Assessment of flash flood risk based on improved analytic hierarchy process method and integrated maximum likelihood clustering algorithm

Kairong Lin[1,2,3*], Haiyan Chen[1], Chong-Yu Xu[4], Ping Yan[2], Tian Lan[1], Zhiyong Liu[1,2,3], and Chunyu Dong[2,3]

[1] School of Geography and Planning, Sun Yat-sen University, Guangzhou, China.

[2] Center for Water Resources and Environment, School of Civil Engineering, Sun Yat-sen University, Guangzhou, China.

[3]Guangdong Key Laboratory of Oceanic Civil Engineering, Guangzhou, China.

[4]Department of Geosciences, University of Oslo, P.O. Box 1047, Blindern, 0316 Oslo, Norway.

[*]Corresponding author: Kairong Lin (linkr@mail.sysu.edu.cn)

Abstract

Flash floods are one of the most severe natural disasters throughout the world, and are responsible for sizeable social and economic losses, as well as countless injuries and death. Risk assessment, which identifies areas susceptible to flooding, has been shown to be an effective tool for managing and mitigating flash floods. The study aims to introduce the methods to determine the weights of the risk indices, and identify the different risk clusters. In this regard, we proposed a methodology for comprehensively assessing flash flood risk in a GIS environment, by the improved analytic hierarchy process (IAHP) method, and an integration of iterative self-organizing data (ISODATA) analysis and maximum likelihood (ISO-Maximum) clustering algorithm. The weight for each risk index is determined by the IAHP, which integrates the subjective characteristics with objective attributes of the assessment data. Based on the data mining technology, the integration of ISO-Maximum clustering algorithm derives a more reasonable classification. The Guangdong Province of China was selected for testing the proposed method's applicability, and we used a receiver operating characteristics (ROC) curve approach to validate the modeling of the flash-flood risk distribution. The validation against the historical flash flood data indicates a high reliability of this method for comprehensive flash flood risk assessment. In order to verify the proposed method's superiority, in addition, the technique for order performance by similarity to ideal solution (TOPSIS)

and the weights-of-evidence (WE) methods are used for comparison with the IAHP and ISO-Maximum clustering algorithm method. Moreover, we analyzed and compared the regularity of flash floods in the rural and urban areas. This study not only provides a new approach for large-scale flash flood comprehensive risk assessment, but also assists researchers and local decision-makers in designing flash flood mitigation strategies.

Keywords: Flash flood   Comprehensive risk assessment   Improved AHP method   ISO-Maximum clustering algorithm   Guangdong Province

1 Introduction

The term ‘flash flood’ is commonly defined as rapidly developing floods that begin within 3-6 hr of heavy rainfalls or other triggers (Hapuarachchi et al., 2011). To date, they are considered to be the most widespread, devastating, and abundant naturally occurring disaster. Contemporary climate projections suggest that the occurrence of high-intensity rainfall events will increase in many areas of the globe in the future, and such incidents are the primary cause of extreme flooding (Kvočka et al., 2016). Previous studies suggest that flash floods rank high among the natural disasters that result in large scale damage in China in the 21st century, and they are responsible for approximately 70 deaths and 260 million USD in annual losses (Centre for Research on the Epidemiology of Disasters, 2017). Thus, the ongoing flood risk management is of high importance to reduce casualties and economic losses (Barredo, 2007; Gaume et al., 2009; Marchi et al., 2010).

Flood risk assessment is an important flood prevention tool, as it offers significant practical applications in flood risk management and can lead to improvements in public awareness of flood risk (Yang et al., 2018). The flash flood disaster system is complex, and includes disaster-causing factors, disaster-pregnant environments, and disaster-bearing bodies. It has the characteristics of high nonlinearity, spatial-temporal dynamics, and uncertainty, and coupling of various challenges in the system may produce extremely complex phenomena (Wei et al., 2001). Therefore, flash flood risk assessment is a difficult task. Our previous research focused on small-scale flash flood risk assessment based on the TOPMODEL coupled with the 1D-2D hydrodynamic model MIKEFLOOD under the condition of lacking hydro-meteorological data (Li et al., 2019). In this study, we intend to develop a suitable methodology for large-scale flash flood risk assessment despite the data scarcity.

In recent years, two typical approaches or theories have been developed and used for deriving regional scientific flood risk maps, i.e. the hydrological-hydraulic modeling (HHM) method and multi-criteria analysis (MCA) method.

The classical method for analyzing flood-prone areas with different risk levels is based on the application of hydrological-hydraulic modeling (Cheng et al., 2017; Hu and Song, 2018; Löwe et al., 2017; Mandal and Chakrabarty, 2016; Mani et al., 2014). For example, Mandal et al. (2016) collected data on past rainfall events that triggered flash floods and applied it to build a simulation model. By using HEC-RAS, and HEC-HMS Software, they obtained the peak discharge time and volume, as well as the total inundation area and determined the high flash flood risk in the Sikkim Darjeeling Himalaya Teesta Watershed. Cheng et al. (2017) employed the InfoWorks ICM 2D hydrodynamic model to simulate historical and designed rainfall events, then recorded the simulate water depth and flow velocity for flood risk assessment in the Jinan City. Löwe et al. (2017) linked the 1D-2D hydrodynamic modeling engine MIKE FLOOD (DHI, 2013) with the urban development model DAnCE4-Water (Urich and Rauch, 2014) to consider 9 scenarios for urban development and climate and 32 potential combinations of flood adaptation measures in Melbourne, Australia. Hu and Song (2018) applied the two-dimensional hydrodynamic model to simulate flash flooding in mountain watersheds with a robust finite volume scheme, which can quickly simulate the rainfall-runoff process and be used for real-time prediction of large-scale flash floods with high-resolution grids. Other scholars have applied different hydrological-hydraulic models to carry out numerous and varied studies on flood risk assessment. However, model simulation methods require much more high-quality data, as the relevant calculations are very complex (Wang et al., 2011). Moreover, there are many unmapped large basins where expensive and time-consuming hydrological-hydraulic simulations are not possible due to data scarcity. An additional limitation of the method is that it is not universally applicable to different regions because it depends on the catchment properties (Kourgialas and Karatzas, 2011). In these cases, using an alternative effective tool to delineate the flash flood-prone areas is necessary.

Multi Criteria Decision Analysis (MCDA) method is a modeling and methodological tool for dealing with complex problems（He et al., 2018; Shen et al., 2016). Especially, it has been widely used in many studies to assess flood risk (Danumah et al., 2016; Guo et al., 2014; Musungu et al., 2012; Shehata and Mizunaga, 2018; Sowmya et al., 2015; Wang et al., 2011). MCA is a broad term used to describe a set of methods that can be applied to support the decision-making processes by considering multiple and often conflicting criteria via a structured framework (Brito and Evers, 2016). The crucial step is to select the methodologies that calculate multiple index weights. Analytic hierarchy process (AHP) method has been applied to flash flood risk assessment with multiple criteria systems (Ghosh and Kar, 2018; Pantelidis et al., 2018; Shehata and Mizunaga, 2018). AHP has a demonstrated ability to assess and map flood risk with good accuracy (Danumah et al., 2016). However, one of the limitations of AHP is its high subjectivity in choosing the weights for each factor since it is significantly affected by the expert’s experience and knowledge (Zhao et al., 2017). Thus, some improved AHP methods were further proposed. For example, Xie et al. (2011) proposed an information fusion method based on DS-AHP (Dempster-Shafer and Analytic Hierarchy Process) to deal with uncertainty information. Zou et al. (2013) introduced fuzzy mathematics in which AHP was combined with trapezoidal fuzzy numbers to calculate assessment indices' weights. Guo et al. (2014) determined the assessment indices weights by combining the minimum relative entropy principle and the AHP. Zhao et al. (2015) introduced game theory to correct the one-sidedness of the single weighting method by integrating AHP weight and entropy weight. Fang et al. (2017) built Grey-AHP model based on the grey theory to overcome uncertainty resulted from determination of some indices' weight. Dahri and Abida (2017) built a function of weights using Monte Carlo simulation and global sensitivity analysis to improve the AHP. However, these methods need a lot of detailed data, and the computation processes for all the above methods are complicated and tedious.

Given the above concerns, the purpose of this study is to propose an integrated method based upon the IAHP method and ISO-Maximum likelihood clustering algorithm for large-scale flash flood risk assessment under conditions of data scarcity. Due to intelligible theories and simple implementation steps, the proposed method offers general applicability. Performing large-scale flash flood risk assessment in China and other developing countries is of great significance, as it can guide stakeholders and government officials to focus on areas prone to flash flood disasters and improve regional management and planning efficiency. IAHP is a comprehensive method for determining weights of the assessment indices, which combines the AHP weight method and the entropy method to reflect empirical judgments of experts and objective variability of assessment data. Furthermore, in order to determine the risk level of different regions, we adopted the ISO-Maximum likelihood clustering algorithm to conduct clustering analysis. The clustering analysis algorithm is a data mining technology and thus overcomes the difficulty in determining the risk classification threshold that is required in traditional flood risk analysis (Xu et al., 2018). Finally, we verified the assessment results qualitatively and quantitatively using the historical data from flash flood disasters. In previous studies, most researchers tended to qualitatively verify the flash flood assessment results (Shehata and Mizunaga, 2018; Zou et al., 2013), so quantitative validation of assessment results is rarely found. Thus, the receiver operating characteristic technique (ROC) is introduced to quantitatively evaluate the established model’s accuracy, which is widely used to assess model accuracy in landslide vulnerability (Bednarik et al., 2010; Bui et al., 2011), groundwater qanat potential (Naghibi et al., 2015), and flash flood susceptibility (Khosravi et al., 2018). ROC is flexible enough for a range of capabilities, and provides a trial for the quantitative validation of the flash flood risk assessment model. Through the above steps, we obtained a reasonable flash flood risk distribution map of the study area. The cartographic products are very useful for helping decision-makers and map users from various fields (such as strategic planning, emergency management, or the public) adapt appropriate actions and measures for flood risk mitigation (Godfrey et al., 2015; Meyer et al., 2012).

Additionally, TOPSIS and WE methods were selected for comparison with the IAHP and ISO-Maximum likelihood clustering algorithm. TOPSIS is extensively applied to water resource and environmental problems (Zagonari and Rossi, 2013), as well as flood risk analysis in previous literature (Chengjie et al., 2017; Lee et al., 2014; Najafabadi et al., 2016; Radmehr and Araghinejad, 2015). The WE method is also adapted to flood or landslide risk research and has achieved reasonable results in interesting areas (Xu et al., 2012; Tehrany et al., 2014; Weed, 2010). Subsequently, we obtained the results through TOPSIS and WE methods, then compared and discussed the similarities and differences obtained by the three methods.

The remainder of this paper is structured as follows. Section 2 introduces the study area and data; while Section 3 shows how we adapted the IAHP method and the ISO-Maximum clustering algorithm for comprehensive flash flood risk assessment. Section 4 displays detailed results of the trial region. In Section 5 we present a series of discussions on the implementation and improvement of the proposed method. Finally, the conclusions are summarized in Section 6.

2 Study area and data

2.1 Study area

Guangdong Province is located on the southernmost tip of China. It includes the Pearl River Delta, which is one of China's most important economic development zones and is an important part of the Guangdong-Hong Kong-Macao Greater Bay Area for the national development strategy. Guangdong Province is situated at 20°13′-25°31′N, 109°39′-117°19′E and covers an area of 179,700 km^2 (Figure 1). It is vulnerable to flash floods because of its unusual geographic location and complex topography. Guangdong Province is one of the wettest areas in China, with an average annual precipitation of 1789 mm. Drainage systems are numerous and complex, and primarily consist of Pearl River, Han River, and many other smaller rivers. In addition, the topography in Guangdong Province is characterized by mountains, hills, platforms, valleys, basins, and plains interlacing with each other. All these above natural conditions tend to facilitate the occurrence of flash floods.

Statistical analysis shows that flash floods in Guangdong Province have occurred in 1182 small watersheds since 1980, in 15 of 69 counties (cities and districts). They have covered an area of 116,800 km^2 and affected a population of 27,177,400 people. About 3.85 million people are regularly threatened by flash floods, of which 3.08 million are living in rural areas and 0.77 million are in towns and cities. Flash floods also directly threaten the safety of industrial and mining enterprises and important infrastructure with fixed assets of 98.99 billion RMB. Therefore, it is critical to establish a suitable flash flood risk assessment model for regional safety and development.

2.2 Data

Three types of data were collected for the proposed method in this study: 1) basic administrative division of the study area; 2) the flash flood risk assessment indices, including the Digital Elevation Model (DEM) data, terrain slope (SL), rainfall, drainage, topographic, population, economic, and urbanization data; and 3) records of historical flash flood events, which are used to verify the assessment results accuracy. The above data are described in detail in section 1 of the supplementary material.

3 Methodology

The overall framework of the proposed method involves two main components:

(1) The IAHP method and the ISO-Maximum likelihood clustering algorithm were used to develop the flash flood risk levels map (Figure 2).

(2) In order to verify the proposed method that was applied to flash flood risk assessment, the distribution map of historical flash flood disasters was employed to qualitatively verify evaluation results and ROC curves were introduced to quantitatively assess the model accuracy.

3.1 Conceptual model

Various studies have used different definitions of risk. This study establishes a conceptual model based on District Disaster System theory (Shi, 1996; Crichton and Mounsey, 1997). The definition of risk is expressed by Eq. 1 (Maskrey, 1989) :

$$Risk = Hazard + Vulnerability \tag{1}$$

where *Hazard* is the premise, which mainly describes the natural environment and hydro-climatic conditions in the assessment area. *Vulnerability* represents socio-economic conditions in the region and describes the potential losses. *Risk* indicates the probability and potential loss based on different intensity floods. Therefore, we adopt a general structure in which risk is a function of both the hazard and vulnerability of the indices at risk. Thus, the conceptual model of regional flash flood risk assessment can be expressed as:

$$R = f(H, V) \tag{2}$$

where

$$H = f(h) = \sum_{i=1}^{n} \omega_i h_i \tag{3}$$

$$V = f(v) = \sum_{j=1}^{m} \omega_j v_j \tag{4}$$

$$R = f(H, V) = \sum_{i=1}^{n} \omega_i h_i + \sum_{j=1}^{m} \omega_j v_j \tag{5}$$

where h_i and v_j represent hazard and vulnerability indices values, respectively, after standardization treatments. ω_j and ω_i are the hazard and vulnerability index weights, respectively.

3.2 IAHP method

a. Selection of risk indices

Flood risk occurrence is a combination of natural and anthropogenic factors, and the selection of risk index variables varies among study areas according to the specific characteristics of each location (Tehrany et al., 2013). After carefully considering the flash flood characteristics associated with hazard and vulnerability in the study area and reviewing the recommendations throughout the literature, we selected eight indices based on available data. The four hazard indices consist of: drainage density (DD), comprehensive rainstorm (CR), slope (SL), and topography (TO); while the four vulnerability indices are: urbanization ratio (UR), population density (PD), primary industry proportion (PIP), and per unit area GDP (PUAGDP). The basic data and detailed process of the eight criteria have showed in the Supplementary Material (Figure S1), all the abbreviations used in.

b. Calculation of weight

AHP, developed by Saaty (1980), is one of the best known and most widely used multi-criteria analysis (MCA) approaches. Furthermore, the AHP method has been shown to comprehensively determine weights by considering the data’s subjective attributes (Xu et al., 2018). In contrast, entropy is a management approach employed in the system to prevent disorder, instability, disturbance, and uncertainties inherent in that system (Pourghasemi et al., 2014). Entropy offers a method for estimating main factors among effective factors of an objective. In other words, it determines variables that are more influential in event occurrence (Haghizadeh et al., 2017). Thus, IAHP combines the subjectivity of AHP and the objectivity of the entropy weight method to comprehensively determine the weights of indices. The specific steps for performing this calculation are as follows:

(1) Entropy weight method to determine weights of risk indices.

Step1: Assuming that there are *m* objects and *n* indices, the judgment matrix R is constructed.

$$R = (r_{ij})_{m \times n} \tag{6}$$

Step2: The matrix R is transformed into a normalized matrix R' to avoid the effect of the different evaluation data units.

$$R' = (r'_{\mathrm{ij}})_{m \times n} \tag{7}$$

The specific normalization formulas are as follows:

(a) Normalized formula for positive indices:

$$r'_{\mathrm{ij}} = \frac{r_{ij} - min(r_{ij})}{max(r_{ij}) - min(r_{ij})} \tag{8}$$

(b) Normalized formula for negative indices:

$$r'_{\mathrm{ij}} = \frac{max(r_{ij}) - r_{ij}}{max(r_{ij}) - min(r_{ij})} \tag{9}$$

Step3: The entropy e_j of the *jth* index is defined as follows:

$$e_j = \frac{-\sum_{i=1}^{m} f_{ij} ln f_{ij}}{ln\, m} \quad (10)$$

where $f_{ij} ln f_{ij}$ is set as zero if f_{ij} is equal to zero and

$$f_{ij} = r_{ij} / \sum_{i=1}^{m} r_{ij} \quad i=1,2,3\ldots,m;j=1,2,3\ldots n \quad (11)$$

Step4: The entropy weight ω_1 is calculated as follows:

$$\omega_1 = 1\text{-}e_j \quad (12)$$

(2) AHP method to determine the weights of risk indices

The AHP method uses hierarchical structures to represent the problem, and then develops the priorities for alternatives based on the user's judgment. The main steps in implementing the AHP method are as follows (Saaty, 1980):

Step1: Break a complex unstructured problem down into its component factors.

Step2: Develop the AHP hierarchy, the AHP model used in the process flash flood risk map is shown in Table 1.

Step3: Design a paired comparison matrix determined by imposing judgments. In the study, we invited relevant experts to determine the relative degree of importance between risk indices, which is the basis for the construction of the judgment matrix (Table 2).

Step4: Assign values to subjective judgments and calculate the relative weights of each criterion. The binary combination for index comparison in Table 3 is based on a scale proposed by Saaty (1980).

Step5: Synthesize judgments to determine the priority variables.

Step6: Check the consistency of assessments and judgments. If the consistency ratio is < 0.1, then the mentioned matrix can be considered as an acceptable consistency.

(3) IAHP method to determine the final weights

The determination of index weight should maximize the balance between subjective intention and objective impartiality to evaluate the results, so the calculation of the final weight ω by the IAHP is as follows (Wang, 2018):

$$\omega = 0.5\omega_1 + 0.5\omega_2 \tag{13}$$

Where ω_2 denotes the subjective weight determined by the AHP method.

c. Making risk assessment index layers

The geographic information system (GIS)-based method employs a spatial analysis function for flood risk assessment, and forms visual flood risk maps to provide useful information for decision-makers (DMs) and insurance companies (Wang et al., 2011). This study mainly uses the ArcGIS Spatial Analysis module function to make the risk assessment index layers. The specific processing steps are detailed in section 2 of the supplementary material.

3.3 ISO-Maximum Likelihood algorithm clustering analysis

Clustering is a popular data analysis and data mining technique, which aims at partitioning a collection of data objects into several groups or clusters, such that intra-cluster dissimilarity is small and inter-cluster dissimilarity is large. In this study, the ISODATA clustering algorithm and the maximum likelihood algorithm were combined for risk clustering analysis. The ISODATA is a widely used partitioning, unsupervised and iterative clustering algorithm. The fundamental difference between the ISODATA clustering algorithm and the traditional clustering algorithm is that the former is a soft classification while the latter is a hard one. Soft classification can recognize the most essential attributes, and most classification objects are unlikely to show during the initial cognition or initial classification (Yang and Luo, 2006; Zeng, 2009). A more detailed explanation concerning the ISODATA clustering algorithm calculation principle is available in Memarsadeghi et al. (2007).

Furthermore, the feature file generated by the ISODATA clustering algorithm is used as the input file for the Maximum likelihood clustering classification, which can better control the classification parameters. All the above steps are completed by GIS techniques, enabling the study to obtain more scientific clustering results for flash flood risk.

3.4 Verification

In this study, we conducted both qualitative and quantitative validation of the assessment results. To begin the qualitative verification, we normalized the historical data of flash flood events, then summed the normalized values to generate the historical flash flood loss distribution map in the GIS environment. The qualitative verification analysis was realized by comparing the historical flash flood loss map with the risk distribution map. In contrast, the ROC was introduced to quantitatively evaluate the proposed method’s accuracy, which has rarely done in previous studies. The ROC curve is a statistical technique that can be used to provide performance predictions and compare different models (sensitivity vs. specificity) (Bui et al., 2011) , by depicting a graphical representation of equilibrium between the negative and positive rate of error for each possible fitness value (Pourghasemi et al., 2014). The curve is a two-dimensional graph, in which the true-positive rate is plotted on the Y-axis and the false-positive rate is plotted on X-axis. The area under the ROC curve (AUC) is a summary of the plot’s information, which can be used to estimate the validity: accuracy or overall quality of the model (Hosmer and Lemeshow, 2000). If the AUC value is close to 1, the model accuracy is considered to be high (Bui et al., 2011). In this study, we selected two representative flood events, including extreme precipitation events during June 2005 and June 2010. The data from these events were entered into the established risk assessment model and used to forecast flash flood likelihood as well as plot the ROC curves to realize quantitative accuracy analysis.

4 Results

4.1 Weights

Based on the detailed description in Section 3.2, the index weights were calculated using the IAHP method, which mainly integrates the entropy weight and the AHP method. To begin, the entropy weights of risk indices in the study area were calculated, as shown in Table 4. The results in Table 5 indicate that the judgment matrices pass the consistency test. Table 4 shows that the weight results determined by the entropy weight and the AHP method are significantly different, so it is more reasonable to adopt the IAHP method, which comprehensively considers the subjective judgment and objective data variability. The final index weights are listed in Table 4. According to the final calculation results, the established evaluation model can be determined as follows:

$$R = f(H,V) = \sum_{i=1}^{n} \omega_i \, h_i + \sum_{j=1}^{m} \omega_j \, v_j = 0.134SL + 0.046DD + 0.136CRV + 0.077TO + 0.064UR + 0.179NPD + 0.076PIP + 0.289PUGDP \quad (14)$$

where R is risk, H is hazard, and V is vulnerability, h_i and v_j represent values of the hazard and vulnerability indices, respectively, after standardization treatments, while ω_j and ω_i are the weights for the hazard and vulnerability indices, respectively.

4.2 Risk distribution

The risk index layer's distribution map was developed using the GIS techniques (more detailed data of the study area are given in section 1 of the supplementary material). Furthermore, following the above calculation steps, we determined the final weight of each index and multiplied it in classes of that index or values related to each index. Weighted maps were added up and final maps of flash flood hazard, vulnerability, and risk were obtained (Figures 3.a.b.c). Finally, the risk clustering map was generated based on the ISO-Maximum likelihood clustering algorithm (Figure 3.d).

A flash flood risk distribution map that only considers the hazard indices should be different from one considering both the hazard and vulnerability indices. In general, both maps have similar space patterns: the risk in the northern low mountainous areas is higher than the southern plain, and the difference in some parts of the study area is greatly influenced by the socio-economic indices. Some high-level flash flood areas showed a low-risk level when the socio-economic indices were considered, e.g., Qujiang, Huidong, and Lechang. In these cases, fewer people, properties and primary industries are located in the areas with a high flood hazard level. As such, the casualties and property losses are expected to be lower, even though the risk of flooding is high. On the contrary, some areas with a low flash flood hazard level have significantly high-risk for damage, e.g., Shenzhen, Guangzhou, Yangxi, and Huilai. If a flash flood occures in these areas, there will be a large number of casualties and property losses due to the dense populations and high property concentrations. Therefore, a comprehensive flash flood risk map acts more representative of the study area due to the involvement of hazard and vulnerability.

According to the results of flash flood risk clustering, three categories of flash flood risk were compared: low, medium, high. As shown in Figure 3.d, low, medium, and high-risk zones accounted for 12.51%, 38.59%, and 48.91%, respectively. The high-risk areas are mainly located in the north, east and southwest parts of Guangdong Province, and the areas with the highest flash flood risk occurred in Guangzhou and Baoan.

The mean index value of the three risk levels was calculated in order to analyze the underlying causes of the risk distribution (Figure 4). As shown in Figure 4, the high- risk zones generally exhibit higher slopes and are distributed over low mountainous and hilly regions. Disaster-causing vulnerability indices, including higher PIP and lower UR more easily induce the flash floods. Thus, the combination of physical and socio-economic variables could result in a high flash flood risk.

Furthermore, Figure 5 shows 8 index values for each of the 20 selected areas in the high risk zones: Xuwen, Qingxin, Zijin, Xinfeng, Lianzhou, Wuhua, Xingning, Renhua, Dongyuan, Shixing, Longmen, Yangchun, Liannan, Wengyuan, Huaiji, Yingde, Lianshan, Yangdong, Yangshan, Longgang, Yangxi. As demonstrated in Figure 5, all the selected areas generally exhibit higher SL and PIP and lower UR. Moreover, most of the areas are located in low mountain regions. It is also evident from Figure 5 that most high-risk areas have higher CRV and DD values than the other areas. In general, high-risk areas tend to have higher slopes, more rainfall, and developed primary industry, a lower urbanization rate, and be located in mountainous regions. These counties (districts) should be a priority for carrying out intensive studies and considering flash flood mitigation measures.

The regularity of flash flooding in the study area was further analyzed by selecting and comparing 20 typical urban and rural areas. The 8 index values of each selected area are shown in Figures 6 and 7, and were used to analyze the main disaster-causing factors. The results demonstrated that the main flash flood disaster-causing factors in rural areas (Figure 7) show more regularities than urban areas (Figure 6), which may indicate that the assessment system based on the IAHP method is more suitable for mountainous areas. For these areas, the flash flood disaster-causing factors include low-lying terrain (such as middle and low mountainous areas), lower UR and higher SL, which is consistent with the flash flood formation theories. The flash flood formation theories emphasize that the terrain in mountainous rural areas is undulating, and the windward side of the mountains provides sufficient water for flash floods. Furthermore, the steep mountains provide dynamic conditions for downward sliding, which is conducive to the rapid accumulation of flash flood waters into valleys. Although the disaster-causing factors of flat urban areas do not depict universal laws, we find high-risk urban areas due to higher rainfall concentrations. Normally, flash flooding directly in urban areas is caused by intense rainfall events, which exceed the capacity of the drainage systems (Blanc et al., 2012; Maksimović et al., 2009). Moreover, inadequate solid-waste management and drain maintenance can lead to clogged drains, which in turn leads to localized flooding even with light rainfall (Satterthwaite et al., 2007).

4.3 Verification

The flash flood historical loss distribution map was derived using the method detailed in the supplementary material (Figure S2), and then overlapped with the flash flood risk distribution map in Figure 8. Results showed that the middle, high-risk areas cover the counties (districts) with severe historical flash flood losses, which preliminarily demonstrates the reliability and rationality of the assessment results. The data also showed that the risk to developed areas along the coast is overestimated, mainly because of excessively abundant rainfall and the concentrated population and economy.

Next, the ROC curves were plotted based on the true-positive and flash-positive degree of identified flash floods as the classification threshold varies. According to the two ROC curves, the AUCs were 0.693 and 0.729 for the selected flash flood events (Figure 9). This indicates that the established flash flood assessment model has relatively good accuracy.

In summary, we obtained relatively reasonable and reliable risk assessment results for Guangdong Province using the IAHP and ISO-Maximum likelihood clustering algorithm. Furthermore, the results were verified as described above. Thus, the flash flood risk map exhibits practical application in regional unity planning and flash flood prevention in the Guangdong Province.

5 Discussions

5.1 Comparison of methods

The TOPSIS method and EW method were compared to the IAHP method to validate the proposed approach in flash flood risk assessment. Figures 10 and 11 present the flash flood risk maps developed by the TOPSIS and EW methods.

Using the TOPSIS method, we produced a risk distribution similar to the assessment results of the IAHP and ISO-Maximum clustering algorithm. In addition, the flash flood risk spatial distribution is approximately identical to the PIP distribution map, more detailed data of study area are displayed in section 1 of supplementary material (Figure S1.g). Furthermore, the proportion of high-risk zones is extremely low (approximately 11.17%), and the maximum and minimum risk values are higher and lower, respectively, than the results of our proposed method. In addition, by comparing the distribution maps of historical flash floods disaster losses, it becomes clear that the risk of many flash flood disaster-prone areas in northeast and west of Guangdong Province, such as Gaozhou, Huazhou, Wuhua, Zijin, Dongyuan, etc., is obviously underestimated. This comparison indicates that the assessment results from the TOPSIS method are potentially problematic and inferior to the method proposed in this paper.

For the flash flood risk distribution, there are noticeable differences between the EW method and the IAHP method. The results shown in Figure 11 are simply unreasonable, as they indicate that the high-risk areas are located in the southwest and east of Guangzhou, while the risk in the northern mountainous areas is lower. Furthermore, comparison with the distribution of the historical flash flood losses indicates that the risk in northern Guangdong Province is obviously underestimated. These results show that the IAHP method is more reasonable than the EW method.

5.2 Advantages and limitations

The IAHP and ISO-Maximum likelihood clustering algorithm were proposed to assess large-scale flash flood risk and were applied to the Guangdong Province as a case study. The results show that the proposed framework can achieve more reliable results in large-scale flash flood risk assessment. The methodology has the following advantages: (1) The model’s construction theory is intelligible. The theoretical basis of the model is flash flood risk formation mechanisms, which builds a conceptual model from two aspects of vulnerability and hazard. (2) The IAHP method is adapted to effectively determine the weights of different risk indices. It takes the objective characteristics of data and the empirical judgment of experts into account. (3) Data mining technology ISO-Maximum likelihood clustering algorithm is used for clustering analysis, which overcomes the deficiency in traditional flash flood risk classification and obtains more reasonable classification results. (4) A series of appropriate operations in the GIS environment improved situations where data deficits originally limited evaluation of flash flood risk, with high efficiency and flexibility.

However, the proposed approach also has some limitations. In large-scale studies, a regional economic development gap will lead to a great change in social vulnerability indices data, and the weights of vulnerability indices are slightly overestimated by the proposed method. The regional economic development of the study area is extremely unbalanced, as the Pearl River Delta region is more developed, while other regions are less developed. Therefore, the variation range of vulnerability indices is much larger than that of the hazard indices, which results in the weights of vulnerability indices being overestimated by the IAHP method. This is also part of the reason why the risk in economically developed areas, such as Shenzhen and Guangzhou, is overestimated. In the future, this problem can be improved by acquiring more detailed data and increasing relative risk indices. Moreover, more detailed work would focus on waterlogging disasters in these urban cities in the future (Yang et al., 2019; Zhu et al., 2019).

When compared to other alternatives, the proposed method has greater reproducibility and applicability, and can obtain relatively good evaluation results based on basic theories and simple operation processes. There are reasons to believe that this method will offer preferable assessment results with the support of high accuracy and abundant data.

5.3 Improvement

Based on our study, the following measures should be considered to further improve the IAHP and ISO-Maximum likelihood clustering algorithm in flash flood risk assessment:

First, physical and social vulnerability factors should be taken into account when analyzing regional vulnerability (Karagiorgos et al., 2016). In this study, only the physical vulnerability was considered with the socio-economic and demographic indicators. More social vulnerability factors are expected in order to improve assessment accuracy, including residency length, the degree of solidarity, the trust of people living in the area, and participation in local associations, etc. (Hurlbert et al., 2000; Kuhlicke et al., 2011).

Second, the variables that trigger flash floods are complex. Accordingly, it is less reasonable to adopt a unified evaluation index system, and risk indices should be determined based on the different regional characteristics.

Third, in order to compute the overall risk, weights calculated by the AHP and entropy method are given equal weight, but some adjustments may be needed in the future studies. The huge gap in regional socio-economic development will lead to overestimation of the vulnerability factor weights. Hazard indices are the source for flash floods. If there was no adverse environment to form flash floods, then no loss would be induced, and the region would not suffer hazards.

Finally, numerous studies focus on flash flood risk in spatial dimension rather than temporal. Thus, determining how to effectively integrate real-time information to establish a dynamic flash flood risk assessment model in the future is currently a hot issue (Adams et al., 2019, Shirisha et al., 2019, Zhang et al., 2019a, Zhang et al., 2019b). There is no doubt that flash flood assessment will be strengthened by collaboration with other disciplines, such as radar technology and remote sensing.

5.4 Prevention of flash floods

This study indicates that most areas in Guangdong Province are encountering high or medium flash flood risks; thus some kinds of appropriate methods are needed to mitigate flash flood risk. Mitigation measures vary, ranging from physical measures, such as flood defense or safe building design, to legislation, and training and improving public awareness. Public officials are suggested to provide some flood control engineering supports in flood-prone areas, such as embankment construction and channel improvement, etc. Furthermore, flash flood risk maps have been shown to greatly support planners and engineers to select suitable locations for implementation of flash flood control measures. For Guangdong Province, the government should also focus on renovating aging and damaged flood control facilities. These measures can provide substantial protection for flash floods in areas prior to such events.

Furthermore, flash flood warning systems (FFEW) present a more efficient approach to flood prevention and mitigation than engineering measures (Li et al., 2018), which can provide real-time forecasting based on developed technologies. The government should increase the density of weather, rainfall, and river monitoring networks and develop radar and satellite technology for acquiring high-quality real-time data. Moreover, the government should also expand the options enabling the masses to receive and share real-time flash flood information-e.g., creating relative applications (APPs).

Protecting people from flash flood disasters is a race against time (Li et al., 2018), as in many areas, the question is not if it will happen, but when. In addition to delivering real-time and useful information, it is also important to improve human response to flash flood disasters. These approaches should be considered for enhancing the public’s ability to cope with flash floods, such as promoting the knowledge of flash flood escape routes and conducting regular flood control exercises and evacuation drills.

By using a combination of the above measures, we believe that the flash flood risk can be effectively mitigated, thus reducing the devastation caused by flash floods to human society.

6 Conclusions

Flash flood risk assessment is unquestionably helpful for avoiding and/or reducing death and destruction from flooding. In addition, knowledge and scientific understanding of flash flood risk distribution are clearly beneficial to policymakers, as well as the public. The study provides a new approach for large-scale flash flood comprehensive risk assessment with data scarcity, which integrates IAHP with ISO-Maximum clustering algorithm. In the proposed method, the IAHP approach was used to determining the weights of risk indices, which additionally considers entropy weights to modify the subjectivity of traditional AHP. It is the important step to realize a comprehensive assessment. The ISO-Maximum likelihood clustering algorithm was used to resolve the artificial determination of the flash flood risk clusters' threshold, which could obtain more reasonable classification results. Besides, the ROC curve was introduced to evaluate the accuracy of flash flood risk assessment model quantitatively, which was rarely shown in previous studies. Conclusions are drawn as follows:

(1) The good agreement between the assessment results and historical spatial patterns of the flash flood events indicates that the IAHP and ISO-Maximum clustering algorithm method exhibits good suitability for practical applications.

(2) The results of the study area indicate that flash flood risk of Guangdong Province is classified into three categories: low, medium, and high. Most of the areas are located in middle- or high-risk level, and high-risk zones account for 48.91% of total area. In general, the assessment result matches well with the historical data of flood events. Meanwhile, the credibility and reliability of the results derived from the proposed method are obvious as compared with the TOPSIS and WE methods.

(3) We further analyzed the regularity of flash flooding through the assessment results in the study area. The high-risk blocks mainly cover in the north, east and southwest of study area. The main indices cause the high-risk including higher SL, CRV, lower UR and complex terrain. For rural areas, the flash flood disaster-causing factors include low-lying terrain, lower UR and higher SL. Higher rainfall concentrations are the disaster-causing factor to flash flood of urban areas where are more prone to waterlogging disasters.

Acknowledgments

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List of Tables

Table 1

AHP hierarchy model of the study area

Goal	**Flash flood risk**	
Criteria	Hazard	Vulnerability
Index	CRV	PD
	TO	UR
	SL	PUAGDP
	DD	PIP

Table 2

Judgment matrices in AHP

Hazard-Vulnerability			**Hazard-Index**					**Vulnerability-Index**				
	H	V		CRV	TO	SL	DD		PD	UR	PUAGDP	PIP
H	1	3/2	CRV	1	5/2	15/14	3	PD	1	3/2	1	3/2
			TO	2/5	1	3/7	6/5	UR	2/3	1	2/3	1
V	2/3	1	SL	14/15	7/3	1	14/5	PUAGDP	1	3/2	1	3/2
			DD	1/3	5/6	5/14	1	PIP	2/3	2	2/3	1

Table 3

Index comparison based on binary combination *Saaty* (1980)

Scale	Judgment of preference	Description
1	Equal Importance	Two factors contribute equally to the objective
3	Moderate Importance	Experience and judgment slightly favor one over the other
5	Essential Importance	Experience and judgment strongly important favor one over the other
7	Very/strong Importance	Experience and judgment strongly important favor one over the other
9	Extreme Importance	The evidence favoring one over the other is of the highest possible validity
2,4,6,8	Intermediate preference between adjacent scales	When compromised is needed

Table 4

Determination of the index weights of assessment indices

Methods	Index							
	SL	DD	CRV	TO	UR	PD	PIP	PUAGDP

AHP	0.210	0.075	0.225	0.090	0.080	0.120	0.080	0.120
Entropy weight	0.057	0.017	0.046	0.064	0.049	0.238	0.072	0.457
Improved AHP	0.134	0.046	0.136	0.077	0.064	0.179	0.076	0.289

Table 5

The consistency test matrices by the relative experts for flash flood risk assessment.

Judge matrix	λ_{max}	**m**	**RI**	**CI**	**CR**	**Consistency**
H-V	2	2	\	0	0	Yes
Hazard-Index	4	4	0.89	0	0	Yes
Hazard-Index	4	4	0.89	0	0	Yes

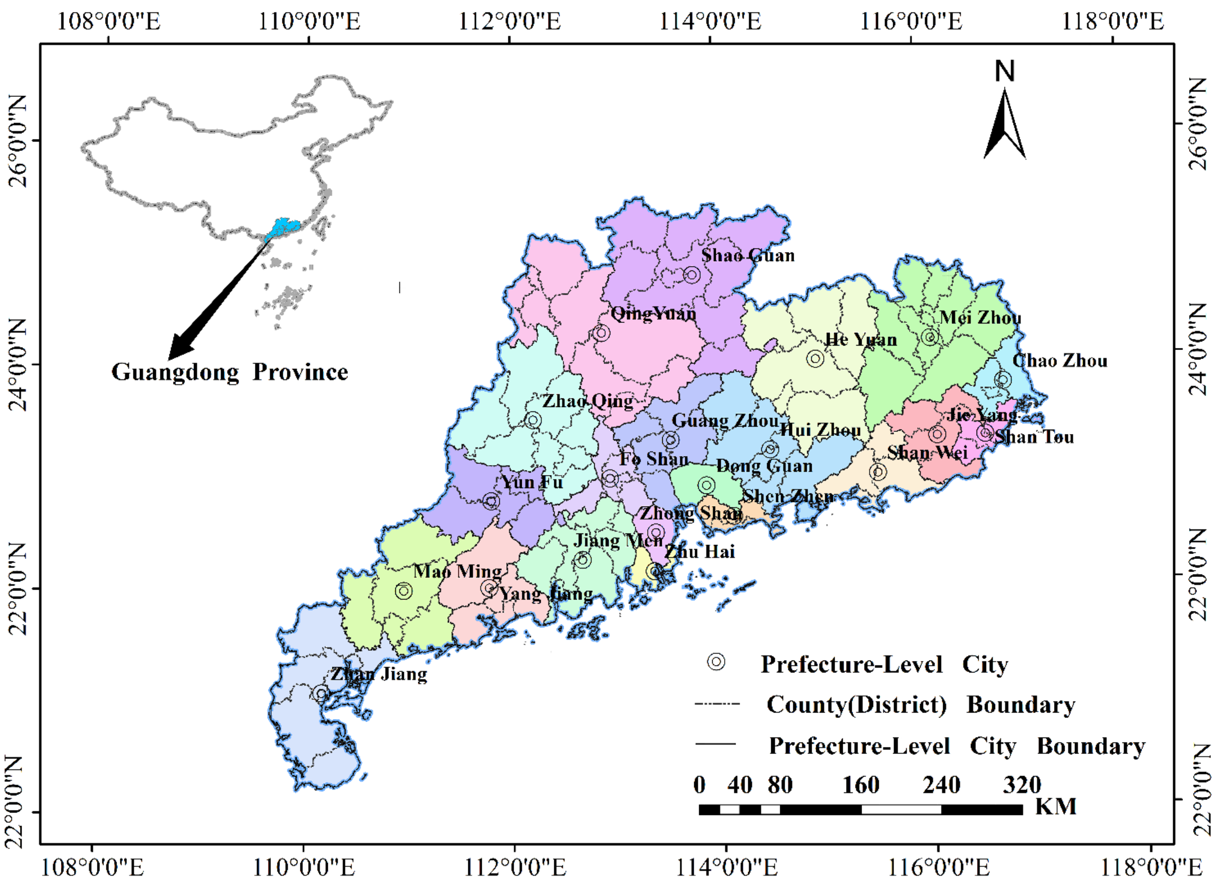
λ_{max} , m, RI, CR and CI represent the judgment matix' largerst eigenvalue, order, random consistency idicator, random cnsistency index and consistency ratio, respectively.

List of Figures

Figure 10 Spatial distribution of flash flood risk is developed by the TOPSIS method in study area.

Figure 11 Spatial distribution of flash flood risk is developed by the EW method in study area.

848



849 **Figure 1**

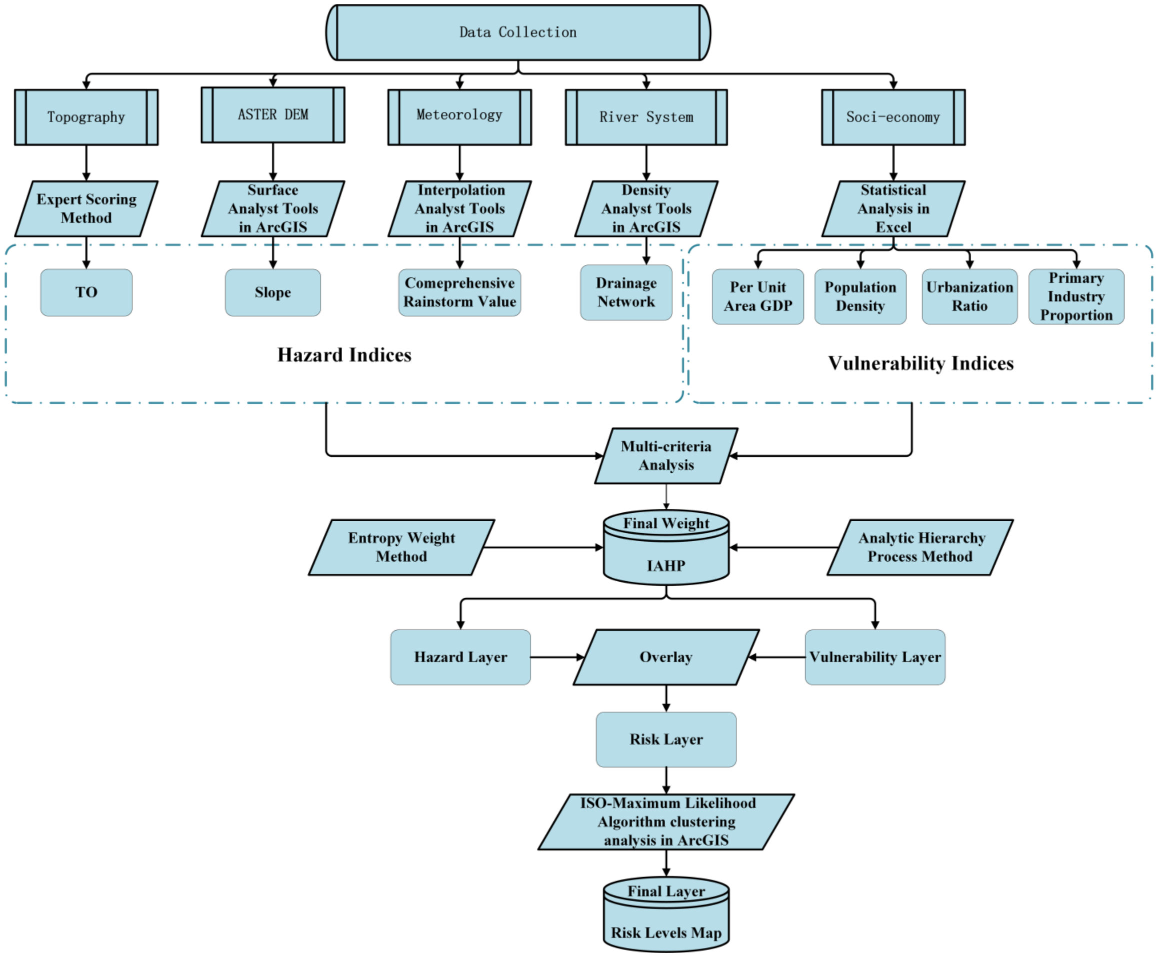

Data Collection
Topography
ASTER DEM
Meteorology
River System
Soci-economy
Expert Scoring Method
Surface Analyst Tools in ArcGIS
Interpolation Analyst Tools in ArcGIS
Density Analyst Tools in ArcGIS
Statistical Analysis in Excel
TO
Slope
Comeprehensive Rainstorm Value
Drainage Network
Per Unit Area GDP
Population Density
Urbanization Ratio
Primary Industry Proportion
Hazard Indices
Vulnerability Indices
Multi-criteria Analysis
Entropy Weight Method
Final Weight
IAHP
Analytic Hierarchy Process Method
Hazard Layer
Overlay
Vulnerability Layer
Risk Layer
ISO-Maximum Likelihood Algorithm clustering analysis in ArcGIS
Final Layer
Risk Levels Map

Figure 2

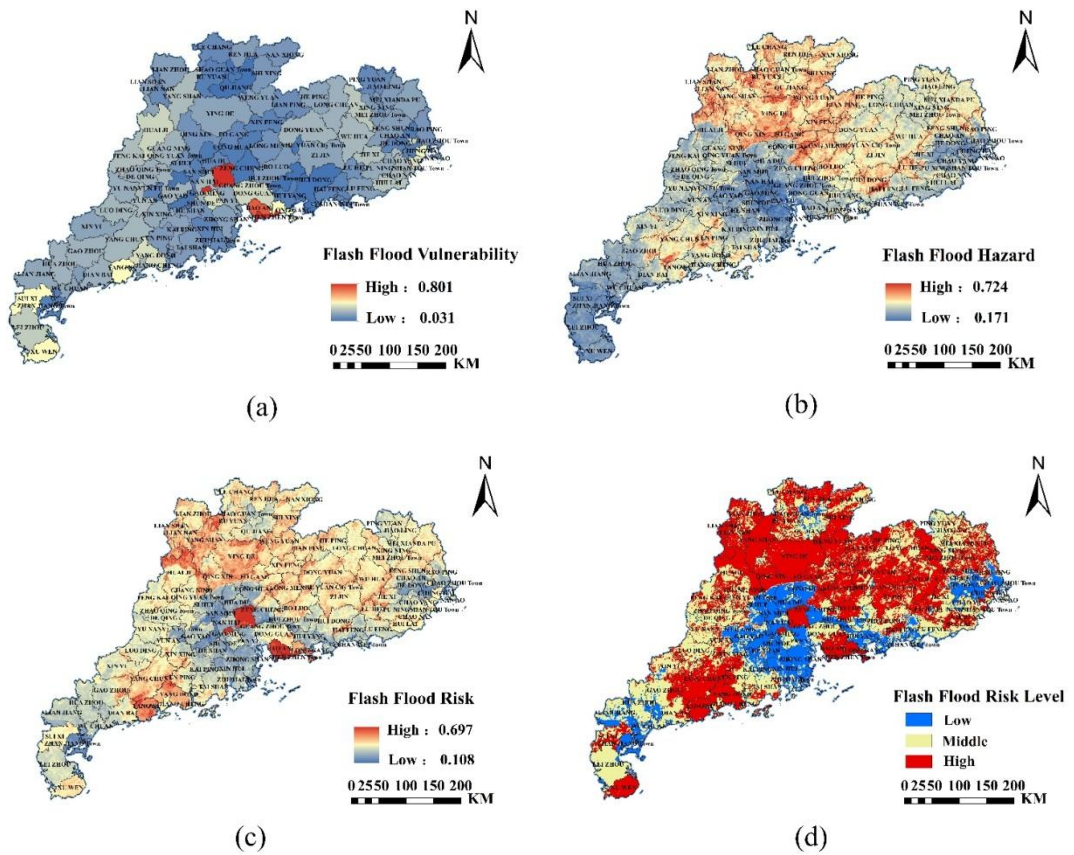
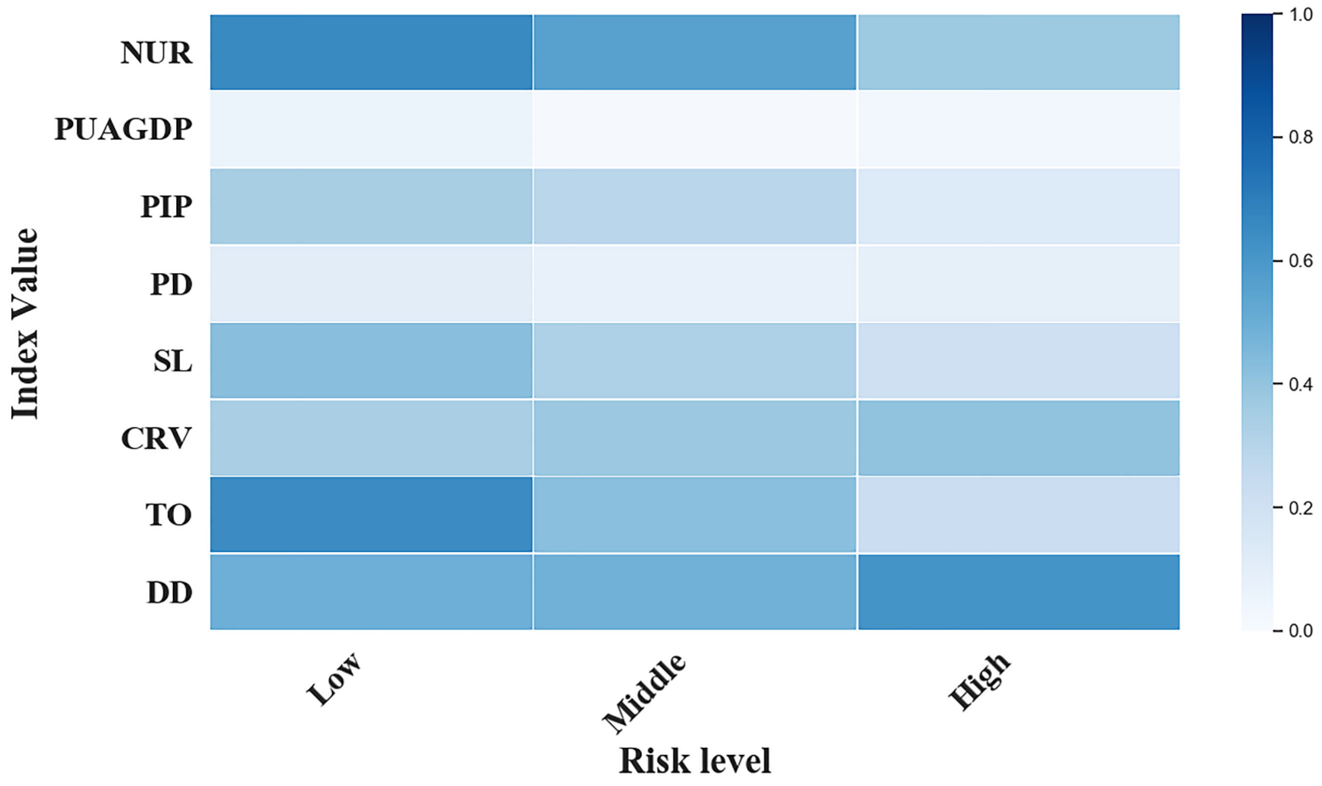
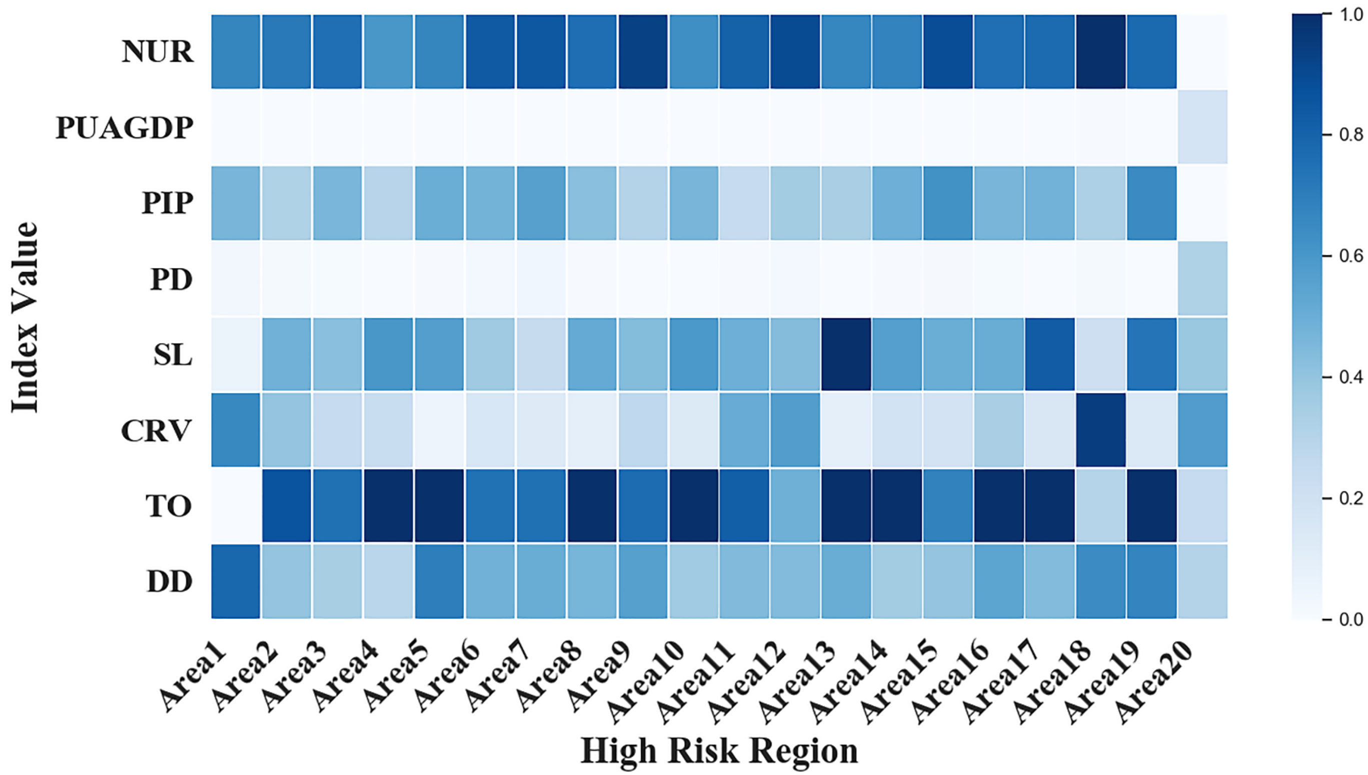

N
Flash Flood Vulnerability
High : 0.801
Low : 0.031
0 25 50 100 150 200
KM
(a)
N
Flash Flood Hazard
High : 0.724
Low : 0.171
0 25 50 100 150 200
KM
(b)
N
Flash Flood Risk
High : 0.697
Low : 0.108
0 25 50 100 150 200
KM
(c)
N
Flash Flood Risk Level
Low
Middle
High
0 25 50 100 150 200
KM
(d)

Figure 3



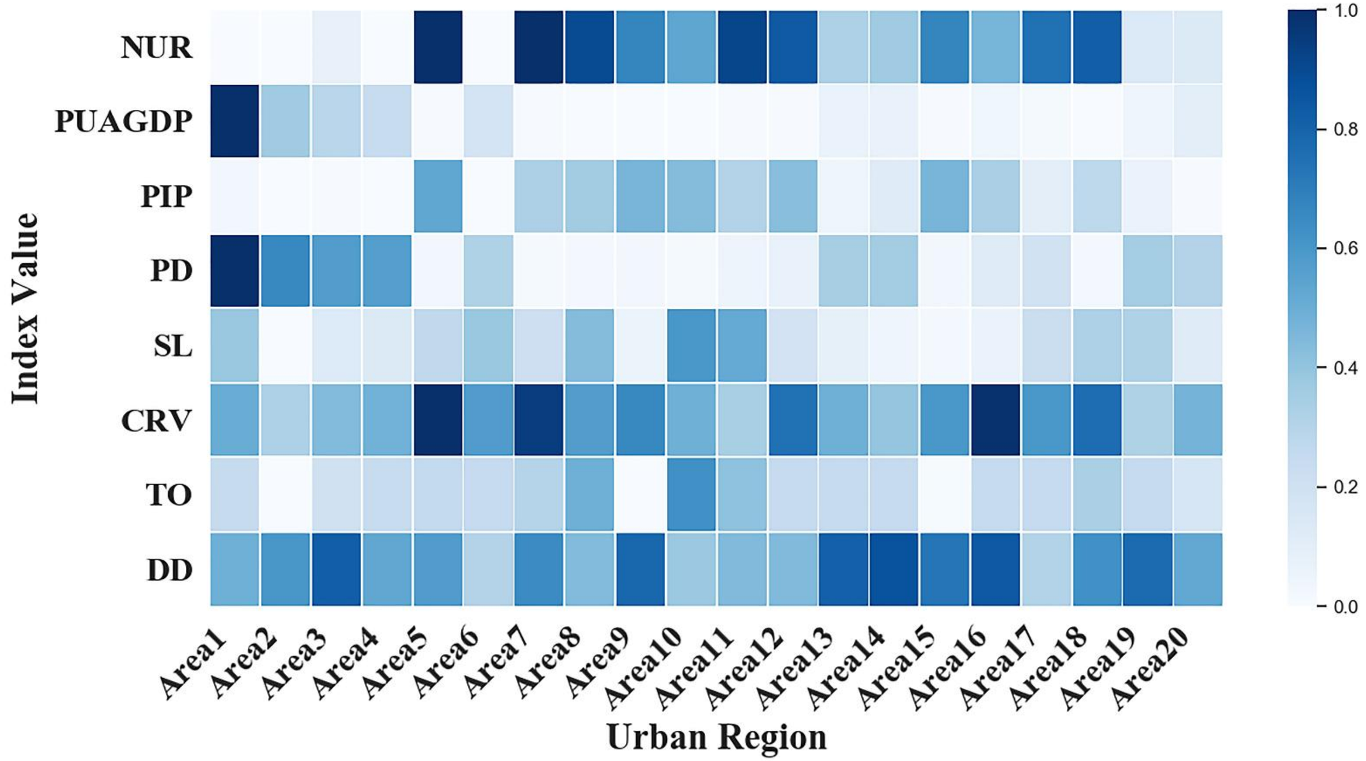
854

855 **Figure 4**



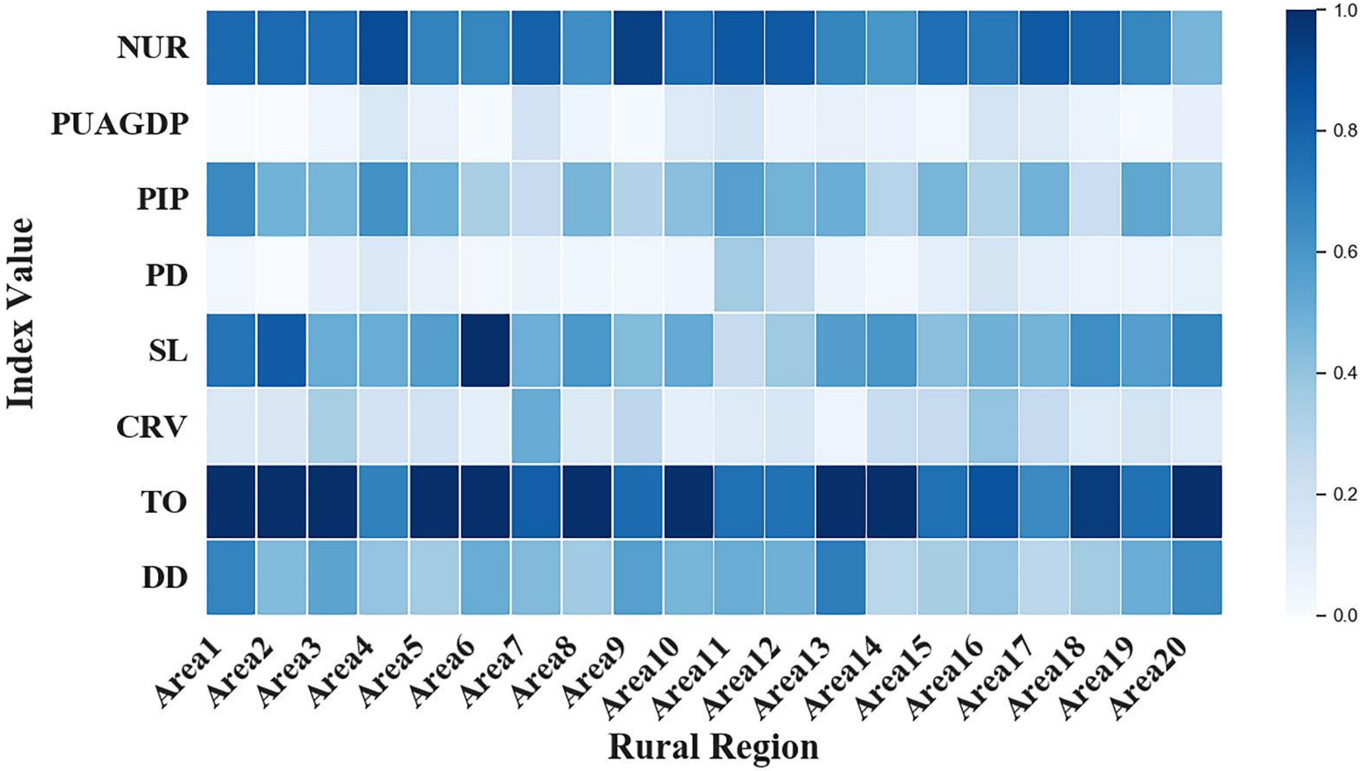
NUR
PUAGDP
PIP
PD
SL
CRV
TO
DD
Index Value
Area1
Area2
Area3
Area4
Area5
Area6
Area7
Area8
Area9
Area10
Area11
Area12
Area13
Area14
Area15
Area16
Area17
Area18
Area19
Area20
High Risk Region
1.0
0.8
0.6
0.4
0.2
0.0

Figure 5



858

859 **Figure 6**



860

861 **Figure 7**

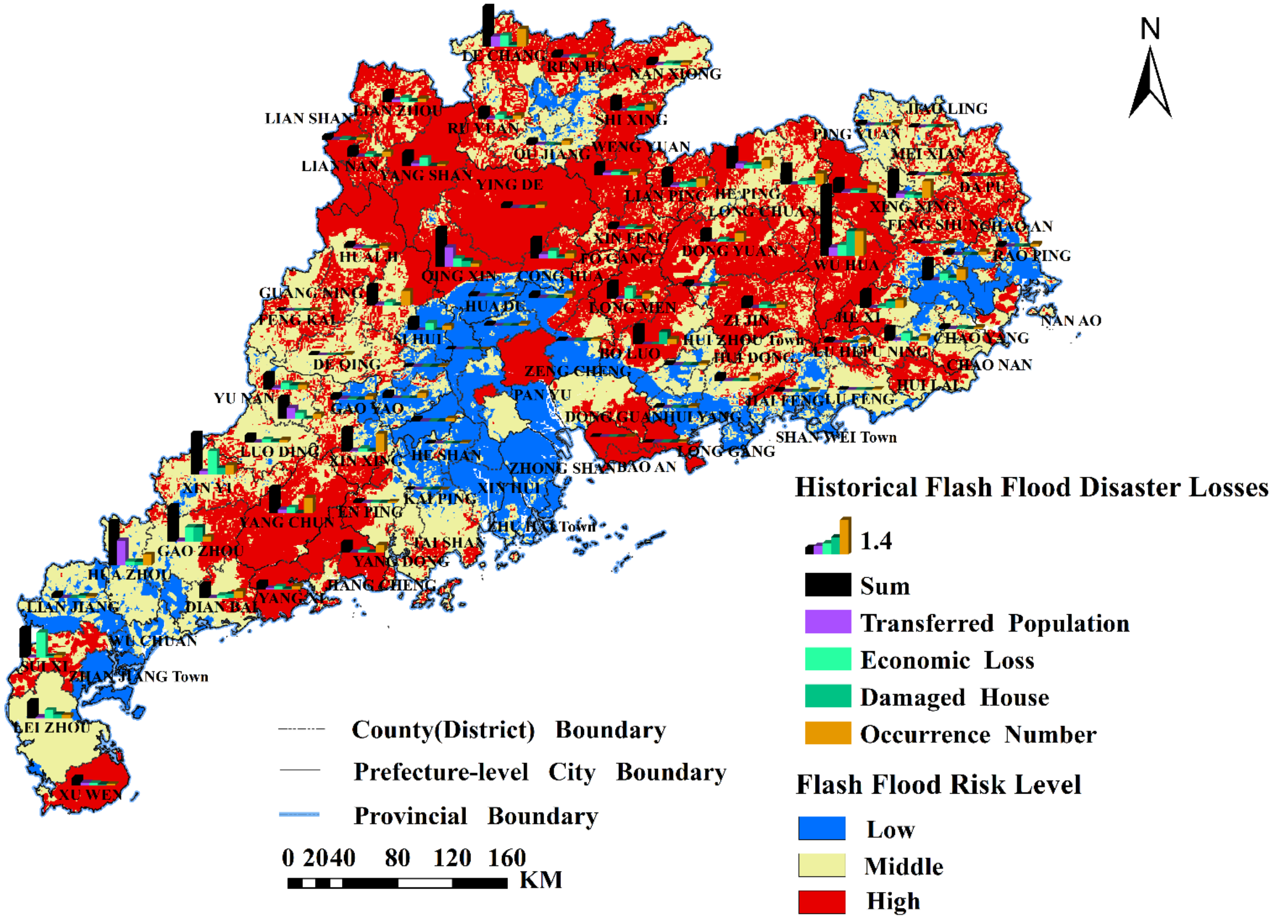
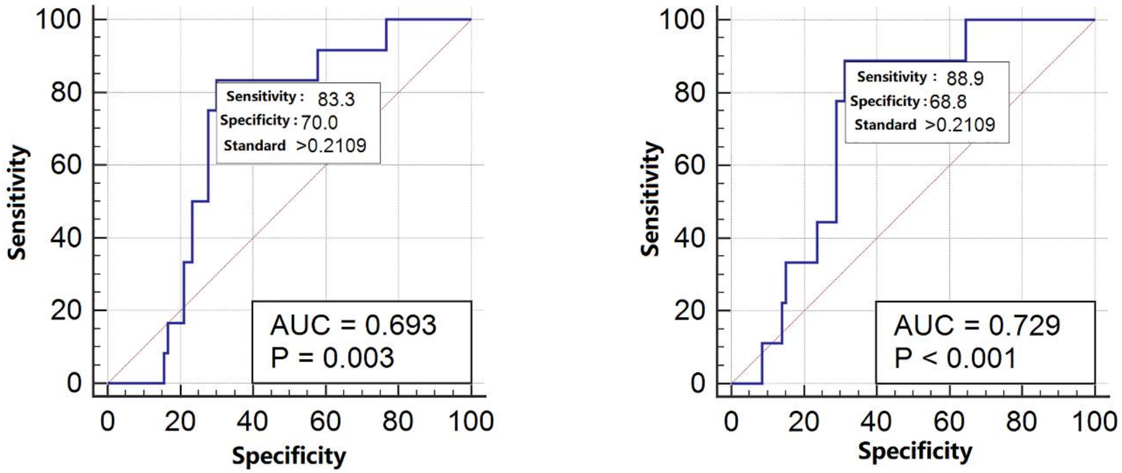

N
Historical Flash Flood Disaster Losses
1.4
Sum
Transferred Population
Economic Loss
Damaged House
Occurrence Number
Flash Flood Risk Level
Low
Middle
High
County(District) Boundary
Prefecture-level City Boundary
Provincial Boundary
0 2040 80 120 160
KM

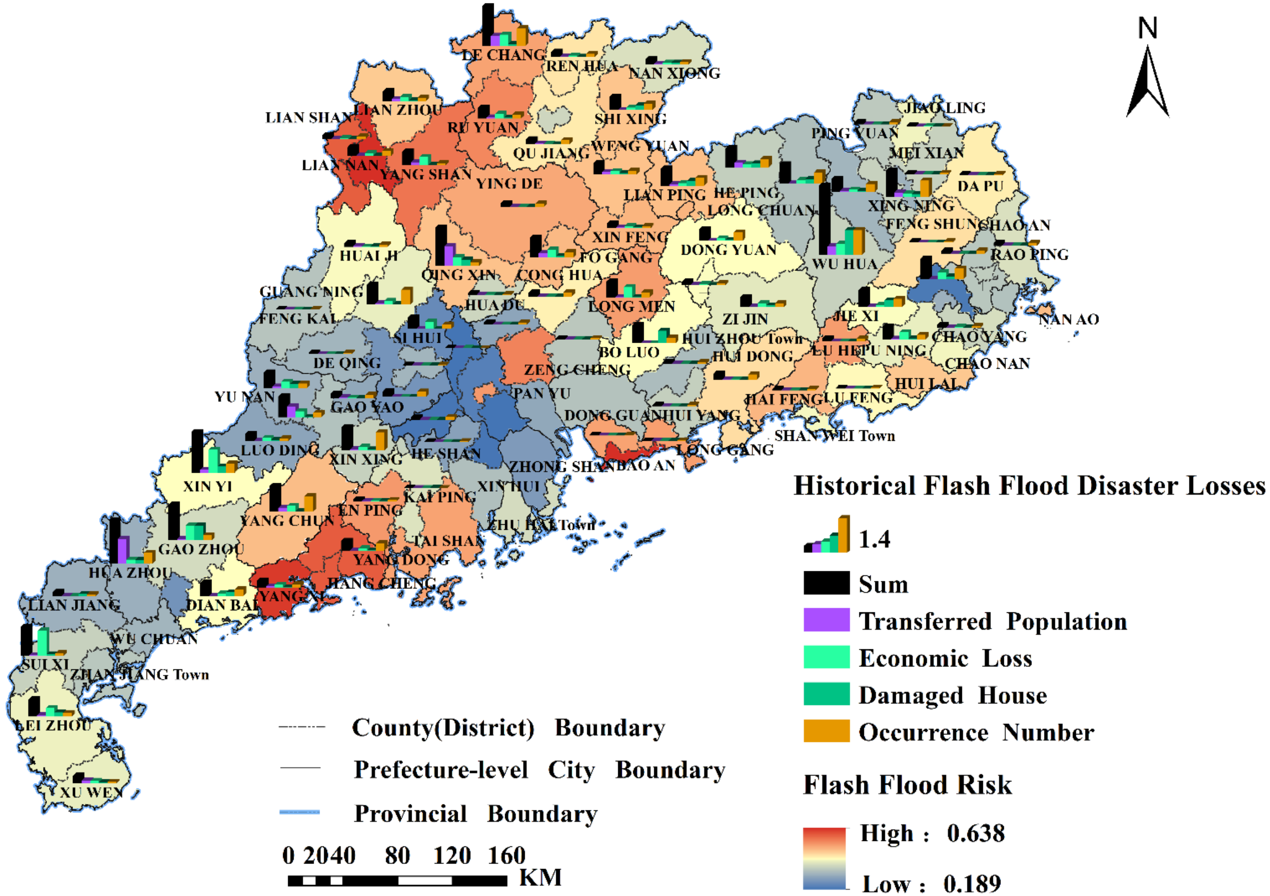
Figure 8


Sensitivity : 83.3
Specificity : 70.0
Standard >0.2109
AUC = 0.693
P = 0.003
Sensitivity
Specificity
0
20
40
60
80
100
Sensitivity : 88.9
Specificity : 68.8
Standard >0.2109
AUC = 0.729
P < 0.001

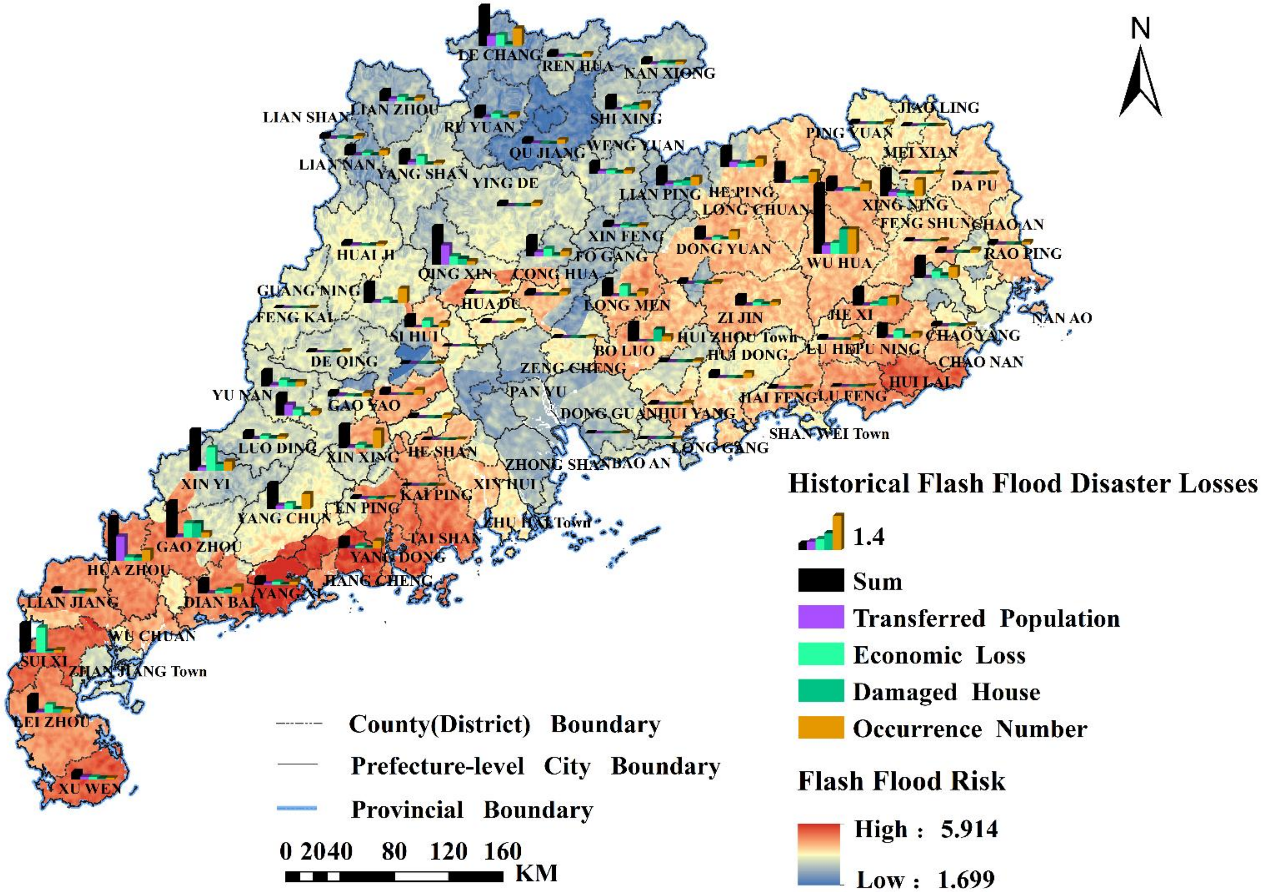
(a) (b)

Figure 9

866



867 **Figure 10**



868

869 **Figure 11**