



An emergency-oriented risk assessment method for typhoon storm surge disasters

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Abstract. Typhoon storm surge disaster (TSSD) is one of the most severe marine disasters affecting China's coastal areas, and risk assessment plays a crucial role in disaster prevention and mitigation. Existing studies primarily focus on risk zoning and long-term disaster reduction strategies, whereas risk assessment for an imminent TSSD, which is essential for pre-disaster emergency response, remains insufficient. The main challenges lie in quantifying hazard uncertainty and in representing the multiple dimensions of vulnerability. To address these challenges, this study develops an emergency-oriented risk assessment method for an imminent TSSD that integrates ensemble forecasting into a complete risk assessment framework. For hazard assessment, ensemble forecasting techniques are employed to address hazard uncertainty. A controlled scenario is generated by integrating multi-source forecast data, and perturbed scenarios are derived based on historical forecast errors. These scenarios form an ensemble of 15 scenarios for hydrodynamic simulations, with the mean and maximum water depths characterizing the hazard intensity grade. For vulnerability assessment, land use types and densely populated facilities are selected as two categories of vulnerability. The water depth-loss relative grade relationship for 11 land use types is established, and Point of Interest (POI) density is introduced to represent potential casualty vulnerability. Comprehensive risk is calculated by combining the results of hazard and vulnerability assessments. The method is validated through a case study of the Hato TSSD (2017) in Zhuhai, with the forecast initialization time set at approximately 24 hours before landfall. The proposed method can be re-executed to provide dynamic risk assessment updates as forecast data evolve, providing timely support for emergency decision-making.

1 Introduction

30 Typhoon storm surge disaster (TSSD) is one of the most destructive natural disasters worldwide (Needham et al., 2013; Resio and Irish, 2015). In China, all coastal areas are affected by TSSDs, and the impact of a single disaster can extend across multiple coastal provinces from south to north (Lin et al., 2023; Wang et al., 2021b). By coupling storm surge with astronomical



tides, TSSDs cause coastal water level rise and inundation, damaging fishery facilities, inundating farmlands, and destroying coastal engineering structures or residential buildings, resulting in multifaceted losses in nearshore and coastal areas (Wang et al., 2022). During 2013–2023, the average annual direct economic loss caused by TSSDs in China accounted for over 80% of total marine disaster losses, rising to 99% in 2023 (Bulletin of China Marine Disaster 2023, 2026). These statistics indicate that TSSDs in China are characterized by extensive geographic coverage, diverse sources of loss, and substantial economic losses.

Climate change and accelerating urbanization will exacerbate the threat of TSSDs (Hallegatte et al., 2013; Hudson et al., 2019). For example, sea level rise elevates the baseline water level for storm surge (Fang et al., 2016), and global warming may intensify tropical cyclone activity (Dasgupta et al., 2009; Vermaire et al., 2013), which increases storm surge heights (Lin et al., 2012; Vousdoukas et al., 2016). As a result, the hazard intensity of TSSDs in coastal areas is increasing (Horsburgh et al., 2017; Rahmstorf, 2017; Vousdoukas et al., 2018). Furthermore, land subsidence causes relative sea level rise, weakens the protective capacity of seawalls, and amplifies disaster threats (Wang et al., 2012). In addition, increasing coastal development exposes larger populations and assets to TSSDs, thereby amplifying overall vulnerability (Helderop and Grubestic, 2019).

Risk assessment for TSSDs is of great significance for scientific disaster prevention and mitigation. To date, existing studies on TSSD risk assessment can be broadly categorized into two types. The first is scenario-based risk assessment for future TSSD scenarios. This approach typically assesses risk for designed scenarios through hydrodynamic simulations. The second is the indicator-based risk assessment for regional risk. This method typically constructs indicator systems based on historical disaster data and related risk factor data.

For scenario-based risk assessment, one category of studies establish relationships between disaster frequency and losses by constructing numerous TSSD scenarios (Hisamatsu et al., 2020; Hsu et al., 2018). Another category assesses risk for designed TSSD scenarios. For the latter, in hazard assessment, typical return periods (Li and Li, 2011) or probable maximum storm surge scenarios (Shi et al., 2020; Wang et al., 2021d; Zhang et al., 2016) are usually simulated to obtain inundation characteristics in coastal areas as a measure of hazard intensity. For vulnerability assessment, water depth-loss (rate) functions (Shi et al., 2024) or indicator-based vulnerability assessment methods (Chen et al., 2019a) are commonly employed to obtain vulnerability values or vulnerability grades. For risk calculation, most studies adopt water depth-loss (rate) functions or integrated functions combining hazard and vulnerability assessments, with loss values or risk grades under designed scenarios representing the risk (Li et al., 2017).

For indicator system-based risk assessment, studies (Gao et al., 2014; Liu et al., 2020) typically first select relevant indicators according to risk elements to construct a hierarchical indicator system, where the first level represents risk elements and the second or third level comprises specific indicators. Normalized indicator values are then fed into the assessment model to generate risk grades. The aforementioned studies primarily serve risk zoning and long-term disaster prevention and mitigation strategy formulation. However, risk assessment for an imminent TSSD is equally significant for pre-disaster emergency preparedness and response decision-making, yet current research in this area remains limited. The main challenges are twofold: first, hazard uncertainty is difficult to quantify; second, vulnerability assessment involves multiple dimensions.



To address uncertainty in hazard assessment, numerical forecasting of typhoon storm surge provides a reliable basis for hazard quantification. Current numerical forecasting models for storm surge are well established (Kohn et al., 2018), with forecast accuracy primarily depending on meteorological forecast accuracy. To mitigate the impact of meteorological forecast errors, ensemble forecasting techniques for typhoon storm surge have been developed, generating multiple possible scenarios based on tropical cyclone forecast errors. Typical methods include: the Probabilistic Hurricane Storm Surge model adopted by the U.S. National Weather Service (Glahn et al., 2009; Taylor and Glahn, 2008), the Dynamical Tropical Cyclone Storm Surge Forecast System employed by the Australian Bureau of Meteorology (Greenslade et al., 2017, 2018), and the tropical cyclone track clustering method (Hasegawa et al., 2017) and probabilistic circle method (Higaki et al., 2009) used by the Japan Meteorological Agency. Drawing on the probabilistic circle method, some studies utilize error circles to construct multiple typhoon storm surge scenarios (Sun et al., 2015). Others reduce the impact of forecast errors by employing different numerical forecast models (Wang et al., 2013) or adopting tropical cyclone forecast data from different sources (Ding et al., 2016). Although operational ensemble forecasting systems have been established by meteorological and oceanographic agencies, they generally focus on predicting storm surges rather than simulating coastal inundation or translating forecast uncertainty into risk information for emergency response. Accordingly, this study integrates ensemble forecasting into a complete risk assessment framework oriented toward emergency response, extending the chain from storm surge prediction to inundation simulation and risk assessment. Within this framework, and given the data and computational conditions typical of a research context, a controlled scenario is generated by integrating openly available multi-source forecast data, and perturbed scenarios are derived based on historical forecast errors, forming an ensemble of 15 typhoon storm surge scenarios. Building on the ensemble typhoon wind field construction method proposed by Chen et al. (2013), this procedure does not depend on the specialized infrastructure or data assimilation used in operational systems, and is applicable for pre-disaster risk assessment. Beyond hazard assessment, vulnerability assessment presents equally important yet distinct challenges. Vulnerability assessment of TSSDs requires a systematic treatment of both economic loss and potential casualties. For economic loss assessment, existing studies establish quantitative relationships between hazard intensity and direct economic losses (rates) for different vulnerability categories through historical disaster data, disaster surveys, experimental simulations, and other methods (Krzysztofowicz and Davis, 1983; Smith, 1994). Since typhoon storm surge causes inundation in coastal areas, hazard intensity is commonly characterized by inundation depth, flood velocity, and inundation duration, with inundation depth being the most widely used (Abu Bakar et al., 2015; Salman and Li, 2018). In addition, existing quantitative analyses of vulnerability mostly focus on calculating direct economic losses based on water depth-loss (rate) functions of land use types (Wang et al., 2021c). However, two aspects remain insufficiently addressed in water depth-loss (rate) function-based vulnerability assessment. First, existing water depth-land use loss functions lack coverage for a broad range of land use types, making it difficult to comprehensively characterize vulnerability differences across diverse coastal areas under varying water depth. Second, potential casualty vulnerability is rarely considered alongside economic loss. When casualty vulnerability is assessed independently, quantitative relationships between hazard intensity and casualties are typically established, such as water depth-mortality (rate) curves and relationships between flood protection standards and population deaths (Boyd, 2010; De Bruijn et



100 al., 2014; Di Mauro et al., 2012), without accounting for economic loss. Overall, existing studies on disaster vulnerability assessment tend to focus on a single dimension, either economic loss or potential casualties. A clear and unified methodology for simultaneously incorporating both dimensions to support emergency-oriented TSSD risk assessment is therefore still lacking.

In light of these limitations, this study selects land use types and densely populated facilities as two categories of vulnerability. 105 For land use types, multi-source land use classification data and water depth-loss (rate) functions are integrated to establish the water depth-loss relative grade relationship, enhancing the comprehensiveness of vulnerability assessment in coastal areas. To represent the potential casualty vulnerability, the Point of Interest (POI) density of densely populated facilities is introduced, following the approach of Cai et al. (2019).

Building on the above analysis, this study develops an emergency-oriented risk assessment method for TSSDs. The novelty 110 lies not in the forecasting technique itself, which builds on existing ensemble approaches, but in integrating forecast uncertainty into a complete, emergency-oriented risk assessment framework. This method defines risk as a function of hazard and vulnerability. For hazard assessment, ensemble forecasting techniques and the numerical simulation model (MIKE 21) are integrated to address hazard uncertainty, with water depth representing the hazard intensity grade. For vulnerability assessment, land use types and densely populated facilities are treated as two categories of vulnerability, with their respective assessment 115 results integrated to systematically evaluate economic loss and potential casualty vulnerability. For risk calculation, comprehensive risk grades are derived by integrating these two components. As forecast data are updated over time, this method can be re-executed to generate dynamic risk assessment updates, providing timely and evidence-based decision support for pre-disaster emergency preparedness and response. The Hato TSSD (2017) in Zhuhai serves as a case study to validate the proposed method, with the forecast initialization time set at approximately 24 hours before landfall.

120 The remainder of this paper is structured as follows: Sect. 2 introduces the methodology for risk assessment of an imminent TSSD, including hazard assessment, vulnerability assessment, and risk calculation methods; Sect. 3 applies the proposed method to a case study of the Hato TSSD in 2017, covering the study area and data sources, and hydrodynamic model setup; Sect. 4 presents and discusses the results of scenario generation, hazard assessment, vulnerability assessment, and risk assessment; Sect. 5 summarizes this study.

125 2 Methodology

2.1 Risk assessment framework

The risk assessment framework for an imminent TSSD consists of three components: hazard assessment, vulnerability assessment, and risk calculation, as illustrated in Fig. 1. The following subsections describe each component in detail.

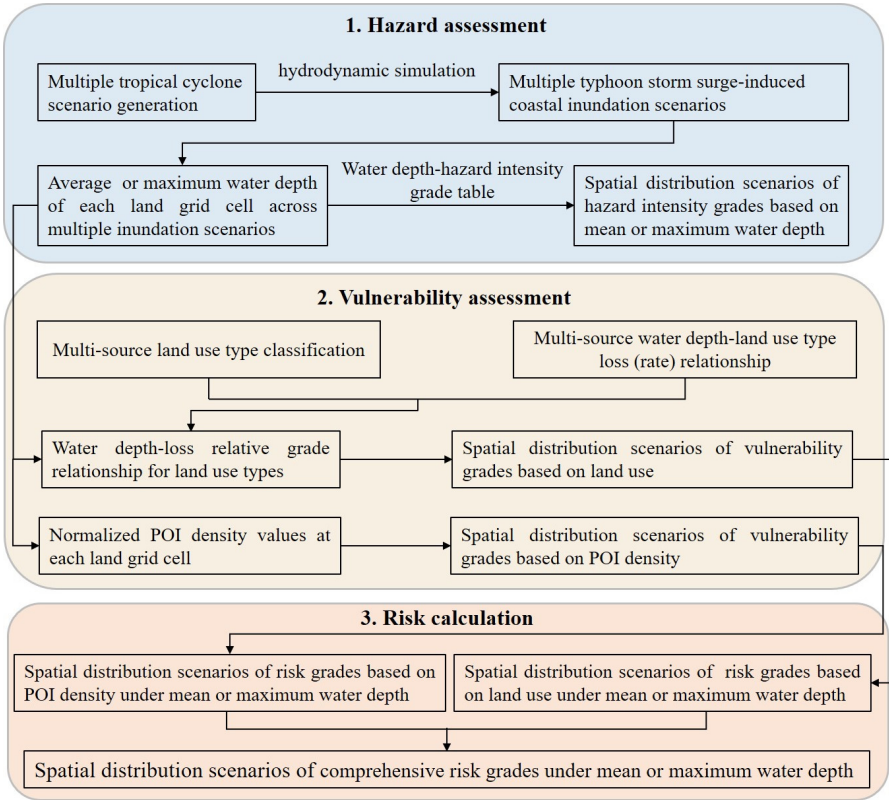


Figure 1: Risk assessment framework for an imminent TSSD.

2.2 Hazard assessment

Hazard assessment includes six components (Fig. 2): controlled track scenario generation, perturbed track scenario generation, perturbed intensity scenario generation, tropical cyclone scenario ensemble, typhoon storm surge and inundation scenario simulation, and hazard intensity grade calculation.

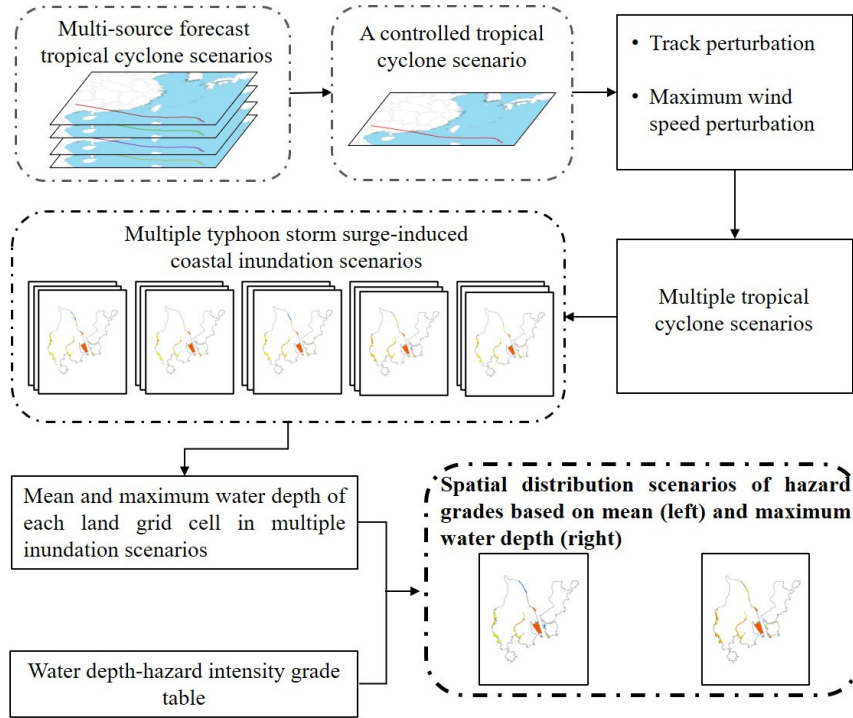


Figure 2: Steps of hazard assessment.

(1) Controlled track scenario generation

- 140 The controlled tropical cyclone information consists of observed data at and prior to the forecast initialization time, and forecast data thereafter. The observed track and intensity prior to the forecast initialization time are provided by the National Meteorological Centre of the China Meteorological Administration (NMC). The observed data at the forecast initialization time and the forecast track and intensity thereafter are jointly provided by four agencies: NMC, Hong Kong Observatory (HKO), Japan Meteorological Agency (JMA), and Joint Typhoon Warning Center (JTWC). The cyclone track and intensity
- 145 are calculated using Eqs. (1) to (3).

$$S_{CT} = \{(T_i, CL_i, MSW_i)\}$$

$$= \{(T_1, CL_1, MSW_1), (T_2, CL_2, MSW_2), \dots, (T_{s-1}, CL_{s-1}, MSW_{s-1}), \dots, (T_s, CL_s, MSW_s), (T_{s+1}, CL_{s+1}, MSW_{s+1}), \dots, (T_e, CL_e, MSW_e)\}$$
(1)

$$CL_i = \begin{cases} CL_{i(NMC)} & (0 \leq i < s) \\ \frac{1}{4} \sum_{j=1}^4 CL_{i(j)} & (s \leq i \leq p) \end{cases}$$
(2)



$$MSW_i = \begin{cases} MSW_{i(NMC)} & (0 \leq i < s) \\ \frac{1}{4} \sum_j^4 MSW_{i(j)} & (s \leq i \leq p) \end{cases}, \quad (3)$$

where S_{CT} represents the controlled tropical cyclone, (T_i, CL_i, MSW_i) represents the time, center location, and intensity of the i_{th} track point of the controlled tropical cyclone. s represents the forecast initialization time. When $0 \leq i < s$, (T_i, CL_i, MSW_i) represents the observed data for the controlled tropical cyclone provided by NMC, when $s \leq i \leq p$, (T_i, CL_i, MSW_i) represents the observed data at the forecast initialization time and forecast data provided by the four agencies, where $j = \{1, 2, 3, 4\}$ denotes the forecast data from NMC, HKO, JMA, and JTWC. Since different agencies use maximum wind speeds at different time intervals to characterize tropical cyclone intensity, this study converts the intensity data from all agencies to a uniform 2-min maximum wind speed using established conversion relationships (Harper et al., 2010).

(2) Perturbed track scenario generation

Chen et al. (2015, 2017, 2018, 2019b; 2014) provide statistical analyses of track forecast errors in the Northwest Pacific from four forecast agencies during 2013–2017, based on the best-track dataset of tropical cyclones from the Shanghai Typhoon Institute of the China Meteorological Administration. This study derives the multi-source average forecast track errors from these analyses using Eqs. (4) to (5), taking the 24-h forecast lead time as an example. The results indicate that the multi-source forecast track errors at 24-h, 48-h, and 72-h lead times are 78 km, 136 km, and 213 km, respectively.

$$SCL_{Ej(24\text{ h})} = \frac{1}{5} \sum_{y=2013}^{2017} ACLE_{y(24\text{ h})}^j, \quad (4)$$

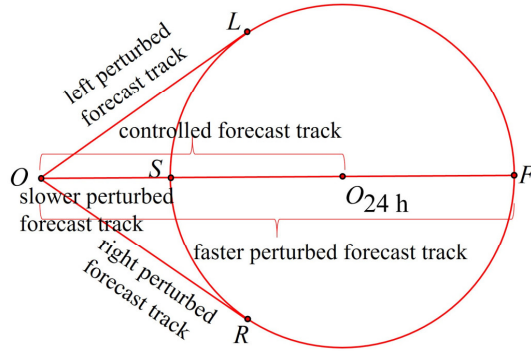
$$CL_{Error(24\text{ h})} = \frac{1}{4} \sum_{j=1}^4 SCL_{Ej(24\text{ h})}, \quad (5)$$

Where $ACLE_{y(24\text{ h})}^j$ represents the total track error of the j_{th} forecast agency in year y at the 24-h forecast lead time; $SCL_{Ej(24\text{ h})}$ represents the annual average track error of the j_{th} forecast agency during 2013–2017 at the 24-h forecast lead time; $CL_{Error(24\text{ h})}$ represents the average track error of the multi-source forecast at the 24-h forecast lead time.

Perturbed tracks are then generated, which consist of two parts: the observed track of the controlled tropical cyclone and perturbed forecast tracks. For perturbed forecast tracks, error circles are constructed using the forecast track points of the controlled track as centers and the multi-source forecast errors at corresponding forecast lead times as radii. Four perturbed tracks can thus be generated: left, right, fast, and slow (Higaki and Tajima, 2020). Taking the 24-h forecast lead time as an example (Fig. 3), the detailed generation procedure is described as follows. Step 1: Using the 24-h forecast track point of the controlled cyclone ($O_{24\text{ h}}$) as the center and the multi-source forecast track error (78 km) as the radius, an error circle is constructed. Step 2: From the forecast initialization time point (O), a left tangent line is drawn to the error circle (with tangent point L), and the line segment between point O and point L is the left perturbed forecast track (OL); the right perturbed forecast track is generated similarly (OR). Step 3: Connecting the forecast initialization time point O and the 24-h forecast track point



O_{24h} , the error circle intersects at point, and the line segment between them forms the slow perturbed forecast track (OS). Extending the controlled forecast track by one error circle radius along the tropical cyclone movement direction, it intersects the error circle at point F , and the line segment between them is the fast perturbed forecast track (OF).



180 **Figure 3: Schematic diagram of constructing left, right, fast, and slow perturbed forecast tracks using the error circle method.**

(3) Perturbed intensity scenario generation

Using the intensity forecast errors of tropical cyclones in the Northwest Pacific from the four forecast agencies during 2013–2017 (Chen et al., 2015, 2017, 2018, 2019b; Chen and Cao, 2014), this study calculates the multi-source forecast intensity errors using Eqs. (6) to (7), taking the 24-h forecast lead time as an example. The results indicate that the multi-source forecast
185 intensity errors at 24-h, 48-h, and 72-h lead times are 4.70 m/s, 6.87 m/s, and 7.87 m/s, respectively.

$$SMSWE_{j(24h)} = \frac{1}{5} \sum_{y=2013}^{2017} AMSWE_{y(24h)}^j, \quad (6)$$

$$MSW_{Error(24h)} = \frac{1}{4} \sum_{j=1}^4 SMSWE_{j(24h)}, \quad (7)$$

Where $AMSWE_{y(24h)}^j$ represents the total intensity error of the j_{th} forecast agency in year y at the 24-h forecast lead time; $SMSWE_{j(24h)}$ represents the annual average intensity error of the j_{th} forecast agency during 2013–2017 at the 24-h forecast
190 lead time; $MSW_{Error(24h)}$ represents the average intensity error of the multi-source forecast at the 24-h forecast lead time.

Perturbed intensities are then generated, which consist of two parts: the observed intensity of the controlled tropical cyclone and perturbed forecast intensities. Perturbed forecast intensities are generated by applying positive or negative perturbations of the multi-source forecast intensity error (MSW_{Error}) at the corresponding forecast lead time to the controlled forecast



intensity. This produces two scenarios: the high-intensity (MSW_i^{E+}) scenario and the low-intensity (MSW_i^{E-}) scenario, as shown in Eqs. (8) to (9).

$$MSW_i^{E+} = \frac{1}{4} \sum_j^4 MSW_{i(j)} + MSW_{i(Error)} \quad (s \leq i \leq p), \quad (8)$$

$$MSW_i^{E-} = \frac{1}{4} \sum_j^4 MSW_{i(j)} - MSW_{i(Error)} \quad (s \leq i \leq p), \quad (9)$$

(4) Tropical cyclone scenario ensemble

By combining five tracks (the controlled track and four perturbed tracks) with three intensities (the controlled intensity and two perturbed intensities), this study generates 15 tropical cyclone scenarios (Table 1). This systematic combination of track and intensity perturbations ensures comprehensive representation of tropical cyclone forecast uncertainty within a computationally feasible ensemble.

Table 1: Tropical cyclone scenario ensemble.

Intensity type	Track type				
	Controlled track (C)	Left track (L _e)	Right track (R)	Fast track (F)	Slow track (S)
Controlled high intensity (H _D)	C-H _D	L _e -H _D	R-H _D	F-H _D	S-H _D
Controlled intensity (M _D)	C-M _D	L _e -M _D	R-M _D	F-M _D	S-M _D
Controlled low intensity (L _D)	C-L _D	L _e -L _D	R-L _D	F-L _D	S-L _D

(5) Typhoon storm surge and inundation scenario simulation

Using the 15 tropical cyclone scenarios as input conditions, typhoon storm surge processes are simulated to derive coastal inundation scenarios. This study employs the MIKE 21 hydrodynamic model developed by the Danish Hydraulic Institute, which has been widely applied in studies of typhoon storm surge and coastal inundation (Machineni et al., 2019; Siahserani et al., 2021). However, wave simulation is not included in this study, as coupling a wave model would considerably increase the computational cost, which is difficult to reconcile with the timeliness required for emergency risk assessment under the present conditions.

(6) Hazard intensity grade calculation

Based on the water depth (D_n) at each grid cell from the 15 simulation scenarios, the mean (D_{mean}) and maximum (D_{max}) water depths are calculated, as shown in Eqs. (10) to (11). Table 2 presents the relationship between water depth and hazard



intensity grade. Using this relationship, the spatial distributions of hazard intensity grades under the mean and maximum water
215 depth scenarios are derived.

$$D_{mean} = \frac{1}{15} \sum_{n=1}^{15} D_n, \quad (10)$$

$$D_{max} = \max_{1 \leq j \leq 15} D_n, \quad (11)$$

Table 2: Water depth-hazard intensity grade relationship.

Water depth (m)	Hazard intensity grade
(0.0, 0.5)	V
[0.5, 1.0)	IV
[1.0, 2.0)	III
[2.0, 3.0)	II
[3.0, +∞)	I

2.3 Vulnerability assessment

220 This study selects land use types and densely populated facilities as two categories of vulnerability. In the vulnerability assessment, the water depth refers to the inundation depth obtained from the hazard assessment, which serves as the input for evaluating direct economic loss. The vulnerability assessment for land use focuses on establishing the water depth-loss relative grade relationship through four steps: land use classification, water depth-loss rate sources, direct economic loss per unit area calculation, and relative grade table construction. The vulnerability assessment for densely populated facilities focuses on
225 calculating vulnerability grades through normalization of POI density. The detailed assessment processes are illustrated in Fig. 4 and described in the following subsections.

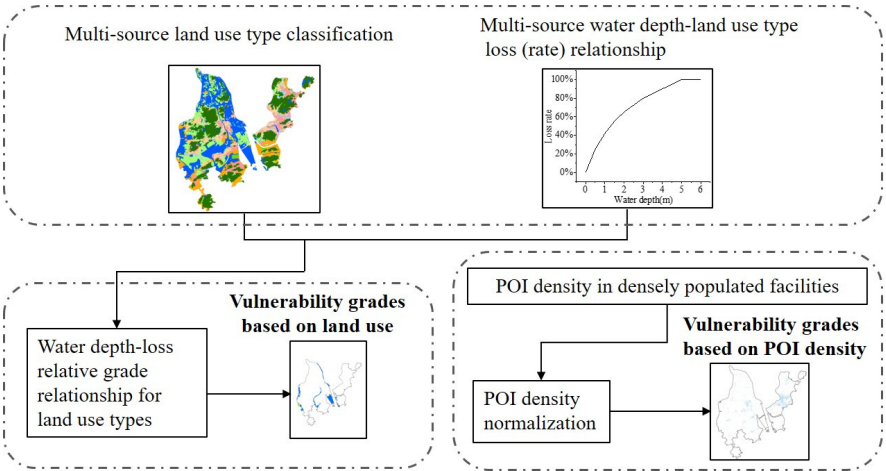


Figure 4: Steps of vulnerability assessment.

230 (1) The water depth-loss relative grade relationship for land use types
(a) Land use classification

By combining the China Land Use/Cover Dataset (CNLUCC) and Essential Urban Land Use Categories (EULUC), both from 2018 (Gong et al., 2020; Xu et al., 2018), this study classifies coastal land use into 11 categories (Table 3).

Table 3: Land use classification in coastal areas.

Serial number	1	2	3	4	5	6
Land use type	Cropland	Forest land	Grassland	Water body	Bare land	Residential land
Serial number	7	8	9	10	11	
Land use type	Commercial land	Industrial land	Transportation	Public management and service	Other construction land	

235 (b) Water depth-loss rate sources

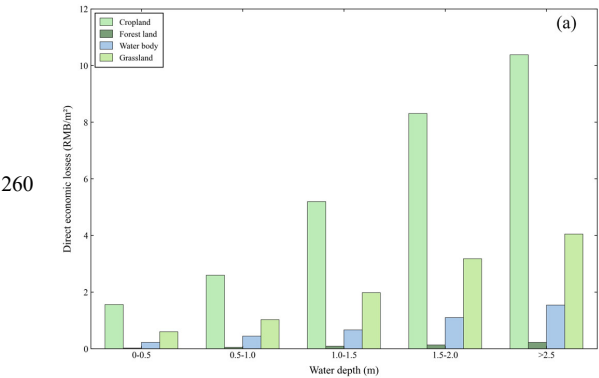
The water depth-loss rate for different land use types is established by synthesizing data from multiple sources. For example, Zheng & Sun (Z study) (Zheng and Sun, 2020) provide water depth-loss rates for cropland, forest land, and water body, as well as for built-up areas and developed areas. In the Z study, water depth is divided into 5 intervals: 0–0.5 m, 0.5–1.0 m, 1.0–1.5 m, 1.5–2.0 m, and 2.0–2.5 m. In addition, Huizinga et al. (2017) (H study) establish loss rates for 6 land use types at 9



240 water depth levels (0 m, 0.5 m, 1 m, 1.5 m, 2 m, 3 m, 4 m, 5 m, and 6 m), including residential land, commercial land, industrial
land, transportation, infrastructure (road) land, and agricultural land. "Technical Guidelines for Marine Disaster Risk
Assessment and Zoning Part 1: Storm Surge" (hereinafter referred to as "the Guidelines") (Ministry of Natural Resources of
the People's Republic of China, 2019) provide reference vulnerability grades covering all land use types. Although these
grades do not vary with water depth, they indicate the relative vulnerability among land use types, providing a basis for
245 estimating loss values for the types not covered by the Z and H studies. It is noted that the Z study reports mean direct economic
losses per unit area, while the H study reports maximum values. This difference is mitigated by the normalization procedure
applied in step (d), which derives relative grades independently within each dataset.

(c) Direct economic loss per unit area calculation

The Z study and H study together provide direct economic loss per unit area for 7 land use types under different water depths.
250 In particular, the Z study provides mean direct economic loss per unit area for land use types numbered 1, 2, and 4; the H study
provides maximum direct economic loss per unit area for land use types numbered 6–9, where transportation includes
transportation facility land and road land. For the remaining 4 land use types (numbers 3, 5, 10, and 11), this study estimates
loss values based on data from land use types with similar vulnerability grades. Grassland (number 3) shares the same
vulnerability grade as cropland, forest land, and water body in the Guidelines, so the average direct economic loss per unit
255 area of these three types is adopted; bare land (number 5) is assigned the lowest grade across all water depths. Public
management and service land (number 10) has a vulnerability grade similar to land use types numbered 6–9 in the Guidelines,
so the average of these four types is adopted; other construction land (number 11) primarily comprises industrial land and
transportation land, so the average of these two types is adopted. The data sources for all 11 land use types are summarized in
Fig. 5 and Table 4.



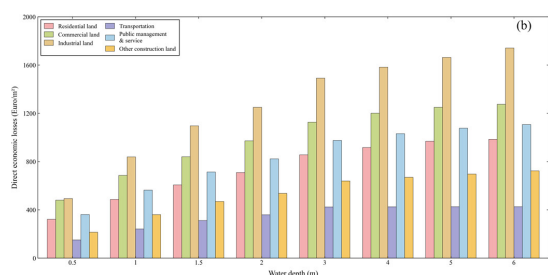


Figure 5: Direct economic loss versus water depth for land use types in (a) the Z study and (b) the H study.

Table 4: Data sources for direct economic loss per unit area of land use types.

Serial number	Land use type	Data source for direct economic loss per unit area of land use types
1	Cropland	Z study
2	Forest land	Z study
3	Grassland	Average value of direct economic loss per unit area for cropland, forestland, and water body in the Z study
4	Water body	Z study
5	Bare land	Lowest vulnerability grade
6	Residential land	H study
7	Commercial land	H study
8	Industrial land	H study
9	Transportation	H study (includes transportation facility land and road land)
10	Public management and service	Average value of direct economic loss per unit area for residential land, commercial land, industrial land, and transportation in the H study
11	Other construction land	Average value of direct economic loss per unit area for industrial land and transportation in the H study

(d) Relative grade table construction



265 This study normalizes the direct economic loss per unit area for each land use type using Eq. (12) to calculate the relative grades of direct economic loss.

$$UL_{kd}^S = \frac{UL_{kd} - \min UL}{\max UL - \min UL}, \quad (12)$$

Where UL_{kd} represents the direct economic loss per unit area of the k_{th} land use type in Table 4 under the d_{th} water depth. When k takes values from 1 to 4, $\max UL$ and $\min UL$ represent the maximum and minimum losses per unit area among grassland and all land use types in the Z study under the 5 water depth intervals. When k takes values from 6 to 11, $\max UL$ and $\min UL$ represent the maximum and minimum losses per unit area among transportation, public management and service land, other construction land, and all land use types in the H study under the 9 water depth levels. UL_{kd}^S represents the normalized value of UL_{kd} .

270 Since the water depth conditions in the Z study and the H study are not directly comparable, integration rules are established as follows. This study divides water depth into 9 intervals (in meters): (0.0, 0.5], (0.5, 1.0], (1.0, 1.5], (1.5, 2.0], (2.0, 3.0], (3.0, 4.0], (4.0, 5.0], (5.0, 6.0], and (6.0, $+\infty$). The normalized values of direct economic loss are divided into five grades with corresponding assigned values: grade V (0.0–0.2, value 1), grade IV (0.2–0.4, value 2), grade III (0.4–0.6, value 3), grade II (0.6–0.8, value 4), and grade I (0.8–1.0, value 5). The relative grades of direct economic loss for 11 land use types under the 9 water depth intervals are presented in Table 5. As shown in Table 5, cropland, forest land, grassland, water body, and bare land are all grade V under all water depth conditions, while the grades of the remaining 6 land use types increase with increasing water depth.

Table 5 Relative grades of direct economic loss for land use types under different water depths.

Land use type	(0.0, 0.5]	(0.5, 1.0]	(1.0, 1.5]	(1.5, 2.0]	(2.0, 3.0]	(3.0, 4.0]	(4.0, 5.0]	(5.0, 6.0]	(6.0, $+\infty$)
1. Cropland	V	V	V	V	V	V	V	V	V
2. Forest land	V	V	V	V	V	V	V	V	V
3. Grassland	V	V	V	V	V	V	V	V	V
4. Water body	V	V	V	V	V	V	V	V	V
5. Bare land	V	V	V	V	V	V	V	V	V
6. Residential land	V	IV	IV	III	III	III	III	III	III
7. Commercial land	IV	IV	III	III	II	II	II	II	II
8. Industrial land	IV	III	II	II	I	I	I	I	I
9. Transportation	V	V	V	IV	IV	IV	IV	IV	IV



Land use type	(0.0, 0.5]	(0.5, 1.0]	(1.0, 1.5]	(1.5, 2.0]	(2.0, 3.0]	(3.0, 4.0]	(4.0, 5.0]	(5.0, 6.0]	(6.0, +∞)
10. Public management and service	IV	IV	III	III	III	III	II	II	II
11. Other construction land	V	IV	IV	IV	IV	IV	IV	III	III

(2) Vulnerability based on densely populated facilities

Following the classification of densely populated facilities proposed by Zhang et al. (2016), this study selects 5 facility types: schools, hospitals, transportation hubs (railway stations, bus stations, airports), hotels and restaurants (hotels, inns, guesthouses), and commercial venues (shopping plazas). The POI density of densely populated facilities is calculated at each grid cell and then normalized using Eq. (13). The normalized POI density values are divided into five vulnerability grades with corresponding assigned values: grade V (0.0–0.2, value 1), grade IV (0.2–0.4, value 2), grade III (0.4–0.6, value 3), grade II (0.6–0.8, value 4), and grade I (0.8–1.0, value 5).

$$PD_m^S = \frac{PD_m - \min PD}{\max PD - \min PD}, \quad (13)$$

Where PD_m represents the POI density at the m_{th} grid cell, $\max PD$ and $\min PD$ represent the maximum and minimum values of POI density across all grid cells, and PD_m^S represents the normalized value of PD_m .

2.4 Risk calculation

This study derives comprehensive risk grades by integrating land use type-based risk grades and densely populated facility-based risk grades (Fig. 6).

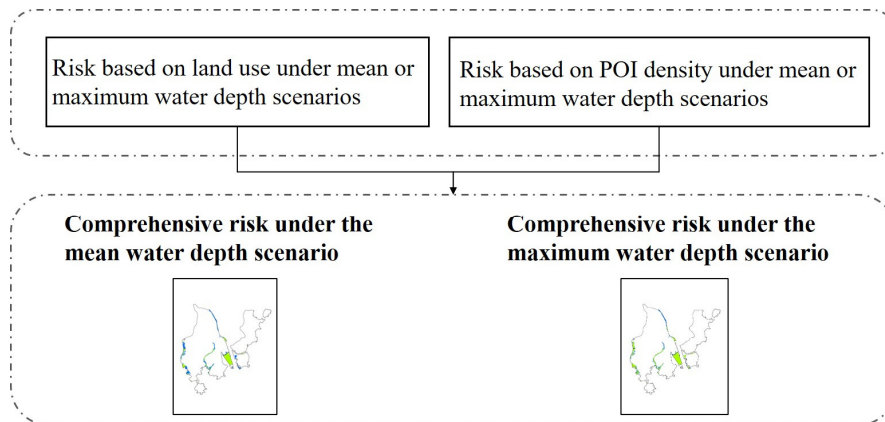




Figure 6: Steps of risk calculation.

The specific calculation steps are as follows:

- 300 (1) Land use type-based risk calculation: the relative grade of direct economic loss for each grid cell is determined from the water depth (Sect. 2.2) and the water depth-loss relative grade relationship (Table 5). The relative grade is then converted to an assigned value, representing the land use type-based risk grade (R_{UL}) calculated using Eq. (14).
- (2) Densely populated facility-based risk calculation: the vulnerability grade of densely populated facilities is converted to an assigned value (V_{PD}). The densely populated facility-based risk grade (R_{PD}) is then calculated using Eq. (15).
- 305 (3) Comprehensive risk calculation: the comprehensive risk value is obtained by combining land use type-based risk and densely populated facility-based risk using Eqs. (16) to (17), reflecting the relative contributions of economic loss and potential casualty vulnerability to overall disaster risk. This design is grounded in the characteristic of TSSDs, wherein economic losses constitute the predominant form of damage while casualties are comparatively limited (Wang et al., 2021a). The risk value is then converted to a risk grade, where values of 1, 2, 3, 4, and 5 correspond to grades V, IV, III, II, and I, respectively, consistent
- 310 with the number of hazard and vulnerability grades. The spatial distributions of comprehensive risk grades are then mapped.

$$R_{UL} = f(H, V_{UL}) = V_{UL} \quad (H \neq 0), \quad (14)$$

$$R_{PD} = f(H, V_{PD}) = V_{PD} \quad (H \neq 0), \quad (15)$$

$$R_{LP} = f(R_{UL}, R_{PD}) = \begin{cases} R_{UL} & (R_{PD}=0) \\ R_{UL}+1 & (R_{PD}=1, 2) \\ R_{UL}+2 & (R_{PD}=3) \\ R_{UL}+3 & (R_{PD}=4, 5) \end{cases}, \quad (16)$$

$$R = \begin{cases} R_{LP} & (R_{LP} \leq 5) \\ 5 & (R_{LP} > 5) \end{cases}, \quad (17)$$

315 3 Case study

Typhoon Hato (the 13th typhoon of 2017) made landfall in Zhuhai, Guangdong province of China, at 12:50 on 23 August (Beijing Time, the same hereinafter), with maximum wind speed near the center reaching 45 m/s and minimum central pressure of 950 hPa. It triggered a significant TSSD along the Guangdong coast, causing direct economic losses of 5.154 billion RMB in Guangdong, with losses in Zhuhai exceeding 4.4 billion RMB. The Hato TSSD is selected as the case study for two reasons:

320 it caused severe impacts on the Pearl River Delta coast, and multi-source forecast data from the four agencies are available for the 24 hours prior to landfall. This study applies the proposed method to assess the risk of the Hato TSSD, with the forecast initialization time set at approximately 24 hours before landfall (14:00 on 22 August 2017).



3.1 Study area and data sources

325 Zhuhai is located in the southwest of the Pearl River Estuary (Fig. 7), bordering the South China Sea to the south, with vast sea areas and numerous islands. The Pearl River Estuary is one of the typhoon storm surge-prone areas in China, and Zhuhai has historically suffered repeated TSSDs (Pang et al., 2020). The following datasets are used in this study:

- (1) Administrative boundary data: the administrative boundaries of Zhuhai are from the Database of Global Administrative Areas (GADM) (Database of Global Administrative Areas, 2026).
- 330 (2) Tropical cyclone data: the forecast data and the observed data at the forecast initialization time from the four agencies for Typhoon Hato are obtained from the Integrated Multi-Agency Tropical Cyclone Forecast provided by Typhoon2000 (Typhoon2000, 2026), and the observed data prior to the forecast initialization time are obtained from NMC (National Meteorological Centre of the China Meteorological Administration, 2026).
- (3) Topographic data: offshore water depth is from the ETOPO1 dataset with a resolution of 1 arc-minute (NOAA National Centers for Environmental Information, 2026); nearshore water depth is from electronic navigational charts (Zhejianghaitu, 335 2026); coastal land elevation is derived from the ASTER GDEM V3 dataset with a resolution of 1 arc-second (NASA/METI/AIST/Japan Spacesystems and U.S./Japan ASTER Science Team, 2026). Before calculation, all data are converted to the mean sea level datum using vertical datum conversion relationships (He et al., 2016; Jiao et al., 2002).
- (4) Land use data: land use data for Zhuhai are jointly provided by CNLUCC and EULUC.
- (5) POI data: POI data for densely populated facilities in Zhuhai are from Amap dataset (Amap, 2026).

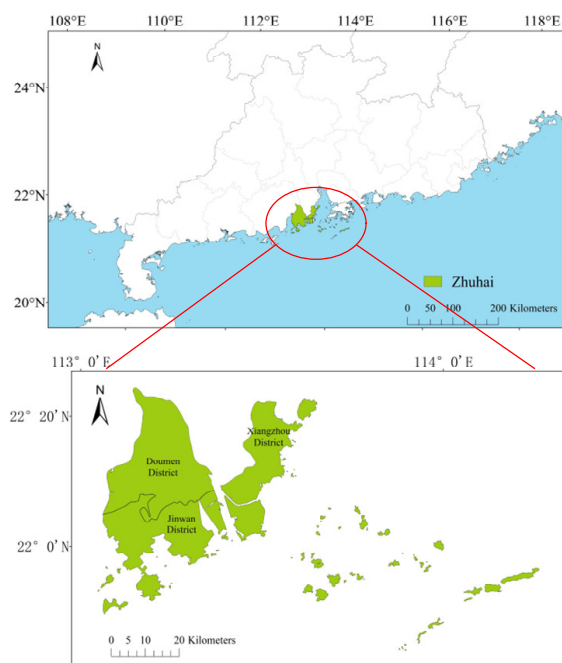


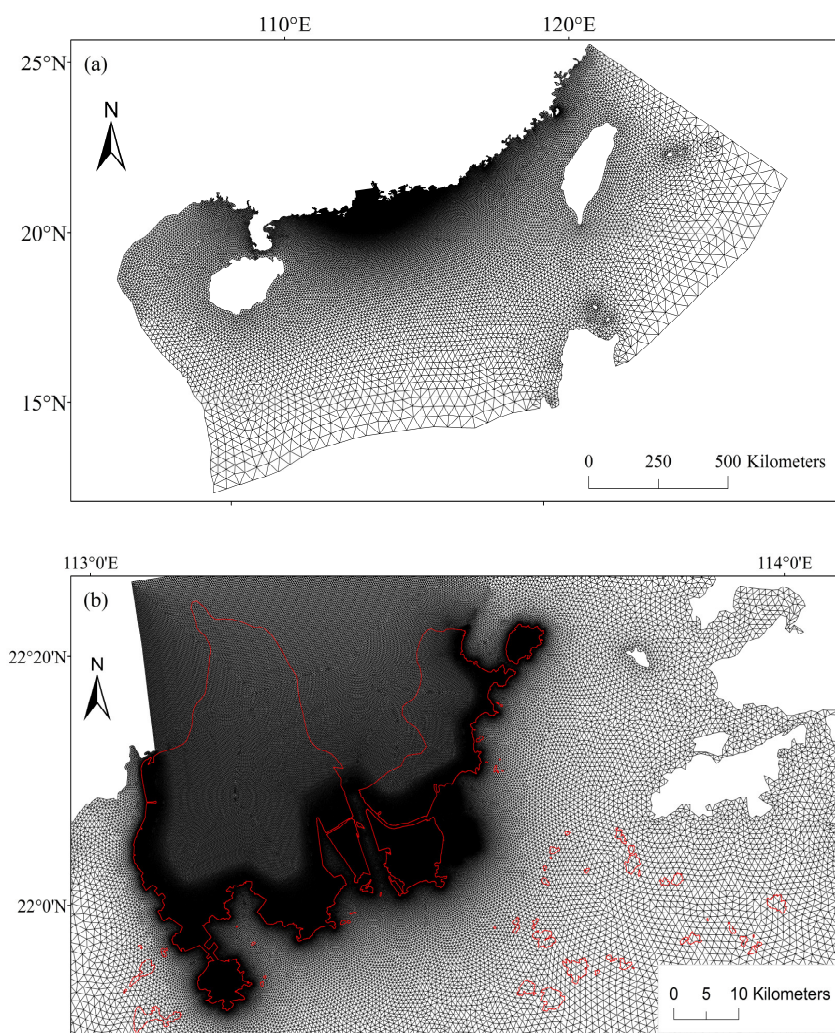
Figure 7: Geographic location of Zhuhai.

3.2 Hydrodynamic model setup

Following the hydrodynamic modeling framework described in Sect. 2.2, the MIKE 21 model is configured for the Zhuhai case study as follows.

(1) Grid setup for the computational domain

The computational domain is 12°N–28°N, 105°E–128°E. An unstructured grid is used for discretization, with grid resolution gradually transitioning from 300 m in inland areas of Zhuhai to 100 m in coastal areas, and further to 50 km in offshore areas. The grid comprises 362,654 triangular elements and 182,874 nodes. The computational grids for the full domain and the Zhuhai area are shown in Fig. 8(a) and (b), respectively. The bathymetric and topographic data are then clipped, merged, and interpolated onto the unstructured grid to obtain the elevation distribution of the computational domain (Fig. 9).



355 **Figure 8: Unstructured grids of the computational domain.**

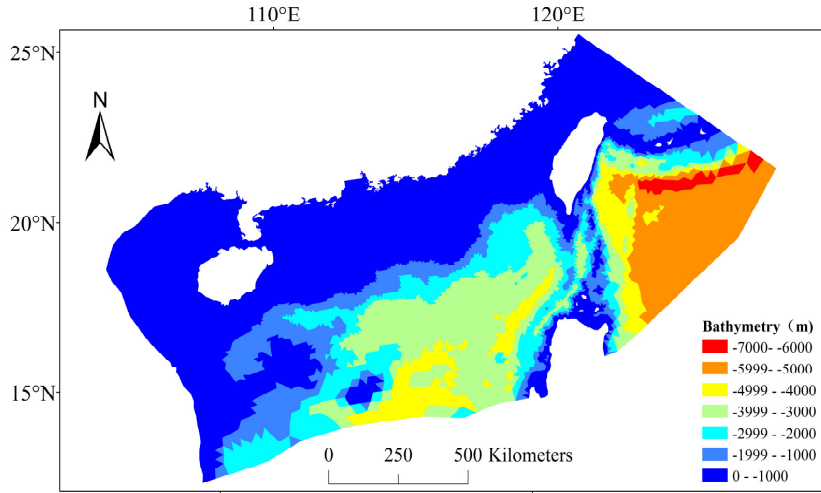


Figure 9: Elevation distribution of the computational domain.

(2) Selection of relevant parameters

360 The MIKE 21 toolbox provides various parameterization options for calculating wind and pressure fields. This study employs the Holland model to calculate the wind and pressure fields of Typhoon Hato, as shown in Eqs. (18) to (19).

$$p(r) = p_c + (p_n - p_c) \exp\left(-\frac{R_{mw}}{r}\right)^B, \quad (18)$$

$$V_g(r) = \sqrt{(p_n - p_c) \frac{B}{\rho_A} \left(\frac{R_{mw}}{r}\right)^B \exp\left(-\frac{R_{mw}}{r}\right)^B + \left(\frac{rf}{2}\right)^2 - \frac{r|f|}{2}}, \quad (19)$$

where $p(r)$ represents the sea surface pressure at distance r from the cyclone center, p_c represents the central pressure of the cyclone, p_n represents the sea surface pressure far from the cyclone (also called ambient pressure, set to 1010 hPa in this study), $V_g(r)$ represents the gradient wind speed at distance r from the cyclone center, ρ_A represents air density, f represents the Coriolis parameter, R_{mw} represents the radius of maximum wind speed, and B represents the model parameter.

Following the R_{mw} settings adopted in typhoon storm surge simulations in the Pearl River Delta (Jian et al., 2021), this study calculates R_{mw} using Eq. (20). This equation introduces a coefficient of variation C_v into the empirical formula proposed by Willoughby and Rahn for calculating R_{mw} . Yang et al. (2019) determine the coefficient of variation of 0.58 for Typhoon Hato. Based on the discussion by Shao et al. (2018) on the Holland model parameter B for tropical cyclones in the South China Sea and East China Sea, and considering the available input data, parameter B is calculated using Eq. (21).

$$R_{mw} = C_v \cdot 51.6 \exp(-0.0223v_{\max} + 0.0281\varphi), \quad (20)$$



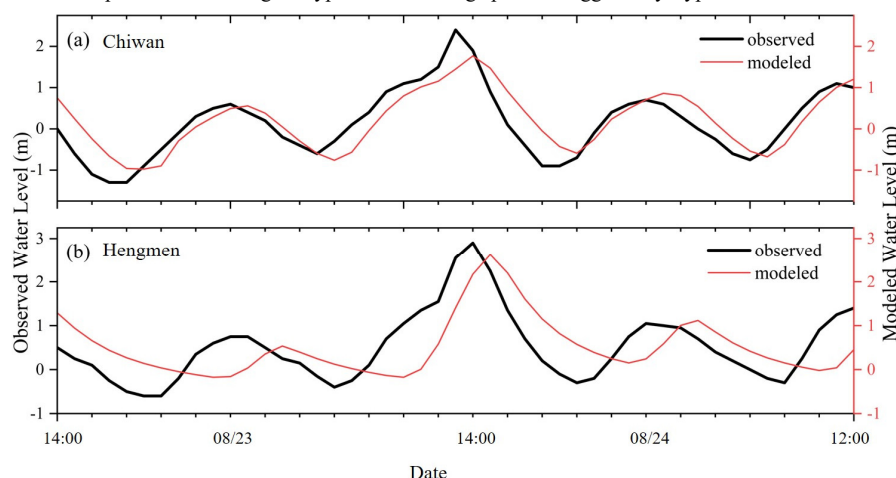
$$B = 1.881 - 0.00557R_{mw} - 0.01295\varphi, \quad (21)$$

375 Where φ represents the latitude of the tropical cyclone center.

The global tidal model embedded in MIKE 21 provides the spatiotemporal variation of the astronomical tide at the water level open boundary. As noted in Sect. 2.2, wave simulation is excluded from this study. The water level simulation, therefore, considers only the coupling of storm surge and astronomical tide.

(3) Model validation

380 This study uses observed water levels during Typhoon Hato for model validation, covering the period from 14:00 on 22 August to 12:00 on 24 August 2017. The simulated maximum water levels and their occurrence times at Chiwan Station (Fig. 10(a)) and Hengmen Station (Fig. 10(b)) show reasonable agreement with the observed data, demonstrating that the hydrodynamic model is capable of simulating the typhoon storm surge process triggered by Typhoon Hato.



385 **Figure 10: Model validation results**

4 Results and discussion

4.1 Scenario generation

(1) Typhoon storm surge scenario generation

390 The forecast initialization time is set to approximately 24 hours before landfall (14:00 on 22 August). Forecast data from the four agencies, retrieved from the Typhoon2000 website, all include 24-h and 48-h forecast lead times. This study uses forecast data from the four agencies, with a maximum forecast lead time of 48-h and observed data from NMC to generate the scenario ensemble for the Hato TSSD. The track of Typhoon Hato initialized at 14:00 on 22 August 2017 is shown in Fig. 11. This



study generates a controlled typhoon scenario using Eqs. (1) to (3), with its controlled track shown in Fig. 12. Using the
controlled track points at 24-h and 48-h forecast lead times as centers and the corresponding multi-source forecast track errors
(78 km and 136 km) as radii, error circles are constructed. Four perturbed tracks—left, right, fast, and slow—are generated
accordingly, as shown in Fig. 13.

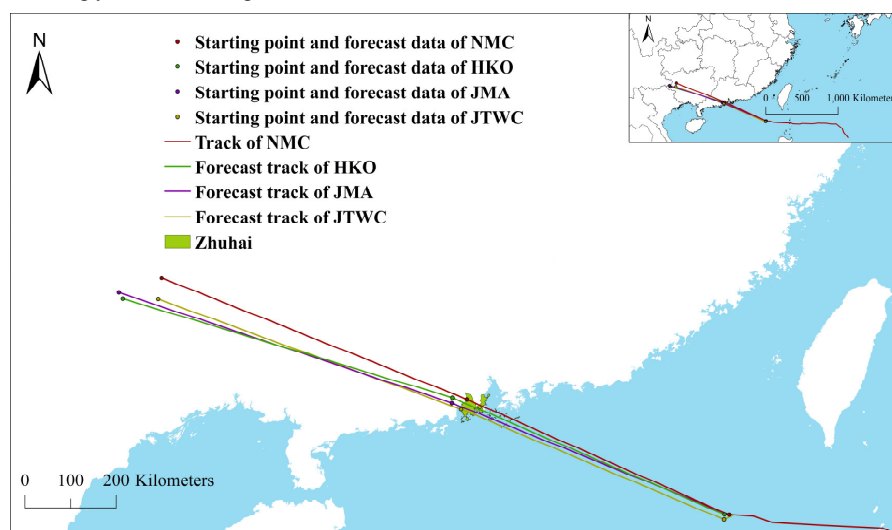


Figure 11: Tracks of Typhoon Hato initialized at 14:00 on 22 August 2017.





400 **Figure 12: Controlled track of Typhoon Hato initialized at 14:00 on 22 August 2017.**

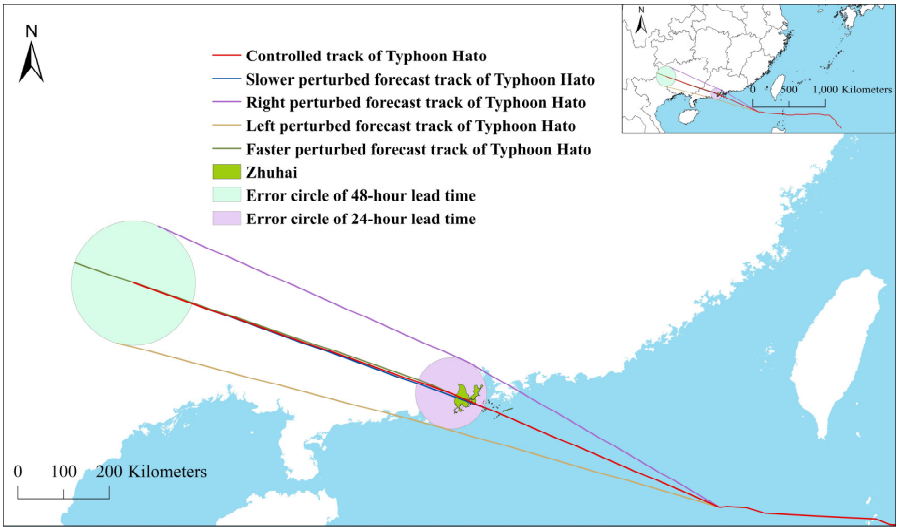


Figure 13: Controlled track and perturbed tracks of Typhoon Hato.

For the controlled track, high-intensity and low-intensity scenarios are generated at the 24-h and 48-h forecast lead times using Eqs. (8) to (9). By combining 5 tracks with 3 intensity conditions (Table 1), this study generates 15 tropical cyclone scenarios. The 15 typhoon scenarios are imported to the calibrated MIKE 21 hydrodynamic model (Sect. 3.2), which simulates the corresponding typhoon storm surge and inundation processes in Zhuhai, yielding 15 inundation scenarios.

(2) Validation of the rationality of the controlled scenario generation method

To assess the validity of this method, the controlled scenario and forecast scenarios from the four agencies are compared with the post-disaster best-track data in terms of position and intensity errors. Results are presented in Table 6.

For the 24-h forecast lead time, the position error of the controlled scenario is 18.9 km, falling between the minimum value (both HKO and JMA at 11.1 km) and the maximum value (NMC at 38 km) among the forecast sources. The intensity error is 4.0 m/s, which is an intermediate level within the range of errors from the forecast sources (0.1–8.0 m/s). For the 48-h forecast lead time, the controlled scenario demonstrates more pronounced advantages: the position error is only 3.5 km, much smaller than those of the forecast sources (37.8–52.6 km). The intensity error is 0.2 m/s, also substantially lower than those of the forecast sources (1.0–6.6 m/s). Therefore, the controlled scenario can reasonably approximate the actual track and intensity of the tropical cyclone, providing reliable input conditions for typhoon storm surge simulations.

Table 6: Position and intensity errors.



	Controlled scenario data	NMC forecast data	HKO forecast data	JMA forecast data	JTWC forecast data
24-h forecast lead time position error (km)	18.9	38	11.1	11.1	20.6
24-h forecast lead time intensity error (m/s)	4.0	2.0	6.0	0.1	8.0
48-h forecast lead time position error (km)	3.5	52.6	37.8	42.3	42.3
48-h forecast lead time intensity error (m/s)	0.2	1.0	2.7	6.6	5.6

(3) Discussion on the ensemble forecasting approach

Despite the satisfactory performance of the controlled scenario, a single deterministic forecast cannot fully capture typhoon storm surge variability arising from inherent forecast uncertainty. Therefore, this study generates perturbed scenarios based on the controlled scenario and error circle method, using historical forecast errors in track and intensity to form an ensemble of 15 tropical cyclone scenarios. The validity of this method is reflected in the following aspects:

(a) The perturbation parameter settings have a statistical basis. The magnitudes of the perturbed tracks and intensities are determined based on the average forecast errors of tracks and intensities from the four forecast agencies during 2013–2017, reflecting the statistical characteristics of forecast uncertainty.

(b) The dual inundation outputs serve distinct purposes in emergency decision-making. Based on the 15 simulation results, hazard intensity grades are characterized through two indicators: mean water depth and maximum water depth. The mean water depth scenario represents the expected inundation state of the ensemble, suitable for routine emergency resource allocation. The maximum water depth scenario represents the worst-case inundation, supporting resident evacuation and protection decisions under extreme conditions.

(c) The ensemble generation in this study is designed to be feasible under the data and computational conditions of a research context, without relying on the high-resolution models and data assimilation available to operational forecasting systems. This represents a reasonable trade-off for emergency-oriented assessment, with the focus placed on integrating forecast uncertainty



into a complete risk assessment framework. The case study demonstrates that the resulting ensemble provides a reasonable
435 representation of possible hazard conditions, sufficient to support pre-disaster emergency decision-making.

4.2 Hazard assessment results

Applying the hazard assessment framework established in Sect. 2.2, the spatial distributions of hazard intensity grades under
the mean water depth scenario (Fig. 14(a)) and maximum water depth scenario (Fig. 14(b)) for Zhuhai are derived. The
simulated inundation extent is broadly consistent with that reported by Du et al. (2020), providing additional confidence in the
440 hydrodynamic model performance.

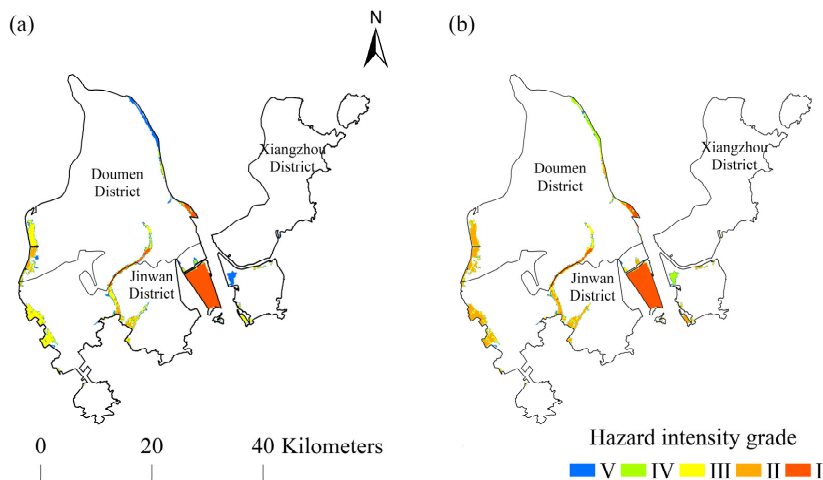


Figure 14: Spatial distribution of hazard intensity grades in Zhuhai

Under both water depth scenarios, inundation is mainly concentrated in Doumen and Jinwan Districts, as shown in Fig. 14(a)
and (b). This spatial pattern is primarily attributable to the low-lying coastal topography of Doumen and Jinwan Districts.
445 Under the mean water depth scenario, hazard intensity grades range from grade V to grade I. Grade V areas are concentrated
in a small area in the northeastern Doumen District, accounting for a small proportion of the total inundated area. The western
inundated areas of Doumen and Jinwan Districts are predominantly grade III, while grade I areas are concentrated in eastern
Jinwan District. Under the maximum water depth scenario, a small area in the eastern Doumen District shows grade IV, and
the western inundated areas of Doumen and Jinwan Districts are predominantly grade II. The distribution of grade I areas
450 remains consistent with that under the mean water depth scenario. The higher hazard intensity grades under the maximum
water depth scenario highlight the importance of accounting for forecast uncertainty in emergency decision-making.



4.3 Vulnerability assessment results

Based on the vulnerability assessment methodology outlined in Sect. 2.3, land use classification for Zhuhai is conducted using the CNLUCC and EULUC datasets, following the classification rules in Table 3. Zhuhai is characterized by a land use pattern dominated by forest land, water body, and concentrated urban construction land (land use types 6–10 in Table 3). In Doumen District, as a traditional agricultural area, cropland, forest land, and water body account for the majority of the land area. In Jinwan District, cropland is primarily distributed in the western part, forest land in the southern part, and water body and urban construction land in the central part. In Xiangzhou District, urban construction land is the dominant land use type, concentrated in the central part, with other construction land mainly distributed in the southern part. Based on the water depth-loss relative grade relationship established in Sect. 2.3 (Table 5), the vulnerability grades for each land use type in Zhuhai under varying water depths are determined and presented together with the land use classification results in Fig. 15.

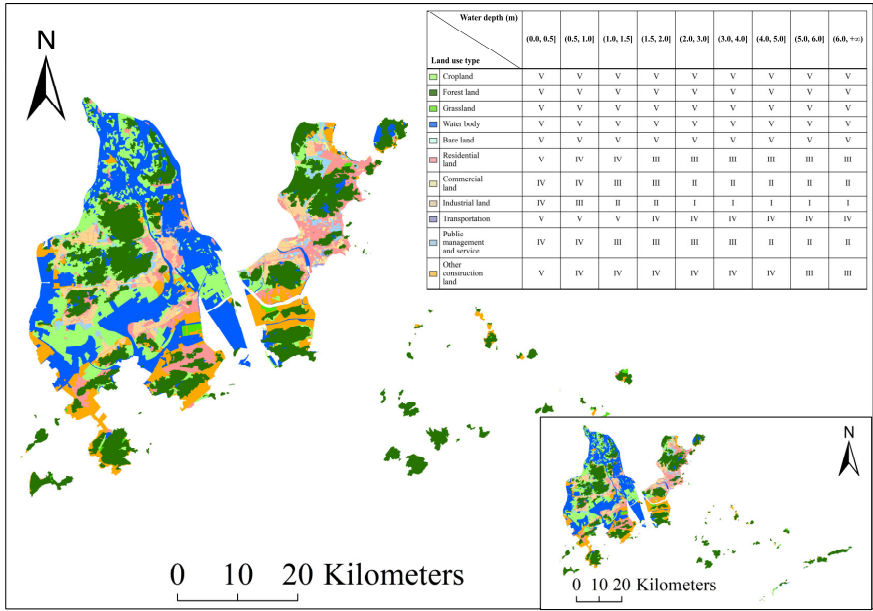
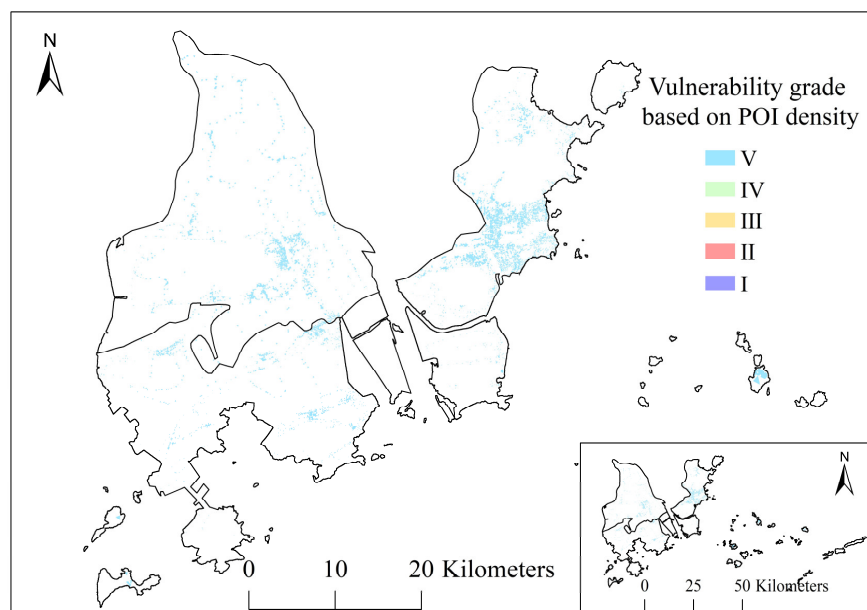


Figure 15: Spatial distribution of vulnerability based on land use types in Zhuhai.

The normalized POI density values for densely populated facilities in Zhuhai are calculated using Eq. (13). The spatial distribution of vulnerability grades for densely populated facilities is derived and presented in Fig. 16. The vulnerability grades for densely populated facilities in Zhuhai are predominantly grade V. The land use type-based and POI density-based vulnerability grades serve as inputs for risk calculation in Sect. 4.4, where they are used to derive comprehensive risk grades.



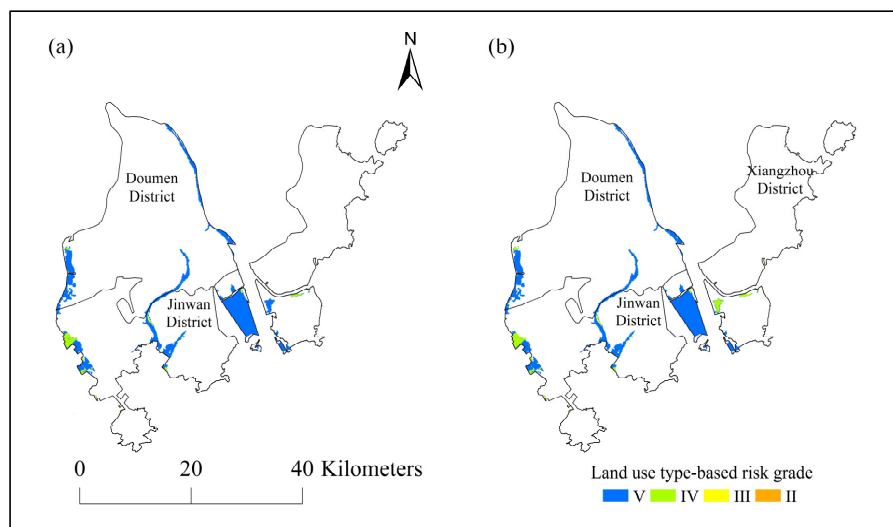
470 **Figure 16: Spatial distribution of vulnerability based on densely populated facilities in Zhuhai.**

4.4 Risk assessment results

Applying the risk calculation framework established in Sect. 2.4, the relative grades of direct economic loss for each land use type in Zhuhai are derived based on the simulated water depth and water depth-loss relative grade relationship. The land use type-based risk grades are then calculated using Eq. (14). The spatial distributions of land use type-based risk grades under the mean and maximum water depth scenarios are presented in Fig. 17(a) and (b), respectively.

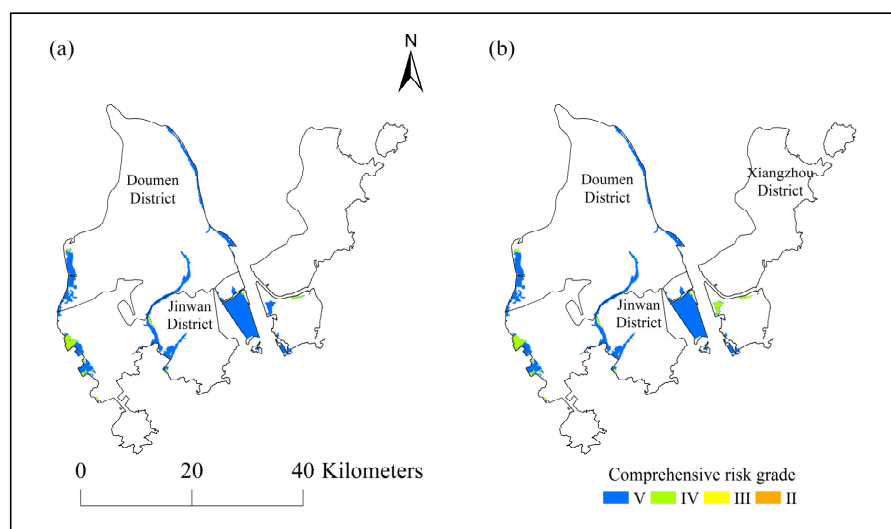
The spatial extent of land use type-based risk grades under both water depth scenarios is consistent with that of hazard intensity grades (Fig. 14). Although the highest hazard intensity grade reaches grade I under both scenarios, the land use type-based risk grades remain predominantly grade V. This pattern is attributable to the dominance of water body in the inundated areas (Fig. 15), for which the relative grade of direct economic loss is grade V under any water depth condition (Table 5).

480 Under both water depth scenarios, inundation in the distribution areas of densely populated facilities is negligible, with only 11 grid cells recording non-zero vulnerability grades. Consequently, the spatial extent of densely populated facility-based risk grades is also highly limited.



485 **Figure 17: Spatial distribution of land use type-based risk grades in Zhuhai.**

The comprehensive risk grades for Zhuhai under both water depth scenarios are calculated using Eqs. (16) to (17). The spatial distributions of comprehensive risk grades under the mean and maximum water depth scenarios are presented in Fig. 18(a) and (b), respectively. Under both water depth scenarios, the highest comprehensive risk grade reaches grade II, although grade II areas are spatially limited, with risk grades predominantly grade V. Nevertheless, the presence of grade II risk areas, albeit
490 limited in spatial extent, warrants particular attention from emergency managers, as these grade II zones, where high hazard intensity coincides with significant economic vulnerability, should be prioritized for pre-positioning of emergency resources, targeted early warnings, and accelerated evacuation planning.



495 **Figure 18: Spatial distribution of comprehensive risk grades in Zhuhai.**

Given the negligible spatial extent of densely populated facility-based risk, the spatial distribution and grade composition of comprehensive risk grades closely resemble those of land use type-based risk grades. It should be noted that the risk assessment results reflect inundation conditions under the simulated typhoon storm surge scenarios, and therefore may not fully capture the actual damage patterns observed during the Hato TSSD. The value of this method lies in its ability to generate risk information approximately 24 hours before landfall, supporting spatially informed emergency preparedness decisions. Furthermore, as forecast data are updated over time, the risk assessment results can be dynamically refreshed, enabling continuous refinement of emergency response strategies as a typhoon approaches.

The simulated inundation area differs from the actual affected area during the Hato TSSD (Tu et al., 2021). This is due to the inherent constraints of pre-disaster forecast-based assessment, including reliance on forecasts rather than post-event track data and the exclusion of seawall breach effects. First, inherent errors in forecast track and intensity propagate through the storm surge simulation, introducing discrepancies in the final inundation results. More significantly, seawall breaches during the actual event led to extensive inundation in previously protected zones, an effect not captured by the present model. Additionally, the limited resolution of elevation data inadequately captures the local micro-topography, and wave overtopping effects are not accounted for. Addressing these limitations in future work would further enhance the accuracy and applicability of the proposed method.



5 Conclusions

This study develops an emergency-oriented risk assessment method for imminent TSSDs and validates it through a case study of the Hato TSSD affecting Zhuhai in 2017. The main contribution lies in integrating forecast uncertainty into a complete, emergency-oriented risk assessment framework, rather than in the forecasting technique itself. First, ensemble forecasting techniques are introduced into hazard assessment to address hazard uncertainty, extending the chain from storm surge prediction to inundation and risk assessment; the ensemble generation relies on openly available multi-source forecast data without depending on specialized operational infrastructure. In the case study, the controlled scenario achieves a smaller position error at the 48-h forecast lead time than any individual forecast source, and the resulting ensemble of 15 tropical cyclone scenarios provides a reasonable representation of possible hazard conditions. Second, land use types and densely populated facilities are selected as two categories of vulnerability—through the water depth-loss relative grade relationship for 11 land use types and POI density-based potential casualty vulnerability—enabling simultaneous consideration of both economic loss and casualty dimensions and extending existing studies that typically focus on a single vulnerability dimension. Third, comprehensive risk grades are derived by combining the two categories, generating spatial risk information approximately 24 hours before landfall that can be re-executed to provide dynamic risk assessment updates as forecast data evolve, providing useful spatial references to help emergency decision-makers identify high-priority zones for defensive measures and resource allocation in advance.

The proposed method also enables dynamic risk assessment as forecast data evolve, allowing continuous refinement of emergency response strategies. Nevertheless, several limitations remain. The exclusion of seawall breach effects and wave overtopping, together with constraints in topographic data resolution, may reduce the accuracy of simulated inundation extents. Future work could address these limitations by incorporating seawall failure mechanisms, coupling wave models, and integrating high-resolution topographic data, while extending the method to a broader range of TSSDs to evaluate its generalizability.

Code and data availability

The hydrodynamic simulations in this study were performed using the commercial software MIKE 21, which was licensed and purchased by the research group and is available from DHI (<https://www.mikepoweredbydhi.com>). No custom code was developed in this study; all other calculations were carried out using standard software. All data used in this study are publicly available from the sources cited in the main text.

Author contributions

KW conceptualized the study, developed the methodology and software, performed the simulations and analysis, and prepared the manuscript. YY contributed to the conceptualization, methodology and software, supervised the work, and edited the



manuscript. JL contributed to the methodology and provided supervision. QH contributed to the conceptualization and provided supervision.

Competing interests

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

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During the preparation of this manuscript, the authors used AI-assisted tools for language polishing. All content was subsequently reviewed and edited by the authors, who take full responsibility for the content of the publication.

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