Urban-Resilience Computation Simulation

Subjects: Urban Studies
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Urban resilience refers to the ability of an urban system to withstand, absorb, recover, and adapt to man-made or natural disturbances and to learn timely control of current and future expectations. Simulating the dynamic process of urban resilience and analyzing the mechanism of resilience-influencing factors are of great significance to improve the intelligent decision-making ability of resilient urban planning.

Keywords: urban resilience ; computational simulation ; urban planning

1. Introduction

The modern urban system is facing increasing challenges due to climate change, natural disasters, pandemics, population growth, economic crises, and energy consumption. Improving urban resilience is a critical need for coping with uncertainty, reducing disaster risk, and promoting urban sustainable development [1]. With the proposal of 100 Resilient Cities, the Sustainable Development Goals (SDGs), and the New Urban Agenda, resilience has become a significant concept in urban planning, governance, and academic research [2][3]. “Resilience” comes from the field of engineering and originally meant “the ability of an object to return to its original state under the action of external forces.” In the 1970s, C. S. Holling introduced “resilience” into the ecology and proposed “ecological resilience,” which emphasizes alternative stable states [4]. Then, “resilience” gradually extended to the fields of economics, sociology, urban planning, and geography, with the connotation evolving from “engineering resilience (single balance)” to “ecological resilience (multiple balance)” and then to “social–ecological resilience (complex adaptive system)” [5][6][7][8]. Currently, existing literature focus on the conceptual framework of urban resilience [9], urban resilience-evaluation index systems [10], urban-resilience application and promotion strategies [5], urban-resilience quantitative simulation [11], urban-disaster risk reduction, urban sustainable development and resilience, and smart cities [12][13][14][15]. With the development of cities and the increase of complexity, there is a need for further research related to urban-resilience computation simulation adopting new methods and technologies.

As urban resilience is a multi-dimensional and dynamic phenomenon, building resilient cities is a dynamic and complex process. The internal mechanism of various resilience-influencing factors has not yet been captured [13][16]. How to scientifically simulate this complex, dynamic interaction process is the key procedure of urban-resilience research. Moreover, in the context of smart cities, the response speed of risk is crucial to urban resilience [2][17][18]. Real-time big-data technology can reduce the impact of disaster losses and improve the ability of urban rapid recovery [19][20]. Increasingly more studies have been concerned with the quantitative assessment, spatial visualization, and dynamic simulation of urban resilience. However, most studies quantitatively simulate resilience from a single perspective or a certain dimension, and are mostly conceptual rather than operational. The research on the multi-element dynamic-evolution process of urban resilience is still limited [6]. Therefore, future work should emphasize urban-resilience computation simulation leveraging an advanced “smart” approach (e.g., big data, urban computing, and artificial intelligence) to realize the transition from static mode to dynamic process and strengthen the ability of intelligent decision-making in cities [6][18][19].

2. Definition of Urban-Resilience Computation Simulation

Urban resilience refers to the ability of an urban system to withstand, absorb, recover, and adapt to man-made or natural disturbances and to learn timely control of current and future expectations [21][22][23], as shown in **Figure 1**. With the rapid development of information and communications technologies (ICTs), the modern urban system is no longer a static materialized place, but a “complex system” that is made up of multidimensional components and dynamic interactions between economy, society, institution, ecology, and infrastructure [24][25]. In this context, urban resilience can also be understood as a series of complex solutions under complex uncertainty risks, including climate change, natural disasters, terrorist attacks, technical accidents, epidemics, and other risks [26]. By leveraging big data, artificial intelligence, the

Internet of Things, and urban-computing technologies, urban-resilience computation simulation aims to quantitatively evaluate urban risk and vulnerability, assess urban-response ability and resilience under different scenarios, and investigate the nonlinearity and spatial heterogeneity of the resilience-recovery process, focusing especially on the complexity, dynamic adaptability, internal operation mechanism, and cause–effect chain of the urban system. It can not only provide decision-making solutions for resilient urban planning, construction, and management, but also provide strong support for urban response to emergencies and disaster scenarios (**Figure 2**).

Figure 1. The connotation of a resilient city (source: author).

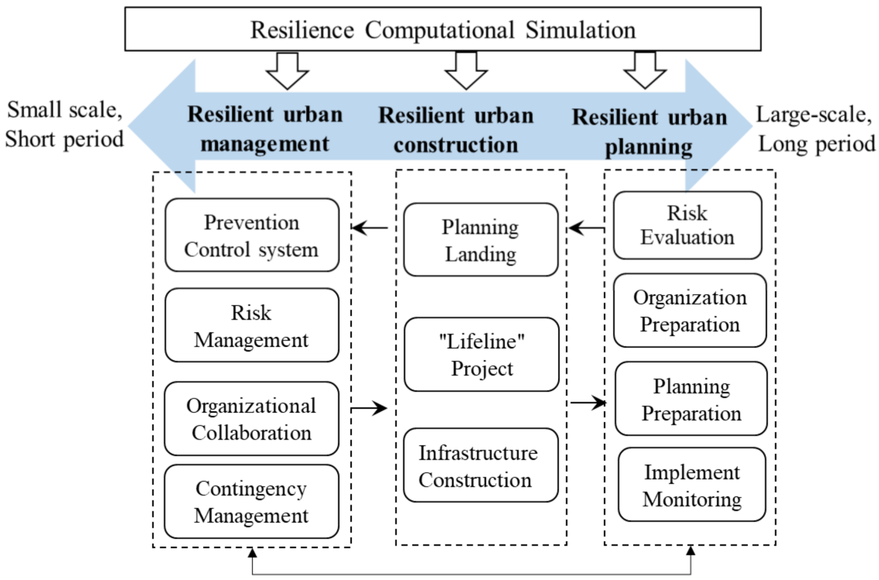

Figure 2. The hierarchy of urban-resilience computation simulation (source: author).

3. Research Progress of Urban-Resilience Computation Simulation

3.1. "Soft"-Resilience Computation Simulation

The "soft" resilience of cities includes socio-economic resilience and organizational resilience. Socio-economic resilience concentrates on urban economic diversity, employment level, economic-operation ability when risks occur, and the ability of different social groups to cope with risks [27][28]. Organizational resilience is referred to as the dynamic management, intervention, and adaptive capacity of government agencies, social organizations, and street communities in the event of disaster risks [29][30]. For "soft"-resilience computation simulation, the studies focused on resilience assessment, public behavior analysis, post-disaster simulation, and prediction by various methods, which could be categorized into three types: mathematical-statistics method, social big-data technology, and the dynamic-modeling method.

3.1.1. Mathematical-Statistics Method

Many scholars collected individual data by questionnaire surveys and interviews to construct a resilience-score or -rating system consisting of various indicators and used statistical methods to measure resilience. Forrest et al. [31] analyzed the social–spatial inequality of resilience in Anham City, the Netherlands, under flood risk by combining quantitative-resilience indicators with resident interviews. Nejat et al. [32] used the spatial-regression model to predict the probability of housing-reconstruction probability after Hurricane Sandy based on household data and identified the hotspots of housing reconstruction to assist post-disaster planning decisions. Heinzlef et al. [33] developed a spatial decision-support system based on a collaborative mechanism and a dependency curve to assist the decision-making of the organizational resilience of Quebec City in Canada under flood risk.

3.1.2. Social Big-Data Technology

Related research combined the social-media data, large-scale mobility data, point-of-interest (POI) data, and geographic-information data to evaluate the simulation of urban resilience from a bottom-up perspective [34][35][36][37][38]. Wang et al. [39] demonstrated a novel approach using the fusion of social-media data, land-use data, and other information to evaluate public response to flooding in Nanjing, China, supporting the formulation of urban flood-resilience policies. Hong et al. [40] utilized large-scale mobility data to measure community resilience and public-evacuation patterns of Harris County in the United States before, during, and after Hurricane Harvey to support resource-allocation decisions and long-term planning strategies. Chen et al. [41] integrated Baidu map location-based data, POI data, and population-density data to analyze urban human-flow disruptions in Shenzhen, China, during the 2018 Typhoon Mangkhut Ty and examine the impact of different urban functions on human flow. Sun et al. [42] fused a variety of data (e.g., ecological-environment data, urban-facilities data, and resident-mobility data) to evaluate urban haze-disaster resilience and its spatial characteristics from the perspective of residents using accessibility-analysis and network-analysis methods.

3.1.3. Dynamic-Modeling Method

Dynamic models such as the system-dynamics, game-theory, and agent-based models are also widely used in “soft”-resilience computation simulation [43]. Links et al. [44] proposed a system-dynamics computational model, COPEWELL, for predicting the recovery time of community function after an earthquake to quantify community resilience in the United States. Gao et al. [45] constructed an agent-based model to simulate the evacuation behavior of residents under different hurricane-warning levels and discovered that geo-targeted warnings can encourage individuals to make evacuation decisions. Grinberger et al. [46] combined a population-allocation algorithm with the a simulation platform to propose an agent-based model to simulate the welfare impacts of an earthquake in the central business district of Jerusalem on the economic resilience of people with different incomes.

3.2. “Hard”-Resilience Computation Simulation

“Hard” urban resilience consists of two dimensions: physical and natural. Physical resilience refers to the resilience of urban infrastructures [30][47], including urban pipelines, shelters and defense works, etc. Natural resilience includes ecological and environmental resilience [22][48]. “Hard” urban resilience is the key field of resilience-computation simulation. Many scholars have conducted extensive research on ecological-resilience evolution, risk-assessment and vulnerability analysis, and infrastructure-resilience simulation.

3.2.1. Ecological-Resilience Evolution

Taking climate change, urban morphology, environmental change, and ecological policy as objects of study, existing research mostly utilized numerical simulation, scenario simulation, landscape-index analysis, spatial analysis, and trend analysis of geostatistics to conduct ecological-resilience simulation [49]. Zhang et al. [50] leveraged the scenario-simulation method based on ordered weighted average (OWA) to quantitatively evaluate the social–ecological-landscape resilience of Mizhi county, China, from ecology, society, and production-system dimensions, and explored the spatiotemporal heterogeneity and evolution pattern. Using the numerical-simulation method, Peng et al. [51] simulated the physical-environment elements (e.g., wind speed, solar radiation, and noise) of the community and presented resilient-community planning-optimization strategies based on multi-objective simulation. Feng et al. [52] proposed a “scale-density-morphology” resilience model based on theories of landscape ecology to investigate the evolution characteristics of resilience in Shenyang, China; analyze the relationship between urban resilience with landscape elements quantitatively; and provide the adjusted strategy according to local conditions.

3.2.2. Risk-Assessment and Vulnerability Analysis

Probabilistic risk assessment, fragility curves, and empirical approaches were widely used to calculate the vulnerability of or risk to infrastructure under emergencies (e.g., earthquakes, floods, and hurricanes). The probability risk-assessment model (PRA) is a comprehensive process to estimate risk by quantifying the statistical uncertainty [53]. PRA has been used in an extensive array of studies of the risk of complex engineering systems in accident scenarios [54]. Fragility curves have been applied to the assessment of physical facility-structure damage after a disaster [55]. Dong et al. [55] combined the community's physical vulnerability of interruption of access to critical facilities with the public's tolerance of service interruption to analyze the spatial distribution of urban resilience in Harris County under flooding. Kammouh et al. [56] analyzed the recovery curves of urban lifelines (e.g., power, water, natural gas, and telecommunications) by using the data of 32 earthquakes and simulated their interaction mechanism. Moreover, empirical models [57], fuzzy logic [58], and probability models [59] are also applied to simulate the fragility curve of power lines in storm scenarios and predict and estimate the downtime of power and telecommunications systems after earthquakes.

3.2.3. Infrastructure-Resilience Simulation

The popular approaches preferred by most researchers for infrastructure-resilience simulation are complex networks, system-dynamics models, agent-based models, game theory, and probability dynamics [60][61][62][63]. For example, Nateghi et al. [64] leveraged a multivariate ensemble-tree-boosting algorithm to simultaneously predict the number of power outages, the number of users without power, and the cumulative time of power outage in the Central Gulf Coast Region of the U.S., impacted by Hurricane Katrina. Based on complex network and OpenStreetMap data, Yan et al. [65] built a measurement model to simulate the resilience level of urban-street networks in five global cities in two disturbance scenarios: random disturbance and sequence disturbance. Sun et al. [66] quantified the seismic capacity of the power-supply system based on the agent model. Marasco et al. [67] proposed a comprehensive data analysis and real-time computing platform integrating buildings, roads, water, electricity, and transportation networks to simulate the resilience of urban critical infrastructure in earthquakes.

Recently, the application of big data and deep-learning algorithms has also been broached by many scholars in urban-resilience computation simulation. For example, Kasmalkar et al. [68] simulated the regional-traffic pattern under flood by integrating multi-source data, and quantified the impact of flood-exposure, commuting-pattern, and road-network characteristics on traffic resilience. Wang al. [69] integrated a Diffusion Graph Convolution Recurrent Neutral Network and a transportation-resilience dynamic-capturing algorithm to evaluate and predict the spatial–temporal pattern of traffic resilience under extreme weather events based on DiDi Chuxing data and meteorological-grid data.

3.3. Comprehensive-Resilience Computation Simulation

Comprehensive urban-resilience simulation refers to the employment of several or all dimensions of urban system (e.g., socio-economic, organizational, physical, and natural) in computational simulation. Existing research focused on assessment, vulnerability assessment, and risk assessment for comprehensive urban resilience. The research methods involved statistics, geography, sociology, system dynamics, and other disciplines, which are mainly divided into mathematical statistics, spatial analysis, and dynamic modeling.

3.3.1. Mathematical-Statistics and Spatial-Analysis Methods

Relevant studies mainly involved principal component analysis, wavelet transform, trend analysis, variable analysis, structural-equation modeling (SEM), and the analytic hierarchy process (AHP) to quantize comprehensive urban resilience [70][71]. For example, Chen et al. [72] used the entropy-weighting TOPSIS method to analyze the spatial–temporal pattern and dynamic evolution of the comprehensive resilience in the Harbin-Changchun urban agglomeration in China from 2010 to 2018. Liu et al. [73] revealed the spatial–temporal pattern and evolution trend of social–ecological resilience of Shenyang Central City, China, in 1995 and 2015 by spatial analysis, landscape–pattern analysis, and spatial statistical analysis based on remote-sensing images. Chen et al. [74] constructed an urban-resilience evaluation-index system considering three attributes of resilience—resistance, recovery capability, and adaptive capacity—and utilized TOPSIS improved by the KL formula to evaluate Wuhan, China's, urban resilience to rainstorm-flood disasters from 2009 to 2015. Wang et al. [47] evaluated the urban-flood resilience of Nanjing, China, from 1997 to 2017 by wavelet-transform and trend analysis, and systematically discussed the impact of social, economic, natural, physical, political, and institutional subsystems on the urban functional resilience. Li et al. [75] combined GIS and AHP to build a quantitative evaluation model for urban-waterlogging resilience and applied the model in Kunshan City, Jiangsu Province, China.

3.3.2. Dynamic-Modeling Method

The commonly used dynamic-modeling methods include complex networks, system dynamics, game theory, agent-based models, and scenario simulation [76][77][78][79]. For instance, Datola et al. [80] constructed the framework of a complex urban system from three aspects of environment, elements, and structure, leveraging complex adaptive-system theory (CAS). Li et al. [81] analyzed the causal-feedback and dynamic-interaction mechanism between urban-subsystem resilience using a system-dynamics model, and simulated the change process of Beijing's comprehensive resilience by 2025. Chen et al. [82] proposed a new model for urban resilience considering adaptability, resistance, and recovery to simulate the resilience-change characteristics of Taiwan, China, during the Morakot. Maksims et al. [83] introduced a dynamic urban natural disaster-resilience assessment tool integrating system dynamics, a probabilistic approach, and a composite-indicator approach, and took the flood in Yergawa city, Latvia, as an example to realize urban-resilience assessment under different scenarios. Huang et al. [84] built an urban flood-resilience simulation model evolving the system-dynamics model and scenario simulation to investigate the dynamic changes of flood resilience of Nanjing, China, under four scenarios from 2009 to 2025. Li et al. [85] built a high-precision urban-rainstorm model in Huangpu District in Shanghai, China, based on numerical simulation and scenario simulation, and conducted flooding-risk simulation for different rainfall scenarios, providing resilience-improvement strategies for flood disasters. RuiBa et al. [86] proposed a multi-disaster analysis method integrating experiments and simulations, multi-hazard field investigation, and scenario analysis and response, taking the T3 terminal of Urumqi Diwopu International Airport in China under the coupling of wind, snow, and multi-disaster as the research object.

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