Efficient Compound Flooding Scenario Evaluation via Hydrodynamic Modelling and Coordinate Based Neural Surrogates

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ABSTRACT

Compound flooding is an increasing challenge for coastal resilience because coincident drivers can amplify inundation beyond what single driver analyses capture. Focusing on Tofino on the outer coast of Vancouver Island, we develop a scenario-based framework that combines joint extreme characterization of coastal water levels and precipitation with physics-based inundation modelling and a machine learning surrogate for rapid evaluation. Joint compound scenarios are derived from ERA5 reanalysis (1970 to 2019) (Hersbach et al., 2020) and simulated with LISFLOOD FP (Sharifian et al., 2023; Bates et al., 2013) to produce high resolution flood depth and extent fields. A coordinate based neural surrogate is then trained to emulate these inundation outcomes directly from compound forcing, enabling orders of magnitude faster scenario screening than full hydrodynamic simulation. The approach supports efficient exploration of joint return period conditions and provides a practical basis for compound flood risk assessment and climate informed stress testing.

KEYWORDS: Compound flooding; surrogate modelling; LISFLOOD-FP; Copula dependence modelling; storm surge; precipitation

1 INTRODUCTION AND BACKGROUND

Compound flooding occurs when multiple flood drivers coincide and interact through synergistic effects, producing impacts greater than those expected from any driver acting alone. In coastal communities, a common and particularly damaging combination is intense precipitation occurring near the time of elevated coastal water levels driven by storm surges and tides. For Tofino, British Columbia (Figure 1), this interaction is highly relevant because Pacific storm systems can generate both heavy rainfall and elevated coastal water levels, while the local shoreline geometry and low-lying infrastructure can amplify inundation pathways.

A central difficulty in compound flood risk assessment is that the hazard space is inherently multivariate. It is not enough to characterize extreme rainfall or extreme coastal water levels independently. What matters for inundation is their joint behaviour, including dependence, timing, and how these combined boundary conditions translate into overland flow across complex topography. This has direct implications for planning and design because risk estimates can be biased if joint extremes are under sampled or treated as independent, and because the most consequential impacts often arise from plausible combinations rather than record breaking single driver events.

Physics based hydrodynamic models can represent these interactions credibly, but compound flooding assessments quickly become computationally demanding when they require large scenario ensembles across a range of joint return periods or when they are used for stress testing under future climate conditions. As a result, there is a practical need for workflows that preserve physical realism while enabling rapid exploration of compound scenarios and clear interpretation for risk assessment.

In this study, we present a scenario-based framework for compound flooding in Tofino that combines joint extreme characterization with physics-based inundation modelling and a machine learning surrogate. We use historical reanalysis (1970 to 2019) to generate synthetic compound scenarios that represent the co-occurrence of precipitation and elevated coastal water levels, then simulate inundation with LISFLOOD FP v8.2 (Sharifian et al., 2023; Bates et al., 2013) on a 5 m digital elevation model. A coordinate based neural surrogate is trained on the resulting inundation fields to provide fast reconstruction of flood depth and extent for new compound scenarios. The purpose of the surrogate is not to replace the hydrodynamic model, but to enable rapid screening of compound flood risk across many scenarios, support sensitivity studies, and make joint return period analysis more tractable for decision making.

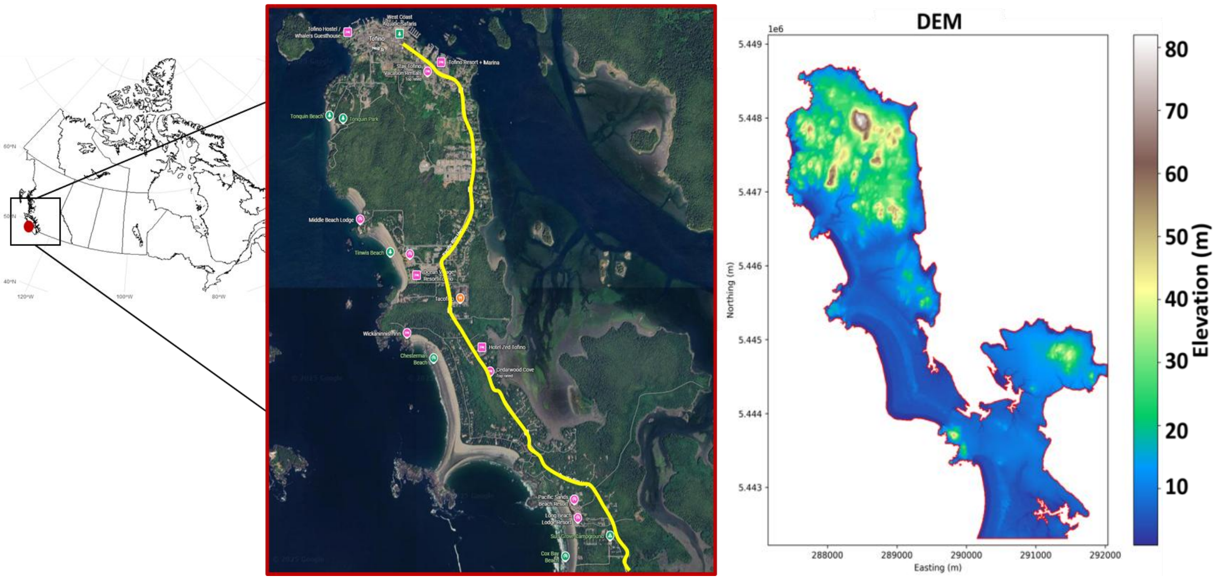

Figure 1: Tofino study area: location in North America, model domain, and DEM

2 METHODOLOGY

We developed a scenario-based workflow for compound flooding in Tofino that links joint extreme characterization of the compound drivers to physics-based inundation modelling and rapid emulation for efficient risk assessment. Historical reanalysis (1970 to 2019) (Hersbach et al., 2020) was used to describe extremes in precipitation and storm surge using a peaks-over-threshold approach, and dependence between drivers was represented with a copula-based model. This enabled sampling of synthetic compound scenarios across the joint space and joint return period regimes. Each scenario was translated into three-day time series boundary conditions so that the hydrodynamic model is forced by physically meaningful temporal evolution of both rainfall and coastal water levels.

Inundation was simulated with LISFLOOD FP v8.2 over a 5 m digital elevation model of Tofino referenced to CGVD2013. Simulations were run for a three-day window using the local inertial formulation with adaptive time stepping and GPU acceleration through the CUDA solver. The physics-based ensemble was executed on HPC as a SLURM job array to support large scenario counts while keeping runs traceable and computationally manageable. The resulting outputs are spatial flood depth and extent fields for each compound scenario.

To enable rapid scenario exploration for flood risk assessment, we trained a machine learning surrogate, specifically a coordinate based neural implicit model with event conditioning, to emulate LISFLOOD FP inundation outcomes from the compound forcing. The surrogate's role in this conference paper is pragmatic: it provides near real time reconstruction of flood maps for new compound scenarios so that joint return period conditions can be screened efficiently, sensitivity to compound forcing can be explored, and risk relevant summaries can be generated without repeatedly running the full hydrodynamic model. Detailed architectural and training choices are beyond the scope of this conference paper and are reserved for journal publication.

Figure 2 summarizes this Physics–AI framework and should be interpreted as follows: the only observational information enters through the event-based context used for evaluation, while the flood depth and inundation fields shown are model outputs. Where 2018 and 2021 events are referenced, the observations consist of documented impacts and reported flooding extents from Department of Transportation reports and publicly available news sources, and these are used to corroborate plausibility of the modelled inundation patterns rather than to directly provide gridded water depth observations.

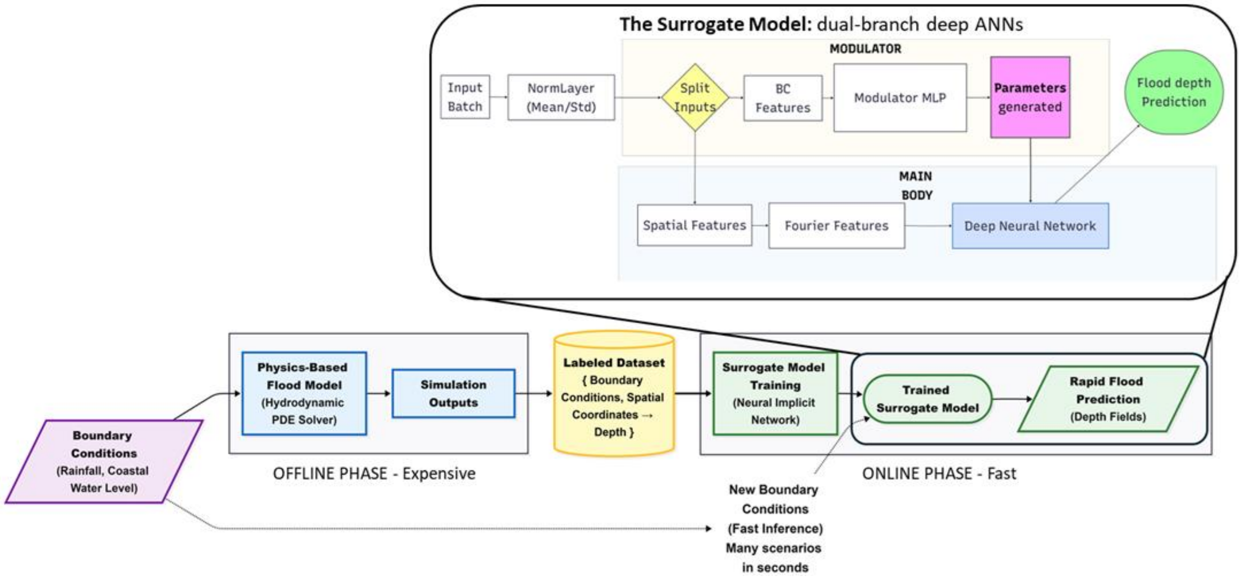

Figure 2: Physics–AI framework for compound flood inundation modelling

3 KEY RESULTS

Key results are summarized in Figure 3 (a–e) and emphasize the main implication for flood risk assessment: the framework enables rapid, scenario-based screening of compound flood hazard across a wide range of joint conditions while preserving the spatial patterns needed for local decision making. The physics-based ensemble provides a consistent mapping from compound forcing to inundation outcomes, allowing flood depth and extent to be evaluated in terms of both spatial footprint and distributional behaviour. Figure 3a and 3b illustrate a representative event and the corresponding depth statistics from the physics-based model, which together highlight how compound scenarios can shift not only maximum depths but also the proportion of the domain that becomes inundated. Figure 3c and 3d then show that the surrogate reproduces the key inundation pathways and extents of the physics-based simulation under the same forcing, making it practical to sweep large numbers of joint return period scenarios that would otherwise be computationally prohibitive. Figure 3e indicates that differences between the surrogate and the physics-based solution remain small for the evaluated case, supporting the use of the surrogate as an efficient front end for compound flood risk screening. Event based context from the 2018 and 2021 floods, supported by District of Tofino reports and publicly available news sources, provides an external check that the simulated inundation patterns are plausible for real world events.

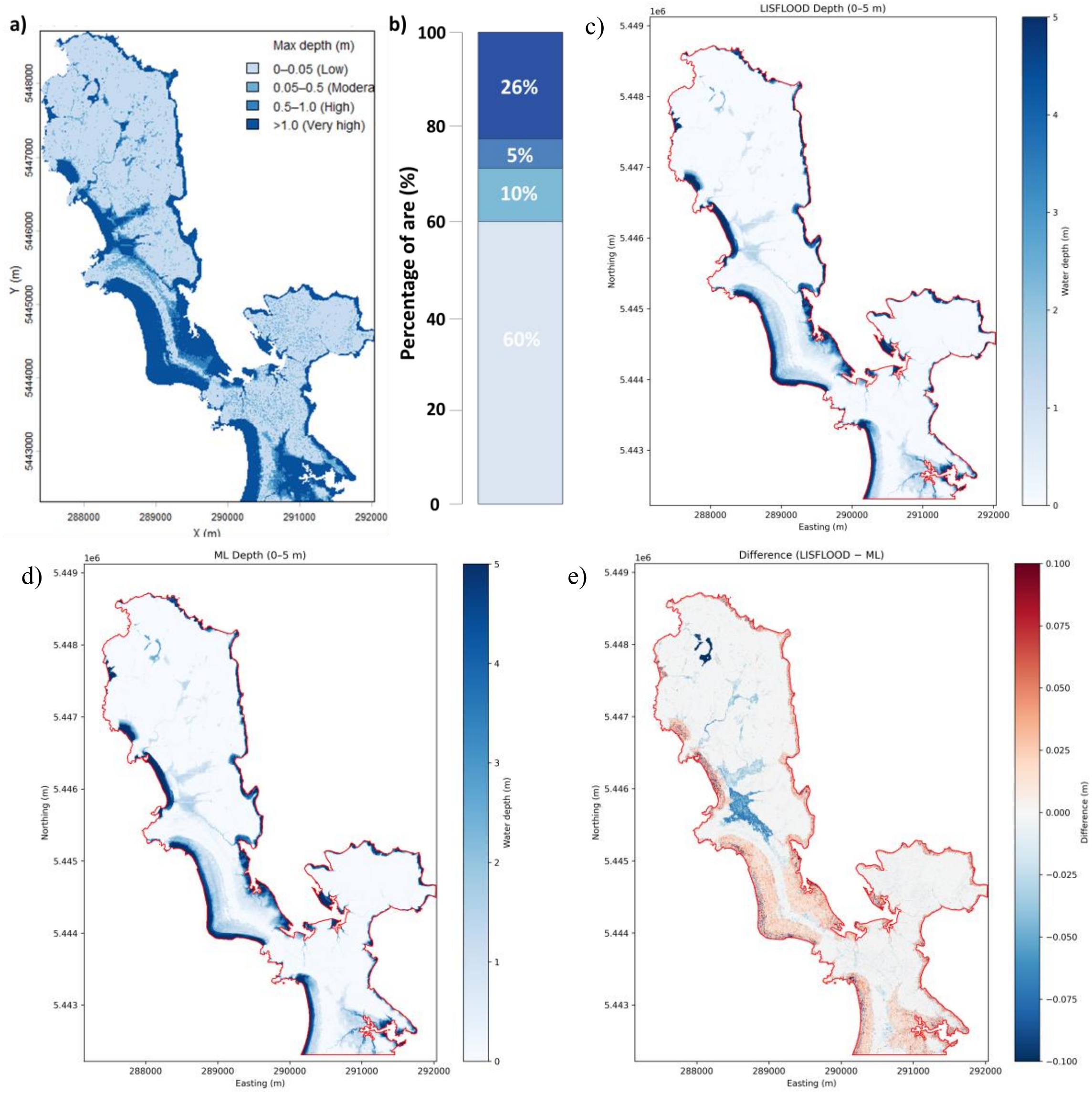

Figure 3: Validation of physics based and surrogate compound flood modeling for a representative event. (a) Physics based flood depth field. (b) Statistical descriptors of simulated flood depths from the physics-based model. (c) Inundation extent from LISFLOOD FP. (d) Inundation extent for the same event predicted by the surrogate. (e) Flood depth error (surrogate minus physics) showing differences within a 10 cm bound

4 CONCLUSION

In conclusion, this study presents a practical framework for scenario-based compound flood risk assessment in Tofino that links joint extreme characterization to physics-based inundation modelling and rapid emulation. The key outcome is that compound flooding can be explored across a wide range of joint conditions and return period regimes without the prohibitive computational cost of running a full hydrodynamic model for every scenario. LISFLOOD FP provides physically consistent inundation maps for representative compound events, and a machine learning surrogate, implemented as a coordinate based neural implicit model, is used to rapidly reproduce flood depth and extent fields for additional scenarios. Comparisons against the 2018 and 2021 events, supported by documented impacts and publicly available reports, indicate that the modelled inundation patterns are plausible at the event scale. Overall, the framework enables efficient screening, sensitivity analysis, and stress testing of compound flood hazard while retaining the spatial detail needed for local decision making and prioritization.

5 ACKNOWLEDGEMENTS

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