frwa.2023.1278205>, 2023.
- Reimann, L., Vafeidis, A. T., and Honsel, L. E.: Population development as a driver of coastal risk: Current trends and future pathways, *Cambridge Prisms: Coastal Futures*, 1, e14, <https://doi.org/10.1017/cft.2023.3>, 2023.
- 565 Samela, C., Troy, T. J., and Manfreda, S.: Geomorphic classifiers for flood-prone areas delineation for data-scarce environments, *Advances in Water Resources*, 102, 13–28, <https://doi.org/10.1016/j.advwatres.2017.01.007>, 2017.
- Santiago-Collazo, F. L., Bilskie, M. V., and Hagen, S. C.: A comprehensive review of compound inundation models in low-gradient coastal watersheds, *Environmental Modelling & Software*, 119, 166–181, <https://doi.org/10.1016/j.envsoft.2019.06.002>, 2019.
- Santiago-Collazo, F. L., Bilskie, M. V., Bacopoulos, P., and Hagen, S. C.: Compound Inundation Modeling of a 1-D Idealized Coastal Watershed Using a Reduced-Physics Approach, *Water Resources Research*, 60, e2023WR035718, <https://doi.org/10.1029/2023WR035718>, [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2023WR035718](https://onlinelibrary.wiley.com/doi/pdf/10.1029/2023WR035718), 2024.
- 570 Schwarz, G. E., Jackson, S. E., and Wieczorek, M. E.: Select Attributes for NHDPlus Version 2.1 Reach Catchments and Modified Network Routed Upstream Watersheds for the Conterminous United States (ver. 4.0, August 2023), <https://doi.org/10.5066/F7765D7V>, 2018.
- Scriven, B. W. G., McGrath, H., and Stefanakis, E.: GIS derived synthetic rating curves and HAND model to support on-the-fly flood mapping, *Natural Hazards*, 109, 1629–1653, <https://doi.org/10.1007/s11069-021-04892-6>, 2021.
- 575 Sebastian, A., Bader, D. J., Nederhoff, C. M., Leijnse, T. W. B., Bricker, J. D., and Aarninkhof, S. G. J.: Hindcast of pluvial, fluvial, and coastal flood damage in Houston, Texas during Hurricane Harvey (2017) using SFINCS, *Natural Hazards*, 109, 2343–2362, <https://doi.org/10.1007/s11069-021-04922-3>, 2021.
- SETx-UIFL: Southeast Texas Urban Integrated Field Laboratory Annual Report Year 2, <https://utexas.app.box.com/s/b9cu8a3qupi8zip32xg2p2xcvi2bvike>, 2024.
- 580 Shen, Y., Morsy, M. M., Huxley, C., Tahvildari, N., and Goodall, J. L.: Flood risk assessment and increased resilience for coastal urban watersheds under the combined impact of storm tide and heavy rainfall, *Journal of Hydrology*, 579, 124–159, <https://doi.org/10.1016/j.jhydrol.2019.124159>, 2019.
- Shi, P., Lyu, K., Li, Z., Yang, T., Xu, C.-Y., Hao, X., and Xiao, J.: A Novel Topography-Based Approach for Real-Time Flood Inundation Mapping, *Water Resources Research*, 61, e2024WR037851, <https://doi.org/10.1029/2024WR037851>, [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2024WR037851](https://onlinelibrary.wiley.com/doi/pdf/10.1029/2024WR037851), 2025.

- Silverman, A. I., Brain, T., Branco, B., Challagonda, P. s. v., Choi, P., Fischman, R., Graziano, K., Hénaff, E., Mydlarz, C., Rothman, P., and Toledo-Crow, R.: Making waves: Uses of real-time, hyperlocal flood sensor data for emergency management, resiliency planning, and flood impact mitigation, *Water Research*, 220, 118 648, <https://doi.org/10.1016/j.watres.2022.118648>, 2022.
- 590 Smith, A. B.: U.S. Billion-dollar Weather and Climate Disasters, <https://doi.org/10.25921/STKW-7W73>, 2024.
- Sohrabi, M., Moftakhari, H., and Moradkhani, H.: Analyzing Compound Flooding Drivers Across the US Gulf Coast States, *Geophysical Research Letters*, 52, e2025GL114 769, <https://doi.org/10.1029/2025GL114769>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2025GL114769>, 2025.
- Tellman, B., Sullivan, J. A., Kuhn, C., Kettner, A. J., Doyle, C. S., Brakenridge, G. R., Erickson, T. A., and Slayback, D. A.: Satellite imaging reveals increased proportion of population exposed to floods, *Nature*, 596, 80–86, <https://doi.org/10.1038/s41586-021-03695-w>, 2021.
- 595 Teng, J., Jakeman, A. J., Vaze, J., Croke, B. F. W., Dutta, D., and Kim, S.: Flood inundation modelling: A review of methods, recent advances and uncertainty analysis, *Environmental Modelling and Software*, 90, 201–216, <https://doi.org/10.1016/j.envsoft.2017.01.006>, 2017.
- Timilsina, S. and Passalacqua, P.: A comparative analysis of national water model versions 2.1 and 3.0 reveals advances and challenges in streamflow predictions during storm events, *Journal of Hydrology: Regional Studies*, 58, 102 196, <https://doi.org/10.1016/j.ejrh.2025.102196>, 2025.
- 600 TNRIS: Jefferson, Liberty, & Chambers Counties Lidar, <https://data.geographic.texas.gov/collection/?c=12342f12-2d74-44c4-9f00-a5c12ac2659c>, 2017.
- TxDOT: Hurricane preparation - evacuation and contraflow routes, <https://www.txdot.gov/safety/severe-weather/hurricane-preparation.html>, 2025.
- 605 US Census Bureau: TIGER/Line Shapefiles, <https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html>, section: Government, 2025.
- U.S. Congress: JEC Report on Economic Cost of Flooding, <https://www.jec.senate.gov/public/index.cfm/democrats/2024/6/flooding-costs-the-u-s-between-179-8-and-496-0-billion-each-year>, 2024.
- US EPA: NHDPlus Texas Data (Vector Processing Unit 12), <https://www.epa.gov/waterdata/nhdplus-texas-data-vector-processing-unit-12>, 2015.
- 610 USACE: HEC-RAS 2D User’s Manual, <https://www.hec.usace.army.mil/confluence/rasdocs/r2dum/latest>, 2025.
- USGS: 3D Elevation Program Digital Elevation Models, <https://apps.nationalmap.gov/downloader/#/>, 2024.
- USGS: Annual National Land Cover Database (NLCD) Collection 1 Products (ver. 1.1, June 2025), <https://doi.org/10.5066/P94UXNTS>, 2025.
- 615 USGS and Arctur, D.: USGS - Harvey High Water Marks, <https://doi.org/10.4211/hs.615d426f70cc4346875c725b4b8fdc59>, 2018.
- van Ormondt, M., Leijnse, T., de Goede, R., Nederhoff, K., and van Dongeren, A.: Subgrid corrections for the linear inertial equations of a compound flood model – a case study using SFINCS 2.1.1 Dollerup release, *Geoscientific Model Development*, 18, 843–861, <https://doi.org/10.5194/gmd-18-843-2025>, 2025.
- Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., Carey, C. J., Polat, I., Feng, Y., Moore, E. W., VanderPlas, J., Laxalde, D., Perktold, J., Cimrman, R., Henriksen, I., Quintero, E. A., Harris, C. R., Archibald, A. M., Ribeiro, A. H., Pedregosa, F., van Mulbregt, P., and SciPy 1.0 Contributors: SciPy 1.0: fundamental algorithms for scientific computing in Python, *Nature Methods*, 17, 261–272, <https://doi.org/10.1038/s41592-019-0686-2>, 2020.
- 620

- Wahl, T., Jain, S., Bender, J., Meyers, S. D., and Luther, M. E.: Increasing risk of compound flooding from storm surge and rainfall for major
625 US cities, *Nature Climate Change*, 5, 1093–1097, <https://doi.org/10.1038/nclimate2736>, 2015.
- Wallemacq, P., Below, R., and McClean, D.: *Economic losses, poverty & disasters: 1998-2017*, United Nations Office for Disaster Risk
Reduction, 2018.
- Wang, M., Passalacqua, P., Cai, S., and Dawson, C.: c-HAND: near real-time coastal flood mapping, *Frontiers in Water*, 6,
<https://doi.org/10.3389/frwa.2024.1329109>, 2024.
- 630 Westerink, J. J., Luettich, R. A., Baptista, A. M., Scheffner, N. W., and Farrar, P.: Tide and Storm Surge Predictions Using Finite Element
Model, *Journal of Hydraulic Engineering*, 118, 1373–1390, [https://doi.org/10.1061/\(ASCE\)0733-9429\(1992\)118:10\(1373\)](https://doi.org/10.1061/(ASCE)0733-9429(1992)118:10(1373)), 1992.
- Wijetunge, J. J. and Neluwala, N. G. P. B.: Compound flood hazard assessment and analysis due to tropical cyclone-induced storm
surges, waves and precipitation: a case study for coastal lowlands of Kelani river basin in Sri Lanka, *Natural Hazards*, 116, 3979–4007,
<https://doi.org/10.1007/s11069-023-05846-w>, 2023.
- 635 Williams, W. A., Jensen, M. E., Winne, J. C., and Redmond, R. L.: An Automated Technique for Delineating and Characterizing Valley-
Bottom Settings, *Environmental Monitoring and Assessment*, 64, 105–114, <https://doi.org/10.1023/A:1006471427421>, 2000.
- Zheng, F., Westra, S., and Sisson, S. A.: Quantifying the dependence between extreme rainfall and storm surge in the coastal zone, *Journal
of Hydrology*, 505, 172–187, <https://doi.org/10.1016/j.jhydrol.2013.09.054>, 2013.
- Zheng, F., Westra, S., Leonard, M., and Sisson, S. A.: Modeling dependence between extreme rainfall and storm surge
640 to estimate coastal flooding risk, *Water Resources Research*, 50, 2050–2071, <https://doi.org/10.1002/2013WR014616>, _eprint:
<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2013WR014616>, 2014.
- Zheng, X., Maidment, D. R., Tarboton, D. G., Liu, Y. Y., and Passalacqua, P.: GeoFlood: Large-Scale Flood Inundation Mapping Based on
High-Resolution Terrain Analysis, *Water Resources Research*, 54, 10,013–10,033, <https://doi.org/10.1029/2018WR023457>, 2018.
- Zheng, X., D’Angelo, C., Maidment, D. R., and Passalacqua, P.: Application of a Large-Scale Terrain-Analysis-Based Flood Mapping
645 System to Hurricane Harvey, *JAWRA Journal of the American Water Resources Association*, 58, 149–163, <https://doi.org/10.1111/1752-1688.12987>, 2022.
- Zscheischler, J., Westra, S., Hurk, B. J. J. M. V. D., Seneviratne, S. I., Ward, P. J., Pitman, A., Aghakouchak, A., Bresch, D. N., Leonard, M.,
Wahl, T., and Zhang, X.: Future climate risk from compound events, *Nature Climate Change*, 8, 469–477, <https://doi.org/10.1038/s41558-018-0156-3>, 2018.
- 650 Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., van den Hurk, B., AghaKouchak, A., Jézéquel, A.,
Mahecha, M. D., Maraun, D., Ramos, A. M., Ridder, N. N., Thiery, W., and Vignotto, E.: A typology of compound weather and climate
events, *Nature Reviews Earth & Environment*, 1, 333–347, <https://doi.org/10.1038/s43017-020-0060-z>, 2020.

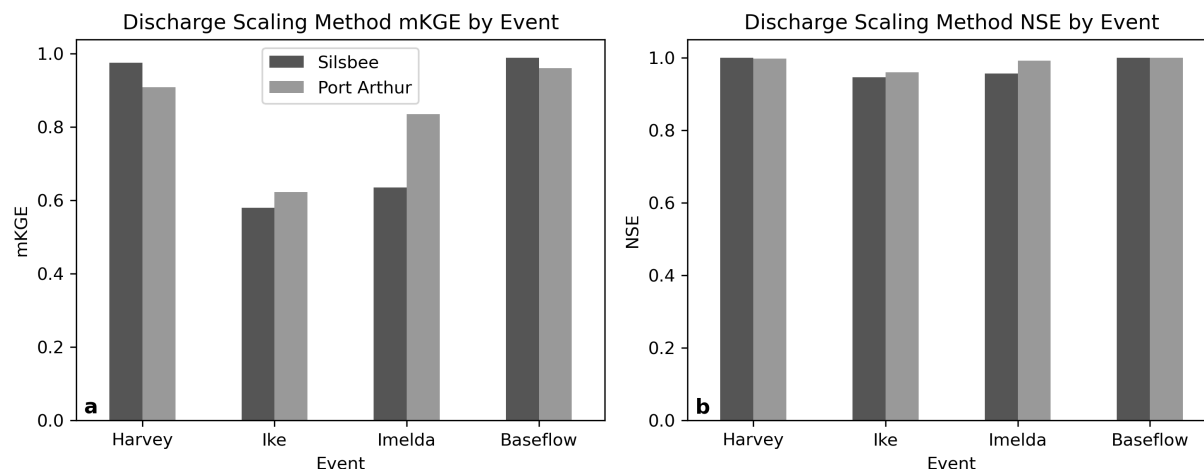


Figure S1. Performance of the discharge scaling method across historical flood events and a representative low-flow (baseflow) snapshot from NWM in Silsbee and Port Arthur. Bars show agreement between scaled synthetic and NWM peak discharges across stream reaches using (a) modified Kling-Gupta Efficiency (mKGE) and (b) Nash-Sutcliffe Efficiency (NSE). Values closer to 1 indicate better agreement.

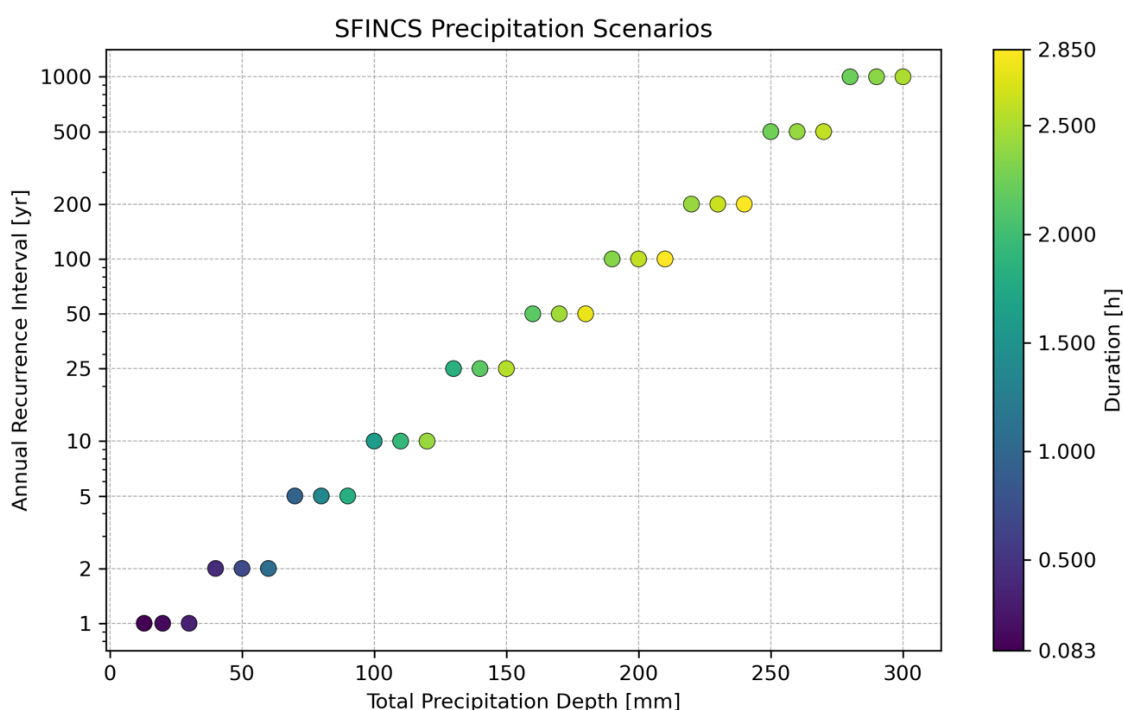


Figure S2. SFINCS precipitation scenarios: annual recurrence interval (log scale) vs. total precipitation depth, colored by duration. The minimum depth is 13~mm, corresponding to the 1-year, 5-minute event provided by NOAA.

Rating Surfaces for Quantifying Compound Flooding at Points of Interest

Mark Wang¹, Paola Passalacqua^{2,3,1}, Hamed Moftakhari⁴, and Bailey Hardage¹

¹Fariborz Maseeh Department of Civil, Architectural, and Environmental Engineering, Center for Water and the Environment, University of Texas at Austin, Austin, USA

²Institute of Environmental Engineering, Department of Civil, Environmental and Geomatic Engineering, ETH Zürich, Zürich, CH

³Eawag, Swiss Federal Institute of Aquatic Science and Technology, Dübendorf, CH

⁴Department of Civil, Construction and Environmental Engineering, Center for Complex Hydrosystems Research, University of Alabama, Tuscaloosa, USA

Correspondence: Paola Passalacqua (ppassalacqua@ethz.ch)

Abstract. Compound flooding in low-relief coastal regions arises from interactions among coastal water levels, river discharge, and precipitation. Capturing these interactions typically requires coupled hydrodynamic models, which can be computationally ~~intensive~~expensive, limiting their use in high-resolution or large-ensemble analyses. In this study, we introduce ~~rating surfaces:~~
the rating surface, a model-agnostic framework that transforms ensembles of flood inundation simulations into two-dimensional
5 ~~plots that provide~~ contours of compound flood depth at points of interest ~~given~~across pairs of potentially interacting flood
drivers. Using Southeast Texas as a testbed, we generate synthetic inundation scenarios with both efficient terrain-based models
(c-HAND, GeoFlood, and Fill-Spill-Merge) and the reduced-physics hydrodynamic model SFINCS. Sampling these scenarios
at points of interest yields rating surfaces that characterize how precipitation, discharge, and coastal water level ~~jointly~~
maximum compound flood depth. Across locations, simplified and hydrodynamic models produce similar depth patterns, but
10 SFINCS captures finer-scale nonlinearities. The two approaches provide comparable depth estimates ~~–~~and their prediction
envelope typically includes the observed high-water marks. Rating surfaces provide an efficient tool for ~~evaluating compound~~
~~flooding in settings where computational constraints challenge traditional hydrodynamic modeling, offering a framework for~~
scenario assessment and ~~communication of~~communicating compound flood hazards at points of interest.

Copyright statement. Author(s) 2026. This work is distributed under the Creative Commons Attribution 4.0 License.

15 1 Introduction

Flooding is the most frequent and widespread natural disaster; ~~it has affected~~, affecting over 2 billion people globally from
1998 to 2017 (Wallemacq et al., 2018) and ~~it costs~~costing the United States ~~over \$~~more than USD 180 billion annually
(U.S. Congress, 2024). Over 50% of the U.S. population now lives in coastal watersheds (Crossett et al., 2013), and the
global coastal population is projected to exceed 1 billion by 2060 (Neumann et al., 2015; Reimann et al., 2023). ~~Tropical~~

20 ~~eyelones~~ These populations are particularly vulnerable to tropical cyclones, which threaten coastal areas (Dullaart et al., 2021) ~~causing damages over \$~~worldwide (Dullaart et al., 2021) and have caused over USD 1.425 trillion in ~~damages in~~ the United States from 1980 to 2024, with an average cost of ~~\$USD~~ 22.3 billion per event (Smith, 2024). ~~Tropical cyclones have caused severe and deadly coastal flooding in recent years, with examples including~~ Recent tropical cyclones that produced severe flooding in the United States include Hurricane Harvey (2017), Tropical Storm Imelda (2019), Hurricanes Isaias ~~and~~ Laura 25 (2020), Hurricane Ida (2021), ~~Helene, and Hurricanes Helene~~ and Milton (2024). As coastal populations grow and ~~face~~ increasing their exposure to flooding and tropical cyclones ~~increases~~, understanding the interplay ~~between among~~ multiple flood drivers is crucial.

~~Extreme coastal flooding events frequently involve compound hazards, where~~ Compound events are natural hazards that co-occur over time or space and threaten society and the environment (Zscheischler et al., 2020). In coastal settings, compound 30 ~~flooding often occurs when~~ storm surge, riverine flooding, and heavy rainfall ~~may interact to amplify impacts~~. Compound ~~coastal flooding poses~~ interact, amplifying flood impacts beyond those caused by any single driver (Bevacqua et al., 2020; Hao and Singh, 2020). ~~These events pose~~ considerable challenges for prediction and hazard assessment, especially in low-relief coastal regions ~~Compound events are natural hazards that co-occur over time or space and threaten society and the environment (Zscheischler et al., 2020)~~ ~~Coastal residents are particularly vulnerable to compound coastal flooding, which arises from the interaction of where~~ 35 ~~coastal residents are highly exposed~~. Compound flooding is often triggered by tropical cyclones, which can generate storm surge, fluvial flooding, and pluvial flooding ~~which are often triggered by tropical cyclones (Green et al., 2025)~~. Compound ~~floods can lead to more severe impacts than floods caused by a single driver (Bevacqua et al., 2020; Hao and Singh, 2020)~~. (Green et al., 2025). The primary drivers of compound ~~coastal flooding coastal flooding coastal~~ water levels, precipitation, and river ~~flow are flow are~~ interdependent and inherently correlated (Zheng et al., 2013; Wahl et al., 2015; Moftakhari et al., 40 2017; Hendry et al., 2019). These ~~mechanisms drivers~~ can act simultaneously or sequentially, ~~leading to producing~~ dynamic interactions that amplify flood hazards. Predicting ~~compound coastal flooding these interactions~~ is particularly challenging in low-relief flood transition zones, where hydrologic and coastal flood ~~drivers interact in a nonlinear manner processes interact nonlinearly~~ (Shen et al., 2019; Bilskie et al., 2021; Santiago-Collazo et al., 2024). ~~Storm~~ For example, storm surge, driven by strong winds and low atmospheric pressure, raises coastal water levels ~~which and~~ can impede river discharge, ~~leading to~~ 45 ~~causing~~ backwater effects and prolonged inland flooding (~~Santiago-Collazo et al., 2019~~) (Lewis et al., 2013; Wijetunge and Neluwala, 2023). Similarly, heavy precipitation can saturate soils, ~~reducing infiltration and exacerbating~~ ~~reduce infiltration, and increase~~ runoff, while high tides and waves can further elevate water levels (Bilskie and Hagen, 2018).

~~Accurate flood prediction~~

~~Accurate flood estimation~~ is essential for flood management; however, no single ~~modeling~~ approach is ideally suited to 50 ~~capture compound coastal fully capture compound~~ flood events. Researchers and policymakers use three broad ~~categories of flood inundation models to support decision-making approaches to estimate flooding~~; empirical methods, hydrodynamic models, and simplified conceptual models (Teng et al., 2017). These ~~models address flood-related flood estimation approaches help address~~ challenges in planning, impact assessment, and emergency response (Bates, 2022). ~~Each, but each~~ approach has strengths and limitations that influence its ~~applicability~~.

55 ~~Empirical methods produce utility. Empirical methods provide~~ direct observations of compound flooding, including remote sensing, sensor data, and crowdsourced information (Tellman et al., 2021; Hamidi et al., 2023; Silverman et al., 2022; Dasgupta et al., 2022). While empirical methods are invaluable for planning and post-event assessments, ~~these methods are less applicable to real-time decision support and~~ observed inundation alone is less suited to predictive and scenario-based compound flood analysis-, which requires representing interacting flood drivers such as coastal water level, rainfall, and riverine
60 flow (Santiago-Collazo et al., 2019; Loveland et al., 2021). As a result, process-based and simplified modeling approaches are often needed to estimate flooding under current or hypothetical forcing conditions.

Hydrodynamic models estimate flow using the Navier-Stokes equations, ~~making them and are~~ widely adopted for flood simulations (Bates, 2022). To balance accuracy and efficiency, hydrodynamic modelers often simplify the Navier-Stokes equations ~~;~~ using two-dimensional shallow-water or one-dimensional Saint-Venant formulations (Westerink et al., 1992; Horritt and Bates,
65 2002; USACE, 2025). Coupled hydrodynamic models have been developed to describe compound flood processes, with some tools optimized for computational efficiency (~~Leijnse et al., 2021~~)(Leijnse et al., 2021; Lee et al., 2025). However, computational demands limit hydrodynamic models' applicability to real-time or high-resolution scenarios (~~Santiago-Collazo et al., 2019; Miura et al., 2021b~~).

Simplified conceptual models use physical principles, geographic information systems (GIS), and terrain analysis to estimate flood extent and depth efficiently (Teng et al., 2017; Bates, 2022). These models do not ~~explicitly~~ simulate flood dynamics ~~but can approximate compound flooding using available-~~, but instead can estimate static flood extent and depth by applying geomorphic and proximity-based approaches to topographic and hydrologic data. Early applications automated valley bottom detection to designate flood-prone areas (Williams et al., 2000; Gallant and Dowling, 2003). Some simplified conceptual models distribute water volume across terrain (Lhomme et al., 2009; Miura et al., 2021b; Shi et al., 2025), while others classify
75 floodplains based on digital elevation models (Nardi et al., 2006; Manfreda et al., 2011; Samela et al., 2017). Simplified conceptual models enable large-scale, high-resolution flood hazard assessments and support rapid decision-making in emergency response scenarios (~~Preisser et al., 2023; Jafarzadegan et al., 2023~~)(Murphy et al., 2025; Jafarzadegan et al., 2023; Preisser et al., 2023)

~~In this study, we employ two approaches to predict compound flooding: a) superimpose individual~~ Although coupled
80 hydrodynamic models can resolve compound flood processes, their computational cost limits systematic simulation of large-ensemble forcing scenarios at high spatial resolution (Santiago-Collazo et al., 2019; Miura et al., 2021a). Conversely, simplified conceptual models ~~of fluvial, pluvial, and coastal flooding (Preisser et al., 2022; Zheng et al., 2018; Wang et al., 2024); and b) use SFINCS, a hydrodynamic model that captures fluvial, pluvial, and coastal flooding (Leijnse et al., 2021; Lee et al., 2025).~~ Simplified models can rapidly generate synthetic flood inundation scenarios and are attractive for planning assessments of flood
85 hazard (Murphy et al., 2025). SFINCS provides a benchmark hydrodynamic simulation that we compare with the simplified model results. We use these models to develop a framework for quantifying compound flood depth at points of interest (POIs).

~~This study aims to quantify~~ can efficiently estimate static inundation maps across many forcing scenarios, but they do not resolve hydrodynamics or nonlinear interactions among flood drivers (Teng et al., 2017). Beyond this modeling tradeoff, compound flood assessment also poses a communication challenge: flood managers need location-specific summaries of how

90 ~~flood driver combinations affect compound flood depth at POIs given ranges of possible coastal flood drivers. We model our approach on the rating curve, which depicts stage as a function of river. Rating curves provide such summaries for riverine flooding by relating stage to discharge at a river gage location, and is used to communicate compound flood impacts with planners, flood managers, and stakeholders. Recognizing that compound flood depth, which is analogous to stage height in a rating curve, depends on contributions from three flood drivers in coastal areas: precipitation, coastal gage, but no comparable~~
 95 ~~tool exists for compound flooding, where flood depth depends on multiple drivers. Together, these challenges leave a practical gap: a need for an efficient and interpretable tool that communicates how flood depth varies across combinations of coastal water level, and river discharge, we restructure the rating curve to consider any two of these three drivers and plot their corresponding and precipitation at a given location. We address this gap by proposing rating surfaces, which extend the logic of rating curves from one-dimensional stage-discharge relationships to two-dimensional contours of compound flood depth at any POI. Though we model up to three coastal flood drivers at each POI, we plot rating surfaces as two-dimensional contours of forcing spaces that represent maximum flood depth across pairs of flood forcings at points of interest.~~

Specifically, in this manuscript we address three research questions:

1. Can rating surfaces, constructed from a finite ensemble of flood inundation simulations, efficiently estimate maximum compound flood depth for any combination of two flood drivers at points of interest (POIs)?
- 105 2. What do rating surfaces reveal about the local influence of different flood drivers on maximum compound flood depth to present multiple data sources simply and clearly. Our approach is similar to the fluvial-coastal surfaces for water levels in navigation channels at POIs?
3. To what extent do rating surfaces constructed from simplified conceptual models agree with those constructed from SFINCS, a hydrodynamic model?
- 110 Our approach builds on the fluvial-coastal water level surfaces proposed by Muñoz et al. (2022). We, but differs by focusing on maximum compound flood depth at POIs, considering coastal-pluvial, fluvial-coastal, and fluvial-pluvial forcing pairs, and comparing surfaces derived from both simplified conceptual and hydrodynamic models. Using Southeast Texas as a testbed, we generate high-resolution (1 m) compound flood inundation scenarios using public datasets and open-source flood models, extending this concept and providing a general framework for assessing compound flood depth at POIs models, sample the
 115 resulting maximum depth grids at point locations to calculate rating surfaces, and compare rating surface-predicted depths with high-water marks observed during Hurricane Harvey.

2 Methods

2.1 Study areas

Our study areas are the inland town of Silsbee and the coastal city of Port Arthur, both located in Southeast Texas on low-
 120 relief topography susceptible to ~~coastal~~ compound flooding (Fig. 1). We choose POIs within regions designated as flood-prone

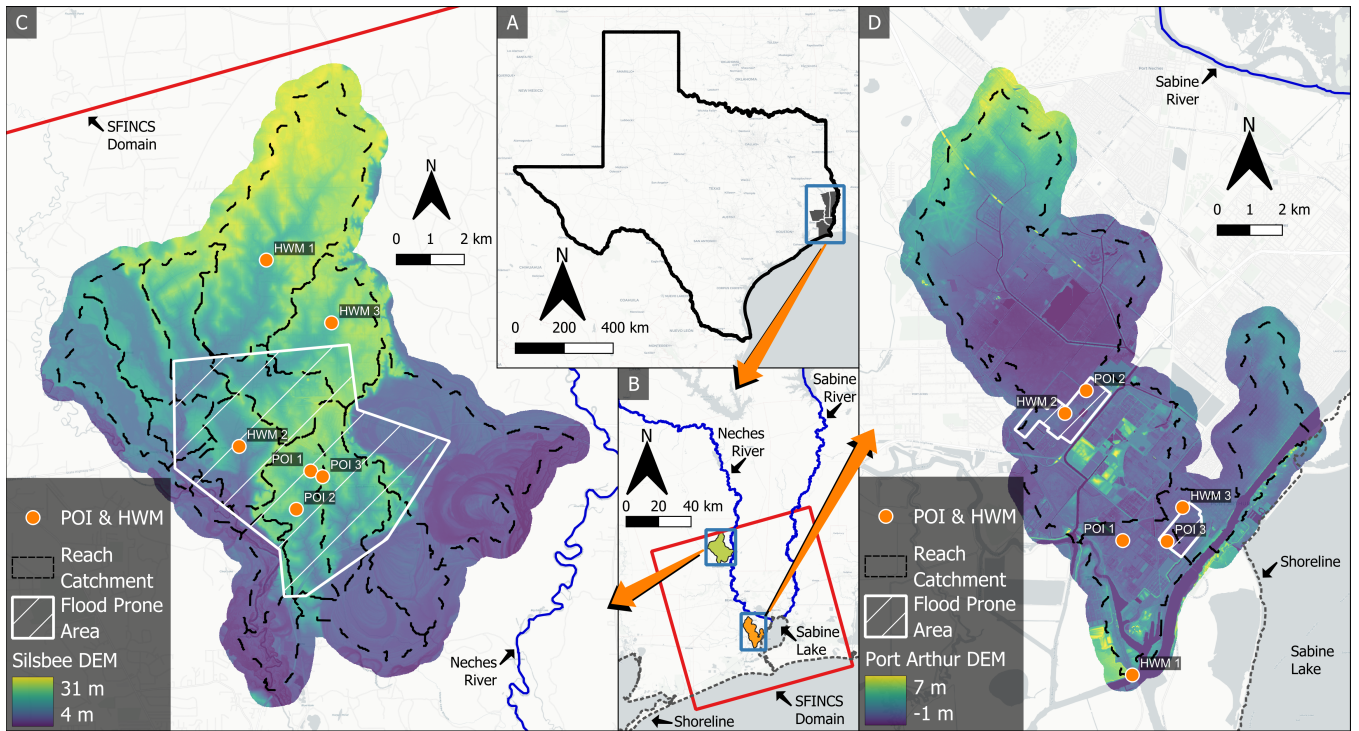


Figure 1. Location of (A) Southeast Texas within the state of Texas, (B) the Silsbee and Port Arthur study areas within Southeast Texas, as well as the SFINCS domain, (C) the Silsbee study area extent and datasets, and (D) the Port Arthur study area extent and datasets. [The vertical datum of the DEMs is NAVD88.](#) Basemap © OpenStreetMap contributors, © CARTO.

by local stakeholders working with the Southeast Texas Urban Integrated Field Laboratory (SETx-UIFL, 2024). POIs in the study areas are situated near socially vulnerable populations and critical energy infrastructure. The Southeast Texas region encompasses the Beaumont-Port Arthur metropolitan area, smaller towns like Silsbee, agricultural lands, forests, and swamps. Tropical cyclones including Beryl (2024), Imelda (2019), and Harvey (2017) have impacted the area. The region is drained by the Sabine, Neches, and Trinity and Neches Rivers and their tributaries. Terrain slopes gently toward the Gulf of Mexico, which is typical of the Texas Coastal Plains. The ~~area contains Galveston Bay and Sabine Lake~~ [Sabine Lake is the major estuary in Southeast Texas.](#)

2.2 Simplified conceptual models

[We use three simplified conceptual models \(SCMs\) to separately estimate the coastal, fluvial, and pluvial components of compound flooding. Each model produces a maximum inundation depth grid corresponding to one flood driver using high-resolution terrain data, forcing conditions, and physical approximations. We combine these individual flood driver depth grids to estimate compound flood depth \(Sec. 2.2.1\).](#)

c-HAND produces coastal flood inundation scenarios (Wang et al., 2024). c-HAND is a static method that uses high-resolution elevation data and a coastal water level forecast to estimate coastal flood extent and depth. It is a modification of the HAND method and estimates coastal inundation by enforcing an ocean connectivity constraint. A c-HAND backcast of coastal inundation from Hurricane Ike showed reasonable agreement with an ADCIRC simulation (Wang et al., 2024). We force c-HAND with coastal water levels (Sec. 2.5.1).

We generate synthetic fluvial flood inundation scenarios with a modification of the GeoFlood workflow (Zheng et al., 2018). GeoFlood ~~has been used to model fluvial inundation~~ estimates fluvial flood extent and depth from river discharge and terrain-analysis operations, and has been validated against observations from Hurricane Harvey (Zheng et al., 2022). We force GeoFlood with synthetic river discharge scenarios (Sec. 2.5.2) in the NHDPlusV2 MR stream reach catchments containing our POI/HWM.

We estimate pluvial flooding with Fill-Spill-Merge, a terrain depression flow routing algorithm that can be applied to a broad range of natural phenomena (Barnes et al., 2021). Fill-Spill-Merge has been used to map pluvial flooding in Texas (Preisser et al., 2022, 2023). We force Fill-Spill-Merge with uniform precipitation depths (Sec. 2.5.3). Because Fill-Spill-Merge does not take drainage infrastructure or infiltration into account, we assume that soil is saturated and the drainage system is at capacity ~~-, which is likely for during~~ large precipitation events. This assumption is consistent with soil moisture observations during recent tropical cyclones in Southeast Texas -, and local regulations that allow roadway ponding for severe events (Case et al., 2021; Jefferson County Drainage District No. 7, 2019). We will discuss the implications and limitations of this assumption (Sec. 4.4).

2.2.1 Compound flood depth with simplified conceptual models

We produce 1 m resolution coastal, fluvial, and pluvial maximum flood depth grids separately across the study area with ~~the models described above. The depth grid for each forcing corresponds to the maximum inundation depth and extent achieved under that forcing. To approximate SCMs (Sec. 2.2). To estimate~~ compound flood depth ~~at each POI/HWM, we superimpose the estimated depths from two from these single-forcing maximum flood depth grids, we combine pairs of~~ forcing scenarios (Eq. 1–3) ~~:-~~. We analyze pairwise combinations of flood drivers to show how compound flood depth responds to variation in two drivers while the third driver remains constant (Sec. 2.6).

$$h_{\text{fluvial-pluvial}} = h_{\text{pluvial}} + h_{\text{fluvial}} \quad (1)$$

$$h_{\text{coastal-pluvial}} = \max(h_{\text{coastal}}, h_{\text{pluvial}}) \quad (2)$$

$$h_{\text{fluvial-coastal}} = \max(h_{\text{coastal}}, h_{\text{fluvial}}) \quad (3)$$

where $h_{\text{fluvial-pluvial}}$ is the compound ~~fluvial-pluvial~~fluvial-pluvial flood depth, $h_{\text{coastal-pluvial}}$ is the compound ~~coastal-pluvial~~coastal-pluvial flood depth, $h_{\text{fluvial-coastal}}$ is the compound ~~fluvial-coastal~~fluvial-coastal flood depth, h_{fluvial} is the fluvial flood depth, h_{pluvial} is the pluvial flood depth, and h_{coastal} is the coastal flood depth.

We use the compound flood depths resulting from Eq. 1–3 to construct rating surfaces for pairs of forcings at each POI/HWM.

165 We sum pluvial and fluvial inundation because fluvial inundation is calculated on a depression-removed DEM and pluvial inundation is calculated on a DEM including depressions. We take the maximum of coastal and ~~both fluvial and either~~fluvial or pluvial inundation because coastal inundation acts as a downstream boundary condition that controls water surface elevations across low-lying terrain. ~~This approach yields a conservative lower-bound estimate of~~These equations do not represent hydrodynamics or nonlinear interactions among flood drivers (Sec. 4.4). Rather, these equations provide an

170 efficient approximation of maximum compound flood depth ~~, as the interaction between coastal and inland flooding is nonlinear (Bilskie and Hagen, 2018), with~~SCMs. We evaluate SCM-derived compound flood depth against SFINCS, which couples coastal, fluvial, and pluvial forcings (Sec. 3).

2.3 SFINCS model setup

The SFINCS model domain spans ~~1000~~100 $\times$ ~~1000~~100 km and uses a 50×50 m regular grid with a 1×1 m subgrid scheme

175 that resolves fine-scale topography (van Ormondt et al., 2025). We mosaic the topography and bathymetry datasets to cover the full SFINCS domain (Fig. 2). We apply outflow boundary conditions at domain edges intersecting land and constant water level boundary conditions at domain edges intersecting the ocean. We assign inflow boundary conditions where stream reaches intersect the model boundary and at headwaters within the domain. The subgrid tables include NHDPlusV2 MR stream reach centerline geometry, bankfull width and depth, and channel roughness, as well as land cover-based roughness outside of

180 stream reaches. We disable infiltration in SFINCS to reduce systematic model bias and maintain consistency with the ~~simplified conceptual models~~SCMs, which omit infiltration. ~~Infiltration is also unlikely to have a strong influence on maximum depths at our POIs, which are located on impervious surfaces. We will discuss the implications and limitations of this assumption (Sec. 4.4).~~ We run seven-day SFINCS simulations with coastal, pluvial, and fluvial forcing scenarios.

2.3.1 SFINCS compound scenario selection

185 We generate compound flooding scenarios by pairing coastal, fluvial, and pluvial forcings across their full ranges (Sec. 2.5.1–2.5.3). SFINCS receives each forcing combination as a seven-day simulation that shares a common domain, boundary setup, and subgrid configuration. The only difference among SFINCS scenario setups is the choice of forcing magnitudes.

For each pair of flood drivers, we construct a continuous two-dimensional forcing space, discretized with a deterministic Halton sequence (Halton, 1960). The Halton sequence distributes sample points uniformly across the forcing space. We hold

190 the third driver at a constant low value so that maps are representative of the inundation resulting from two drivers, as with the ~~simplified conceptual models~~SCMs (Table 1). We describe the physical basis for the forcing ranges we list in Table 1 (Sec. 2.5). Similar to the SCMs, we apply a uniform precipitation depth throughout the SFINCS domain. We set coastal water level to 0 m NAVD88 for ~~fluvial-pluvial~~fluvial-pluvial scenarios, which falls between mean low water (-0.07 m NAVD88) and

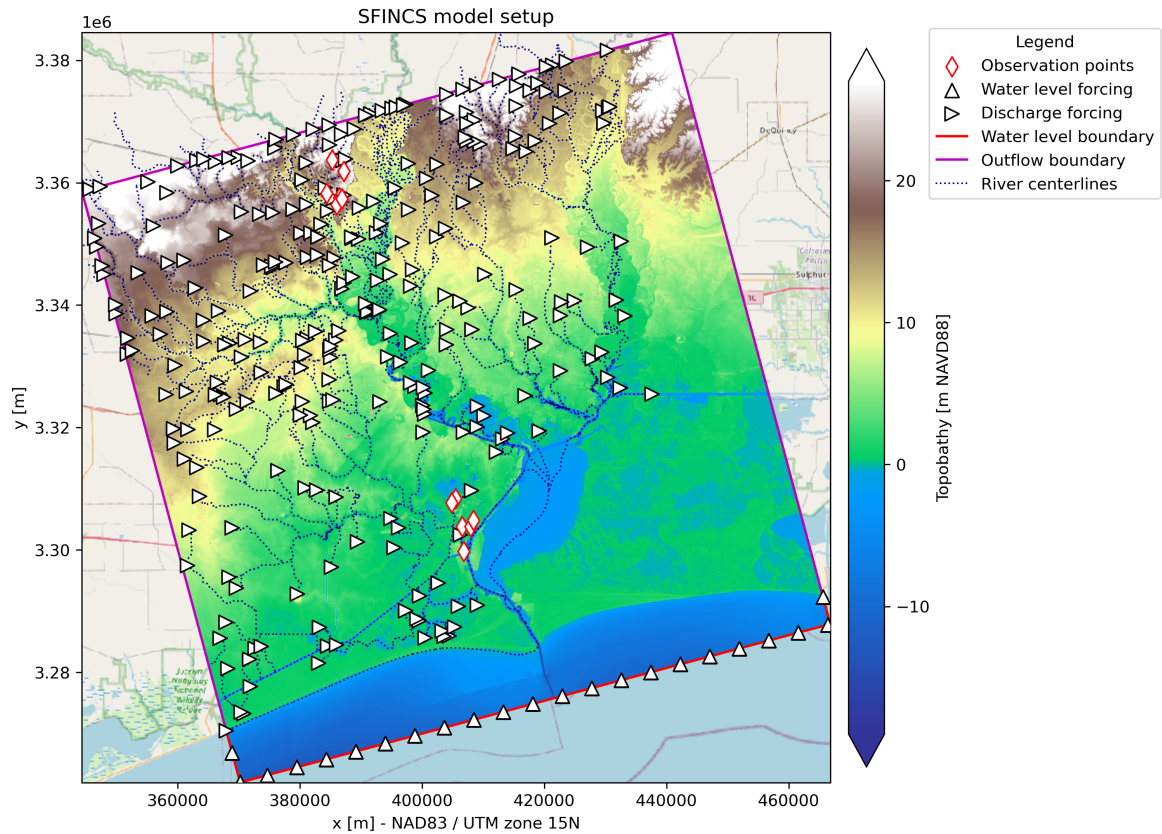


Figure 2. SFINCS model setup. Basemap © OpenStreetMap contributors.

Table 1. SFINCS compound scenario types and corresponding forcing ranges.

Scenario type	Forcings		
	Coastal [m NAVD88]	Fluvial ^a [m ³ s ⁻¹]	Pluvial [mm]
Fluvial–pluvial	0	25 to 20000	10 to 300
Coastal–pluvial	0.1 to 2.0	baseflow ^b	10 to 300
Fluvial–coastal	0.1 to 2.0	25 to 20000	0

^a Represents maximum discharge within the watershed.

^b [Historical NWM baseflow condition \(Sec. 2.5.2\).](#)

mean sea level (0.07 m NAVD88) at the Port Arthur tide gage. We set discharge to baseflow for [coastal-pluvial](#) [coastal-pluvial](#) scenarios and set precipitation depth to 0 mm for [fluvial-coastal](#) [fluvial-coastal](#) scenarios.

We generate 1000 forcing combinations [for each pair across the three pairs](#) of drivers. The three forcing grids ([fluvial-pluvial](#), [coastal-pluvial](#), and [coastal-fluvial](#) [coastal-pluvial](#), [fluvial-pluvial](#), and [fluvial-coastal](#)) span the full ranges of coastal water

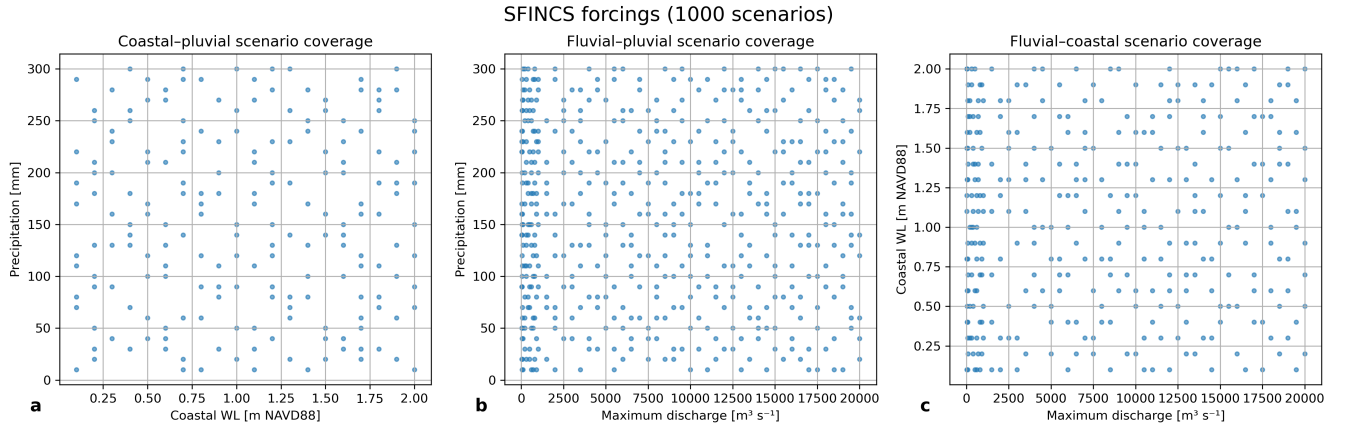


Figure 3. Halton-sequence coverage of compound forcing spaces used for SFINCS simulations. The three panels show 1000 forcing combinations across each pair the three pairs of drivers: (A) coastal-pluvial, (B) fluvial-pluvial, and (C) fluvial-coastal. Apparent clustering near zero discharge reflects the non-uniform spacing of fluvial forcing magnitudes, where resolution at low flows is increased (Sec. 2.5.2).

level, maximum discharge, and precipitation depth. The Halton-sampled points evenly fill each forcing space (Fig. 3). This approach provides broad coverage while keeping the total number of SFINCS simulations computationally feasible.

Each SFINCS run produces a time series of water surface elevation on the 50 m grid. We compute the maximum value over the full seven-day period at every coarse grid cell and downscale the coarse maximum water surface grid to a 1 m depth grid. We sample the 1 m maximum depth grid at each POI/HWM. The sampled depths form the inputs to the rating-surface-for rating surface construction (Sec. 2.6).

2.4 Datasets

We obtain 1 m resolution bare-earth digital elevation models (DEM) from the USGS 3D Elevation Program for Silsbee and areas outside of Jefferson County (USGS, 2024) and from the TNRIS StratMap Program for Port Arthur and areas within Jefferson County (TNRIS, 2017) (Fig. 1). We obtain bathymetry with the finest available resolution of 4 m from NOAA BlueTopo (NOAA, 2025a). We delineate the coastline using U.S. Census TIGER/Line data (US Census Bureau, 2025). All geospatial datasets reference UTM Zone 15N coordinates (EPSG:26915) and the NAVD88 vertical datum (EPSG:54035703).

Stream reaches, gage-adjusted mean annual flow for each stream reach, and stream reach catchments are from the National Hydrography Dataset Version 2 Medium Resolution (NHDPlusV2 MR) Dataset, which is maintained by the USGS (McKay et al., 2012). The National Water Model (NWM) provides historical flow rates (Cosgrove et al., 2024) and the USGS provides hydraulic geometry estimates including bankfull width and depth (Schwarz et al., 2018) for each NHDPlusV2 MR stream reach. We assign channel Manning's n by stream order following GeoFlood's current implementation, and where stream order is unavailable we assign n to 0.03. Outside of stream channels, we assign roughness based on the 2023 National Land

Table 2. High-water mark (HWM) and point-of-interest (POI) information.

Site	Location	Type
Port Arthur POI 1 ^a	S Gulfway Dr & Valero Refinery Gates	Industrial
Port Arthur POI 2	Linkwood St & Austin Ave	Residential
Port Arthur POI 3	W 10th St & Herget Ave	Residential
Port Arthur HWM 1 ^a	Under West Port Arthur Bridge	Bridge crossing
Port Arthur HWM 2	Back of St John’s Catholic Church	Drainage swale
Port Arthur HWM 3	Across from Booker T. Washington Elementary	Drainage swale
Silsbee POI 1 ^a	Hwy 96 & FM 327	Downtown
Silsbee POI 2	Maxwell Dr & Lindsey	Residential
Silsbee POI 3	Watts Rd & FM 327	Highway underpass
Silsbee HWM 1	Upstream side of bridge on FM 1122	Bridge crossing
Silsbee HWM 2	Upstream of culvert on FM 327	Culvert crossing
Silsbee HWM 3 ^a	Downstream of bridge on FM 92	Bridge crossing

^a Located on or adjacent to a TxDOT-designated evacuation route.

Cover Database 30 m dataset (USGS, 2025) with recommended land cover class–Manning’s n mappings from the HEC-RAS manual (USACE, 2025).

We calculate rating surfaces at 12 point locations: three POIs and three HWMs in both Silsbee and Port Arthur (Table 2). We select POIs at locations where estimating compound flood depth for specific combinations of hydrological forcings is important for identifying management strategies. POI-POIs are located in residential areas, along hurricane evacuation routes (TxDOT, 2025), and near critical infrastructure (Fig. 1). USGS collected the HWMs after Hurricane Harvey (USGS and Arctur, 2018).

For model validation To validate the rating surfaces, we use observed forcing magnitudes from Hurricane Harvey. Peak stream segment discharges were $6140 \text{ m}^3 \text{ s}^{-1}$ at Silsbee and $14440 \text{ m}^3 \text{ s}^{-1}$ at Port Arthur according to NWM retrospective data. Coastal water level at the Port Arthur tide gage reached 1.13 m NAVD88. The National Hurricane Center reported 173 mm of rainfall within one hour over Southeast Texas during Hurricane Harvey (Blake and Zelinsky, 2018). This depth corresponds to the 1000 yr, 1 h event at Beaumont (NOAA, 2025b), which we adopt as the representative precipitation depth for validation. These values are used as inputs to the rating surfaces to evaluate modeled flood depths against the observed high-water marks.

2.5 Compound flood forcings

We select coastal, fluvial, and pluvial forcing ranges to generate a broad set of synthetic forcing scenarios for which we simulate flooding and construct rating surfaces. The individual drivers in each scenario span a forcing envelope from baseline conditions to values above recently observed tropical cyclone flood conditions in Southeast Texas. We simulate these scenarios with both SCMs (Sec. 2.2) and SFINCS (Sec. 2.3). We design these scenarios to evaluate compound flood depth sensitivity across relevant conditions in Southeast Texas. Pairing high-magnitude compound flood forcings produces rare combinations; multivariate

statistical methods are required to estimate the joint likelihood of these combinations (Jane et al., 2025; Zheng et al., 2014).
 235 This study is concerned with simulating physically relevant combinations to evaluate possible compound flood depth responses at points of interest, rather than assigning probabilities to each joint occurrence. Coastal water levels span typical to extreme values at the Port Arthur tide gage (Sec. 2.5.1), discharge scenarios span below-baseflow to greater-than-Harvey conditions (Sec. 2.5.2), and precipitation depths span frequent to rare rainfall totals based on NOAA depth-duration-frequency (DDF) estimates for Beaumont (Sec. 2.5.3).

240 2.5.1 Coastal

We apply coastal water levels ranging from 0.1 m to 2.0 m by increments of 0.1 m. The maximum water surface elevation measured by the NOAA tide gage at Port Arthur (Station 8770475) is 1.13 m (record begins in 2004). c-HAND calculates a static maximum coastal inundation map for each coastal water level, while we force SFINCS with a constant coastal water level throughout each seven-day simulation and obtain the corresponding downscaled maximum inundation maps. We
 245 apply constant coastal water levels to the SFINCS hydrodynamic simulations for parity with c-HAND, which estimates static maximum inundation extent for a specified coastal water level. We apply this constant forcing to estimate maximum inundation conditional on a specified coastal water level.

2.5.2 Fluvial

We generate fluvial scenarios consisting of discharge ensembles. First we obtain gage-adjusted mean annual discharge from
 250 the NHDPlusV2 EROM dataset (US EPA, 2015). Then we assign discharge to each stream reach based on its mean annual discharge relative to the minimum and maximum in the study area, resulting in a vector of normalized discharges ranging from 0 to 1 (Eq. 4). We multiply this vector by a constant value to generate a corresponding synthetic discharge scenario (Eq. 5):

$$Q_{i,\text{norm}} = \frac{Q_i - Q_{\min}}{Q_{\max} - Q_{\min}} \quad \forall i \quad (4)$$

$$Q_{\text{scenario}} = C \times Q_{\text{norm}} \quad (5)$$

255 where $Q_{i,\text{norm}}$ is the normalized discharge at stream segment i , Q_i is mean annual discharge at stream segment i , $Q_{\min}$ is the minimum mean annual discharge of a stream segment in the study area, $Q_{\max}$ is the maximum mean annual discharge of a stream segment in the study area, Q_{scenario} is the vector of discharges corresponding to a synthetic discharge ensemble, C is the scaling factor corresponding to the maximum discharge ($\text{m}^3 \text{s}^{-1}$) for a given synthetic scenario, and Q_{norm} is a dimensionless vector of the normalized discharges at each stream segment. We force GeoFlood and SFINCS using fluvial scenarios defined
 260 by scaling factors C corresponding to maximum discharges ranging from $25 \text{ m}^3 \text{s}^{-1}$ to $20000 \text{ m}^3 \text{s}^{-1}$ (from less than baseflow

to greater than Harvey)¹. GeoFlood produces a static maximum inundation map associated with each fluvial scenario, while we force SFINCS with each constant fluvial scenario throughout each seven-day simulation and obtain the corresponding downscaled maximum inundation maps.

To validate the discharge scaling method, we compare scaled synthetic discharges with maximum NWM discharges from three major flood events in Southeast Texas—Hurricane Ike, Hurricane Harvey, and Tropical Storm Imelda—as well as baseflow conditions. We ~~evaluate the comparison using normalized root-mean-square-error (nRMSE)~~ use the modified Kling-Gupta Efficiency (mKGE) and the Nash-Sutcliffe Efficiency (NSE) to evaluate agreement between scaled synthetic discharges and observed NWM peak discharges across stream reaches (Kling et al., 2012; Nash and Sutcliffe, 1970):

$$\text{RMSENSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (Q_{\text{pred},i} - Q_{\text{obs},i})^2} \frac{1 - \frac{\sum_{i=1}^n (Q_{\text{obs},i} - Q_{\text{pred},i})^2}{\sum_{i=1}^n (Q_{\text{obs},i} - \bar{Q}_{\text{obs}})^2}}{1} \quad (6)$$

$$\text{nRMSE}_{\text{mKGE}} = \frac{\text{RMSE}}{\bar{Q}_{\text{obs}}} \frac{1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2}}{2} \quad (7)$$

$$\beta = \frac{\bar{Q}_{\text{pred}}}{\bar{Q}_{\text{obs}}} \quad (8)$$

$$\gamma = \frac{\text{CV}_{\text{pred}}}{\text{CV}_{\text{obs}}} = \frac{\sigma_{\text{pred}}/\bar{Q}_{\text{pred}}}{\sigma_{\text{obs}}/\bar{Q}_{\text{obs}}} \quad (9)$$

where $Q_{\text{pred},i}$ and $Q_{\text{obs},i}$ are the predicted ~~(synthetic) and observed (NWM)~~ synthetic and observed NWM peak discharges at stream segment i , respectively, n is the number of stream segments, and $\bar{Q}_{\text{obs}}$ ~~is the mean~~ the terms $\bar{Q}$, CV, and σ are the mean, coefficient of variation, and standard deviation of peak discharge, respectively, across stream segments for a given site and event. The mKGE terms r , β , and γ represent the Pearson correlation coefficient, bias ratio, and variability ratio, respectively; all three terms are dimensionless. We report mKGE and NSE as dimensionless measures of the observed peak discharges across a site. We report nRMSE as a dimensionless measure of model performance to clearly compare events across different magnitudes and sites. The nRMSE Both the NSE and mKGE metrics range from $-\infty$ to an optimum value of 1. mKGE values closer to 1 indicate better agreement in the correlation, bias, and variability of predicted and observed peak discharges across stream segments. NSE values closer to 1 indicate better agreement between predicted and observed peak discharges; a value of 0 indicates that predicting the mean observed peak discharge for every stream segment performs as well as the predicted discharges. The mKGE values range from 0.03 to 0.33 0.5804 to 0.9893 (Fig. S1S1a), indicating that the

¹C [m³ s⁻¹]: 25, 50, 75, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500, 5000, 5500, 6000, 6500, 7000, 7500, 8000, 8500, 9000, 9500, 10000, 10500, 11000, 11500, 12000, 12500, 13000, 13500, 14000, 14500, 15000, 15500, 16000, 16500, 17000, 17500, 18000, 18500, 19000, 19500, 20000.

discharge scaling method provides an efficient, approximate technique for systematic generation of multiple synthetic fluvial
285 scenarios. The NSE values range from 0.9460 to 0.9998 (Fig. S1b), however, because we scale synthetic discharges by their
corresponding NWM peak flows (Eq. 4–5), NSE values tend to be high.

2.5.3 Pluvial

We generate pluvial scenarios with total precipitation depths ranging from 10 mm to 300 mm, incremented by 10 mm. Fill-
Spill-Merge calculates a static maximum inundation map for each depth, while we force SFINCS with precipitation time series
290 corresponding to each depth. SFINCS requires a precipitation time series rather than a total depth, ~~which we derive.~~ We
derive these time series using the NOAA precipitation ~~depth-duration-frequency (DDF)~~ DDF table for Beaumont (Station ID
41-0611), ~~at which is located near~~ the geographic midpoint between Silsbee and Port Arthur (NOAA, 2025b).

To generate the SFINCS precipitation time series for each depth scenario, we assign an annual recurrence interval (ARI)
ranging from 1 yr to 1000 yr, with larger ARI values assigned to larger depths (Fig. S2). We then enter the DDF table with the
295 scenario's ARI ~~(frequency)~~ and depth, using regular grid interpolation to extract the corresponding ~~duration.~~ The time series
consists of the constant precipitation intensity that applies storm duration. We calculate the precipitation intensity as a constant
rate that is a function of the scenario's depth over its interpolated duration, and the calculated intensity is applied assigned depth
and interpolated duration: the intensity is the scenario depth divided by the interpolated duration. The resulting precipitation
scenario is a hyetograph with a spatially uniform and temporally constant intensity applied over the interpolated duration at the
300 beginning of ~~the each seven-day simulation, followed by zero rainfall for the remainder of the~~ simulation.

For example, we assign a 2 yr ARI to the 50 mm depth scenario. Interpolating the DDF table ~~,we determine shows that~~ this
ARI and depth combination ~~correspond corresponds~~ to a storm duration of 0.7 h at Beaumont. The constant intensity needed
to apply 50 mm of precipitation over 0.7 h is 71.43 mm h^{-1} . The precipitation time series ~~we supply supplied~~ to SFINCS for
the 50 mm ~~scenario depth scenario therefore~~ consists of 71.43 mm h^{-1} for the first 0.7 h of the seven-day simulation, followed
305 by 0 mm h^{-1} for the remainder of the simulation. We repeat this process for each pluvial scenario.

2.6 Rating surfaces

We define rating surfaces as contour plots of maximum compound flood depth ~~generated from across~~ pairwise combinations
of flood drivers. We first estimate ~~compound flood inundation across a range flood inundation for a finite ensemble~~ of forc-
ing combinations and magnitudes ~~,and then with a compound flood model, in this case SCMs or SFINCS. Any model that~~
310 outputs maximum flood inundation depth grids given varying magnitudes of compound flood forcings may be used. Then we
construct rating surfaces by sampling the resulting high-resolution maximum depth grids at POI/HWM ~~.Two-dimensional
contours of depth illustrate the and interpolating two-dimensional contours of compound flood depth. These contours illustrate
the compound flood depth~~ response to variation in two flood drivers at a fixed location while the third driver remains con-
stant. ~~We apply Gaussian smoothing with $\sigma = 3$ to reduce small-scale noise in the interpolated SFINCS rating surfaces~~
315 ~~(Virtanen et al., 2020). Simplified conceptual model rating surfaces remain unsmoothed because they exhibit linear patterns
without noise~~ Rating surfaces allow estimation of compound flood depth for forcing combinations that were not explicitly

simulated, given that the forcing combination of interest is within the simulated forcing range. Though we model up to three compound flood drivers at each POI, we plot rating surfaces as two-dimensional contours of compound flood depth to present multiple data sources simply and clearly. Representing compound flood depth as a function of three forcings is possible, but pairwise contours, which represent compound flood depth as a function of two forcings, improve interpretability and clarify individual and joint effects. We apply Gaussian smoothing with $\sigma = 3$ to reduce small-scale noise in the interpolated SFINCS rating surfaces (Virtanen et al., 2020). SCM rating surfaces remain unsmoothed because they exhibit linear patterns without noise.

3 Results

We evaluate compound flood rating surfaces generated from simplified conceptual models (SCM) and SFINCS to compare how each modeling approach represents flood depth responses to varying forcings. For each of the three forcing pairs, the rating surfaces summarize maximum flood depth at POI/HWM across identical ranges of precipitation, river discharge, and coastal water level (Figs. 4–6). SCM and SFINCS rating surfaces show similar broad patterns across most locations. SCM capture smooth, linear depth gradients, while SFINCS introduces finer variability and nonlinear patterns. We also validate the rating surfaces approach by comparing flood depths extracted from rating surfaces with observed HWM depths.

Compound flood depth rating surfaces from coastal–pluvial forcing combinations (Fig. 4) Coastal–pluvial rating surfaces show that maximum flood depth at Port Arthur increases primarily with coastal water level and more modestly with precipitation. At inland Silsbee, maximum flood depth is largely insensitive to coastal water level and varies mainly with precipitation. The overall depth ranges are similar between SCM and SFINCS at each POI/HWM.

Rating surfaces for fluvial–coastal forcing combinations (Fig. 5) again indicate that coastal water level controls maximum flood depth at Port Arthur, with river discharge exerting only minor influence. At Silsbee the pattern reverses with river discharge accounting for most of the variation in maximum flood depth. Depth ranges are comparable between SCM and SFINCS at most POI/HWM, though SCM produces greater depths than SFINCS at Silsbee POI 4a–l). SCM estimates at Port Arthur HWM 1 and 2.

For fluvial–pluvial forcing combinations (Fig. 6), SFINCS-derived rating surfaces show maximum flood depth increasing primarily with precipitation. In contrast, SCM-derived surfaces show maximum flood depth varying with both precipitation and river discharge. The ranges of maximum flood depth are similar between SCM and SFINCS at roughly half of the POI/HWM, with the largest differences again occurring at Silsbee POI 1 and 2.

Coastal–pluvial rating surfaces derived from simplified conceptual models (SCMs; left columns) and SFINCS (right columns). Panels show compound flood depth as a function of coastal water level and precipitation across POI/HWM in both study areas. Fluvial–coastal rating surfaces derived from simplified conceptual models (SCMs; left columns) and SFINCS (right columns). Panels show compound flood depth as a function of maximum discharge and coastal water level across POI/HWM in both study areas.

Fluvial-pluvial rating surfaces derived from simplified conceptual models (SCMs; left columns) and SFINCS (right columns). Panels show compound flood depth as a function of maximum discharge and precipitation across POI/HWM in the Port Arthur and Silsbee study areas.

We validate the rating surfaces approach by comparing predicted flood depths against observed Hurricane Harvey HWMs in Port Arthur and Silsbee (Fig. 7). At each site we extract predicted depths from SCM and SFINCS derived rating surfaces using forcing magnitudes observed during Hurricane Harvey (maximum coastal water level, river discharge, and 1-hour precipitation depth). At Port Arthur, depth errors range from -0.52 m to 0.56 m with SCM and -0.52 m to 0.56 m with SFINCS. At Silsbee, depth errors range from -0.53 m to 2.26 m with SCM and -0.53 m to 1.99 m with SFINCS. With the exceptions of HWM-2 at Port Arthur and HWM-3 at Silsbee, observed HWMs lie within the envelope of depths predicted across the three forcing combinations.

Observed and predicted high-water mark (HWM) flood depths at Port Arthur and Silsbee. Observed Harvey HWM depths are shown with predicted depths extracted from coastal-pluvial, fluvial-coastal, and fluvial-pluvial rating surfaces derived from SFINCS and simplified conceptual models (SCM).

4 Discussion

Coastal-pluvial rating surfaces demonstrate the greatest agreement between SCM and SFINCS among the three forcing pairs. Each model shows the same broad patterns and depth ranges given varying coastal and pluvial forcings, with SFINCS exhibiting more refined variation due to its nonlinear representation of compounding effects (Fig. 4). Coastal-pluvial rating surfaces at Port Arthur (Fig. 4a-l) show that compound flood depth varies as a function of both precipitation rate and coastal water level, with the exceptions of SCM estimations at HWM-1 and 2, which vary only with coastal water level (Fig. 4g,i). This result is expected given Port Arthur's low-relief topography and proximity to the coast. At Silsbee, coastal-pluvial rating surfaces show compound flood depth varying with precipitation depth (Fig. 4m-x). While coastal inundation never reaches Silsbee, SFINCS inland Silsbee, maximum flood depth varies mainly with precipitation and is largely insensitive to coastal water level, as coastal inundation does not reach these locations (Fig. 4n,p,r,t,v,x) captures nonlinear effects that are missed by SCM (Fig. 4m,o,q,s,u,w), explaining the noisier contours in its rating surfaces m-x).

Fluvial-coastal rating surfaces also show Coastal-pluvial rating surfaces show the closest agreement between SCM and SFINCS capturing similar patterns of compound flood inundation (Fig. 5). Port Arthur fluvial-coastal rating surfaces among the three forcing pairs. The models produce similar overall response patterns and depth ranges at most Port Arthur POI/HWM locations and at Silsbee POI 3. However, SFINCS captures more localized variation across the forcing combinations. The largest differences occur at Silsbee POI 1-2 and HWM 1-2, where the SCM and SFINCS rating surfaces predict different precipitation-driven responses (Fig. 5a-l) show compound flood depth dominated 4m-p,s-v).

Fluvial-coastal rating surfaces show that maximum flood depth at Port Arthur is controlled primarily by coastal water level variation, with only SCM showing a river discharge effect at POI 1, with river discharge exerting a minor influence (Fig. 5a). Conversely, Silsbee fluvial-coastal rating surfaces a-l). The exception is the SCM estimate at POI 1, which also varies

with river discharge (Fig. 5m-x) show compound flood depth dominated by river discharge, which aligns with Silsbee's inland position relative to Port Arthur. Fluvial-coastal forcing pairs do not yield any inundation at several locations in Silsbee a). At inland Silsbee, the pattern reverses, with maximum flood depth varying primarily with river discharge rather than coastal water level (Fig. 5m-x). Several Silsbee locations are not inundated under the fluvial-coastal forcing combinations (Fig. 5n,p,q,r,u,v), suggesting that pluvial flooding is a more dominant regime at those locations. These locations. SCMs and SFINCS produce similar response patterns at most POI/HWM locations. However, SCMs predict substantially greater depths than SFINCS at Silsbee POI 1 and 2 exhibit considerable deviations in rating surface depth range between SCM and SFINCS (Fig. 5m, o), with, with maximum differences of nearly 2 m and 7 m, respectively (Fig. 5m-p). We will discuss the cause of these discrepancies (Sec. 4). This difference is due to a known limitation of GeoFlood and the Height Above Nearest Drainage (HAND) method that causes increased inundation depth in isolated river segment catchments (Aristizabal et al., 2023).

Fluvial-pluvial rating surfaces show mixed agreement between SCM and SFINCS (Fig. 6). At Port Arthur, fluvial-pluvial rating surface depths (Fig. 6a-l) are mainly influenced by maximum flood depth varies primarily with precipitation, with GeoFlood also showing river discharge contributing to depth variation the exception of the SCM estimate at POI 1, which indicates river discharge as the dominant flood driver (Fig. 6a), where the terrain depression reaches capacity at a precipitation depth of around a-l). Port Arthur POI 1 is located within a terrain depression that is filled by the SCM Fill-Spill-Merge after approximately 200 mm. SCM and SFINCS produce zero or nearly zero fluvial-pluvial compound of precipitation, after which river discharge contributes to additional depth variation. Both SCMs and SFINCS predict zero or nearly zero inundation at Port Arthur POI HWM 1 and 2 under most fluvial-pluvial forcing combinations, indicating that coastal forcing is the primary cause of flooding at those locations (Fig. 6g-j). At Silsbee, SCM fluvial-pluvial rating surfaces show flood depth varying considerably with both fluvial and pluvial forcings, while SFINCS shows variation mainly with precipitation depth with both precipitation and river discharge, whereas SFINCS rating surfaces vary primarily with precipitation (Fig. 6m-x). POI 1 and m-x). The largest differences in depth range again occur at Silsbee POI 1 and 2, where SCMs predict depths more than 2 show greater deviations in rating surface depth range between SCM and SFINCS than we observed from the fluvial-coastal rating surfaces, with differences of > 2 m and > 7 m greater than SFINCS, respectively (Fig. 6m,o). We also attribute this discrepancy to the segment catchment limitation of HAND-GeoFlood. The deviations are greater here than for fluvial-coastal rating surfaces because we sum fluvial-pluvial SCM depth (GeoFlood is run on a depression-removed DEM, Fill-Spill-Merge is not) rather than taking the maximum. Interestingly, despite SCM and SFINCS predicting different fluvial-pluvial contributions to compound flood depth, m-p). Despite these differences in predicted forcing contributions, SCMs and SFINCS predict similar depths at the Silsbee HWM rating surfaces yield similar extracted depths locations when evaluated using Hurricane Harvey forcings (Fig. 6s-x-s-x).

To assess the accuracy of the

We validate the rating surfaces approach, we by comparing predicted flood depths against observed Hurricane Harvey HWMs in Port Arthur and Silsbee (Fig. 7). We select three HWMs collected during Hurricane Harvey for each study area and calculate rating surfaces at their locations (Figs. 4-6s-x-6, panels s-x). We extract predicted HWM elevations maximum flood depths from each rating surface using the observed maximum fluvial, pluvial, and coastal forcings observed during Harvey

Coastal-Pluvial Rating Surfaces (L: SCM, R: SFINCS)

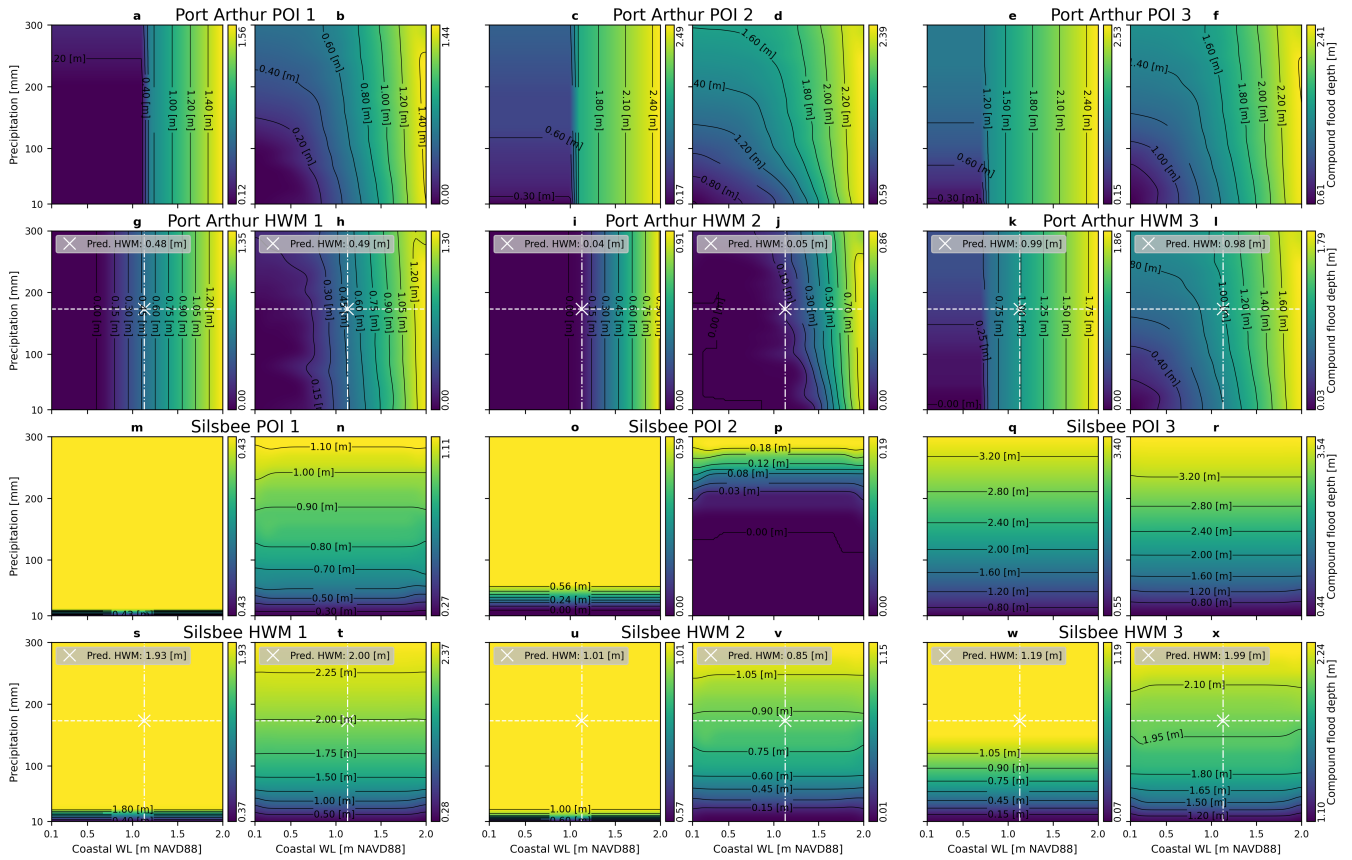


Figure 4. Coastal-pluvial rating surfaces derived from simplified conceptual models (SCMs; left columns) and SFINCS (right columns). Panels show compound flood depth as a function of coastal water level and precipitation across POI/HWM in both study areas.

(Sec. 2.4). At Port Arthur, depth errors range from -0.52 m to 0.56 m for both SCM and SFINCS. At Silsbee, depth errors range from -0.53 m to 2.26 m with SCMs and -0.53 m to 1.99 m with SFINCS. With the exceptions of HWM 2 at Port Arthur and HWM 3 at Silsbee, observed HWMs lie within the envelope of depths predicted across the three forcing pairs. Across both study areas, SCM and SFINCS predictions given the Harvey forcing combination are broadly similar, even at sites where predicted and observed depths diverge, ~~indicating that simplified models~~. This result may indicate that SCMs capture dominant patterns of hydrodynamic simulations despite their ~~reduced physics approximations~~. The largest discrepancies occur at the inland Silsbee sites, where pluvial and fluvial contributions are more uncertain due to low-relief topography and HWM collection near bridges and culverts. ~~Additional uncertainty arises from the Harvey forcings themselves: peak rainfall rates exceeded many gage capacities (Blake and Zelinsky, 2018), NWM peak discharges carry uncertainty (Timilsina and Passalacqua, 2025), and small differences in local topography can shift HWM elevations~~ Uncertainties in the observed Hurricane Harvey forcings, including

Fluvial-Coastal Rating Surfaces (L: SCM, R: SFINCS)

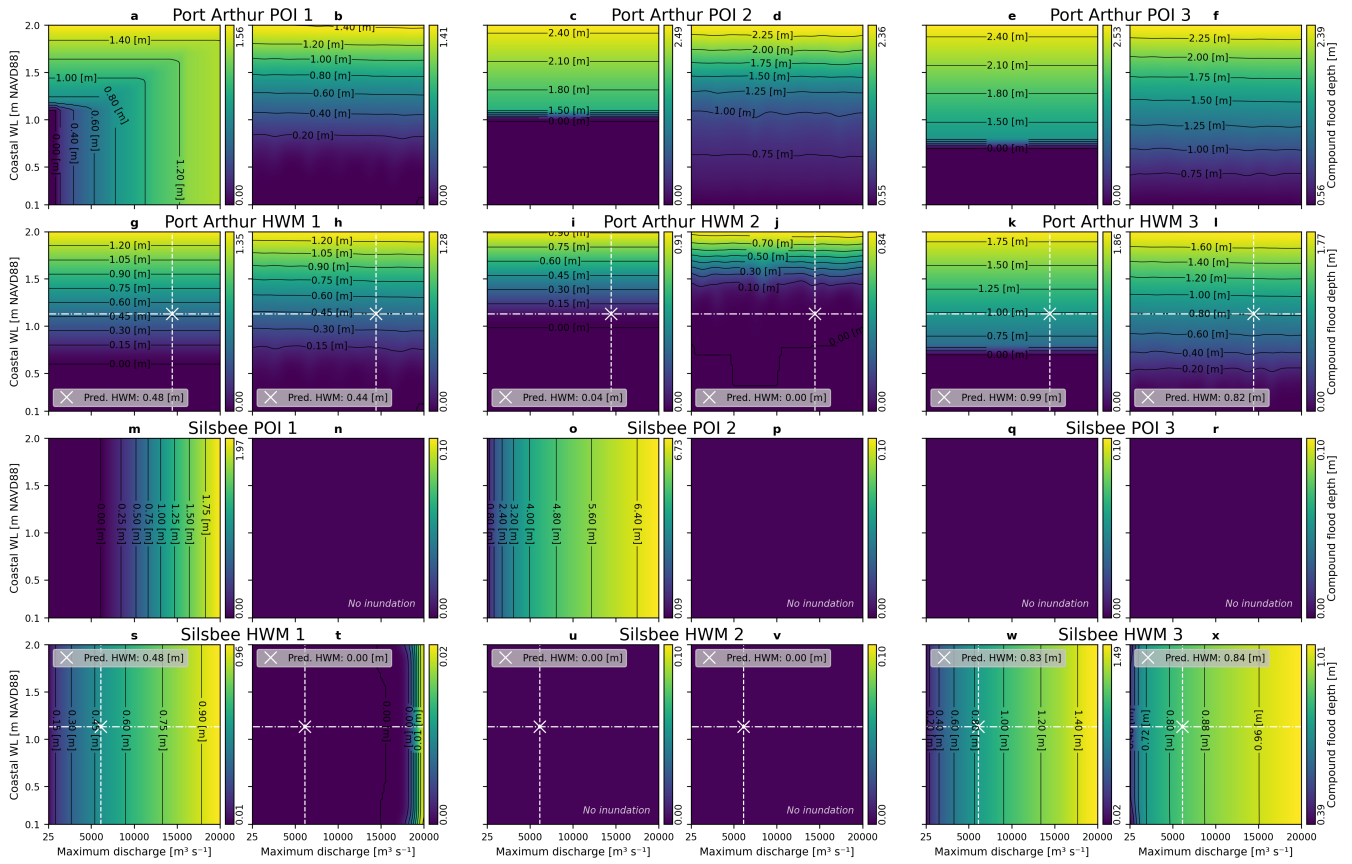


Figure 5. Fluvial-coastal rating surfaces derived from simplified conceptual models (SCMs; left columns) and SFINCS (right columns).

Panels show compound flood depth as a function of maximum discharge and coastal water level across POI/HWM in both study areas.

peak discharge reported by the NWM (Timilsina and Passalacqua, 2025) and extreme rainfall observations (Blake and Zelinsky, 2018), may also impact the accuracy of their corresponding rating surface-derived depths.

4 Discussion

- 430 The rating surface framework is model-agnostic, only requiring flood depth grids corresponding to compound flood driver forcings, which allows for flexibility in the choice of modeling techniques. Hydrodynamic models such as HEC-RAS and SFINCS capture physical processes with high fidelity when appropriately configured, but producing a large number of high-resolution scenarios is expensive, limiting accessibility and scale. Simplified conceptual models offer an efficient alternative, but lack the capability to simulate nonlinear. Rating surfaces constructed from ensemble simulations allow maximum compound flood depth
- 435 estimation across any pair of flood drivers within the modeled forcing range. The results reveal local variation in flood driver

Fluvial-Pluvial Rating Surfaces (L: SCM, R: SFINCS)

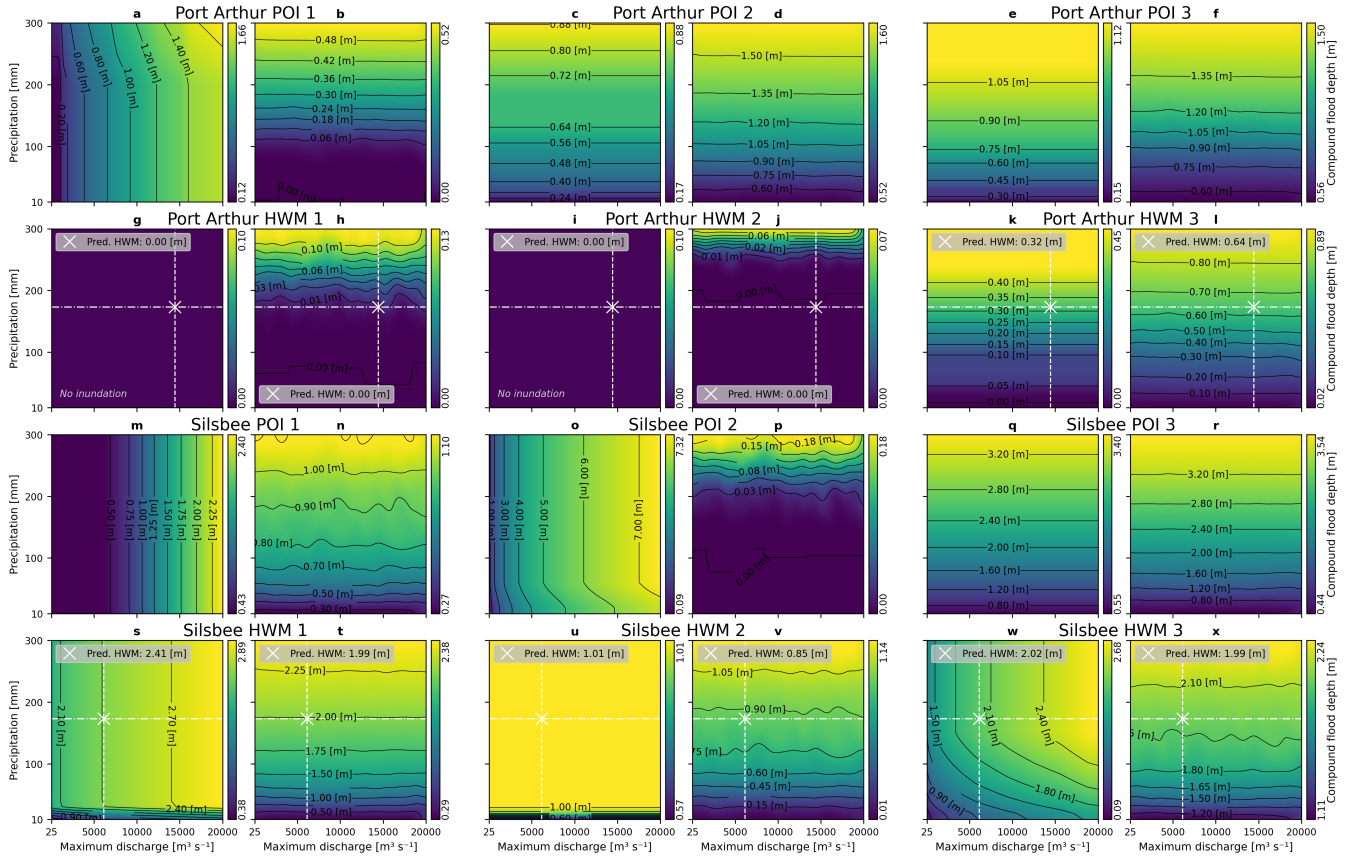


Figure 6. Fluvial–pluvial rating surfaces derived from simplified conceptual models (SCMs; left columns) and SFINCS (right columns). Panels show compound flood depth as a function of maximum discharge and precipitation across POI/HWM in the Port Arthur and Silsbee study areas.

influence on maximum compound flood depth. Comparing rating surfaces constructed from different model classes helps to clarify where higher-fidelity hydrodynamic simulations improve estimates. In this section we revisit the research questions posed in the introduction, discuss limitations and uncertainties, and conclude.

4.1 RQ1: Estimating compound flood depth with rating surfaces

440 Rating surfaces convert ensembles of flood inundation simulations into location-specific relationships between maximum compound flood depth and pairs of forcing variables. Within the sampled forcing range, rating surfaces provide depth estimates for all forcing pairs, including pairs that were not explicitly simulated. We construct rating surfaces from both SCM and SFINCS simulations, demonstrating that the framework is independent of the underlying flood inundation model. Extending prior fluvial–coastal response surfaces for channel water levels (Muñoz et al., 2022), the rating surfaces we develop here

Observed and Predicted Flood Depths at High-Water Mark Sites

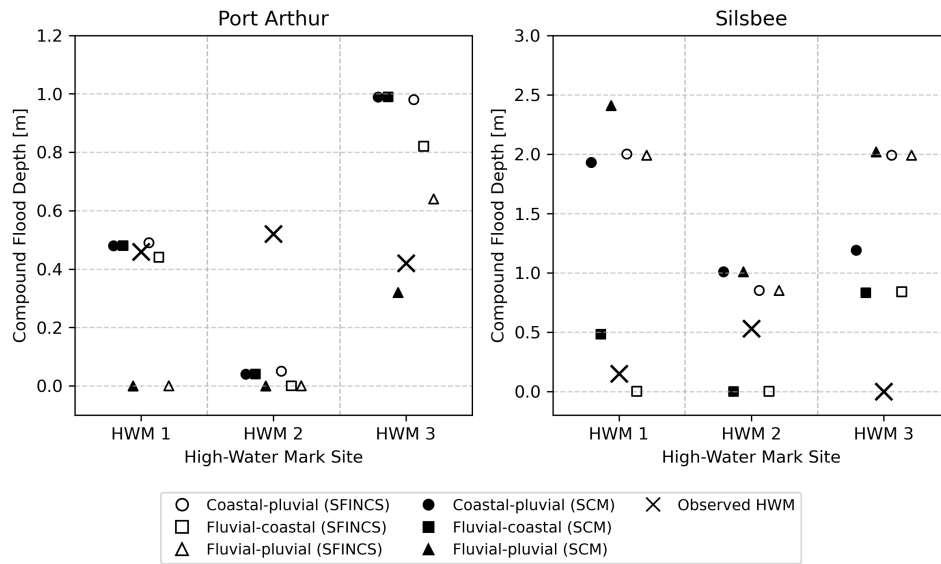


Figure 7. Observed and predicted high-water mark (HWM) flood depths at Port Arthur and Silsbee. Observed Harvey HWM depths are shown with predicted depths extracted from coastal-pluvial, fluvial-coastal, and fluvial-pluvial rating surfaces derived from SFINCS and simplified conceptual models (SCM).

represent maximum compound flood depth at POIs and HWMs across coastal-pluvial, fluvial-coastal, and fluvial-pluvial forcing pairs. This representation makes it possible to identify the relative influence of coastal water level, river discharge, and precipitation on maximum flood depth at nearby locations.

4.2 RQ2: Local compound flood depth response

Rating surfaces reveal that the relative influence of flood drivers on maximum compound flood depth varies across POIs and HWMs. At Port Arthur, coastal-pluvial and compound interactions among coastal, fluvial, and pluvial drivers fluvial-coastal rating surfaces vary strongly with coastal water level across most locations, while precipitation also modifies depth and river discharge has a less pronounced influence. In contrast, fluvial-pluvial rating surfaces at Port Arthur vary primarily with precipitation. These patterns are consistent with the low-lying coastal setting of Port Arthur, where coastal water levels strongly influence maximum inundation depth. The Silsbee rating surfaces exhibit greater spatial heterogeneity. Coastal water level has little influence on maximum compound flood depth at these inland sites; instead, precipitation, river discharge, or both account for the largest variation. This heterogeneity is particularly apparent in the fluvial-pluvial surfaces at Silsbee, where SCM estimates vary with both precipitation and river discharge, while SFINCS estimates vary primarily with precipitation. This result shows that even among nearby inland locations, the relative importance of flood drivers can vary spatially and depend on the underlying flood model.

460 4.3 RQ3: Agreement between SCM- and SFINCS-derived rating surfaces

SCM-derived rating surfaces reproduce the first-order patterns of SFINCS-derived rating surfaces at many locations, particularly for coastal-pluvial scenarios in Port Arthur. Both approaches identify the same dominant flood driver in the majority of cases and produce comparable depth ranges at many POIs and HWMs. However, the agreement between SCMs and SFINCS is not uniform. Large discrepancies occur at Silsbee POI 1 and POI 2, where SCMs estimate greater fluvial contributions than SFINCS for both fluvial-coastal and fluvial-pluvial forcing pairs. These differences are due to a known limitation of HAND-based methods that causes increased inundation depth in isolated river segment catchments (Aristizabal et al., 2023). Because SFINCS is a hydrodynamic model, the SFINCS rating surfaces contain localized curvature and nonlinear patterns that SCMs do not reproduce with their simplified combination rules (Sec. 2.2.1).

4.4 Limitations and uncertainties

Rating surfaces inherit structural limitations from their underlying flood inundation mapping tools. In the case of SCM-based rating surfaces, we estimate inundation extent and depth with static topographic relationships, rather than solving a form of the shallow-water equations. SCM-based estimates do not consider hydrodynamic processes such as flow routing, backwater effects, or drainage infrastructure. These limitations are particularly important on low-relief terrain, where static approaches like HAND and c-HAND may overestimate flood inundation (Johnson et al., 2019; Garousi-Nejad et al., 2019; Scriven et al., 2021; Wang et al., 2021). Depth estimates derived from SCMs should be interpreted as efficient, first-order approximations of maximum inundation scenarios, rather than event-specific hydrodynamic predictions. The interaction between coastal and inland flooding is nonlinear (Bilskie and Hagen, 2018); accordingly, SCM-derived rating surfaces may under- or overestimate compound flood depth at individual locations. We compare with SFINCS to identify where our SCM combination rules for compound flood depth (Eqs. 1–3) reproduce first-order depth patterns and where explicit hydrodynamic representation becomes important.

We construct rating surfaces from pairwise combinations of flood drivers, varying two flood drivers while holding the third driver at a baseline value. In reality compound flood depth may depend on interactions between three or more flood drivers (Zscheischler et al., 2018). We depict maximum compound flood depth at POIs as two-dimensional rating surfaces to facilitate interpretability and comparison between SCM and SFINCS results. In addition to limiting our analysis to two varying flood drivers, we simplify the spatial and temporal representation of the individual forcings within each scenario. The coastal simulations in this study apply a constant water level boundary rather than a tidal or storm-surge hydrograph. This choice supports comparison with static maximum coastal inundation estimates from c-HAND, but does not represent event-specific details including surge timing or tidal effects. Similarly, we apply spatially uniform precipitation with a simplified temporal distribution for the SFINCS simulations. Rating surfaces should therefore be interpreted as conditional maximum inundation approximations, rather than reconstructions of time-varying flood events. In this study SFINCS modeling cost nearly 6,000 node-hours on a supercomputer, while simplified models cost less than 100 node-hours.

~~The accuracy of rating surfaces~~ We assume saturated soil and an at-capacity drainage system for both SCMs and SFINCS. Fill-Spill-Merge does not represent infiltration or drainage infrastructure; we neglect infiltration in SFINCS to impose a

consistent saturated, drainage-limited condition across approaches. This choice avoids confounding the model comparison with differences in infiltration representation, allowing results to be interpreted more directly in terms of model structure.

495 Soil moisture observations during Hurricane Harvey and Tropical Storm Imelda in Southeast Texas support the plausibility of saturated soil conditions during intense rainfall events, and local drainage regulations indicate that drainage systems may also be capacity-limited during those events (Case et al., 2021; Jefferson County Drainage District No. 7, 2019). However, representing infiltration does improve the accuracy of extreme flood simulations (Li et al., 2022). By neglecting infiltration, we may overestimate pluvial contributions to compound flood depth at POIs. So, maximum compound flood depths predicted by rating surfaces may

500 be more applicable during intense events where saturated soil and capacity-limited drainage are more likely.

Rating surface accuracy also depends on the quality of ~~underlying datasets and models~~ input datasets, including elevation, hydrography, land cover, and forcings. Missing or inaccurate hydrography can affect fluvial inundation ~~representation. For accuracy, for~~ example, the absence of an NHDPlusV2 MR flowline along part of the ~~Sabine–Neches Waterway likely biased Sabine–Neches Waterway may bias~~ local fluvial depth estimates. ~~Uncertainty in historical forcings also~~ Modeled flood depth

505 is also sensitive to DEM quality, especially on low-relief terrain. Additionally, uncertainty in observed forcings during a given event affects the accuracy of maximum flood depths extracted from rating surfaces. ~~In addition, low-relief terrain may cause HAND-GeoFlood to overestimate inundation (Johnson et al., 2019; Garousi-Nejad et al., 2019; Scriven et al., 2021; Richardson and Beigh~~

~~. A natural extension of rating surfaces would be a pairing~~ Although prior studies have evaluated the models used in this study (other than Fill-Spill-Merge) against past events (Zheng et al., 2022; Wang et al., 2024; Sebastian et al., 2021; Chowdhury et al., 2026)

510 , and we compare rating surface estimates of maximum compound flood depth with Hurricane Harvey high-water marks (Fig. 7), this study does not calibrate to or validate against other tropical cyclones that have impacted Southeast Texas.

4.5 Conclusions and future work

Independent of the underlying flood model, rating surfaces allow maximum compound flood depth to be estimated for any pair of forcings within the modeled range. This representation permits exploration of an arbitrary number of forcing scenarios

515 without requiring additional model runs, despite modeling only a finite subset of scenarios. In this sense, rating surfaces extend the role of a stage-discharge rating curve to compound flooding by providing a compact, location-specific relationship between multiple flood drivers and maximum flood depth.

Rating surfaces do not characterize the frequency at which forcing combinations occur or the relative contributions of flood drivers to historical events, which can vary spatially and seasonally (Sohrabi et al., 2025). We select forcing combinations

520 in this study that span physically relevant conditions in Southeast Texas, without addressing their probabilities of occurring jointly. In order to quantify the joint likelihood of paired coastal, fluvial, or pluvial forcings, multivariate statistical analysis is required (e.g., Jane et al., 2025; Moftakhari et al., 2019; Zheng et al., 2014). Future work could pair rating surfaces with joint probability models of compound ~~drivers, as~~ flood drivers, similar to some probabilistic flood hazard assessments that have been implemented in Dutch regulatory frameworks ~~that summarize probabilistic flood hazards using two-dimensional sea~~

525 ~~level–discharge isolines corresponding to flood-defense failure thresholds~~ (Geerse et al., 2011; Duits, M. T., 2004).

This study introduces rating surfaces as a method to quantify and visualize compound flood depth as a function of two ~~interacting~~-flood drivers at points of interest. We generate large ensembles of high-resolution inundation scenarios using both simplified conceptual models and a hydrodynamic model and sample these scenarios at POIs to construct rating surfaces. The resulting surfaces provide an interpretable representation of how local flood depth responds to combinations of precipitation, discharge, and coastal water level.

Rating surfaces from both simplified and hydrodynamic modeling approaches capture relatively consistent first-order patterns across the range of forcings ~~that we investigate. However, the hydrodynamic model captures finer-scale nonlinearities and local differences in interactions among flood drivers that the simplified models do not represent. These differences suggest that simplified models may be well suited to rapid scenario exploration, but hydrodynamic modeling is necessary when~~ nonlinear interactions substantially affect local compound flood depth estimates. Validation against Hurricane Harvey high-water marks shows that rating surfaces reproduce event-scale magnitudes within the limits of underlying topography, hydrography, and historical forcing uncertainties. The spatial variability we observe across nearby POIs underscores the importance of neighborhood-scale analyses and high-resolution elevation data when assessing flood hazards in developed low-lying areas. ~~Future work could apply this framework to other geographic settings and storm events, incorporate additional hydrodynamic models, and evaluate the influence of improved hydrography and precipitation datasets.~~ Rating surfaces are a flexible tool for representing compound flooding at locations of interest across diverse modeling environments.

Supplement. The supplement related to this article is available online at [x].

Code and data availability. All datasets used in this study are publicly available online from the USGS, TNIRIS, NOAA, and the U. S. Census Bureau. pyGeoFlood (which implements GeoFlood, c-HAND, and Fill-Spill-Merge) and SFINCS are free and open-source software (<https://passah2o.github.io/pygeoflood/>, <https://sfincs.readthedocs.io/en/latest/>).

Author contributions. MW obtained the datasets, performed the analysis, and wrote the original draft. PP and HM contributed to this study's conceptualization and design. PP, HM, and MW edited the draft. PP provided research supervision and funding acquisition. BH assisted with data analysis.

Competing interests. The contact author has declared that none of the authors has any competing interests.

Acknowledgements. We ~~thank Dr. Wonhyun Lee of the Bureau of Economic Geology at UT Austin for his feedback on the SFINCS model, and are grateful to Wonhyun Lee and David Maidment for helpful conversations, as well as~~ the Texas Advanced Computing Center

(TACC) at UT Austin for providing computational resources that have contributed to the research results reported within this paper. (URL: <http://www.tacc.utexas.edu>). We thank two anonymous reviewers for feedback that greatly improved this paper.

555 *Financial support.* This material is based upon work supported by the U.S. Department of Energy, Office of Science, Biological and Environmental Research Program under Award Number DE-SC0023216, the NOAA Adaptation Sciences Program (NOAA-OAR-CPO-2021-2006389), the Cockrell School of Engineering, and Planet Texas 2050, a research grand challenge at the University of Texas at Austin.

References

- Aristizabal, F., Salas, F., Petrochenkov, G., Grout, T., Avant, B., Bates, B., Spies, R., Chadwick, N., Wills, Z., and Judge, J.: Extending Height Above Nearest Drainage to Model Multiple Fluvial Sources in Flood Inundation Mapping Applications for the U.S. National Water Model, *Water Resources Research*, 59, e2022WR032039, <https://doi.org/10.1029/2022WR032039>, 2023.
- Barnes, R., Callaghan, K. L., and Wickert, A. D.: Computing water flow through complex landscapes - Part 3: Fill-Spill-Merge: Flow routing in depression hierarchies, *Earth Surface Dynamics*, 9, 105–121, <https://doi.org/10.5194/esurf-9-105-2021>, 2021.
- Bates, P. D.: Flood Inundation Prediction, *Annual Review of Fluid Mechanics*, 54, 287–315, <https://doi.org/10.1146/annurev-fluid-030121-113138>, 2022.
- Bevacqua, E., Vousdoukas, M. I., Zappa, G., Hodges, K., Shepherd, T. G., Maraun, D., Mentaschi, L., and Feyen, L.: More meteorological events that drive compound coastal flooding are projected under climate change, *Communications Earth & Environment*, 1, 1–11, <https://doi.org/10.1038/s43247-020-00044-z>, 2020.
- Bilskie, M. V. and Hagen, S. C.: Defining Flood Zone Transitions in Low-Gradient Coastal Regions, *Geophysical Research Letters*, 45, 2761–2770, <https://doi.org/10.1002/2018GL077524>, 2018.
- Bilskie, M. V., Zhao, H., Resio, D., Atkinson, J., Cobell, Z., and Hagen, S. C.: Enhancing Flood Hazard Assessments in Coastal Louisiana Through Coupled Hydrologic and Surge Processes, *Frontiers in Water*, 3, <https://doi.org/10.3389/frwa.2021.609231>, 2021.
- Blake, E. S. and Zelinsky, D. A.: National Hurricane Center Tropical Cyclone Report: Hurricane Harvey, https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf, 2018.
- Case, J. L., Wood, L. T., Blaes, J. L., White, K. D., Hain, C. R., and Schultz, C. J.: Soil Moisture Responses Associated with Significant Tropical Cyclone Rainfall Events, *Journal of Operational Meteorology*, pp. 1–17, <https://doi.org/10.15191/nwajom.2021.0901>, 2021.
- Chowdhury, M. E., Lee, J.-W., and Lee, W.: Spatiotemporal quantification of relative contributions of compound flood drivers using Shapley value-based approach, *Journal of Hydrology*, 677, 135–150, <https://doi.org/10.1016/j.jhydrol.2026.135808>, 2026.
- Cosgrove, B., Gochis, D., Flowers, T., Dugger, A., Ogden, F., Graziano, T., Clark, E., Cabell, R., Casiday, N., Cui, Z., Eicher, K., Fall, G., Feng, X., Fitzgerald, K., Frazier, N., George, C., Gibbs, R., Hernandez, L., Johnson, D., Jones, R., Karsten, L., Kefelegn, H., Kitzmiller, D., Lee, H., Liu, Y., Mashriqui, H., Mattern, D., McCluskey, A., McCreight, J. L., McDaniel, R., Midekisa, A., Newman, A., Pan, L., Pham, C., RafieeiNasab, A., Rasmussen, R., Read, L., Rezaeianzadeh, M., Salas, F., Sang, D., Sampson, K., Schneider, T., Shi, Q., Sood, G., Wood, A., Wu, W., Yates, D., Yu, W., and Zhang, Y.: NOAA’s National Water Model: Advancing operational hydrology through continental-scale modeling, *JAWRA Journal of the American Water Resources Association*, 60, 247–272, <https://doi.org/10.1111/1752-1688.13184>, 2024.
- Crossett, K., Ache, B., Pacheco, P., and Haber, K.: National Coastal Population Report, <https://cdn.oceanservice.noaa.gov/oceanserviceprod/facts/coastal-population-report.pdf>, 2013.
- Dasgupta, A., Grimaldi, S., Ramsankaran, R., Pauwels, V. R. N., and Walker, J. P.: A simple framework for calibrating hydraulic flood inundation models using Crowd-sourced water levels, *Journal of Hydrology*, 614, 128–147, <https://doi.org/10.1016/j.jhydrol.2022.128467>, 2022.
- Duits, M. T.: Handleiding Hydra-B – Geavanceerde gebruikers (versie 3.0), Rijkswaterstaat, 221559, <https://open.rijkswaterstaat.nl/@167823/handleiding-hydra-geavanceerde/>, 2004.
- Dullaart, J. C. M., Muis, S., Bloemendaal, N., Chertova, M. V., Couasnon, A., and Aerts, J. C. J. H.: Accounting for tropical cyclones more than doubles the global population exposed to low-probability coastal flooding, *Communications Earth & Environment*, 2, 1–11, <https://doi.org/10.1038/s43247-021-00204-9>, 2021.

Gallant, J. C. and Dowling, T. I.: A multiresolution index of valley bottom flatness for mapping depositional areas, *Water Resources Research*, 39, <https://doi.org/10.1029/2002WR001426>, [_eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2002WR001426](https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2002WR001426), 2003.

Garousi-Nejad, I., Tarboton, D. G., Aboutalebi, M., and Torres-Rua, A. F.: Terrain Analysis Enhancements to the Height Above Nearest Drainage Flood Inundation Mapping Method, *Water Resources Research*, 55, 7983–8009, <https://doi.org/10.1029/2019WR024837>, [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2019WR024837](https://onlinelibrary.wiley.com/doi/pdf/10.1029/2019WR024837), 2019.

Geerse, C., Slomp, R., and de Waal, H.: Hydra-Zoet for the fresh water systems in the Netherlands, *Rijkswaterstaat*, 501244, <https://open.rijkswaterstaat.nl/@171393/hydra-zoet-probabilistic-model-for-the/>, 2011.

Green, J., Haigh, I. D., Quinn, N., Neal, J., Wahl, T., Wood, M., Eilander, D., de Ruiter, M., Ward, P., and Camus, P.: Review article: A comprehensive review of compound flooding literature with a focus on coastal and estuarine regions, *Natural Hazards and Earth System Sciences*, 25, 747–816, <https://doi.org/10.5194/nhess-25-747-2025>, 2025.

Halton, J. H.: On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals, *Numerische Mathematik*, 2, 84–90, <https://doi.org/10.1007/BF01386213>, 1960.

Hamidi, E., Peter, B. G., Muñoz, D. F., Moftakhari, H., and Moradkhani, H.: Fast Flood Extent Monitoring With SAR Change Detection Using Google Earth Engine, *IEEE Transactions on Geoscience and Remote Sensing*, 61, 1–19, <https://doi.org/10.1109/TGRS.2023.3240097>, conference Name: IEEE Transactions on Geoscience and Remote Sensing, 2023.

Hao, Z. and Singh, V. P.: Compound Events under Global Warming: A Dependence Perspective, *Journal of Hydrologic Engineering*, 25, 03120001, [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0001991](https://doi.org/10.1061/(ASCE)HE.1943-5584.0001991), 2020.

Hendry, A., Haigh, I. D., Nicholls, R. J., Winter, H., Neal, R., Wahl, T., Joly-Laugel, A., and Darby, S. E.: Assessing the characteristics and drivers of compound flooding events around the UK coast, *Hydrology and Earth System Sciences*, 23, 3117–3139, <https://doi.org/10.5194/hess-23-3117-2019>, 2019.

Horritt, M. and Bates, P.: Evaluation of 1D and 2D numerical models for predicting river flood inundation, *Journal of hydrology*, 268, 87–99, 2002.

Jafarzadegan, K., Moradkhani, H., Pappenberger, F., Moftakhari, H., Bates, P., Abbaszadeh, P., Marsooli, R., Ferreira, C., Cloke, H. L., Ogden, F., and Duan, Q.: Recent Advances and New Frontiers in Riverine and Coastal Flood Modeling, *Reviews of Geophysics*, 61, e2022RG000788, <https://doi.org/10.1029/2022RG000788>, 2023.

Jane, R., Santiago-Collazo, F. L., Serafin, K. A., Gori, A., Peña, F., and Wahl, T.: Chapter 5 - Compound hazards during tropical cyclones, in: *Tropical Cyclones and Associated Impacts*, edited by Villarini, G., Vecchi, G. A., and Scoccimarro, E., pp. 95–119, Elsevier, ISBN 978-0-323-95390-0, <https://doi.org/10.1016/B978-0-323-95390-0.00005-4>, 2025.

Jefferson County Drainage District No. 7: Drainage Criteria Manual, https://www.dd7.org/files/6d75b42a9/DD7+Drainage+Criteria+Manual+11-19-19-Final_1.pdf, 2019.

Johnson, J. M., Munasinghe, D., Eyelade, D., and Cohen, S.: An integrated evaluation of the National Water Model (NWM)–Height Above Nearest Drainage (HAND) flood mapping methodology, *Natural Hazards and Earth System Sciences*, 19, 2405–2420, <https://doi.org/10.5194/nhess-19-2405-2019>, 2019.

Kling, H., Fuchs, M., and Paulin, M.: Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios, *Journal of Hydrology*, 424–425, 264–277, <https://doi.org/10.1016/j.jhydrol.2012.01.011>, 2012.

Lee, W., Sun, A. Y., and Scanlon, B. R.: Probabilistic storm surge and flood-inundation modeling of the Texas gulf coast using super-fast INundation of CoastS (SFINCS), *Coastal Engineering*, 198, 104721, <https://doi.org/10.1016/j.coastaleng.2025.104721>, 2025.

- Leijnse, T., van Ormondt, M., Nederhoff, K., and van Dongeren, A.: Modeling compound flooding in coastal systems using a computationally efficient reduced-physics solver: Including fluvial, pluvial, tidal, wind- and wave-driven processes, *Coastal Engineering*, 163, 103 796, <https://doi.org/10.1016/j.coastaleng.2020.103796>, 2021.
- Lewis, M., Bates, P., Horsburgh, K., Neal, J., and Schumann, G.: A storm surge inundation model of the northern Bay of Bengal using publicly available data, *Quarterly Journal of the Royal Meteorological Society*, 139, 358–369, <https://doi.org/10.1002/qj.2040>, <https://rsmets.onlinelibrary.wiley.com/doi/pdf/10.1002/qj.2040>, 2013.
- Lhomme, J., Sayers, P., Gouldby, B., Samuels, P., Wills, M., and Mulet-Marti, J.: Recent development and application of a rapid flood spreading method, in: *Flood Risk Management: Research and Practice*, pp. 15–24, Taylor & Francis Group, London, ISBN 978-0-415-48507-4, http://www.sayersandpartners.co.uk/uploads/6/2/0/9/6209349/2008_lhomme_sayers_et_al_-_recent_development_and_application_of_a_rapid_flood_spreading_method_floodrisk08.pdf, 2009.
- Li, Z., Chen, M., Gao, S., Wen, Y., Gourley, J. J., Yang, T., Kolar, R., and Hong, Y.: Can re-infiltration process be ignored for flood inundation mapping and prediction during extreme storms? A case study in Texas Gulf Coast region, *Environmental Modelling & Software*, 155, 105 450, <https://doi.org/10.1016/j.envsoft.2022.105450>, 2022.
- Loveland, M., Kiaghadi, A., Dawson, C. N., Rifai, H. S., Misra, S., Mosser, H., and Parola, A.: Developing a Modeling Framework to Simulate Compound Flooding: When Storm Surge Interacts With Riverine Flow, *Frontiers in Climate*, 2, <https://doi.org/10.3389/fclim.2020.609610>, 2021.
- Manfreda, S., Di Leo, M., and Sole, A.: Detection of Flood-Prone Areas Using Digital Elevation Models, *Journal of Hydrologic Engineering*, 16, 781–790, [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0000367](https://doi.org/10.1061/(ASCE)HE.1943-5584.0000367), 2011.
- McKay, L., Bondelid, T., Dewald, T., Johnston, J., Moore, R., and Rea, A.: NHDPlus Version 2: User Guide, https://www.epa.gov/system/files/documents/2023-04/NHDPlusV2_User_Guide.pdf, 2012.
- Miura, Y., Dinenis, P. C., Mandli, K. T., Deodatis, G., and Bienstock, D.: Optimization of Coastal Protections in the Presence of Climate Change, *Frontiers in Climate*, 3, <https://doi.org/10.3389/fclim.2021.613293>, 2021a.
- Miura, Y., Mandli, K. T., and Deodatis, G.: High-Speed GIS-Based Simulation of Storm Surge–Induced Flooding Accounting for Sea Level Rise, *Natural Hazards Review*, 22, 04021 018, [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000465](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000465), 2021b.
- Moftakhari, H., Schubert, J. E., AghaKouchak, A., Matthew, R. A., and Sanders, B. F.: Linking statistical and hydrodynamic modeling for compound flood hazard assessment in tidal channels and estuaries, *Advances in Water Resources*, 128, 28–38, <https://doi.org/10.1016/j.advwatres.2019.04.009>, 2019.
- Moftakhari, H. R., Salvadori, G., AghaKouchak, A., Sanders, B. F., and Matthew, R. A.: Compounding effects of sea level rise and fluvial flooding, *Proceedings of the National Academy of Sciences*, 114, 9785–9790, <https://doi.org/10.1073/pnas.1620325114>, 2017.
- Murphy, S., Wang, M., Cheng, C.-S., Passalacqua, P., and Leite, F.: Land-use analysis using infrastructure representations and high-resolution flood inundation mapping techniques, *International Journal of Disaster Risk Reduction*, 123, 105 518, <https://doi.org/10.1016/j.ijdr.2025.105518>, 2025.
- Muñoz, D. F., Moftakhari, H., Kumar, M., and Moradkhani, H.: Compound Effects of Flood Drivers, Sea Level Rise, and Dredging Protocols on Vessel Navigability and Wetland Inundation Dynamics, *Frontiers in Marine Science*, 9, <https://doi.org/10.3389/fmars.2022.906376>, 2022.
- Nardi, F., Vivoni, E. R., and Grimaldi, S.: Investigating a floodplain scaling relation using a hydrogeomorphic delineation method, *Water Resources Research*, 42, <https://doi.org/10.1029/2005WR004155>, 2006.

- Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models part I — A discussion of principles, *Journal of Hydrology*, 10, 282–290, [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6), 1970.
- 670 Neumann, B., Vafeidis, A. T., Zimmermann, J., and Nicholls, R. J.: Future Coastal Population Growth and Exposure to Sea-Level Rise and Coastal Flooding - A Global Assessment, *PLOS ONE*, 10, e0118571, <https://doi.org/10.1371/journal.pone.0118571>, 2015.
- NOAA: BlueTopo, <https://www.fisheries.noaa.gov/inport/item/75311>, 2025a.
- NOAA: NOAA Atlas 14 Point Precipitation Frequency Estimates: TX, https://hdsc.nws.noaa.gov/pfds/pfds_map_cont.html?bkmrk=tx, 2025b.
- 675 Preisser, M., Passalacqua, P., Bixler, R. P., and Hofmann, J.: Intersecting near-real time fluvial and pluvial inundation estimates with sociodemographic vulnerability to quantify a household flood impact index, *Hydrology and Earth System Sciences*, 26, 3941–3964, <https://doi.org/10.5194/hess-26-3941-2022>, 2022.
- Preisser, M., Passalacqua, P., Bixler, R. P., and Boyles, S.: A network-based analysis of critical resource accessibility during floods, *Frontiers in Water*, 5, <https://www.frontiersin.org/journals/water/articles/10.3389/frwa.2023.1278205>, 2023.
- 680 Reimann, L., Vafeidis, A. T., and Honsel, L. E.: Population development as a driver of coastal risk: Current trends and future pathways, *Cambridge Prisms: Coastal Futures*, 1, e14, <https://doi.org/10.1017/cft.2023.3>, 2023.
- Richardson, C. A. and Beighley, R. E.: Optimizing Height Above Nearest Drainage parameters to enable rapid flood mapping in North Carolina, *Frontiers in Water*, 5, <https://doi.org/10.3389/frwa.2023.1296434>, 2024.
- Samela, C., Troy, T. J., and Manfreda, S.: Geomorphic classifiers for flood-prone areas delineation for data-scarce environments, *Advances in Water Resources*, 102, 13–28, <https://doi.org/10.1016/j.advwatres.2017.01.007>, 2017.
- 685 Santiago-Collazo, F. L., Bilskie, M. V., and Hagen, S. C.: A comprehensive review of compound inundation models in low-gradient coastal watersheds, *Environmental Modelling & Software*, 119, 166–181, <https://doi.org/10.1016/j.envsoft.2019.06.002>, 2019.
- Santiago-Collazo, F. L., Bilskie, M. V., Bacopoulos, P., and Hagen, S. C.: Compound Inundation Modeling of a 1-D Idealized Coastal Watershed Using a Reduced-Physics Approach, *Water Resources Research*, 60, e2023WR035718, <https://doi.org/10.1029/2023WR035718>,
 690 _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2023WR035718>, 2024.
- Schwarz, G. E., Jackson, S. E., and Wiczorek, M. E.: Select Attributes for NHDPlus Version 2.1 Reach Catchments and Modified Network Routed Upstream Watersheds for the Conterminous United States (ver. 4.0, August 2023), <https://doi.org/10.5066/F7765D7V>, 2018.
- Scriven, B. W. G., McGrath, H., and Stefanakis, E.: GIS derived synthetic rating curves and HAND model to support on-the-fly flood mapping, *Natural Hazards*, 109, 1629–1653, <https://doi.org/10.1007/s11069-021-04892-6>, 2021.
- 695 Sebastian, A., Bader, D. J., Nederhoff, C. M., Leijnse, T. W. B., Bricker, J. D., and Aarninkhof, S. G. J.: Hindcast of pluvial, fluvial, and coastal flood damage in Houston, Texas during Hurricane Harvey (2017) using SFINCS, *Natural Hazards*, 109, 2343–2362, <https://doi.org/10.1007/s11069-021-04922-3>, 2021.
- SETx-UIFL: Southeast Texas Urban Integrated Field Laboratory Annual Report Year 2, <https://utexas.app.box.com/s/b9cu8a3qupi8zip32xg2p2xcvi2bvike>, 2024.
- 700 Shen, Y., Morsy, M. M., Huxley, C., Tahvildari, N., and Goodall, J. L.: Flood risk assessment and increased resilience for coastal urban watersheds under the combined impact of storm tide and heavy rainfall, *Journal of Hydrology*, 579, 124–159, <https://doi.org/10.1016/j.jhydrol.2019.124159>, 2019.
- Shi, P., Lyu, K., Li, Z., Yang, T., Xu, C.-Y., Hao, X., and Xiao, J.: A Novel Topography-Based Approach for Real-Time Flood Inundation Mapping, *Water Resources Research*, 61, e2024WR037851, <https://doi.org/10.1029/2024WR037851>, _eprint:
 705 <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2024WR037851>, 2025.

- Silverman, A. I., Brain, T., Branco, B., Challagonda, P. s. v., Choi, P., Fischman, R., Graziano, K., Hénaff, E., Mydlarz, C., Rothman, P., and Toledo-Crow, R.: Making waves: Uses of real-time, hyperlocal flood sensor data for emergency management, resiliency planning, and flood impact mitigation, *Water Research*, 220, 118 648, <https://doi.org/10.1016/j.watres.2022.118648>, 2022.
- Smith, A. B.: U.S. Billion-dollar Weather and Climate Disasters, <https://doi.org/10.25921/STKW-7W73>, 2024.
- 710 Sohrabi, M., Moftakhari, H., and Moradkhani, H.: Analyzing Compound Flooding Drivers Across the US Gulf Coast States, *Geophysical Research Letters*, 52, e2025GL114 769, <https://doi.org/10.1029/2025GL114769>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2025GL114769>, 2025.
- Tellman, B., Sullivan, J. A., Kuhn, C., Kettner, A. J., Doyle, C. S., Brakenridge, G. R., Erickson, T. A., and Slayback, D. A.: Satellite imaging reveals increased proportion of population exposed to floods, *Nature*, 596, 80–86, <https://doi.org/10.1038/s41586-021-03695-w>, 2021.
- 715 Teng, J., Jakeman, A. J., Vaze, J., Croke, B. F. W., Dutta, D., and Kim, S.: Flood inundation modelling: A review of methods, recent advances and uncertainty analysis, *Environmental Modelling and Software*, 90, 201–216, <https://doi.org/10.1016/j.envsoft.2017.01.006>, 2017.
- Timilsina, S. and Passalacqua, P.: A comparative analysis of national water model versions 2.1 and 3.0 reveals advances and challenges in streamflow predictions during storm events, *Journal of Hydrology: Regional Studies*, 58, 102 196, <https://doi.org/10.1016/j.ejrh.2025.102196>, 2025.
- 720 TNIRIS: Jefferson, Liberty, & Chambers Counties Lidar, <https://data.geographic.texas.gov/collection/?c=12342f12-2d74-44c4-9f00-a5c12ac2659c>, 2017.
- TxDOT: Hurricane preparation - evacuation and contraflow routes, <https://www.txdot.gov/safety/severe-weather/hurricane-preparation.html>, 2025.
- US Census Bureau: TIGER/Line Shapefiles, <https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html>, section: 725 Government, 2025.
- U.S. Congress: JEC Report on Economic Cost of Flooding, <https://www.jec.senate.gov/public/index.cfm/democrats/2024/6/flooding-costs-the-u-s-between-179-8-and-496-0-billion-each-year>, 2024.
- US EPA: NHDPlus Texas Data (Vector Processing Unit 12), <https://www.epa.gov/waterdata/nhdplus-texas-data-vector-processing-unit-12>, 2015.
- 730 USACE: HEC-RAS 2D User’s Manual, <https://www.hec.usace.army.mil/confluence/rasdocs/r2dum/latest>, 2025.
- USGS: 3D Elevation Program Digital Elevation Models, <https://apps.nationalmap.gov/downloader/#/>, 2024.
- USGS: Annual National Land Cover Database (NLCD) Collection 1 Products (ver. 1.1, June 2025), <https://doi.org/10.5066/P94UXNTS>, 2025.
- USGS and Arctur, D.: USGS - Harvey High Water Marks, <https://doi.org/10.4211/hs.615d426f70cc4346875c725b4b8fdc59>, 2018.
- 735 van Ormondt, M., Leijnse, T., de Goede, R., Nederhoff, K., and van Dongeren, A.: Subgrid corrections for the linear inertial equations of a compound flood model – a case study using SFINCS 2.1.1 Dollerup release, *Geoscientific Model Development*, 18, 843–861, <https://doi.org/10.5194/gmd-18-843-2025>, 2025.
- Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., Carey, C. J., 740 Polat, I., Feng, Y., Moore, E. W., VanderPlas, J., Laxalde, D., Perktold, J., Cimrman, R., Henriksen, I., Quintero, E. A., Harris, C. R., Archibald, A. M., Ribeiro, A. H., Pedregosa, F., van Mulbregt, P., and SciPy 1.0 Contributors: SciPy 1.0: fundamental algorithms for scientific computing in Python, *Nature Methods*, 17, 261–272, <https://doi.org/10.1038/s41592-019-0686-2>, 2020.

- Wahl, T., Jain, S., Bender, J., Meyers, S. D., and Luther, M. E.: Increasing risk of compound flooding from storm surge and rainfall for major US cities, *Nature Climate Change*, 5, 1093–1097, <https://doi.org/10.1038/nclimate2736>, 2015.
- 745 Wallemacq, P., Below, R., and McClean, D.: Economic losses, poverty & disasters: 1998–2017, United Nations Office for Disaster Risk Reduction, 2018.
- Wang, M., Passalacqua, P., Cai, S., and Dawson, C.: c-HAND: near real-time coastal flood mapping, *Frontiers in Water*, 6, <https://doi.org/10.3389/frwa.2024.1329109>, 2024.
- Westerink, J. J., Luettich, R. A., Baptista, A. M., Scheffner, N. W., and Farrar, P.: Tide and Storm Surge Predictions Using Finite Element
750 Model, *Journal of Hydraulic Engineering*, 118, 1373–1390, [https://doi.org/10.1061/\(ASCE\)0733-9429\(1992\)118:10\(1373\)](https://doi.org/10.1061/(ASCE)0733-9429(1992)118:10(1373)), 1992.
- Wijetunge, J. J. and Neluwala, N. G. P. B.: Compound flood hazard assessment and analysis due to tropical cyclone-induced storm surges, waves and precipitation: a case study for coastal lowlands of Kelani river basin in Sri Lanka, *Natural Hazards*, 116, 3979–4007, <https://doi.org/10.1007/s11069-023-05846-w>, 2023.
- Williams, W. A., Jensen, M. E., Winne, J. C., and Redmond, R. L.: An Automated Technique for Delineating and Characterizing Valley-
755 Bottom Settings, *Environmental Monitoring and Assessment*, 64, 105–114, <https://doi.org/10.1023/A:1006471427421>, 2000.
- Zheng, F., Westra, S., and Sisson, S. A.: Quantifying the dependence between extreme rainfall and storm surge in the coastal zone, *Journal of Hydrology*, 505, 172–187, <https://doi.org/10.1016/j.jhydrol.2013.09.054>, 2013.
- Zheng, F., Westra, S., Leonard, M., and Sisson, S. A.: Modeling dependence between extreme rainfall and storm surge to estimate coastal flooding risk, *Water Resources Research*, 50, 2050–2071, <https://doi.org/10.1002/2013WR014616>, _eprint:
760 <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2013WR014616>, 2014.
- Zheng, X., Maidment, D. R., Tarboton, D. G., Liu, Y. Y., and Passalacqua, P.: GeoFlood: Large-Scale Flood Inundation Mapping Based on High-Resolution Terrain Analysis, *Water Resources Research*, 54, 10,013–10,033, <https://doi.org/10.1029/2018WR023457>, 2018.
- Zheng, X., D’Angelo, C., Maidment, D. R., and Passalacqua, P.: Application of a Large-Scale Terrain-Analysis-Based Flood Mapping System to Hurricane Harvey, *JAWRA Journal of the American Water Resources Association*, 58, 149–163, [https://doi.org/10.1111/1752-
765 1688.12987](https://doi.org/10.1111/1752-1688.12987), 2022.
- Zscheischler, J., Westra, S., Hurk, B. J. J. M. V. D., Seneviratne, S. I., Ward, P. J., Pitman, A., Aghakouchak, A., Bresch, D. N., Leonard, M., Wahl, T., and Zhang, X.: Future climate risk from compound events, *Nature Climate Change*, 8, 469–477, <https://doi.org/10.1038/s41558-018-0156-3>, 2018.
- Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., van den Hurk, B., AghaKouchak, A., Jézéquel, A.,
770 Mahecha, M. D., Maraun, D., Ramos, A. M., Ridder, N. N., Thiery, W., and Vignotto, E.: A typology of compound weather and climate events, *Nature Reviews Earth & Environment*, 1, 333–347, <https://doi.org/10.1038/s43017-020-0060-z>, 2020.