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Review

Review on Urban Flood Risk Assessment

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Abstract: Under the background of rapid urban development and continuous climate change, frequent floods around the world have caused serious economic losses and social problems, which has become the main reason for the sustainable development of cities. Flood disaster risk assessment is an important non-engineering measure in urban disaster prevention and mitigation, and scientific flood disaster risk assessment is the premise and foundation of flood disaster risk management. This paper summarizes the current situation of flood risk assessment by analyzing the international literature in recent 20 years. The mechanism of flood disaster is mainly discussed. The flood disaster assessment methods are summarized, including historical disaster statistics method, multi-criteria index system method, remote sensing and GIS (Geographic Information System) coupling method, scenario simulation evaluation method and machine learning method. Furthermore, the development status of flood risk analysis and forecasting is summarized. Finally, the development trend and direction of flood risk assessment are put forward.

Keywords: urban flood; risk assessment; disaster-causing mechanism; review; assessment indicators; flooding forecast

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1. Introduction

With the changing global climate and the impact of human activities on the environment, extreme rainfall events in urban areas are increasing. Rainstorm and flood disasters have become one of the main natural disasters affecting the social and economic development of urban areas and the safety of people's lives and property [1,2]. Many scholars have pointed out that with the acceleration of urban development, the frequency of urban floods is increasing, and the impact on cities is also greatly enhanced [3,4]. As shown in Figure 1, the frequency of global flood disasters has shown an upward trend in the past three decades.

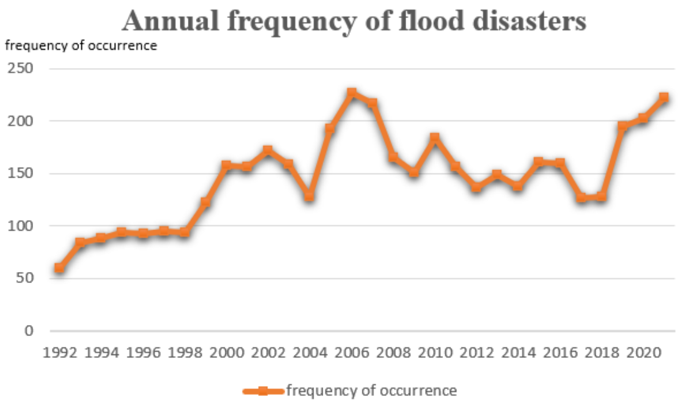

Figure 1. Frequency of flood disasters from 1992 to 2021.

Flood disaster is considered to be one of the most frequent disasters in the world. According to statistics, the proportion of rainstorm flood disaster is about 40% of the global losses caused by natural disasters [5]. Globally, floods have caused huge economic and social losses, and they continue to increase [6]. For example, rapid climate change has led to more frequent floods in Canada and wider spread [7]. Between December 2010 and January 2011, parts of Australia experienced widespread flooding, resulting in 37 deaths and total economic losses of more than A $30 billion [8]. In the UK, annual flood damage is estimated at £ 1.1 billion and, without additional adaptation measures, is expected to rise to £27 billion by 2080 under the worst climate change scenario [9]. In 2021, China 's flood disasters caused a total of 59.01 million people affected, 590 people died and disappeared, 152,000 houses collapsed, and direct economic losses of 245.89 billion yuan. From 14 June to 30 August 2021, severe floods occurred in Pakistan, resulting in 1162 deaths, 3554 injuries, more than 33 million people affected, and direct economic losses of more than USD 10 billion. The global losses caused by floods cannot be underestimated. Figure 2 shows the number of deaths and missing persons caused by floods in the world in the past 30 years.

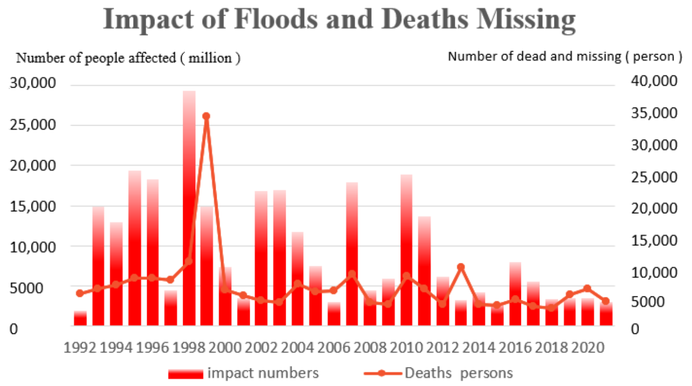

Figure 2. Number of dead, missing and affected by floods, 1992–2021.

Under the influence of human activities and climate change, the form and mechanism of urban flood disasters have undergone dramatic changes. The change of underlying surface caused by urbanization has affected the mechanism of runoff and confluence, and to some extent destroyed the urban drainage and waterlogging system [10,11]. The construction of urban flood control and disaster reduction system is facing new pressures and challenges, and the risk of urban flood disaster is on the rise [12]. Facing the severe flood disaster situation, carrying out flood disaster monitoring and risk assessment has become an urgent need to enhance the capacity of disaster prevention and mitigation [13]. In order to alleviate the current increasing urban flood disaster problem, it is imperative to strengthen the systematic research on urban flood disaster risk assessment.

Flood disaster risk assessment is a series of processes to analyze and evaluate the vulnerability of disaster-causing factors and disaster-bearing bodies that may bring potential threats or injuries to life, property, livelihoods, and the environment on which humans depend, and then determine the nature, scope, and loss of flood risks. It aims to improve the accuracy of mastering the spatial distribution of flood disaster risks, and comprehensively evaluates the natural and social attributes of flood disasters [14]. The basic process can be summarized as [15]. (1): risk identification, that is, to find out the risk source of flood disaster; (2): Risk assessment, according to a certain definition of risk, gives the quantitative analysis results, the results of the form of risk zoning map [16] and damage statistics [17], provide the basis for risk management; (3): Risk analysis, including risk analysis, vulnerability analysis and exposure analysis.

Flood disaster risk assessment is one of the foundations of disaster prevention plan formulation, and also an important basis and means for formulating disaster prevention and mitigation policies and measures. Before the occurrence of disasters, corresponding disaster prevention methods, measures and priorities can be formulated for various possible disaster situations. It is also possible to use multi-year disaster prevention and mitigation data to compile a disaster prevention expert system and formulate various emergency plans to cope with various emergencies. According to the results of flood risk assessment, the area is forecasted in advance, and the decision-makers are given sufficient decision-making time, which can reasonably determine the flood disaster prevention standards, optimize the order of rescue and disaster relief, optimize the implementation order of disaster prevention system construction, and provide scientific basis for disaster risk area management.

Therefore, it is necessary to systematically sort out and summarize the research of flood disaster risk assessment to provide better theoretical and technical support for subsequent researchers. The purpose of this paper is to review and summarize the research progress of urban flood risk assessment technology from a scientific and professional perspective. In this context, this paper first systematically expounds the mechanism of urban flood disaster, summarizes the methods of urban flood risk assessment, and expounds the latest research status of each method, then summarizes the research status of flood risk analysis and forecasting, and finally emphasizes the key research points in three aspects: model construction, data utilization and discipline integration.

2. Mechanism of Urban Flood Disaster

Scientific and systematic understanding of the disaster-causing mechanism of urban waterlogging disasters is helpful to find the source of urban waterlogging disasters, explore the driving force of their occurrence and development, and find corresponding solutions in urban flood disaster management. As shown in Figure 3, global climate change, urbanization, urban water system shrinkage and municipal facilities lag have seriously affected the occurrence of urban flood disasters. Therefore, we expound the formation mechanism of urban flood disaster from these three aspects.

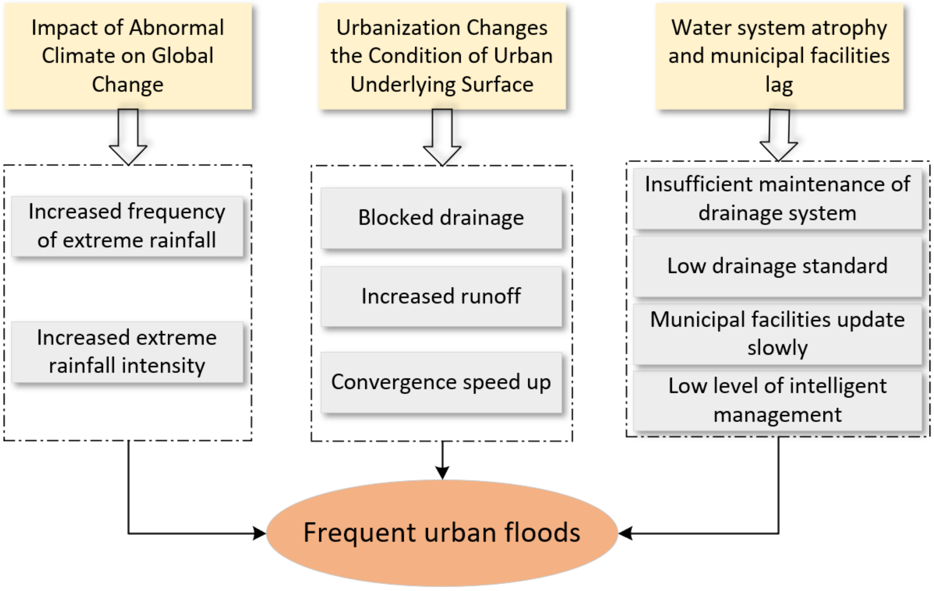

Figure 3. Factors Affecting Urban Flood Disaster.

2.1. Global Climate Change Leads to Frequent Extreme Rainfall

In 2021, extreme cold weather will break out in the United States, South Africa and Brazil; after entering the summer, the United States, Canada, Kuwait and Algeria continuously set high temperature records. In July, China's Henan Province encountered extreme heavy rainfall, which is rare in history. Zhengzhou broke the rainfall record and rained nearly a year in a day. At the same time, Western Europe also suffered heavy rains, resulting in hundreds of deaths. The frequent occurrence of extreme weather warns us that global climate change is an indisputable fact, and climate change and its consequences are considered to be one of the most important challenges facing contemporary mankind [18]. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the global average surface temperature increased by about 0.85 degrees from 1880 to 2012 [19], posing a huge challenge to the sustainable development and utilization of global and regional water resources [20,21]. Global warming has led to more intense and frequent atmospheric activities, changing the climate pattern in the continental region, especially in the middle and high latitudes. Extreme precipitation weather occurs frequently and has an increasing trend [22].

Extreme rainfall is the most direct driving factor for urban flood events, and climate change directly leads to changes in global and regional precipitation. Many studies have analyzed the temporal and spatial evolution characteristics and causes of global and regional precipitation in a changing environment. Trenberth's study showed that global land surface rainfall increased by 2% since the 20th century [23]. Konapala et al. divided the world into nine regions according to rainfall characteristics, and analyzed the characteristics of precipitation and evaporation in nine regions of the world. The results showed that the precipitation increased in four of the nine regions of the world, and the evaporation decreased in the remaining five regions, but the average precipitation and evaporation in nine regions showed an increasing trend [24]. Studies by Schuster et al. show that the frequency and magnitude of heavy rainfall events in the midwestern United States are increasing due to climate change [25]. Many scholars have analyzed the temporal and spatial evolution characteristics and causes of changes in China's annual average precipitation and extreme precipitation. Studies have shown that the annual average precipitation in southwestern, northwestern and eastern China has increased significantly in the past few decades. The extreme rainfall events in the North China Plain are more random, and the maximum rainfall in history is much higher than the common heavy rainfall in the North China Plain [26,27].

At present, the problem of extreme rainfall caused by climate change has attracted wide attention around the world, and further in-depth research work is needed. Therefore, we should strengthen international cooperation, realize low-carbon emission reduction, green and high-quality development, carry out ecological environment protection, comprehensively enhance green and low-carbon energy conservation and environmental protection awareness, reduce greenhouse gas emissions, slow down climate warming, and reduce the impact of extreme weather.

2.2. Urbanization Leads to Vegetation Reduction and Underlying Surface Hardening

Urbanization is a common phenomenon worldwide. With the rapid urbanization process, the number of urban population is growing rapidly. According to statistics, 52 percent of the world's population lives in urban areas and the number of urban populations is projected to continue to grow, with nearly 67 percent of the world's population expected to live in urban areas in 2050 [28]. In the process of rapid urbanization, the trend and speed of urban underlying surface hardening and imperviousness are increasing year by year. Studies have shown that during the rapid urbanization of the four central cities of Iowa in the United States from 1940 to 2011, the annual average total impervious surface change rate of the city increased from 2.42% (1940–1961) to 4.17% (1990–2002).

The development of urbanization will inevitably lead to the increase of urban construction area, and the surface vegetation such as grassland and trees in the city will be transformed into urban infrastructure construction land such as high-rise buildings and asphalt roads. As a result, the underlying surface is gradually hardened, and the ability and area to absorb rainwater are gradually reduced. The original 'breathing ground' becomes unable to infiltrate naturally, and a large amount of rainwater is retained on the urban ground [29]. At present, many scholars have carried out research on the hydrological effects of urbanization with the help of hydrological and hydrodynamic models. It is generally believed that the expansion of urbanization has increased the runoff and peak flow of urban watersheds, aggravated the degree of urban flood disasters, and reduced the interaction process between the base flow of urban watersheds and groundwater and surface water in the surrounding areas of cities [30–33].

Therefore, rational planning of urban green space and transportation, increasing the area of green plants, enhancing the permeability of underlying surface, and increasing the use of low-impact development design are effective means to reduce urban rainwater surface runoff, restore urban natural hydrological cycle, and reduce urban vulnerability [34].

2.3. The Shrinkage of Urban River Network and the Lag of Municipal Facilities

The single influencing factor of continuous precipitation or heavy precipitation is not enough to cause urban waterlogging. Another key point is that the drainage of the city's drainage pipe network is not smooth and the drainage is not timely, resulting in an increasing depth of water in the city and an increasing time of water retention, which ultimately leads to the occurrence of urban waterlogging disasters [35].

Due to the planning and design requirements of rapid drainage of urban municipal facilities and the timing of construction, municipal facilities are updated slowly and overloaded. This has led to the problems of urban water accumulation, slow construction of municipal facilities in urban fringe areas, and lack of water storage capacity in pipeline networks. When the rainfall is large, the pipe network system water collection and drainage speed is slow, rainwater overflow phenomenon [36]. In addition, urban municipal facilities are not only an important means of urban waterlogging prevention, but also a vulnerable point when urban waterlogging disasters occur. Especially lifeline projects, once affected by disasters, may lead to a series of secondary disasters and cause huge losses to the city. At the same time, the storage function of urban water system is neglected due to the value of urban land. Urban construction often artificially interferes with river regulation and storage, changes the natural catchment pattern and regulation and storage function pattern, and reduces the anti-waterlogging function of urban rivers and ponds [37].

Therefore, it is necessary to focus on a larger urban basin to rationally arrange municipal water conservancy facilities, reduce the conflict between cities and cities in dense urban clusters on the relief and utilization of water resources, promote the recovery of natural hydrology, and promote the construction of urban sustainable flood control system.

3. Flood Risk Assessment Method

The selection of flood risk assessment methods is generally based on the spatial scale of evaluation and the completeness of basic data. The use of methods directly affects the timeliness of analysis results and the accuracy of evaluation results. The current flood assessment methods have some limitations. Aiming at these problems, this paper comprehensively divides the flood assessment methods into five aspects, namely, historical disaster mathematical statistics method, multi-criteria index system method, remote sensing and GIS coupling method, scenario simulation evaluation method and machine learning method, and expounds its current situation, advantages and limitations.

3.1. Historical Disaster Mathematical Statistics

The historical disaster mathematical statistics method generally uses the historical flood event disaster data released by the government or relevant departments, such as the number of affected people, the number of house damage, the inundation range, and the facility damage data caused by a flood disaster event. According to the law of flood disaster, the mathematical statistics method is used to analyze these data and predict the frequency, depth and direct loss of flood disasters in different spatial locations [38]. This method is an early method used in flood disaster assessment research. In the absence of existing assessment data, it analyzes the law and trend of risk based on historical data, and then assesses the current or future risk.

Some researchers use historical rainstorm and flood data to construct vulnerability curves and conduct quantitative or qualitative flood risk analysis in the study area [39–42]. On the basis of historical disasters, combined with land use type data [43] and hydrological model [44], the spatial transformation and damage of flood risk are evaluated in more detail. Benito integrated multidisciplinary knowledge and methods to assess flood risk in the study area using long time series of historical flood data [38]. Liu used the historical flood disaster data of the affected counties and cities as the basic unit to comprehensively analyze the flood disaster risk degree of the study area by Markov chain [45]. Li proposed a quantitative assessment model for flood disaster losses by studying the database and the spatial distribution method of socioeconomic data [46]. Denis studied flood risk management on the basis of historical flood disaster records [47].

The historical disaster statistics method has clear thinking and simple calculation, and its evaluation results are in good agreement with the actual situation. However, the data it relies on are usually of poor spatial accuracy and time lag, which is only suitable for large-scale spatial areas such as cities and provinces [14]. In addition, this method requires the study area to have more detailed and abundant historical disaster data [48], which is more sensitive to missing data.

3.2. Multi-Criteria Index System Method

Multi-criteria index system is the most widely used flood risk assessment method. According to the natural characteristics and socio-economic particularity of the study area, it selects a number of direct and indirect index factors related to the formation of urban flood disasters, constructs the flood risk assessment index system of the study area, and applies certain mathematical models or methods (such as analytic hierarchy process, set pair analysis, fuzzy comprehensive evaluation method) to evaluate the comprehensive impact of different factors on the flood risk of the study area, so as to define the risk size of the study area. Then select the corresponding evaluation methods for risk assessment, such as analytic hierarchy process, set pair analysis, fuzzy comprehensive evaluation method and so on.

Most researchers have selected indicators such as slope, land use, precipitation, and population density to construct a multi-index system, and used the analytic hierarchy process to quantify the index weights to conduct risk assessments in the study area [49–51]. In the risk assessment of flood disaster, Gilbert F. White took the human response to the disaster as one of the basis for the first time, and incorporated the characteristics of population and housing structure into the evaluation system [52,53]. Jiang determined the indicators affecting the flood risk of each county from the four aspects of flood risk, exposure, vulnerability, and regional disaster prevention and mitigation capabilities, and integrated them into a flood risk index. On this basis, the flood risk zoning map of the Songhua River Basin was obtained [54]. When using this method for risk analysis, the determination of index weight is an important research issue. Therefore, researchers will use different methods such as subjective and objective weight determination to determine the weight of the selected indicators. For example, Lyu used the analytic hierarchy process and the interval analytic hierarchy process [55], Cabrera used the analytic hierarchy process and the maximum entropy model [56] to distribute the weights of the indicators. Feng found that there are many factors involved in the process of estimating regional vulnerability, and it is an effective way to use fuzzy comprehensive evaluation method to carry out comprehensive research. Using fuzzy comprehensive method, we can understand the vulnerability of the region in an all-round way [57]. In order to assess the housing risk, agricultural risk and comprehensive risk in Malaysia, Jiang established a risk assessment model library by using fuzzy comprehensive evaluation method, simple fuzzy classification method and fuzzy similarity method [58]. Chen used the projection pursuit method to evaluate the flood disaster in Sichuan Province [59]. With the deepening of research, it has become more popular to combine with geographic information system technology to study flood risk grade map and carry out risk zoning in the study area [60,61].

The multi-criteria index evaluation method can flexibly select indicators according to regional characteristics and data availability, and can flexibly select index quantification methods to evaluate flood risk. It is not only suitable for regions with different spatial scales, but also can intuitively reflect the relationship between each index and flood risk. However, when applying the multi-criteria index evaluation method, the difficulty lies in the selection of indicators and the determination of weights [62]. The selection of indicators is limited by factors such as data availability, characteristics of the study area, and data accuracy [16], and the determination of weights is affected by the analysis method. At present, the weight calculation method is mostly based on expert knowledge and experience [61], which makes the evaluation results of multi-index evaluation method subjective.

3.3. Coupling Method of RS and GIS

The method based on the coupling of RS and GIS is to use remote sensing technology to obtain information such as water area, inundation duration, and disaster-bearing bodies in the disaster area, and then input these information into GIS tools for spatial analysis.

Based on time series Radarsat remote sensing images and other geographic information data, Chubey constructed a prediction model that coupled Markov model and spatial logistic regression model. Based on this model, they predicted the intensity and spatial distribution of future floods in the Red River Basin in southern Manitoba [63]. Using IRS-1D and LISS-III data from 2002 to 2003, Chowdary evaluated the surface and subsurface flooding areas in the pre-monsoon and post-monsoon seasons of the Bihar flood-prone areas in a GIS environment [64]. Barredo analyzed the spatial distribution of flood disasters in Europe for many years by means of GIS data set, and obtained the trend map of flood disasters in the study area [65]. Mateeul Haq used MODIS data in 2011, the study area is Sindh Province, Pakistan, combined with his population distribution, vegetation cover, etc., while using RS and GIS for loss assessment and flood warning [66]. Using NOAA AVHRR images, Md. Monirul Islam extracted flood inundation frequency information and used it as an indicator in flood risk assessment [67]. On the basis of regional risk identification, Cheng selected appropriate evaluation indicators from the aspects of disaster-causing factors, disaster-pregnant environment and hazard-affected bodies, and established an evaluation index system to evaluate flood disaster risk from the composite scenario of various indicators through scenario analysis technology [68]. Liu used GIS technology and AHP method to obtain the disaster vulnerability assessment map and disaster risk assessment map of the study area, and determined the high risk level distribution area of the area [69]. Liu used GIS technology and RS technology to find that the fusion of multi-source remote sensing data has a good effect on the timely and accurate assessment of flood disasters [70]. Based on long time series of AVHRR and MODIS images, Huang studied the inundation range of flood water bodies in the area and analyzed the inundation frequency of flood water bodies. The flood risk model was constructed from four aspects: hazard, vulnerability, exposure and disaster prevention and mitigation capacity, and the expression of risk assessment results was expressed from two scales of grid and administrative unit [71]. Li used 10 years of MODIS images to extract the submerged area of water body, analyzed the spatial and temporal changes, and evaluated the flood loss [72]. Taking Quzhou City, Zhejiang Province as the research area, Xiao used gridded geographical background data, spatial socio-economic data, combined with remote sensing data of the research area, and used GIS to evaluate the flood risk of the research area [73]. Considering the risk and vulnerability, Jiang selected suitable index factors, applied GIS to spatialize each factor, and combined with the analytic hierarchy process to determine the weight, and obtained the flood disaster risk distribution map of Zhejiang Province [74].

The use of RS technology can quickly obtain the flood risk information of the study area, which is more practical for the study of large flood disasters. However, for small floods, due to the short duration, remote sensing data often cannot accurately capture the flood process, and there are great limitations in spatial scale and time resolution [75]. In the future, using multi-source fusion data and GIS integrated application for flood risk analysis will become a key research direction [76].

3.4. Scenario Simulation Evaluation Method

Based on hydrological and hydrodynamic models, scenario simulation assessment is a method for dynamic simulation and assessment of disaster processes in the study area by designing disaster scenarios of specific frequency and intensity (design rainfall) [35]. This method can intuitively and accurately give the spatial distribution characteristics of urban flood disaster risk, which can provide some reference for managers' disaster prevention and mitigation and risk management decision-making, and provide data support for disaster risk transfer [77].

Since the end of the 20th century, hydrological and hydrodynamic research has made great progress, objectively promoting the application of scenario simulation in flood risk assessment. One-dimensional pipe network hydraulic model is the first widely used numerical model, because the required data is relatively simple and the model results are more accurate, such as SWMM model [78], SIPSON model [79]. Based on the one-dimensional hydraulic model, two-dimensional numerical models have gradually begun to be promoted. These models can accurately simulate the evolution of surface floods during the entire rainfall process because they can couple one-dimensional surface, river channel and two-dimensional surface, such as commercial models MIKE [80], Info Works ICM [81]. In order to achieve a more realistic simulation results, three-dimensional numerical model has also been the attention of researchers, such as Delft3D model, FLOW-3D model, water quality simulation and flow field simulation. Table 1 is the current mainstream flood simulation model.

Table 1. Flood model.

Model	The Model Characteristic	The Input Parameters	Development Organizations
SWMM	Provides distributed hydrological module, one-dimensional hydrodynamic module.	Land use, terrain data, rainfall, rainfall intensity, pipe network data, etc.	EAP United States Environmental Protection Agency
HEC-RAS	One-dimensional and two-dimensional hydrodynamic modules are provided.	Topographic and hydrological data	U.S. Army Corps of Engineers Hydrological Engineering Center
PCSWMM	With SWMM as the core, it provides pre-processing and post-processing modules, and can simplify the calculation of two-dimensional surface.	Land use, terrain data, rainfall, rainfall intensity, pipe network data, etc.	Canadian Hydraulic Calculation Institute
LISFLOOD-FP	Provide two-dimensional hydrodynamic module.	Terrain and hydrological data, pipe network data	University of Bristol
InfoWorks ICM	Highly integrated, fully functional, realizes the coupling simulation of hydrology, hydrodynamics and water quality, and has strong pre- and post-processing functions.	Pipe network data, terrain data	UK HR Wallingford
MIKE	It includes MIKE URBAN, MIKE FLOOD, MIKE21 and other modules. Each module is relatively independent and fully functional, and is widely used in various projects.	Topographic and hydrological data, roughness, waves, tide levels, etc.	Danish Hydraulic Institute DHI
EFDC	Provide water quality module, can simulate point source pollution, non-point source pollution, organic matter migration process.	River network data, pipe network data, terrain data	Virginia Institute of Oceanography
Delft3D	It is suitable for three-dimensional hydrodynamic water quality simulation, which can simulate the hydrodynamics of estuary and port.	Terrain and hydrological data, grid data	Delft Hydraulic Research Institute, Netherlands

Table 1. *Cont.*

Model	The Model Characteristic	The Input Parameters	Development Organizations
FLO-2D	Provide two-dimensional hydrodynamic module, one-dimensional calculation embedded SWMM module.	Topographic and hydrological data	FLO-2D Software, Inc.
FLOW-3D	CFD software, provides three-dimensional hydrodynamic module, suitable for analysis of three-dimensional flow field.	Terrain data, hydrological data	Flow Science, USA
Flood Simulation Model	Based on the unstructured grid, the coupling of urban ground flooding and pipeline is realized for the first time.	Pipe network data, terrain data	China institute of water resources and hydropower research
HydroInfo	Numerical simulation of complex water flow and transport process is provided.	Pipe network data, river network data, terrain data	Dalian university of technology
HydroMPM	The numerical method is used to simulate the dynamic processes such as water flow, water quality and sediment and their associated processes.	Hydrological data, river network data	Zhujiang Institute of Water Conservancy Science
GAST	The Godunov scheme is used to solve the two-dimensional Saint Venant equations, and the GPU parallel computing technology is used to accelerate the calculation.	Hydrological data, pipe network data, terrain data	Xi'an university of technology
IFMS/Urban	Based on the self-developed GIS platform, one-dimensional and two-dimensional coupling calculation is realized.	Terrain and hydrological data, river network data	China institute of water resources and hydropower research

Based on the hydrological and hydrodynamic model, the researchers carried out scenario simulation and flood risk assessment in the study area. Some scholars coupled one-dimensional pipe network model with two-dimensional surface model [82], and even proposed two-dimensional flood simulation model based on empirical formula and artificial intelligence [83]. For example, Xu pointed out that the scenario simulation method is the trend of future risk assessment. Taking the sponge city demonstration area of Jinan City as the research area, combined with the simulation results of the hydrological hydrodynamic model, the risk zoning based on the submerged depth and time threshold and the risk zoning based on the empirical formula were compared [38]. Suarez evaluated the impact of floods and climate change on Boston's urban transport system using scenario simulations [84]. By designing different rainfall scenarios, Su constructed a two-dimensional hydraulic simulation to simulate the spatial and temporal distribution of rainstorm waterlogging, and then evaluated the rainstorm waterlogging in Xinluo District, Longyan City, Fujian Province in combination with the vulnerability curve [85]. Bisht compared the simulation effect of one-dimensional SWMM hydrological model with that of two-dimensional Mike Urban hydrodynamic model in the study area, and found that the two-dimensional hydrodynamic Mike Urban model overcomes the limitations of one-dimensional SWMM hydrological model in simulating flood inundation range and water depth, and the simulation effect is better [86]. Zeng coupled the one-dimensional SWMM hydrological model with the two-dimensional Lis Flood-FP hydrodynamic model, and realized the simulation of the submerged range and submerged depth of rainstorm and flood in the study area. The accuracy of the coupling model was verified by field investigation [87]. In addition, some researchers constructed coupling models, designed simulated rainfall under different scenarios, and assessed the risk of precipitation inundation in the study area. Jing analyzed the vulnerability of rainstorm flood disaster in Pudong area of Shanghai by designing rainstorm runoff scenarios with different return periods [88]. Huang used Info Works ICM software to construct a rain and flood model for the Donghao River Basin in Guangzhou, and combined with eight indicators to form an index system to evaluate the flood risk of the study area under the 1-year, 5-year and 50-year rainstorm scenarios [89]. Zhang used the MIKE hydrological and hydrodynamic model to simulate the flood in the downstream area of Yindongnan Plain under the rainstorm scenarios of 5-year return period, 11-year return period, 20-year return period, 50-year return period and 100-year return period, and dynamically evaluated the flood risk by combining the evaluation index system composed of flood depth, population density and GDP per area [90].

Because of its advantages of intuitive and high-precision reflection of the influence range and influence degree of disaster events (the characterization effect of disaster-causing factors), the scenario simulation assessment method has been widely used in related disaster refined simulation scenarios at home and abroad. At the same time, this method is also one of the main methods considered in future flood disaster risk assessment research. However, the scenario simulation method has high requirements for the geographical data of the study area, the model is not universal, and greatly depends on the constructed stormwater model. Due to the strictness of the data required for modeling and the complexity of the modeling process, this method is not suitable for large study areas and generally lacks consideration of the vulnerability of hazard-affected bodies [16].

3.5. Machine Learning

Machine learning method is a new method for flood risk assessment in recent years. It relies on intelligent algorithms to learn the characteristics of flood risk and automatically acquires the input-output relationship between driving factors and flood risk, providing a more flexible, objective and rapid flood risk assessment method.

At present, some machine learning models have been applied to flood risk assessment and have shown good evaluation results, such as random forest model, extreme gradient boosting model [91], support vector machine [92], etc. For example, Thanh used random forest and support vector machine to evaluate flood risk in urbanized areas, and found that the overall accuracy and Kappa coefficient of the evaluation were high [93]. Random forest model is more suitable for flood risk assessment than support vector machine model [94,95]. Studies have also shown that it is necessary to use machine learning methods to develop reliable flood risk assessment maps. Shu conducted back propagation neural network training on flood disaster data in the study area to generate flood risk distribution map. The results are basically consistent with the results obtained by the emergy method [96]. Ma introduced the XGBoost model for risk assessment and found that this method is an effective way to obtain high-quality county-level flood risk maps [97]. Phama uses a risk assessment method based on the combination of deep learning network and analytic hierarchy process. Research shows that the combination of the two can more accurately develop regional flood risk assessment maps [98] Many researchers use different machine learning models in the same research area to compare the effects of the models. Khosravi applied three index evaluation methods (VIKOR, TOPSIS and SAW) and two machine learning models (NBT and NB) to the flood risk assessment of Ningdu County. The results show that the NBT model performs best in the field of flood risk assessment [99]. Li proposed a set of rainstorm waterlogging disaster prediction index system by comprehensively considering disaster-causing factors, exposure and vulnerability, and constructed the BP model and XGBoost model for rainstorm waterlogging disaster prediction. The results show that when the combination of indicators that comprehensively consider disaster-causing factors, exposure and vulnerability indicators and do not reduce the dimension by principal component analysis is used as the rainstorm waterlogging disaster prediction index system, the prediction accuracy of BP model and XGBoost model is optimal [100].

With the development of computer technology and the progress of various machine learning algorithms in recent years, machine learning methods have great potential in flood risk assessment. However, the machine learning method relies heavily on the completeness and reliability of the sample data set, which directly affects the rationality of the flood characteristics and risk assessment results learned by the model.

As shown in Table 2, there is a certain correlation between the five flood disaster risk assessment methods. Different evaluation methods have their applicability. In the face of different research objects, it is necessary to select the appropriate evaluation method according to the characteristics of the research area, considering the requirements of the research scale and the accuracy of the research results.

Table 2. Comparison of flood risk assessment methods.

Appraisal Procedure	Appraisal Unit	Methods and Principles	Method Advantages	Method Disadvantages
Historical disaster mathematical statistics	Province, city, county	For the randomness of flood disasters, historical samples are used to estimate the probability of flood disasters.	The idea is clear, the calculation is simple, and the evaluation results are in good agreement with the actual situation.	The study area is required to have more detailed and abundant historical disaster data. More sensitive to missing data.
Multi-criteria index system method	Province, city, county, grid unit	Select indicators to build index system, determine the weight and establish a comprehensive function of indicators to obtain the risk index of the evaluation area.	Suitable for different spatial scales of the region, and can intuitively reflect the relationship between the indicators and flood risk.	The selection of indicators and the determination of weights greatly affect the evaluation results.
Coupling Method of Remote Sensing and GIS	Province, city, county, grid unit	The analysis method of remote sensing and geospatial data processing combined with GIS analysis.	Using RS technology can quickly obtain the flood risk information of the study area, which is more practical for large-scale flood disaster research.	For small floods, due to the short duration, remote sensing data often cannot accurately capture the flood process, and there are great limitations in spatial scale and time resolution.
Scenario simulation evaluation method	city, county, grid unit	Hydrological and hydrodynamic models are used to simulate the process of disaster occurrence and dynamically show the temporal and spatial evolution of disaster.	Intuitively and accurately reflect the scope and extent of the impact of disaster events.	The requirements for geographic data in the study area are high, and the model is not universal, which greatly depends on the constructed stormwater model.
machine learning	Province, city, county	Machine learning methods such as support vector machine and random forest are used to evaluate flood risk in the evaluation area.	Effectively improve the accuracy and efficiency of assessment.	Over-reliance on the reliability of sample data.

4. Analysis of Urban Flood Risk Assessment and Flood Forecast

The flood risk assessment process mainly includes three parts: risk identification, risk analysis and risk assessment, as shown in Figure 4. Among them, the selection of risk analysis indicators is the key link, and the selection of appropriate evaluation indicators to construct an index system is particularly important for improving the quality of flood risk assessment [16]. According to the theory of disaster science, the disaster process is determined by the circular feedback process composed of the three elements of disaster environment, disaster-causing factor and disaster-bearing body. The stability of the disaster environment, the risk of disaster-causing factors and the vulnerability of disaster-bearing bodies determine the size of the disaster.

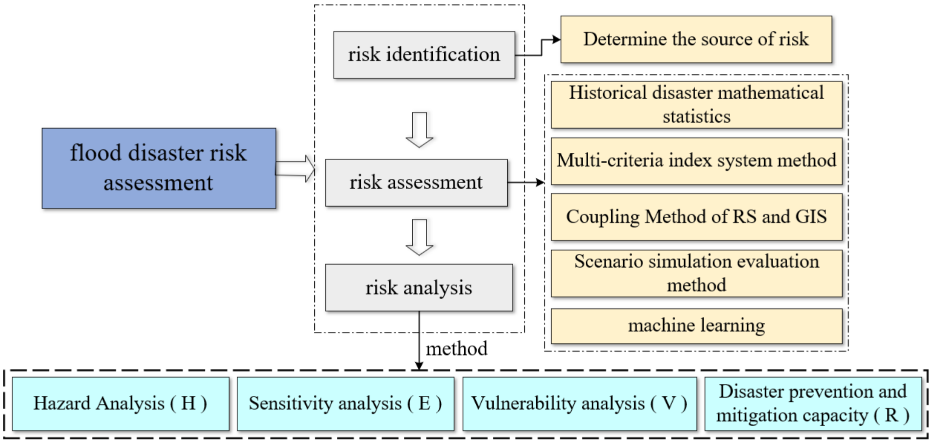

Figure 4. Flood disaster risk assessment process.

4.1. Flood Disaster Theory

In the process of flood disaster risk research, different scholars have given different flood disaster risk expressions. Some scholars have given the definition of flood disaster risk: combined with the characteristics of flood disaster, flood disaster risk is a comprehensive representation of Hazard × Vulnerability [101,102]. Meyer et al. proposed the expression 'flood risk = Probability × Consequence' [103]. Some other scholars have given the expression of 'flood risk = Hazard × Exposure × Vulnerability', and believe that flood risk is the result of the interaction of hazard, exposure and vulnerability (H-E-V framework) [104,105]. In addition, under the framework of 'H-E-V', some scholars considered the weakening effect of regional emergency capability on disaster risk, added the factor of disaster prevention and mitigation capability, and put forward the expression of 'flood risk = Hazard × Exposure × Vulnerability × Emergency (H-E-V-R framework)' [106,107]. The existing flood disaster system theory is shown in Table 3.

Table 3. Summary of flood disaster theory.

System Components	Risk Expression	Researchers (Source)
Hazard-vulnerability	R = f(H,V)	Zhou et al. [102]; Xu et al. [101]
Hazard-Exposure-vulnerability	R = f(H,E,V)	Kron [104]; Li et al. [105]
Hazard-Exposure-vulnerability-Emergency	R = f(H,E,V,R)	Zhang et al. [106]; Du et al. [107]

4.2. Risk Result Analysis of Flood Disaster

The urban flood assessment framework adopted in the IPCC Fifth Assessment Report is Hazard × Exposure × Vulnerability, that is, the 'H-E-V' framework. In order to analyze the causes of flood disaster risk more comprehensively and deeply, and fully consider the importance of disaster prevention and mitigation capacity to flood disaster assessment, based on the 'H-E-V-R' framework, this paper sorts out the main research contents of the four major elements of disaster-causing factor risk, disaster-pregnant environment sensitivity, disaster-affected body vulnerability, and disaster prevention and mitigation capacity, and summarizes the commonly used assessment indicators [108].

4.2.1. Risk of Disastrous Factors

Disaster-causing factors, that is, various abnormal factors produced by the disaster-pregnant environment, are rare or extreme events that can adversely affect human life, property or various activities in a natural or man-made environment and cause disaster procedures. In general, the greater the intensity of the disaster-causing factor, the higher the probability, the greater the risk, and the greater the possibility of serious disaster [109].

The disaster-causing factor is the main hazard source of urban rainstorm flood disaster and an important factor inducing rainstorm flood disaster. Therefore, hazard analysis of disaster-causing factors is usually the first step in disaster risk analysis, analyzing the time (probability), intensity, scale and spatial location of disasters. The elements needed for flood disaster risk analysis include rainfall, water depth, water flow rate, water range, etc., to analyze and quantify the risk characteristics of disaster-causing factors such as disaster intensity, impact range and duration of different frequencies [38].

The risk analysis of flood disaster-causing factors is mainly divided into two types: (1) Simulation analysis of flow scale based on probability distribution theory. For example, the linear matrix method of extreme value distribution and P-III probability distribution is used to divide the flood frequency in different magnitude regions, the flood frequency is predicted by the binary Gumbel-Logistic model, and the annual flood peak flow and annual flood volume are predicted by the Copula model. (2) Submergence simulation analysis based on watershed runoff and runoff. In the geographic information system, based on the digital elevation model (DEM), the submerged depth and range are simulated by inputting rainfall, historical flow data, watershed characteristics, surface coverage characteristics and other data. There are SCS, TOPMDEL, SWMM and other common models (Table 4).

Table 4. Flood disaster risk assessment index system.

Influencing Factor	Index
hazard factor	Submerged water depth, submerged duration, submerged range, flow velocity, precipitation, flood frequency . . .
disaster environment	Ground height, slope, river system, topographic relief, land use type . . .
vulnerability	Population density, economic density, land use, labor index, urban lifeline, regional GDP, population age composition ratio . . .
preventing disasters and reducing damages	Monitoring and early warning capacity, flood control and drainage capacity, disaster relief capacity, disaster prevention publicity and education level, emergency shelter layout distribution . . .

4.2.2. Environmental Sensitivity of Disaster

The sensitivity of hazard inducing environment refers to the sensitivity of the natural environment in the disaster area to the disaster. The sensitive elements include river system, topography, etc. Many scholars have studied the sensitivity of hazard inducing environment [1]. Under the same damage intensity, the more sensitive the study area, the greater the risk of disaster [110]. Mo et al. used GIS technology to assess the sensitivity of flood hazard-formative environments in Guangxi Province [111]. Su et al. analyzed the relationship between the rapid growth rate of urban space and the frequency of flood disasters in Jiangning Development Zone from the perspective of the characteristics of flood-pregnant environment [112].

4.2.3. Carrier Vulnerability

Vulnerability of hazard-affected bodies refers to the degree of vulnerability of hazard-affected bodies to disasters, including various aspects of human and social development, such as transportation, education and culture, various disaster reduction engineering facilities, and various wealth accumulated by people [113]. Sanyal et al. used a combination of GIS and remote sensing to assess the vulnerability of residential areas in West Bengal in the eastern Ganges Plain, India [114]. Ge et al. used analytic hierarchy process and fuzzy evaluation theory to evaluate the vulnerability of flood disaster bearing bodies in Nanjing [115].

4.2.4. Disaster Prevention and Mitigation Capacity

Disaster prevention and mitigation is the response measures taken by people to reduce the impact of flood damage, including emergency management capacity, emergency team building, emergency supplies reserves, disaster reduction funding and resource preparation [116]. A region's disaster prevention and mitigation capacity is relatively high, indicating that the region has invested more in disaster prevention and mitigation management, and the economic losses and casualties caused by disasters will be lower.

In the study of flood disaster risk assessment, there are also many studies on disaster prevention and mitigation capabilities. For example, Cao et al. used the analytic hierarchy process and fuzzy comprehensive evaluation method to evaluate the disaster prevention and mitigation capabilities of Ningbo City [117]. Wang applied the multi-level fuzzy comprehensive evaluation model to quantitatively evaluate the disaster reduction ability of typhoon-flood-geological disaster chain [118]. According to the results of flood assessment and the actual situation, Chen et al. put forward suggestions for disaster prevention and mitigation [119]. Lu used AHP method to stratify the risk of flood disaster, and took the ability of disaster prevention and mitigation as the first-level index to evaluate the risk, so as to provide reference for the risk control and disaster relief of flood disaster in Changzhou [120].

4.3. Flooding Forecast

Flood models and forecasts are key to managing and responding to extreme floods. Comprehensive flood forecasting can provide the possibility of upcoming extreme events and related risk loss instructions, so that people can carry out scientific disaster prevention and mitigation. Longer forecast time can win the important opportunity of disaster relief and prevention. There are many techniques for flood forecasting, among which the main models are numerical weather prediction (NWP) model and ensemble forecasting model. In flood forecasting, most models use precipitation data as an important input parameter. The following mainly classifies and summarizes the precipitation data used in flood forecasting technology and expounds the research status of two main forecasting models.

4.3.1. Common Precipitation Data for Flood Forecast

Heavy rainfall is an important cause of urban flood disasters, and its accuracy seriously affects the accuracy of urban flood simulation and rainstorm flood forecasting results. According to the different data sources and processing methods used in the current rainstorm flood forecasting research, this paper summarizes the commonly used precipitation input data into five types. Table 5 is a summary of five precipitation data.

(1) Spatial grid precipitation data simulated by regional NWP model. The numerical forecast simulation technology has been rapidly developed. The new generation of regional convective-scale weather forecast model has significantly improved the ability to simulate heavy rainfall, and can predict regional rainstorms several days or even a week in advance. However, the uncertainty of the model itself makes the precipitation intensity and precipitation area deviate from the actual observation [121,122]. Therefore, when using this data, it is necessary to evaluate and optimize the regional applicability of each parameter configuration of the model in advance, so as to reduce the impact on the numerical precipitation forecast results [123].

(2) Spatial gridded precipitation products from global mesoscale circulation model. This kind of numerical precipitation forecast product is a kind of data that is relatively easy to obtain. At present, there are more than 20 meteorological operation centers in the world that can provide precipitation forecast products with a resolution of 10 km and 7 h. Using this type of data, it performs well in describing frontal precipitation processes, but performs poorly in capturing convective precipitation characteristics [124,125]. In practical applications, statistical downscaling or multi-model integrated forecasting methods are usually used to correct the precipitation forecast results [126,127] to predict the probability of rainstorm and flood in the future.

(3) Precipitation data obtained by radar or remote sensing interpretation. This kind of data has high spatial and temporal resolution, and can predict surface precipitation several hours in advance by interpreting high-altitude precipitation information.

However, the forecast results are easily affected by local climate and deviate from the actual observation. In practical applications, mathematical statistical methods or NWP models are often used to correct precipitation data to reduce the initial error of flood simulation and forecast [128–130].

(4) Historical long sequence site observation data. Long time series and high accuracy are the main advantages of this kind of data, but its spatial representativeness is low, so it is unable to obtain enough regional spatial precipitation information. In practical applications, such data are mainly used as the basis for the design of return period precipitation, which is used to simulate typical rainstorm events or predict rainstorm floods under different rainstorm scenarios, and provide scenario forecast sets for rainstorm flood disaster prediction.

(5) Real-time station observation of precipitation data. With the increase of the density of the national precipitation observation network, the current available station observation data has been significantly improved in terms of spatial representation compared with the historical long series observation data. Stormwater model driven by real-time observed precipitation data can provide forecasting information of near or real-time rainstorm and flood disasters for urban areas with high accuracy. In practice, this data is usually not directly used for the input parameters of precipitation forecast model, but used to correct other sources of precipitation interpretation or forecast products.

Table 5. Rainstorm and flood common precipitation data.

Type	Advantage	Disadvantage	Ways to Reduce Disadvantages
Spatial grid precipitation data simulated by regional NWP model	Significant increase in simulated heavy precipitation capacity	The uncertainty of the model itself makes the precipitation intensity and precipitation area deviate from the actual observation	Evaluation and optimization of regional applicability of model parameters in advance
Spatial gridded precipitation products output by global mesoscale circulation model	Easy to obtain and performs well in describing frontal precipitation processes	Poor performance in capturing convective precipitation characteristics	Correction of precipitation forecast results by statistical downscaling or multi-model ensemble forecast
Precipitation data obtained by radar or remote sensing interpretation	High spatial resolution to predict surface precipitation hours in advance	The forecasted precipitation results are easily affected by local climate and deviate from the actual situation	Precipitation data are corrected using mathematical statistics or NWP models to reduce initial errors in flood simulation and forecasting
Historical long sequence site observation data	Long time series and high accuracy	Low spatial representativeness, insufficient regional spatial precipitation information available	In practical applications, such data are mainly used as the basis for design of return period precipitation
Real-time site observation precipitation data	It can provide near or real-time rainstorm and flood disaster forecast information for urban areas with high accuracy.	The length of the forecast period is limited by the catchment time	This data is often used to correct precipitation interpretation or forecast products from other sources

4.3.2. Research Progress of Numerical Weather Prediction Technology

Accurate NWP model is an important part of flood forecasting system, which can provide reliable rainfall forecast. NWP is a method to predict the atmospheric motion state and weather phenomena in a certain period of time in the future by numerically solving the thermodynamic and hydrodynamic equations describing the weather process under given initial conditions according to the actual situation of the atmosphere.

The history of NWP can be traced back to the early 20th century. However, due to the limitations of computing power and observation technology at that time, it was not until the emergence of computers in 1949 that it was possible to solve atmospheric physical equations by computers. In the same year, the first real NWP model appeared [125]. In the second half of the 20th century, there have been a number of mesoscale NWP models that can be used for global or regional operational forecasting, such as MM5 model, UKMO model, ETA model, RAMS model and so on. In the 1990s, the rapid development of high-altitude detection technology and computer technology provided driving data for the NWP model to perform higher-resolution simulations, and also provided the possibility for analyzing and processing these data to improve the development of more complex physical process parameterization schemes. On this basis, a new generation NWP model (such as weather research and forecasting model, WRF model [131]) is developed to simulate the regional convective precipitation process more accurately, and it shows good performance in simulating and forecasting heavy precipitation [125]. The rapid improvement of the new generation NWP model in the simulation and prediction of precipitation, especially heavy precipitation, has led more and more institutions and scholars to apply the NWP model to the simulation and prediction of regional rainstorm and flood disasters [132,133].

Although the ability of the new generation NWP model to simulate regional-scale heavy precipitation has been gradually recognized, precipitation is still one of the most difficult variables for NWP model simulation and prediction due to the influence of model structure error, initial error and chaotic properties of weather system. Rama Rao et al. [134] used WRF model to simulate a heavy precipitation process in Guyana, South America. The results showed that WRF model could capture the main characteristics of this precipitation process, but the simulated value of precipitation was smaller than the measured value. Efstathiou et al. [135] simulated a heavy rainfall process in the Chalkidiki area of Greece based on the WRF model. The results showed that the WRF model could well simulate the process and range of the heavy rainfall, but the output precipitation value was too large, and the range and center position of the rainstorm were somewhat deviated. Since the numerical weather prediction is actually an approximate simulation of the atmospheric motion process, the lack of human understanding of the atmospheric motion mechanism and the model's description of the subgrid process, coupled with the amplification effect of the nonlinear chaotic properties of the atmosphere itself on the model structure error and initial error, there are many uncertainties in the precipitation results output by the NWP model [123,125].

4.3.3. Ensemble Forecasts Research Progress

Due to the growth of combined numerical weather and climate prediction and the expansion of high performance computing, flood ensemble prediction has gained significant momentum in the past decade. Ensemble prediction can not only provide deterministic ensemble average prediction results, but also estimate the prediction error of the results. At the same time, it can also give the possibility of events we are concerned about through probability prediction.

Studies have shown that ensemble forecast can greatly extend the validity of flood forecast [136]. Even if the numerical model is extended to the forecast time of 5–6 d, the precipitation forecast is only 2–3 d, and the forecast time of flood cannot be extended [137]. Burger obtained the precipitation and temperature forecast information from the ECM-WF ensemble forecast system for a 10-year 12-h period and a forecast period of 1–5 days in a small watershed area [138]. The hydrological model was used to obtain the probability forecast runoff value, and it was compared with the measured flood process, which proved the application advantages of ensemble forecast in flood warning. Bao constructed a flood forecasting model based on the combination of hydrology and hydraulics driven by TIGGE [139]. The flood forecasting model was driven by the forecast precipitation of each member of the ensemble forecasting system, and the flood forecasting was obtained with the same number of ensemble forecast members. The flood forecasting and early warning of complex water systems were realized by probabilistic forecasting. The early warning and forecasting of flood in Huaihe River from 2007 to 2008 showed that the flood forecast period was extended by 3~5 days. Zhang et al. [140] and Xu used the ensemble forecast system of NMC, ECMWF and NCEP in the Linyi Basin of the lower reaches of the Huaihe River, and used the GRAPES mesoscale model downscaling to obtain a 6 h precipitation-driven hydrological model for early warning of floods [141]. It is feasible and effective. Another study used TIGGE ensemble forecast as a driver to improve the soil moisture simulation results [142]. In addition, He's case study and uncertainty analysis of multi-center and multi-model TIGGE ensemble forecast in flood forecasting in the Huaihe River Basin of China show that the probability attribute of ensemble forecast is still retained [143].

The development of ensemble forecast still faces many severe challenges. Countries should make a lot of preparations in the application of key technologies of ensemble forecast, so as to promote the early application of ensemble numerical forecast products in actual flood forecasting.

5. Summary and Discussion

Under the dual influence of urban expansion and climate change, the global urban flood disaster problem is becoming more and more serious. Flood risk assessment can provide a scientific basis for current and future urban flood management, especially for flood disaster relief and prevention decisions. Because of the complex process of flood disaster occurrence and development, there are still many problems to be solved. Based on a detailed review of the current status of urban flood disaster research, we identified the challenges in current research and outlined potential future research opportunities.

(1) Urban flood risk assessment is an important research hotspot. There are a lot of researchers evaluating the loss of urban areas after floods. However, most studies only conducted a large-scale assessment, and did not conduct a more detailed risk assessment for small-scale (similar to community). In the context of global big data sharing, it becomes easier to obtain finer data. To make full use of the advantages of big data in the current context, to establish a more sophisticated small-scale assessment model.

(2) Urban flood management can effectively regulate people's development and flood control behavior, reduce the impact of flood disaster, and urban flood risk assessment can provide more accurate decision for flood management. However, whether the current urban flood risk assessment research can provide sufficient, accurate and reliable assessment results to the flood management department, and whether the results can be applied by the urban flood management department is a question worth considering. Blindly carrying out a large number of flood risk assessment studies can not be applied to the actual urban management, which will only cause waste of personnel and resources.

(3) Under the background of global climate change and urbanization, multi-scenario flood risk assessment is a hot and difficult topic in flood disaster management research. By comparing and analyzing the five current mainstream flood assessment methods, it is found that each method has certain limitations, which directly affects the accuracy, exposure and vulnerability assessment of flood risk assessment, and will affect the effectiveness of the entire flood risk assessment results. In the construction of flood risk assessment model, we should make full use of RS and GIS technology to establish a more refined and dynamic flood simulation model suitable for urban areas, and form an urban flood simulation system with good human-computer interaction function and multi-functions such as early warning, forecasting and decision support [94].

(4) In the process of flood risk assessment, sensitivity and vulnerability analysis has always occupied an important position. However, in the sensitivity analysis, the spatial and temporal resolution of data has been restricting the accuracy and timeliness of urban flood risk assessment; in terms of vulnerability analysis, vulnerability assessment and quantitative flood risk assessment have not been supported by sufficient data. Nowadays, international flood risk management has begun to pay attention to the impact of multi-dimensional characteristics of social economy, environment, culture

and policy on urban comprehensive flood vulnerability. The development of artificial intelligence and big data provides data and technical support for flood risk assessment, which is conducive to the study of big data refinement and multi-dimensional flood risk assessment under flood disasters.

(5) The smooth progress of disaster risk assessment can provide a scientific basis for disaster prevention and mitigation, risk prediction, disaster transfer and other decision-making, and provide technical support for disaster management departments. The occurrence of flood disasters is often not an independent event, it is bound to cause other secondary disasters. Therefore, it is the trend of disaster risk assessment to improve the accuracy of risk assessment and enhance the reliability of the results by multidisciplinary joint, from single disaster risk assessment to integrated flood risk assessment.

6. Conclusions

Under the background of increasingly serious urban flood problems worldwide, this paper combs the disaster mechanism and evaluation index framework of urban flood risk assessment, summarizes five flood assessment methods, compares and analyzes the advantages and disadvantages of different research methods, and finally discusses the development trend of urban flood risk assessment under urban flood management. The main conclusions are as follows:

(1) In terms of the mechanism of urban flood disaster, the problem of urban flood is becoming more and more serious. In addition to natural factors, it is mainly caused by the unscientific development behavior of the city. Therefore, in the process of urban development, we should pay attention to the protection of ecological environment, that is, we should consider the social and ecological benefits while developing the economy. The urban planning management department should scientifically plan and improve the urban drainage pipe network system, and protect the urban wetland and other green space resources with water storage function.

(2) In the future research of urban flood risk assessment methods, we should make full use of the effective resources in the era of big data, and make full use of emerging methods such as data mining and machine learning to improve the efficiency and accuracy of flood risk assessment. At the same time, it is necessary to strengthen the connection between different disciplines and different flood assessment methods, and build a more adaptable flood assessment model to provide a more scientific decision-making basis for disaster management departments.

(3) In terms of the reliability of flood risk assessment results and the division of risk areas, it is necessary to give full play to the role of cross-fusion of different methods and models. Different methods and models were used for risk assessment in the same research area to verify the reliability of the methods and models. At the same time, it is necessary to further improve the theoretical system of flood disaster risk zoning, which can provide a scientific basis for urban resource allocation and emergency plans of relevant departments.

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