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Influencing Factor Identification and Simulation for Urban Metro System Operation Processes—A Resilience Enhancement Perspective

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Abstract: When confronted with rainstorms and flood disturbances, the operational processes of urban metro systems demonstrate vulnerabilities to attacks, inadequate resistance, and sluggish recovery characteristics. The flood resilience of UMS operational processes requires urgent enhancements. This paper aims to enhance the flood resilience of urban metro operation processes by proposing a three-stage PEL resilience enhancement framework: prevention resilience, response resilience, and learning resilience. Additionally, it summarizes the influencing factors on UMS flood resilience from five dimensions: natural-physical-social-management-economic (NPSME). By employing system dynamics as a simulation tool, this study elucidates the logical interconnections among these influential factors. Furthermore, by utilizing economic change conditions as an illustrative example, it effectively simulates the response characteristics of both standardized benchmark scenarios and economic change scenarios. Based on these simulation results, corresponding strategies for flood resilience enhancement are proposed to offer valuable insights for metro operation management. The Nanjing metro system was taken as a case study, where relevant historical data were collected and strategies were simulated for different development scenarios to validate the effectiveness and rationality of the proposed method for enhancing resilience. The simulation results demonstrate that changes in economic conditions and population structure are the primary factors influencing the enhancement of flood resilience in UMS operations.

Keywords: metro operation; flood resilience; influencing factors; resilience enhancement; system simulation



Citation: Li, K.; Xiahou, X.; Wu, Z.; Shi, P.; Tang, L.; Li, Q. Influencing Factor Identification and Simulation for Urban Metro System Operation Processes—A Resilience Enhancement Perspective. *Systems* **2024**, *12*, 43. <https://doi.org/10.3390/systems12020043>

Academic Editor: Tao Wang

Received: 26 December 2023

Revised: 23 January 2024

Accepted: 26 January 2024

Published: 29 January 2024



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1. Introduction

The urban metro system serves as a vital lifeline infrastructure, catering to the daily commuting and travel needs of the majority of residents. With no fewer than four lines forming an interconnected network, the metro systems in large and medium-sized cities worldwide have demonstrated efficient network operations and are witnessing a continuous expansion trend. The growing complexity of line network structures, physical equipment, and facilities, coupled with frequent occurrences of natural disasters and human disturbance events, pose new challenges to the operation and management of UMS.

Different from the above-ground infrastructure in urban areas, the UMS line network and station structure are predominantly located underground, necessitating meticulous space planning and utilization. This subterranean nature renders it susceptible to environmental disturbances, posing challenges for network information communication, equipment ventilation, and facility lighting conditions. Frequent occurrences of rainwater backflooding have resulted in a series of safety accidents. In emergency situations, material

dispatch and evacuation become hindered due to unfavorable drainage conditions. Consequently, UMS is prone to attacks with limited recovery capabilities and adaptability issues. Enhancements are required for operational security and service performance during the operation and maintenance period [1,2].

The study of disaster prevention and mitigation strategies at UMS necessitates a transition from the conventional accident analysis paradigm of post-processing to the systematic safety research paradigm encompassing comprehensive prevention and proactive recovery [3]. The attribute of resilience, inherent to the system, is widely recognized as the pinnacle of safety and occupies a central position in disaster prevention and reduction management. Investigating its formation mechanism and implementing effective enhancements represents a novel approach towards achieving secure system operations [4–6]. The flood resilience of the UMS operation process is defined in this paper as “the capacity of the UMS operation process to rapidly restore operational performance through system resistance, repair, and adaptation processes when confronted with varying levels of rainstorm or waterlogging events”.

The current research on flood resilience has yielded various assessment methods and theories. In order to facilitate flood disaster management, Liao established a theory of urban flood resilience, that is, urban flood resilience refers to the city’s ability to tolerate floods and the recovery of social economy after disturbance [7]. Based on the 4Rs theory, Li Dezhi established a flood resilience evaluation model for URTN (Urban Road Traffic Network) with 26 indicators. An empirical study was conducted in southern China as an example. The flood resilience of the urban road traffic network was evaluated through a comparison before and after the pipeline reconstruction. The results show that a single traditional engineering measure has some limitations on the flood resilience of URTN. Suggestions on strengthening public participation and enhancing various engineering measures are put forward to further enhance the flood resilience of URTN [8]; Masha et al. conducted an empirical study on the inherent characteristics and abilities of the Tehran area in the background of surface water or river overflow and constructed an evaluation method based on the social, economic, system, infrastructure, community capital, and environment. A hybrid multi-criterion decision approach combining AHP and TOPSIS tools was subsequently developed to incorporate resilience theory into urban development and resilience-oriented urban planning [9]. Kotzee presents a method in which an indicator method is used to measure and map the spatial distribution of flood resilience levels across the region. Using three flood-affected cities in South Africa, 24 resilience indicators related to floods and their related social, ecological, infrastructure, and economic aspects were selected and integrated into a composite index using principal component analysis (PCA) to effectively measure flood resilience values [10].

Based on the evolutionary mechanism of flood resilience during UMS operation, this paper presents a “prevention-response-learning” model for enhancing resilience throughout the entire disaster management process. It identifies the factors influencing UMS flood resilience improvement based on multiple dimensions, including nature, physics, society, management, and the economy. Furthermore, an evaluation index system has been established to enhance flood resilience. By employing the system dynamics method, the process of improving flood resilience is systematically modeled, and key factors in the indicator system are simulated. Subsequently, promotion strategies and practical paths for enhancing UMS flood resilience are derived from simulation results. This provides a foundation for ensuring operational security management at UMS. Taking Nanjing Metro as an empirical research case study, an intelligent management mode for UMS operation processes under extreme natural disasters is proposed.

2. Enhancement Framework for UMS Flood Resilience

2.1. “PFR-EFR-LFR” Whole-Process Theory

“Resilience” is the ability of a complex system to absorb, resist, repair, and adapt to a disturbance. The development of system resilience is accompanied by the whole process of

perturbative events, which are constantly changing over time. The current stage of studying system resilience improvement primarily relies on the utilization of numerical simulation methods and index evaluation methods [11–14]. The Pressure-State-Response (PSR) model is a widely utilized method for constructing index systems. In this model, P represents the external pressure exerted on the system, S denotes the state of the system, and R signifies the human response policy or action taken by the system to mitigate stress-induced effects. The PSR model provides a systematic framework for describing and analyzing the causal logic of interactions between society and the environment [5].

The PSR model assesses the resultant changes in system performance and summarizes the influencing factors based on various dimensions, including nature, economy, society, etc. However, it fails to consider the entire process of disaster occurrence and merely represents the system from three levels without reflecting its continuous response to perturbation events [15]. The PSR model, therefore, lacks dimensionality and suffers from process loss, necessitating corrections to align with the requirements of resilience index system research. The framework of resilience evolution, known as the “PFR-EFR-LFR” (PEL model), is proposed in this paper based on the fundamental principle of the PSR model. The schematic diagram in Figure 1 illustrates the evolutionary process of flood resilience during UMS operation, showcasing the performance variations of the three-stage system prior to, during, and after the event.

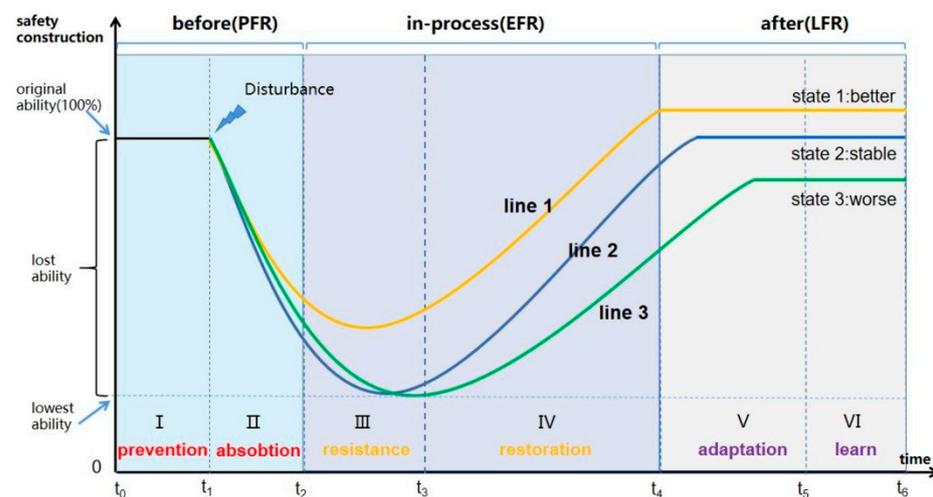


Figure 1. Evolutionary processes of flood resilience during UMS operations.

PFR (prevention for resilience): Preventive resilience is the initial phase in which the disturbance event has not occurred or the event has occurred but has not caused damage to the system. The preventive resilience of the system is reflected in the proactive prediction and absorption capacity of the disturbance. It emphasizes that when the system performance does not change significantly, the hidden trouble of the disturbance can be eliminated in time, thus reducing the probability of system failure, which reflects the preventive effect.

EFR (emergency for resilience): Response resilience is the characteristic of the system in the process of resisting and recovering quickly from the impact of disturbance events. After the buffering effects of the prevention and absorption phases, the EFR phase focuses on the system’s resistance and repair capabilities, minimizing the degradation of system performance while restoring system performance to its original state as quickly as possible.

LFR (learning for resilience): Learning resilience is the resilience characteristic reflected when the system self-respects and learns to improve after the end of the disturbance event. It is mainly reflected in the adaptation and learning ability of the system. Adaptation ability refers to the ability of the system to cope with the disturbance by changing the structure and components of the system again on the basis of resistance and repair [16]. Enhanced

learning ability involves a systematic approach that draws on past incidents and response strategies to effectively manage future disruptions. The principle of the PEL resilience enhancement model is shown in Figure 2.

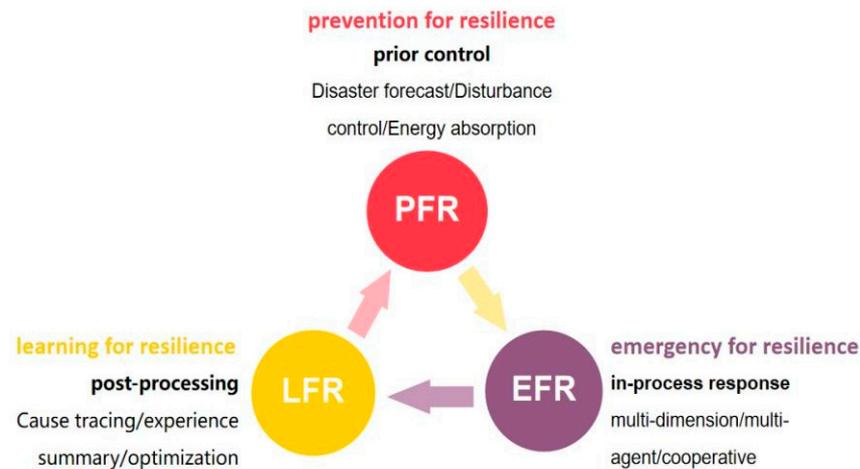


Figure 2. The “PFR-EFR-LFR” resilience enhancement model.

The PEL model uses “prevention-response-learning” as the coping logic for the system to resist disturbance events. Preventive resilience focuses on pre-event management, controlling disturbance events by means of disaster forecasting, absorbing energy from disaster events, and keeping the risk of an event happening as unlikely as possible. Response resilience is the in-process control stage of disaster management. Multi-dimensional management, multi-subject participation, and multi-party collaboration are adopted to minimize the performance damage caused by disaster events and restore system functions at the fastest speed. The learning resilience stage occurs in the later stages of resilience evolution and development. It mainly conducts retrospective investigations on the causes of accidents, summarizes management experience, and forms records to better cope with disaster events.

2.2. “NPSME” Multi-Dimensional Integrated Management Model

The operation process of the urban metro system is highly complex and involves a wide range of areas, including track, electrical equipment, vehicles, equipment, personnel, and other aspects. All subsystems are accurately coordinated to ensure the accuracy of the operation process. The improvement of flood resilience in the UMS operation process is a comprehensive work that can be decomposed into multiple levels for analysis [17,18]. The daily operation of the subway is the result of the coordinated operation of the rail system, physical equipment, and power communication equipment. The management of waterlogging disasters needs the joint management of the overall urban environment, economic measures, and all sectors of society [19,20]. Based on TOSE [21] and the basic idea of social-economic-natural complex ecosystem management, this paper optimizes and expands the commonly used indicator construction dimensions and proposes a multi-dimensional metro operation management model with “NPSME”.

N: nature, the natural dimension. For example, the urban geographical location, landform, long-term hydrological conditions, precipitation conditions, and other factors.

P: physical, the physical dimension. Physical factors include many aspects, including the physical equipment and facilities of the metro system itself, the hardware support of urban roads and traffic, the level of city-level infrastructure construction, etc., which are the concrete representations of physical factors.

S: social, the social dimension. When waterlogging happens, the metro system itself bears the physical blow of the disaster. The publicity and organization of the anti-flooding

work of all social parties and the social structure of the city itself directly determine the UMSs response ability to waterlogging accidents.

M: management, the management dimension. For the prevention and control of waterlogging events, the internal management of the subway system is particularly important. The timely warning of background monitoring, the timely start of flood prevention facilities, and the effective guidance of the station personnel are all manifestations of the level of resilience. At the same time, the improvement of UMS flood resilience is also inseparable from the improvement of the overall management efficiency of the urban environment.

E: economic, the economic dimension. Waterlogging resistance work is not only a technical problem, a management problem, but also an economic problem. The economy is a strong support for improving the resilience of anti-flooding. The capital investment of the subway management, the overall economic situation of the city, and the income level of the residents all play a positive guiding role in the flood resistance level of the subway system.

As shown in Figure 3, the indicators of the flood resilience improvement process of the UMS operation are composed of five dimensions of “N-P-S-M-E”, namely nature, physics, social, management, and economic. The five dimensions correspond to the two subjects of the subway system and the urban system, respectively. The synergistic effect between the five dimensions improves the flood resilience of UMS.

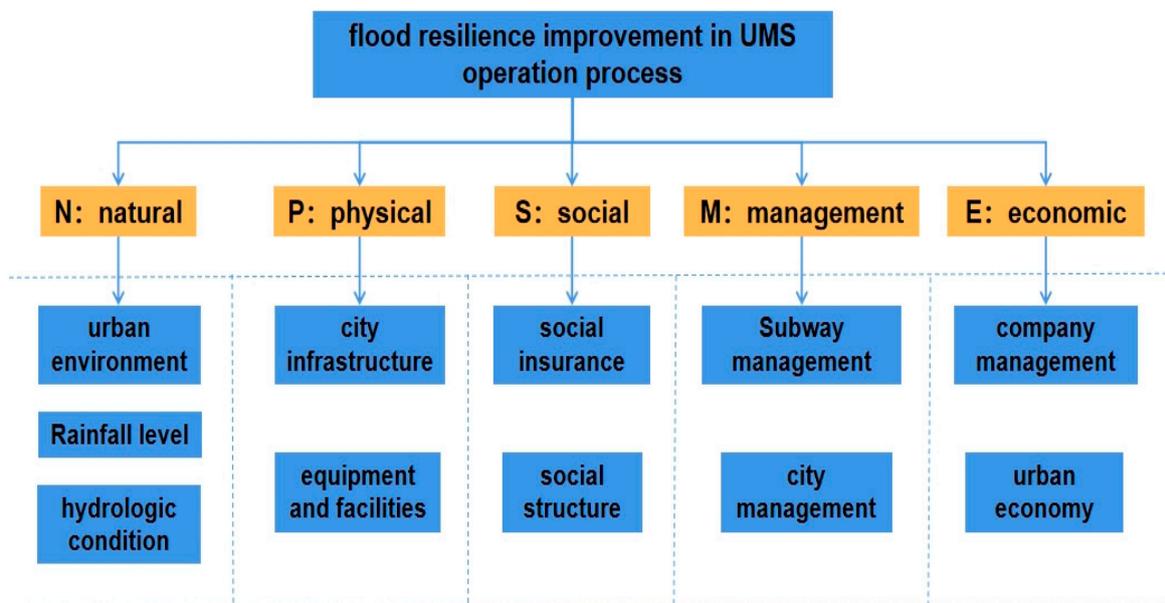


Figure 3. Dimensions of UMS flood resilience improvement index.

2.3. Flood Resilience Identification for the UMS Operation Process

The improvement of system performance is a comprehensive and multi-dimensional process. When the disturbance event occurs, the performance index drops to the lower limit position, and the internal and external resources of the system must be mobilized to repair the system’s performance. After repair, some of the system can return to its original performance state, and the resistance ability does not change significantly when faced with another disturbance. Some system performance cannot be restored to its original state; disturbance events cause irreversible damage to the system; and the system risk increases when faced with another disturbance. Some system performance can be improved to the original level, and when disturbed again, it can show better resistance and adaptability [22–24].

The construction framework of the index system of flood resilience in the UMS operation process is shown in Figure 4. A pyramid structure is formed by 3 major resilience indicators (PFR, EFR, and LFR), 4 major attributes (robustness, redundancy, resourcefulness, and rapidity), 5 major categories (N-P-S-M-E), and 6 major capabilities (prevention,

absorption, resistance, repair, adaptation, and learning). It is a reasonable improvement from the previous research methodology of the resilience index system.



Figure 4. Framework for flood resilience improvement index in UMS operation process.

3. Critical Influencing Factor Identification

The systematic review method (SR) is a new literature review method originating from clinical problems and widely used in basic research, policy research, economic research, and other fields. A systematic review plan should include: background, purpose, standard, literature search strategy, evaluation, and analysis method [25–27]. This study aims to improve the flood resilience of the UMS operation process and to obtain an action path for resilience improvement by mining and analyzing the influencing factors of UMS flood resilience.

At present, in academic research on “resilience”, research subjects are still focused on urban resilience, infrastructure resilience, economic resilience, network resilience, and so on. Most disturbance events are natural disasters or deliberate attacks, and few results focus on the flood resilience of urban metro systems [28,29]. Therefore, when identifying related literature, this study expanded flood resilience to cities and larger areas, not limited to the subway system, and the waterlogging management and flood resilience improvement indicators at the city level are applicable to UMS operations. “Urban resilience”, “Flood resilience”, “Metro Operation”, and “Waterlogging Control” were combined as keywords and searched in the Web of Science and CNKI.

The literature retrieval and review stage includes several steps, such as retrieval, screening, streamlining, and review. First, the search string was defined in the Web of Science core database as $TI = (“urban” OR “flood” OR “metro”) AND (“resilience”) AND (“evaluation” OR “assessment” OR “management”)$ from 2013 to 2023, with 293 articles. The search conditions were defined as (“urban resilience” or “flood resilience” or “subway resilience”) and (“assessment” or “improve”). Until 2023, a total of 73 journal papers and 198 theses were retrieved. Further screen out the literature closely related to resilience improvement indicators, and finally remain 168 papers as an effective reference for the establishment of the UMS operation process flood resilience index system. The literature screening process is shown in Figure 5:

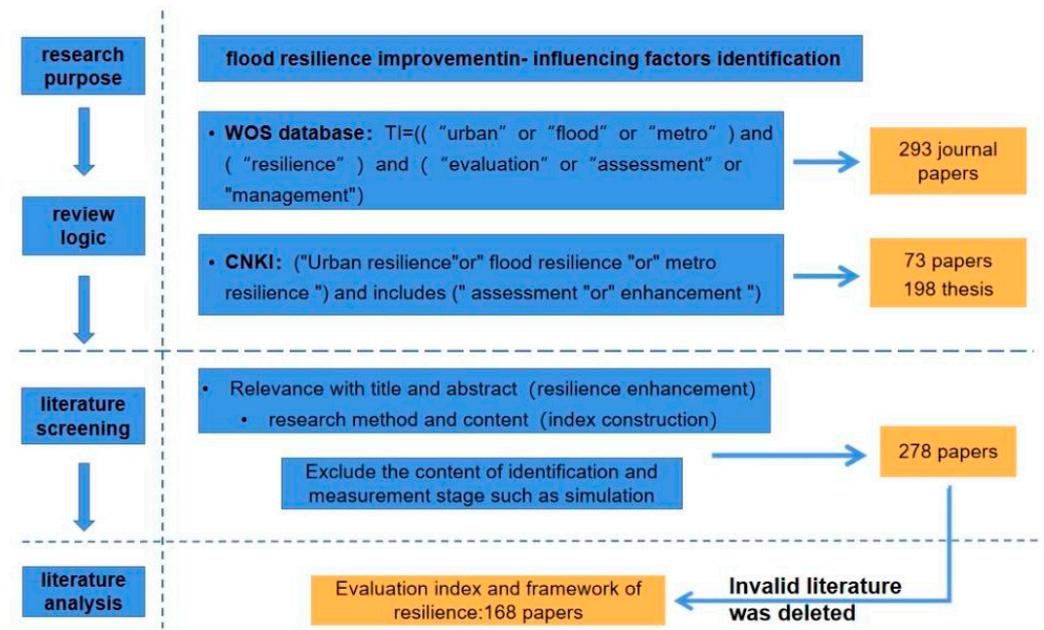


Figure 5. Systematic review method: literature search and review process.

A total of 168 papers were studied in detail. In many studies on resilience index systems, the research subjects of flood resilience are mostly urban systems or large river basins, and the research on flood resilience of metro systems is almost in a blank state. The index system and influencing factors are analyzed, and the high-frequency indexes are summarized in Table 1:

Table 1. High-frequency index of the resilience evaluation system.

Number	Metric	Dimension	Number	Metric	Dimension
1	Urban economic aggregate	economy E	32	The penetration rate of resident medical insurance	society S
2	Urban economic growth	economy E	33	Metro facility maintenance	physics P
3	per capita income of residents	economy E	34	Urban construction and maintenance	physics P
4	Regional employment level	economy E	35	Safety knowledge and publicity work	manage M
5	Urban population structure	society S	36	Extreme climate early-warning capability	manage M
6	Community scale	society S	37	Metro disaster prevention and emergency response plan	manage M
7	Annual consumption of the urban population	economy E	38	Commuting mode of residents	society S
8	Completion degree of infrastructure	physics P	39	Education level of residents	society S
9	Effectiveness of the drainage pipe network	physics P	40	Public self-rescue ability from disasters	manage M
10	Urban hydrological conditions	nature N	41	Water resources regulation and storage	nature N
11	Child-to-population ratio	society S	42	Economic diversity	economy E

Table 1. Cont.

Number	Metric	Dimension	Number	Metric	Dimension
12	The degree of aging	society S	43	Metro operation level	economy E
13	The area ratio of rivers and lakes	nature N	44	Urban transportation investment scale	economy E
14	Urban topography	nature N	45	Anti-flooding door design	physics P
15	Urban greening level	nature N	46	Construction of urban flood control dikes	physics P
16	Subway waterlogging prevention facilities	physics P	47	Disaster prevention planning scheme	manage M
17	Social security	society S	48	Information and communication level	manage M
18	Regional climate change	nature N	49	Fire brigade accessibility	physics P
19	rainfall intensity	nature N	50	Underground drowning scene	nature N
20	land use rate	nature N	51	Power guarantee reliability	physics P
21	Emergency management capability	manage M	52	High school education or above	society S
22	Public responsiveness	manage M	43	Number of institutions of higher learning	society S
23	Flood prevention capital input	economy E	54	City disaster history	society S
24	Subway station elevation	physics P	55	Internet popularity	society S
25	Urban transportation system planning	physics P	56	Ground subsidence level	physics P
26	Government management level	manage M	57	Sponge city construction level	physics P
27	Disaster emergency resources reserve	economy E	58	Infrastructure exposure	physics P
28	Medical assistance level	society S	59	Rain and pollution diversion	physics P
29	Regional long-term rainfall levels	nature N	60	Average daily number of subway passengers	society S
30	Disaster information release platform	manage M	61	Urban comprehensive development index	manage M
31	Safety emergency drill	manage M	62	Urban viaduct construction	physics P

According to Table 1, a total of 62 indicators related to the improvement of flood resilience were selected. The index system was classified according to the five dimensions of “NPSME”. Combined with the three-stage resilience evolution model of “PFR-EFR-LFR”, the indicators were divided according to the development sequence. The influencing factor matrix for improving flood resistance resilience was obtained.

Experts in relevant fields were invited to evaluate the construction framework of the original index system, the meaning of the index, and the research topic of waterlogging and resilience in the UMS operation process, so as to further streamline and optimize the index system. A total of 20 experts were invited from related fields, mainly from the front line of subway operation and management, government waterlogging management departments, universities and research institutions, and municipal design and consulting units. The interviewees are all engaged in the design and planning, disaster prevention, emergency management, and flood management of the subway system and have rich experience in practice and research. Based on the expert evaluation and the interview scoring, the index system was optimized, and the final index system is shown in Table 2. The above 62 indicators do not completely correspond to the operational characteristics of UMS and have

been corrected during the optimization process. Finally, 30 effective indicators are retained, corresponding to the prevention, response, and learning processes of the evolution and development process of flood resilience, which better reflect the operational characteristics of UMS.

Table 2. Research an index system for waterlogging resistance and improvement in the UMS operation process.

	PFR	EFR	LFR
N nature	1 Short-term rainfall intensity 2 topographic and landform features 3 Long-term rainfall levels	4 Urban green coverage rate 5 Water resources regulation and storage capacity	6 Urban climate change
P physical	7 Subway network flooded state 8 Urban road accessibility 9 Diversity of transportation connections	10 Anti-flooding performance of the subway system 11 Road drainage measures 12 Level of information and communication	13 Subway equipment and facilities maintenance 14 urban construction and maintenance capacity
S social	15 Urban population structure 16 Residents' dependence on the subway	17 Information release platform	18 Safety knowledge popularization 19 Social security level
M management	20 Subway emergency management plan 21 Extreme climate early-warning capability	22 Passenger self-rescue capability 23 Medical assistance capacity 24 Fire emergency rescue	25 Safety management training and drill
E economic	26 Living standards of urban residents 27 Government emergency reservation	28 Operating conditions of subway companies	29 Urban economic development status 30 Urban economic diversity

4. Resilience Enhancement Simulation

4.1. SD Simulation Model

The system dynamics method has strong applicability in the research of UMS operation processes. By modeling the real response behavior of the system under various disturbances, the SD method is often used to simulate urban resilience and various policy-making cases. The system dynamics simulation method is based on the principle of iterative calculation. The equation is used to connect the state variables, rate variables, and auxiliary variables so as to restore the actual situation of this research object to the greatest extent. The improvement of flood resilience in the operation process of urban metro systems involves flood management, subway operation, social response, and other aspects. It is a complex and dynamic endeavor, as changes in various indicators across natural, physical, social, management, and economic dimensions dynamically influence its progress. Therefore, system dynamics is an appropriate approach to address this issue. For the flood resilience improvement problem of UMS operation, SD simulation steps are shown in Figure 6:

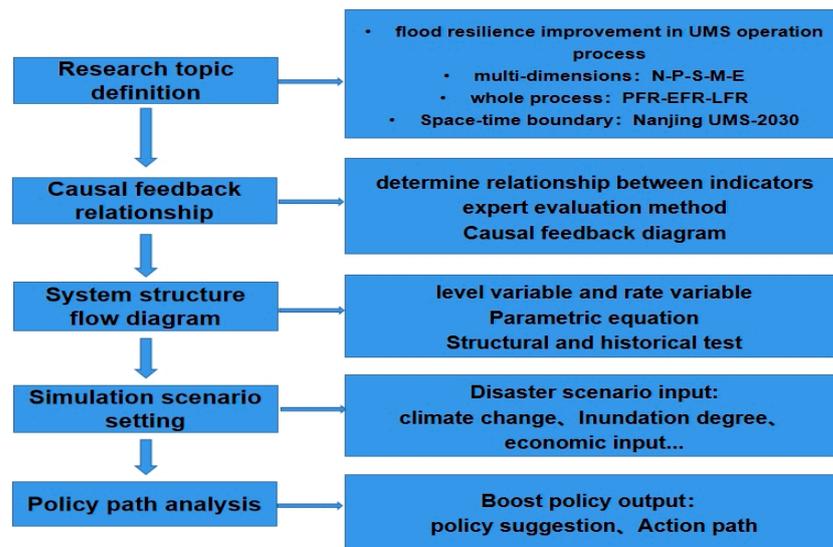


Figure 6. SD simulation steps.

4.2. Causal Analysis of Flood Resilience Enhancement

Based on the comprehensive analysis of the index system for improving flood resilience in the UMS operation process, this section defines the structure level of the system and draws the feedback loop diagram among the factors affecting the flood resilience improvement in the UMS operation process. Positive sign indicates the positive effect of mutual promotion among the indicators, and a negative sign indicates the weakening effect among the indicators. The causal relationship diagram is shown in Figure 7.

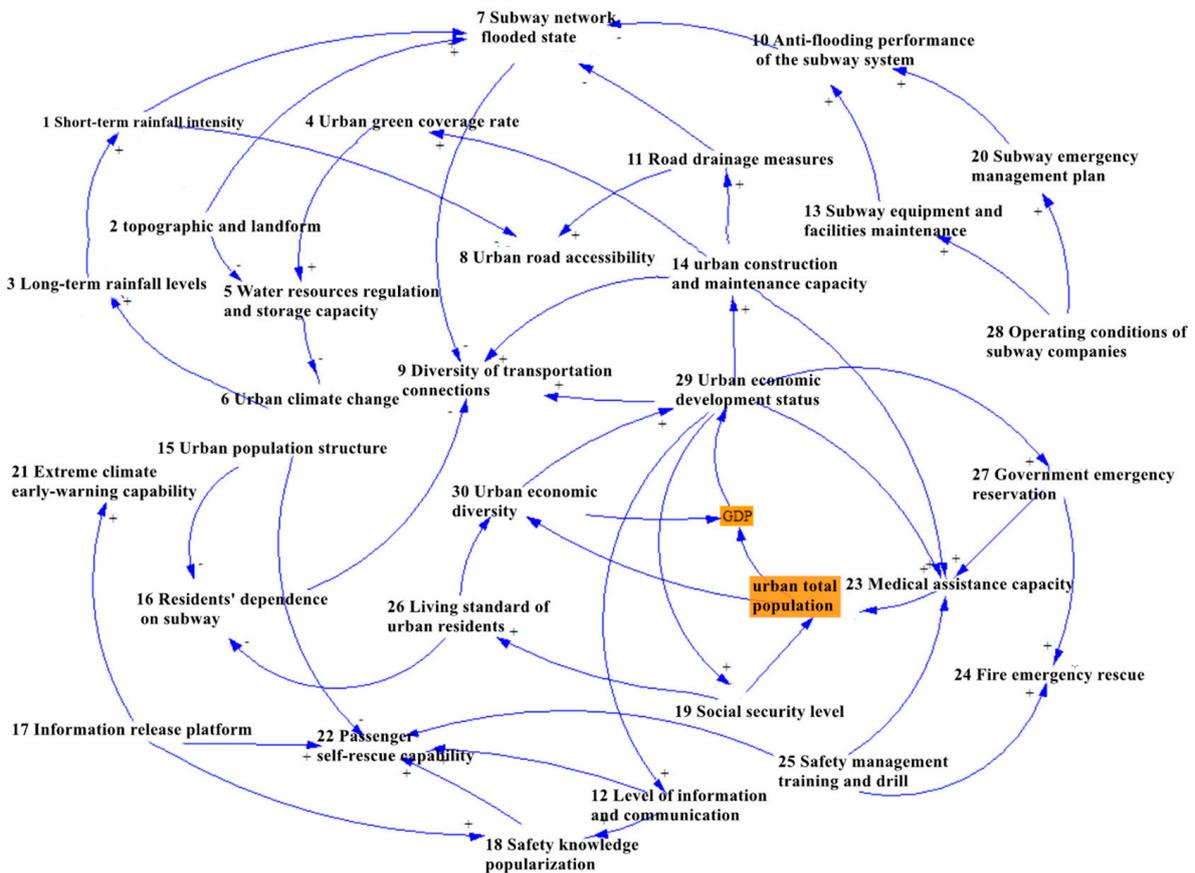


Figure 7. Feedback diagram of flood resilience improvement.

As shown in Figure 7, the causal feedback map, based on the original 30 indicators, added GDP and the total urban population as two regulatory variables to make the causal feedback loop structure self-consistent. In the chart, the urban economic development status and economic diversity indicators are in the core position of the connection, which preliminary shows that economic activities are still the key indicators affecting the improvement of flood resilience in the UMS operation process.

From the above feedback loop, there are complex causal relations among the five subsystems of nature, physics, society, management, and economy. The natural system characterizes the changes in the urban environment and hydrological conditions, and the deterioration of natural conditions causes damage to the physical system of UMS; the economic conditions characterize the urban development and construction maintenance level, and the increase in economic input has a positive impact on the performance of social and management subsystems; the physical system mainly describes the waterlogging resistance level of UMS itself and the construction of urban infrastructure, which is greatly affected by the other subsystems. The improvement of flood resilience in the process of UMS operation is a complex system, and all subsystems play a synergistic role in promoting the improvement of the waterlogging resistance level of the system.

The causal loop diagram of system dynamics can only describe some basic aspects of the feedback structure, but the interaction between the stock, independent variables, constants, and so on is not very clear. As a stock concept, the horizontal variable is the most important variable in system dynamics, but it is not represented in the causal loop diagram. In the system structure flow diagram, the state variables and rate variables are obvious, and the structure flow diagram is the final model for system simulation, as shown in Figure 8.

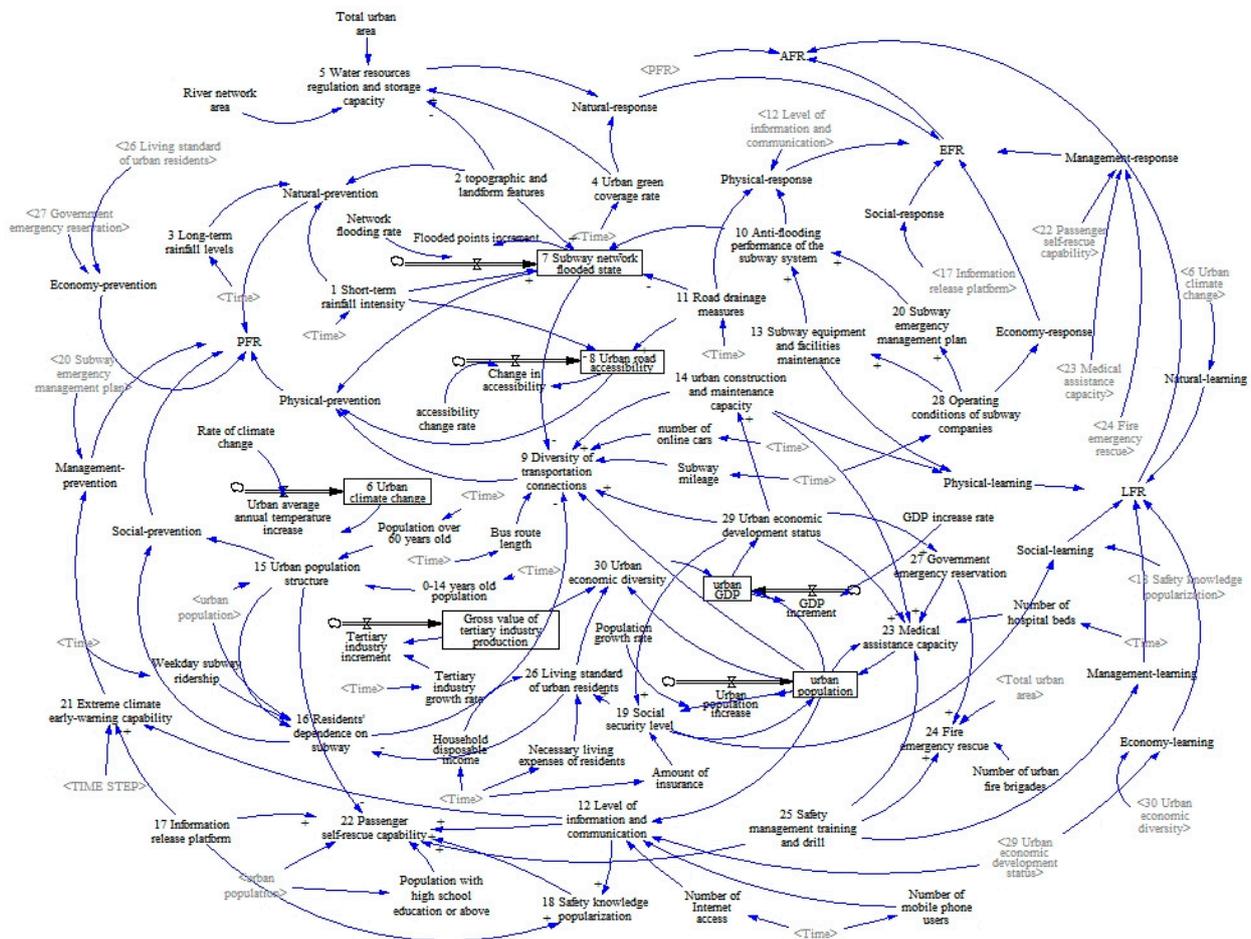


Figure 8. Structural flow diagram for flood resilience improvement.

Based on the basic logic relationship of the system causal loop diagram, level variables, rate variables, and related auxiliary variables are added to establish a simulation model for the improvement of flood resilience in the UMS operation process. There are 6 level variables in the model, namely, urban climate change, subway network inundation state, urban road accessibility, urban GDP, gross product of tertiary industry, and urban population, corresponding to 6 rate variables and 67 auxiliary variables.

The system dynamics simulation model encompasses numerous parameters, each corresponding to distinct estimation methods. During the process of model debugging, parameter determination should be integrated with model operation. Debugging must be conducted within the range of parameter value variations, and if the model exhibits insignificant changes, the parameter values can be finalized. This paper primarily employs the following approaches for parameter estimation:

- (1) Yearbook search: Statistical parameters can be directly obtained from the relevant city statistical yearbook, such as urban GDP, output value of the tertiary industry, and average annual precipitation in urban areas.
- (2) Average value: The average value method is employed for anti-flood resilience (AFR) assessment during UMS operation, which utilizes the parameter value derived from averaging PFR pre-disaster prevention, EFR response during disaster, and LFR post-disaster learning. PFR, EFR, and LFR represent the average values of the next-level indicators.
- (3) Table function method: The table function is used to deal with nonlinear data problems, that are, to input two sets of data in the form of a table to represent the functional relationship between two sets of variables.

The values of the main parameters in this paper are shown in Table 3, which is illustrated by the values of level variables:

Table 3. Values of level variables.

Horizontal Variable	Parameter Values
6 Urban climate change	INTEG (average annual increase in urban temperature, 37) Urban average annual temperature increment = "6 urban climate change" * Climate change rate Climate change rate = 0.001
7 The subway network is submerged state	INTEG (submerged point increment, 3) Inundation point increment = "7 submerged states of the subway line network" * submerged rate of the line network Line network inundation rate = 0.03
8 Urban road accessibility	INTEG (accessibility variation, 20) Change in accessibility = "8 urban road accessibility" * Rate of change in accessibility Rate of change in accessibility = -0.01
city GDP	INTEG (GDP increment, 2800) GDP increment = urban GDP * GDP growth rate GDP growth rate = 0.083
urban population	INTEG (Urban population increment, 614.85) Urban population increment = population growth rate * urban population Population growth rate = 0.0195
The GDP of the tertiary industry	INTEG (Third Industry Increments, 524.11) Increment of tertiary industry = growth rate of tertiary industry * GDP of tertiary industry The growth rate of the tertiary industry = IF THEN ELSE (Time ≤ 2010, 0.16, 0) + IF THEN ELSE (2010 < Time: AND: Time ≤ 2018, 0.13, 0) + IF THEN ELSE (Time > 2018, 0.1, 0)

4.3. Scenario Simulation for Flood Resilience Improvement

The improvement of flood resilience in the UMS operation process is a comprehensive result of the natural environment, line network facilities, economic investment, government management, and social response. The scenario simulation method describes the real environment and simulates the real policy environment through adjusting variable parameters. This section sets different policy scenarios, explores the coping strategies for improving flood resilience in the UMS operation process under different combinations of modes of variables, and puts forward targeted guidance plans.

4.3.1. Model Testing

After setting the model parameters, it is essential to conduct a thorough validation of the constructed model. The purpose of system dynamics model testing is to ensure the congruence between the established model and the actual system, as well as to verify whether the information and behavior derived from the model accurately reflect the characteristics and dynamic patterns of the real system. In this section, a historical test method is employed to validate the effectiveness of the model prior to its implementation.

The historical test involves extracting significant variables and comparing the actual data of these variables from historical periods with the simulated values generated by the SD model in order to validate the accuracy of the simulation results. Typically, a 10% error range is employed to assess the disparity between real and simulated variable values. If this error falls below 10%, it indicates that the model is deemed reliable. The formula for test deviation is as follows:

$$D = (X_s - X_r) / X_r \quad (1)$$

The model test deviation value, denoted as D , is considered against a test standard of 10%. X_s represents the simulation value of the system dynamics model for the corresponding years, while X_r refers to the actual index value.

The horizontal variable has been chosen as the testing index for conducting a historical test in the model. Figure 9 displays the comparison results between actual and simulated values of urban GDP, urban population, and gross product of tertiary industry. The data were collected from 2000 to 2021 for the actual values, while the simulated values were generated for the period of 2000 to 2030. Throughout the historical testing period, there was a strong concurrence between the actual and simulated values. The test GDP values show a slight deviation from the actual values between 2000 and 2010, with a good fit observed in the later period. The actual urban population values fluctuated irregularly between 2010 and 2015, making it difficult to achieve full fitting, but returned to normal levels in the later period. The fitting curve of tertiary industry gross product exhibits high accuracy with respect to actual values, indicating that the constructed model is suitable for research aimed at enhancing flood resistance resilience during UMS operation.

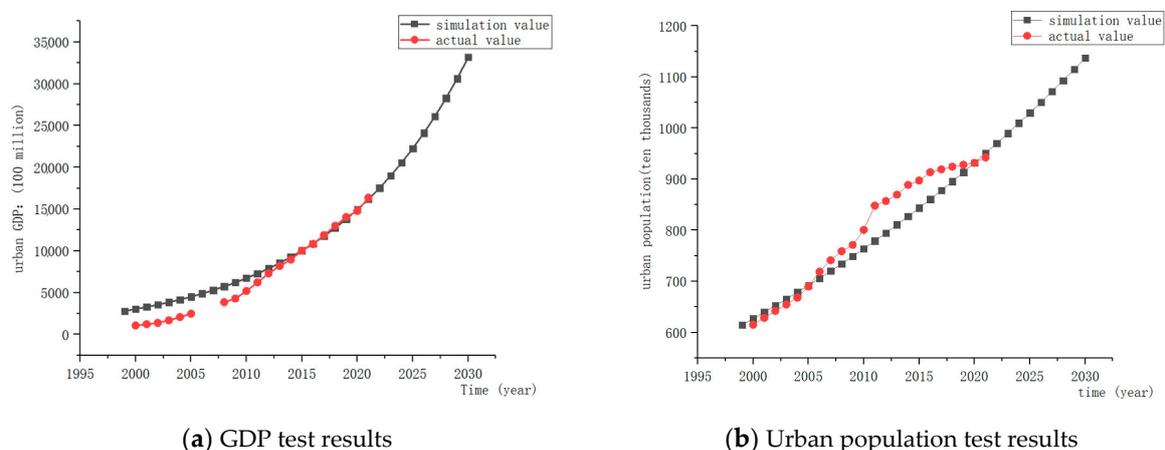
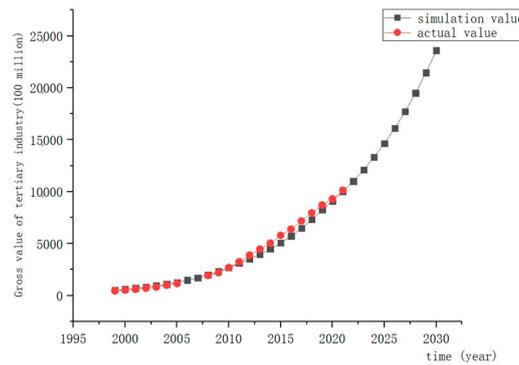


Figure 9. Cont.



(c) Gross product of tertiary industry test results

Figure 9. SD model historical test results.

4.3.2. Simulation Scenario Setting

The scenario setting is based on level variable setting conditions: “normalization benchmark condition”, “climate change condition”, “economic change condition”, “population change condition”, “line network change condition” and “traffic change condition”. Take the normalization benchmark conditions and the economic change conditions as examples to describe:

The normalization benchmark condition is to simulate system performance changes in the future based on the existing policy environment and index data. The normalized benchmark condition is the closest to the real environment and can be used as a comprehensive reference model for policy formulation.

Economic conditions: the economy is the most direct indicator of urban development. Urban construction and maintenance capacity, medical assistance level, subway operation mileage, and social security level are directly or indirectly linked to the economic level. The waterlogging prevention work of the subway system requires the dual input of material resources and human resources, with economic conditions as the basic guarantee, which plays a decisive role in improving flood resilience in the operation process of UMS. “Economic change condition” is controlled by two indicators of “urban GDP” and “tertiary industry GDP” in the SD model, while the other level variables and auxiliary variables remain unchanged to verify the influence of economic level on flood resilience.

The parameter settings of the six simulated scenarios are shown in Table 4:

Table 4. Parameter values of the SD model scenario.

	GDP Speed Increase	Increase Rate of Tertiary Industry	Climate Change Rate	Line Network Flooding Rate	Accessibility Change Rate	Growth Rate of Population
Normalized conditions	0.083	0.1	0.001	0.03	−0.01	0.0195
Climate change conditions	0.083	0.1	0.004	0.03	−0.01	0.0195
Economic change conditions	0.11	0.1	0.001	0.03	−0.01	0.0195
Population change conditions	0.083	0.1	0.001	0.03	−0.01	0.03
Line network change conditions	0.083	0.1	0.001	0.05	−0.01	0.0195
Traffic change conditions	0.083	0.1	0.001	0.03	−0.03	0.0195

The control method is used to set the parameters of the scenario simulation. When a certain parameter is adjusted, the values of other parameters remain unchanged, and the influence of this parameter on the overall model performance can be obtained.

4.3.3. Flood Resilience Enhancement Strategies and Simulation

After determining the parameter values of the simulation scenario, the strategy simulation is conducted on the flood resilience improvement of the UMS operation process under six scenarios. According to the establishment process and SD model of the aforementioned index system, the whole process of PFR, EFR, and LFR jointly promotes the improvement of UMS flood resilience. Therefore, the strategy simulation mainly focuses on the three secondary indicators of PFR, EFR, and LFR and each sub-index. Still, take the normal benchmark conditions and economic change conditions as examples to express.

(1) Normal benchmark conditions. The benchmark condition reflects the performance development under the current policy environment and urban development situation in the future, which is a continuation of the historical test scenario. The performance representation of the UMS operation process in this scenario is shown in Figure 10:

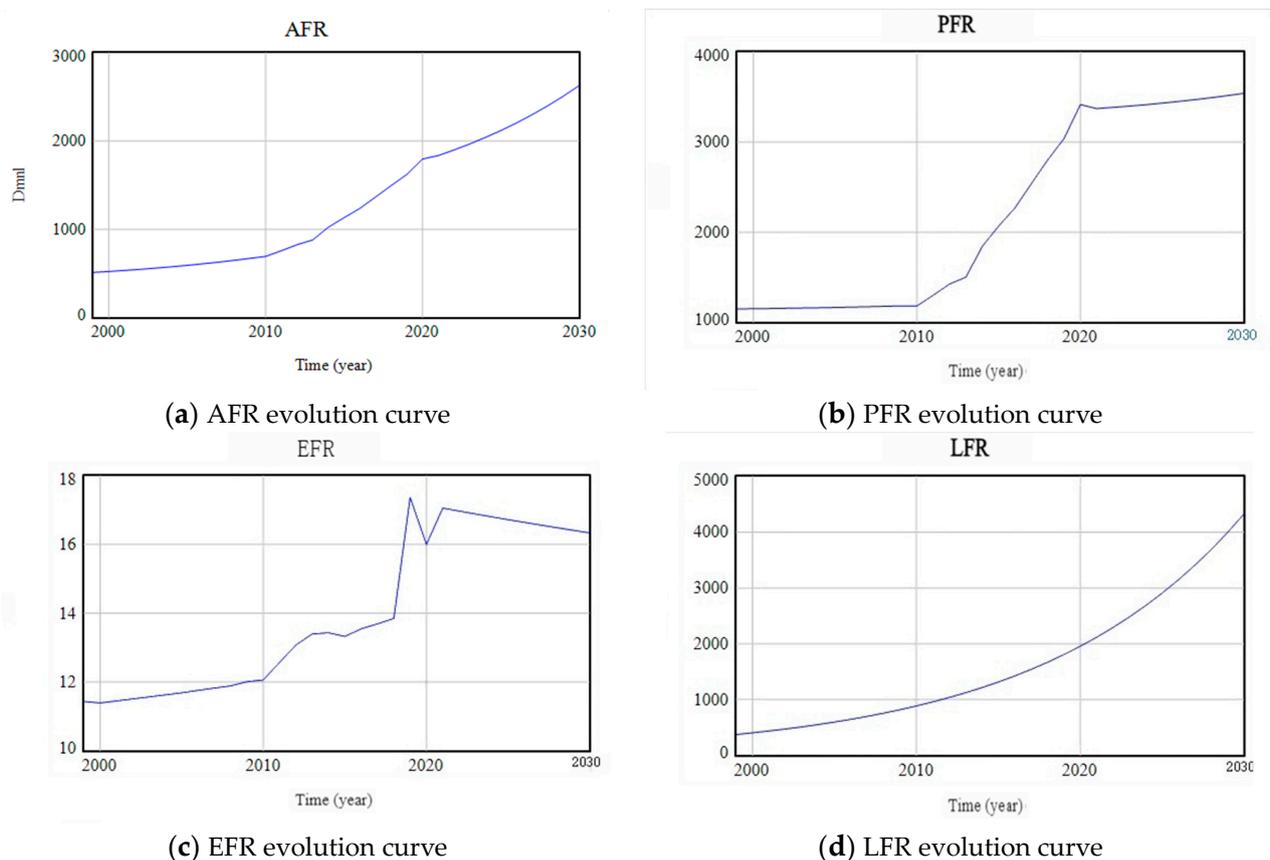


Figure 10. Simulation results of the normalized baseline conditions.

As can be seen from Figure 10, under the normal scenario, the flood resilience of the UMS operation process increases with time, and the growth rate of flood resilience increases in 10 years. The evolution trend of PFR predisaster prevention is similar to that of flood resilience, with rapid growth from 2010 to 2020; the response capacity fluctuated sharply in the EFR period and showed a downward trend after 2020; and the LFR post-disaster learning stage showed an upward curve.

Based on the flood resilience improvement index in the UMS operation process, PFR, EFR, and LFR are all composed of five dimensions of “N-P-S-M-E”. Therefore, the analysis of pre-disaster prevention, in-disaster response, and post-disaster learning ability is all

carried out from these five aspects. Figure 11 shows the changes in factors affecting PFR, EFR, and LFR in each dimension. Under the dimension of PFR, physical prevention and social prevention declined for a long time. Further analysis of sub-indicators found that the diversity of traffic connections, the continuous decline of urban population structure, and residents' dependence on subway travel led to a decline in the prevention level of physical and social dimensions. At the post-disaster learning level of LFR, the social learning ability fluctuated greatly and gradually declined. After the analysis of the subsystem, it was found that the continuous decline in the level of popularization of safety knowledge led to a lack of social learning ability. All dimensions of response capacity in EFR are in a steady and rising state.

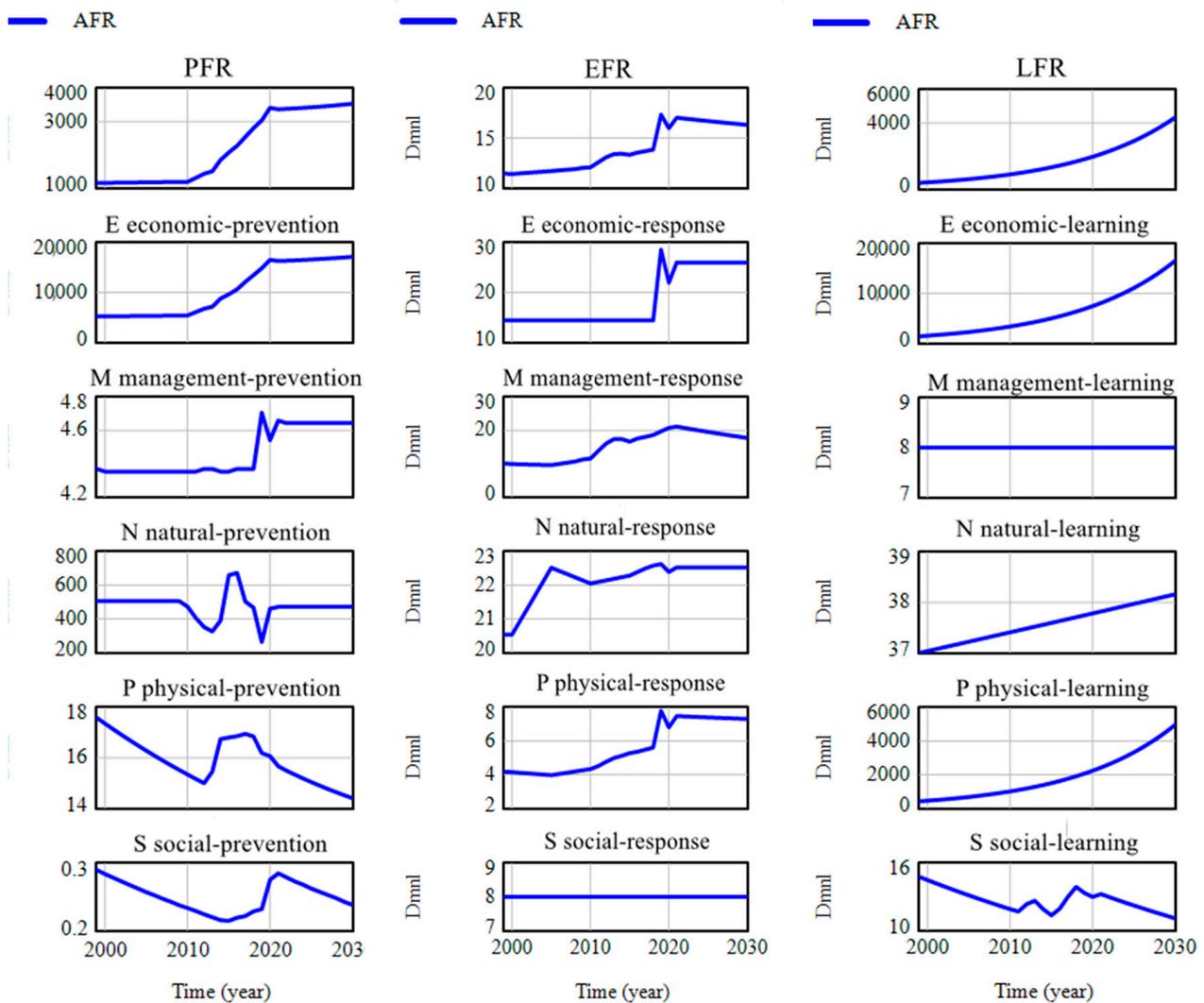


Figure 11. Whole process evolution trend diagram of flood resilience improvement.

(2) Economic change conditions. The economic change scenario is to change the growth rate of urban GDP while the other indicators remain unchanged to verify the impact of the economic development degree on the waterlogging resistance level of the subway system. The GDP of Nanjing in 2021 is 1635 billion yuan, and under the benchmark scenario simulation, the GDP of 2030 is expected to be 3316 billion yuan. Under the scenario of economic change, the GDP growth rate is 0.11; that is, under the state of rapid economic development, the GDP in 2030 will be about 7114 billion yuan. In this case, it can be seen from Figure 12 that the AFR curve shows rapid growth after 2020. The PFR value only increased slightly in late 2020, and the EFR value remained unchanged compared with

the benchmark scenario, while the change trend of the LFR value was similar to the AFR, showing rapid growth, indicating that the growth of the economic level had a positive effect on the improvement of the post-disaster learning stage, and the short-term utility was not obvious. The improvement of flood resilience in the subway system should be invested in as soon as possible and arranged in advance in order to achieve results.

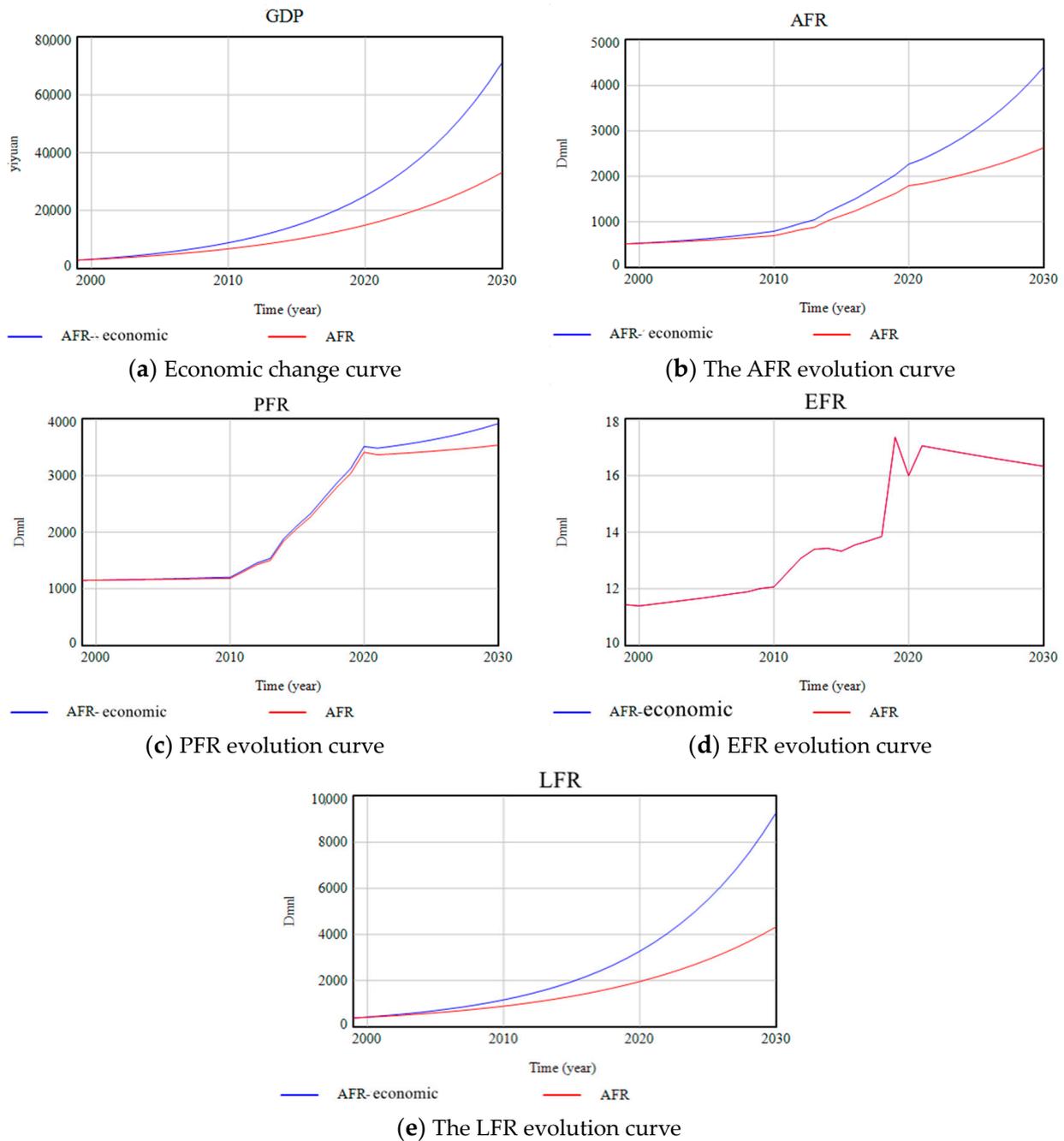


Figure 12. Simulation results under economic change conditions.

According to the whole process of development and evolution (Figure 13), economic investment has the most significant effect on economic learning and physical learning in post-disaster learning. Corresponding to the next level of indicators, urban economic development and urban construction and maintenance ability have been effectively improved, which further affects the improvement of flood resilience in the UMS operation process.

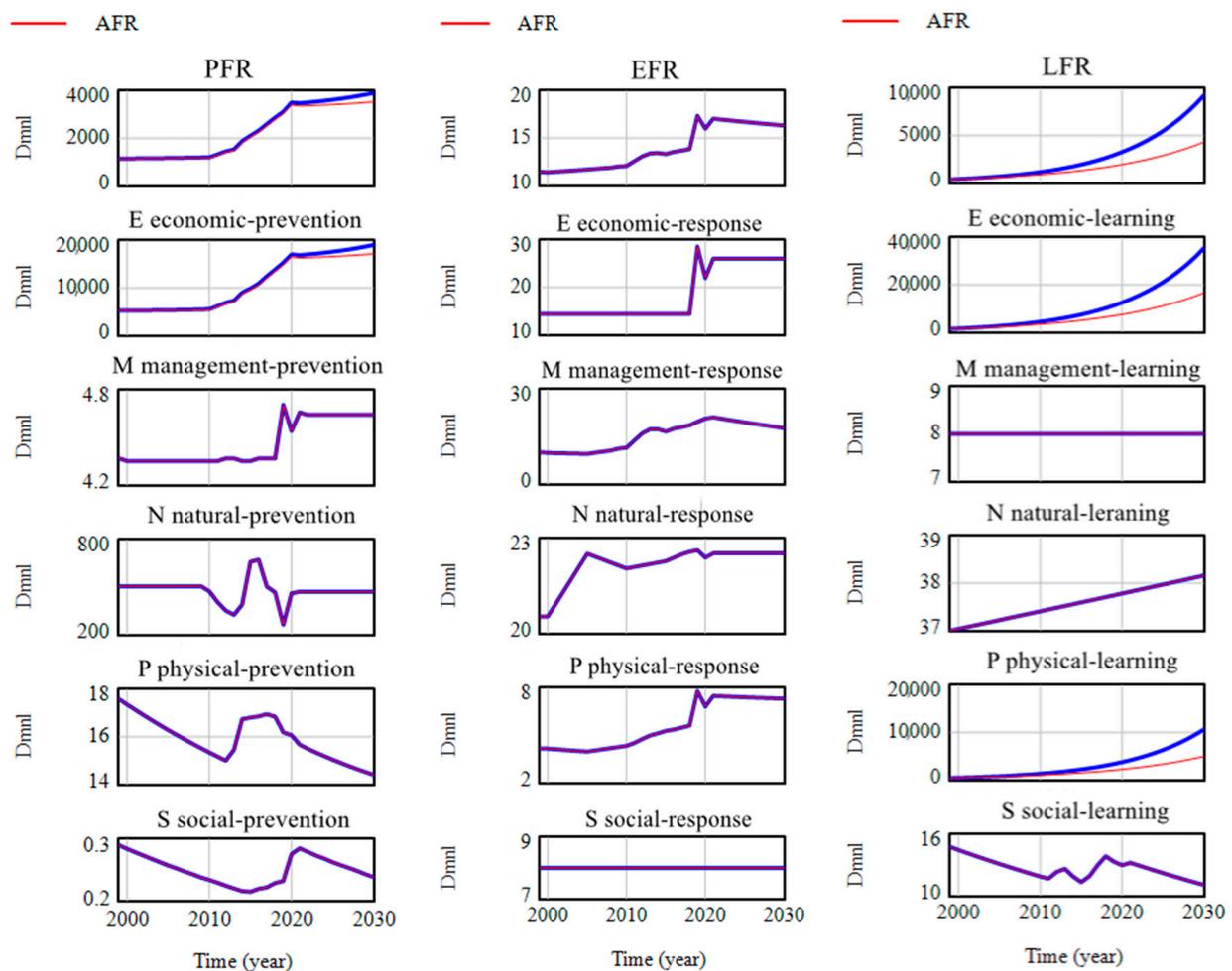
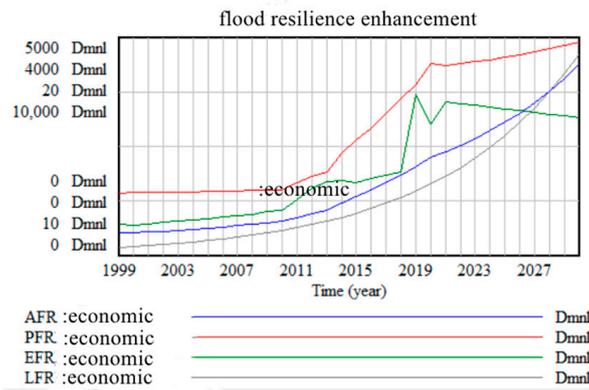


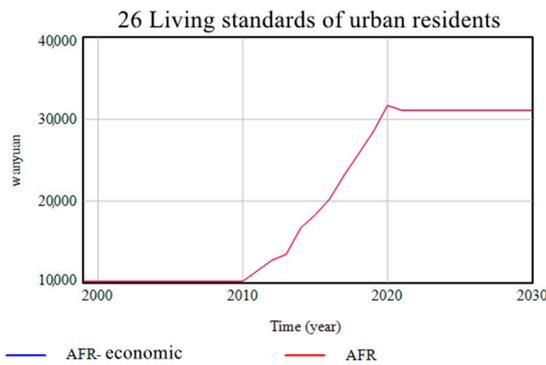
Figure 13. Development trend of flood resistance in UMS.

Figure 14a shows the overall evolution curve of flood resilience in the UMS operation process under changing economic conditions. AFR showed steady growth under the combined action of PFR, EFR, and LFR. PFR, EFR, and LFR were all dimensionless values. From the perspective of magnitude, $PFR > EFR > AFR > LFR$. The EFR value has shown a downward trend since 2020, indicating that the emergency rescue capacity of the metro system does not match the speed of economic development. Reviewing the development trend of the sub-indicators, it can be seen that the medical assistance capacity and information communication level did not keep up with the economic development trend. In the future, the UMS management process should focus on the coordinated update of supporting facilities for emergency response.

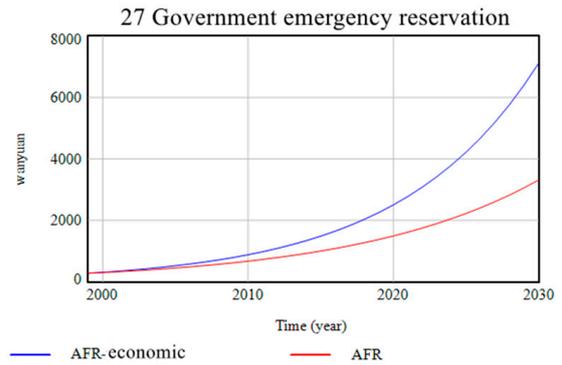
Figure 14b–f shows the evolution and development of various economic indicators in the flood resilience improvement index system during UMS operation. From the chart, even if urban GDP growth doubles, the living standard index of urban residents with disposable income has not changed much, and the residents’ ability to resist accidents has not improved. Due to economic growth, the amount of emergency reserve under urban management has increased significantly, which provides strong support for the emergency management of waterlogging events. Due to the limitations of the population, the operating conditions of subway companies will no longer rise after reaching a certain peak value. The amount of subway operating income also directly determines the ability of subway management departments to prevent and control disaster events. The diversity of the urban economy is controlled by the proportion of the tertiary industry. In this case, the economic diversity has not changed significantly, indicating that the total economic volume of the city has doubled, but the economic activity is still not high enough.



(a) Overall evolution curve of the AFR



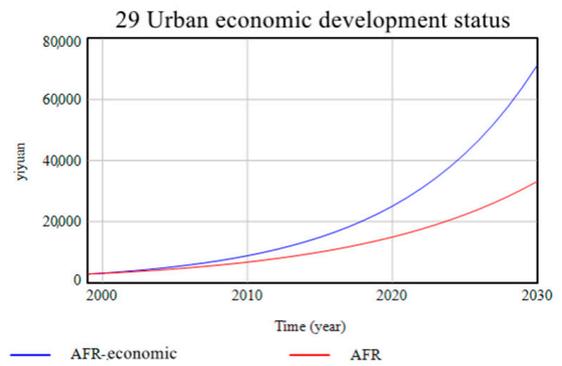
(b) Changes in living standards of urban residents



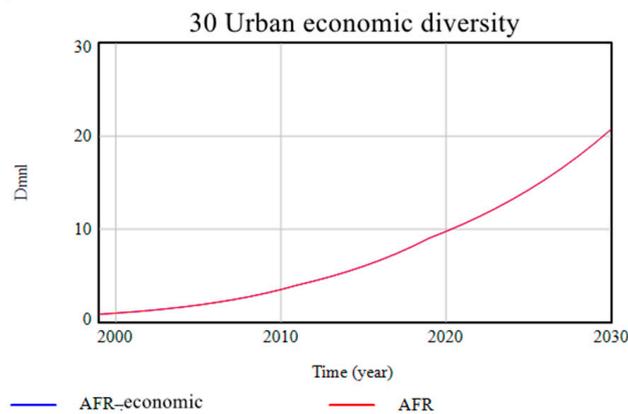
(c) Changes in government emergency reservations



(d) Operation status of metro companies



(e) The economic development of city



(f) Urban economic diversity

Figure 14. Impact chart of each economic system indicator on AFR.

Under the situation of economic change, the waterlogging management of the subway system should consider external factors, such as the medical rescue level of the city, and the communication level of the residents should be improved to meet the needs of the response capacity in the disaster. Secondly, the income from the subway system and more funds and resources can be put into the emergency management of the system. From the perspective of urban development, the disposable income of the residents should have sufficient material basis and confidence to resist disasters.

5. Conclusions

In the operational process of urban metro systems, waterlogging events pose a significant vulnerability. These events can easily lead to a decline in the structural connectivity of the line network and the accessibility of the traffic network, potentially resulting in a total or partial interruption of operations. Considering the practical challenges posed by waterlogging in UMS operations, this study aims to improve flood resilience within UMS by systematically summarizing factors influencing such improvement and employing system dynamics methods under various change scenarios. The main research findings are as follows:

The flood resilience of UMS operations evolves over time, exhibiting the response characteristics of absorption, resistance, repair, and adaptation. Based on the temporal development characteristics and formation mechanisms of flood resilience, this paper proposes a three-stage progressive model for improving resilience: preventive resilience, response resilience, and learning resilience. The system's preventive resilience is reflected in its proactive forecasting and disturbance absorption capabilities, emphasizing the ability to eliminate hidden risks during the EFR stage. The resistance and repair abilities of the system are emphasized to minimize performance attenuation values and restore the system's performance to its original state as quickly as possible. Learning ability refers to the system's capacity to refine and summarize the causes of previous incidents along with countermeasures in order to better cope with future disturbances.

The daily operation of the subway is the result of the coordinated functioning of the rail system, physical equipment, and power communication equipment. Waterlogging disaster management requires comprehensive urban environmental management and economic measures in collaboration with all sectors of society. This paper enhances the traditional identification system for determining resilience factors and summarizes five aspects—nature; physics; society; management; and economy—that influence the improvement of resilience in urban subway system operations. It combines 30 high-frequency influencing factors with the PEL resilience improvement model to provide theoretical and model support for enhancing UMS resilience from a holistic perspective encompassing multiple dimensions.

The enhancement of flood resilience in the UMS operation process is a comprehensive outcome resulting from the interplay of natural environmental factors, network infrastructure facilities, economic investments, government management, and societal responses. This study employs the system dynamics approach to simulate the progression of improving flood resilience in the UMS operation process. Various simulation scenarios are established based on different levels of variables. Taking normal benchmark conditions and economic change conditions as examples, this simulation models the evolutionary trajectory of flood resilience, preventive resilience, response resilience, and learning resilience curves from 2000 to 2030. Under normal conditions, analysis reveals that a continuous decline in transportation diversity regarding traffic connections, urban population structure variations, and residents' reliance on subway travel contributes to diminishing levels of physical and social dimension prevention measures. Furthermore, there is an ongoing decrease in safety knowledge dissemination, which hampers social learning capabilities. Simulation results under economic changes demonstrate that managing waterlogging within metro systems should consider external factors such as the city's medical rescue capacity and residents' information communication level while ensuring improvements

in disposable income for residents, thereby enhancing flood resilience within the UMS operation process.

The present study employs the system dynamics approach to conduct policy and scenario simulations aimed at enhancing flood resilience in UMS operation processes. However, the current index system fails to fully capture the actual behavior of the system, while the intricate logical relationship between various influencing factors is more complex than depicted in the model. The factors considered by the existing SD model remain somewhat limited. Future research endeavors will focus on optimizing both the index system and model to better align with real operating conditions.

Author Contributions: Conceptualization, K.L.; methodology, X.X. and Z.W.; software, Z.W. and L.T.; validation, K.L. and X.X.; formal analysis, K.L.; investigation, P.S.; resources, Z.W. and P.S.; data curation, P.S.; writing—original draft preparation, K.L.; writing—review and editing, L.T.; visualization, L.T.; supervision, Q.L.; project administration, Q.L.; funding acquisition, Q.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (No. 51978164 and 72101054). Ministry of Education in the humanities and social sciences of China (No.20YJCZH182).

Data Availability Statement: The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: Authors Zhou Wu and Peng Shi are employed by the company China Construction Eighth Engineering Division Co., Ltd., and declared that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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