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Guangzhou Metropolitan Area as a case study

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Scenario-based flood risk assessment for urbanizing deltas using future land-use simulation (FLUS): Guangzhou Metropolitan Area as a case study

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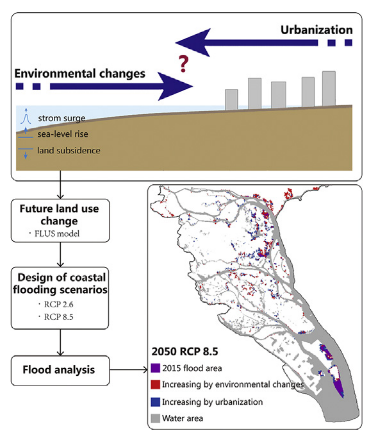
HIGHLIGHTS

- This study presents a scenario-based flood risk assessment approach.
- There will be a substantial increase in flooded urban areas in the future.
- Croplands and built-up areas are more sensitive to the increased risk of floods.

GRAPHICAL ABSTRACT



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ABSTRACT

Preparing cities for sea-level rise is one of the critical challenges of the twenty-first century. Extreme weather events, natural hazards, and the failure of climate mitigation and adaptation are substantial risks. These risks are especially significant in fast-urbanizing deltas, such as the Pearl River Delta in China, because the conflict between urbanization and flooding caused by climate change will be more significant in the future. This paper elaborates on an approach that employs a future land-use simulation (FLUS) model for scenario-based 100-year coastal flood risk assessment. Storylines of future scenarios from the Intergovernmental Panel on Climate Change (IPCC), called the representative concentration pathways (RCPs) 2.6 and 8.5, are utilized in the present study. The Guangzhou Metropolitan Area (GMA) is used as a case study to explore the probable implications of future land-use changes due to the ongoing urbanization process in the region in relation to projected environmental changes (sea-level rise, storm surge, and land subsidence). The results indicate that there will be a significant increase in flooded urban areas in the future. The simulations show that, as compared to 2015, the built-up area in the GMA will increase by 246.57 km^2 in 2030 and 513.03 km^2 in 2050. As compared to 2015, the flooding of built-up areas in 2030 and 2050 will respectively increase by about 31.32 km^2 and 48.49 km^2 under the RCP 8.5 scenario. It is also found that, as the main driving factor, urbanization will increase the flooding of built-up areas in Guangzhou in 2030 and 2050 by about 1.9 km^2 and 5.9 km^2, respectively, under the RCP 2.6 scenario as compared to 2015. Additionally, due to environmental changes, the flooding of built-up areas in Guangzhou will

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increase by about 24.2 km^2 and 26.8 km^2, respectively, under the RCP 8.5 scenario by 2030 and 2050 as compared to 2015. This increasing flood risk information determined by the simulation provides insight into the spatial distribution of future flood-prone urban areas to facilitate the development and prioritization of flood mitigation measures at the most critical locations in the region.

1. Introduction

Climate change and urbanization are critical challenges in the twenty-first century (Carter, 2018; Hinkel et al., 2014; Pecl et al., 2017;). Coastal flooding and waterlogging have produced widespread and significant effects all over the world, especially in urban deltas (Francesca-Huidobro et al., 2017; Jongman et al., 2012; Meyer et al., 2017; Tessler et al., 2015). Due to the advantages of their geographical positions and the availability of natural resources, such as fertile land, deltaic areas have become prominent for human society and economic and cultural activities (Meyer and Nijhuis, 2013). Currently, about 25% of the world's population lives in coastal cities such as Lagos, Hong Kong, Rotterdam, and Guangzhou, which are mostly located in deltas and estuaries of significant rivers (Syvitski et al., 2005). The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) estimates a sea-level rise that ranges from 0.45 to 0.82 m in 2100, following the representative concentration pathway (RCP) 8.5 scenario (Hinkel et al., 2015). Even if humans adopt measures to reduce emissions, global sea levels will continue to rise (Meehl et al., 2012). Additionally, if the effects of land subsidence are taken into account, the impact of sea-level rise in the future will be even more significant (Vousdoukas et al., 2018). Globally, 85% of deltas have already experienced severe flooding in recent years, with the temporary submergence of approximately 260,000 km^2 of land (Syvitski et al., 2009).

In fast-urbanizing deltas, such as the Pearl River Delta in China, the conflict between urbanization and flooding caused by climate change will be particularly significant in the future. Therefore, climate adaptation and mitigation are priority issues to safeguard the economic development and livability of urbanizing deltas, and there is a need for knowledge and tools to address the conflict between urbanization and flood risk (Carter et al., 2015; Haynes et al., 2018; Wang et al., 2015; Wu et al., 2017). For example, current climate adaptation policies do not address the spatial consequences of flooding (Berke et al., 2019; Lai et al., 2016). Additionally, some of the spatial changes are associated with the urbanization process, such as land-use change, as demonstrated by Szwagrzyk et al. (2018) and Gori et al. (2019), both of which consider future land-use change in the flood risk assessment process. However, these studies do not take into account factors for land-use change using multi-resources data (social economy data, traffic data, points of interest (POI), environmental factors, and planning constraints) in relation to flood risk (Feng et al., 2018b; Long and Wu, 2016). The lack of awareness of the consequences of flooding results in insufficient government investments in climate adaptation actions (Gill and Lange, 2015; Reckien et al., 2018). Thus, there is an urgent need for more comprehensive approaches that take into account the complexity of the parameters involved in urbanization in relation to flood risk.

As a basis for the planning and design of flood risk mitigation, computational scenario-based assessment is a powerful and integrative approach by which to deal with the complexity of the involved parameters and to identify the most vulnerable locations (Feng et al., 2018a; Long et al., 2014; Lai et al., 2020). For example, Muis et al. (2015) used a land-change model based on GEOMOD to assess future flood risk and adaptation strategies in Indonesia. Mustafa et al. (2018) studied the effects of spatial planning and future flood risk in the Wallonia region in Belgium using an agent-based model (ABM). Cellular automata (CA)-based Markov chain modeling, LUCIA modeling, and the Land-use Scanner have also been successfully applied (Bouwer et al., 2010; Feng and Liu, 2016; Hansen, 2010; Lang et al., 2018; Lu et al., 2018).

This paper elaborates on an approach that employs a future land-use simulation (FLUS) model for computational scenario-based flood risk assessment. The FLUS model interactively combines an artificial intelligence approach (an artificial neural network, ANN) and a CA model to simulate nonlinear land-use change while taking into account parameters related to the environment, social economy, climate change, etc. (Li et al., 2017). The model also employs self-adaptive and competitive mechanisms to stimulate the complex interactions of different land-use types, including neighborhood influence, weight factors, self-adaptive land inertia, conversion costs, and roulette wheel selection (Li et al., 2017). The FLUS model has a high simulation accuracy as compared with other mainstream land-use change models, such as CA models and CLUE-S (Liu et al., 2017). This study also exemplifies the integration of the FLUS model with environmental change-based storm surge inundation. The Guangzhou Metropolitan Area (GMA) located in the Pearl River Delta in China, one of the fastest urbanizing deltas in the world, is used as a case study to explore the probable implications of future land-use changes due to the ongoing urbanization process in the region in relation to projected environmental changes (sea-level rise, storm surge, and land subsidence). The findings of this research can aid in the development of effective spatial strategies for climate-adaptive urban development.

2. Materials and methods

2.1. Study area

The Guangzhou Metropolitan Area (GMA) covers an area of 7434 km^2 (Fig. 1) and has a high population density as compared to other metropolitan areas in the world. The area has a subtropical monsoon climate. From 1979 to 2013, the built-up areas in Guangzhou increased by 1512.25 km^2 (Wu et al., 2016). During the process of rapid urbanization, dispersed urban development has a great impact on the water management and ecological and cultural values of the ecological-agricultural dike-pond system that is characteristic of the western inner delta (Liu et al., 2020). The land reclamation and sand mining activities in the estuaries reduce their ability to naturally cushion storm surge flooding and absorb river water from the hinterland (Xiong and Nijhuis, 2019). Due to subsidence, climate change, etc., Guangzhou flooding loss is projected to rank first of the 136 port cities in the world in 2050 (Hallegatte et al., 2013). According to the Guangdong province 100-year coastal flooding comprehensive assessment, the south area of Guangzhou was found to be at extremely high-risk (LI and LI, 2013). Additionally, increasing sea-level rise, the increasing frequency and intensity of storm surge, and land subsidence in combination with urban development in flood-prone areas make Guangzhou one of the most vulnerable metropolitan regions for flood risk in the upcoming decades (Hallegatte et al., 2013; Han et al., 2010; Zhang, 2009).

2.2. Data

Social, economic, and transportation parameters, as well as important POI, environmental factors, and planning constraints, were determined to be spatial factors of the flood risk assessment of the GMA. Land-use data of the years 2010 and 2015 supplied by the Data Center

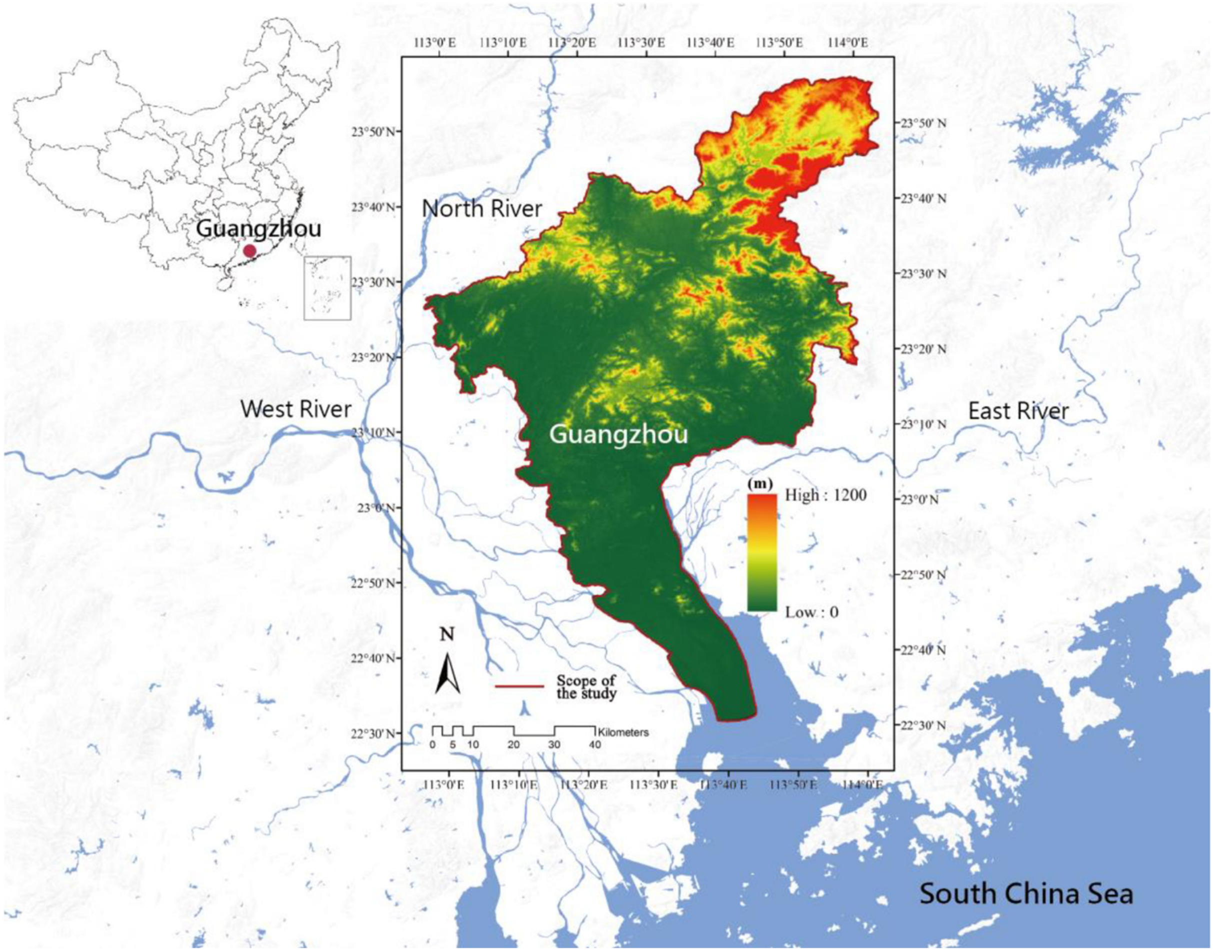

Fig. 1. The study area of Guangzhou City.

for Resources and Environmental Sciences of the Chinese Academy of Sciences was used as the basis for the analysis, and a manual visual correction of the raw land-use data was conducted. The classification scheme developed by the Chinese Academy of Sciences was utilized, and six types of land use, namely cropland, woodland, grassland, water areas, built-up land, and unused land, were identified (Liu et al., 2003). The Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM), which has a 30-meter resolution, served as the basis for data on terrain heights and the calculation of slopes and aspects. Data on the soil characteristics (e.g., clay content, slit content, sand content, and type of soil), temperature, precipitation, gross domestic product (GDP), and population were provided by the Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences. Traffic data were collected from open-source data retrieved from OpenStreetMap (OSM). POI data were extracted from Gaode Map. The limiting factors of space were considered to be the basic ecological control line and permanent basic cropland as outlined in the 2017–2035 Guangzhou City Master Plan. An unified coordinate transformation was performed with ArcGIS. POI and traffic data were calculated using the ArcGIS Euclidean distance. All materials were converted into 100×100-m grid data via resampling. All data sources are listed in Table 1.

2.3. Methodology

The presented approach for scenario-based flood risk assessment in urbanizing deltas is the integration of the FLUS model, a Markov chain model, and ArcGIS. The FLUS model is an improved future land-use change model proposed by Sun Yat-Sen University, which includes a top-down land-use change prediction model and a down-top CA model. It can solve complex land-use demand projection and land-use allocation issues. Additionally, an ANN model is embedded to train non-linear relationships between historical land-use types and complex driving factors, which can be used to calculate the probability of distribution. A self-adaptive inertia and competition mechanism is also designed to stimulate the complexity of transformation between different land-use types. A Markov chain model is used to predict land-use demand in a business-as-usual (BAU) scenario, which is one of the crucial data inputs in the FLUS model. Finally, the ArcGIS overlay function is used to analyze coastal flooding and the impacts of urbanization and environmental changes under the RCP 2.6 and 8.5 scenarios in 2030 and 2050. The overall framework of scenario-based future flood risk assessment is illustrated in Fig. 2.

In the framework, the FLUS model and Markov chain model are designed to stimulate complexity and dynamic land-use change processes through 2050 while considering 25 factors, which include planning policy factors and land-use data from 2010 and 2015. Moreover, this study considers environment change factors (sea-level rise, storm surge, and land subsidence), and the scenarios of coastal flooding are divided into the RCP 2.6 and 8.5 scenarios in 2030 and 2050. Finally, via ArcGIS spatial analysis, the flooding of different land types are calculated employing different flooding scenarios. The present work therefore provides an opportunity to determine a comprehensive and adaptive path, such as flood risk management, in delta areas based on the proposed scenario-based flood risk assessment framework.

Table 1
The sources of data used in this study.

No.	Data type	Description	Source	Resolution
1	Land use	2010, 2015 land use	www.resdc.cn	30 m
2	Social economy	2015 GDP and population data	www.resdc.cn	1 km
3	Elevation	DEM	www.gscloud.cn	30 m
4	Traffic	Highway, primary, secondary, and other roads	www.openstreetmap.org	
5	Points of interest	Region centers, businesses, airports, bus stations, city center, gardens, education centers, residential areas, subway stations, and train stations	https://lbs.amap.com/	
6	Environmental factors	Slope and aspect	DEM	30 m
		Clay content, slit content, sand content, type of soil, temperature, and precipitation	www.resdc.cn	1 km
7	Planning constraints	The basic ecological control line and permanent basic cropland	2017–2035 Guangzhou City Master Plan	

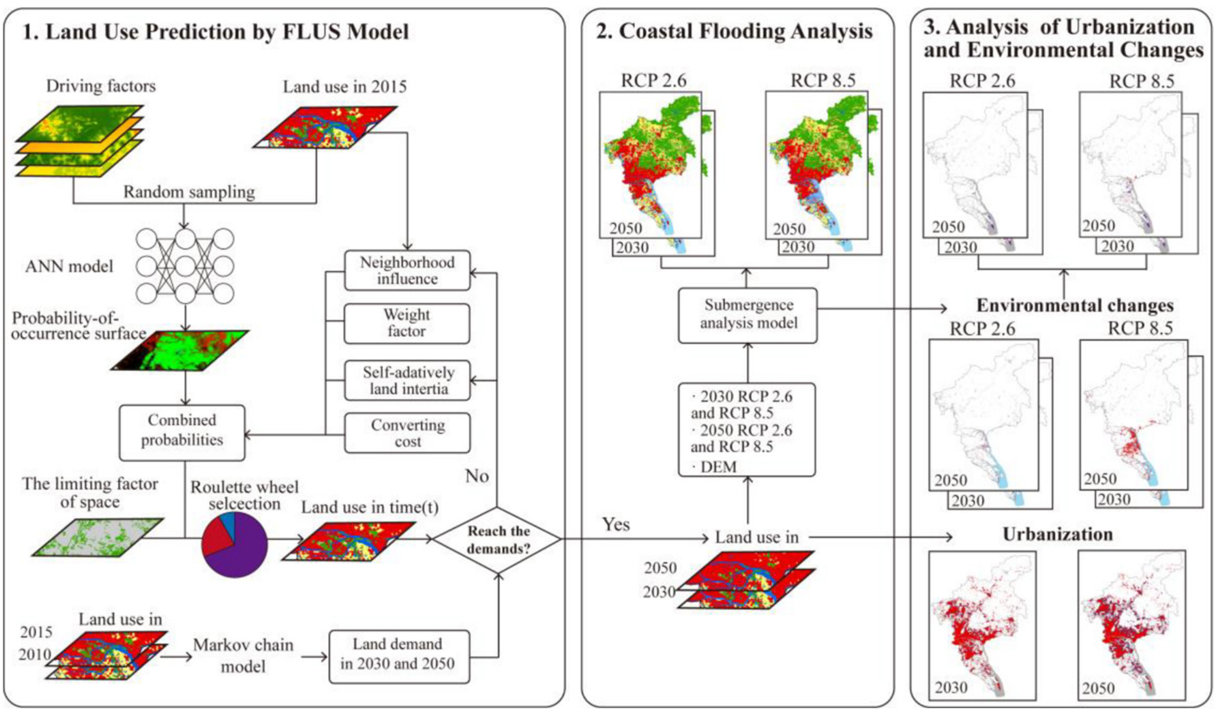

Fig. 2. The overall framework of scenario-based future flood risk assessment.

2.3.1. Markov chain model

The Markov chain model is based on stochastic process theory (Lu et al., 2018); it predicts dynamic variation characteristics and is characterized by both high operational precision and high prediction accuracy. It has been widely used in the prediction of land-use changes (Arsanjani et al., 2013; Gounaridis et al., 2019; Keshtkar and Voigt, 2016).

In this study, land-use information from 2010 and 2015 was extracted, and the Markov model transfer matrix was used to analyze the mutual transformation relationship of different land-use types, from which the conversion probability matrix of land conversion was calculated. The formula is as follows:

$$P = [P_{11} \quad \cdots \quad P_{1n} \vdots \cdots \vdots P_{n1} \cdots P_{nn}] \tag{1}$$

where n is the number of land-use types and P_{ij} is the transition probability that land-use type i is converted to land-use type j; P_{ij} must meet the following two requirements: $0 \le P_{ij} \le 1$, .

The total amounts of future land-use types in 2030 and 2050 were predicted with five years as the step of the transformation matrix, and the findings are reported in Table 2.

2.3.2. The FLUS model and accuracy verification

The FLUS model is a land-use change simulation model that combines deep learning with CA and neural networks. Liu et al. (2017) published the working mechanism of the FLUS model, which considers neighborhood influence, weight factors, self-adaptive land inertia, and conversion costs; the model was found to achieve higher simulation accuracy than the CA and CLUE-S models. Since its proposition, the FLUS model has been applied to research at different scales and for different purposes, such as the delineation of urban growth boundaries, land-use projections under global socioeconomic and emission scenarios, and functional connectivity under urban expansion scenarios (Dong et al., 2018; Huang et al., 2018; Liang et al., 2018).

Table 2
Results of land-use forecast (grid of 100 × 100 m).

Year	Cropland	Woodland	Grassland	Water area	Built-up land	Unused land
2015	210,224	304,329	9641	71,128	145,387	220
2030	195,407	297,158	9758	68,323	170,044	239
2050	180,780	288,087	9854	65,264	196,690	254

Therefore, the FLUS model was adopted for spatial simulation in the present study. First, according to the land-use types in mainland China, land use was divided into six classes. Additionally, via the reverse neural network model, a three-layer BP-ANN model was adopted. Twenty-five spatial driving factors (including data on the social economy, DEM, traffic, points of interest, and environmental factors) were selected to train the ANN model (see Table 1). There were 6 output layers corresponding to the six types of land use. The model was trained on driving factors and land-use data to obtain a probability distribution map. Second, the adaptive inertial competition module of the FLUS model was used to simulate the land-use change in 2015 with the land use in 2010 as the starting year, and the simulation results were compared with the real 2015 land-use map via a Kappa test, as follows:

$$\text{Kappa} = (P_0 - P_c)/(P_p - P_c) \tag{2}$$

where P_0 represents the correct proportion of the simulation, P_c represents the correct proportion of the model in the random case, and P_p represents the proportion of the correct simulation in the case of ideal classification. The verification results revealed that the overall accuracy and kappa coefficient reached 94.25% and 91.81%, respectively. This demonstrates that the accuracy of the simulation met the requirements, and that the model can realistically reflect the rule of land-use change in Guangzhou. The simulation results are therefore reliable and can be used for future prediction in 2030 and 2050.

2.3.3. Design of future coastal flooding scenarios

Future coastal flooding is affected by numerous complex factors, such as storm surge and sea-level rise. Storm surge is associated with low-pressure weather systems, such as tropical cyclones and intense extratropical cyclones, and sea-level rise is related to the future emission path, which is deeply uncertain. Therefore, the prediction of future changes based on historical monitoring data is an effective way to reduce uncertainty. He et al. (2015) used the EEMD-BP (ensemble empirical mode decomposition-back propagation) model to predict future sea-level rises in the Pearl River Delta via historical sea-level data from 1959 to 2011 acquired from the Zhapo monitoring station. Li and Li (2013) and Li and Li (2010) previously published articles about the risks of storm surge in the Pearl River Delta based on historical monitoring data. Based on this, Kang et al. (2016) integrated the findings to evaluate future farmland losses via historical sea-level rise and storm surge data in the Pearl River Delta, and categorized 1-in-100-year storm surge data into low- and high-estimation scenarios in 2030, 2050, and 2100.

In the present study, the data from Kang et al. (2016) was employed as the input of the scenario design. However, this data did not consider land subsidence, which is an essential factor in delta areas. With reference to the research of Hallegatte et al. (2013) on flooding loss in the major coastal cities, the values of land subsidence in 2030 and 2050 were selected to be 0.2 m and 0.4 m, respectively. In the 2015 scenario, the height of the storm surge in a 1-in-100-year storm was 3.01 m (Li and Li, 2010). This study utilized similar storylines of future scenarios from the IPCC, namely the RCP 2.6 and 8.5 scenarios. For the 2030 and 2050 scenarios, the RCP 2.6 and 8.5 scenarios were respectively defined to correspond to the low- and high-estimation scenarios of Kang et al. (2016) (see Table 3).

Table 3
Different future coastal flooding scenarios in 2030 and 2050.

Scenario	2030	2050
RCP 2.6	3.43 m	3.69 m
RCP 8.5	4.70 m	4.98 m

3. Results

3.1. Future spatial-temporal land-use change in Guangzhou

Due to the construction of infrastructure, the effect of radiation in the surrounding area, the flat terrain, and sufficient room for development and utilization in terms of policy restrictions, there was urban sprawl in the western and southern regions (see Fig. 3). Overall, the built-up land areas in 2030 and 2050 were respectively projected to increase by 246.57 km^2 and 513.03 km^2 as compared to 2015, accounting for approximately 3.33% and 6.92% of the total area. The most significant reduction was found for cropland, which was predicted to decrease by 148.17 km^2 and 294.44 km^2 as compared to 2015, respectively, in 2030 and 2050, accounting for approximately 2.00% and 3.97% of the total area. The mountain terrain in the northern region is not suitable for large-scale development. Additionally, large amounts of mountainous land and farmland in the region are listed as ecological protection areas, so the growth of these areas is not expected.

3.2. Analysis of different scenarios

The elevation data was enhanced to improve the accuracy of the flood prediction. In this study, 2-m contours were created via the ArcGIS "create contour" function from the 30-m evaluation. Then, 10-m-precision DEM data were created by the "Create TIN" and "TIN to Raster" functions from the 2-m contour data. To prevent the overestimation of the submersion values, only areas connected to a body of water were selected as the submerged range. Additionally, the ArcGIS "raster calculator" function was used to extract different land types inundated in the GMA (see Fig. 4). From 2030 to 2050, with the consideration of sea-level rise and storm surge, the inundations of various classes of land in Guangzhou exhibited increasing trends, and the increase of agricultural land was the most obvious. Specifically, the inundation of water land was found to be the largest (297.64 km^2, accounting for approximately 86.44% of the total inundation area) under the RCP 2.6 scenario in 2030. Cropland and built-up land are the other two primary types of calculations used for submerged areas; the inundations of these land types were calculated to be 27.28 km^2 and 17.94 km^2, respectively, accounting for approximately 7.92% and 5.21% of the total inundation area under the RCP 2.6 scenario in 2030. Under the RCP 8.5 scenario, the flooding of built-up areas in 2030 and 2050 was respectively calculated to cover about 46.39 km^2 and 63.56 km^2, accounting for approximately 9% and 12% of the total flooded areas in these years. As compared to 2015, the flooding of built-up areas under the RCP 8.5 scenario was calculated to increase by about 31.32 km^2 and 48.49 km^2 in 2030 and 2050, respectively. Further, with the continuation of time and under different scenarios, the exposure of various types of land was found to increase, and built-up land and cropland were predicted to be the most impacted. The exposure of cropland in 2030 under the RCP 8.5 scenario was found to be 101.91 km^2 greater than that under the RCP 2.6 scenario. The exposure of built-up land in 2030 under the RCP 8.5 scenario was found to be 28.45 km^2 greater than that under the RCP 2.6 scenario. In 2050, the exposures of cropland and built-up areas were also predicted to be the most dominant; under the RCP 2.6 scenario, the exposures of cropland and built-up land were respectively predicted to be 27.76 km^2 and 22.52 km^2. Additionally, as compared to the RCP 2.6 scenario in 2050, the exposures of cropland and built-up areas were found to increase by 101.76 km^2 and 41.04 km^2, respectively, under the RCP 8.5 scenario.

3.3. Impacts of urbanization and environmental changes on built-up land exposure

By comparing the scenarios in 2015, 2030, and 2050, it is evident that the exposures of various types of land exhibit increasing trends with time, and the two most important factors of the exposure of built-up land are urbanization and environmental changes. Therefore,

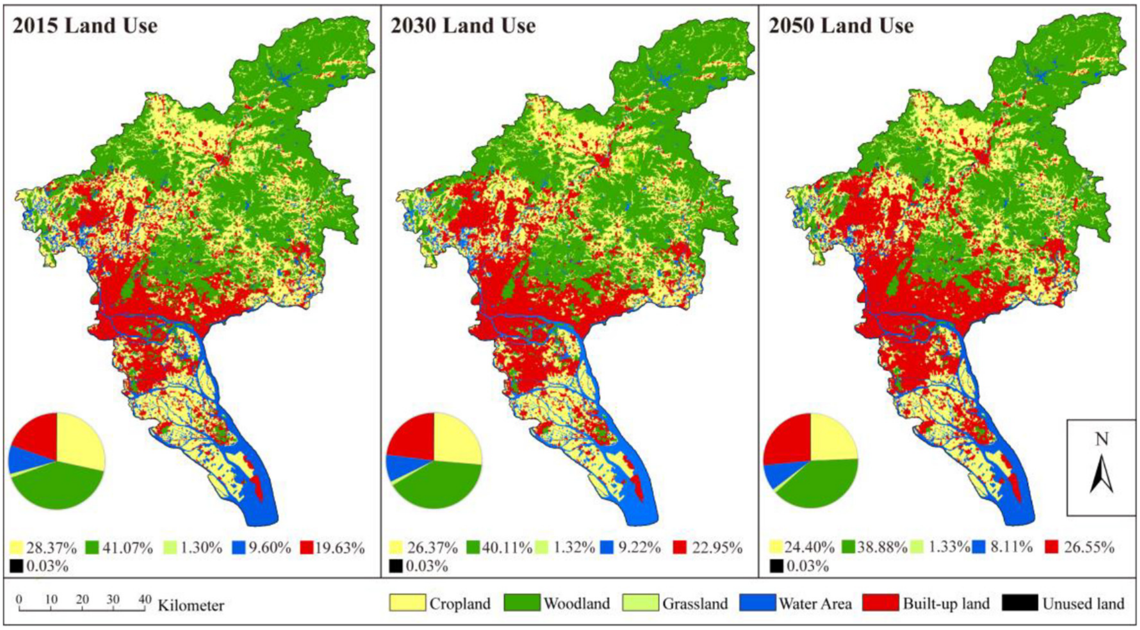

Fig. 3. Land-use simulation results.

the impacts of these two factors were investigated, as presented in Figs. 5 and 6. It was found that, as the main driving factor, urbanization will result in the increase of the flooding of built-up areas in Guangzhou by 1.9 km^2 and 5.9 km^2 under the RCP 2.6 scenario in 2030 and 2050, respectively, as compared to 2015. Due to environmental changes, the flooding of built-up areas in Guangzhou was projected to increase by 24.2 km^2 and 26.8 km^2 under the RCP 8.5 scenario in 2030 and 2050, respectively, as compared to 2015. Whether under the RCP 2.6 or 8.5 scenario, the impact of urban expansion was projected to increase over time. Under the RCP 8.5 scenario in 2030, the land area that will be exposed due to environmental change was found to be over 17.1 km^2 greater than that which will be exposed due to urban development; under the RCP 8.5 scenario, this gap was found to narrow to approximately 5.1 km^2 in 2050. These two factors were found to be the primary contributors to the exposure of built-up land, together accounting for about 76% of the total. Overall, the impacts of urban expansion and environmental changes should be the foremost targets for future coastal flood risk management. Under the RCP 8.5 scenario, environmental changes are the priority for policy development and spatial planning. Additionally, urban expansion restrictions are crucial for informing the long-term goals of climate-adaptive governance.

4. Discussion

The analysis of the confrontation of future urbanization processes and environmental changes, such as sea-level rise due to climate change is essential for the development of more resilient urban deltas, and the relationships between these factors are complex and dynamic. As exemplified by the present study, computational scenario-based assessment is a powerful and integrative approach that can handle the complexity of the involved parameters, and is a useful method for the identification of the most vulnerable locations as a basis for the planning and design of flood risk mitigation efforts.

4.1. Evaluation and related uncertainties of the proposed approach

The proposed approach provides a practical and comprehensive way to deal with the complexity and dynamics related to urbanization (urban sprawl) and environmental changes (sea-level rise, storm surge, and land subsidence). First, the FLUS model embedded with an ANN can efficiently integrate the relationship between all driving factors and land-use changes, and can therefore obtain more realistic simulation results. Second, storm surge is affected by many factors, e.g., climate change, tropical cyclones, sea-level rise, etc. Therefore, historical sea-level monitoring data of the Pearl River Delta was employed as input data for scenario design in the present study, which is a useful way to consider these complex factors. Further, based on the scenario, the analysis of future flood risk due to environmental changes and urbanism can offer new insight with which to adjust future spatial targeting. Therefore, the efficiency of the proposed future coastal flood risk assessment framework to guide future flood risk management is guaranteed.

The uncertainties of this approach result from the DEM and flood modeling. The SRTM DEM is a type of digital surface model, and the model elevation is usually higher than the actual value in built-up areas due to the effects of buildings, which will affect the simulation results. As compared to the prediction of future coastal flooding risk by the statistical analysis of historical data, hydrodynamic models, such as MIKE, will obtain different stimulation results due to their different data computation processes (Wu et al., 2018). The uncertainties from different data resolutions and data sources, such as transformation by resampling, can also result in errors. Overall, although uncertainties cannot be avoided in the assessment of coastal flood risks, the deviation of the outputs of the proposed approach is acceptable, and scenario analyses are deemed satisfactory for future coastal flood risk prediction.

4.2. Review of simulation results

By applying the proposed framework to data from Guangzhou, China, it was found that both cropland and built-up land will be sensitive to future changes. This is primarily because most of the low-lying areas in the southern region are cropland, and urban expansion extends to floodplain areas. Additionally, grasslands are primarily concentrated in high-altitude areas, so they will not experience a significant impact in future scenarios. Moreover, cropland is the main type of land in lowland areas; thus, although the amount of cropland will decrease in the future, the flooding of cropland will still inevitability increase.

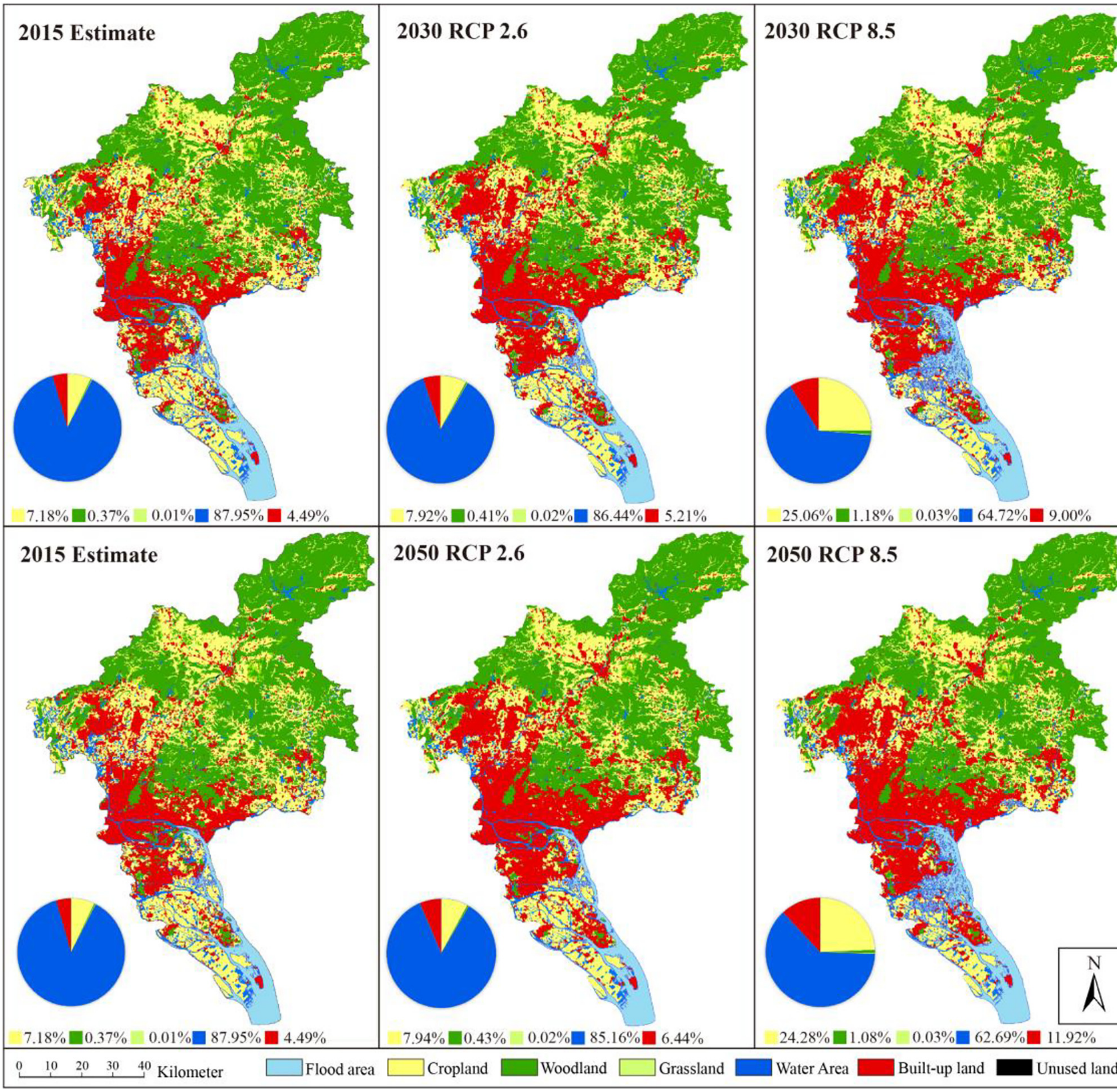

Fig. 4. Simulation results of different scenarios in 2030 and 2050.

As expected, the simulation revealed that the main flooding areas are often near the main river. The reason for this is that current spatial planning seldom considers flood risk, and mainly focuses on the protection of ecology such as permanent basic farmland. It was found that, under the RCP 2.6 and 8.5 scenarios, urbanization and environment changes (sea-level rise, storm surge, and land subsidence) are respectively the main driving factors for the flooding of built-up land areas.

Thus, in consideration of the deep uncertainty related to future dynamic changes in the GMA, the results of the present study can help decision-makers to understand future coastal flooding characteristics and verify whether current preparation measures for climate adaptation are sufficient. The findings can also promote interdisciplinary cooperation with all stakeholders and authorities to manage future flood risks. Depending on the future development pathways of urbanization and environmental changes, policies can be endowed with more resilience and flexibility and thus greater cost-benefit characteristics, which may be a process of nonlinear and review by repetition.

4.3. Flood adaptation strategies and policies

In the twenty-first century, preparing cities for coastal flooding is a critical challenge, and the relevant authorities require guidance from risk analysis to define flood adaptation strategies and policies. The present study can support decision-makers to decide how to invest in adaptive measures that avoid unnecessary flood defenses and the limiting of economic development (spatial limitation in inundation areas). In the near future, the GMA must consider increasing engineering measures and spatial planning, such as its drainage system, sluice gates, and flood buffer zones, in the increasing inundation areas to support urban development. Recently Liu et al. (2019) and Sajjad et al. (2018) argued that nature-based and hybrid (nature engineering mixed) approaches towards climate change adaptation measures have a multitude of benefits. Therefore the GMA needs to include and prioritize conservation and restoration of coastal natural systems, such as coastal wetlands, mangroves and dune ecosystems, in policy and regulations.

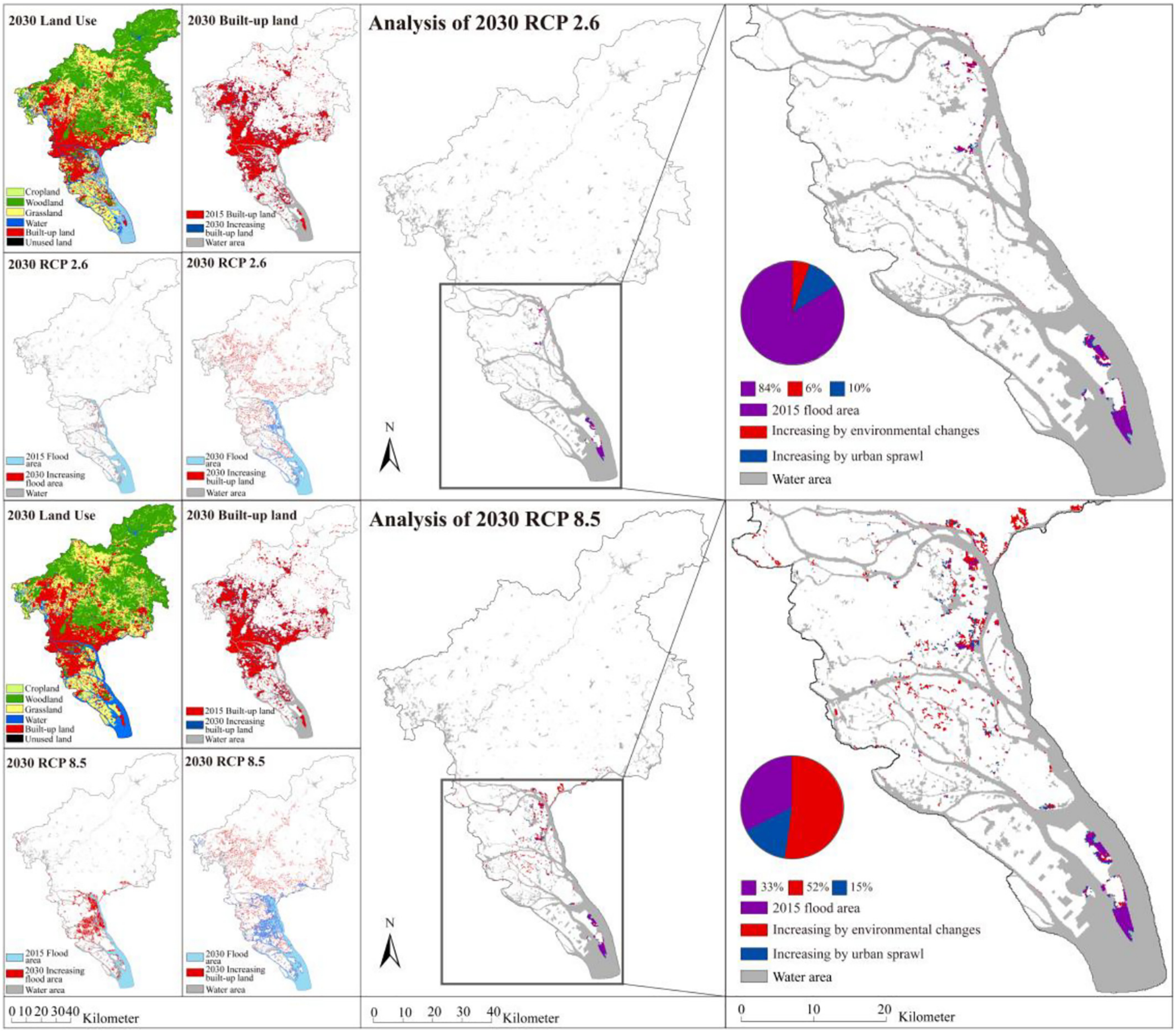

Fig. 5. Analysis of the impacts of urbanization and environmental changes on the exposure of built-up land in 2030.

A flexible and multi-spatial-scale flood management scheme must be considered for both current and developing built-up areas. Socioeconomic development and land-use functions also require dynamic adjustment for future flooding scenarios. For example, the economic model of agriculture may transform into a model of aquaculture. Regarding the planning of building types, it is suggested that the GMA implement a compacted urban structure and develop innovations in construction techniques, such as floating buildings. In addition, to ensure safety, the GMA must establish an emergency strategy for flood risk management that includes evacuation routes, rescue systems, and assistance mechanisms. Overall, the applicable approach for the GMA may provide guidance for coastal flood risk management in other cities.

4.4. Limitations and future work

Because of the focus on estuaries and not on inner deltas, waterlogging and the defense of the regional dike system, which are also severe challenges to Guangzhou due to the change of future precipitation patterns, were not discussed in the present study. Additionally, the FLUS model did not take into account future flood risk management in the urban environment, which may lead to an overestimation of flood risk. Thus, more research must be conducted in the future when solid data is available. Additionally, land-use forecasts via socioeconomic pathways (SSPs) will make this approach more realistic and able to assume different urbanization scenarios.

5. Conclusion

For the development of more resilient urban deltas, computational scenario-based assessment was found to be a powerful approach for the determination of the locations most vulnerable to flood risk. By considering the effects of urbanization and environmental changes, the model provided significant insights into the range and spatial distribution of flood risk in the GMA, and results indicate that there will be a substantial increase of flooded urban areas in the future. The simulations revealed that the built-up area will increase by 246.57 km^2 in 2030 and 513.03 km^2 in 2050 as compared to 2015. Under the RCP 8.5 scenario, the flooding of built-up areas in 2030 and 2050 was calculated

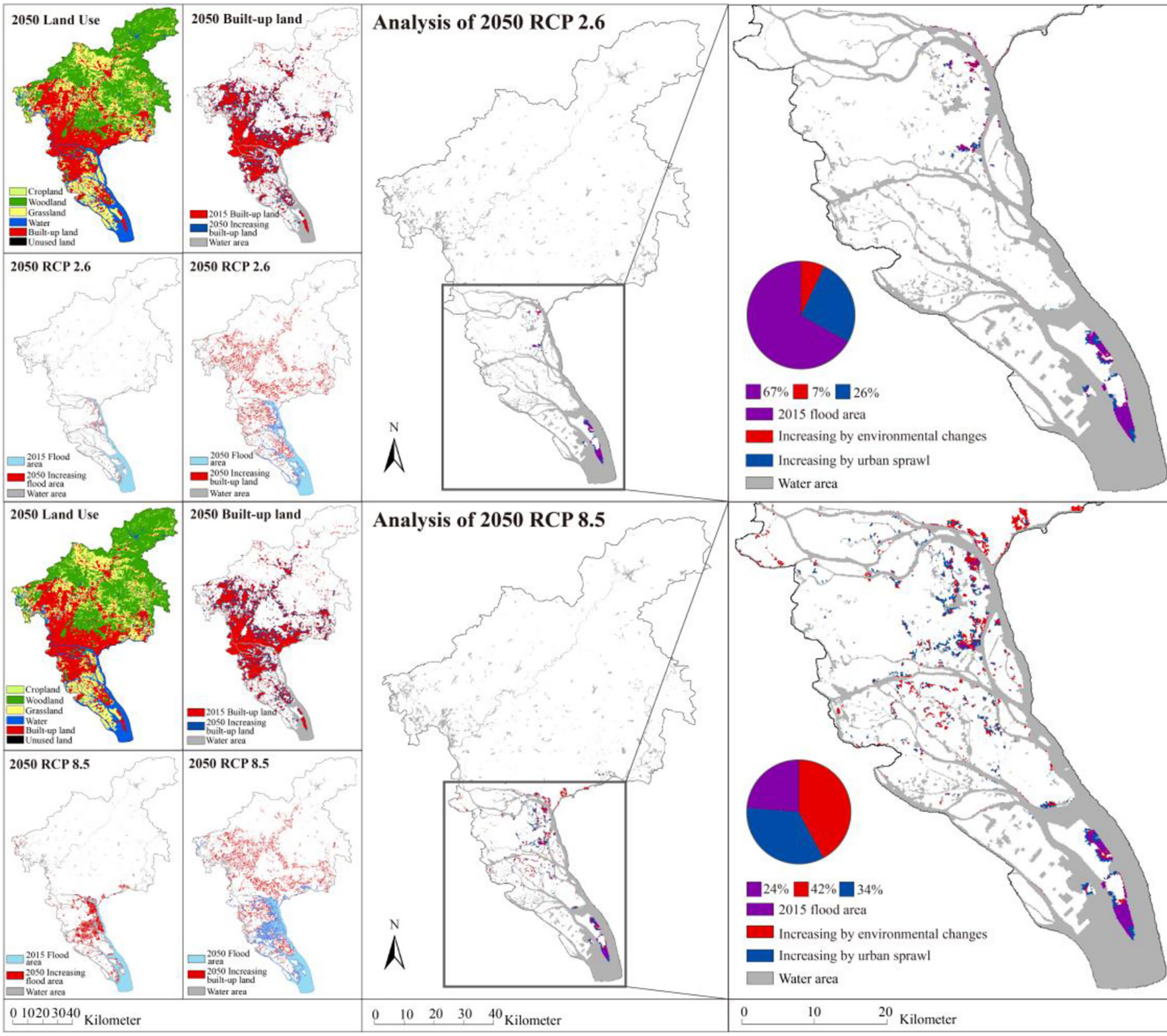

Fig. 6. Analysis of the impact of urbanization and environmental changes on the exposure of built-up land in 2050.

to cover about 46.39 km^2 and 63.56 km^2, respectively, accounting for approximately 9% and 12% of the total flooded areas. As compared to 2015, the flooding of built-up areas was calculated to increase by about 31.32 km^2 and 48.49 km^2 in 2030 and 2050, respectively, under the RCP 8.5 scenario. It was also found that, as the main driving factor, urbanization will increase the flooding of built-up areas in Guangzhou by 1.9 km^2 and 5.9 km^2 under the RCP 2.6 scenario in 2030 and 2050, respectively, as compared to 2015. Due to environmental changes, the flooding of built-up areas in Guangzhou was predicted to increase by 24.2 km^2 and 26.8 km^2 under the RCP 8.5 scenario in 2030 and 2050, respectively, as compared to 2015. This flood risk information determined by the simulations provides insight into the spatial distribution of future flood-prone urban areas in the region.

From the perspective of adaptive urban planning, scenario-based flood risk assessment using the FLUS model not only facilitates a more comprehensive understanding of the development of urbanizing deltas and its related challenges, but also enables the prioritization of flood mitigation measures at the most critical locations in the region.

CRediT authorship contribution statement

Weibin Lin: Conceptualization, Methodology, Formal analysis, Visualization, Writing - review & editing.**Yimin Sun:**Conceptualization, Methodology, Resources.**Steffen Nijhuis:**Methodology, Writing - review & editing.**Zhaoli Wang:**Software, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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