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Quickly Assess the Direct Loss of Houses Caused by a Typhoon-Rainstorm-Storm Surge–Flood Chain: Case of Haikou City

Jinhong Wan [1,2], Lisha Wang [1], Yaojie Yue [1,*] and Zhiyuan Wang [1,3]

[1] Key Laboratory of Environmental Change and Natural Disasters of Chinese Ministry of Education, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
[2] China Institute of Water Resources and Hydropower Research, Beijing 100038, China
[3] Hangzhou Yongxing School, Hangzhou 310053, China
* Correspondence: yjyue@bnu.edu.cn; Tel.: +86-(0)10-5880-6399

Abstract: With changing climate, coastal areas are facing increasingly threats from the typhoon–rainstorm–storm surge-flood (TRSSF) chain. However, among various exposures of the TRSSF chain, it is still a great challenge to quickly assess the direct losses of houses, due to the complex mechanisms underlying building damage. The objective of this article is therefore to explore a simple method of quickly assessing the house losses caused by the TRSSF chain, based on a small amount of data. To achieve this goal, a method of multi factors regression and a spatial information network were proposed. The results in Haikou City show that the loss rate of house assets is significantly lower than that of indoor property. Spatially, the areas with higher loss rates are generally distributed along the Nandu River. The direct economic losses associated with houses in the return periods of 10, 20, 50, and 100 years range from 1.3 to 2 billion RMB. Our findings highlight the significance and possibility of quickly assessing the direct house losses caused by TRSSF chain using a small amount of data. It indicates that the house losses are not only determined by TRSSF intensity, but also closely related to socio-economic, topography and house location.

Keywords: typhoon-rainstorm-storm surge–flood chain; multifactors regression; passive inundation; direct economic loss of house; Haikou City

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1. Introduction

Typhoons are one of the disasters causing tremendous losses and casualties to human society. The economic loss caused by typhoons can reach about 260 billion dollars every year globally [1]. There are about 80–100 typhoons in the world every year, mainly in the Northwest Pacific Ocean, the Caribbean Sea, the Indian Ocean, the Eastern Pacific Ocean, and the northern waters of Oceania. Among them, the frequency of typhoons in the Northwest Pacific is the highest, accounting for more than 1/3 of the global total [2,3]. Located in the Northwest Pacific coast, China is severely affected by typhoons. Haikou City, the capital of Hainan province of China, is highly concentrated in population and economy, severely affected by the typhoons [4]. With the development of economy and the impact of climate change, the risk of typhoons in Haikou City may further increase in the future.

Rainstorms, storm surges, and floods caused by typhoons represent widespread and destructive natural hazards in coastal regions worldwide. However, rainstorms and storm surges are also the sources of floods, and they can occur together as a hazard chain, named typhoon–rainstorm–storm surge-flood (TRSSF) chain [5,6]. Among them, floods are the most important and ultimate factor that leads to various losses in this chain [7]. Specifically, flood erosion and waterlogging immersion usually cause severe damage to or even the collapse of a large number of houses, which is an essential part of the direct economic losses in this hazard chain [8–10]. Numerous studies have assessed the losses caused

by individual hazards, such as typhoons, rainstorms, storm surges, and floods [11–15]. However, few studies have focused on the losses caused by floods induced by the combined effect of typhoons, rainstorms, and storm surges, because the influencing factors of the TRSSF chain are diverse and the mechanism underlying disaster formation is complex. Therefore, it is difficult to assess the economic losses caused by the TRSSF chain quickly, which makes it a significant research issue that needs to be addressed.

The economic losses assessment methods for floods caused by typhoons, rainstorms, and storm surges mainly include statistical analysis, machine learning, and spatial information network-based models. Among them, the statistical analysis method usually assesses economic losses by regression analysis, taking hazard intensity, such as wind speed, rainfall, river network density, flood velocity, submerged water depth, submerged duration, as explanatory variables, and the losses of the exposure as target variables [16–18]. This method can be grouped into single independent variable regression [19,20], multiple independent variable regression, and transcendence probability-loss models [21,22], according to the type of regression model. However, statistical analysis methods are mostly data-oriented. For the TRSSF chain, this method usually requires a variety of disaster data sets, which needs to spend lots of time collecting and processing, or the accuracy of the regression method cannot be guaranteed. In addition, increasing the number of explanatory variables also increases the difficulty of constructing the equation, not to mention that data are often insufficient.

The machine learning modeling method has been widely applied to assess the losses of elements at the TRSSF chain. This method builds a losses assessment model by establishing the relationship between the losses of exposure and hazard intensity of the TRSSF chain [23–27]. Among various machine learning algorithms, the artificial neural network (ANN) [28] and random forest (RF) [29] are the two main types. For example, based on the six times of floods in the Taihu Lake Basin as the sample set data, Huang and Wang built the regional economic loss assessment model using the ANN model [30]. Guo and Liu quantitatively assessed the building losses caused by floods in five southeastern provinces of China by applying the RF model [31]. However, the machine learning modeling method also requires a large number of training samples, i.e., historical disaster data. Therefore, the loss assessment model built by this method is usually limited to a specific research area, making the constructed model hardly suitable for other study areas.

With the support of disaster spatial data, i.e., the flood intensity and the socio-economic losses, the spatial information network-based model is capable of outputting spatial characteristics of the economic losses of the TRSSF chain by applying spatial analysis technology [32–36]. For example, Dutta et al. established a real-time floods losses assessment model composed of a hydrological model and grid-based loss data [33]. Yi et al. predicted the economic losses of floods in different regions of the study area using the flood water level grid model and the house asset spatial data [35]. However, this method requires a large amount of disaster spatial information data, besides attribute data sets used in methods of statistical analysis and machine learning. Additionally, it has a relatively complex grid establishment process. Therefore, this method is not suitable for rapid assessments of asset losses.

In summary, the above methods all have the limitation of data hunger, which makes a quick assessment of house losses caused by the TRSSF chain impossible. In particular, the process of how the TRSSF chain leads to economic losses of houses is very complex. There are multiple factors causing house losses including typhoons, rainstorms, storm surges, and the floods that result from them. What's more, the interaction process and mechanism of these factors are particularly complex. Ideally, the house losses assessment model should be built according to the process and mechanism of flood formation coupling multiple factors including typhoons, rain storms, and storm surges. However, this requires a large amount of data to support and the modeling workload is very huge, which constrains the rapid assessment of house losses caused by the TRSSF chain. According to a newly proposed theory [37], we argue that the hazard-forming process and the disaster losses are

similar among different regions with similar geographical environments and socioeconomic conditions. That is, it is possible to apply a house losses model constructed in one region to other areas with the same or similar levels of socioeconomic development. Therefore, quickly assessing the house losses caused by the TRSSF chain can be achieved by adopting the existing regional models that have been validated and are similar to our study area.

Therefore, the objectives of this paper are to explore how to quickly assess the direct losses of houses caused by the TRSSF chain, based on a small amount of data; and to provide a basis for rapid assessment of house losses by reversely analyzing how these specific house losses levels correlate to flood intensity, the intensities of typhoons, rainstorms and storm surges. To achieve the above goals, the economic losses of houses in Haikou City caused by the TRSSF chain in four return periods were quantified, using the regression analysis method and spatial information grid method. Furthermore, the combined effect of the TRSSF chain was linked to the economic losses of houses by empirical analysis.

2. Materials and Methods

2.1. Study Area

Haikou City (19°31′~20°04′ N, 110°07′~110°42′ E) is located at the mouth of the lower reaches of the Nandu River, undertaking a large amount of river water (Figure 1). According to the seventh national census, the resident population of Haikou City is 2,873,358 total. Furthermore, Xiuying District, Longhua District, Qiongshan District and Meilan District has 567,108, 797,684, 6555,553 and 853,013 people, respectively.

Most of the city is plain with an elevation of lower than 100 m. The northwest and southeast are relatively higher, whereas the central part along the Nandu River is the lowest and most flat. Since 1990, 44 typhoons have landed in Hainan Province and affected the precipitation in Haikou City. The average annual precipitation in Haikou City is 1639 mm, and the average annual rain day is 150 days. Dominated by storms, thundershowers, and frontal rain, the precipitation is mainly concentrated in the typhoon season in the second half of the year, which is prone to destructive floods. At the same time, torrential rains and storm surges caused by typhoons will also lead to the occurrence of floods in Haikou City.

2.2. Data Processing

In the present study, Haikou City was divided into two research units urban and rural, according to administrative districts (Figure 1). Where the "urban area" is a built-up area and was further divided into five subunits, i.e., urban areas I to V. The rural areas were 24 subunits according to the township division.

Data applied in this study include two types, i.e., flood and housing. The former includes the digital elevation model (DEM) data (https://earthdata.nasa.gov/ (accessed on 22 May 2020)) and flood (tide) level data from the "Emergency Plan for Wind and Flood Prevention in Haikou City" (http://www.haikou.gov.cn/ (accessed on 22 May 2020)). Housing data include the average building age, indoor properties, and housing assets in urban areas and towns, derived from the "2018 Haikou City Statistical Yearbook" and the "Haikou City National Economic and Social Development Statistical Bulletin" (http://www.haikou.gov.cn/ (accessed on 22 May 2020)) (Table 1).

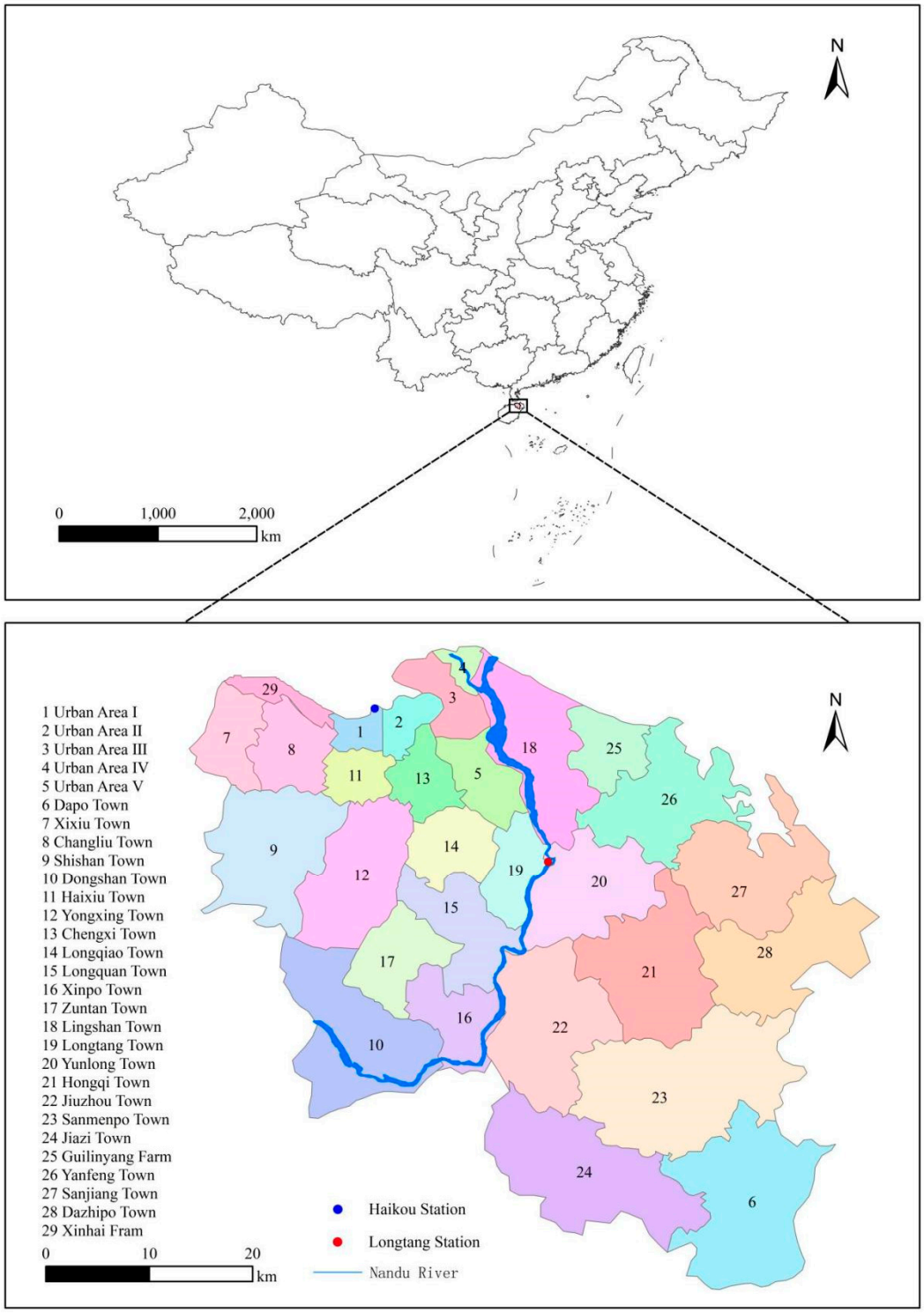

Figure 1. Location of Haikou City and the assessment units.

Table 1. Data and Sources.

Data Name	Data Description	Data Source
Population Data	The agricultural and non-agricultural population exposed to disasters in each urban area or town of Haikou City in 2017; Number of agricultural and non-agricultural households exposed to disasters in each urban area or town of Haikou City in 2017	"2018 Haikou City Statistical Yearbook" (http://www.haikou.gov.cn/ (accessed on 22 May 2020)) and "2018 Yuyao City Statistical Yearbook" (http://www.yy.gov.cn/ (accessed on 22 May 2020))
Housing area per capita	Housing area per capita in urban and rural area in 2017	
Housing value per unit area	Housing value per unit area of urban and rural houses in 2017	
Regional GDP data	GDP of Haikou City and Yuyao City in 2018	
Housing completion area data	Completed area of urban real estate houses and the completed residential area of rural individual houses in Haikou City from 1997 to 2016	"Haikou City National Economic and Social Development Statistical Bulletin" (http://www.haikou.gov.cn/ (accessed on 22 May 2020))
Flood (tide) level data	Flood (tide) level of Haikou Station and Longtang Station in the case of 10-year, 20-year, 50-year and 100-year flood return period.	"Emergency Plan for Wind and Flood Prevention in Haikou City" (http://www.haikou.gov.cn/ (accessed on 22 May 2020))
ASTGTM v003	At a spatial resolution of 1 arc second (approximately 30 m horizontal posting at the equator)	Earthdata search (https://earthdata.nasa.gov/ (accessed on 22 May 2020))

The housing assets were calculated using data of the per capita housing area and the value of housing per unit area in urban and rural units, respectively, according to the agricultural and nonagricultural population exposed to floods in Haikou. Indoor property was calculated using the mean value of indoor property data in urban and rural units, respectively, according to the number of agricultural and nonagricultural households exposed to floods in Haikou City. Since the mean value of indoor property in urban and rural areas of Haikou City could not be obtained directly, the mean indoor property value of Yuyao City was adopted. We further revised it based on the GDP ratio of Haikou City and Yuyao City in 2018, of which the GDP data and indoor property data of Yuyao City were obtained from the "2018 Yuyao Statistical Yearbook" (Http://www.yy.gov.cn/ (accessed on 22 May 2020)).

The building age in urban or rural areas was calculated based on the completed area of urban real estate houses and the completed residential area of rural individual houses in Haikou City from 1997 to 2016. Then, the average building age of Haikou City was calculated according to the proportion of agricultural and nonagricultural populations. We further demonstrated the rationality of the data and methods used in this paper in the Discussion section, considering that some data are from outside the study area.

2.3. Analysis Method of Flooding Depth

The depth of flood inundation was calculated using the raster calculator tool in ArcGIS according to the principle of "passive inundation" [38]. This method is suitable for studying flood inundation in flat and large areas quickly like Haikou city. The model is as follows (Equation (1)).

$$\Delta h = \begin{cases} 0 & h_{max} \leq h_i \\ h_{max} - h_i & h_{max} > h_i \end{cases} \quad (1)$$

where Δh refers to the submerged water depth, h_{max} refers to the highest water level, and h_i refers to the elevation.

Floods in Haikou City are mainly of two types, i.e., coastal floods and river floods. Among these, coastal floods were mainly caused by storm surges, while river floods were caused by rainstorms in the inland area along the river. Therefore, in coastal areas (including Urban Areas I, II, III, and IV and the towns Xixiu, Lingshan, Yanfeng, and Sanjiang), the tidal level of Haikou station is adopted as the hmax. Whereas in the inland areas (including Urban Area V and all other towns), we take the flood water level at Longtang Station as the hmax (Table 2).

Table 2. Typhoon and rainstorm threshold to reach different flood (tide) levels under different early water levels.

Haikou Station	Early Water Levels (m)	Maximum Wind Speed Conditions Required V_{max} (m/s)	Increased Water Volume ΔH (m)	Needed Water Level h_{max} (m)
10-year flood	2.00	43.45	1.65	3.65
20-year flood	2.00	46.21	1.89	3.89
50-year flood	2.00	50.57	2.27	4.27
100-year flood	2.00	52.64	2.45	4.45
Longtang station	**Early water levels (m)**	**Rainfall conditions required X (mm)**	**Increased water volume ΔH (m)**	**Needed Water level h_{max} (m)**
10-year flood	7.00	390	6.77	13.77
	8.00	277	5.77	
	9.00	260	4.77	
	10.00	234	3.77	
	11.00	220	2.77	
20-year flood	7.00	439	7.52	14.52
	8.00	321	6.52	
	9.00	305	5.52	
	10.00	275	4.52	
	11.00	267	3.52	
50-year flood	7.00	504	8.37	15.37
	8.00	377	7.37	
	9.00	362	6.37	
	10.00	325	5.37	
	11.00	331	4.37	
100-year flood	7.00	563	9.00	16.00
	8.00	425	8.00	
	9.00	412	7.00	
	10.00	368	6.00	
	11.00	388	5.00	

Note: Haikou station's warning tide level is 2.90 m, and Longtang Town's warning flood water level is 11.50 m.

2.4. TRSSF Chain Transmission Analysis

The house losses caused by the TRSSF chain to the coastal and inland areas of Haikou City are not the same. Floods in coastal areas are often caused by rising tide levels, while inland floods are mainly caused by large amounts of rainwater from heavy precipitation. In order to better reveal the influence mechanism of each factor in the coastal and inland TRSSF Chain on house losses, we discuss the transmission process of the TRSSF chain in coastal areas and inland areas separately.

For coastal areas, seawater backfilling is the main cause of floods, so the level of tidewater determines the intensity of the TRSSF chain. In addition to astronomical tides, storm surges brought by typhoons can cause a surge in tide levels, which will exacerbate floods. To calculate the increase in the tide level induced by the storm surge caused by the typhoon, the relationship between the maximum wind speed and the tide level increase established by Xu Yang in Quanzhou City [39] where is similar to Haikou City, was adopted (Equation (2)).

$$\Delta H = 0.087 \times V_{max} - 2.13 \quad (2)$$

The average annual maximum astronomical tide level of Haikou Station, i.e., 2.00 m, was used as the benchmark for calculating the tide level in this study. Conversely, the maximum wind speed of typhoons required to reach the tide level of floods at four return periods, i.e., 10, 20, 50 and 100 years could be calculated.

Inland floods of Haikou City are mainly caused by the rainstorms brought by typhoons. Therefore, to analyze the transmission process of the TRSSF chain in inland areas, the relationship between precipitation and flood water level should be established. In this study, the relationship curves between surface precipitation and flood water level at different early water levels established by Zhang et al. [40] were adopted. The maximum flood water level h_{max} (mm) of return periods of 10, 20, 50 and 100 years at Longtang station were used to obtain surface precipitation X (mm) (Table 3).

Table 3. Relationship curves of the surface rainfall and flood water level at Longtang station in Haikou City for different early water levels.

Early Water Levels	Relationship Curves of Surface Precipitation (X) and Flood Water Level (h_{max})
7 m	$h_{max} = -0.00002X^2 + 0.032X + 4.3304$
8 m	$h_{max} = -0.00002X^2 + 0.0292X + 7.2115$
9 m	$h_{max} = -0.00002X^2 + 0.0282X + 7.7873$
10 m	$h_{max} = -0.00002X^2 + 0.0.0287X + 8.1556$
11 m	$h_{max} = -0.00002X^2 + 0.0.0254X + 9.1593$

2.5. Houses Losses Assessment Method

The typhoon-induced TRSSF chain is very complex, because wind speed, precipitation, and the tide of storm surges all have negative impacts on houses. However, the economic losses caused by the TRSSF chain often depend on regional exposure and vulnerability, that is, closely related to socioeconomic conditions. Therefore, based on the assumption that the hazard-forming process and the disaster losses are similar where similar geographical environments and socio-economic conditions are, the most appropriate models were selected to calculate the economic loss rate of Haikou City [20,41–43].

The direct economic losses of the house caused by the TRSSF chain include losses of housing assets and indoor property. The losses of housing assets refer to the losses caused by the damage to the main body of the building, and the losses of indoor property are the losses of household property including furniture and appliances. The model is as follows:

$$L = p_1 \times \beta_1 + p_2 \times \beta_2, \tag{3}$$

where L is the direct economic loss of houses in a certain urban area or town (10,000 RMB), p_1 is the total housing assets that may be exposed to the TRSSF chain, β_1 is the loss rate of housing assets (%), p_2 is the total indoor property that may be exposed to the TRSSF chain, and β_2 is the loss rate of indoor property (%).

The losses of housing assets are mostly affected by water depth and building age. The deeper the house is soaked by floods, the worse the damage it will suffer. Furthermore, the older the house is, the less its resistance to floods will be. That is, the older the house and the deeper the flood water, the greater the loss rate to the house. Based on the above, a multiple regression model applicable to calculate the loss rate of housing assets [16] was adopted after a comprehensive comparative study. The model is as follows:

$$\beta_1 = -5.9 + 0.24 \times y + 7.77 \times \Delta h \tag{4}$$

where β_1 is the loss rate of the housing assets (%), y is the building age (year), and Δh is the flood depth (m).

The losses of indoor property are mostly influenced by flood depth. The deeper the flood water is, the more properties are likely damaged by floods. In the present study, we

adopted well-validated models (Table 4) to calculate the indoor property loss in Haikou City [37–39]. These models (Table 4) calculated the indoor property loss rate of houses in urban and rural areas in coastal and inland regions separately.

Table 4. Applicable curve of the indoor property loss rate of buildings in different areas of Haikou City.

Area	Indoor Property Loss Rate Assessing Models of Buildings	Reference
Urban areas in coastal zone	$\beta_2 = 100/[1 + 20.43 \times \mathrm{Exp}\,(-3.835 \times \Delta h)]$	[41]
Rural areas in coastal zone	$\beta_2 = 100/[1 + 52.88 \times \mathrm{Exp}\,(-4.876 \times \Delta h)]$	[41]
Urban areas in inland zone	$\beta_2 = 11.298 \times \mathrm{Ln}\,(\Delta h) + 37.534$	[42]
Rural areas in inland zone	$\beta_2 = 100/[1 + 9.05^{*}\mathrm{Exp}\,(-2.71 \times \Delta h)]$	[43]

Note: where β_2 is the loss rate of indoor property (%), Δh is the flood depth (m).

The method we proposed achieves the purpose of simply and quickly assessing house losses caused by the TRSSF chain. However, some models in this method are not established based on the data of Haikou City, so there may be some uncertainty in the calculation results. Therefore, we compared our results with government disaster bulletins and field survey data, and discussed the feasibility and reliability of our method, see Discussion for details.

3. Results

3.1. The TRSSF Chain in Haikou City

The wind speed and rainstorm intensity of typhoons needed for coastal and inland regions to occur floods in different return periods in Haikou City, as shown in Table 2, were obtained. It indicated that strong typhoons and super typhoons will cause floods in the coastal areas. While heavy rainstorms and extremely heavy rainstorms will lead to floods in inland areas.

In the case of an astronomical water level of 2 m in Haikou Station, strong typhoons can induce a 10-year, 20-year and 50-year flood, and super typhoons are prone to a 100-year flood. When the early water level of Longtang station is 10 and 11 m, heavy rainstorms can form a 10-year flood. In other cases, they can cause a 10-year, 20-year, 50-year and even 100-year flood. However, Haikou City has rarely encountered strong and super typhoons historically, while the heavy rainstorms brought by typhoons are more frequent, so that the inland areas of Haikou City are more prone to floods.

Immerged depth of floods induced by the TRSSF chain in different return periods in Haikou City is shown in Figure 2. The areas seriously affected by floods are concentrated along the Nandu River and north of Haikou City. Furthermore, with the increase in flood return period, the submerged area and submerged depth of the whole city increased. Specifically, the areas that have been seriously flooded include urban area III, IV and V, Longtang Town, Longquan Town, Xinpo Town, and Dongshan Town, which are along the Nandu River channel, indicating that river flood is the main flood type in Haikou City.

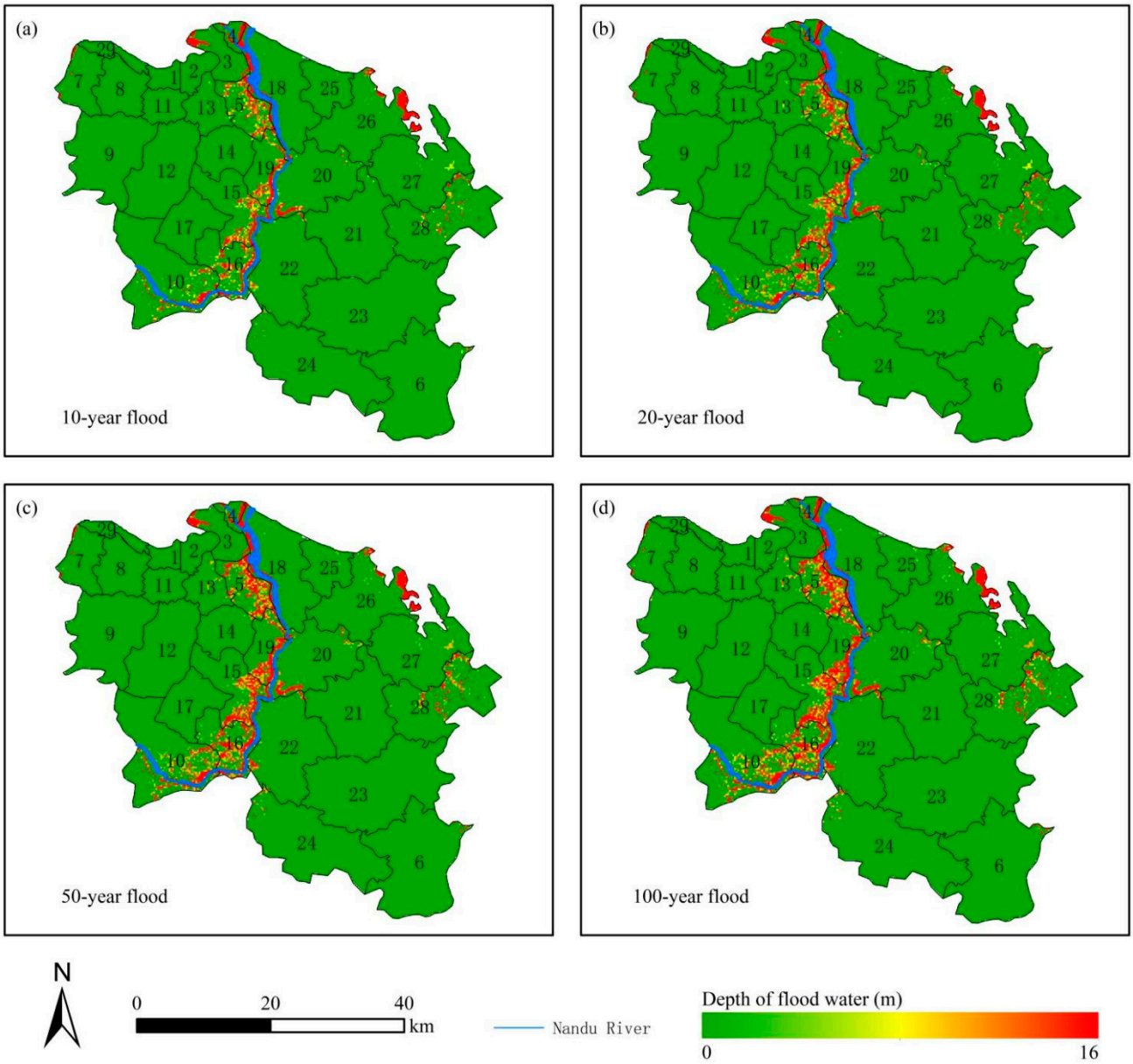

Figure 2. Immerged depth of floods in different return periods in Haikou City. (**a**) 10-year, (**b**) 20-year, (**c**) 50-year (**d**) 100-year. Note: The numbers represent assessment units.

In the northern coastal region, a few towns, such as Dazhipo Town, Sanjiang Town and Yanfeng Town, are prone to local water accumulation due to the low terrain and are also threatened by coastal floods. In addition to the strong impact of the TRSSF chain on floods, topography and distance to coast are also critical elements affecting the inundated situation. This leads to in some inland areas of Haikou city that are not along the seas and rivers, the possibility of being damaged by floods is much less.

3.2. House Losses Caused by the TRSSF Chain in Haikou City

Generally, the areas with a high loss rate of housing assets and indoor property are both concentrated along the Nandu River channel (Figures 3 and 4). Causing the loss rate in the inland areas along the river is even more serious than that in the coastal areas. At the same time, the city-wide house loss rate also increases with the increase of the flood return period.

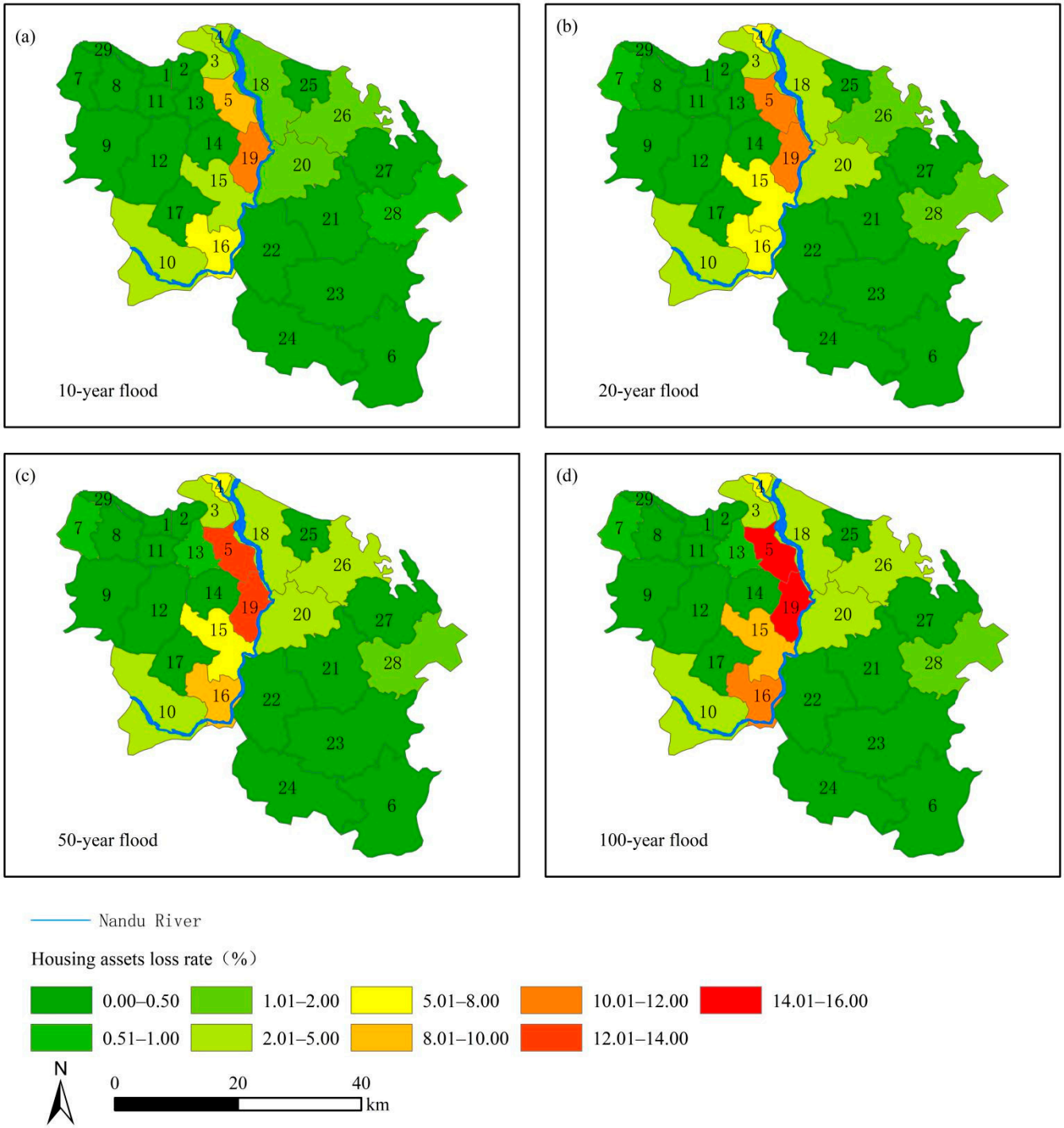

Figure 3. Housing asset loss rate in different flood return periods in Haikou City. (**a**) 10-year, (**b**) 20-year, (**c**) 50-year, (**d**) 100-year.

Figure 3 shows that, under different flood return periods, the loss rate of housing assets in different assessment units in Haikou is between 0–16%. The units with relatively high housing assets loss rate of over 8% increase significantly with increasing flood return periods. In particular, in the case of the 50-year return period, the area with housing assets loss rate of over 8% increases to 4% of the total area of Haikou City. When it comes to the 100-year return period, it increases to 6%, with the areas of very high loss rate exceeding 14% accounting for 4%.

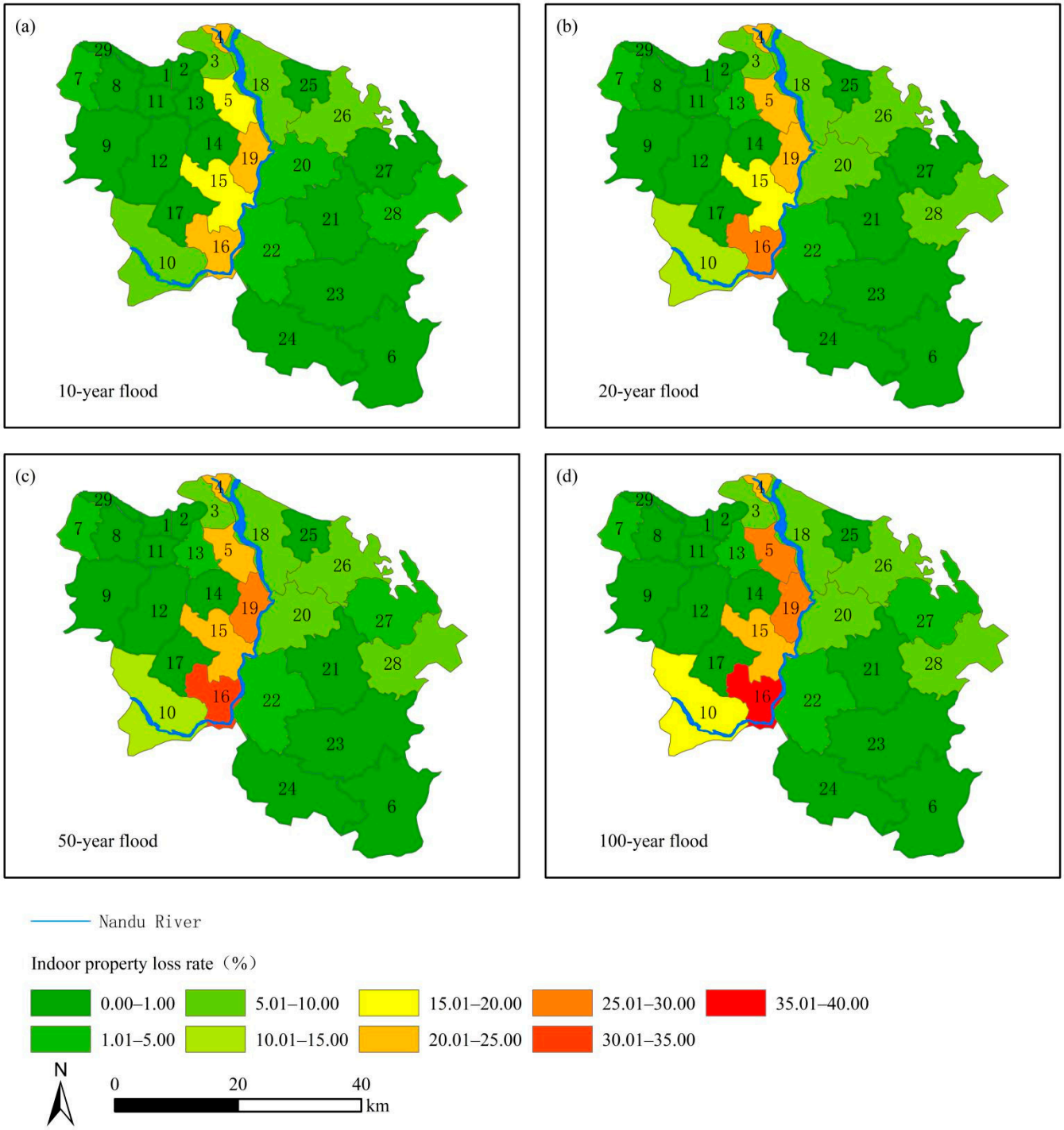

Figure 4. Indoor property loss rate in different flood return periods in Haikou City. (**a**) 10-year, (**b**) 20-year, (**c**) 50-year, (**d**) 100-year. Note: The numbers represent assessment units.

Figure 3 also shows that urban areas IV and V, and rural areas of Longquan Town, Xinpo Town, Longtang Town are areas with large housing assets loss rates. In comparison, the townships located in the hilly areas of the northwest and southeast, such as Shishan Town, Yongxing Town, Zuntan Town, Sanmenpo Town, Dapo Town, and Jiazi Town, suffer from a lower direct economic loss rate of housing assets.

Figure 4 shows that, under different flood return periods, the loss rate of indoor property in different assessment units in Haikou is between 0–40%, which is much higher than the loss rate of housing assets. The units with relatively high indoor property loss

rate of over 20% increase significantly with increasing flood return periods. In particular, in the case of the 50-year return period, the area with indoor property loss rate of over 20% increase to 10% of the total area of Haikou City. When it comes to the 100-year return period, it creases to 16%, with the areas of very high loss rate exceeding 35% accounting for 2%.

Figure 4 also shows that urban areas IV and V, and rural areas of Longquan Town, Xinpo Town, Longtang Town, and Dongshan Town are areas with large indoor property loss rates, where the Nandu River flows. While the villages and towns in the northwest and southeast hilly areas, such as Changliu Town, Haixiu Town, Yongxing Town, Zuntan Town, and Sanmenpo Town are almost unaffected.

Combined with the results of the housing asset loss rate and indoor property loss rate, the direct economic losses of houses under four different flood return periods in Haikou City were 1.327, 1.536, 1.813, and 2.037 billion RMB, respectively (Table 5). The direct economic losses of houses in Haikou City from high to low are Qiongshan District, Longhua District, Meilan District, and Xiuying District.

Table 5. Direct house losses in different flood return periods in the subdistrict of Haikou City.

Districts of Haikou City	Direct Economic Losses of Housing (10,000 RMB)			
	10-Year Return Period	20-Year Return Period	50-Year Return Period	100-Year Return Period
Xiuying District	16,305.85	20,119.66	25,452.06	30,032.33
Longhua District	37,496.44	45,583.69	56,025.09	64,542.06
Qiongshan District	42,753.77	49,655.50	58,355.36	65,665.93
Meilan District	36,146.92	38,223.86	41,459.58	43,461.48
Total	132,702.98	153,582.71	181,292.10	203,701.81

As shown in Figure 5, the direct economic losses of the affected houses in different areas of Haikou are quite different. The losses of the urban areas and towns along the Nandu River are generally more than 50 million RMB, while those of towns and villages in the hilly areas of the northwest and southeast are less than 200,000 RMB. This shows that the house losses caused by floods of the TRSSF chain are significantly influenced by the terrain, indicating that we should pay close attention to flood prevention in the low-lying areas where the river flows.

Figure 5 shows that, under different flood return periods, the direct house losses in different assessment units in Haikou City up to 370 million RMB. Even in the case of a 10-year flood return period, the direct losses of houses in nearly seven assessment units exceed 100 million, which are Dongshan Town of Xiuying District, Longquan Town and Xinpo Town of Longhua District, Longtang Town and Urban District V of Qiongshan District, and Lingshan Town and Urban District III of Meilan District. These units mainly distributed along the Nandu River channel. This further emphasizes that special attention should be paid to the lowland, which is highly influenced by the TRSSF chain. Especially for houses in urban and rural settlements, it is necessary to strengthen flood prevention measures along the river channel, under the situation that fast economic development leads to the rapid growth of housing assets and indoor properties.

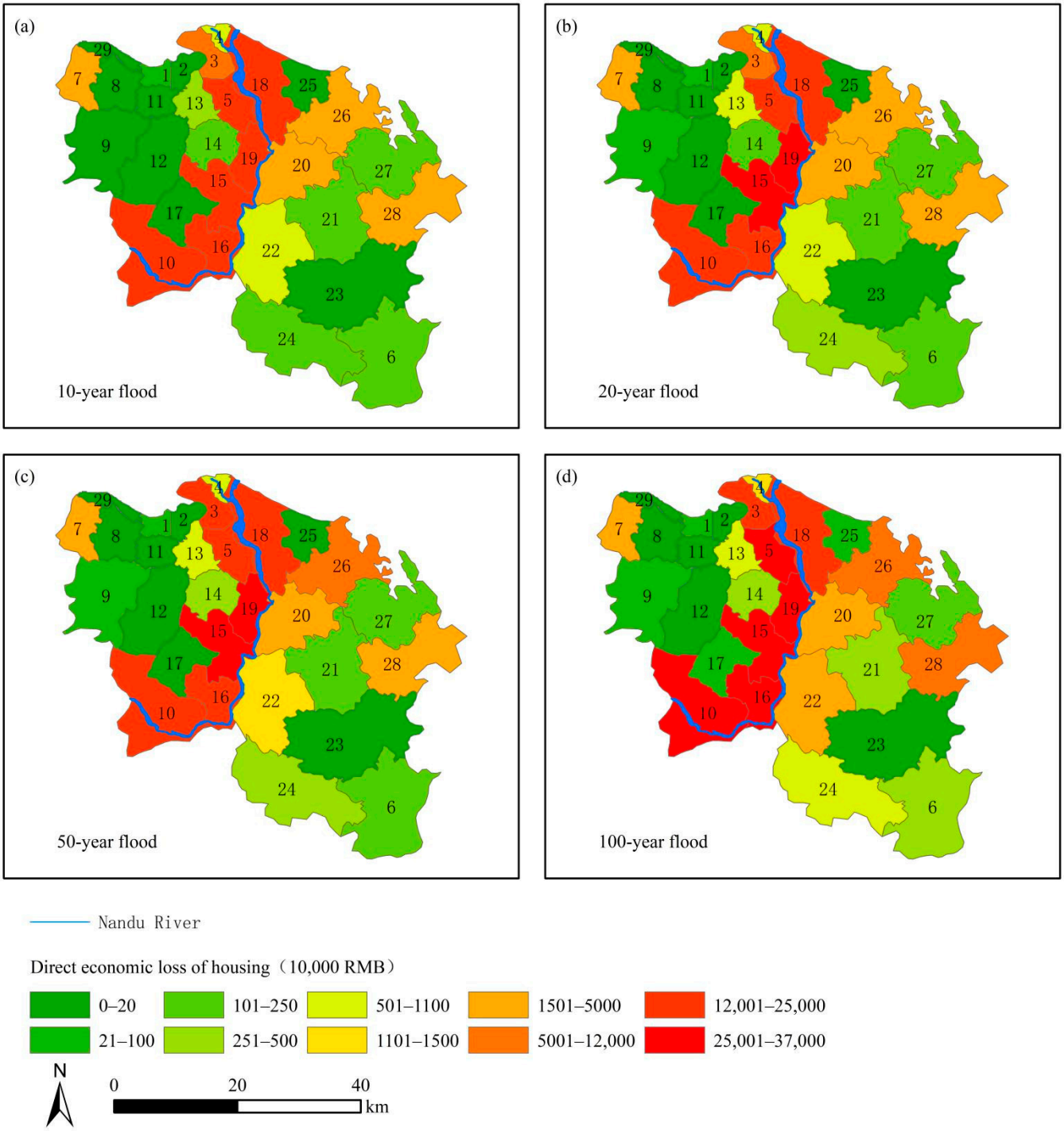

Figure 5. Direct house losses in different assessment units of Haikou City in different flood return periods. (**a**) 10-year, (**b**) 20-year, (**c**) 50-year, (**d**) 100-year. Note: The numbers represent assessment units.

4. Discussion

In the present study, a method of assessing house losses caused by the TRSSF chain was proposed. Then, this method was applied to assess the direct house losses in Haikou City. The results show that the areas where the Nandu River flows, such as Urban Area IV, Urban Area V, Longquan Town, Xinpo Town, Longtang Town, and Dongshan Town, are greatly affected by the TRSSF chain, while the towns located in the hilly areas of the northwest and southeast are less affected, and the houses losses of the inland areas along the river are more serious than the coastal areas (Figure 5). Our research results are highly

consistent with the actual disaster spatial distribution. According to the "Emergency Plan for Wind and Flood Prevention in Haikou City" provided by the Haikou Government Portal of China (http://www.haikou.gov.cn/, accessed on 22 May 2020), Longquan Town, Xinpo Town, Dongshan Town, Jiuzhou Town and Xinbu Island located in Urban Area IV are the most severely affected by floods. The spatial layout of disaster prevention and mitigation in Haikou City is based on historical actual floods distribution. Usually, towns with severe historical floods are designated as key prevention and mitigation areas. We, therefore, concluded that our results have relatively high credibility.

We also found that the direct economic losses of houses in Haikou City in four flood return periods range from 1.3 to 2 billion RMB (Table 5). Taking super typhoon "Rammasun" as an example, which affected Haikou in 2014, the official website of the Haikou City Government indicates that Rammasun caused direct economic losses of 8.386 billion RMB, among which the loss of houses was approximately 0.4 billion RMB and the loss of agricultural production and infrastructure was 2.582 billion RMB. Specifically, it caused the complete collapse of 1356 rural houses and destroyed 43,822 houses. That means the results of our assessment are much higher than what the government reported. Further analysis shows that our results are more reasonable because Rammasun landed in Hainan Province in Wengtian Town of Wenchang City, not in Haikou City. While the disaster statistics only focused on residential areas, neither take into account the losses of indoor property nor rural houses. In contrast, this paper evaluates the direct economic loss of housing more comprehensively, which is more in line with the actual loss situation.

For verifying the rationality of indoor property of towns in Haikou City used in this paper, a field survey of housing assets and indoor properties was carried out in November 2021 in Hainan Province on the basis of random sampling. The survey area covers the urban and rural areas of the coast and the inland. A total of 377 houses in eight cities including Haikou and Wenchang were investigated taking household as a unit. The survey indicators include the number of floors, the number of rooms, the building age, the distance from the house to the coastline (m), house structure, indoor property type, number of indoor properties, total indoor property value, etc. Furthermore, the indoor property of towns in Haikou City that were used in the present study (Figure S1) was compared to those based on samples of survey (Figure S2). Although the value of indoor property used in present study and that based on investigation cannot be directly compared, because they have different statistical unit, i.e., RMB/m^2 and RMB/household, respectively. They are well matched in in spatial distribution pattern (Figures S1 and S2), indicating townships with high indoor property exposure are concentrated along the west side of Nandu River. This proves that the method and result of indoor property calculation used in this paper are rational.

One innovation in our approach is the use of reverse derivation to reproduce the thresholds of typhoons, rainstorms, and storm surges required to cause floods of a specific intensity. This provides an idea for building a simple, fast, and relatively high-accuracy house losses assessment model in the TRSSF chain. That is, when a certain hazard factor, e.g., typhoon, reaches a certain intensity, the possible losses to the house can be quickly estimated. This method does not require a large amount of data and complex simulation operations, and although the mechanism is relatively weak, it can still obtain high accuracy after verification. In previous studies, the transmission process of the TRSSF chain has not received sufficient attention. For example, Guo et al. evaluated the number of collapsed houses based on the vulnerability curve of a typhoon–flood chain [31]. However, this work took the cumulative rainfall, river network index, topographic index, and strongest wind speed as explanatory variables but did not consider the link between typhoons and floods.

In terms of the house losses assessment, the factor regression analysis method [18] was applied in the present study based on the principle of geographical similarity [37,44]. Specifically, we took the flood depth and building age into account and selected widely acknowledged models [20,41–43] to assess the loss rate of housing assets and indoor property in Haikou City. It cannot deny that there are significant differences between

regions, and applying models developed in other regions may lead to greater uncertainty in Haikou City. However, we argue that although the models constructed by predecessors based on the actual situation of other regions have certain regional limitations, they still have reference value for regions with similar physical geography and social economy, such as Haikou City. Furthermore, we also suggest that the idea and the method proposed in this paper can be applied to other coastal areas on a global scale. Of course, this needs to be scientifically demonstrated and carefully verified.

There is still room for improving our study. DEM data are important for the calculation of submerged water depth. In the present study, NASA's DEM data were used because it is publicly available. However, these DEM data have relatively low resolution, which may introduce larger uncertainty to the results. Therefore, the results of future study may be greatly improved if higher resolution DEM data are available from local institutions. In addition, though our proposed method is easy to apply, the research results may have certain biases due to the lack of insufficient consideration of the mechanism of the TRSSF chain. Future studies may consider introducing mechanistic models. Further, the number of floors, rooms (size) and distance to coast are also factors affecting the economic loss of the houses in the TRSSF chain. However, due to the lack of detailed housing data, these factors were not taken into consideration in the present study. This should also be improved in future research.

5. Conclusions

Motivated by quickly assessing the house losses caused by the TRSSF chain using a small amount of data, we proposed a method according to the geographical similarity law and the idea of inverse deduction. Through this method, the losses of housing assets and indoor property in two different units of urban and rural areas caused by a typhoon–rainstorm–storm surge-induced flood can be quickly and quantitatively assessed. Furthermore, the typhoon, rainstorm, and storm surge intensity parameters required to cause a certain degree of house losses can be obtained. This can be an important reference for building an assessment model of house losses caused by the TRSSF chain. Since this method does not require a large amount of meteorological data and complex meteorological-hydro logical-loss simulations, it is very easy to implement and only requires a small amount of data to achieve a relatively accurate quantitative value of house losses. Therefore, the research ideas and methods proposed in this paper have the potential to be extended in similar regions.

The results show that the direct economic losses of houses (including housing assets and indoor property) in Haikou City in the 10-year, 20-year, 50-year, and 100-year return periods are 1.327, 1.536, 1.813, and 2.037 billion RMB, respectively. Based on data obtained from field surveys, our results are more consistent with the actual loss situation compared to the disaster statistics and reports from the government.

Furthermore, a comprehensive evaluation of housing assets and indoor property losses in two different units, urban and rural, respectively, was conducted. The direct economic losses of houses in each district from high to low are Qiongshan district, Longhua district, Meilan district, and Xiuying district. Additionally, the areas where the Nandu River flows, such as Urban Area IV, Urban Area V, Longquan, Xinpo, Longtang, and Dongshan, are affected more than the northwest and southeast hilly areas and even the coastal areas by the TRSSF chain. This indicated that topographic relief may have a strong influence on the risk of the TRSSF chain. These findings are beneficial for accurately revealing the spatial pattern of house losses caused by TRSSF chains. This provides the basis for risk management of the TRSSF chain in different administrative units and geographic units.

It also indicates that the loss rate of housing assets is significantly lower than that of indoor property, implying that the TRSSF chain may not cause a serious loss of the house building itself, but may cause a large number of indoor property losses. Especially with the fast development of the economy, the types and values of indoor properties will grow rapidly. This emphasizes that the assessment of indoor property losses caused by the TRSSF

chain should be paid more attention to. This requires extensive and detailed fieldwork to support.

Limited by data availability, NASA's DEM data at a 30 m spatial resolution were used in the present study. This may introduce a relatively larger uncertainty. In addition, the proposed method may have certain biases due to the lack of detailed housing data and insufficient consideration of the mechanism of the TRSSF chain. Therefore, mechanistic models based house losses assessment with support of higher resolution DEM data and detailed housing data, shall be a direction of future research.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w14193037/s1, Figure S1. Exposure of indoor property of towns in Haikou City used in this paper; Figure S2. Exposure of indoor property of towns in Haikou City calculated with field survey data.

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