

Article

Rapid Assessment of Waterlogging Risk Induced by Typhoon Rainfall: A Case Study of Typhoon Haikui (2311) in South China

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Abstract

Typhoon rainfall can trigger urban waterlogging within hours, but hydrodynamic modelling is impractical for rapid screening. For Typhoon Haikui (2311) across Guangdong, Guangxi, and Hainan, we integrated half-hourly Integrated Multi-satellite Retrievals for Global Precipitation Measurement (IMERG) Final Run V07 precipitation, LandScan population exposure (E), and an impervious-surface factor (I) derived from the China Land Cover Dataset into a Typhoon Rainfall Risk Index (TRRI). Rainfall hazard (H) combines event-total rainfall, rainfall duration, and maximum 3 h rainfall. Hazard clustered along the Guangdong coast, where maximum event-total and 24 h rainfall reached 529.7 and 272.8 mm, respectively. TRRI high-risk zones occupied 12.45% of the three-province land area. Defined by the largest weighted component, H -, E -, and I -dominated cells accounted for 60.5%, 33.4%, and 6.1% of the high-risk class. Of 22 reported waterlogging locations in the event-focused domain, 19 fell in high-risk zones; the 86.36% hit rate versus a 26.09% background area yielded an enrichment ratio of 3.31 ($p < 0.001$). In a descriptive full-domain check, all 49 distinct locations were medium or high. Relative to H alone, TRRI reclassified 20.59% of land upward and 20.64% downward, while 58.77% remained unchanged. TRRI supports rapid event-scale screening and risk prioritization for targeted disaster-prevention decision-making.

Keywords: urban waterlogging; typhoon rainfall; rapid assessment; population exposure; impervious surface; TRRI; Typhoon Haikui

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1. Introduction

Typhoon rainfall is one of the main meteorological hazards affecting the coastal regions of South and Southeast China [1]. Under a warming climate, climate extremes in China have become more intense, and extreme precipitation has become an important driver of flood and waterlogging risk in coastal urban regions [2–7]. From a disaster-risk perspective, climate-related risk is not determined by hazard alone but by the interaction among hazard, exposure, and vulnerability [8–11]. Rapid urbanization further amplifies

this problem. Dense populations, large impervious surfaces, and stressed drainage systems can turn short-duration or persistent rainfall into severe urban waterlogging [6,12]. Therefore, event-scale methods are needed to rapidly identify where typhoon rainfall is most likely to cause waterlogging impacts.

Previous studies can be grouped into three broad approaches. Process-based hydrodynamic models simulate runoff and inundation in detail and can provide water depth, flow velocity, and inundation extent, but they require high-resolution topography, drainage networks, boundary conditions, calibration data, and substantial computation [13–15]. Statistical and indicator-based assessments combine rainfall, land-surface, exposure, and socioeconomic variables to support comparative risk zoning [16–21]. These methods have progressed from conventional weighted overlays to multidimensional disaster-risk frameworks, typhoon-rainfall process indices, and machine-learning-assisted indicator selection. However, their indicator systems and weights are often case-specific, and the final composite score is not always decomposed to show how individual components contribute to the mapped risk. Multi-source remote sensing approaches improve regional coverage and data accessibility [22–24]. Nevertheless, three gaps remain in rapid event-scale regional assessment. First, rainfall hazard is still frequently represented by a single accumulation or intensity metric, despite the value of retaining rainfall-process information. Second, integrated indices do not always distinguish whether high mapped values are primarily associated with rainfall hazard, exposed population, or urban surface conditions. Third, validation often emphasizes the proportion of reported waterlogging locations falling within higher-risk classes without accounting for the areal prevalence of those classes or testing the influence of alternative weighting schemes.

Typhoon Haikui in 2023 provides a useful case for testing a rapid waterlogging-risk assessment framework. After landfall, the remnant vortex of Haikui remained near the Pearl River Estuary and caused persistent extreme rainfall over the Guangdong–Hong Kong–Macao Greater Bay Area and surrounding regions [25–29]. Previous studies have shown that the long-lasting remnant circulation, persistent low-level convergence, sustained moisture transport, and urban effects contributed to the extreme rainfall in the Pearl River Delta [25,27–29]. This event had strong rainfall intensity, long rainfall duration, and a set of reported waterlogging locations, making it suitable for examining whether an integrated index can capture both rainfall hazard and the urban conditions that influence waterlogging risk.

Multi-source remote sensing and gridded geospatial datasets provide a practical basis for rapid event-scale mapping. The Integrated Multi-satellitE Retrievals for Global Precipitation Measurement (IMERG) Final Run V07 product provides half-hourly precipitation estimates that can describe the temporal evolution of typhoon rainfall. The China Land Cover Dataset (CLCD) can be used to extract impervious surfaces, which reflect urban surface conditions related to runoff generation. Impervious surfaces were selected because they directly reduce infiltration and regulate runoff generation and concentration and can be mapped consistently across the study domain. They are therefore treated as an underlying-surface factor rather than as a proxy for classical vulnerability. Classical vulnerability encompasses broader physical, social, economic, and ecological predispositions and should not be represented by imperviousness alone. For the present rapid-screening objective, population exposure is represented separately using LandScan, while imperviousness is retained only as a physical surface regulator. LandScan HD China population data represent the spatial distribution of the exposed population. When these datasets are harmonized to a common 1 km grid, they allow a reproducible assessment without requiring detailed drainage-network data, high-resolution hydrodynamic inputs, or complete post-event field surveys. This data setting provides a rapid way to identify where typhoon rainfall is most likely to translate into waterlogging impacts.

This study advances rapid event-scale assessment in four specific ways. First, rainfall hazard retains accumulated rainfall, duration, and 3 h concentration rather than a single rainfall metric. Second, the framework distinguishes rainfall hazard (H), population exposure (E), and an impervious-surface factor (I) within a simple and reproducible index, with weights supported by a six-expert analytic hierarchy process consultation. Because H , E , and I are retained as separate layers before integration, TRRI can be decomposed to identify the largest weighted contribution at each grid cell rather than functioning only as an undifferentiated composite score. Third, point correspondence is evaluated using the hit rate, high-risk background-area proportion, enrichment ratio, positional buffers, and a full-domain province-stratified check. Fourth, the sensitivities of the mapped results to component weights and analysis-domain extent are quantified. Together, these features extend previous indicator-based assessments by combining parsimonious rainfall-process representation, component-wise interpretation, and area-aware evaluation within one regional screening framework. The framework provides a transparent screening layer for prioritizing locations that warrant field verification or detailed modelling.

2. Materials and Methods

2.1. Study Area and Typhoon Event

The regional screening domain covers Guangdong, Guangxi, and Hainan in South China. These regions were not selected solely in advance from an administrative definition: the event-data compilation identified 51 waterlogging reports during the study period, including 15 in Guangdong, 27 in Guangxi, and 9 in Hainan. Direct Haikui attribution is strongest for the Guangdong and Guangxi records; the Hainan records are conservatively described as event-period waterlogging evidence. The three-province domain therefore captures both the principal impact corridor and adjacent affected or lower-rainfall areas, while allowing the effect of domain extent to be tested explicitly.

Because Haikui's main rainfall impact was concentrated along coastal Guangdong, we defined 110.05°E–118.0°E and 20.35°N–24.65°N as an event-focused domain for the enrichment and buffer analyses. The complete three-province result remains the regional screening output. A separate sensitivity analysis recalculated normalization and Fisher–Jenks breaks within the event-focused domain to quantify whether extensive lower-value areas in Guangxi and Hainan altered the class thresholds.

Typhoon Haikui was selected because it produced a long-duration rainfall process over coastal South China. Figure 1 summarizes the event context. Track position, maximum sustained wind, and central pressure were obtained from NOAA's International Best Track Archive for Climate Stewardship (IBTrACS) v4.0 [30]. For wind and pressure separately, the agency series with the greatest number of valid records was selected from the available WMO, USA, Tokyo, CMA, and BOM fields; wind speed was converted from knots to m s^{-1} . Times are reported in UTC.

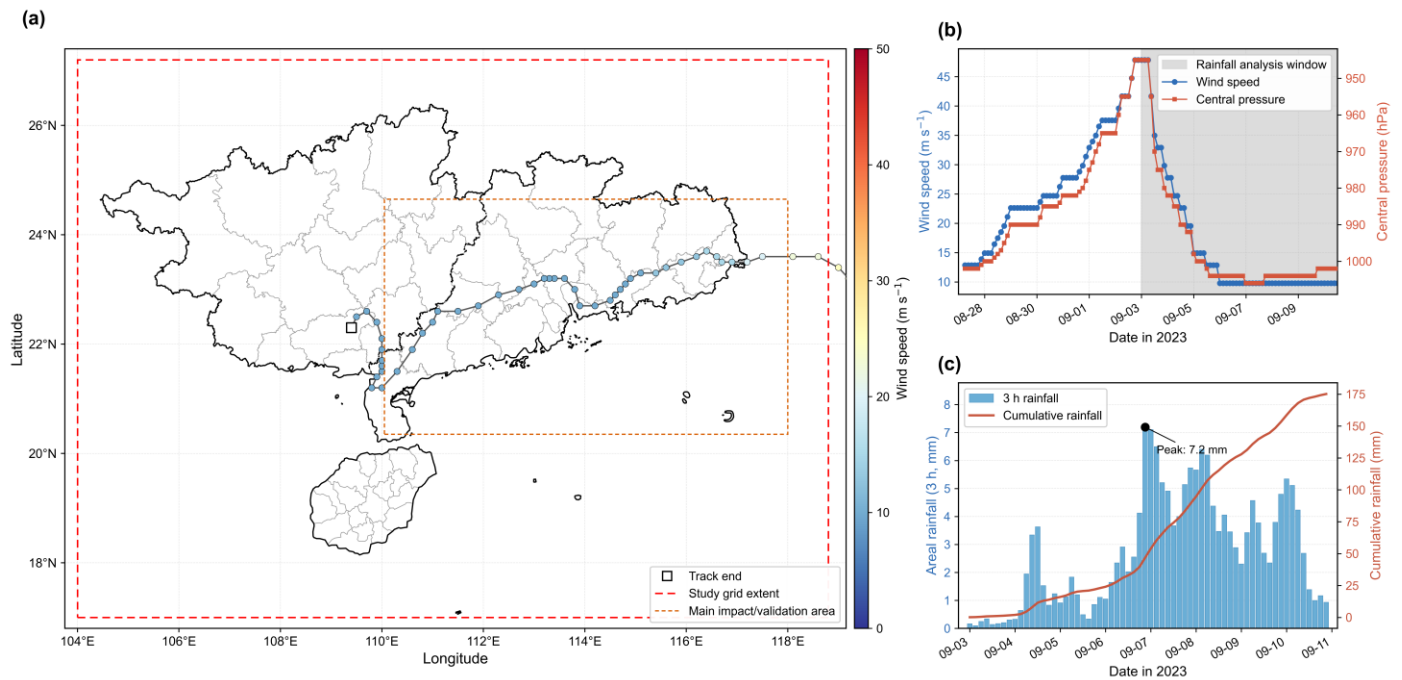


Figure 1. Overview of Typhoon Haikui and the rainfall process over South China. **(a)** Typhoon track from NOAA IBTrACS v4.0; the red dashed box indicates the 1 km study grid extent covering Guangdong, Guangxi, and Hainan, and the orange dashed box indicates the main impact and validation area. **(b)** Best-track maximum sustained wind (m s^{-1}) and central pressure (hPa), using the available agency series with the greatest temporal completeness. The grey shading indicates the rainfall analysis window used in this study. **(c)** Three-hourly areal rainfall (3h mm) and cumulative rainfall (mm) derived from GPM IMERG Final Run V07. Times are in UTC.

2.2. Data Sources and Preprocessing

This study integrated multiple remote sensing products, tropical cyclone best track data, and gridded geospatial datasets (Table 1). Precipitation estimates at 30 min intervals from GPM IMERG Final Run V07 (GPM_3IMERGHH.07) were obtained for 3–10 September 2023 [31]. The precipitation variable was provided as a rainfall rate, r , in mm h^{-1} for each 30 min interval. The rainfall depth for each interval was calculated as $r \times 0.5 \text{ h}$ and expressed in millimetres. The 48 interval depths within each day were summed to obtain daily rainfall, and the daily totals were then summed to obtain rainfall for the full event. All 384 expected files were available. The precipitation fields were resampled to the common 1 km analysis grid using bilinear interpolation.

Despite some uncertainty inherent in satellite precipitation retrievals, previous evaluations have demonstrated that IMERG V07 improves precipitation estimates over V06 across multiple temporal and spatial scales in China [32–36]. These improvements, together with its demonstrated applicability in regional precipitation studies, support the use of IMERG Final Run V07 to characterize the spatial pattern and temporal evolution of Typhoon Haikui rainfall.

Tropical cyclone track and intensity data were obtained from IBTrACS v4.0 [30]. The cyclone centre position, maximum sustained wind speed, and central pressure were extracted from this dataset solely to prepare Figure 1 and describe the background meteorological conditions of the typhoon. These variables were not used in the subsequent calculation of TRRI. Cyclone centre positions were retained in WGS 84. The availability of valid values across the agency series was checked, and wind speeds were converted from knots to m s^{-1} .

LandScan HD China v1.0 was used to represent population exposure [37]. Produced by Oak Ridge National Laboratory, this dataset provides gridded population estimates for China at a spatial resolution of 3 arc seconds. Population counts were aggregated to the 1 km analysis grid using sum resampling so that the population total within each target cell was preserved. The study area land mask was applied before normalization.

Impervious surfaces were extracted from the China Land Cover Dataset (CLCD) [38,39]. The impervious surface data were aggregated to the 1 km analysis grid using average resampling, and the impervious surface fraction was calculated for each grid cell. This fraction was defined as the impervious surface factor (I), which represents an urban underlying surface property that affects infiltration, runoff generation, and runoff concentration. It was not used as a proxy for the multidimensional vulnerability of exposed elements.

A total of 51 waterlogging reports compiled during the event were collected, including 15 in Guangdong, 27 in Guangxi, and 9 in Hainan. Two pairs of reports in Guangxi had identical coordinates, resulting in 49 distinct geocoded locations for the descriptive assessment across the full study area. The enrichment and positional buffer analyses used the 22 locations within the predefined event analysis domain, including 15 in Guangdong and 7 in Guangxi, with no locations in Hainan. The full domain dataset and the subset of 22 locations were analyzed separately because the report sources and geocoding precision were not uniform among the three provinces. The complete report inventory, coordinate precision, duplicate flags, and results stratified by province are provided in Tables S2 and S3 and Figure S1. The specific workflow is shown in Figure 2.

Table 1. Multi-source remote sensing and gridded datasets used for rapid TRRI mapping.

Dataset	Role in TRRI Framework	Main Preprocessing	Derived Variable
GPM IMERG Final Run V07 precipitation	Rainfall hazard from event rainfall, duration, and concentration	Half-hourly rate converted to rainfall amount; resampled to 1 km grid	P, T, C, H
NOAA IBTrACS v4.0	Track/intensity context for Figure 1.	Valid agency series; knots converted to m s^{-1} .	Track, wind, pressure
CLCD land-cover/impervious surface	Impervious-surface factor I .	Impervious fraction aggregated to 1 km and normalized.	I
LandScan HD China v1.0 population data	Population exposure.	Resampled to 1 km; $\ln(1 + \text{Pop})$ transformation and min-max normalization.	E
Administrative boundaries	Study-area mask and land-only statistics.	Projected to WGS 84 and rasterized to 1 km.	land mask
Reported waterlogging locations	Event-focused and full-domain checks.	Coordinates standardized; duplicates identified; class overlay.	validation points

2.3. Construction of the Rainfall Hazard Index

We constructed the rainfall hazard index from three dimensions: event accumulated rainfall (P), rainfall duration (T), and rainfall concentration (C). P is the event accumulated rainfall at each 1 km grid cell, calculated by converting each half-hourly IMERG precipitation rate from mm h^{-1} to rainfall depth and summing all half-hourly values during 3–10 September 2023. T describes rainfall persistence. It was calculated by aggregating every two consecutive half-hourly rainfall fields into hourly totals and counting the number of hours with rainfall greater than 1 mm at each grid cell. C describes short-duration rainfall concentration. It was calculated as the maximum moving 3 h accumulated rainfall divided by P , where the maximum 3 h rainfall was obtained from the largest sum of six consecutive half-hourly rainfall fields during the event period.

Each indicator was normalized to the range of 0–1 within the land area:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X is the original indicator value, X' is the normalized value, and X_{min} and X_{max} are the minimum and maximum values within the land mask.

We then calculated the raw rainfall hazard index as:

$$H_{raw} = 0.4P' + 0.3T' + 0.3C' \quad (2)$$

where P' , T' , and C' are the normalized event accumulated rainfall, rainfall duration, and rainfall concentration, respectively. Their weights were obtained using the analytic hierarchy process (AHP) [40,41]. Six experts independently compared the three criteria using Saaty's 1–9 scale. Each judgement matrix was converted to a normalized priority vector, individual judgments were aggregated by the geometric mean, and consistency was evaluated using $CR < 0.10$. The aggregated P/T/C weights were 0.4003/0.3037/0.2961 (group $CR = 0.0004$); all six individual matrices passed the consistency test. For operational simplicity and consistency with the original formulation, these values were rounded to 0.40/0.30/0.30. The expert identifiers, scale definitions, individual priority vectors, and consistency ratios are reported in Tables S5 and S6. Alternative P -, T -, and C -dominant and equal-weight schemes were retained as a sensitivity analysis (Table S8). We further normalized H_{raw} to obtain the final rainfall hazard index:

$$H = \frac{H_{raw} - H_{raw,min}}{H_{raw,max} - H_{raw,min}} \quad (3)$$

The final H ranges from 0 to 1. A higher value indicates stronger rainfall hazard. We classified H into low-, medium-, and high-hazard classes using the Jenks natural breaks method. This method highlights the natural spatial differentiation of rainfall hazard values [42].

2.4. Population Exposure and Impervious-Surface Factor

We constructed population exposure E from the LandScan population data. Because gridded population values are usually highly skewed, a small number of dense urban cells can dominate linear normalization. We therefore applied the natural logarithm $\ln(1 + \text{Pop})$ before normalization:

$$E = \frac{\ln(1 + \text{Pop}) - \min[\ln(1 + \text{Pop})]}{\max[\ln(1 + \text{Pop})] - \min[\ln(1 + \text{Pop})]} \quad (4)$$

where Pop is the population count in each 1 km grid cell. The final E ranges from 0 to 1. A higher value indicates higher population exposure.

We used the impervious-surface fraction within each 1 km grid cell to represent impervious-surface factor I . The value of I ranges from 0 to 1 and represents the proportion of impervious surface in each grid cell. This indicator provides a simplified regional representation of how urban hard surfaces may amplify runoff generation and waterlogging risk. Previous studies have shown that impervious surfaces can reduce infiltration, change rainfall–runoff response, and increase local urban flood risk [6,12].

2.5. Integrated TRRI

We constructed the TRRI by integrating rainfall hazard H , population exposure E , and impervious-surface factor I . This is an impact-oriented rapid screening index. We calculated the raw TRRI as:

$$TRRI_{raw} = 0.4H + 0.3E + 0.3I \quad (5)$$

where H , E , and I represent rainfall hazard, population exposure, and impervious-surface factor, respectively. The same six-expert AHP procedure produced aggregated $H/E/I$ weights of 0.3969/0.2992/0.3040 (group CR = 0.0241); all six individual matrices had CR < 0.10, and the largest individual CR across both AHP groups was 0.0462. The weights were rounded to 0.40/0.30/0.30 in the implemented TRRI. The $H/E/I$ judgement scale and expert-level results are reported in Tables S5 and S7. Alternative H -, E -, and I -dominant and equal-weight schemes were evaluated to quantify residual weighting uncertainty.

To support spatial comparison, we normalized $TRRI_{raw}$ within the land area:

$$TRRI = \frac{TRRI_{raw} - TRRI_{raw,min}}{TRRI_{raw,max} - TRRI_{raw,min}} \quad (6)$$

TRRI is a relative risk index. It is used to identify the spatial pattern of waterlogging risk during a single typhoon rainfall event. It is not intended to estimate absolute economic loss, water depth, or drainage processes. We classified TRRI into low-, medium-, and high-risk classes using the Jenks natural breaks method [42].

To interpret high-risk zones, we compared $0.4H$, $0.3E$, and $0.3I$. For each high-risk cell, the largest weighted term defined the dominant label. Thus, H -dominated, E -dominated, and I -dominated mean that $0.4H$, $0.3E$, or $0.3I$ is largest; the labels do not imply that the other components are absent or that the outcome has a single cause.

2.6. Waterlogging-Point Validation and Risk-Class Reconfiguration

We first evaluated the spatial correspondence between TRRI and observed waterlogging points. We calculated the proportion of observed points falling within each TRRI risk class. The direct high-risk hit rate was defined as the number of waterlogging points located in high-risk zones divided by the total number of effective waterlogging points.

Because the hit rate can be affected by the size of the high-risk zone, we also calculated the background area ratio of high-risk zones and the enrichment ratio. The enrichment ratio was defined as:

$$ER = \frac{P_{hit}}{P_{area}} \quad (7)$$

where P_{hit} is the proportion of waterlogging points falling within high-risk zones, and P_{area} is the area ratio of high-risk zones within the validation area. When ($ER > 1$), observed waterlogging points are more concentrated in high-risk zones than expected under a random spatial distribution. We further used a binomial test to examine whether the high-risk hit rate was significantly higher than the background high-risk area ratio.

Waterlogging reports may contain reporting and geocoding uncertainty. We calculated high-risk hit rates within 1, 3, and 5 km buffers for the 22-location event-focused subset. Separately, the 49 distinct geocoded locations from all 51 reports were overlaid on the full-domain map for a descriptive province-stratified consistency check. These are presence-only observations; they do not provide systematically sampled non-impact locations.

To assess the added value of TRRI compared with rainfall hazard alone, we compared the rainfall hazard class and the TRRI risk class cell by cell. If the TRRI class was higher than the rainfall hazard class, the cell was defined as amplified. If the two classes were the same, the cell was defined as consistent. If the TRRI class was lower than the rainfall hazard class, the cell was defined as attenuated. We also built a transition matrix from rainfall hazard classes to TRRI risk classes. This matrix quantifies how population exposure and impervious-surface factor reconfigure the risk pattern relative to rainfall hazard alone.

2.7. Weight Sensitivity Analysis

To examine weight sensitivity, the Jaccard index measured overlap between the baseline result and each alternative scheme [43]:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (8)$$

where A represents the baseline high-risk or high-hazard zone, and B represents the corresponding zone derived from an alternative weighting scheme. A Jaccard value closer to 1 indicates stronger spatial consistency, whereas a lower value indicates greater sensitivity to the weighting scheme.

For H , alternatives emphasized P , T , or C or used equal weights. For TRRI, alternatives emphasized H , E , or I or used equal weights. The AHP-derived rounded 0.40/0.30/0.30 schemes were used as the baselines.

To ensure a fair comparison, the target-class area was held fixed across weighting schemes: 17.04% for the H high-hazard class and 12.45% for the TRRI high-risk class. We then calculated Jaccard overlap with the corresponding baseline.

We also tested analysis-domain sensitivity. The baseline min–max normalization and three-class Fisher–Jenks breaks were calculated over the full three-province land mask. Both operations were then recalculated within the event-focused domain, and the resulting breaks, high-risk area, Jaccard overlap, three-class agreement, and classifications of the 22 event-focused locations were compared (Table S4).

Data and harmonization

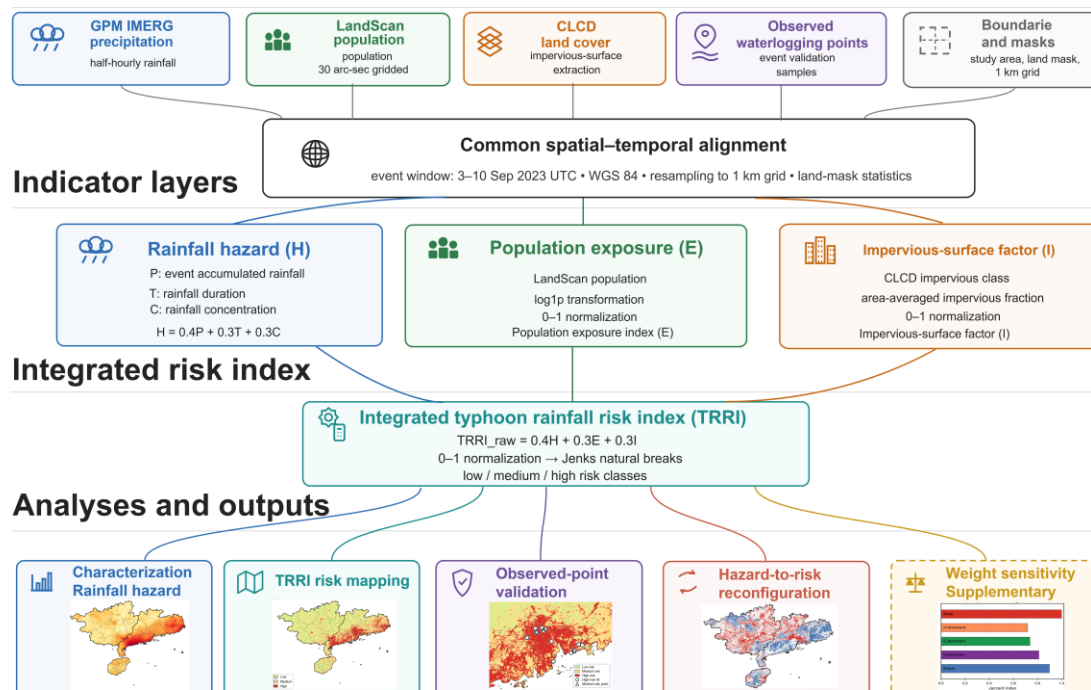


Figure 2. Workflow of the TRRI-based rapid assessment framework for typhoon-rainfall-induced waterlogging risk. GPM IMERG precipitation, LandScan population, CLCD-derived impervious surfaces, event-period waterlogging reports, and boundary/mask data were harmonized to the 3–10 Sep. 2023 event window, WGS 84 coordinates, a 1 km grid, and land-mask statistics. Rainfall hazard H , population exposure E , and the impervious-surface factor I were then constructed and integrated into TRRI. Outputs include rainfall-hazard characterization, TRRI mapping, spatial-consistency checks, hazard-to-risk reconfiguration, and sensitivity analyses.

3. Results

3.1. Spatial Pattern of Rainfall Hazard During Typhoon Haikui

During Typhoon Haikui, rainfall over Guangdong, Guangxi, and Hainan showed clear coastal clustering and long rainfall persistence. High event accumulated rainfall was mainly concentrated along the Guangdong coast, including western Guangdong near Yangjiang, the Pearl River Estuary, the central-eastern Guangdong coast, and eastern Guangdong. The maximum event accumulated rainfall in the study area reached 529.7 mm (Figure 3a). The spatial pattern of maximum 24 h rainfall was generally consistent with that of event accumulated rainfall. High maximum 24 h rainfall was also concentrated along the Guangdong coast, with a maximum value of 272.8 mm (Figure 3b). These results show that Typhoon Haikui produced both large rainfall totals and persistent heavy rainfall in local coastal areas. This pattern is consistent with previous studies that reported record-breaking rainfall caused by Typhoon Haikui over the South China megacity region and the Pearl River Estuary [28,29].

Rainfall duration further revealed the persistence of the event. Long-duration rainfall was mainly distributed along the Guangdong coastal belt, including western Guangdong, the Pearl River Estuary, the central-eastern Guangdong coast, and eastern Guangdong. These areas were spatially consistent with the zones of high accumulated rainfall (Figure 3c). The longest rainfall duration in the study area reached 91.0 h, indicating that some coastal areas experienced rainfall for an extended period during the typhoon event. Together, accumulated rainfall and rainfall duration show that the Guangdong coast was the core rainfall hazard area of Typhoon Haikui.

Rainfall concentration showed a different spatial pattern from accumulated rainfall and rainfall duration (Figure 3d). Some areas in western and northern Guangxi and local parts of Hainan had high rainfall concentration, whereas the strongest rainfall core along the Guangdong coast did not show the highest concentration values. Rainfall concentration reflects the relative contribution of short-duration heavy rainfall to the event accumulated rainfall, rather than absolute rainfall intensity. Therefore, concentration can be high where total rainfall is low but rainfall occurs within a short period. In contrast, in coastal areas with large accumulated rainfall and long rainfall duration, the short-duration peak may account for a smaller proportion of the event total. This result shows that rainfall concentration provides process information that differs from rainfall amount and duration. It also supports the need to consider rainfall amount, persistence, and short-term concentration together when assessing typhoon rainfall hazard [7,19].

After accumulated rainfall, rainfall duration, and rainfall concentration were integrated, high values of the rainfall hazard index H were mainly located along the Guangdong coastal rainfall belt, especially western Guangdong near Yangjiang, the Pearl River Estuary, the central-eastern Guangdong coast, and eastern Guangdong (Figure 3e). Although rainfall concentration was high in some inland and peripheral areas, accumulated rainfall and rainfall duration exerted stronger control on the spatial pattern of H in the integrated hazard index. The Jenks classification results showed that low-, medium-, and high-hazard zones accounted for 52.0%, 30.9%, and 17.1% of the land area, respectively (Figure 3f). Overall, the rainfall hazard of Typhoon Haikui had a clear coastal clustering pattern. High-hazard zones were mainly distributed along the strong rainfall core of the Guangdong coast, while most areas in Guangxi and Hainan showed low to medium hazard levels.

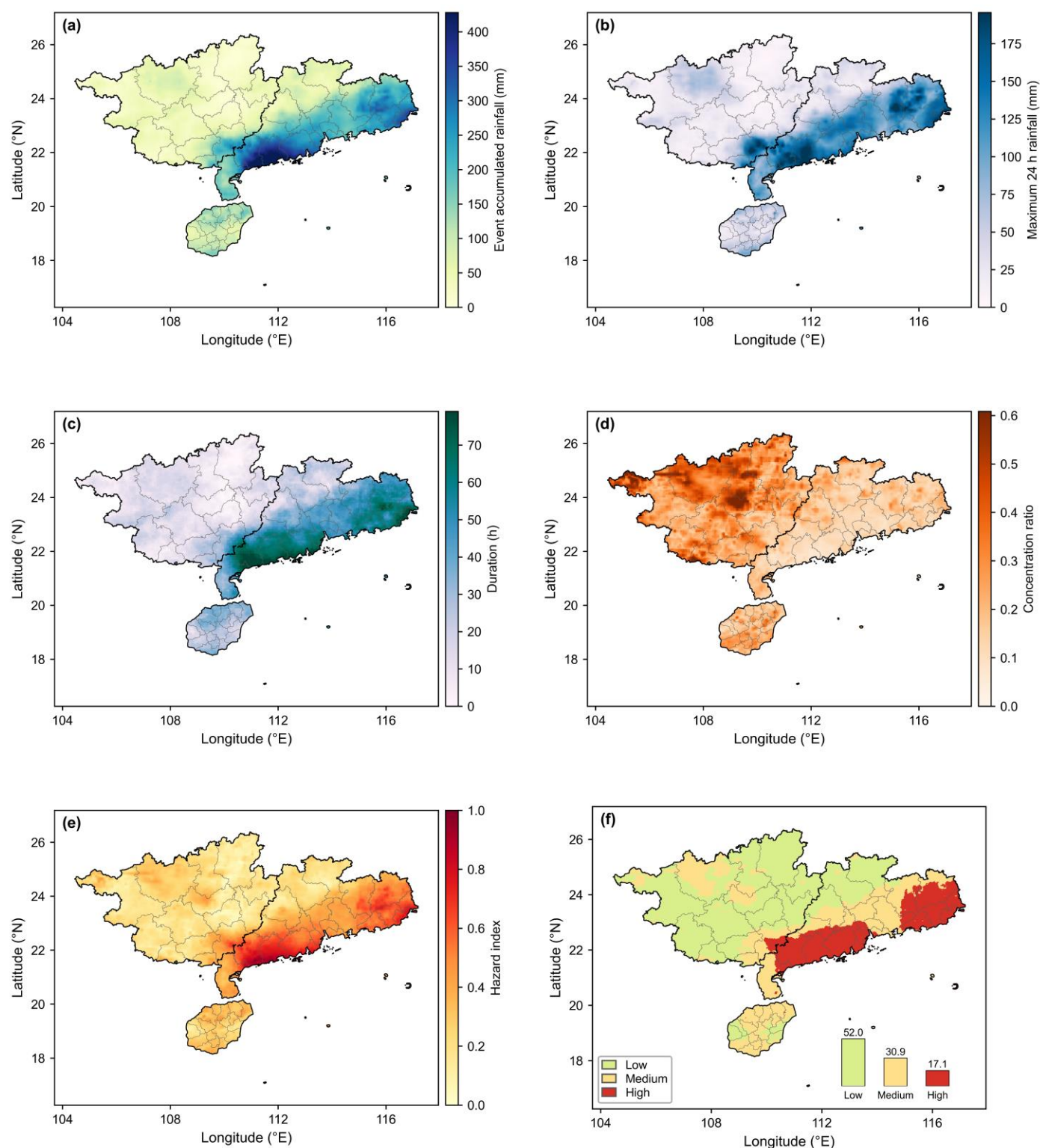


Figure 3. Rainfall hazard characteristics during Typhoon Haikui. (a) Event accumulated rainfall; (b) maximum 24 h rainfall; (c) rainfall duration; (d) rainfall concentration; (e) integrated rainfall hazard index H ; and (f) rainfall hazard classes, with the inset bar chart showing the area ratios of the low-, medium-, and high-hazard classes. The integrated hazard index combines rainfall amount, persistence, and concentration, and identifies high-hazard zones mainly along western Guangdong, the Pearl River Estuary, the central-eastern Guangdong coast, and eastern Guangdong.

3.2. Spatial Coupling of Exposure, Impervious Surfaces, and Integrated TRRI Risk

The spatial distributions of population exposure and the impervious surface factor showed that waterlogging risk associated with typhoon rainfall was not controlled by rainfall hazard alone. It was also shaped by the spatial distributions of the exposed population and urban surface conditions. Population exposure (E), derived from LandScan population data, showed clear urban clustering. High E values were mainly distributed in the Pearl River Delta, along the eastern Guangdong coast, in several urban areas of Guangxi, and in the northern urban areas of Hainan (Figure 4a). The mean E value across the study area was 0.265, and approximately 61.23% of the land grid cells had population values greater than zero. This distribution showed a strong spatial imbalance in population exposure.

The impervious surface factor (I) showed a more concentrated spatial pattern. High I values were mainly located in the Pearl River Delta urban agglomeration, the Shantou–Chaozhou–Jieyang urban belt, Zhanjiang, and Haikou (Figure 4b). The mean I value across the study area was only 0.035, whereas the 95th and 99th percentiles reached 0.205 and 0.762, respectively. Most areas therefore had low impervious surface fractions, while a small number of urban cores had very high impervious surface coverage. This concentrated spatial pattern indicated that impervious surfaces mainly acted as local risk amplifiers in urban areas. Previous studies have also shown that increasing impervious surface coverage can reduce infiltration, alter rainfall runoff responses, and increase local urban flood risk [6,12].

After rainfall hazard (H), population exposure (E), and the impervious surface factor (I) were integrated, the zones classified as high risk by TRRI were mainly located on both sides of the Pearl River Estuary, along the central and eastern sections of the Guangdong coast, in the eastern Guangdong urban cluster, and in several coastal cities of western Guangdong (Figure 4c). The Jenks thresholds for TRRI were 0.200262 between low and medium risk and 0.411099 between medium and high risk. Within the land area of Guangdong, Guangxi, and Hainan, zones classified as low, medium, and high risk accounted for 46.61%, 40.94%, and 12.45%, respectively. The zones classified as high risk did not extend broadly across the entire study area. Instead, they were concentrated where strong rainfall hazard overlapped with high population exposure, high impervious surface fractions, or both.

To identify the factors contributing to the formation of zones classified as high risk, we compared the three weighted contribution terms within these zones: rainfall hazard ($0.4H$), population exposure ($0.3E$), and the impervious surface factor ($0.3I$). For each grid cell classified as high risk, the factor with the largest weighted contribution was identified as the dominant factor. Areas dominated by H accounted for 60.5% of the total area classified as high risk. These areas were mainly distributed along the central and eastern sections of the Guangdong coast, around the Pearl River Estuary, and within the eastern Guangdong rainfall impact area (Figure 4d). Areas dominated by E accounted for 33.4% and were mainly concentrated in the Pearl River Delta and other densely populated urban areas. This pattern indicated that population exposure strongly modified the spatial clustering of integrated risk. Areas dominated by I accounted for 6.1%. Although their total area was relatively small, they were mainly located in urban cores with high impervious surface fractions. Impervious surfaces therefore acted primarily as local amplifiers rather than as the main regional driver of risk.

Overall, the zones classified as high risk by TRRI were not a simple reproduction of areas with high rainfall hazard. They represented areas of compound risk formed through the spatial coupling of strong rainfall, population concentration, and urban surface conditions. Rainfall hazard established the basic spatial pattern of risk. Population exposure

increased integrated risk in densely populated coastal and urban areas, while the impervious surface factor amplified risk locally within urban cores. These results demonstrate the value of integrating multiple gridded data sources when mapping waterlogging risk associated with typhoon rainfall.

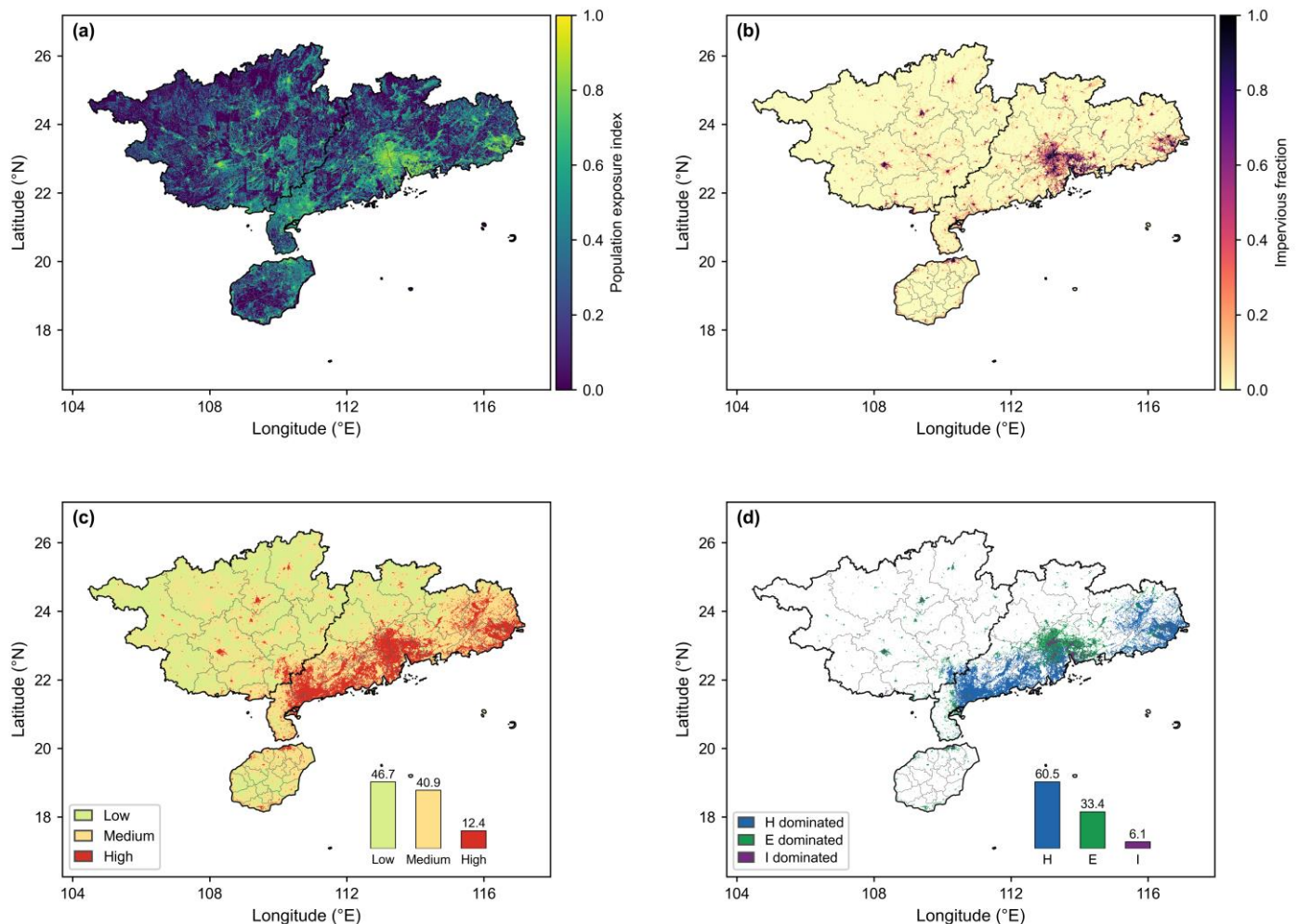


Figure 4. Spatial coupling of exposure, impervious surface factor, and integrated typhoon rainfall risk. (a) Population exposure; (b) impervious-surface factor; (c) integrated TRRI risk classification; and (d) dominant factors in TRRI high-risk areas. Dominant factors were classified as *H*-, *E*-, or *I*-dominated according to the largest weighted contribution among $0.4H$, $0.3E$, and $0.3I$ within high-risk zones. The inset bars in panel (d) show the area composition of the three dominant factor types.

3.3. Evaluation of TRRI Using Reported Waterlogging Locations

Using 22 reported waterlogging locations within the predefined event analysis domain, we evaluated their spatial correspondence with the TRRI classes (Table S1). The spatial overlay showed that most reported locations were situated within or near zones classified as high risk by TRRI (Figure 5a). Of the 22 locations, 19 fell directly within zones classified as high risk, giving a direct hit rate of 86.4%. The remaining three locations were situated in zones classified as medium risk. Therefore, the combined hit rate for the medium and high-risk classes reached 100.0%. Within the available event subset, these results showed close spatial correspondence between the TRRI classes and the reported occurrence of waterlogging during Typhoon Haikui.

To interpret the hit rate relative to the spatial extent of the high-risk class, we compared the point proportion with its background area proportion. Zones classified as high

risk accounted for only 26.1% of the land area within the event analysis domain but contained 86.4% of the reported waterlogging locations (Figure 5b). The resulting enrichment ratio was 3.31. Thus, the proportion of reported locations in the high-risk class was 3.31 times its proportion of the validation area. A binomial test using 26.1% as the background probability showed that this enrichment was statistically significant ($p < 0.001$). The high direct hit rate was therefore not simply a consequence of an excessively large high-risk class.

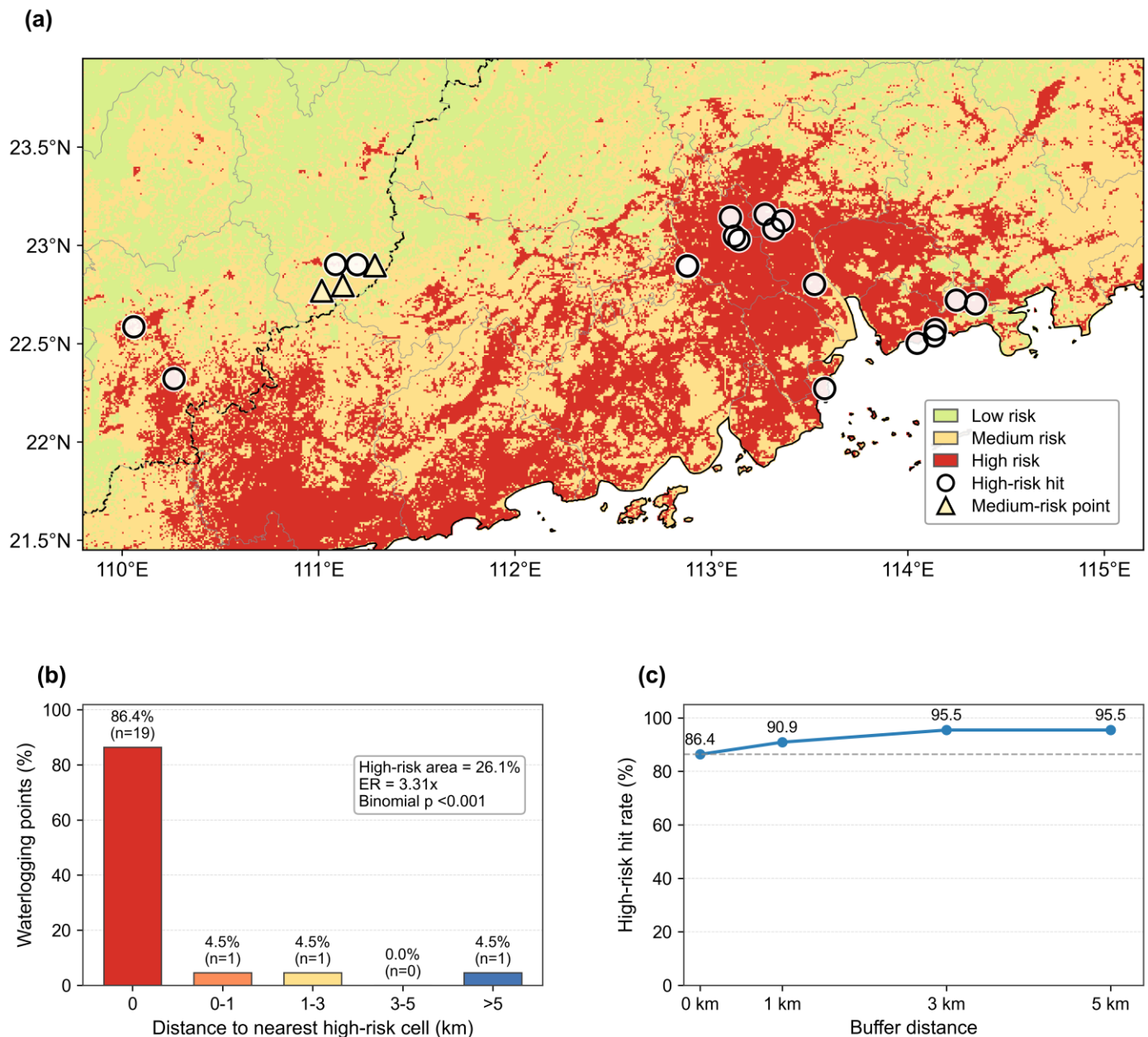


Figure 5. Spatial validation of TRRI using observed waterlogging points. (a) Spatial overlay between TRRI risk classes and observed waterlogging points; (b) distance distribution from observed waterlogging points to the nearest TRRI high-risk cell, with the enrichment ratio and binomial test result shown in the inset; and (c) high-risk hit rate under different buffer distances. The background in panel (a) represents low-, medium-, and high-risk TRRI zones. Circles indicate points located in high-risk zones, and triangles indicate points located in medium-risk zones. Among the 22 effective waterlogging points, 19 points fell directly within high-risk zones, giving a direct hit rate of 86.4%; the remaining three points fell within medium-risk zones, and no observed points were located in low-risk zones.

Because disaster locations compiled from public reports may contain geocoding errors and positional uncertainty, we also conducted an evaluation using different buffer distances. The direct hit rate without a buffer was 86.4%. When reported locations within 1 km of a zone classified as high risk were treated as hits, the hit rate increased to 90.9%. At buffer distances of 3 and 5 km, the hit rate reached 95.5% in both cases (Figure 5c). The spatial correspondence therefore remained high after allowing for possible positional uncertainty in the reported locations.

The three locations that did not fall directly within zones classified as high risk were all situated in zones classified as medium risk. No reported waterlogging location in the event subset was classified as low risk. These mismatches may reflect local terrain depressions, drainage capacity, runoff convergence, uncertainty in road-based reports, or geocoding errors. However, the available data do not allow the contribution of these local factors to be determined individually.

Taken together, these results provide event specific evidence that the reported waterlogging locations were concentrated in areas assigned higher TRRI values. Given the limited number and uneven spatial distribution of the reports, this evaluation represents a test of spatial correspondence within the available event dataset rather than comprehensive independent validation across all of South China. A complementary descriptive assessment using all 49 distinct geocoded locations across Guangdong, Guangxi, and Hainan is provided in Tables S2 and S3 and Figure S1.

3.4. Risk Class Reconfiguration from Rainfall Hazard to TRRI Risk

To identify how population exposure and the impervious surface factor modified the rainfall hazard pattern, we compared the rainfall hazard classes with the final TRRI risk classes. The rainfall hazard classes identified where rainfall was intense or persistent during Typhoon Haikui (Figure 3f). Areas classified as high hazard were distributed along the Guangdong coastal rainfall belt. These areas included western Guangdong, the Pearl River Estuary, the central and eastern sections of the Guangdong coast, and eastern Guangdong. However, the rainfall hazard map alone did not show whether heavy rainfall occurred over sparsely populated areas, densely populated urban districts, or areas with high impervious surface fractions. Consequently, areas with similar rainfall hazard could have different potential impacts depending on their population exposure and urban surface conditions.

The class change map showed how the integration of population exposure and the impervious surface factor reconfigured the rainfall hazard pattern (Figure 6a). Relative to the rainfall hazard classes, 20.59% of the valid land area increased by at least one class, 20.64% decreased, and 58.77% remained unchanged. Thus, TRRI retained the rainfall signal across more than half of the study area. Population exposure and the impervious surface factor selectively adjusted the remaining areas according to their potential impacts. Areas shifted to a higher class were mainly associated with concentrated populations or high impervious surface fractions. Areas shifted to a lower class generally had relatively high rainfall hazard but low population exposure, low impervious surface fractions, or both. TRRI therefore converted the broad rainfall hazard pattern into a more spatially differentiated waterlogging risk pattern.

The transition matrix further showed how this reconfiguration occurred (Figure 6b). The largest stable category was the transition from low rainfall hazard to low TRRI risk, accounting for 34.9% of the valid land area. TRRI therefore preserved the broad background areas characterized by relatively low rainfall hazard and risk. Of the valid land area, 16.5% shifted from low rainfall hazard to medium TRRI risk, while 0.6% shifted to high TRRI risk. These transitions occurred where population exposure, the impervious surface factor, or both increased the integrated risk class despite relatively low rainfall

hazard. A further 3.4% shifted from medium rainfall hazard to high TRRI risk, whereas 11.8% shifted from medium rainfall hazard to low TRRI risk. Among areas initially classified as high rainfall hazard, 8.3% remained at high TRRI risk and 8.8% shifted to medium TRRI risk. Almost none of these areas shifted directly from high rainfall hazard to low TRRI risk. These transitions confirmed that rainfall hazard remained the principal basis of TRRI, while population exposure and impervious surface conditions further differentiated the final risk classes.

The comparison with reported waterlogging locations further illustrated the effect of this reconfiguration (Figure 6c). Within the event analysis domain, areas classified as high rainfall hazard covered 39.0% of the land area but contained only 13.6% of the reported waterlogging locations. The resulting enrichment ratio was 0.35. In comparison, areas classified as high TRRI risk covered 26.1% of the land area but contained 86.4% of the reported locations. Their enrichment ratio reached 3.31. TRRI therefore reduced the spatial extent of the highest class while increasing its correspondence with reported waterlogging within the available event subset. This comparison showed that TRRI produced a more spatially targeted screening result than the rainfall hazard map alone.

Overall, TRRI retained the main rainfall hazard signal while incorporating the impact related information provided by population exposure and the impervious surface factor. By integrating multiple remote sensing products and gridded geospatial datasets, TRRI produced a more spatially selective assessment of waterlogging risk associated with typhoon rainfall. Its rapid mapping value lies in the transition from rainfall monitoring to spatial risk screening. The resulting maps can support the prioritization of locations where strong rainfall coincides with concentrated populations, high impervious surface fractions, or both.

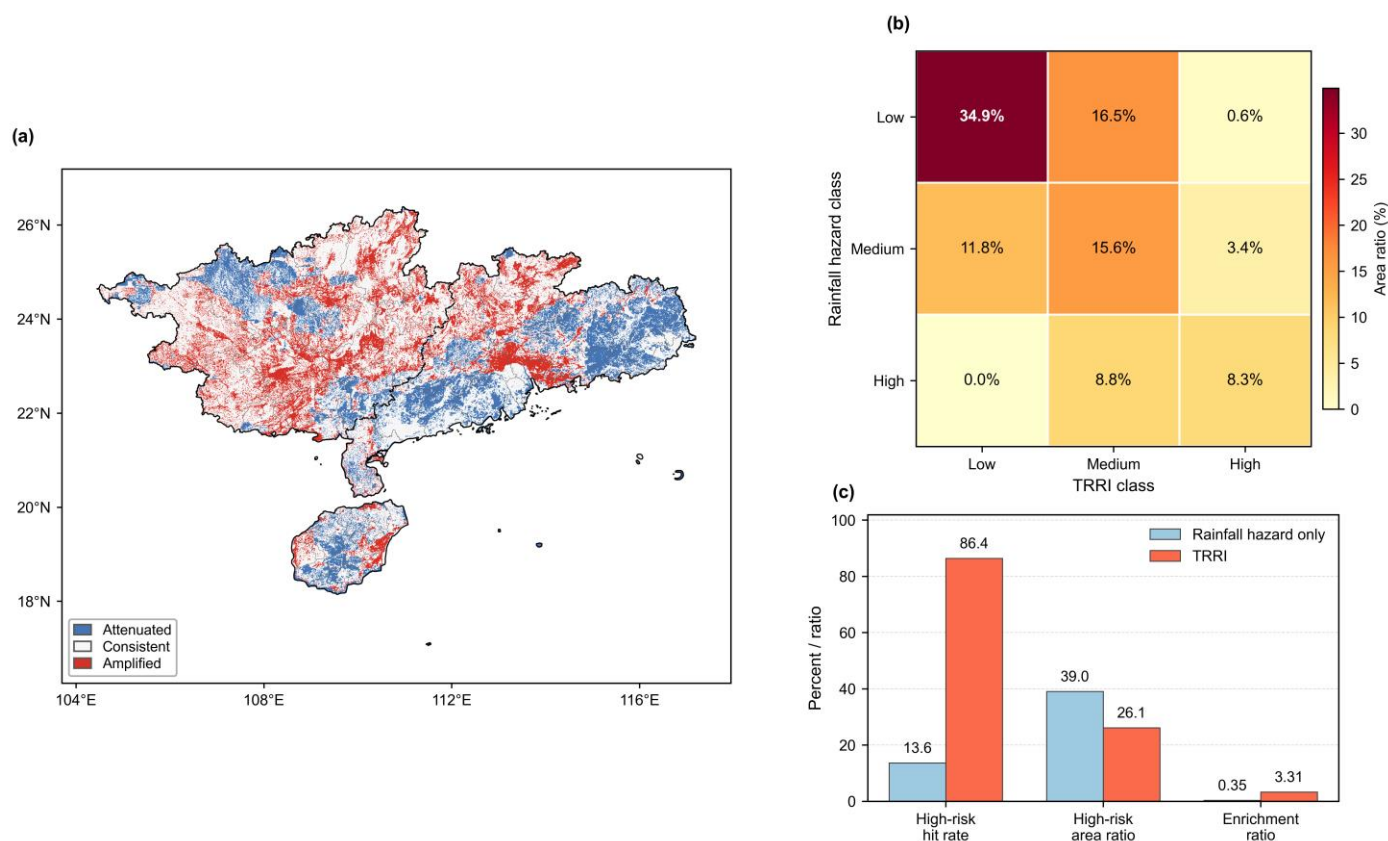


Figure 6. Risk class reconfiguration from rainfall hazard to TRRI risk. (a) Class changes from rainfall hazard to TRRI risk, where red indicates amplified areas, blue indicates attenuated areas, and white indicates consistent areas; (b) transition matrix from rainfall hazard classes to TRRI classes, with

values representing the percentage of valid land area in each transition type; and (c) validation comparison between rainfall hazard alone and TRRI, showing the high-risk hit rate, high-risk area ratio, and enrichment ratio.

4. Discussion

This study developed a rapid TRRI framework by combining GPM IMERG precipitation, impervious surface information derived from CLCD, LandScan gridded population data, and reported waterlogging locations. The framework was designed for event scale waterlogging risk screening rather than detailed hydrodynamic simulation. This rapid assessment capacity is relevant because tropical cyclone rainfall is a major driver of coastal flooding, and its intensity and spatial extent may change under global warming [44,45]. By integrating satellite precipitation, remotely sensed land cover, and gridded exposure data, TRRI produces a reproducible 1 km risk map. It does not require drainage network data, street scale topographic information, or complete field surveys immediately after a typhoon rainfall event.

The results showed that rainfall hazard during Typhoon Haikui was concentrated along the Guangdong coastal rainfall belt. The principal areas included western Guangdong near Yangjiang, the Pearl River Estuary, the central and eastern sections of the Guangdong coast, and eastern Guangdong. TRRI retained this rainfall driven background but produced a more localized pattern of relative risk. This structure is related to classical frameworks in which disaster risk arises from interactions among hazard, exposure, and vulnerability [8–11]. However, TRRI does not claim to represent the complete multidimensional vulnerability of exposed people, assets, or systems. The impervious surface factor (*I*) was included as a rapidly available urban surface indicator because impervious cover directly affects infiltration, runoff generation, and runoff concentration. Population exposure identified where people were concentrated, while *I* represented local surface conditions that could amplify rainfall runoff responses. This interpretation is consistent with studies linking impervious surface expansion to increased urban flood risk [6,12] and with assessments combining rainfall, exposed elements, land surface conditions, and drainage environments [13,20,21].

The reconfiguration of risk classes is central to the interpretation of TRRI. Relative to the rainfall hazard classes, TRRI shifted 20.59% of the study area to a higher class, shifted 20.64% to a lower class, and left 58.77% unchanged. TRRI therefore retained the principal rainfall signal while differentiating areas according to population exposure and impervious surface conditions. It should not be interpreted as producing a more accurate rainfall map. Instead, it provides a separate screening layer that identifies where rainfall hazard coincides with factors related to potential impacts. This integrated perspective is more relevant to emergency response and drainage inspection than rainfall hazard mapping alone [11,46]. Within the event analysis domain, areas classified as high TRRI risk covered 26.1% of the land area but contained 86.4% of the reported waterlogging locations.

The baseline weights for both *P/T/C* and *H/E/I* were derived from an AHP consultation with six experts and rounded to 0.40, 0.30, and 0.30. We further examined whether the main TRRI pattern was sensitive to these weight settings. Five *H/E/I* weighting schemes were compared, including the baseline, *H* dominant, *E* dominant, *I* dominant, and equal weight schemes (Figure 7). When the area classified as high risk was fixed at 12.45%, the alternative schemes produced Jaccard overlaps of 0.718–0.899 with the rounded AHP baseline. The areas classified as high risk remained concentrated along the Guangdong coastal belt, particularly around the Pearl River Estuary and the central and eastern sections of the Guangdong coast. For the rainfall hazard index (*H*), the *P* dominant, *T* dominant, and equal weight schemes produced Jaccard overlaps of 0.944–0.984 with the baseline. The *C* dominant scheme showed greater sensitivity, with an overlap of 0.596.

The broad coastal pattern was therefore relatively stable under the tested weights, although the classification of individual grid cells remained dependent on the selected scheme. Applications to other regions should reassess the weights using local expert consultation, published evidence, or independent event data.

The geographical analysis domain also affected the relative risk classes. Guangdong, Guangxi, and Hainan were retained because the event report inventory documented waterlogging in all three regions, although the main rainfall footprint was concentrated in Guangdong. The lower value areas in Guangxi and Hainan therefore formed part of the declared regional comparison rather than being treated as irrelevant background. Recalculating the analysis within the event analysis domain did not change the raw TRRI range of 0–0.8958 or the resulting minimum and maximum scaling. However, the two Fisher–Jenks thresholds increased from 0.2003 and 0.4111 to 0.2566 and 0.4798. Within this domain, the area classified as high risk decreased from 25.99% to 15.47%. The Jaccard overlap for the high-risk class was 0.595, and the overall agreement among the three classes was 75.88%. The number of reported locations classified directly as high risk decreased from 19 to 15, but all 22 locations remained in the medium or high-risk classes. These results confirm that the exact Jenks thresholds and high-risk boundaries depend on the selected geographical domain. Continuous TRRI values should therefore be treated as the primary analytical output, while Jenks classes represent secondary categories for relative prioritization within a declared domain.

The evaluation using reported waterlogging locations should be interpreted as evidence of spatial correspondence rather than proof of predictive accuracy at individual locations [47]. The subset of 22 locations was small and spatially concentrated, while the complete inventory contained 49 distinct locations derived from 51 reports with differing sources and geocoding precision. All 49 distinct locations were classified as medium or high risk in the descriptive full domain assessment. However, these reports represent presence data and do not include systematically sampled locations without waterlogging. Consequently, the false alarm rate and general predictive validity of TRRI could not be determined. Within the available dataset, combining the hit rate, background area proportion, enrichment ratio, and buffer distance analysis provided a more balanced evaluation than the hit rate alone. Satellite observations and gridded exposure datasets may provide additional information for future flood risk assessments [22].

Several uncertainties remain. Although IMERG V07 precipitation estimates contain some uncertainty, the product's documented improvements relative to V06 support its application to regional rainfall pattern analysis [32–36]. LandScan provides a static representation of population exposure, while the impervious surface factor represents only one aspect of urban surface conditions. These datasets do not represent population movement, drainage capacity, fine scale topographic depressions, river network convergence, or street specific waterlogging processes. Detailed urban inundation modelling would require high resolution elevation data, drainage system information, river and road networks, and appropriate boundary conditions [13–15]. Future studies should also incorporate larger samples from multiple events, more systematic records of locations with and without waterlogging, and inundation maps derived from satellite observations. Over longer periods, flood risk may also be influenced by changing rainfall hazards, population growth, asset concentration, urban expansion, early warning capacity, and resilience strategies [48–55].

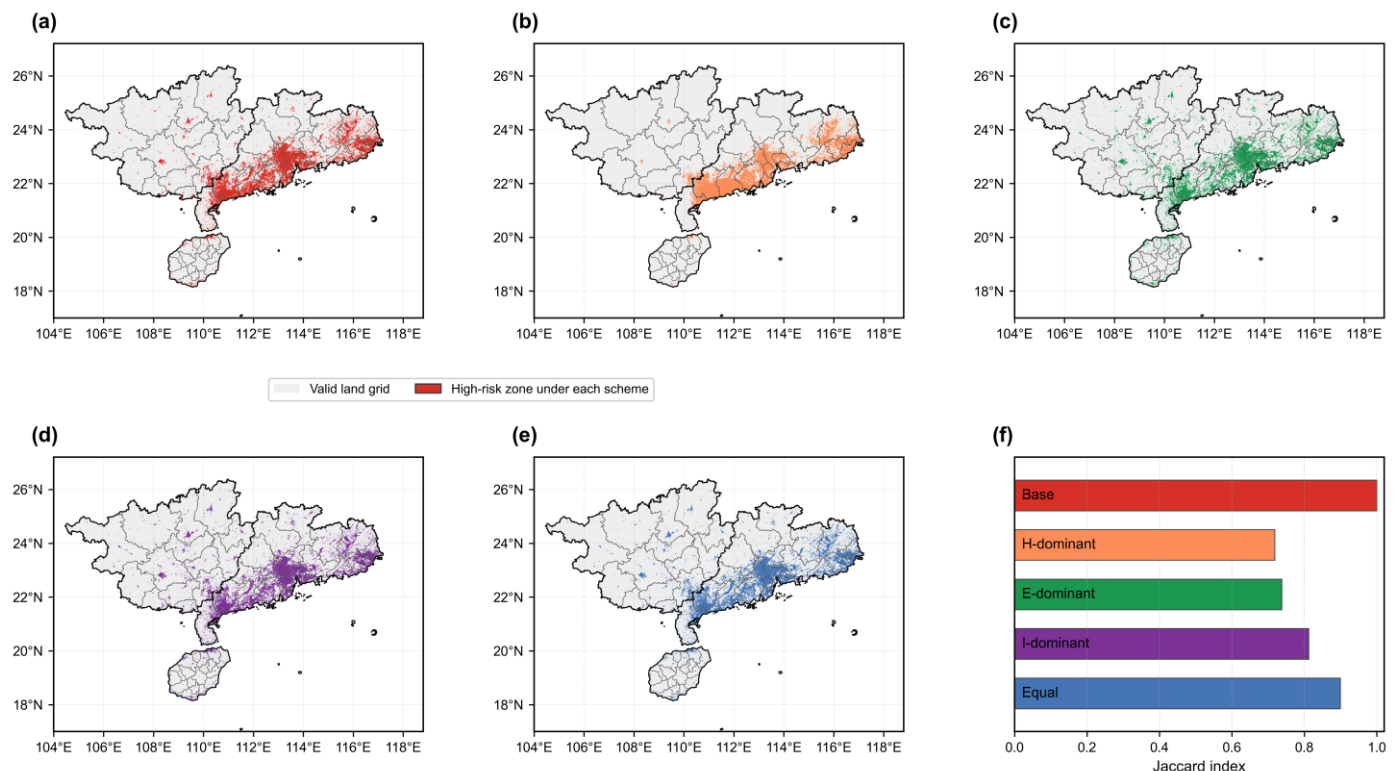


Figure 7. Sensitivity of TRRI high-risk zones to alternative weighting schemes. Panels (a–e) show (a) AHP-rounded baseline $H/E/I$ weights 0.40/0.30/0.30; (b) H -dominant 0.60/0.20/0.20; (c) E -dominant 0.25/0.50/0.25; (d) I -dominant 0.25/0.25/0.50; and (e) equal weights. The high-risk area was fixed at 12.45%. Panel (f) shows Jaccard overlap with the baseline.

5. Conclusions

We developed TRRI as a rapid framework for assessing waterlogging risk induced by typhoon rainfall and applied it to Typhoon Haikui in South China. The framework integrated GPM IMERG precipitation estimates at 30 min intervals, LandScan population data, CLCD impervious surfaces, and reported waterlogging locations on a common 1 km grid. Rainfall hazard (H), population exposure (E), and the impervious surface factor (I) were combined to identify areas requiring priority attention during an event.

Rainfall hazard was strongly concentrated along the Guangdong coast. High accumulated rainfall, maximum 24 h rainfall, and long rainfall duration mainly occurred in western Guangdong, around the Pearl River Estuary, and along the central and eastern sections of the Guangdong coast. The maximum accumulated rainfall for the event reached 529.7 mm, while the maximum 24 h rainfall reached 272.8 mm. After accumulated rainfall, rainfall duration, and rainfall concentration were integrated, high H values remained concentrated along the principal Guangdong coastal rainfall belt.

Areas classified as high risk by TRRI accounted for 12.45% of the land area of Guangdong, Guangxi, and Hainan. They were mainly located on both sides of the Pearl River Estuary, along the central and eastern Guangdong coast, within the eastern Guangdong urban cluster, and around several coastal cities. Areas dominated by H accounted for 60.5% of the total area classified as high risk. Areas dominated by E and I accounted for 33.4% and 6.1%, respectively. Rainfall hazard therefore established the main regional pattern, while population exposure and impervious surface conditions further differentiated risk within urban and coastal areas.

The reported waterlogging locations provided event specific evidence of spatial correspondence with the TRRI pattern. Of the 22 locations within the event analysis domain,

19 were classified as high risk and three as medium risk. The direct hit rate for the high-risk class was 86.4%. This class covered 26.1% of the validation area, resulting in an enrichment ratio of 3.31. After allowing for positional uncertainty, the hit rate increased to 90.9% within 1 km and 95.5% within 3 and 5 km. In the descriptive assessment across the complete study area, all 49 distinct geocoded locations were classified as medium or high risk.

The comparison between rainfall hazard and TRRI showed that 20.59% of the valid land area shifted to a higher class, 20.64% shifted to a lower class, and 58.77% remained unchanged. Areas shifted upward were generally associated with higher population exposure, higher impervious surface fractions, or both. Areas shifted downward generally combined high rainfall hazard with relatively low population exposure and limited impervious surfaces. Alternative weighting schemes retained the broad coastal risk pattern, indicating that the regional result was not determined by a single weight setting. However, the analysis range test showed that the exact Fisher–Jenks thresholds and the extent of the high-risk class depended on the selected geographical domain. Continuous TRRI values should therefore be treated as the primary analytical result, while the classified zones represent relative priorities within a predefined domain.

Scientifically, the contribution of TRRI lies not simply in combining several spatial datasets, but in providing a transparent and separable representation of event scale waterlogging risk. The rainfall hazard index retains information on rainfall amount, duration, and short duration concentration. TRRI then distinguishes the contributions of rainfall hazard, population exposure, and the impervious surface factor. The dominant factor and class transition analyses further show whether a high priority grid cell is primarily associated with severe rainfall, concentrated population, or impervious urban surfaces. This structure provides an interpretable connection between rainfall hazard monitoring and relative risk screening without treating impervious surfaces as multidimensional vulnerability.

In practice, the population, impervious surface, boundary, and template grid layers can be prepared before the typhoon season. Once rainfall data for an event become available, only the rainfall indices and TRRI need to be updated. The resulting 1 km map can serve as a first stage regional screening layer for identifying locations that warrant priority field verification, collection of waterlogging information, road and drainage inspection, or detailed hydrodynamic modelling. The dominant factor map can also inform the focus of subsequent checks. Areas dominated by *H* warrant closer examination of rainfall impacts, areas dominated by *E* require greater attention to potentially affected populations, and areas dominated by *I* warrant inspection of urban drainage and surface runoff conditions. These outputs provide prioritization information rather than automatic instructions for evacuation or resource deployment.

The rapid value of TRRI lies in its ability to generate a regional screening result efficiently once the required datasets are available, rather than in real time inundation forecasting. Within this defined scope, TRRI provides a reproducible way to narrow a large regional domain into a smaller set of priority locations for field verification, targeted inspection, and more detailed assessment. It therefore supports disaster prevention decisions by helping decision makers determine where limited attention and investigative resources should be directed first.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/w18151804/s1>, Figure S1: Full-domain spatial coverage of event-period waterlogging reports; Table S1: Event-focused waterlogging locations used for enrichment and buffer analyses; Table S2: Full inventory of 51 event-period reports; Table S3: Province-stratified classes for 49 distinct geocoded locations; Table S4: Analysis-domain sensitivity; Table S5:

AHP judgement scale; Table S6: P/T/C AHP results; Table S7: H/E/I AHP results; Table S8: Rainfall-hazard weight sensitivity.

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Data Availability Statement: GPM IMERG Final Run V07 is available from NASA GES DISC; NOAA IBTrACS v4.0 is available from NOAA NCEI; CLCD is available from Zenodo; and LandScan HD China is available from Oak Ridge National Laboratory subject to its access terms. The compiled event-period report inventory, distinct-location summaries, AHP results, and sensitivity results used in this revision are provided in the Supplementary Materials.

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References

1. Zhang, S.; Zheng, Y.; Liu, C.; Huang, Z.; Weng, H.; Xu, J.; Tu, S. Climatology of different classifications of tropical cyclones landfalling in Guangdong Province of China during 1951–2020. *Atmosphere* **2022**, *13*, 1306. <https://doi.org/10.3390/atmos13081306>.
2. Yin, Z.; Zhou, B.; Duan, M.; Chen, H.; Wang, H. Climate extremes become increasingly fierce in China. *Innovation* **2023**, *4*, 100406. <https://doi.org/10.1016/j.xinn.2023.100406>.
3. Li, W.; Sun, B.; Wang, H.; Zhou, B.; Li, H.; Xue, R.; Duan, M.; Luo, X.; Ai, W. Anthropogenic impact on the severity of compound extreme high temperature and drought/rain events in China. *npj Clim. Atmos. Sci.* **2023**, *6*, 79. <https://doi.org/10.1038/s41612-023-00413-3>.
4. Chen, X.; Zhang, H.; Chen, W.; Huang, G. Urbanization and climate change impacts on future flood risk in the Pearl River Delta under shared socioeconomic pathways. *Sci. Total Environ.* **2021**, *762*, 143144. <https://doi.org/10.1016/j.scitotenv.2020.143144>.
5. Zhang, H.; Wu, C.; Chen, W.; Huang, G. Assessing the impact of climate change on the waterlogging risk in coastal cities: A case study of Guangzhou, South China. *J. Hydrometeorol.* **2017**, *18*, 1549–1562. <https://doi.org/10.1175/JHM-D-16-0157.1>.
6. Qi, M.; Huang, H.; Liu, L.; Chen, X. An integrated approach for urban pluvial flood risk assessment at catchment level. *Water* **2022**, *14*, 2000. <https://doi.org/10.3390/w14132000>.
7. Qin, X.; Wu, Y.; Lin, T.; Gao, L. Urban flood dynamic risk assessment based on typhoon rainfall process: A case study of Typhoon “Lupit” (2109) in Fuzhou, China. *Remote Sens.* **2023**, *15*, 3116. <https://doi.org/10.3390/rs15123116>.
8. IPCC. *Climate Change 2022: Impacts, Adaptation and Vulnerability*; Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change; Pörtner, H.-O., Roberts, D.C., Tignor, M., Poloczanska, E.S., Mintenbeck, K., Alegria, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., et al., Eds.; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2022. <https://doi.org/10.1017/9781009325844>.

9. Dilley, M.; Chen, R.S.; Deichmann, U.; Lerner-Lam, A.L.; Arnold, M.; Agwe, J.; Buys, P.; Kjekstad, O.; Lyon, B.; Yetman, G. *Natural Disaster Hotspots: A Global Risk Analysis*; World Bank: Washington, DC, USA, 2005.
10. Shi, P. Re-discussion on theory and practice of disaster research. *J. Nat. Disasters* **1996**, *5*, 6–17. <https://doi.org/10.13577/j.jnd.1996.0402>. (In Chinese).
11. Koks, E.E.; Jongman, B.; Husby, T.G.; Botzen, W.J.W. Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. *Environ. Sci. Policy* **2015**, *47*, 42–52. <https://doi.org/10.1016/j.envsci.2014.10.013>.
12. Sohn, W.; Kim, J.-H.; Li, M.-H.; Brown, R.D.; Jaber, F.H. How does increasing impervious surfaces affect urban flooding in response to climate variability? *Ecol. Indic.* **2020**, *118*, 106774. <https://doi.org/10.1016/j.ecolind.2020.106774>.
13. Guo, K.; Guan, M.; Yu, D. Urban surface water flood modelling—A comprehensive review of current models and future challenges. *Hydrol. Earth Syst. Sci.* **2021**, *25*, 2843–2860. <https://doi.org/10.5194/hess-25-2843-2021>.
14. Sampson, C.C.; Smith, A.M.; Bates, P.D.; Neal, J.C.; Alfieri, L.; Freer, J.E. A high-resolution global flood hazard model. *Water Resour. Res.* **2015**, *51*, 7358–7381. <https://doi.org/10.1002/2015WR016954>.
15. Bates, P.D.; Horritt, M.S.; Fewtrell, T.J. A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. *J. Hydrol.* **2010**, *387*, 33–45. <https://doi.org/10.1016/j.jhydrol.2010.03.027>.
16. Yin, J.; Dai, E.; Wu, S. Integrated risk assessment and zoning of typhoon disasters in China. *Sci. Geogr. Sin.* **2013**, *33*, 1370–1376. (In Chinese)
17. Ding, Y.; Shi, P. Fuzzy risk assessment model of typhoon disasters. *J. Nat. Disasters* **2002**, *11*, 34–43. (In Chinese)
18. Liu, B.; Zhao, F.; Wang, X.; Yan, X.; Lin, S. Multi-source data-driven modeling of typhoon dynamic risk assessment. *Trop. Geogr.* **2024**, *44*, 1102–1112. <https://doi.org/10.13284/j.cnki.rddl.003883>. (In Chinese)
19. Wang, L.; Wang, X.; Wang, W. Research and application of a comprehensive intensity evaluation method for regional rainfall processes in China. *J. Nat. Disasters* **2015**, *24*, 186–194. <https://doi.org/10.13577/j.jnd.2015.0224>. (In Chinese)
20. Li, C.; Sun, N.; Lu, Y.; Guo, B.; Wang, Y.; Sun, X.; Yao, Y. Review on urban flood risk assessment. *Sustainability* **2023**, *15*, 765. <https://doi.org/10.3390/su15010765>.
21. Zhang, W.; Hu, B.; Liu, Y.; Zhang, X.; Li, Z. Urban flood risk assessment through the integration of natural and human resilience based on machine learning models. *Remote Sens.* **2023**, *15*, 3678. <https://doi.org/10.3390/rs15143678>.
22. Tellman, B.; Sullivan, J.A.; Kuhn, C.; Kettner, A.J.; Doyle, C.S.; Brakenridge, G.R.; Erickson, T.A.; Slayback, D.A. Satellite imaging reveals increased proportion of population exposed to floods. *Nature* **2021**, *596*, 80–86. <https://doi.org/10.1038/s41586-021-03695-w>.
23. Pan, X.; Wu, H.; Chen, S.; Nanding, N.; Huang, Z.; Chen, W.; Li, C.; Li, X. Evaluation and applicability analysis of GPM satellite precipitation over Mainland China. *Remote Sens.* **2023**, *15*, 2866. <https://doi.org/10.3390/rs15112866>.
24. Fang, J.; Yang, W.; Luan, Y.; Du, J.; Lin, A.; Zhao, L. Evaluation of the TRMM 3B42 and GPM IMERG products for extreme precipitation analysis over China. *Atmos. Res.* **2019**, *223*, 24–38. <https://doi.org/10.1016/j.atmosres.2019.03.001>.
25. Chen, T.; Li, J.; Xu, X.; Chen, Y. Structure and organization of convection during extreme precipitation associated with the remnant vortex of Typhoon Haikui. *Trans. Atmos. Sci.* **2025**, *48*, 77–92. <https://doi.org/10.13878/j.cnki.dqkxxb.20240418002>. (In Chinese).
26. Wang, H.; Zhang, L.; Dong, L.; Xiang, C.; Xu, Y.; Nie, G. Forecast difficulties and model performances in Typhoon Haikui (2311) forecasting. *Meteorol. Mon.* **2024**, *50*, 1331–1342. (In Chinese)
27. Chen, X.; Xu, T.; Wang, R.; Li, Y.; Zhang, S.; Wang, S.; Wang, M.; Chen, Y. Fine observation characteristics and causes of the “9·7” extreme heavy rainstorm over Pearl River Delta, China. *J. Appl. Meteorol. Sci.* **2024**, *35*(1), 1–16. (In Chinese)
28. Shan, Z.; Zhou, A.; Chen, H.; Zhao, K.; Wang, S.; Chan, J.C.L.; Chan, P.-W.; Huang, H.; Yang, Y. The century-record-breaking extreme precipitation from Typhoon Haikui enhanced by the megacities in South China. *J. Geophys. Res. Atmos.* **2026**, *131*, e2025JD046081. <https://doi.org/10.1029/2025JD046081>.
29. Tam, H.C.; He, Y.H.; Chan, P.W.; Yu, S.; Mo, H.; Su, H.; Hsiao, L.-F.; Gong, Y. Historical rainstorm in Hong Kong on 7–8 September 2023: Diagnosis, forecasting and nowcasting. *Atmos. Sci. Lett.* **2025**, *26*, e1284. <https://doi.org/10.1002/asl.1284>.
30. Knapp, K.R.; Kruk, M.C.; Levinson, D.H.; Diamond, H.J.; Neumann, C.J. The International Best Track Archive for Climate Stewardship (IBTrACS): Unifying tropical cyclone best track data. *Bull. Am. Meteorol. Soc.* **2010**, *91*, 363–376. <https://doi.org/10.1175/2009BAMS2755.1>.
31. Huffman, G.J.; Stocker, E.F.; Bolvin, D.T.; Nelkin, E.J.; Tan, J. *GPM IMERG Final Precipitation L3 Half Hourly 0.1 Degree × 0.1 Degree V07*; Goddard Earth Sciences Data and Information Services Center (GES DISC): Greenbelt, MD, USA, 2023. <https://doi.org/10.5067/GPM/IMERG/3B-HH/07>.

32. Wang, Y.; Li, Z.; Gao, L.; Zhong, Y.; Peng, X. Comparison of GPM IMERG Version 06 Final Run products and its latest Version 07 precipitation products across scales: Similarities, differences and improvements. *Remote Sens.* **2023**, *15*, 5622. <https://doi.org/10.3390/rs15235622>.
33. Lyu, X.; Li, Z.; Li, X. Evaluation of GPM IMERG satellite precipitation products in event-based flood modeling over the Sunshui River Basin in Southwestern China. *Remote Sens.* **2024**, *16*, 2333. <https://doi.org/10.3390/rs16132333>.
34. Li, X.; Liu, J.; Cui, W.; Wang, H.; Liao, A.; Wang, Y.; Gao, W. Comparative evaluation of GPM IMERG V07 Early, Late and Final Run products compared to IMERG V06 in Sichuan Province, China. *Theor. Appl. Climatol.* **2025**, *156*, 354. <https://doi.org/10.1007/s00704-025-05569-x>.
35. Yu, L.; Leng, G.; Python, A.; Peng, J. A comprehensive evaluation of latest GPM IMERG V06 Early, Late and Final precipitation products across China. *Remote Sens.* **2021**, *13*, 1208. <https://doi.org/10.3390/rs13061208>.
36. Guo, H.; Tian, Y.; Li, J.; Guo, C.; Meng, X.; Wang, W.; De Maeyer, P. Has IMERG_V07 improved the precision of precipitation retrieval in Mainland China compared to IMERG_V06? *Remote Sens.* **2024**, *16*, 2671. <https://doi.org/10.3390/rs16142671>.
37. Moehl, J.; Reith, A.; McKee, J.; Weber, E.; Laverdiere, M.; Swan, B.; Yang, H.; Hauser, T.; Rose, A.; Walters, S.; et al. *LandScan HD China v1.0*; Oak Ridge National Laboratory: Oak Ridge, TN, USA, 2023. <https://doi.org/10.48690/1524248>.
38. Yang, J.; Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. <https://doi.org/10.5194/essd-13-3907-2021>.
39. Yang, J.; Huang, X. *The 30 m Annual Land Cover Datasets and Its Dynamics in China from 1985 to 2023*; Version 1.0.3; Zenodo: Geneva, Switzerland, 2024. <https://doi.org/10.5281/zenodo.12779975>.
40. Saaty, T.L. Decision making with the analytic hierarchy process. *Int. J. Serv. Sci.* **2008**, *1*, 83–98. <https://doi.org/10.1504/IJSSCI.2008.017590>.
41. Forman, E.; Peniwati, K. Aggregating individual judgments and priorities with the analytic hierarchy process. *Eur. J. Oper. Res.* **1998**, *108*, 165–169. [https://doi.org/10.1016/S0377-2217\(97\)00244-0](https://doi.org/10.1016/S0377-2217(97)00244-0).
42. Jenks, G.F. The data model concept in statistical mapping. In *International Yearbook of Cartography*; George Philip: London, UK, 1967; Volume 7, pp. 186–190.
43. Jaccard, P. The distribution of the flora in the alpine zone. *New Phytol.* **1912**, *11*, 37–50. <https://doi.org/10.1111/j.1469-8137.1912.tb05611.x>.
44. Knutson, T.; Camargo, S.J.; Chan, J.C.L.; Emanuel, K.; Ho, C.-H.; Kossin, J.; Mohapatra, M.; Satoh, M.; Sugi, M.; Walsh, K.; et al. Tropical cyclones and climate change assessment: Part II: Projected response to anthropogenic warming. *Bull. Am. Meteorol. Soc.* **2020**, *101*, E303–E322. <https://doi.org/10.1175/BAMS-D-18-0194.1>.
45. Qin, L.; Zhu, L.; Liu, B.; Li, Z.; Tian, Y.; Mitchell, G.; Shen, S.; Xu, W.; Chen, J. Global expansion of tropical cyclone precipitation footprint. *Nat. Commun.* **2024**, *15*, 4824. <https://doi.org/10.1038/s41467-024-49115-1>.
46. Jongman, B.; Ward, P.J.; Aerts, J.C.J.H. Global exposure to river and coastal flooding: Long term trends and changes. *Glob. Environ. Change* **2012**, *22*, 823–835. <https://doi.org/10.1016/j.gloenvcha.2012.07.004>.
47. Molinari, D.; De Bruijn, K.M.; Castillo-Rodríguez, J.T.; Aronica, G.T.; Bouwer, L.M. Validation of flood risk models: Current practice and possible improvements. *Int. J. Disaster Risk Reduct.* **2019**, *33*, 441–448. <https://doi.org/10.1016/j.ijdr.2018.10.022>.
48. Hallegatte, S.; Green, C.; Nicholls, R.J.; Corfee-Morlot, J. Future flood losses in major coastal cities. *Nat. Clim. Change* **2013**, *3*, 802–806. <https://doi.org/10.1038/nclimate1979>.
49. Winsemius, H.C.; Aerts, J.C.J.H.; van Beek, L.P.H.; Bierkens, M.F.P.; Bouwman, A.; Jongman, B.; Kwadijk, J.C.J.; Ligtvoet, W.; Lucas, P.L.; van Vuuren, D.P.; et al. Global drivers of future river flood risk. *Nat. Clim. Change* **2016**, *6*, 381–385. <https://doi.org/10.1038/nclimate2893>.
50. de Moel, H.; van Alphen, J.; Aerts, J.C.J.H. Flood maps in Europe—Methods, availability and use. *Nat. Hazards Earth Syst. Sci.* **2009**, *9*, 289–301. <https://doi.org/10.5194/nhess-9-289-2009>.
51. Merz, B.; Kreibich, H.; Schwarze, R.; Thieken, A. Assessment of economic flood damage. *Nat. Hazards Earth Syst. Sci.* **2010**, *10*, 1697–1724. <https://doi.org/10.5194/nhess-10-1697-2010>.
52. Pappenberger, F.; Cloke, H.L.; Parker, D.J.; Wetterhall, F.; Richardson, D.S.; Thielen, J. The monetary benefit of early flood warnings in Europe. *Environ. Sci. Policy* **2015**, *51*, 278–291. <https://doi.org/10.1016/j.envsci.2015.04.016>.
53. Aerts, J.C.J.H.; Botzen, W.J.W.; Emanuel, K.; Lin, N.; de Moel, H.; Michel-Kerjan, E.O. Evaluating flood resilience strategies for coastal megacities. *Science* **2014**, *344*, 473–475. <https://doi.org/10.1126/science.1248222>.

54. Merz, B.; Hall, J.; Disse, M.; Schumann, A. Fluvial flood risk management in a changing world. *Nat. Hazards Earth Syst. Sci.* **2010**, *10*, 509–527. <https://doi.org/10.5194/nhess-10-509-2010>.
55. Jongman, B.; Hochrainer-Stigler, S.; Feyen, L.; Aerts, J.C.J.H.; Mechler, R.; Botzen, W.J.W.; Bouwer, L.M.; Pflug, G.; Rojas, R.; Ward, P.J. Increasing stress on disaster-risk finance due to large floods. *Nat. Clim. Change* **2014**, *4*, 264–268. <https://doi.org/10.1038/nclimate2124>.

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