Cities 136 (2023) 104265

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Urban resilience under the COVID-19 pandemic: A quantitative assessment framework based on system dynamics

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ARTICLE INFO

Keywords:
Urban resilience
Epidemic response policy
Emergency management
System dynamics
Epidemic simulation

ABSTRACT

The COVID-19 pandemic, which lasted for three years, has had a great impact on the public health system, society and economy of cities, revealing the insufficiency of urban resilience under large-scale public health events (PHEs). Given that a city is a networked and multidimensional system with complex interactions, it is helpful to improve urban resilience under PHEs based on system thinking. Therefore, this paper proposes a dynamic and systematic urban resilience framework that incorporates four subsystems (governance, infrastructures, socioeconomy and energy-material flows). The composite index, system dynamics and epidemic simulation model are integrated into the framework to show the nonlinear relationships in the urban system and reflect the changing trend of urban resilience under PHEs. Then, urban resilience under different epidemic scenarios and response policy scenarios is calculated and discussed to provide some suggestions for decision-makers when faced with the trade-off between the control of PHEs and the maintenance of city operation. The paper concludes that control policies could be adjusted according to the characteristics of PHEs; strict control policies under a severe epidemic could lead to a significant decrease in urban resilience, while a more flexible control strategy can be adopted under a mild epidemic scenario to ensure the normal operation of urban functions. Moreover, the critical functions and impact factors of each subsystem are identified.

1. Introduction

With accelerating urbanization, diversification of urban functions and population growth, cities are faced with increasing disaster risks and losses caused by these disasters (Shi et al., 2021). The application of resilience in disaster-reduction research and its importance have been recognized and emphasized by governments and the academic and industrial sectors (Cutter et al., 2010). For instance, the Rockefeller Foundation initiated the 100 Resilient Cities (100RC) to mitigate urban risks and respond to disasters (Fitzgibbons & Mitchell, 2019), and the Sustainable Development Goals (SDGs) provided by the United Nations also attach resilience to the sustainable development of cities (Wang et al. 2019b). At the same time, cities are gradually becoming networked and multilevel systems (Borsekova et al., 2018). Resources can flow from one subsystem to another, but crises can also spread, exerting an amplification effect (Li, Kou, Wang, Yang, 2020a), which means that natural or man-made disasters are likely to have greater impacts on the normal operation of cities and human activities (Wang et al. 2019a). Therefore, the resilience of the urban system should be emphasized, and disaster reduction and response policies should be addressed based on system thinking (Koren et al., 2017).

The COVID-19 pandemic outbreak in early 2020 has evolved from a public health event (PHE) into a global economic and social crisis and has severely affected people's lives and the socioeconomic system (Tai et al., 2021), showing that cities lack sufficient capacity to prevent and control PHEs. Due to the high mobility and complex interconnections of cities, they are probably more vulnerable to the COVID-19 pandemic, so evaluating the impact of the pandemic on cities is imperative (Chu et al., 2021). In addition, given that COVID-19 can be long-standing and recurring, finding the optimal response actions to control the spread of the epidemic and maintain the normal operation of cities simultaneously is of great significance. Unlike natural disasters that attack cities and destroy infrastructures instantaneously, large-scale PHEs do not reduce the functions of physical facilities in a direct way, but they can spread through the dynamic connectivity in an urban system, impeding urban operation and changing people's demand for some infrastructures in the long run (Paydar & Fard, 2021). Moreover, the response strategies for epidemic control could also cause negative effects on cities; for instance,

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https://doi.org/10.1016/j.cities.2023.104265
Received 13 April 2022; Received in revised form 14 December 2022; Accepted 22 February 2023
Available online 28 February 2023

strict quarantine or lockdown policies will reduce economic activities, slowing economic growth and energy flow. Thus, to evaluate the results of PHEs and develop reasonable response strategies, the dynamic connections among different urban subsystems and the complex impact mechanism through which PHEs affect cities should be revealed.

Despite massive numbers of publications focusing on epidemics, response strategies and impact assessments, there is still a lack of comprehensive assessments on the impact of large-scale public health crises on the entire city (Kontogiannis, 2021). To fill this gap, this paper aims to (1) identify the main interconnections in the complex urban system and clarify the impact mechanism through which large-scale PHEs affect cities and (2) quantify the dynamic change in urban resilience under large-scale PHEs from a systematic perspective and compare the effects of different response policies for PHEs. To achieve our research aims, we first establish a dynamic and inclusive urban system resilience framework that includes four subsystems (governance, infrastructures, socioeconomy, energy and material (EM) flows) based on the system dynamic (SD) approach, where the key factors, interactions and feedback among urban subsystems can be identified. Then, a detailed susceptible-exposed-infectious-recovered population (SEIR) model is integrated into the SD model to simulate the spread process of the COVID virus with different characteristics, and the change in urban resilience under different epidemic scenarios can be calculated through the composite indicators embedded in the SD-based framework. Finally, several types of response policy scenarios are simulated, and policy effects are discussed, which can provide support for local governments in their decisions to trade off normal urban operations against public health crisis control and implement the optimal strategy.

2. Literature review

This paper aims to discuss the system resilience of the entire city under large-scale PHEs from the perspective of urban functions. Therefore, this paper first reviews the relevant studies on urban resilience under external shocks, then summarizes the urban functions listed in the literature, and finally discusses resilience assessment approaches.

2.1. Topics of urban resilience

Holling (1973) first promoted the concept of resilience in ecological environmental systems and explained it as a measure of the ability of a system to absorb changes in variables and still persist. The term resilience has been widely applied in different research fields, such as critical infrastructures (Comes et al., 2020, Feofilovs & Romagnoli, 2021), the environment and ecosystem (Ran et al., 2022), the economy (Wang et al., 2021) and the supply chain (Laguna-Salvado et al., 2019). Despite extensive research, there is no consensus on its definition due to the different contexts in which it is applied (Southwick et al., 2014). Considering the complex and nonlinear interrelations in urban systems, researchers are attempting to establish the urban resilience concept in system thinking instead of focusing on only a single dimension. In this regard, we highlight the definition of urban resilience proposed by Meerow et al. (2016), namely, ‘the ability of an urban system (and all its constituent socioecological and sociotechnical networks across temporal and spatial scales) to maintain or rapidly return to desired functions in the face of a disturbance, to adapt, to change, and to quickly transform systems that limit current or future adaptive capacity’.

Much academic effort has been devoted to analyzing urban resilience in the context of PHEs from different dimensions, including infrastructures, material and energy supply, socio-economic development and governance capacity:

In the field of critical infrastructures, Forcellini (2022) took the occupancy of intensive care units (ICUs) as a reference parameter to assess the resilience and recovery capacity of health infrastructure systems in some European countries during the pandemic, Cao et al. (2022) further discussed the application and potential of mobile technology and facilities in health services to prevent and control PHEs, which indicated the indispensable role of information and communication technology (ICT) in improving urban resilience during the pandemic. In fact, the pandemic has changed the landscape of critical infrastructures broadly despite the lack of physical damages. Galbusera et al. (2021) conducted a survey that involved the main stakeholders in infrastructure operation, showing that, with the exception of the health sector, ICT and water utilities, most industries in critical infrastructure field suffered negative impacts in demand, supplier, operation and profitability. For example, Teixeira et al. (2021) and Valenzuela-Levi et al. (2021) acknowledged that COVID-19 influenced the transportation infrastructure by changing people's travel demand and modes.

Likewise, the energy and material flow in cities have been disturbed to a certain extent due to confinement measures for epidemic control. Li et al. (2022) reported a significant reduction in electricity demand, and as Lazo et al. (2022) stated, such a reduction will impede the resilience of the electricity sector from technical and financial aspects. Burgos & Ivanov (2021) simulated the performance of food retail supply chain under the lockdown scenarios and proved that the resilience of food supply chain is triangulated by governmental measures, inventory-ordering dynamics and customer behaviors. Moreover, researchers have emphasized the threat of healthcare wastes to the urban environment and pointed out the insufficiency of conventional treatment methods in removing emerging contaminants, proposing new strategies to improve the waste treatment facilities in the cities (Parida et al., 2022; Thakur, 2022).

The social and economic resilience of cities during COVID-19 has also been discussed. Ntounis et al. (2021) analyzed economic resilience from the perspective of industry resilience, and a novel business resilience composite score was established to compare the resilience of tourism and hospitality industries with other economic activities. Hu et al. (2022) further explored the factors that impact economic resilience and found that economic resilience amid the pandemic was related to both economic structural factors and government control measures.

Researchers have acknowledged that governments play an essential role in the response of large-scale public health events like COVID-19 (Wang, 2022), and their governance quality and policies have been investigated. Shi et al. (2022) analyzed the governance resilience of urban communities with different geographical locations and social classes during the pandemic. Yan & Cao (2022) summarized China's experience of public procurement strategies in the COVID-19 response and then constructed a procurement and supply system of emergency supplies. Christensen & Laegreid (2020) also discussed the government's response strategies to the PHEs and identified the key factors to have positive policy effects.

It can be seen that single dimensions of urban resilience amid the pandemic have been widely discussed from different perspectives; however, given the complex interactions among different urban systems, studies that enable the assessment of the multidimensional impacts of such PHEs on cities from a systematic perspective are still needed. In this regard, some researchers have discussed the urban resilience of an energy-economy (Wang & Wu, 2021, Shehabi, 2022) or a social-ecologic dimension (Botequilha-Leitão & Díaz-Varela, 2020; Hua et al., 2022), but few of them have attempted to evaluate the impact of large-scale PHEs from a comprehensive and city-scale perspective. Their impact mechanism on cities is not clear, and a holistic and inclusive framework is needed to reflect the dynamic connections among different urban systems.

2.2. Indicators of urban resilience

As resilience cannot be measured directly, most studies rely on a series of proxy variables to describe the characteristics of urban resilience (Tariq et al., 2021), such as redundancy, robustness, resourcefulness and rapidity (Ribeiro & Gonçalves, 2019). Copeland et al. (2020) stated that proxy indicators should correspond to the underlying understanding of resilience. However, Kim & Song (2018) claimed that there were gaps in the relationship between conceptual attributes and measurement variables. Therefore, this paper applied urban functions to properly assess urban resilience. One reason for this choice is that this paper adopted the concept of urban resilience proposed by Meerow et al. (2016), which highlighted the “desired functions in the face of disturbance”. Moreover, the normal operation of a city is supported by critical functions, and the evaluation of urban functions is the premise of resilience measurement (Zhang et al., 2021).

The existing studies classified the urban functions based on diverse criteria. One approach is to divide urban functions based on human activities and the urban spaces where these activities take place (Chen et al., 2020; Qian et al., 2021; Ye et al., 2021), mainly including living, working, commerce, education, transportation and recreation; the second is to identify urban functions by the critical physical facilities, such as energy, transportation, communication, healthcare, education and government (Zhang et al., 2021). In addition, Kim and Song (2018) classified urban functions into basic, developmental, sustainable and maintenance functions from the perspective of urban development. Obviously, some of the urban functions in these studies overlap to a certain extent, and which urban functions need to be highlighted in the context of large-scale PHEs is not obvious. Therefore, it is necessary to identify the critical functions when considering the impact of COVID-19.

2.3. Assessment methods of urban resilience

Various methodologies are adopted in urban resilience assessments based on the available data, backgrounds and urban dimensions.

2.3.1. Qualitative methods

Qualitative methods such as content analysis (Du & Tan, 2022), interviews (Yan & Cao, 2022) and qualitative comparative analysis (QCA) (Mena et al., 2022; Shi et al., 2022) are applied to determine the impact factors of urban resilience, and semiquantitative methods such as the decision-making trial and evaluation laboratory (DEMATEL) are also used to identify the impact mechanism of urban resilience under external shocks (Kumar et al., 2022). However, they are mostly case-based or rely on interviews, which makes reflecting the factors of resilience from different urban systems difficult.

2.3.2. Index approach

The index approach is the most common way to evaluate the resilience level, which is operative, multidimensional and easy to make a horizontal comparison. Previous studies selected urban resilience indicators from both its dimensions (economy, society, health, physical facilities, governance, environment, etc.) and characteristics (redundancy, robustness, connectivity, resources, diversity, inclusion, etc.) (Fan & Fang, 2019; Ribeiro & Gonçalves, 2019). Various index frameworks have been proposed to evaluate urban resilience under disasters, such as resilience index measurement and analysis (RIMA) (FAO, 2016) and PEOPLES (Cimellaro et al., 2010). However, the city is a system of systems with interdependence and interlinkages, and the static frameworks are not suitable to reflect the dynamic changes and nonlinear connectivity in the urban systems (Copeland et al., 2020; Li et al. 2021a). To describe the dynamic changes in urban resilience under external shocks, a dynamic resilience assessment approach is needed. Thus, Hodbod et al. (2021) and Jiang et al. (2022) then combined the index approach with econometric models to explore the relationship among various factors in economic resilience. However, the econometric models rely heavily on statistical data. They are widely used to reflect the mechanism of resilience changing in a long run, instead of reflecting the urban resilience in a short time under external shocks.

2.3.3. Simulation models

To solve the above problems, some computer-based simulation models were developed to measure resilience under external shocks dynamically. Ganin et al. (2017) constructed a networked model to assess the resilience of urban transportation systems that combined the network nature of urban road systems and geographic information. Similarly, Bozza et al. (2017) developed a hybrid social-physical network following complex network theory to estimate the resilience of urban ecosystems under natural disaster conditions. The network-based model is quite suitable for simulating physical infrastructures with an inherently networked nature, such as transportation, water and power facilities (Galbusera et al., 2018), but is not suitable for simulating the interactions in social or economic systems. Thus, researchers applied the agent-based model (ABM) to estimate resilience in the social and economic dimensions in disaster risk reduction (Marasco et al., 2021). Li et al. (2021b) discussed the ripple effect in supply chain networks caused by disruptions during the pandemic, in which the behaviors and interaction rules of related firms were simulated through agent-based models. The agent-based can be a useful tool for simulating and predicting the performance and interactions of complex systems; however, it requires more data for model calibration and is scarcely applied to simulate the urban system as a whole. Saja et al. (2019) also concluded that most of the current resilience assessment approaches had limitations in terms of capturing the dynamic interactions between social and other dimensions.

System dynamics (SD) can visualize system behaviors and mechanisms, including causal relationships, feedback loops, delay and decision rules, and is widely applied in studies related to infrastructures (Phonphoton & Pharino, 2019), social and economic systems (Zarghami & Dumrak, 2021) and ecological systems (Pagano et al., 2019). SD can integrate subsystems with various features into one model, that is, it can integrate both the physical components and social components in cities; therefore, researchers use it to simulate the complicated and dynamic interactions between different urban subsystems. Li et al. (2020a) assessed the long-term urban resilience of Beijing by the SD model, and infrastructure, economy, social and governance factors were embedded within the model. Mou et al. (2021) evaluated the resilience of the urban economy, environment, population and technology under the constraint of water resources. In addition, SD provides an open framework that can be linked with other disaster scenarios or probability simulation tools, making it suitable for calculating the resilience of urban systems under different external shocks (Feofilovs & Romagnoli, 2020). For example, Hossain et al. (2020) established a qualitative causal loop diagram through the SD model to show the interactions of human and natural components natural hazard conditions, and Feofilovs & Romagnoli (2021) incorporated the disaster probability simulation model and SD model into the same framework to show the urban resilience under random shocks. For large-scale PHEs, Kontogiannis (2021) established a qualitative SD model to show urban resilience and vulnerability under COVID-19, and Jia et al. (2021) further discussed the supervision strategies amid the pandemic using the SD model. However, few studies have conducted quantitative analyses of the impact of COVID-19 on an entire city. Furthermore, as the pandemic will continue for a long time and the virus continues to mutate, diversified response strategies should be proposed and discussed for the sake of the healthy development of the urban economy and society in the long run.

To fill the gaps in research topics and methods, this paper proposes an integrated model to quantify the impact of COVID-19 on an entire city, where the epidemic simulation model and composite indicator system are introduced into an urban resilience assessment model based on SD. The contributions of our paper are threefold, as follows: (1) urban resilience is measured based on the change in urban functions in different subsystems, shortening the gap between conceptual attributes and measurement variables; (2) the integrated model in this paper enables us to solve the problem regarding the inability of static indicators to simulate dynamic urban systems under external shocks, proposing a novel solution for resilience assessment; and (3) more pandemic scenarios with different features will be simulated, and multiple response strategies will be tested, which can enrich the research topics of COVID-

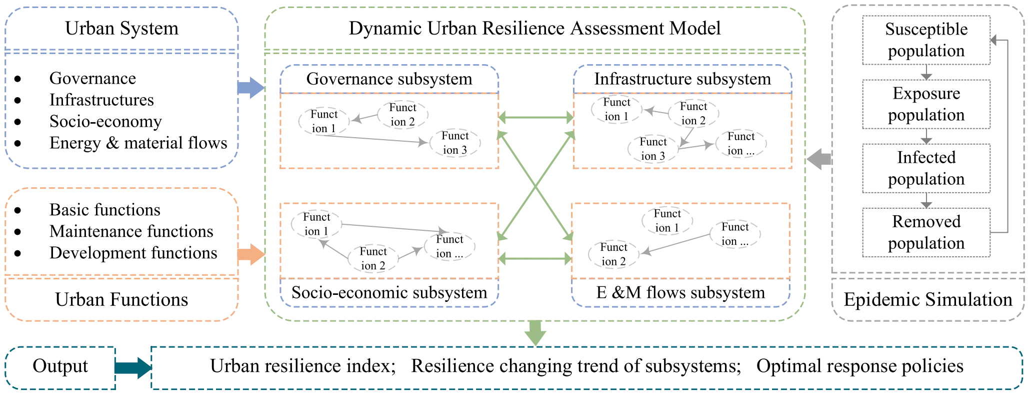


Fig. 1. The conceptual model of the urban resilience assessment framework under an epidemic.

19 and provide suggestions for decision-makers.

3. Methodology

To calculate the variation in urban resilience under PHEs, a multi-method assessment framework was built, as shown in Fig. 1. First, the specific urban subsystems and critical functions related to basic human needs were identified based on a review of existing publications, and the proxy indicators for each function were selected to build the urban resilience index system. Then, the SD approach was used to reflect the impact mechanism of COVID-19 and construct the resilience measurement model, where the interconnections among different urban functions are shown by causal loop diagrams (CLDs) and quantified by stock-flow diagrams (SFDs). Finally, an epidemic simulation model that can show the PHE scenarios was established and linked with the resilience assessment model. With such an integrated model, disaster management departments can evaluate the urban resilience and develop optimal policy sets to improve urban resilience under large-scale PHEs like COVID-19.

3.1. Urban subsystems and functions

The physical, social, technical, and ecological components make the city a massive and complicated system. It is common to divide the urban system into several main subsystems to reveal the rule of a city's operation. For example, Pelorosso et al. (2017) divided the urban system into 12 components including industrial, commerce, building, transportation, governance, etc.; Ribeiro et al. (2019) assessed urban resilience from 5 dimensions, including physical, natural, economics, institutional and social dimensions. Despite the terminology and focus varying across the research, the division of urban subsystems are similar or overlaps. Therefore, this paper divided the whole city into four subsystems (governance, infrastructure, socioeconomic system, and energy & material flows) according to Resilience Resilience Alliance (2007), Meerow et al. (2016) and Li et al. (2021a). The four subsystems are inclusive enough to incorporate both physical and managerial aspects of a city: the governance subsystem refers to the actors and institutions whose decisions shape the urban systems; the infrastructure subsystem covers the built environment, green space and urban ecological environment; the socioeconomic subsystem means the monetary capacity, production activities and social factors like demographics and education; the energy & material flows refer to the water, energy, food and waste consumed or produced by the urban system (Meerow et al., 2016). Moreover, such an urban framework is highly flexible, in this paper, we emphasize the basic human needs impacted by the PHEs in a short time scale, while the framework can also be further extended to show more elements in the urban system from a long-term perspective.

The damage to urban functions might have a more direct impact on human life and city operation (Bruneau et al., 2003). In this paper, we reviewed and summarized the basic urban functions that are likely to be damaged in PHEs based on related literature and matched these functions with different urban subsystems, as shown in Table 1. Since this paper focuses on the short-term impact of PHEs on the basic human needs, the functional changes in environmental and ecological aspects are ignored.

Table 1
Urban subsystems and corresponding functions.

Subsystems	Functions	References
Infrastructures	Transportation	Cao et al. (2020); Tu et al. (2017); Xia et al. (2021); Kim and Song (2018); Qian et al. (2021); Shen and Karimi (2016)
	Communication	Ye et al. (2021);
	Health care	Cao et al. (2020); Xia et al. (2021); Chen et al. (2020); Shen and Karimi (2016)
Socioeconomic system	Industrial production	Chen et al. (2020); Zhang et al. (2021); Kim and Song (2018); Cao et al. (2020)
	Consumption (Commerce)	Chen et al. (2020); Qian et al. (2021); Shen and Karimi (2016); Tu et al. (2017); Cao et al. (2020)
	Entertainment & recreation	Qian et al. (2021); Shen and Karimi (2016); Kim and Song (2018); Tu et al. (2017)
	Tourism	Chen et al. (2020); Shen and Karimi (2016)
Governance	Public services	Chen et al. (2020); Zhang et al. (2021); Shen and Karimi (2016); Cao et al. (2020)
	Disaster prevention & safety	Zhang et al. (2021); Kim and Song (2018)
Energy & Material (EM) Flows	Food supply	Shen and Karimi (2016); Ye et al. (2021)
	Energy supply	Zhang et al. (2021); Xia et al. (2021)
	Water & sanitation	Zhang et al. (2021)
	Waste treatment	Zhang et al. (2021); Xia et al. (2021)

The interactions between urban subsystems and functions are intricate and complex, this paper abstracts the main relationships between the four subsystems under PHEs, see Fig. 2. The policies and actions taken by decision-makers in the governance subsystem will influence the operation of the other subsystems. The human and production activities in the socio-economic subsystem provide fiscal support for the governance subsystem and create demand for the infrastructures and energy & material flows.

Fig. 2 also shows the overall impact mechanism of PHEs on the urban system, unlike natural disasters that occur in specific places and cause damage to the physical environment, the large-scale PHEs will not damage the physical facilities, but the negative impact might derive from the rapid spreading speed, invisible spreading paths and long-term

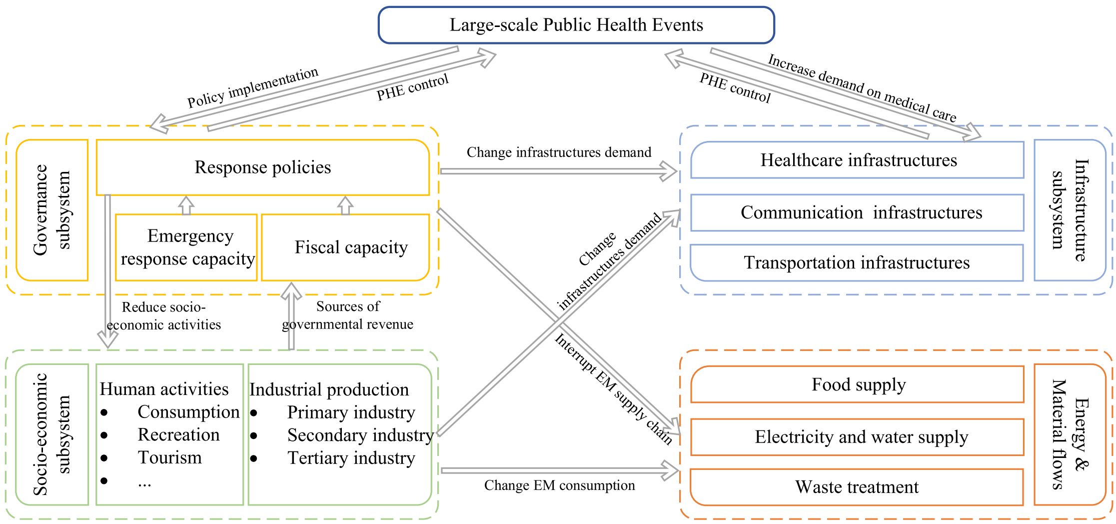


Fig. 2. Impact mechanism of PHEs on urban subsystems.

Table 2
Component descriptions of the SD model.

Legends	Components	Description
text	Variable	Variables in CLDs and SFDs
<text>	Shadow variable	Variables that have been defined in other submodels
	Link	Arrows between variables that indicate causal relationships
+	Link	Two variables change in the same direction
−	Link	Two variables change in opposite directions
	Link with time delay	Arrows with a time delay between variables
−	Balancing loop	Loops that act in certain ways to maintain their original goals
+	Reinforcing loop	Loops that generate positive feedback
stock	Stock variable	Cumulative value of in- and out- flows, indicating the state of a system
	Flow	Change rate of stock variables

Table 3
Indicators in the governance subsystem.

Subsystem	Functions	Indicators
Governance	Disaster prevention Public services	Emergency response capacity Government financial capacity

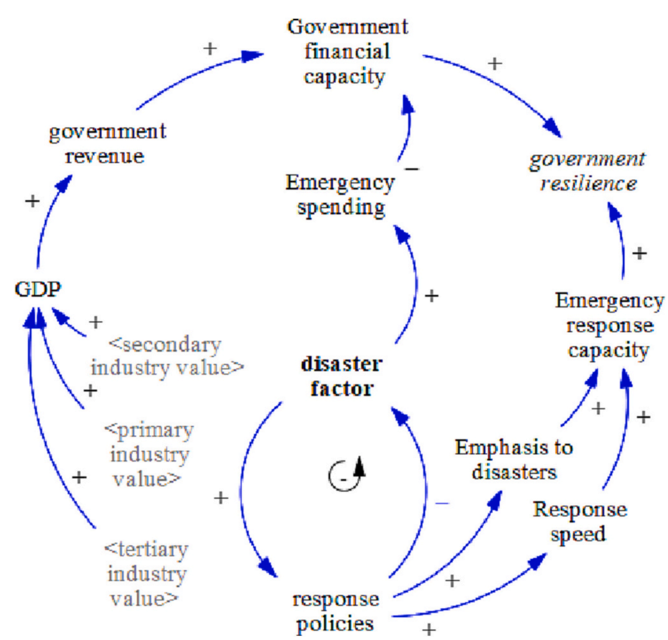


Fig. 3. CLD of the governance subsystem.

existence of diseases. Two direct impact paths are identified: (1) the occurrence of PHEs with a high fatality rate will lead the decision-makers to propose response policies, challenging the emergency and fiscal capacity of local governments; (2) the fast-spreading speed of PHEs like COVID-19 will sharply increase the demand for medical care services in a short time, striking the urban medical system. Besides the direct shocks of PHEs on healthcare infrastructures, the response policies to prevent the wide spreading of the diseases are likely to exert a wider influence on urban functioning through the interlinkage of urban subsystems, the main indirect impact paths are as follows: (3) the response policies will cause suspension in transportation and logistics network, which will reduce the supply of transportation service and interrupt the material supply chain; (4) response policies will reduce the socio-economic activities to some extent, resulting in the change of infrastructure service and energy demand; (5) as the main sources of government revenue, the function decrease in socio-economic subsystem will, in turn, impede the operation of governance subsystem and the effect of response policies.

Compared to natural disasters, the actions and strategies for large-scale PHEs are two-sided, the positive effects of PHE control may come at the cost of the normal operation of urban system. Therefore, the trade-off in response policies if especially significant under PHEs like COVID-19.

3.2. Impact mechanism of PHEs on urban subsystems

The SD model is applied to show the mechanism of COVID-19 impacts on different subsystems and the entire city. The causal feedback loops are the basis of SD analysis, which simulates the interconnections and causal relationships among different factors, transmitting the results of historical behavior to the system itself to influence the behavior of the next time step (Tai et al., 2021). This paper selected proxy indicators for critical urban functions and drew the causal loop diagrams (CLD) for each urban subsystem under the shock of COVID-19. The component descriptions of the SD model are shown in Table 2.

Table 4
Indicators in the socioeconomic subsystem.

Subsystem	Functions	Indicators
Socioeconomic	Industrial production	Primary, secondary and tertiary industrial value
	Consumption (Commerce)	Consumer goods delivery
	Entertainment & recreation	Value of the culture & recreation industry
	Tourism	Value of the tourism & hotel industry

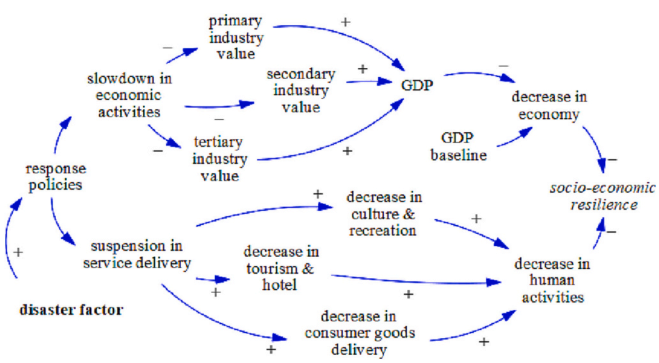


Fig. 4. CLD of the socioeconomic subsystem.

3.2.1. *Causal loop diagram of the governance subsystem*

An increasing number of studies have highlighted the significance of governance in urban resilience improvement (Wang, 2022; Yan & Cao, 2022). This paper constructed the CLD of governance resilience from the perspective of the emergency management of local governments. The specific indicators are listed in Table 3, and the interconnections are shown in Fig. 3.

To reduce the impact of disaster factors, governments and related departments should take corresponding actions and provide financial support. We assume that the intensity of response actions is positively related to the severity of a disaster; at the same time, the policies and actions taken by local governments can control the disaster, forming a balancing loop. In the emergency response process, the emphasis on disasters and the response speed of related departments can be evaluated to reflect the emergency response capacity. Moreover, it is assumed that emergency spending for medical assistance, damaged facilities maintenance and social relief are mainly supported by the local government revenue. As government revenue mainly comes from tax revenue, which is closely related to local industries, government revenue in this paper is calculated based on local industrial value. The financial capacity of the government is the difference value between government revenue and public spending. It is worth noting that response policies with a greater intensity might lead to higher spending and a greater negative effect on government financial capacity, and the trade-off between the effects and costs of response policies needs to be considered.

3.2.2. *Causal loop diagram of the socioeconomic subsystem*

Large-scale PHEs impede the development of urban society and the economy in the long run. For example, COVID-19 has caused the slowdown of economic activities and the reduction of human well-being (Sachs et al., 2021). Therefore, this paper evaluates socioeconomic resilience from two aspects, namely, economic activities and human activities, and the indicators are listed in Table 4. The value of primary, secondary and tertiary industries was used to represent the economic activities, and the industrial values of consumption, recreation and tourism were adopted to show the change in human activities. The socioeconomic resilience is shown in Fig. 4.

Table 5
Indicators in the infrastructure subsystem.

Subsystem	Functions	Indicators
Infrastructure	Healthcare	Beds of health institutions
	Public transportation	Utilization rate of metros, transit systems and taxis
	Information & communication	Internet penetration rate

3.2.3. *Causal loop diagram of the infrastructure subsystem*

Different disasters can cause damage to infrastructures in diverse ways. Large-scale PHEs do not cause physical damage to infrastructures. Therefore, this paper focuses on the changes to infrastructures due to the changing demands of people amid the disaster period. During the COVID-19 pandemic, people have been required to maintain social distance or remain in quarantine, leading to an increase in online business and a decrease in public transportation utilization. Meanwhile, the increasing infectious population also poses great pressure on health care infrastructures. Therefore, gaps in healthcare, public transportation and ICT were used to calculate infrastructure resilience; see Table 5 and Fig. 5.

3.2.4. *Causal loop diagram of the energy - material flows subsystem*

The energy and material (EM) flows reflect the most basic needs of human beings during disaster periods, including energy, food, water and waste treatment; see Table 6. The impact of epidemic disasters on EM flows mainly stems from the following two aspects: the first is that the slowdown of economic and social activities might reduce the demand for power and water, and the second is that the suspension in logistics, the supply chain and the reduction in the workforce might impede the supply capacity of energy and materials. Therefore, the gaps in electricity, water, food and waste treatment capacity were adopted to estimate the change in resilience in the EM flow system (see Fig. 6).

3.3. *Simulation of the COVID-19 pandemic*

This paper takes the COVID-19 pandemic as an example to simulate the development of large-scale infectious diseases; in this regard, the variable *disaster factor* can be replaced by the disease simulation model when assessing resilience under COVID-19. The susceptible-infectious-removed population (SIR) epidemic model is a compartment-based model that has been widely applied to infectious disease studies, so this paper used the SIR model to simulate the development and spread of COVID-19. Given the delay period between a person becoming infected with COVID-19 and showing symptoms, this paper extended the SIR model to the susceptible-exposed-infectious-recovered population (SEIR) model by introducing the variable *exposed population* to show the change in COVID-19 in a more realistic way. In addition, asymptomatic carriers were taken into consideration, whose incubation time was supposed to be longer. The SEIR model can show the development of pandemics in a daily time step, making it possible for decision-makers to capture more details and adjust control policies in time. To make it easier to link with the resilience assessment framework, the epidemic model was also built based on the SD approach (see Fig. 7). The COVID-19 crisis was linked with the urban resilience assessment framework by the variable *response policies*. The emergency spending mainly included the cost of medical treatment, epidemiological investigation, quarantine and testing.

3.4. *Urban resilience assessment*

Based on the COVID-19 impact mechanism on the urban subsystems and a series of proxy indicators defined in Sections 3.2 and 3.3, we can further establish the composite indicator system and calculate the dynamic urban resilience value under external shocks. In general, external

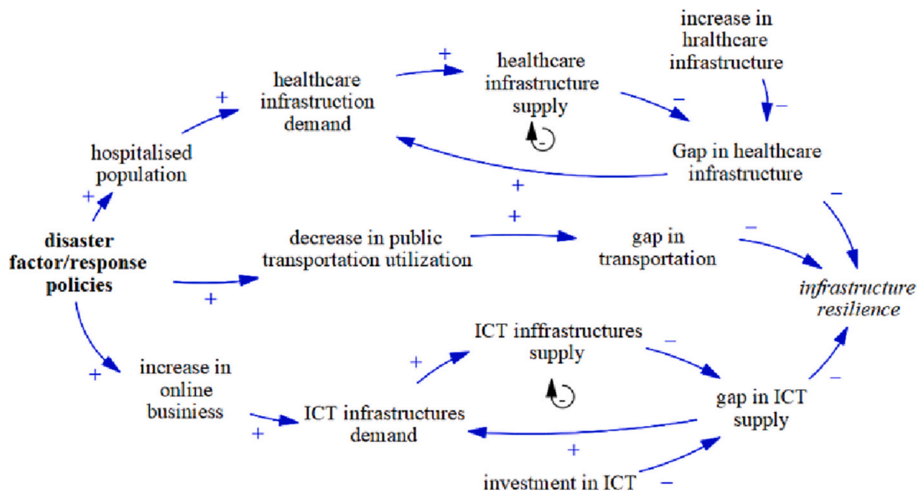


Fig. 5. CLD of the infrastructure subsystem.

Table 6
Indicators in EM flow subsystem.

Subsystem	Functions	Indicators
EM flows	Food supply	Daily food demand, daily food supply
	Energy supply	Electricity demand, electricity supply
	Water & sanitation	Water demand, water supply
	Waste treatment	Living garbage production, garbage treatment

disruption might cause damage to urban functions, showing some gaps between the desired and actual performance. With the response policies and actions taken by related departments, the urban functions will gradually recover (see Fig. 8a), so the urban system resilience can be calculated according to the variation in the urban function level under external shocks. As Kontokosta & Malik (2018) and Hong et al. (2021) stated, resilience quantification should include not only the impact on the system but also the time-to-recover, so we use the stock-flow diagram (SFD) in the SD model to estimate the value of urban subsystem resilience (see Fig. 8b), where Resilience of Subsystem S(t) is the cumulative value of in- and out-flows.

We adopted the calculation of the disaster impact magnitude at time t from Hong et al. (2021) to reflect the change in urban functions, and turned them into dimensionless variables, as follows:

$$Gap(t)_{F\_si} = 1 - \frac{AP(t)_{F\_si}}{Baseline\ performance\ (t)_{F\_si}} \tag{1}$$

where Gap_{F_si} refers to the decrease of an urban function (i) in an urban subsystem (s) under external shocks at the time (t), the time step in this paper is one day. *Baseline performance* $(t)_{F\_si}$ is the desired level of urban function (i) at the time (t), which is predicted by the actual operation situations and data in previous years before disruptions, $AP(t)_{F\_si}$ represents the actual performance of urban function (i) at the time (t). so, the change of urban resilience at time t can be quantified based on Eq. (1) and the composite indicator system:

$$resilience\ variation\ rate(t)_S = Gap(t)_{F\_si} . \omega_{F\_si} \tag{2}$$

where *resilience variation rate*$(t)_S$ refers to the variation rate of resilience of an urban subsystem (s) under external shocks at the time (t), ω_{F_si} is the weight of urban functions (i) in a subsystem (s). Considering both the magnitude of impact and the time-to-recover (Hong et al., 2021), the subsystem resilience can be calculated based on Eq. (3):

$$subsystem\ resilience\ (t)_S = \int_{t_0}^{t_2} - resilience\ variation\ rate(t)_S\, dt \tag{3}$$

and the urban system resilience is a function of all the subsystem resilience, as shown below:

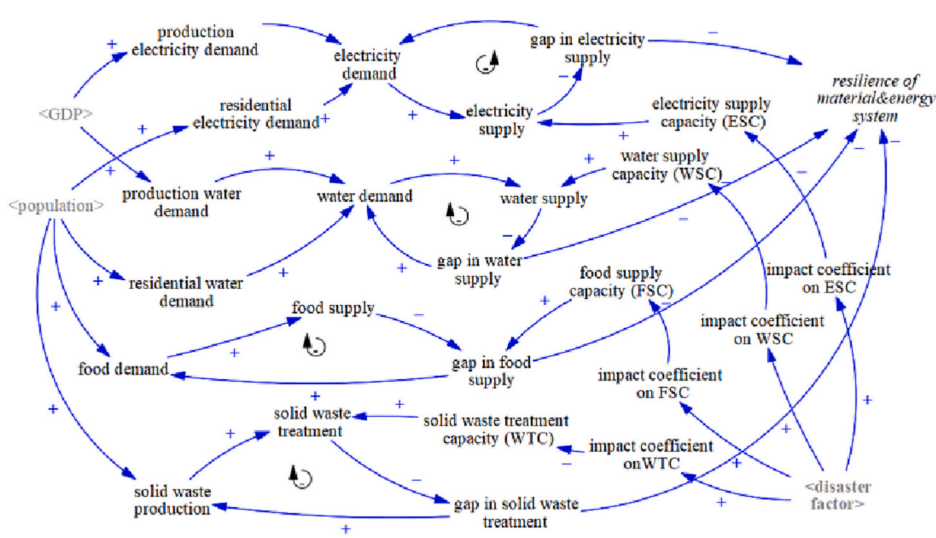


Fig. 6. CLD of the EM flow subsystem.

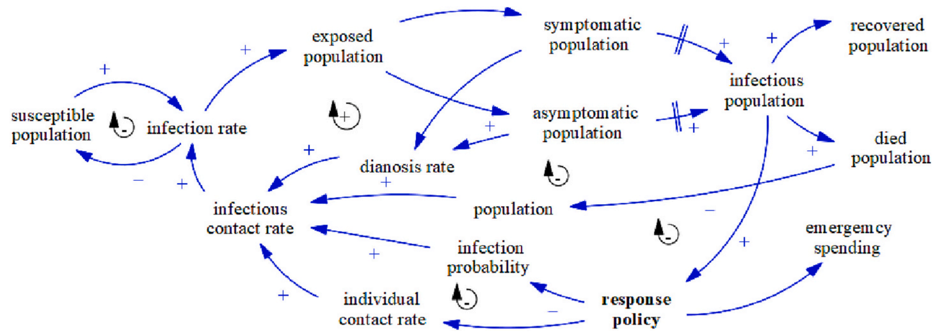
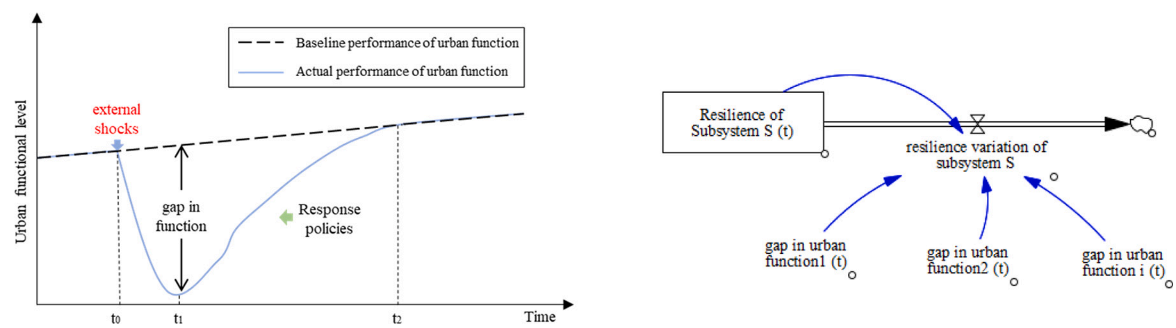


Fig. 7. CLD of the pandemic.



a Change in the urban functional level under disruption

b Subsystem resilience calculation model based on SFD

Fig. 8. a Change in the urban functional level under disruption
b Subsystem resilience calculation model based on SFD.

$$urban\ system\ resilience = \int_{t_0}^{t_2} (Governance\ resilience + Socio - economic\ resilience + Infrastructure\ resilience + E\&M\ resilience)\ dt \tag{4}$$

where t_0 is the period in which a pandemic occurs, and t_2 is the time for urban systems to reach a post-event equilibrium.

3.5. Urban system resilience under pandemics

To assess the changing trend of urban system resilience under COVID-19, this paper links all the CLDs of subsystems and the epidemic simulation model together through the causal relationships among variables in different subsystems, and Fig. 9 shows the main correlations in urban systems.

According to the integrated CLD of the urban system and the calculation of urban resilience in Section 3.4, the stock-flow diagram (SFD) of the entire city can be constructed, where the relationships among variables are defined by mathematical equations (Appendix Tables A1-A3). Fig. A1 in Appendix A shows the SFD of the urban system resilience assessment framework under COVID-19; to make it clearer, different colors were used to clarify different subsystems. Fig. A1 shows that the gaps in urban functions cause the variation in subsystem resilience, and the integral of the *variation rate (t)* during the pandemic time can reflect the resilience of the subsystems. The same calculation process is applied when quantifying the urban system resilience amid the COVID-19 pandemic. The variation rate of different subsystem resilience values leads to the variation of urban system resilience, thus changing the value of stock variable *urban system resilience (t)*.

4. Case study

To test the proposed urban resilience assessment framework, case studies were conducted. Considering that the cities around the world have diverse characteristics and COVID viruses are constantly changing, this paper selected two provincial capital cities in China, Wuhan and Nanjing. Wuhan was the first city to report the virus and experienced a severe pandemic in early 2020, and Nanjing also experienced a large-scale pandemic in July 2021. These two cities have different geographical locations, population sizes and industrial structures. In addition, the virus types, scales, outbreak times and reasons for the outbreaks in the two cities are diverse, causing city managers to adopt different intensities of response policies to control the epidemic. Therefore, it is representative to compare the impacts of COVID-19 and the response actions of these two cities.

4.1. Data sources and processing

The epidemic and city-level data were input into the assessment framework. The epidemic data, such as the susceptible population, daily

P1	Infectious population	→	response policies	→	emergency spending	→	government financial capacity	→	governance resilience		
P2	Infectious population	→	response policies	→	response speed	→	emergency response capacity	→	governance resilience		
P3	Infectious population	→	emphasis to COVID	→	emergency response capacity	→	governance resilience				
P4	GDP	→	governmental revenue	→	government financial capacity	→	governance resilience				
P5	Infectious population	→	health care infrastructure demand	→	shortage in beds in health institutions	→	health care infrastructure supply	→	shortage in beds in health institutions	→	infrastructure resilience
P6	response policies	→	utilization of public transport service	→	infrastructure resilience						
P7	response policies	→	increase in online business	→	gap in ICT infrastructure	→	infrastructure resilience				
P8	GDP	→	gap in ICT infrastructure	→	infrastructure resilience						
P9	response policies	→	production activities	→	GDP	→	socio-economic resilience				
P10	response policies	→	consumption& entertainment activities	→	socio-economic resilience						
P11	production activities /population	→	electricity demand	→	electricity supply	→	gap in electricity supply	→	EM resilience		
P12	production activities/ population	→	water demand	→	water supply	→	gap in water supply	→	EM resilience		
P13	Population	→	water demand	→	water supply	→	gap in water supply	→	EM resilience		
P14	Population	→	living garbage	→	living garbage treatment	→	gap in garbage treatment	→	EM resilience		
P15	Population response policies	→ →	food demand disruption on supply chain	→	food supply	→	gap in food supply	→	EM resilience		

Fig. 9. Main causal relationships in the urban system.

and accumulative infectious population, and recovered and dead population, were collected from the daily reports released by local health commissions. The parameter values of the individual contact rate, infection probability, incubation and treatment time were obtained from related studies and then adjusted by comparing the simulated results and actual epidemic development process. The simulation process of the epidemic is shown in Table A1 in Appendix A. To control the epidemic, some response policies, such as social distancing, quarantine or lockdowns, will be applied, which can also have a great impact on cities' operations. We assumed that the value of parameter response policies was 1 when the governments took measures to control the spread of the epidemic; otherwise, it would be 0.

All the urban functions have indispensable roles in the operation of cities, so this paper assumed that all the urban functions have equal weight when evaluating their performance. Given that the gaps in functions before and after external shocks were used to calculate urban resilience, the value of each function variable in the urban system before and after COVID-19 should be estimated. The city-level data and value of parameters embedded in urban resilience subsystems were obtained in several ways, as follows: (1) collected based on the previous statistical yearbooks or official epidemic-related news reports, for example, the initial value of *health care infrastructure supply* was represented by the numbers of beds in healthcare institutions that was collected from the last statistical yearbook and the value of the flow bed increasing rate and was collected from the news released by local governments; (2) calculated or predicted based on the previous statistical yearbooks from 2006 to 2020, for instance, some baseline values, such as expected GDP (GDP baseline) without the epidemic, were evaluated by the GDP value in the past 15 years and the exponential smoothing method; and (3) derived from the causal loops or table functions in SFD, such as the daily *energy and food supply* in energy and material flows. The initial settings of the model, data sources and processing methods are listed in Table A2.

To show more details about the impact of COVID-19 on urban resilience, this paper estimated the resilience change trend at a daily time step. The simulation process for each subsystem is as follows:

The infrastructure subsystem includes health care, ICT and public transport. The daily change in infectious population indicates the change in health care infrastructure demand. With the data of health care resource supply collected from local news and government documents, the shortages and gaps in the health care infrastructure can be simulated on a daily basis. The change in demand for ICT and public transport depends on the response policies for COVID-19. We assumed that the policies (lock down, dynamic zero, etc.) would increase online business and reduce the utilization of public transport during the pandemic, so the *if-then-else* function was used to show the different utilization rates of ICT and public transport before and after COVID-19 (see Appendix Table A3).

For the socioeconomic subsystem, it is difficult to obtain the

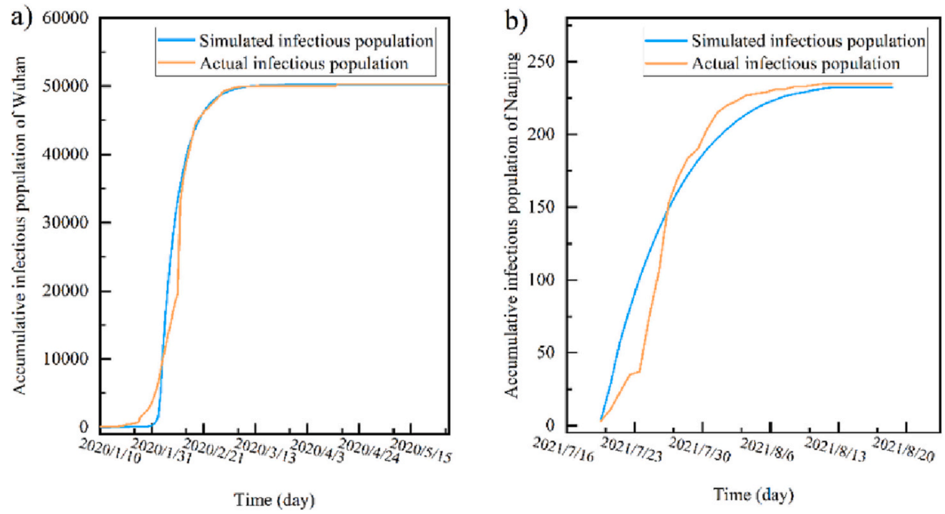


Fig. 10. Simulated results of COVID-19 in Wuhan and Nanjing.

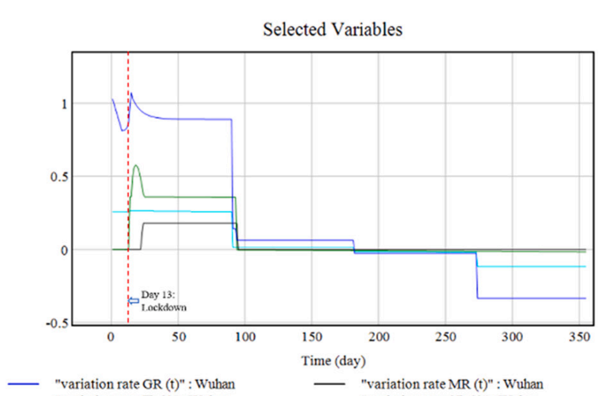
Table 7
Characteristics of the epidemic in the case cities.

	Wuhan	Nanjing
Susceptible population	1.244×10^7	9.42×10^6
Virus type	Alpha	Delta
Fatality rate	0.076	0.003
Response strategies	Lockdown	Dynamic zero
Infectious probability without response strategies	0.17	0.32
Infectious probability with response strategies	0.038	0.06
Individual contact rate without response strategies	15	15
Individual contact rate with response strategies	4	6
Actual accumulative confirmed population	50,340	235
Simulated accumulative confirmed population	50,273	230

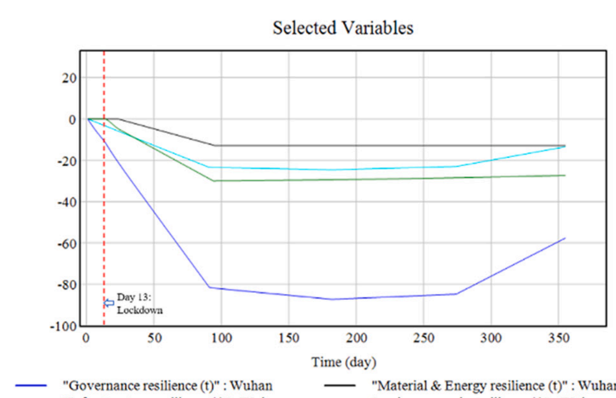
available daily economic data or predict the economic and social activities on a day-to-day basis. Therefore, monthly or quarterly data for the economic and social industry value were collected from the statistical year books and bulletins; then, these data were averaged on a daily basis and embedded within the SFD through table functions (see Table A3). The *GDP baseline* indicates the expected GDP value without the epidemic; it is first predicted by using the GDP value over the past 15 years and the exponential smoothing method. Then, the daily average is calculated and input into the flow of the SFD.

In the governance subsystem, we assume that the flow variable *governmental revenue rate* comes from the daily average GDP. The public cost rate consists of COVID-related emergency spending and other public spending. Since the epidemic can be simulated daily, we can also estimate the daily change in COVID-related emergency spending. Other public spending is represented by the daily mean of the difference value of the total public cost and COVID-related cost. For the *emphasis on COVID-19* and *response speed*, instead of quantifying them directly, we apply the *if-then-else* functions to show their variation under the epidemic; see Table A3 in Appendix A.

For the energy and material subsystem, the electricity and water demand data come from production and residential use, which can be estimated through the daily average GDP and population, respectively. The food demand and garbage production data also derive from the population, since the daily resource and food consumption data for citizens are easy to find in statistical yearbooks. Similarly, the supply capacity of water, electricity, food and garbage treatment data are provided in statistical yearbooks. Here, we make some assumptions about the impact coefficient of COVID-19 and response policies to the resource and food supply capacity according to the government documents amid the pandemic. More details can be found in Tables A1 and A3 in Appendix A.



a Functional level variation rate of subsystems in Wuhan



b Resilience of subsystems in Wuhan

Fig. 11. a Functional level variation rate of subsystems in Wuhan
b Resilience of subsystems in Wuhan.

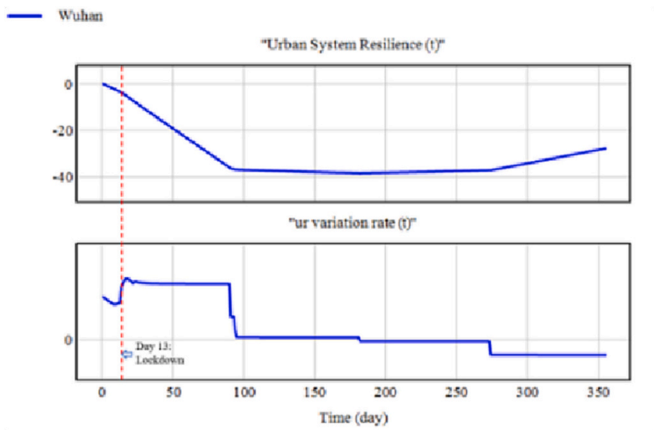


Fig. 12. Urban resilience and variation rate in Wuhan.

4.2. Results of the epidemic

This paper simulated the process of COVID-19 spread in Wuhan and Nanjing by using a time interval of one day. The parameters in the SEIR model were calibrated according to the actual epidemic development process in two cities, and the results are shown in Fig. 10. Fig. 10a shows the results of the simulated and actual cumulative confirmed population of Wuhan, and Fig. 10b shows the results of Nanjing, which showed that the results derived from the SEIR model fit the actual development trend of COVID-19.

The occurrences of the epidemic in the two cities showed diverse characteristics, and the governments of Wuhan and Nanjing adopted different response policies to control the epidemic. Table 7 lists the values of the parameters used in the SEIR model and the simulated results. The epidemic in Wuhan had a higher fatality rate, and the local government could not obtain more information when faced with the first epidemic outbreak, so decision-makers adopted a strict lockdown policy to control the spread of the epidemic. While the epidemic virus that occurred in Nanjing had a higher infection rate but a lower fatality rate and the government has more experience in epidemic control, so they chose the dynamic zero policy with a less negative effect on city operations.

4.3. Results of urban resilience

The different scales of and actions to control the COVID-19 pandemic will have varying degrees of impact on urban resilience.

The pandemic in Wuhan started on the 8th of December 2019 and ended on the 8th if April 2020, causing 50,340 infections and 3869 deaths, and the lockdown policy lasted for 76 days from the 23rd of January to the 8th of April 2020. This paper simulated the epidemic from the 10th of January 2020 (Day 1), and the lockdown policy was implemented on Day 13. Fig. 11 a) shows the variation rate of functions in the four subsystems during the pandemic period, which indicates the urban functional level decrease rate. This indicates that the functions of the governance subsystem suffered the most severe impacts at the beginning of the outbreak. The decrease before lockdown might have resulted from the neglect of the epidemic by related government departments, and emergency spending to control the epidemic and provide financial support led to an approximately 90 % decrease in the functions of the governance subsystem. For the functional level in the infrastructure subsystem, a large number of infectious populations left a serious shortage of health care infrastructure supply at the early stage, with the maximum gap reaching 64 %; then, the suspension of public transportation and shortage in ICT infrastructures accounted for the decline in infrastructure functions. For the energy and material flows, the electricity and water demand would decline during the pandemic due to

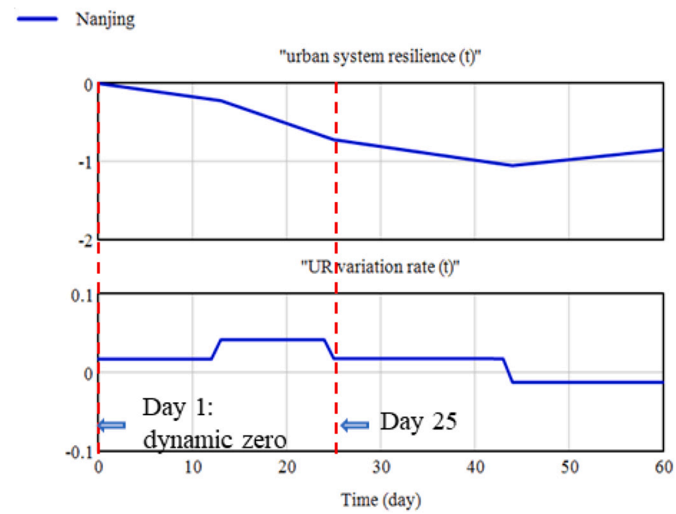


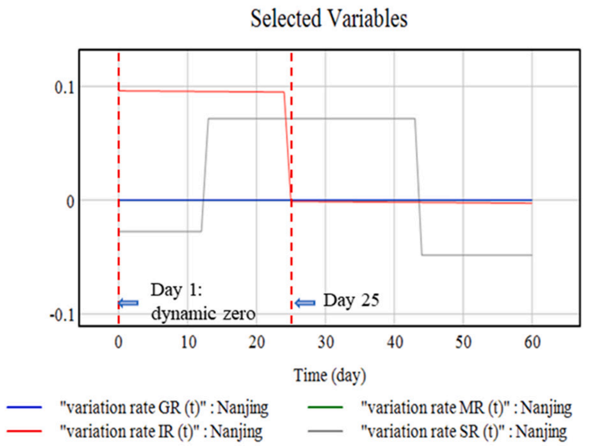
Fig. 13. Resilience of the urban subsystems in Nanjing.

the suspension of economic activities, and there would be no shortage of energy and water. However, the lockdown caused an impact on the food supply due to the interruption of its supply chain, which is the main reason for the functional reduction shown in Fig. 11a. For the socioeconomic subsystem, most economic activities will be suspended amid a lockdown period, especially in the tertiary industry, and human activities such as traveling, shopping and other recreational activities are also reduced significantly. Despite the immediate rebound in the socioeconomic subsystem when the epidemic is under control and the lockdown policy is lifted, economic growth still slows, and the results in Fig. 11a illustrate that socioeconomic resilience did not exceed the baseline until the last three months in 2020.

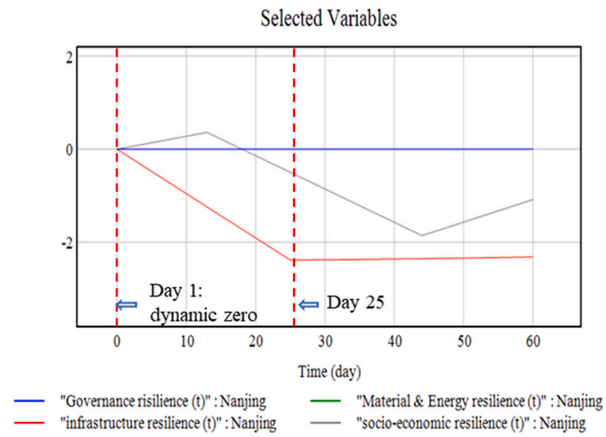
Fig. 11b reflects the changing trend of subsystem resilience of Wuhan during the pandemic. According to Li et al. (2021a) and Hong et al. (2021), we regarded resilience as the integral of functional variations and time; therefore, governance resilience declined the most during the COVID period, followed by infrastructure resilience, socioeconomic resilience and energy & material resilience. It is worth noting that governance resilience and socioeconomic resilience showed an obvious recovery, but resilience gaps still exist in the infrastructure and energy & material subsystems. One possible reason is that economic and social activities can be reopened immediately after COVID-19, but the construction of infrastructure and the material supply chain requires a relatively long time.

Fig. 12 reflects the urban system resilience of Wuhan under COVID-19 and its functional level variation. The urban functional level variation rate is the average value of the subsystem variation rates, and shows an approximately 40 % decrease during the lockdown period (Day 13 to Day 90). The decrease in urban functions impeded the resilience capacity of the whole city, and the downward trend continued until the end of the pandemic. Although the urban functional level can rebound to the pre-COVID level at a rapid speed, this does not mean that the impact of COVID also ends. The change in urban system resilience in Fig. 12 shows that the end of the pandemic only stopped the downward trend in resilience capacity, but a full recovery still takes a long time to achieve. In addition to policies for epidemic control, actions to accelerate recovery after the pandemic also matter.

The epidemic in Nanjing started on the 20th of July 2021 and ended on the 19th of August 2021, causing 235 infections. The local government and departments took action as soon as the epidemic appeared, tracking the close contacts and placing the related places in lockdown. The pandemic duration was short thanks to these timely response actions, and the negative impact on the city was much less than that in Wuhan (see Fig. 13).



a Resilience variation rate of subsystems in Nanjing



b Resilience of subsystems in Nanjing

Fig. 14. a Resilience variation rate of subsystems in Nanjing
b Resilience of subsystems in Nanjing.

Fig. 14 reflects the resilience change of the subsystems of Nanjing. According to Fig. 14a, the main reason for the reduction in urban functions was the decrease in socioeconomic and infrastructure functions. The functional decrease in socioeconomic development resulted from the suspension of economic and social activities in areas where the epidemic occurred, and the loss of infrastructure functions came from the shortage of ICT. The functional level gaps in infrastructures were fulfilled with the change in online business demand after the epidemic, while the growth rate of socioeconomic industries did not return to the pre-epidemic baseline immediately. This indicates that faced with an epidemic with a higher infectious probability but a lower fatality rate, the indirect impact of the pandemic on society and economic growth is greater than its direct impact on health care systems. Since the confirmed population was much less, the epidemic did not cause a great fiscal burden and impede the functions in the governance subsystem. Moreover, the large-scale lockdown policy was replaced by dynamic controls, which avoided interruptions in the supply chains of essential materials, so the functions of energy and material flows would not decrease. The change in subsystem resilience is in line with the change in their functional levels, as shown in Fig. 14b. The resilience levels of the governance and energy and material subsystems are maintained during the epidemic, and socioeconomic resilience starts to redound after a sustained decline. Given the uncertainty of the pandemic and the increasing utilization of ICT infrastructures, infrastructure resilience still needs to be improved.

4.4. Comparison of urban resilience under different epidemic scenarios

Comparing the pandemic in Nanjing with that in Wuhan, it can be found that both the PHE itself and the response actions can impair the urban functions and resilience. For a large-scale PHE with a higher fatality rate, governments are likely to adopt a stricter response strategy, especially in the absence of related experience, which would greatly impede urban resilience, and a relatively long time will be needed for the city to recover. However, for the small-scale epidemics that appear repeatedly after 2020, timely and reasonable control methods such as “dynamic zero” can ensure the safety of citizens and mitigate shocks to urban functions and resilience.

Despite the different features of the epidemic and response policies of the two cities, some common issues can be found when comparing the resilience of Wuhan to that of Nanjing. First, COVID-19 will have a far-reaching influence on social and economic development, and the results have proven that the recovery of socioeconomic functions was slower than the recovery of other subsystems. Since the SD model in this paper assumes that governmental revenue comes from economic activities, the lagging of economic development will probably lead to a decline in the functional level of governance. Second, the functions of infrastructure, energy and food supply can rebound to the pre-epidemic level immediately; however, the change in resilience capacity indicates that the improvement of resilience in the infrastructure and EM subsystem is a long-term process.

5. Discussion

This paper proposes a dynamic resilience assessment framework to quantify the urban resilience of different cities under large-scale PHEs, and the results indicate that urban resilience varies due to the different features of the epidemic and response actions. Since there still exist some controversies about whether to control the epidemic at the cost of city development, we compare the change in resilience under response policies with different intensities. Moreover, sensitivity analysis is conducted to identify the critical functions or variables that exert the greatest impacts on resilience.

5.1. Comparison of response policies

The COVID-19 epidemic will probably spread through different virus variants for a long time; therefore, the control measures should be adjusted with the change in epidemic characteristics. Here, we extend the time period of the epidemic in Nanjing from 60 days to 350 days and compare the resilience results of Wuhan and Nanjing. In addition, we simulate urban resilience when no response policies are taken based on the data of Wuhan, as shown in Fig. 15.

Fig. 15a reflects the policies that a city takes under COVID-19. As shown in the case study, Nanjing adopted the dynamic-zero policy to control the epidemic in a faster and more precise way. Wuhan-baseline refers to the lockdown scenario, and the Wuhan-open scenario means that no additional actions will be taken except for the addition of health care insurance for the infectious population. Compared to the lockdown scenario in Wuhan, the dynamic-zero strategy that was adopted quickly was able to avoid a further spread of the epidemic in a short time, thereby reducing the loss of urban functions and resilience. Fig. 15b reflects the changing trend of urban system resilience with three response policies, urban resilience will drop dramatically in a short

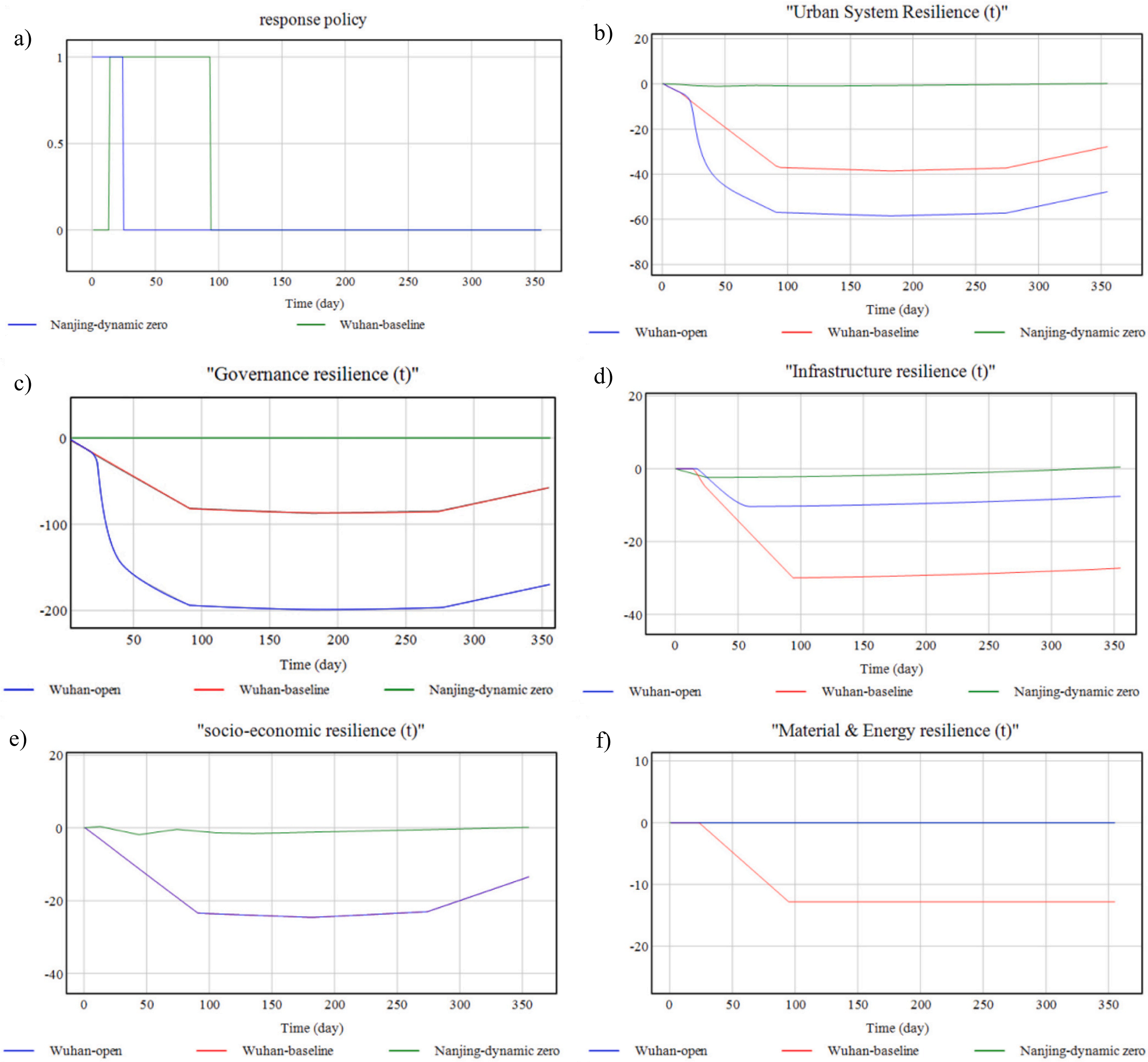


Fig. 15. The resilience of the urban system and subsystems under different response policies.

period of time when no response actions are taken, and such a decrease might possibly lead to a collapse of urban operations, while taking action regardless of whether a lockdown or dynamic zero policy is in effect could reduce the negative impact of COVID-19 on cities. Fig. 15c reveals the main reason for the decline of urban resilience in the open scenario: although the public spending for COVID testing, contact tracking and quarantine can be saved, a large number of infectious people might lead to a large cost for health care insurance, which can also place pressure on fiscal capacity. For the infrastructure resilience shown in Fig. 15d, the resilience reduction of dynamic zero comes from social distancing and remote working during the pandemic period, but to some extent, the pandemic stimulates an increase in ICT business and promotes resilience improvement after the pandemic, while the lockdown and open scenarios indicate an obvious resilience reduction by the shortage of health care service. Fig. 15e and f prove that from a short-term perspective, the pandemic after a dynamic-zero policy could significantly mitigate the negative influence on social and economic activities.

The strict lockdown policy for cities was necessary to control the epidemic without targeted treatment plans and vaccines in the early stage when faced with an epidemic with a high spread rate. However, the lockdown policy is not the optimal choice to control the pandemic all the time. Prolonged and strict lockdowns will cause major threats to society and the economy. Moreover, the epidemic has undergone several changes since 2019, and the probability of infection might be higher, but the proportion of severe and deadly cases might be lower. The case of Nanjing has proven that dynamic zero policy can be an effective strategy for both epidemic control and city development when the epidemic has a lower fatality rate. It is important for governments to increase the speed of emergency response and decision-making due to the rapid spread of the virus, and immediate actions are able to maintain urban resilience and reduce losses effectively.

5.2. Sensitivity analysis of the resilience assessment model

The cities still need to improve their urban resilience and functional levels under such a PHE. Therefore, this paper takes the Wuhan baseline

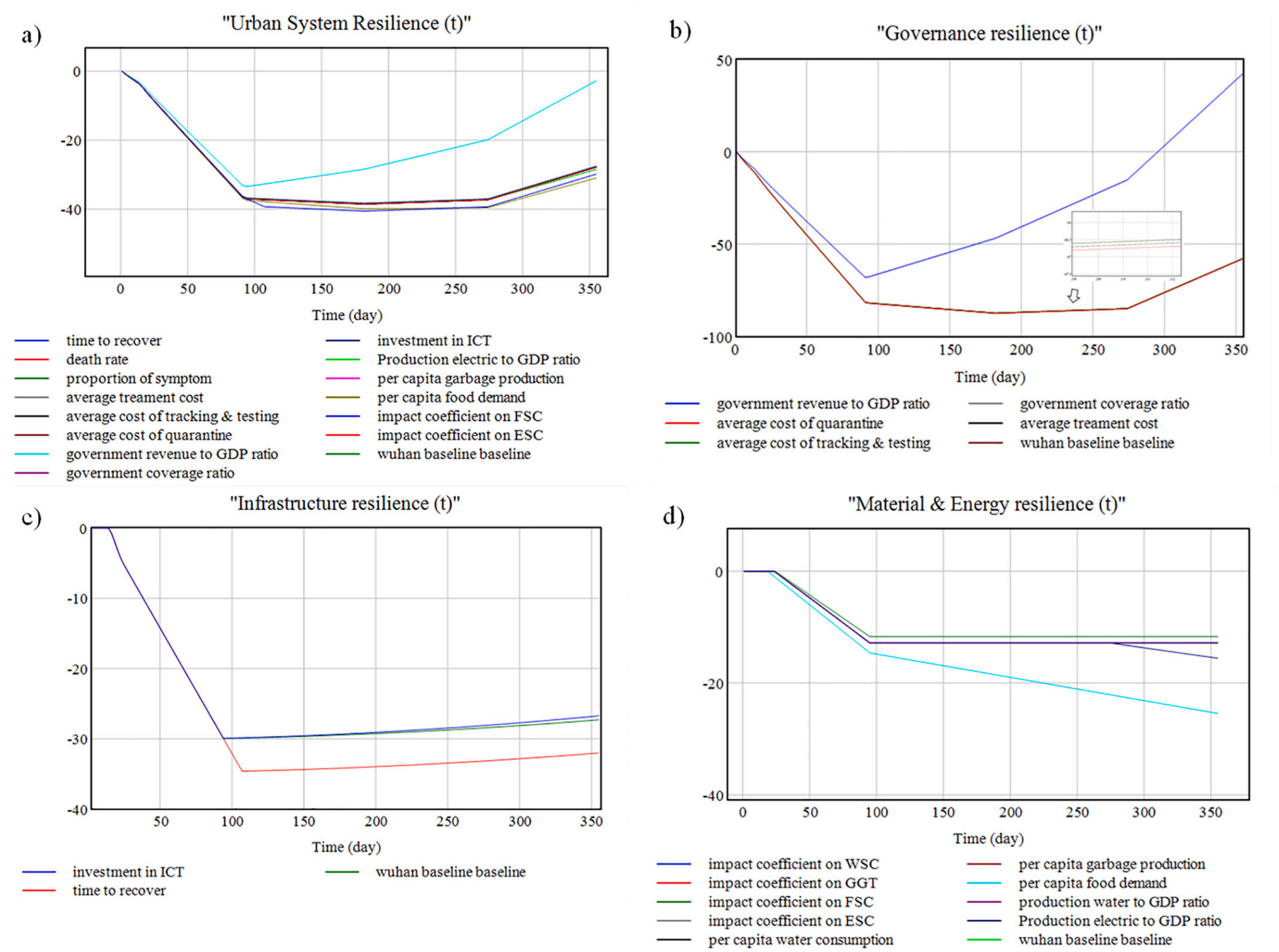


Fig. 16. Sensitivity analysis of urban resilience.

scenario as an example to discuss the critical functions or factors. A sensitivity analysis of our resilience assessment model is conducted. According to Li, Kou, Wang, Yang (2020b), the main constant variables that can influence the results of resilience are identified in this paper, and the value of these constant variables are increased by 20 % to observe their effects on the results. Fig. 16a reflects the main constant variables of our SD model and indicates that the urban resilience level under a large-scale PHE is most sensitive to the variable *government revenue to GDP ratio*. To some extent, it reflects the importance of the fiscal capacity of local governments in the response to PHEs. Moreover, the variable *time to recover* exerts the greatest reduction on urban resilience, which highlights the significance of the medical level and health care infrastructure supply.

The related constant variables of each subsystem are also identified to show the most critical factors and functions of subsystem resilience. In the governance subsystem (Fig. 16b), the function that changes the most with the increase of constant variables is the financial capacity of governments, and the resilience improvement from the rise of governmental revenue is much greater than that gained from the reduction in public cost. For infrastructure (Fig. 16c), the improvement of the hospital admission rate and quality of medical services is crucial, since the time for the infectious population to recover matters most. It is also worth noting that the construction of ICT infrastructures will be accelerated during the pandemic, so the resilience of infrastructure will be improved after the epidemic. The variables that affect the energy and material subsystem most are the per capita *food demand* and *impact coefficient of food supply capacity (FSC)*, see Fig. 16d. According to Calder et al. (2021) and Sharma et al. (2021), a sufficient food supply is not just a simple concept of amount; it requires that the people in cities should have physical, social and economic access to obtain sufficient, safe and nutritious food that meets their dietary needs and food preferences; thus, it is even more important to ensure availability when confronted with the possible mobility restrictions amid the pandemic. Since the resilience of the socioeconomic subsystem is calculated by the table functions and data collected from real cases, there are no constant variables, so we are not able to conduct a numerical sensitivity analysis. However, comparing the changing trend of economic production and social activities during the pandemic, we find that the function of production will be impeded considerably during the pandemic. Human activities such as shopping, tourism and other outdoor recreations are able to recover immediately after the epidemic is cleared, while industrial production

Table 8
Function categories for city development.

Category	Specific functions
Basic function	public transportation, food supply, energy supply, water & sanitation, waste treatment
Maintenance function	disaster prevention, health care, consumption (commerce), entertainment & recreation, tour & hotel
Development function	public services, industrial production, information & communication

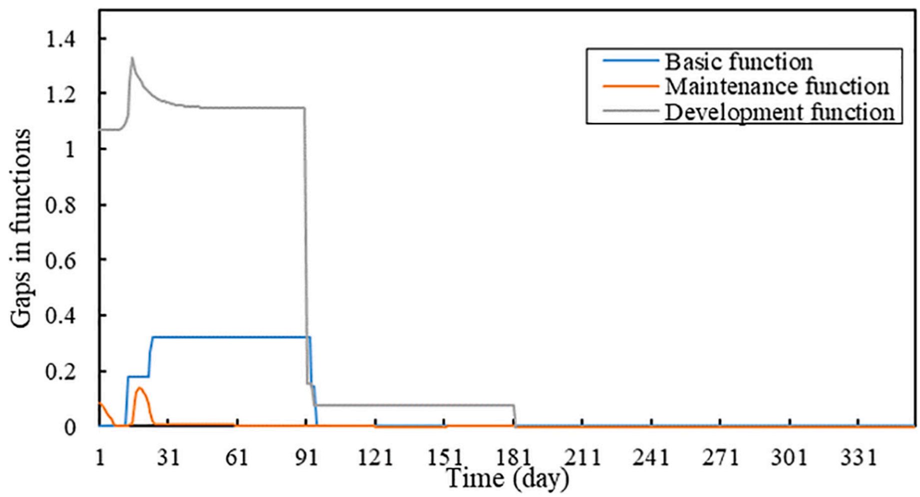


Fig. 17. Impact of the epidemic on urban functions.

will take a rather long time to recover to the pre-epidemic level due to the impact of the global pandemic on trading and supply chains.

5.3. Long-term impact of COVID-19 on cities

This paper mainly focuses on the impact during the occurrence of the large-scale PHEs; however, we could analyze the possible long-term impacts from the perspective of urban functions. Based on Kim and Song (2018), this paper divided these specific urban functions into basic functions, maintenance functions and development functions; see Table 8. The basic functions support the minimum needs of urban residents, the maintenance functions ensure that people, society and the economy run well, and the development functions can facilitate the prosperity of urban residents and the development of cities for a long time.

Fig. 17 illustrates the gaps in the three types of urban function. The decrease in basic functions and maintenance functions can be rapidly addressed after the pandemic; however, the development function was destroyed the most during the pandemic and recovered more slowly, which means that the pandemic will cause a long-term negative effect on urban development.

6. Conclusion

The serious impact of the COVID-19 epidemic outbreak worldwide has exposed the inadequate preparedness of cities for large-scale PHEs. Given that the city is a networked and multidimensional system with complex interrelationships and feedback, the change in urban resilience under a long-standing epidemic needs to be evaluated from a holistic and dynamic perspective. With this in mind, this paper proposes a dynamic urban resilience assessment framework, and the SD approach, epidemic simulation and composite indicator system are integrated into the framework. The framework proposed in this paper selected resilience indicators based on critical urban functions, which coordinated with the underlying understanding of resilience. The interconnections among different urban functions were identified and quantified in the SD-based framework, which showed the impact mechanism of the epidemic on cities directly and reduced the requirement for urban data. Moreover, epidemic development and response policies were also embedded in the framework, making it possible to assess the effect of different response policies and helping decision-makers find proper epidemic control strategies.

Case studies of the epidemic in Wuhan and Nanjing were conducted, and the results demonstrated that a strict policy implemented under serious pandemic scenarios could effectively stop the spread of COVID-19 in a short time, but it damaged the urban system resilience rapidly, and a rather long time will be needed to recover. In such a scenario, governance and socioeconomic resilience would be significantly weakened. Therefore, considering long-standing and recurring epidemics, a more accurate control strategy is needed to reduce the negative effects caused by the suspension of social and economic activities. In addition, the critical function in each subsystem was identified. To improve urban resilience under the epidemic, the local government should ensure the functions of public finance, health care resources and food supply.

The framework proposed in this paper was inclusive and could be applied to estimate the dynamic change in urban resilience under different kinds of disasters by linking disaster simulation methods with the urban system model. However, there are still some limitations in the framework. First, the changing trend of socioeconomic resilience might be lagged or averaged, as day-to-day data in economic and social sectors are not always available. The second is that this paper focuses on resilience within cities during the period of outbreak, so the intercity spread of the epidemic and the development of vaccines and specific medicine are not considered in this paper. Therefore, in the future, the SD resilience assessment model could be improved from both variable selection and data collection. More related factors of urban system and epidemic scenarios could be added into the model, and more appropriate proxy variables in social and economic sectors should be selected to reflect the socioeconomic activities in a more accurate way. In addition, the SD-based model provides alternative temporal scales, which enable us to further discuss the influence of PHEs from a long-term perspective.

CRediT authorship contribution statement

Jiaming Zhang: Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Visualization. **Tao Wang:** Conceptualization, Validation, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (No.71871235, No.72074034, No.72134002), Key Projects of Philosophy and Social Sciences Research, Ministry of Education of China (No. 21JZD029), Bayu Scholar Program (No. YS2020001), Chongqing Talents Program (No. CQYC202105082), and Fundamental Research Funds for the Central Universities of China (No. 2021CDSKXYGG013, No. 2022CDJSKPY17).

Appendix A

Fig. A1 showed the dynamic urban resilience assessment framework proposed in this paper. We take Wuhan as an example to show the calculation process, the mathematical equations of the epidemic simulation are listed in Table A1, and the initial settings, data sources and equations of the urban system are listed in Table A2 and A3. The specific data appearing in these equations indicates the initial value of the stock variables, which is collected from the statistical yearbooks or official online reports.

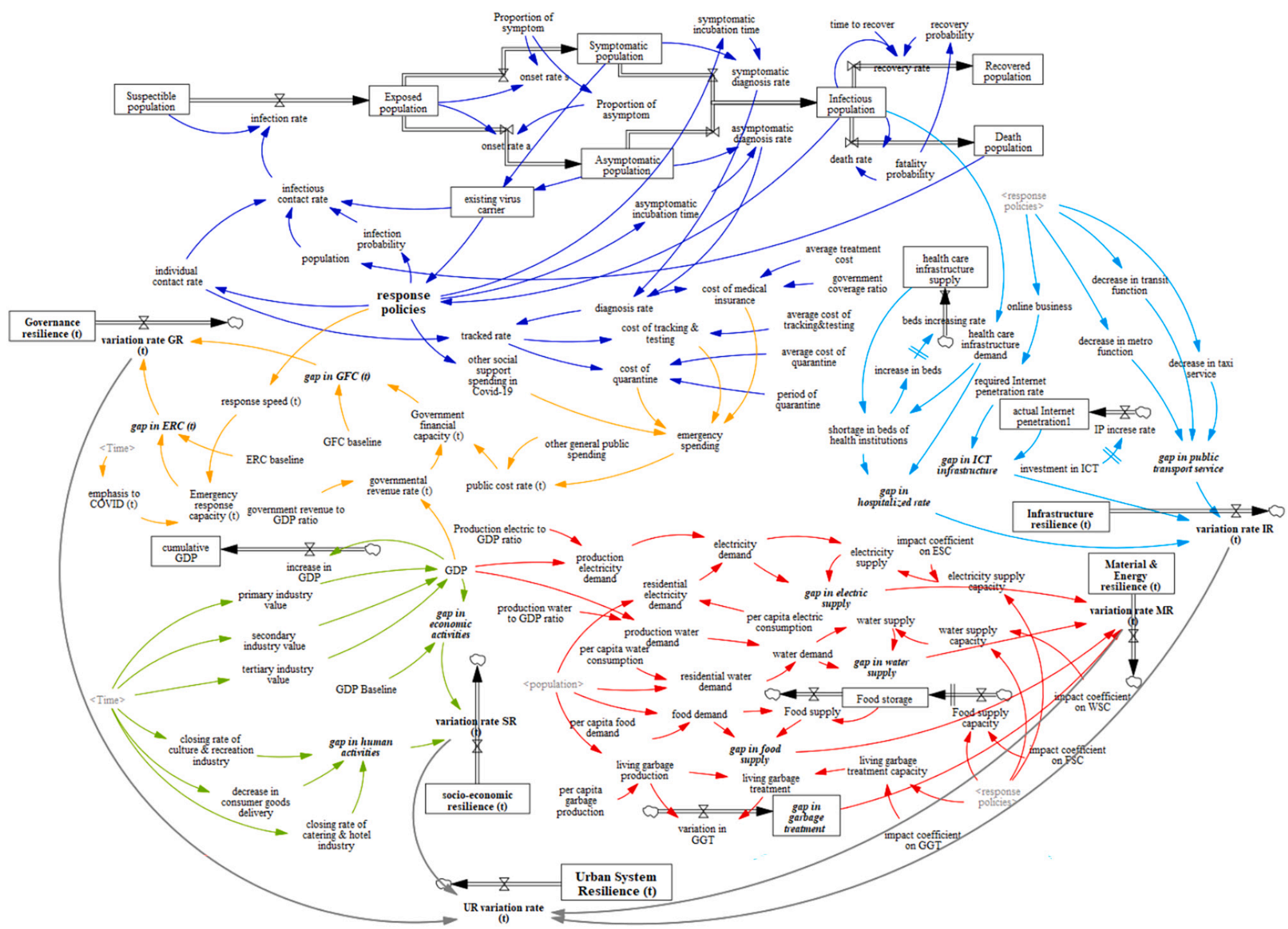


Fig. A1. Urban system resilience assessment framework under COVID-19.

Table A1
Equations of epidemic simulation.

Variables	Equations
Susceptible population	= INTEG (−infection rate, 1.24e+07)
infection rate	= infectious contact rate * Susceptible population
infectious contact rate	= (existing virus carrier*individual contact rate*infection probability) / population
infection probability	= IF THEN ELSE (response policy =1, 0.038, 0.17) (taking Wuhan as an example)
Exposed population	= INTEG (infection rate-onset rate a-onset rate s, 0)
Symptomatic population	= INTEG (onset rate s - diagnosis rate s, 1)
Asymptomatic population	= INTEG (onset rate a - diagnosis rate a, 0)
Existing virus carrier	= Asymptomatic population + Symptomatic population
Infectious population	= INTEG (diagnosis rate a + diagnosis rate s - death rate - recovery rate, 40)
Recovered population	= INTEG (recovery rate, 0)
Death population	= INTEG (death rate, 0)

(continued on next page)

Table A1 (*continued*)

Variables	Equations
cost of medical insurance	= diagnosis rate*government coverage ratio*average treatment cost
cost of quarantine	= average cost of quarantine*period of quarantine*tracked rate
cost of tracking & testing	= average cost of tracking & testing * tracked rate
other social support spending in Covid-19	= IF THEN ELSE (response policy = 1, 49.0146, 0)

Table A2
Initial setting, data sources and processing methods (Wuhan as an example).

Variables	Initial value	Unit	Data sources	Processing methods
Socio-economic subsystem				
primary industry value; secondary industry value; tertiary industry value	–	–	Statistical yearbooks; Statistical bulletin on economic and social development of study cities	1.Calculate the daily averages of monthly or quarterly data; 2. reflect changing trend through table functions
GDP baseline	4539.39	$\times 10^6$ yuan/day	Statistical yearbooks in past 15 years	1.Calculate expected annual GDP without COVID using exponential smoothing method; 2. calculate daily mean value
closing rate of culture & recreation industry; decrease in consumer goods delivery; closing rate of catering & hotel industry	–	–	Statistical yearbooks; Statistical bulletin on economic and social development of Wuhan	1.Calculate the daily averages of monthly or quarterly data; 2.reflect changing trend through table functions
Governance subsystem				
Government revenue to GDP ratio	0.20697	–	Statistical yearbooks in past 15 years	Average value of government revenue to GDP in past 15 years
Other general public spending	646.514	$\times 10^6$ yuan/day	Statistical bulletin on public spending of study cities	Daily average value of annual public spending value
Government financial capacity (GFC) baseline	306.773	$\times 10^6$ yuan/day	Statistical yearbooks in past 15 years	1.Calculate expected annual government revenue without COVID using exponential smoothing method; 2.calculate daily mean value
Emergency response capacity (ERC) baseline	1	–	–	–
Response speed	1	–	–	–
emphasis to COVID	0	–	–	the emphasis to COVID is 0 before COVID and 1 after its occurrence
Infrastructure subsystem				
health care infrastructure supply	6301	–	Statistical yearbook of Wuhan in 2020	Number of beds for infectious diseases before COVID in Wuhan
Increase in beds	100,000	–	News and reports amid COVID	–
Actual Internet penetration	0.813	–	Statistical yearbook of Wuhan in 2020	Number of internet users / permanent residential population
Decrease in metro lines	1	–	Website of Wuhan Metro	Number of suspended metro lines / total number of metro lines
Decrease in transit	1	–	Website of Wuhan transit	Number of suspended transit lines / total number of transit lines
Decrease in taxi service	0.681	–	Government notices amid COVID	Suspended taxies / total taxies
EM flows subsystem				
Production electric to GDP ratio	27,900	kWh / million yuan	Statistical yearbooks in past 15 years	Average value of electricity consumption per unit of GDP in past 15 years
Production water to GDP ratio	0.026072	10,000 tons / million yuan	Statistical yearbooks in past 15 years	Average value of water consumption per unit of GDP in past 15 years
Per capita water consumption	1.85×10^{-5}	10,000 tons / day*people	Statistical yearbooks in past 15 years	Average value of water consumption per capita a day in past 15 years
Per capita electric consumption	2.5413	kWh / day*people	Statistical yearbooks in past 15 years	Average value of electricity consumption per capita a day in past 15 years
Per capita food demand	3.96×10^{-4}	tons / people*day	National statistical yearbook 2020	Daily average value of per capita food consumption
Per capita garbage production	9×10^{-4}	tons / people*day	Statistical yearbook of Wuhan in 2020	Daily average value of per capita garbage production
Electricity supply capacity	1.89×10^{8}	kWh/day	Statistical yearbook of Wuhan in 2020	Daily average value of total electricity consumption
Water supply capacity	541.2	10,000 tons / day	Statistical yearbook of Wuhan in 2020	Daily average value of total water consumption
Food supply capacity	4914.29	tons	National statistical yearbook 2020	Daily average value of total food consumption
Living garbage treatment capacity	13,700	tons / day	National statistical yearbook 2020	–

Table A3
Equations of urban resilience subsystems.

Variables	Equations
Socio-economic subsystem	
primary industry value	= WITH LOOKUP (Time, ([(0,0)-(365,1000)], (1,55.1765), (90,55.1765), (91,100.498), (181,100.498), (182,141.689), (273,141.689), (274,101.413), (365,101.413)))
secondary industry value	= WITH LOOKUP (Time, ([(0,0)-(365,2000)], (1,858.913), (90,858.913), (91,1845.89), (181,1845.89), (182,2083.66), (273,2083.66), (274,1287.81), (365,1287.81)))
tertiary industry value	= WITH LOOKUP (Time, ([(0,0)-(365,5000)], (1,1290.03), (90,1290.03), (91,2475.73), (181,2475.73), (182,2460.33), (273,2460.33), (274,4210.85), (365,4210.85)))
GDP	= primary industry value + secondary industry value + tertiary industry value
GDP Baseline	= Predicted annual GDP value without COVID / 365
gap in economic activities	= (GDP Baseline-GDP)/GDP Baseline
closing rate of culture & recreation industry	=WITH LOOKUP (Time, ([(0,0)-(365,365)], (1,0), (13,0), (14,0.018), (31,0.018), (32,0.00932), (59,0.00932), (60,-0.001677), (90,-0.001677), (120,-0.001677), (121,-0.003), (151,-0.003), (152,-0.0005), (181,-0.0005), (182,-0.000258), (212,-0.000258), (213,0), (243,0), (244,-0.0012667), (273,-0.0012667), (274,-0.000645), (304,-0.000645), (305,-0.0004), (334,-0.0004), (335,-0.001225), (365,-0.001225)))
decrease in consumer goods delivery	= WITH LOOKUP (Time, ([(0,0)-(365,365)], (1,0), (13,0), (14,0.0184), (31,0.0184), (32,0.0091), (59,0.0091), (60,0.0012), (90,0.0012), (91,-0.001267), (120,-0.001267), (121,-0.00129), (151,-0.00129), (152,-0.001167), (181,-0.001167), (182,-0.000645), (212,-0.000645), (213,-0.00071), (243,-0.00071), (244,-0.0007), (273,-0.0007), (274,-0.000839), (304,-0.000839), (305,-0.000667), (334,-0.000667), (335,-0.000839), (365,-0.000839)))
closing rate of catering & hotel industry	= WITH LOOKUP (Time, ([(0,0)-(365,365)], (1,0), (13,0), (14,0.00624), (90,0.00624), (91,0.00325), (181,0.00325), (182,-0.00493), (273,-0.00493), (274,-0.00616), (365,-0.00616)))
gap in human activities	= ("closing rate of catering & hotel industry" + "closing rate of culture & recreation industry" + decrease in consumer goods delivery)/3
variation rate SR (t)	= (gap in economic activities + gap in human activities)/2
socio-economic resilience (t)	= INTEG (−variation rate SR (t), 0)
Governance subsystem	
governmental revenue rate (t)	= GDP*government revenue to GDP ratio
public cost rate (t)	= emergency spending + other general public spending
emergency spending	= cost of medical insurance + cost of quarantine + cost of tracking & testing + other social support spending in Covid-19
Government financial capacity (t)	= governmental revenue rate (t)-public cost rate (t)
gap in GFC	= (GFC baseline-Government financial capacity (t))/GFC baseline
emergency response capacity (t)	= (emphasis to COVID + response speed)/2
gap in ERC (t)	= 1-Emergency response capacity/ERC baseline
variation rate GR (t)	= (gap in ERC (t) + gap in GFC (t))/2
Governance resilience (t)	= INTEG (−variation rate GR (t), 0)
Infrastructure subsystem	
health care infrastructure demand	=Infectious population
shortage in beds of health institutions	= IF THEN ELSE (health care infrastructure demand-health care infrastructure supply>0, health care infrastructure demand-health care infrastructure supply, 0)
increase in beds	= IF THEN ELSE (shortage in beds of health institutions≤100,000, shortage in beds of health institutions, 100,000)
beds increasing rate	= DELAY1(increase in beds, 12) (12 means the time for delay)
health care infrastructure supply	= INTEG (beds increasing rate, 6301)
gap in hospitalized rate	= shortage in beds of health institutions/health care infrastructure demand
online business	= IF THEN ELSE (lockdown policy = 1, 1, 0)
required Internet penetration rate	= IF THEN ELSE (online business = 1, 1, 0.813)
actual internet penetration	= INTEG (IP increase rate, 0.813)
gap in ICT infrastructure	= required Internet penetration rate-actual Internet penetration
decrease in metro function	= IF THEN ELSE (lockdown policy = 1, 1, 0)
decrease in taxi service	= IF THEN ELSE (lockdown policy = 1, 0.681, 0)
decrease in transit function	= IF THEN ELSE (lockdown policy = 1, 1, 0)
gap in public transport service	= (decrease in metro function + decrease in taxi service + decrease in transit function)/3
variation rate IR (t)	= (gap in public transport service + gap in hospitalized rate + gap in ICT infrastructure)/3
Infrastructure resilience (t)	= INTEG (−variation rate IR (t), 0)
EM flows subsystem	
production electricity demand	= GDP*Production electric to GDP ratio
residential electricity demand	= per capita electric consumption*population
electricity demand	= IF THEN ELSE (electricity demand ≥ electricity supply capacity, electricity supply capacity, electricity demand)
electricity supply	= IF THEN ELSE (electricity demand ≥ electricity supply capacity, electricity supply capacity, electricity demand)
electricity supply capacity	= IF THEN ELSE (lockdown policy = 1, 1.8946e+08*impact coefficient on ESC, 1.8946e+08)
gap in electric supply	=IF THEN ELSE (electricity demand ≥ electricity supply, (electricity demand -electricity supply)/electricity demand, 0)
production water demand	= GDP * production water to GDP ratio
residential water demand	= per capita water consumption * population
water demand	= production water demand + residential water demand
water supply	= IF THEN ELSE (water demand ≥ water supply capacity, water supply capacity, water demand)
water supply capacity	= IF THEN ELSE (lockdown policy = 1, impact coefficient on WSC*541.2, 541.2)
gap in water supply	= IF THEN ELSE (water demand ≥ water supply, (water demand-water supply) /water demand, 0)
food demand	= per capita food demand*population
food supply	= IF THEN ELSE (food demand ≥ Food storage, Food storage, food demand)
food supply capacity	= IF THEN ELSE (lockdown policy = 1, DELAY1(4914.29*impact coefficient on FSC,3), 4914.29)
Food storage	= INTEG (Food supply capacity-Food supply, 34,400)
gap in food supply	= IF THEN ELSE (food demand ≤ Food supply, 0, (food demand-Food supply)/food demand)
living garbage production	= per capita garbage production*population
living garbage treatment	= IF THEN ELSE (living garbage production ≥ living garbage treatment capacity, living garbage treatment capacity, living garbage production)

(*continued on next page*)

Table A3 (*continued*)

Variables	Equations
living garbage treatment capacity	= IF THEN ELSE (lockdown policy = 1, impact coefficient on GGT*13700, 13,700)
gap in garbage treatment	= INTEG (variation in GGT, 0)
variation rate MR (t)	= (gap in electric supply + gap in food supply + gap in garbage treatment + gap in water supply)/4
Material & Energy resilience (t)	= INTEG (−variation rate MR (t), 0)

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