Quantitative Stress Test of Compound Coastal-Fluvial Floods in China's Pearl River Delta

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Abstract Floods in river deltas are driven by complex interactions between astronomical tides, sea levels, storm surges, wind waves, rainfall-runoff, and river discharge. Given the anticipated increase in compound flood hazards in river deltas in a warming climate, climate-informed regional to local extreme water levels (EWLs) is thus critical for decision-makers to evaluate flood hazards and take adaptation measures. We develop a simple yet computationally efficient stress test framework, which combines historical and projected climatological information and a state-of-the-art hydrodynamic model, to assess future compound coastal-fluvial flood hazards in river deltas. Our framework is applied in the world’s largest single urban area, China’s Pearl River Delta (PRD), which is also characterized by densely crossed river network. We find that extreme sea level is the dominant driver causing the compound coastal-fluvial flood in the PRD over the past 60 years. Meanwhile, there is large spatial heterogeneity of the individual and compound effects of the typhoon intensity, local sea-level rise, and riverine inflow on coastal-fluvial floods. In a plausible disruptive scenario (e.g., a 0.50 m sea-level rise combined with a 9% increase in typhoon intensity in a 2°C warming), the EWL will increase by 0.76 m on average. An additional 1.54 and 0.56 m increase in EWL will occur in the river network and near the river mouth, respectively, if coastal floods coincide with the upstream mean annual flood. Findings from our modeling framework provide important insights to guide adaptation planning in river deltas to withstand future compound floods under climate change.

Plain Language Summary Compound floods pose serious threats to the dense population living in river deltas worldwide. Climate change could increase the compound flood hazards through stronger tropical cyclones, sea level rise, higher extreme precipitation, and river flows. It is urgent to understand how the so-called grey swan events will evolve under a warming climate in these already flood-prone areas. Here, grey swan events are high-consequence events that are beyond people’s experience but may be foreseeable and thus can be systematically prepared for. In this study, a storyline-based framework is proposed to assess the potential grey swan compound floods under a warming climate. We apply this framework to China’s Pearl River Delta, the world’s largest single urban area. In a plausible disruptive scenario (e.g., a 0.50 m sea-level rise combined with a 9% increase in typhoon intensity in a 2°C warming), we find that extreme water levels will increase by 0.76 m on average. Our flexible and computationally efficient storyline-based framework could guide coastal planners to prepare for the grey swan compound flood hazards under climate change.

1. Introduction

Dense population living in river deltas are facing a great threat from potential flood hazards due to its strong monsoons, tropical cyclone (TC), low-lying topography, and extensive river networks (Merz et al., 2021; Nienhuis et al., 2020; Tellman et al., 2021). Floods in river deltas are commonly categorized into three categories according to their generating mechanisms: pluvial (when water accumulates on a surface due to heavy rainfall), fluvial (when a river overflows its banks), and coastal (due to astronomic tide, storm surge, and wind wave) floods (Bates et al., 2021; He et al., 2020; Nasr et al., 2021a; Ridder et al., 2020; Wei et al., 2020). Since fluvial, pluvial, and coastal floods may occur simultaneously or in close succession, the compound impact could be more devastating than when either occurs separately (Ghanbari et al., 2021; Moftakhari et al., 2017; Muñoz et al., 2020). Additionally, human-induced global warming adds another layer of complexity (Masson-Delmotte et al., 2021) and is likely to lead to more disastrous compound floods in river deltas worldwide (Edmonds et al., 2020; Ward...
et al., 2018). For these reasons, there is an increasing need to robustly quantify extreme water level (EWL) changes over river deltas to evaluate the hazard probability due to extreme weather and climate.

Recent studies document that climate change is increasing the frequency and intensity of extreme rainfall (Kirchmeier-Young & Zhang, 2020; Madakumbura et al., 2021; Myhre et al., 2019; Zhan et al., 2020), the intensity of TCs (Chan et al., 2021; Guzman & Jiang, 2021; Knutson et al., 2020; Vecchi et al., 2021), and the rate of global sea-level rise (DeConto et al., 2021; Edwards et al., 2021; Nicholls et al., 2021; Walker et al., 2021). Rainfall is a key factor causing pluvial and fluvial floods and can be classified into TC rainfall and monsoon rainfall. In contrast, coastal floods are mainly driven by extreme sea levels (ESLs), which is a combination of mean sea level, astronomical tide, and episodic water level fluctuation mainly through storm surge and wind wave (Almar et al., 2021; Arns et al., 2020; Voudouris et al., 2018). Regarding the increasing quantity of these drivers under climate change, based on a 19-year (1998–2016) time series of continuous observations, Guzman and Jiang (2021) found an increasing trend in the average TC rainfall rate of about 1.3% per year and the increasing trend is more pronounced in the Northwestern Pacific and North Atlantic. Knutson et al. (2020) comprehensively assessed climate model projections of TC activity in a 2°C global warming scenario. Specifically, there is at least medium-to-high confidence that projected TC rain rate, TC intensity (defined as maximum surface wind speed during lifetime), the proportion of very intense TCs (category 4 and 5) will increase with a median value of 14%, 5%, and 13%, respectively. For sea-level rise, the global mean sea level (GMSL) is rising (virtually certain) and accelerating (high confidence) (Oppenheimer et al., 2019). By 2100, GMSL will rise by about 0.43 m under the scenario of Representative Concentration Pathway (RCP) 2.6 and 0.84 m under the scenario of RCP8.5 (medium confidence) (DeConto et al., 2021; Frederikse et al., 2020; Khojasteh et al., 2021; Strauss et al., 2021; Walker et al., 2022), and historically rare (e.g., 100-year return period) ESL events will occur annually or more frequently at many coastal locations, which will even happen 30 years from now for many low-lying coastal areas (Marsooli et al., 2019).

Significant progress has been made to better understand the interactions of multiple physical processes (e.g., riverine flow, storm surge, astronomical tide, and sea level rise) and how they contribute to compound floods in a warming climate in river deltas. Statistical methods are routinely used to investigate possible compound mechanisms by examining statistical dependence between proxy variables of different flood types regionally or globally, such as rainfall and storm surge (Lai et al., 2021; Sanuy et al., 2021; Zellou & Rahali, 2019; Zheng et al., 2014), river flow and storm surge (Couasnon et al., 2020; Nasr et al., 2021b), and river flow and sea level (Ghanbari et al., 2021; Piekuch et al., 2018; Ward et al., 2018). Numerical models are widely applied to simulate tide, storm surge, river flow, and their nonlinear interactions on coastal inundation dynamics locally, for example, in Mississippi Delta (Bunya et al., 2010), Ganges-Brahmaputra-Meghna Delta (Ikeuchi et al., 2017), Lee River Delta (Olbert et al., 2017), Shoalhaven Delta (Kumbier et al., 2018), Pearl River Delta (PRD) (De Dominicis et al., 2020), Humber and Dyfi Delta (Harrison et al., 2021), Breede Delta (Kupfer et al., 2021), and Betanzos Delta (Bermúdez et al., 2021). To perform a robust and integrated assessment, intrinsic characteristics of statistical and numerical methods are suggested to be linked for representative compound flood hazard assessments (Moftakhari et al., 2019). Muñoz et al. (2020) employed such a coupled approach to quantify the compound effect of different flood drivers in Savannah Delta. Regarding the impact of global warming on compound flood hazards in river deltas, to our knowledge, there are only a handful of studies that have been carried out with an in-depth analysis. For instance, Lin et al. (2012) couple a GCM-driven TC model with hydrodynamic model to generate large numbers of synthetic storm surges under projected climate and then assess the surge threat. Ganguli et al. (2020) used a dynamically downscaled regional climate model to drive a storm surge model and hydrological model, the joint occurrence of ESLs and associated river peaks is analyzed through a bivariate copula approach. Bermúdez et al. (2021) employ a continuous simulation approach that considers seasonality and correlation between different flood drivers to assess compound flood hazards in Mandeo Delta under historical and future climates. The climatological-hydrodynamic methodology used in these studies tend to be a standard framework to explore the impact of global warming on compound flood hazards in river deltas.

Despite these advances, there are still limitations in existing studies. First, as a critical tool to simulate complex dynamics of compound floods in river deltas, hydrodynamic models usually need to be location-specific and therefore highly rely on users' competency/experience. Lack of objective/general workflows for model development greatly hinders a fair comparison between different studies and the reproducibility of previous research (Fringer et al., 2019). Second, some intrinsic characteristics of river delta add complexity for model development.
Irregular shoreline, dendritic inland tributaries, and complicated bathymetry (e.g., submarine channels, shelf breaks, and isolated banks) can greatly impact the accuracy of flood simulation (Roberts, Pringle, Westerink, Contreras, & Wirasaet, 2019). Yet these features are not systematically described in various hydrodynamic modeling. Lastly, the widely used climatological-hydrodynamic methods are computationally expensive when assessing flood hazards in current or future climate. To avoid underestimating low-probability but high-consequence events, these assessments typically conduct decadal or century-long continuous simulation or synthesize a large number of scenarios to drive the hydrodynamic model. Despite the advantage of routinely used climatological-hydrodynamic methods which can provide a full distribution of EWLs, it might not be flexible enough and computationally efficient for some special adaptation strategies, such as real-time and emergency response planning exercises and preparation for grey swan TC storm surges. Here, grey swan events are defined as those high-consequence events that are beyond people’s experience but may be foreseeable and thus can be systematically prepared for (Lin & Emanuel, 2016; Nafday, 2009; Paté-Cornell, 2012; Stein & Stein, 2014).

To address these research gaps, an automatic and flexible workflow to design unstructured mesh (Roberts, Pringle, & Westerink, 2019) is applied for compound flood modeling in river delta, which significantly reduces subjectivity and improves reproducibility in the modeling of physical processes. This workflow also allows us to design multiscale unstructured meshes by placing high-resolution meshes over targeted regions to capture more geometrically complexed features. Meanwhile, to efficiently assess compound floods in river deltas especially focusing on the grey swan events, a quantitative stress test approach (Albano et al., 2021) is applied by constructing a set of narrow and targeted scenarios discretely at minimal computational cost, which has been used in many planning and research contexts (Tariq et al., 2017; Motavita et al., 2019; He et al., 2021; de Klerk et al., 2021). Thus, the individual and joint impacts of astronomical tide, extreme riverine inflow, SLR, and TC climatology on compound coastal-fluvial floods can be assessed using the integrated framework by combing statistical approaches and physical simulations. This integrated modeling framework is tested in China’s Pearl River Delta (PRD), which is the world’s largest single urban area with more than 86 million population living in an area of ~56,000 km² (by the end of 2020) (HKTDC, 2021; World Bank, 2015). Additionally, PRD is also characterized by a complicated crisscrossing river network with a high density of 0.81 km/km² and 0.88 km/km² for the combined West River and North River Delta and the East Delta, respectively (Ye et al., 2019). Our framework consists of three parts (Figure 1): (a) development of a hyper-resolution hydrodynamic model (Section 3), (b) detecting the dependence structure between coastal floods and upstream riverine inflow in historical periods (Section 4), and (c) quantitative stress test based on the physically consistent storylines depicting several worst-case scenarios (Section 5). Our work will not only accurately, but also efficiently shed light toward resilient coastal planning in future extreme climates.

2. Study Area and Data Sets

2.1. Pearl River Delta

Pearl River Delta refers to the Pearl River Estuary (PRE) and the urban agglomeration of 11 cities including Hong Kong, Macao, and 9 cities in mainland China (Figure 2). The Pearl River is mainly comprised of three tributaries namely the West River, the North River, and the East River, accounting for 72%, 14%, and 7.6% of the streamflow flowing into South China Sea via eight outlets, respectively. The three tributaries contribute to the formation of the PRD region (Figure 2). The Pearl River and residual Lingdingyang estuary coexist a deltaic estuary, namely the PRE, which has a mixed semi-diurnal tidal regime with average tides ranging from 1.0 to 1.7 m. Lying on the eastern and western sides of the PRD, Huangmaohai Bay, and Lingdingyang Bay are funnel-shaped, tide-dominated with a high tidal range and low residual water level, respectively. In contrast, the central part of the channel networks in the PRD is river-dominated with a low tidal range and high residual water level, respectively.

2.2. Shoreline Data Set

Two shoreline data sets are used to define the shoreline boundary when generating the unstructured mesh for our hydrodynamic modeling (see details in Section 3.5). The first is the full-resolution Global Self-consistent Hierarchical High-resolution Shorelines (GSHHS) (Wessel & Smith, 1996). The second data set defining the shoreline of the PRE's complicated river system is extracted using a spectral water index-based approach. This approach can efficiently and accurately map surface water body from Sentinel-2 imagery with Modified
Figure 1. The overall framework summarizing three parts of this study.
2.3. Bathymetric Data Set

Two bathymetric data sets are used in this study, both of which are defined on a regular structured grid, usually in the topo-bathymetric digital elevation model (DEM) format. The first bathymetric data is obtained from the latest General Bathymetric Chart of the Oceans (GEBCO_2020 Grid) (Weatherall et al., 2015), which is applied for the shelf of North South China Sea (NSCS). The GEBCO_2020 Grid provides global elevation for ocean and land on a 15 arc-seconds geographic latitude and longitude grid, assuming all of which to be referred to Mean Sea Level. Negative values represent bathymetric depths while positive values represent topographic heights. The second bathymetric data is derived by merging the water depth measurements from cross-sectional profiles across the Pearl River networks with several naval electric nautical charts among the Lingding Bay. The cross-sectional profiles are obtained from two surveys performed circa 1999 with a resolution of 5 m and performed circa 2014 with 20 m, respectively. The nautical charts are released in 2020 with an average resolution of 200 m. Besides, a higher resolution of 20 m is covered along with the deep-draft navigation and tidal channels. These scattered...
bathymetric points are mapped onto a structured grid at 20 m resolution using a simple kriging method (Yin et al., 2018).

2.4. Hydrological Gauge Data Set

Daily average discharge from 1957 to 2018 at three upstream hydrological stations (i.e., Gaoyao, Shijiao, and Boluo) are extracted from the Annual Hydrological Report P. R. China, whose reliability and homogeneity are strictly inspected by the Hydrology Bureau of Guangdong Province before they were published. These hydrological data are used to analyze the dependence between historical coastal floods and upstream riverine inflows (see Section 3). As our hydrodynamic model (see details in Section 4.3) requires input at hourly timescale, daily discharge time series is linearly interpolated into hourly time step assuming that daily discharge is gauged at 12:00 noon every day.

2.5. Tidal Gauge Data Set

Three hourly water level elevation data sets at tidal stations in the PRE have been collected for model validation. They are gauged during the dry and flood season of 2005 and in August 2017 when the super Typhoon Hato made a landfall. These gauges contain water level elevations from 48, 12, and 18 tidal stations, respectively. In addition, the latest released satellite-assimilated tidal model TPXO9-Altas (Egbert & Erofeeva, 2002) is also collected for our astronomical tide validation.

2.6. Tropical Cyclone Data Set

The best track data set from Joint Typhoon Warning Center (JTWC) is used as the meteorological forcing to drive the hydrodynamic model (see Section 3.2). The International Best Track Archive for Climate Stewardship (IBTrACS) data set (Knapp et al., 2010) from 1957 to 2018 is used to statistically analyze historical Typhoons that hit the PRD. For each storm, the extended best track provides storm names, annual cyclone numbers, warning dates, latitudes, longitudes, maximum sustained wind speed, minimum central pressure at the sea level, a tropical system indicator, wind intensity for certain radius, pressure and radius of the outer closed isobar, radius of max winds, and typhoon eye diameter.

3. Model Development and Validation

Advanced CIRCulation model (ADCIRC) is applied in this study to perform the hydrodynamic simulations of two-dimensional (2D) barotropic tides (Luetich et al., 1992; Westerink et al., 1994). Advanced CIRCulation model adopts the hydrostatic pressure and Boussinesq assumptions to numerically solve the shallow water equations in space using the finite element method and in time using the finite-difference method. Advanced CIRCulation model is a second-order solver that discretizes the domain into linear elements. To simulate compound coastal-fluvial floods, a high-fidelity unstructured mesh is designed using OceanMesh2D, which provides preprocessing and post-processing utilities to generate two-dimensional unstructured triangular meshes for coastal ocean circulation models (Pringle and Roberts, 2020; Roberts, Pringle, Westerink, Contreras, & Wirasaet, 2019, 2019a).

3.1. Governing Equations

The governing equations of ADCIRC are shallow water equations in primitive, nonconservative, and barotropic form:

\[
\frac{\partial \eta}{\partial t} + \nabla \cdot (u H) = 0
\]

\[
\frac{\partial u}{\partial t} + u \cdot \nabla u + f k \times u + g \nabla (\eta - \eta_{FD} - \eta_{SL}) + C_f \frac{|u|u}{H} + Cu
- \frac{1}{H} \nabla \cdot \left[ v \nabla \left( \nabla u + \nabla u^T \right) \right] = 0
\]
where $\eta$ is the surface elevation; $H = h + \eta$ is the total water depth in which $h$ is the still water depth; $u$ is the depth-averaged velocity vector; $g$ is the acceleration due to gravity; $k$ is the vertical unit vector, and $f = 2\Omega \sin \phi$ is the Coriolis parameter in which $\Omega$ is the angular speed of the earth, and $\phi$ is the latitude. The quantity $\eta_{EO}$ is the equilibrium tide potential and $\eta_{SAL}$ is the ocean self-attraction and loading (SAL) tide. In the dissipation term, $C_f$ is the coefficient of bottom friction; $C$ is the dissipation matrix due to the internal tide energy conversion, and $\nu_r$ is the horizontal eddy viscosity coefficient that is calculated through the Smagorinsky model. More details about calculation or model settings of equilibrium tide potential (Luettich et al., 1992), SAL tide (Hendershott, 1972; Lyard et al., 2006), and internal tide energy conversion (Bell, 1975; Jayne & Laurent, 2001; Pringle et al., 2018; Wang et al., 2021; Zaron & Egbert, 2006) can be found in (Text S2, S3 and S4 in Supporting Information S1).

3.2. Meteorological Forcing

The surface wind and atmospheric pressure field associated with a TC are reconstructed from the symmetric Holland parametric vortex model (H80) (Holland, 1980) at each node internally in ADCIRC during the simulation. H80 models the pressure-wind relationship with two scaling parameters $A$ and $B$ in its radial pressure and wind profile equations. By assuming a cyclostrophic balance in the region of maximum winds, where Coriolis force is negligible compared to the pressure gradient and centripetal force in the gradient wind equation, the radius of maximum wind is found to be entirely defined by $A$ and $B$, independent of the central pressure deficit and the maximum wind. The radial pressure and wind profiles are defined as follows:

$$P(r) = P_c + (P_u - P_c) e^{-\left(R_{max}/r\right)^b}$$  \hspace{1cm} (3)

$$V_\delta(r) = \sqrt{V_{max}^2 e^{\left(1-\left(R_{max}/r\right)^b\right)} \left(R_{max}/r\right)^b + \left(\frac{rf}{2}\right)^2 - \left(\frac{rf}{2}\right)}$$  \hspace{1cm} (4)

where $P(r)$ is the pressure at radius $r$ from the center of the cyclone, $P_c$ is the minimum central atmospheric pressure, $e$ is the base of natural logarithm, and $R_{max}$ is the radius of maximum wind. $V_\delta(r)$ is the gradient wind at radius $r$, $V_{max}$ is the maximum sustained wind speed, $f$ is the Coriolis term, $f = 2\omega\sin(latitude)$, and $\omega$ is the rotational frequency of the earth. $B$ is one of the scaling parameters which can be estimated as a function of the maximum sustained wind speed and central pressure drop:

$$B = V_{max}^2 \rho e / (P_u - P_c)$$  \hspace{1cm} (5)

where $\rho$ is air density. It was reasoned by Holland that a plausible range of $B$ would be between 1 and 2.5 to limit the shape and size of the vortex. A great feature of the H80 is that both $A$ and $B$, as well as the radius of maximum wind if it is absent from model inputs, can be empirically derived from a limited set of wind observations. In this study, the parameters of the cyclone including storm eye location, $R_{max}$, $V_{max}$, $P_u$, and $P_c$ required for H80 are obtained from the JTWC ‘Best Track’ data set.

3.3. Riverine Inflow Forcing

To simulate compound coastal-fluvial flood events using ADCIRC hydrodynamic model, areal flux (m$^2$/s) data should be given at the upstream riverine boundaries. However, the source data of riverine flow we usually obtain is the measured discharge time series in a certain cross section where a discharge gauge is located. This discharge usually is volume flux (m$^3$/s). To convert volume flux (m$^3$/s) to areal flux (m$^2$/s), we develop a function wrapper named “Make_f20_volume_flow” based on a simple trapezoidal rule for OceanMesh2D toolbox. Both daily and hourly discharge data are supported for the calculation. Note that the order in making riverine input files should be consistent with the order in making the riverine inflow boundary conditions. More details about making the riverine input files can be found in the OceanMesh2D documentation (Roberts & Pringle, 2018).
Table 1

| Code  | Function expression                                      | PRE  | NSCS |
|-------|----------------------------------------------------------|------|------|
| MinEle| Minimum element size bound                               | $E_R \geq a$ | 30 m  | 1000 m |
| MaxEle| Maximum element size bound                               | $E_R \leq a$ | 2000 m | 20,000 m |
| G     | Element-to-element gradation limiter                     | $\Rightarrow \| \nabla E_R \| < a$ | 0.25  | 0.3   |
| Fs    | Feature width                                            | $E_R = 2 \times \frac{d_t + d_s}{x}$ | 6     | 3     |
| WL    | Wavelength-to-element size ratio                         | $E_R = \frac{t_M}{2} \sqrt{g h}$ | /     | 30    |
| TLS   | Topographic-length-scale                                 | $E_R = \frac{2 \pi}{a} \frac{h}{|\nabla h|}$ | /     | 10    |
| FL    | Low-pass filter length                                   | $h^* = F_p(L) * h$ | /     | 50    |
| Ch    | Channel thalwegs and polylines size                      | $E_R = \frac{h}{a}$ | 0.5   | /     |
| CFL   | Courant-Friedrichs-Lewy limiting                         | $\text{dia} = 2 \tan(\theta)$ | dt = 0 | dt = 0 |

Note. $E_R$ is the mesh size functions used to determine the spatially explicit resolution for each mesh element; $a$ is a user-specified parameter to $xxx$; $d_t$ and $d_s$ are the absolute distance to the nearest shoreline and the medial axis, respectively; $T_M$ is period of the $M_2$ tidal wave; $g$ is the acceleration due to gravity; $h$ is still-water depth, $h^*$ is the low-pass filtered water depth, in which $F_p(L)$ is the low-pass filter with cutoff length $L$; $\text{dia}$ is the diameter of a circular region formed on each thalweg point, where $\theta$ is the angle of slope (default value is 60°); $\mu$ is the magnitude of the flow; $H$ is the total water depth; $\Delta t$ is the time step; $\Delta X$ is the element size.

3.4. Vertical Datum Adjustment

One critical step before model simulation is to make the vertical datum of all data including DEM and water levels consistent with that of the mean sea level in ADCIRC. Note that bathymetry and water level data sets at all hydrological stations or tidal stations in PRE are referenced to the Pearl River Datum. The GEBCO_2020 Grid is referenced to the GMSL. The computed water levels in ADCIRC are relative to local mean sea level. In this study, we unify vertical datum to the Pearl River Datum. The GEBCO_2020 Grid data set is not rectified into Pearl River Datum, since the vertical uncertainty of which is generally larger than the discrepancy between local mean sea level and the Pearl River Datum. We only adjust mean sea level in ADCIRC to the Pearl River Datum to change mean sea level permanently and irreversibly in ADCIRC simulation throughout the ADCIRC run.

3.5. Unstructured Mesh Generation

OceanMesh2D controls mesh resolution according to a variety of feature-driven geometric and topo-bathymetric mesh size functions. Mesh generation is achieved through a force-balance algorithm combined with a few topological improvement strategies aimed at improving the worst triangle quality. The toolbox embeds the mesh generation process into an object-orientated framework that contains preprocessing and post-processing workflows, which makes mesh generation flexible, reproducible, and scriptable. More details about the technical information can be found in the user guide (Roberts & Pringle, 2018).

The multiscale meshing approach is applied to generate our high-fidelity mesh in a nested structure, employing high-resolution elements for the inner PRE, while using a coarser mesh resolution for the adjacent NSCS. Two geospatial data sets (see Section 2.2 and Section 2.3) and several deterministic parameters defined for PRE and NSCS are required as the input to calculate the feature size function and then drive the mesh generation. The final mesh size is determined by taking the minimum of all individual local mesh size functions, applying minimum and maximum mesh size bounds, an element-to-element gradation limiter to bind the transition rate, and the Courant-Friedrichs-Lewy (CFL) limiting condition to ensure numerical stability and accuracy.

Table 1 summarizes the detailed mesh size functions and the corresponding parameter values used for spatially distributing element resolution. Note that minimum element size is the most critical parameter for generating an unstructured mesh to ensure accuracy and efficiency. In this study, we use 30 and 1000 m for the PRE and NSCS, respectively, after performing several sensitivity analyses. The parameter “Windows” used for smoothing the
boundary is set to 30 for the PRE when building the geodata class, while the outer NSCS uses the default value of 5. A bigger “Windows” value can avoid over-resolving the mesh resolution near the PRE’s boundary since the shoreline of PRE with a 10 m high-resolution is extracted by using a remote sensing method (see Section 2.2) thus the shoreline is jagged. The choice of other mesh size functions' and the parameters' specificity are referred to previous studies (Pringle et al., 2020; Roberts, Pringle, & Westerink, 2019, 2019b).

In addition, the time step automatically selecting option is applied to help choose a suitable time step $\Delta t$ to ensure numerical stability. The time step determined for the PRE and the NSCS is 0.9 and 6.5 s, respectively. To ensure numerical stability, the CFL condition by bounding the Courant number to under 0.5 is checked by performing the “CalcCFL” OceanMesh2D function with a 0.9 s time step, which is used for all the ADCIRC simulations.

The final unstructured mesh is presented in Figure 3, containing a total of 327,980 vertices and 575,743 elements (Figure 3a). The inner PRE contains 257,053 vertices and 443,921 elements, while the outer NSCS contains 71,134 vertices and 131,851 elements. More details about interpolating DEM onto vertices and making node string boundary conditions can be found in (Text of S6 and S7 in Supporting Information S1).

### 3.6. Model Performance Evaluation

Model performance is evaluated by comparing model results against the data-assimilated TPXO9-Altas and the measurements from tide gauge and buoy stations for the global astronomical tides validation and the total water level validation among the PRE, respectively.

#### 3.6.1. Error Metric Definition

For astronomical tide validation, the root-mean-square error (RMSE) for a single harmonic constituent at a point can be defined as:

$$\text{RMSE}_i = \left(0.5 \left[ A_o^2 + A_m^2 - 2 A_o A_m \cos(\theta_o - \theta_m) \right] \right)^{1/2}$$  \hspace{1cm} (6)

where $A$ is the tidal amplitude, $\theta$ is the tidal phase lag, and the subscripts “o” and “m” refer to the observed (TPXO9-Altas) and modeled values, respectively. For total water level validation, statistical metrics including RMSE, bias, and Willmott skill are quantified as:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (X_{sim} - X_{obs})^2}{N}}$$  \hspace{1cm} (7)

$$\text{Bias} = \frac{\sum_{i=1}^{N} (X_{sim} - X_{obs})}{N}$$  \hspace{1cm} (8)

$$\text{Skill} = 1 - \frac{\sum_{i=1}^{N} |X_{sim} - X_{obs}|^2}{\sum_{i=1}^{N} (|X_{sim} - X_{obs}| + |X_{obs} - X_{obs}|)^2}$$  \hspace{1cm} (9)

where $X$ is the variable (e.g., total water levels, discharge, or velocity) being compared, the overbar denotes the averaged value over all data points and $N$ is the number of data points. Lower RMSE/bias and higher Willmott’s skill indicate better agreement between model simulations and observations (Willmott, 1981).

#### 3.6.2. Astronomical Tide Validation for the NSCS

A common first step in evaluating the performance of the coastal hydrodynamic model is to assess the simulated accuracy of astronomical tides before the simulation of ESLs. Here, we first validate the accuracy of tidal wave propagation from the Pacific Ocean into the South China Sea through the Luzon straight. It is challenging for simulating such complicated tidal dynamics in this region due to its complex geometry, steep bottom topography, interconnected shallow seas, and island chains. Note that the model is forced only by five leading astronomical tidal constituents ($M_2$, $S_2$, $N_2$, $K_1$, and $O_1$) for 31 days, with 3 days' spin-up and 28 days' harmonic analysis. These five constituents are chosen so that a relatively short 28 days' harmonic analysis can be performed (Ngodock et al., 2016). Otherwise, the period needs to be extended to around 180 days if other constituents are included because of the closeness in their frequencies (e.g., $K_1$ and $P_1$) (Pringle et al., 2020). All other simulations in this study are forced by eight major constituents to obtain more accurate astronomical tide solutions, and the
harmonic analysis is not activated. Figure 4 illustrates the global responses of the $M_2$ and $K_1$ tidal waves and their RMSE discrepancies against the TPXO9-Altimas. Compared with previous studies (Wang et al., 2021; Zu et al., 2008), the general response for both constituents is well described by our model, including the positions of these amphidromes.

### 3.6.3. Total Water Level Validation for the PRE

Total water level validation is performed for three representative hydrological processes (i.e., astronomical tide, fluvial flood, and coastal flood) in the tidal river network. The water level elevation recorded at 48 stations during the astronomical tide event lasted from 18, January to 07 February 2005, covering an entire spring and neap tidal cycle. Due to the small riverine inflows during the dry season, this event can fully reflect the tidal dynamics over

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**Figure 3.** Mesh triangulation and resolution (showed on a “miller” projection) for the whole North South China Sea domain (a), the extracted Pearl River Estuary domain (b), and the Sixianjiao channel where the West and North Rivers meet with each other (c). Blue arrows in (c) indicate water flow directions.
the whole tidal river network. In addition, the water level elevation recorded at 12 stations during the fluvial flood event lasted from 22, June to 01 July 2005. This is the largest fluvial flood during the last two decades in terms of the peak discharge (56,300 m$^3$/s) recorded at Gaoyao station, exceeding the 100-year standard. Riverine inflow is the dominant factor in driving the hydrodynamic process of the tidal river delta. Furthermore, the super typhoon Hato hit PRD with a maximum sustained wind speed reached 100 knots at a distance of only 33.8 km from Macau causing record-breaking storm tides and severe damage among the tidal river delta. Figure 5 shows the model performance in validating these three representative hydrological events. Detailed comparisons between the simulated and measured water levels at each site during the corresponding hydrological events can be found in (Figure S3-1, S3-2, S3-3, S3-4, S4, and S5 in Supporting Information S1).

4. Dependence Quantification Between Coastal and Fluvial Floods

4.1. Identify Historical TCs That Struck the PRD Region

The PRD is one of the most severely TC-affected regions in the West North Pacific (WNP) Ocean, which is one of the most active TC basins in the world, with an average of about 26 named TCs (hereafter we use Typhoons) affecting this region each year. Among the notably destructive Typhoons occurring in recent years are Washi in 2011, Haiyan in 2013, Rammasun in 2014, Soudelor in 2015, Nepartak and Meranti in 2016, Hato in 2017, Jebi and Mangkhut in 2018 (Lee et al., 2020). However, not all Typhoons that occurred in WNP hit the PRD. To provide more valuable information for our later compound flood assessment, it is essential to detect the Typhoons that struck the PRD and have a comprehensive understanding of their characteristics such as occurrence time, frequency, moving path, and intensity. Here, we develop a procedure to achieve this goal. Specifically, we consider the target Typhoons to be that if any point of the track is within a 200-km-radius circle centered on
Macau (113.55°E, 22.2°N) and if the track intensifies to a typhoon (maximum sustained wind speed >63 Knots) during its lifetime. The IBTrACS data from 1957 to 2018 is used to perform this procedure.

A total of 85 Typhoon events are initially detected, but only 76 of them were reserved after deleting 9 tracks that did not make landfall near the PRD. Based on genesis locations and moving path, we further classify these tracks into two groups, the north-forward and west-forward moving path composed of 13 and 63 tracks, respectively (see Figure 6). To indicate the potential impact of these selected Typhoons on the PRD, we also collect each track's maximum sustained wind speed within the 200-km-radius circle centered on Macau. If there are multiple timings that meet the above condition for a particular track, the timing with the minimum distance to Macau is selected. Thus, the relationship between the maximum sustained wind speed within the 200-km-radius circle and

Figure 5. Model performance evaluation for the astronomical tide (left column), fluvial flood (middle column), and Hato-induced coastal flood (right column) using metrics of root-mean-square error (top row), Bias (middle row), and Skill (bottom row), respectively.
the corresponding minimum distance can be expressed in Figure 7. Points within the red box around the bottom right corner indicate Typhoons with the greatest potential impact on the PRD.

4.2. Dependence Between Coastal Floods and Riverine Inflows

Dependence between historical coastal floods induced by the selected 76 typhoons and the upstream riverine inflows has been investigated in this section. Due to limited measurement of hydrological data, only riverine inflows of Gaoyao, Shijiao, and Boluo stations are used for the analysis, which are located at places where West, North, and East River flow into the PRD. The daily discharge corresponding to the timing when maximum sustained wind speed occurred for each track is first extracted (see the bar height of left panel of Figure 8). Taking this timing as a reference, we also extract time series of other daily discharge using time-lags from −2 to +2 days and then collect the maximum daily discharge during the five successive days (see the bar height of the right panel of Figure 8). The dependence between coastal and fluvial flood can be understood by comparing the daily discharge of these three hydrological stations against the magnitude of mean annual flood (see the horizontal black dotted line in each subplot in Figure 8).

Besides, since coastal floods are mainly driven by storm surge and astro-nomic tides, the phase (mainly including spring phase, neap phase, and middle phase) of the astronomical tide when the two coincides directly determine the severity of the coastal flood. Given this, we further group the phase of the astronomical tide based on the timing corresponding to the maximum daily discharge using a Gregorian-Lunar Calendar Conversion from Hong Kong Observatory (see the color of each column in Figure 8). More details about the relationship between the Lunar Calendar and the astronomical tides can be found in Table S3 in Supporting Information S1.

4.3. Dependence Between Fluvial Floods in the West and North River

Meeting at Sixianjiao (Figure 3c), streamflow of the West River and North River are redistributed and then flow into the West River networks and the North River networks through the Makou and Sanshui station, respectively. In contrast, the East River networks are relatively independent. Therefore, we
further investigated the dependence between historical fluvial floods in the West and North Rivers (Figure 9). Over the past 52 years from 1957 to 2008, there is a probability of 23% that the maximum annual flood of the West and North River coincide (see the cyan circles in Figure 9). In general, the coincide situations can be classified into 4 types (see labels of the circles in Figure 9): (a) extreme floods in these two rivers occur simultaneously.
simultaneously, such as the flood in 1994, (b) extreme floods from West River meet regular floods from North River, such as the floods in 1998 and 2005, (c) extreme floods from North River meet regular floods from West River, such as the flood in 2008, (d) regular floods occur simultaneously, such as the floods in 1966, 1968, 1978, 1997, 2001, and 2006.

5. Quantitative Stress Test of the Compound Coastal-Fluvial Flood

5.1. Scenario Construction for Quantitative Stress Test

This section focuses on assessing climate change impacts on the compound coastal-fluvial flood for the PRD, based on a quantitative stress test approach, which is used to create storyline-based (e.g., multiple extreme events) climate scenarios (see the third part of the overall framework in Figure 1). We started with projected changes in TC due to anthropogenic warming. Based on Knutson et al. (2020), Coupled Model Intercomparison Project Phase 5 (CMIP5) models on average project a 2°C global warming, relative to 1986–2005 conditions, by around the year 2055 under the RCP8.5 scenario. Meanwhile, we use the projected local sea-level (LSL) data sets under RCP8.5 developed by Kopp et al. (2014). Therefore, projected metrics such as increasing TC intensity and SLR used in this section are based on the constructed 2°C global warming and RCP8.5 scenarios near 2055, which is corresponding to high-end business-as-usual emissions.

According to the previous analysis in Section 4, Hato ranks second in terms of the maximum sustained wind speed and the corresponding minimum distance from Macau (see Figure 7) among the 76 Typhoons that struck the PRD. The total water level caused by Hato exceeds previous records at many stations of the PRD. Here, we treat the coastal flood induced by Hato as a baseline scenario, which is the worst case in history. We further quantitatively explore how worse things could get under a changing climate in the future through several stress test scenarios we have constructed previously. Specifically, three scenarios are constructed to investigate the individual effect of Typhoon intensity increase (scenario 2), LSL rise (scenario 3), and riverine inflow (scenario 4) on coastal floods. Within each scenario, only one driving factor is modified while holding all others constant. We construct additional two scenarios to investigate the compound effect of increased Typhoon intensity and LSL rise (scenario 5) and the compound effect of increased Typhoon intensity, LSL rise, and riverine inflow (scenario 6) on coastal-fluvial floods (see scenario details in Table 2).

5.2. Individual Effect of TI, SLR, and RI on Coastal-Fluvial Floods

In constructing the Typhoon intensity increase scenario, not only the maximum sustained wind speed (VMAX, also refers to Typhoon intensity) but also the minimum sea-level pressure (MSLP) needs to be changed. This is because the key parameter B in the H80 model completely depends on VMAX and MSLP (see Equation 5), which conform to a certain statistical relationship in a particular basin. Figure 10 shows the climatological correlation and distribution of the VMAX-MSLP relationship using the IBTrACS data set from 1957 to 2018. A fairly typical VMAX-MSLP relationship can be observed during the life cycle of Hato. Here, we assume that the climatological correlation of VMAX-MSLP remains constant even under the future climate, which means that the corresponding MSLP decreases accordingly as Typhoon intensity increases. In this way, the constructed meteorological forcing

| ID | Driving factor | Scenario description | Effect type | Period |
|----|----------------|---------------------|-------------|--------|
| 1  | /              | Coastal flood (Hato) | /           | Baseline |
| 2  | TI             | Hato’s intensity increases 9% (90%) | Individual | Future |
| 3  | LSL            | Hato meets with SLR 0.50 m (95%) |            |        |
| 4  | RI             | Hato meets with MAF  |            |        |
| 5  | TI + LSL       | Intensified Hato meets with SLR | Compound   |        |
| 6  | TI + LSL + RI  | Intensified Hato meets with SLR & MAF |       |        |

Note. TI refers to typhoon intensity, local sea-level refers to local sea level, RI refers to riverine inflow, and MAF refers to mean annual flood.
can be used to drive our hydrodynamic model to investigate the individual effect of Typhoon intensity increases on the coastal-fluvial flood. Although both Knutson et al. (2020) and Cha et al. (2020) provide a complete distribution of projected changes in TC intensity for the WNP under the 2°C anthropogenic global warming, only a 9% increase in typhoon intensity corresponding to 90% quantile is used for our simulation in this scenario.

The LocalizeSL toolbox developed by Kopp et al. (2014) is used to project the localized SLR at the Macau station located in PRD. As mentioned in Section 5.1, the SLR projection under RCP8.5 in 2055 is consistent with the Typhoon climatology change and is thus used for constructing scenario 3 to investigate the individual effect of SLR on coastal-fluvial floods. Similarly, as our focus is on the grey swan events, an SLR value of 0.50 m corresponding to the 95% percentile is used for our simulation in this scenario.

In addition, since a warmer atmosphere holds more water vapor that can rain out, climate change also increases the frequency and intensity of extreme rainfall (Kirchmeier-Young & Zhang, 2020; Madakumbura et al., 2021; Myhre et al., 2019; Tan et al., 2021; Zhan et al., 2020), which in some locations can lead to an increased chance of floods occurring or an increase in their magnitude (Brunner et al., 2021; Sharma et al., 2018; Wasko et al., 2021).

In scenario 4, the MAF is used to investigate the individual effect of riverine inflow on coastal-fluvial floods. Using historical flood information directly can reduce the effort in simulating future floods under a warming climate. The MAF is chosen rather than the flood with a return period of 10%, 5%, 2%, and 1% to avoid overestimation of future compound coastal-fluvial flood hazard based on two considerations. On the one hand, the riverine inflows corresponding to the 76 Typhoon events are basically below the value of MAF at Gaoyao, Shijiao, and Boluo (see Figure 8). On the other hand, more than 90 dams and reservoirs have been constructed in the Pearl River Basin since 1980 and the total flood control storage capacity of the whole basin will reach 13.7 billion m$^3$ after the completion of the Datengxia water conservancy hydropower project in 2023. We assume that riverine floods flow into the PRD can be effectively regulated under accurate flood forecast and joint operation of cascade reservoirs.

The individual effect of Typhoon intensity increase (9%), LSL rise (0.50 m), and riverine inflow (MAF) on coastal-fluvial floods in PRD are expressed by the difference in simulated EWL under different scenarios and that of the Hato hit PRD in history, respectively (see the upper panel of Figure 11). To reflect the spatially varying patterns among the whole PRD region, the 62 water level stations are classified into three types to show

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**Figure 10.** Correlation and distribution of the VMAX-MSLP relationship. Individual storms of Hato are plotted for comparison against the climatology.
the difference between stations in the river network, near the river mouth, and outside the river network (see Figure 2). We find that a hypothetical 9% intensified Hao event will lead to EWL increase by 0.25 m on average, while the EWL at Shaluowei (ID = 36), Fubiaochang (ID = 35), and Dashi (ID = 37) has the largest increase, reaching 0.41 m, 0.39 m, and 0.37 m, respectively. Three stations Hebaodao (ID = 59), Hongkong-b (ID = 61), and Dangantou (ID = 62) are almost unaffected by the increased Typhoon intensity.

We find that a 0.50 m SLR results in a 0.53 m increase in EWL on average, while the largest increase in EWL occurs at Fubiaochang (ID = 35), Dashi (ID = 37), Shaluowei (ID = 36), Daao (ID = 11), Zhongda (ID = 38), and Zhuzhou (ID = 9), reaching 0.67, 0.66, 0.66, 0.64, 0.64, and 0.62 m, respectively. The EWLs beyond SLR (0.50 m) are the items caused by the interaction between SLR and astronomical tide, storm surge, and riverine flow.

In addition, the individual effect of riverine inflow on coastal-fluvial floods is more significant than that of Typhoon intensity increase and SLR, especially in the river network region. Specifically, the EWL increases by 1.65 m on average in the river network, and such an increase is more pronounced in the upstream than downstream. The largest increase occurs at Sanshui (ID = 1), Makou (ID = 2), Nanhua (ID = 15), Tianhe-2 (ID = 3), Zidong (ID = 27), and Shizaisha (ID = 28), reaching 3.44 m, 3.34 m, 2.85 m, 2.82 m, 2.65 m, 2.64 m, respectively. The increased value near the river mouth is 0.62 m on average. The EWLs at stations outside the river network are not affected by the increased riverine inflow.

5.3. Compound Effects of TI, SLR, and RI on Coastal-Fluvial Floods

The difference between the scenario 5 and scenario 6 for investigating compound effect is whether to consider the riverine flood since the riverine flood flow into the PRD can be modulated by upstream reservoirs, while changes in Typhoon climatology and sea-level rise cannot be easily controlled by humans. Generally speaking, the relative increase of EWL in scenario 6 against scenario 5 (see the bottom panel of Figure 11) can be understood as the difference between stations in the river network, near the river mouth, and outside the river network (see Figure 2). We find that a hypothetical 9% intensified Hao event will lead to EWL increase by 0.25 m on average, while the EWL at Shaluowei (ID = 36), Fubiaochang (ID = 35), and Dashi (ID = 37) has the largest increase, reaching 0.41 m, 0.39 m, and 0.37 m, respectively. Three stations Hebaodao (ID = 59), Hongkong-b (ID = 61), and Dangantou (ID = 62) are almost unaffected by the increased Typhoon intensity.

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potential part which can be reduced through accurate forecast and reservoir operation technologies. More specifically, the EWL of scenario 5 (i.e., intensified Typhoon combined with SLR) increases by 0.76 m on average. The EWLs of scenario 6 (i.e., riverine floods coincide with intensified Typhoon on top of SLR) increase by 2.33 m on average in the river network, increasing 1.34 m near the river mouth. Therefore, the potential reducing EWL in the river network is 1.54 m in the river network and 0.56 m near the river mouth on average, respectively.

6. Discussion

Our proposed framework could guide coastal planners and managers to better adapt to gray swan compound floods in a changing climate. First, the well-defined repeatable and automated workflows for generating subjective and detailed unstructured meshes can be applied to simulate physical process for any other delta environments regardless of the coastal modeling engines (Roberts, Pringle, & Westerink, 2019). We believe this workflow would not only save model setup efforts for coastal planners or analysts, but also be helpful for facilitating more direct comparisons between various approaches (Fringer et al., 2019; Klingbeil et al., 2018). Second, the quantitative stress test framework applied in this study can be viewed as a simplified and targeted climatological-hydrodynamic approach, which is originally proposed by Lin et al. (2012). To our best knowledge, this climatological-hydrodynamic methodology tends to be a standard workflow to quantify how global warming affects the compound flood hazards caused by storm surge, sea-level rise, and extreme rainfall in coastal cities (Bermúdez et al., 2021; Ganguli et al., 2020; Garner et al., 2017; Gori et al., 2022; Lin & Emanuel, 2016; Marsooli et al., 2019; Marsooli & Lin, 2020; Rezaie et al., 2021). Instead of driving the hydrodynamic model by large ensembles of synthetic TCs, which are statistically generated from reanalysis or GCM-projected future climate, our framework is based on the physically consistent storylines depicting several worst-case scenarios, making it possible to achieve the same goal but at the minimal computational cost. And the storyline-based scenario is flexible enough to allow users to easily construct any extreme scenarios meeting their needs. Finally, the high-resolution and spatially continuous EWLs provide useful localized information, which can help guide adaptation planning in river deltas at policy relevant scales to withstand future compound floods under climate change.

Several limitations in this study warrant further improvement. First of all, it should be noted that a full-impact risk assessment should jointly consider hazard, exposure, and vulnerability and our study only focuses on the hazard component of risk. Nevertheless, it is critical to accurately simulate physical processes that drive compound hazards before a detailed risk assessment considering exposure and vulnerability. Moreover, full-impact risk assessment requires extra information such as localized flood defense structures to predict inundation extent over floodplains, since exposure depends on the use of floodplains and the economic and population development, while vulnerability is shaped by human adaptive influences, specifically levees, embankments, dikes, and flood walls which are constructed to prevent water from entering floodplains (Hummel et al., 2021; Merz et al., 2021; Tanoue et al., 2021; Vousdoukas et al., 2020; Wing et al., 2019). However, so far inventories of these defenses are very scarce in river deltas, significantly impairing the accuracy of flood inundation maps and obstructing the consideration of vulnerability in risk assessment. To our best knowledge, despite the first open-source global river delta levee data environment (openDELvE) which has been developed by O’Dell et al. (2021), only 152 deltas are included in this delta database, unfortunately none of them are within China. Therefore, once the required information of defenses is accessible for the PRD, together with the latest released Forest And Building removed Copernicus DEM (FABDEM) (Hawker et al., 2022), the goal of simulating a more comprehensive physical process of compound flood, especially the flood flowing over defense structures and inundating the adjacent floodplain or urban area would be possible. The full-impact risk assessment could thus be further addressed to inform risk management and resilience planning in river deltas.

Additionally, only the fluvial and coastal processes are included in our integrated flood assessment framework and we do not consider the pluvial processes. This is limited by current ocean circulation models, which focus on the storm surge and neglect precipitation that falls directly into the simulation domain and the interaction between rainfall-runoff and storm surge. Ignoring these precipitation amounts may result in underestimating the compound flood in river deltas, especially during slow-moving storms which dump an excessive amount of precipitation over a long period of time, such as Hurricane Harvey (2017) (Zhang et al., 2018), Florence (2018) (Ye et al., 2021), Ida (2021) (Flowers, 2021), and super Typhoon In-fa (2021) (Nie & Sun, 2022). Meanwhile, due to the adoption of simplified flow representation (Bates et al., 2005), hydrologic/hydrodynamic models are not feasible to simulate hydrodynamics in deep water, for example, astronomical tides, storm surges, and wind waves.
in offshore areas. Risk assessment incorporating full-component flood processes in river deltas is suggested to extend the ocean circulation model used in our integrated framework to a coupled or linked model which allows information exchange via boundary conditions between the inland hydrologic/hydrodynamic model and the ocean circulation model (Bates et al., 2021; Leijnse et al., 2021; Santiago-Collazo et al., 2019; Sebastian et al., 2021). Moreover, future work should consider TC size when identifying the targeted track or constructing the scenarios of TC climate change. In addition to TC intensity, TC size is another factor that determines the destructive potential of a TC (Ruan & Wu, 2022; Song et al., 2020; Sun et al., 2017, 2017, 2017). However, some practical reasons make it difficult to incorporate the TC size into our integrated framework. On one hand, the TC size information in the historical best track dataset is incomplete. For example, only tracks after 2000 have information of TC size in the JTWC dataset. On the other hand, the characteristics of projected TC sizes under future climate change have so far been done only to a limited extent (Knutson et al., 2020). Last but not the least, the spatial dependence (Brunner et al., 2020; Curtis et al., 2021; Quinn et al., 2019) and temporal coincidence (Donges et al., 2016; He & Sheffield, 2020) of multiple physical processes can be incorporated to our current framework to further improve the compound risk analysis.

Several datasets used in this study can also be upgraded in future studies. The shorelines used as the boundary when generating the unstructured mesh for our hydrodynamic modeling is extracted using the Sentinel-2 imagery taken on 11 Dec 2019. This water body map is deterministic and does not consider the frequency of water existence, thus the real water body might be underestimated especially over the seasonal floodplains. Here, we recommend to extract a dynamic shoreline to take into account the seasonal floodplains, as some previous studies (Hu & Wang, 2022; Pekel et al., 2016) have done. In addition, indiscriminate dig of sediment aggravates river bed evolution in the PRD and may alter flood regimes (Ye et al., 2019). The bathymetric data used in this study is from the survey conducted in 2010 and needs to be updated since the Hato occurred in 2017.

7. Conclusion

Floods in river deltas are driven by complex interactions between astronomical tides, mean sea level state, storm surge, wind wave, rainfall-runoff, and river discharge. Climate change could exacerbate the compound flood hazard by altering the characteristics of these flood drivers. Reliable methods capable of dealing with this complexity are urgently needed to assess future flood conditions in these already flood-prone areas. In this study, a simplified and targeted climatological-hydrodynamic approach is proposed to assess future compound coastal-fluvial flood hazards in a river delta, using a stress test framework to link the historical and projected climatological information and a state-of-the-art hydrodynamic model. Findings from our modeling framework provide important insights to guide adaptation planning in river deltas to withstand future compound floods.

The proposed approach is applied to the world's largest single urban area, the PRD in south China, which is also one of the most severely TC-affected regions in the WNP. This region suffers serious fluvial and coastal flooding in history, but the compound effect of these flooding drivers and its future changes have not been systematically investigated. Main conclusions obtained in this case study can be summarized as follows:

1. The state-of-the-art unstructured mesh generation technology (OceanMesh2D) is applied to develop a hyper-resolution and multiscale hydrodynamic model. This automatic and flexible workflow is useful to reduce subjectivity and improve reproducibility in the modeling of physical processes.

2. ESL is the dominant driver causing the compound coastal-fluvial flood in the PRD over the past 60 years. A total of 76 typhoons struck the PRD during this period. Almost all of the upstream river discharges correspond to the maximum storm surges induced by these typhoons are smaller than the corresponding mean annual floods.

3. Under a hypothetical 9% increase in Typhoon intensity combined with a 0.50 m local sea level rise under a 2°C warming scenario near 2055 (RCP8.5), the individual and compound effects of the typhoon intensity increase, LSL rise, and riverine inflow on the coastal-fluvial flood have large spatial heterogeneity in the PRD. The EWL will increase by 0.76 m on average if an intensified Hato coincides with heightened sea-levels. The increase will reach 2.33 and 1.34 m on average in the river network and near the river mouth, respectively, when this extreme event further overlaps with the upstream mean annual flood.
Although our framework is tested locally in Pearl River Delta, we believe that the generalized methodology can be extended to other geographical regions across the globe.

Data Availability Statement

Some public data sets used for this study are available at https://www.soest.hawaii.edu/pwessel/gshhg/ (GSHHS), https://www.gebco.net/ (GEBCO), https://scihub.copernicus.eu/ (Sentinel-2 Multi-spectral data), http://step.esa.int/main/ (SNAP software), https://www.ncei.noaa.gov/ibtracs/ (IBTrACS), https://www.metoc.navy.mil/jtwc/jtwhc.html/western-pacific (JTWC), https://doi.org/10.5281/zenodo.5152527 (OceanMesh2D), ftp://ftp.legos.obs-mip.fr/pub/FES2012-project/data/LSA/FES2014/ (FES tidal database, to the best of our knowledge, no other option is available yet to access the FES tidal database other than the FTP server), https://zenodo.org/badge/latestdoi/348612968 (Tropical), https://zenodo.org/badge/latestdoi/384060896 (Kalpana), and https://www.hko.gov.hk/tc/gts/time/conversion1.1_text.htm (Gregorian-Lunar Calendar Conversion). The codes used to generate unstructured mesh make ADCIRC input fort files and result visualization can be accessed from the corresponding author upon reasonable request.

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