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Quantifying Urban Disaster Resilience for Informed Mitigation Strategies

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As centers of human activity, cities concentrate populations, resources, and wealth in limited areas. According to the United Nations, 55% of the global population now lives in urban areas [1]. Moreover, the World Economic Forum's "Global Risks Report 2023" [2] highlights natural disasters as a major threat to sustainable development, especially for densely populated cities.

Resilience has emerged as a key focus area in disaster risk reduction efforts aiming to mitigate urban vulnerabilities. Various levels of government—from international bodies such as the United Nations; to national governments such as those of China, the United States, and Japan; to cities such as Beijing, New York City, and San Francisco—have developed plans for resilient cities. However, the concept of resilience remains abstract, and the complexity of urban systems makes it difficult to quantify urban disaster resilience. This complexity presents challenges for policymakers seeking to connect resilience with economic and social outcomes and limits the adoption of effective disaster mitigation strategies.

From an engineering standpoint, disaster resilience refers to a city's ability to withstand, recover from, and adapt to disruptive events. Existing methods have leveraged various models and algorithms to advance resilience assessment frameworks. These methods can be categorized into two types. The first type calculates urban resilience using a weighted aggregation approach, resulting in abstract and dimensionless indexes [3,4]. The second type adopts physics-based modeling to compute resilience indexes for a series of urban infrastructure systems [5,6]. Neither type provides a unified, dimensional index for overall city functionality and resilience. This limitation hinders the ability of existing methods to assess comprehensive urban resilience effectively, especially in terms of cross-city comparisons and informed decision-making for disaster mitigation, as these methods fail to capture the overall functionality and resilience level of a city. Additionally, current resilience assessment models lack flexibility, as they are often built on static features and cannot reflect dynamic changes in system status over time [3,5]. Furthermore, these models insufficiently exploit socioeconomic data. Given the opportunities presented by the data revolution, it is essential to harness the potential of intelligent systems and algorithms to guide data collection and analysis, thereby enhancing the data-driven capacity of urban resilience modeling [7].

There is a pressing need for a more effective approach to quantifying urban disaster resilience. Measuring urban resilience directly in terms of a city's overall functionality through sufficient socioeconomic data exploration while ensuring that the model remains adaptable to dynamic post-disaster conditions has emerged as a promising solution. By focusing on overall city functionality, a unified, dimensional index that encapsulates the complex interplay of urban systems through theoretical modeling and data-driven approaches can be developed. This approach not only overcomes the shortcomings of abstract, dimensionless indexes and infrastructure-level assessments, but could also link the resilience index to the economic and social outcomes of disasters. Importantly, this method should be based on the present state of the urban system and allow the flexible plotting of recovery curves to assess how a city's functionality could return over time to provide valuable insights for disaster mitigation strategies.

To implement this approach, three key issues must be addressed: ① How to measure city functionality, ② how to simulate post-disaster recovery, and ③ how to calculate urban resilience indexes. This research explores these topics and proposes a framework to quantify urban resilience for informed mitigation strategies, as illustrated in Fig. 1. The following sections explore these topics in detail.

1. Measuring city functionality

A city is a complex system comprising buildings (individual structures) and infrastructure networks (e.g., transportation, water, telecommunication, energy, and gas systems), as illustrated in Fig. 1(a). Buildings are spatially distributed point-like units, whereas infrastructure networks form interconnected, web-like configurations. From an engineering perspective, a city's overall functionality can be determined by aggregating the functionalities of its individual components, that is, buildings and infrastructure networks. However, each component may have a distinct functionality measure (e.g., water service for water networks or power supply for energy networks), and strong interactions exist between multiple components. Consequently, city functionality cannot simply be calculated as the sum of the components' functionalities.

To address these challenges, this research proposes that city functionality be measured by focusing on integrating buildings and infrastructure network functionalities. The rationale for this approach lies in the centrality of buildings to human activities,

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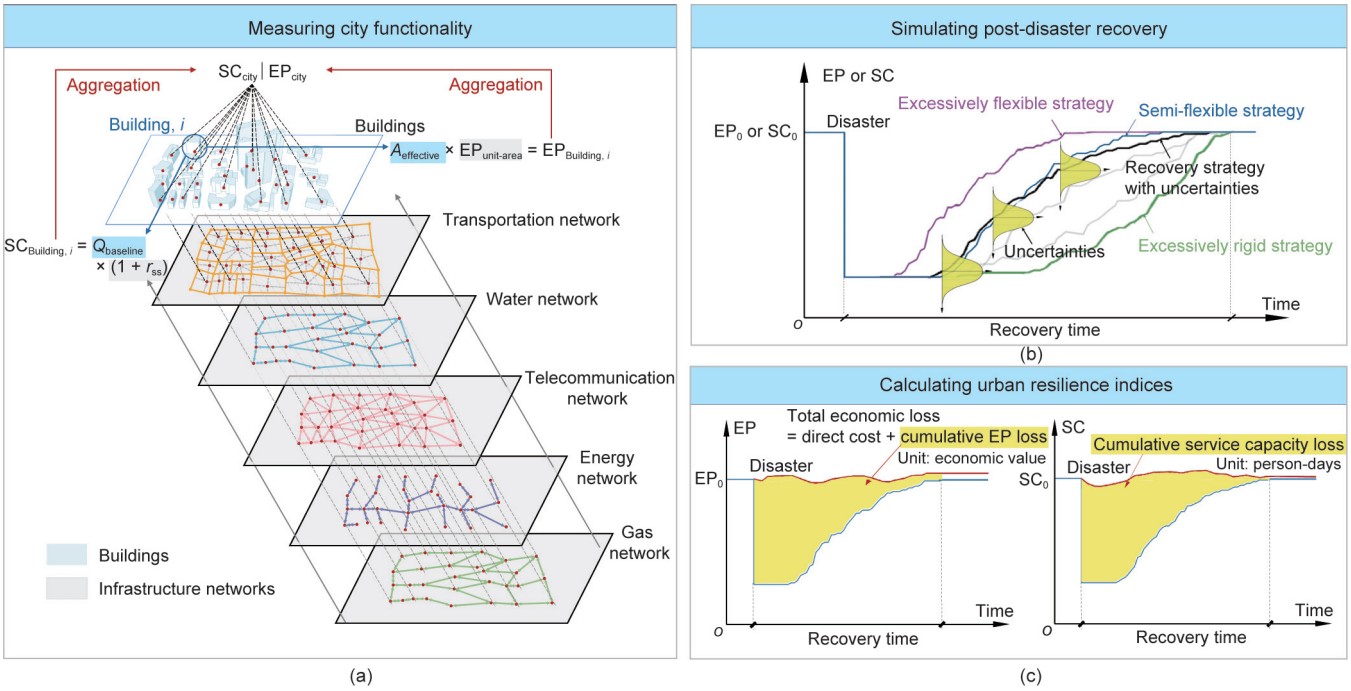

Fig. 1. Framework for quantifying urban resilience for informed mitigation strategies: (a) measuring city functionality, (b) simulating post-disaster recovery, and (c) calculating urban resilience indexes. EP: economic productivity; $A_{effective}$: effective area; $EP_{unit\text{-}area}$: economic productivity per unit area; SC: service capacity; $Q_{baseline}$: baseline occupancy capacity; r_{SS}: supplementary service factor; EP_0: initial economic productivity; SC_0: initial service capacity; EP_{city}: economic productivity of the city; SC_{city}: service capacity of the city; $EP_{building,i}$: economic productivity of the *i*th building; $SC_{building,i}$: service capacity of the *i*th building; *i*: building number.

facilities, and economic productivity. The primary role of infrastructure networks is to support these building-centered activities. Fig. 1(a) illustrates the interconnected relationship between buildings and infrastructure systems, showing how buildings serve as common nodes across multiple networks. This connection suggests that building functionality can act as a proxy for the functionality of associated infrastructure systems. When infrastructure fails to provide adequate service, the functionality of dependent buildings diminishes.

Building on the building-center approach, a framework to measure city functionality is developed, as shown in Fig. 1(a). First, the functionality of each building is measured, incorporating the functionalities of relevant infrastructure systems. These values are then aggregated across all buildings in the city to obtain an overall measure of city functionality.

Given the composite nature of urban resilience assessment, a dual socioeconomic indicator system is both theoretically justified and practically necessary. Social resilience indexes measure a city's capacity to maintain stability and ensure basic service provision under disaster shocks. Cutter et al. [8], in the baseline resilience indicators for communities (BRIC) model, emphasized that social service levels and public service accessibility influence the efficiency of post-disaster recovery, which subsequent studies have quantified as the "service supply rate" and "availability level," respectively. The United Nations Office for Disaster Risk Reduction (UNISDR) [9] further integrated these indicators into the Sustainable Development Goals (SDGs) framework, highlighting that improving resilience can reduce the disruption and damage caused by disasters to essential social services. Thus, service capacity constitutes the "baseline resilience" that safeguards fundamental living conditions. Economic resilience indexes quantify a city's ability to withstand risks and reconfigure productive factors. The Rockefeller Foundation's resilient cities framework underscores that factor mobility and industrial diversification create risk-buffering mechanisms. The Organisation for Economic Co-operation and Development (OECD) [10] further indicates that economic resilience is reflected not only in immediate losses such as gross domestic product (GDP) decline but also in forward-looking metrics such as the "proportion of innovation investment" and "activity output value." Accordingly, the proposed framework in this paper synthesizes the following: the social dimension prioritizes spatial resource allocation to maintain systemic stability while the economic dimension focuses on value generation to drive functional recovery. These two aspects complement each other and form the resilience assessment logic of this framework—social service capacity anchors system survival, while economic productivity drives system evolution. The framework is adaptable to two key functionality measures: "economic productivity" and "service capacity."

1.1. Functionality measure 1: Economic productivity

The economic productivity (EP) index defines a city's functionality as its capacity to generate wealth, as measured by the total net wealth produced per day. A city's EP is the aggregate EP of all its buildings, as most economic activities are concentrated within buildings. For each building, EP is calculated by multiplying its effective area (denoted as $A_{effective}$) by the economic productivity per unit area (denoted as $EP_{unit\text{-}area}$).

$A_{effective}$ varies during the recovery process and must be determined through recovery simulations, as explained in Section 2. $EP_{unit\text{-}area}$, in turn, depends on factors such as the building type and the service satisfaction levels provided by multiple infrastructure networks. This framework embeds infrastructure functionalities into the process through $EP_{unit\text{-}area}$. Statistical analysis of market data can provide $EP_{unit\text{-}area}$ values for different building types and service levels, which can then be archived for future reference. Specifically, $EP_{unit\text{-}area}$ can be calculated through a deep learning-based production model that captures the complex interrelationships among economic production, social characteristics,

and infrastructure services. First, statistical reports and social survey data are utilized to map the relationships between net economic output and various factors, including resource supply, building type, industry type, spatial distribution, labor force, and technological level. On this basis, temporal and static features are extracted: Temporal features represent the dynamic variations in resource consumption, whereas static features characterize the economic attributes of a region. Subsequently, temporal features with strong correlations with net economic output are selected to enhance the model's effectiveness and interpretability. Finally, a hybrid neural network model is trained, in which a recurrent neural network (RNN) encodes temporal features to capture time dependencies and a fully connected neural network encodes static features. These two sets of hidden state features are then concatenated to predict $EP_{unit\text{-}area}$. The production model primarily emphasizes supply-side factors, such as resource availability, the labor force, and technological capabilities. To incorporate demand-side indirect influences, a demand model can be further developed to refine productivity predictions by considering the effects of consumption, price, and quantity. Over the short term, an increase in demand may lead to higher prices and production levels, whereas long-term demand growth may encourage firms to expand investment and labor input. Using this framework, the EP of a city can be quantified for any state of damage before, during, or after a disaster, as illustrated on the right side of Fig. 1(a). In conclusion, this method quantifies economic resilience by assessing its deviation from normal levels.

1.2. Functionality measure 2: Service capacity

The service capacity (SC) index defines a city's functionality as its ability to meet the living and production needs of its population, quantified by the number of people it can support, using basic housing needs as a baseline. Like the EP index, the SC of a city is the total SC of all its buildings. For each building, the SC consists of two distinct components: the baseline occupancy capacity, which considers basic housing needs and is denoted as $Q_{baseline}$, and the supplementary service capacity, which support additional living and productive activities beyond mere occupancy.

Since individuals must live in a building before engaging in other activities, the supplementary service capacity is modeled as a function of the baseline occupancy capacity, represented by $Q_{baseline}$ multiplied by a supplementary service factor, denoted as r_{SS}. Thus, the SC of a building is calculated as $SC = Q_{baseline} \times (1 + r_{SS})$.

Like $A_{effective}$, $Q_{baseline}$ varies during the disaster recovery process and must be determined through recovery simulation, as described in Section 2. On the one hand, r_{SS} measures the relative importance of supplementary services to baseline occupancy, so it varies with building type; on the other hand, by definition, it also varies with the satisfaction rate of services provided by infrastructure networks. Therefore, the functionalities of infrastructure networks are embedded in this framework through r_{SS}. Statistical analysis of social data can provide values for r_{SS} for different building types and service satisfaction rates, which can then be archived for future reference.

To determine the r_{SS}, a machine learning-based random forest approach is employed to capture the complex relationships among service capacity, social characteristics, and infrastructure services. First, resource consumption per capita d_0 is extracted from statistical reports published by national agencies, local governments, resource supply departments, as well as socioeconomic activity data to capture baseline resource demand. Then, socioeconomic characteristics, including population size, daily active population, income per capita, education level, building area, building type, and building age, are collected and mapped to resource consumption per capita, which can be obtained from surveys or other social research methods. Specifically, data are categorized by building type (e.g., residential, office, industrial, and service buildings) to accurately quantify their post-disaster resource support capacity. To identify key features that influence resource consumption and enhance model effectiveness and interpretability, significance analysis (Student's t test, the Kruskal–Wallis test, and analysis of variance (ANOVA)) is employed to evaluate significant differences among feature groups. Based on the selected key features, the random forest model is trained, with each decision tree randomly sampling from the training set and selecting features for splitting during training to learn the tree structure. At any given moment, the model predicts the resource consumption per capita d_t on the basis of building characteristics, the displaced population, and socioeconomic factors, thereby computing the r_{SS} as $r_{SS} = d_t/d_0$. Since the quantification of SC in this method is based on a capability model under given conditions, the impact of population redistribution on the urban SC can be considered once population redistribution occurs or when a predictive model for population redistribution patterns is established. Similarly, because key building parameters such as the number of people to be relocated and building types are adjustable during the recovery process, this framework can also describe the post-disaster conversion of building functions, as well as the changes in urban social capacity caused by the construction of temporary shelters. For example, after a disaster, stadiums may be repurposed as temporary shelters, and new temporary shelters may also be constructed. Using this framework, the SC of a city can be calculated for any given city damage state, whether before, during, or after a disaster, as illustrated in the left side of Fig. 1(a). Finally, by calculating the total population to be sheltered, the present demand can be described, thereby dynamically quantifying the resilience of the social dimension through the relationship between supply and demand.

1.3. The socio-economic factors-driven adjustment of functional quantification

Urban resilience assessments need to consider the evolving nature of both social and economic dimensions. Various evolving models can be integrated into the assessment framework, with one promising candidate being the agent-based modeling (ABM) approach. The ABM simulates the decision-making processes of social agents (e.g., residents, businesses, and governments) within urban systems, dynamically capturing the impacts of system recovery and socioeconomic changes. Agents make decisions based on the current state of resources and services, and these decisions, through feedback mechanisms, influence the surrounding environmental conditions, which in turn affect the decisions of other agents. This interaction creates a dynamic and interdependent system evolution process. Through this mechanism, the key input parameters of the $EP_{unit\text{-}area}$ and r_{SS} models are dynamically adjusted, which in turn results in corresponding changes in the calculated values of EP and SC. By utilizing ABM, the model allows for a more detailed simulation of both immediate and long-term recovery, providing a more dynamic and accurate approach to evaluate urban resilience.

2. Simulating post-disaster recovery

In addition to measuring city functionality, a critical aspect of assessing city resilience is simulating a city's recovery process after disasters. A key challenge here lies in the fact that disaster resilience is a multidimensional and critical attribute of a city that must be evaluated before a disaster occurs. However, once a disaster strikes, multiple potential recovery paths may unfold, each leading

to different levels of resilience. This highlights the importance of recognizing that the effectiveness of recovery strategies significantly influences a city's overall resilience. However, recovery strategies are often unknown prior to a disaster and carry substantial uncertainties at different stages, as illustrated in Fig.1(b).

To address this challenge, the proposed framework draws from established methodologies for assessing the seismic resilience of buildings, such as Federal Emergency Management Agency (FEMA) P-58 [11], Resilience-Based Earthquake Design Initiative (REDi) [12], and GB/T 38591–2020 [13,14]. These methodologies typically employ predefined, rational recovery strategies that prioritize repairs on the basis of factors such as component type and resource availability. By adopting this systematic order of recovery, it becomes possible to evaluate the resilience of a building without being hindered by uncertainties in recovery strategies.

Similarly, in urban disaster resilience assessment, a predefined rational recovery strategy can be employed. However, city-scale recovery differs significantly from building-scale recovery in several key aspects, necessitating a more flexible approach. These differences include more substantial economic and social implications and a broader range of adjustment options. Consequently, a rational recovery strategy for cities should strike a balance between rigidity and flexibility. An overly rigid strategy may fail to adapt to unforeseen challenges during recovery, whereas an excessively flexible strategy could lead to inefficiencies due to constraints such as information availability and implementation processes. These two extremes could result in recovery curves that are either overly pessimistic or overly optimistic, as illustrated in Fig. 1(b).

A more effective approach involves adopting a semiflexible strategy. This strategy incorporates the following key features:

(1) Resource constraints: Limitations on recovery resources, such as workers and materials, are explicitly considered.

(2) Commitment constraints: Recovery resources, such as workers, are allocated to specific tasks for a designated period or until completion.

Within these constraints, a dynamic optimization method is applied, allowing for the reassignment of resources to maximize short-term gains in city functionality. This method formulates differentiated recovery strategies for point-based (e.g., building clusters) and network-based (e.g., infrastructure networks) engineering systems. For network-based engineering systems with redundant characteristics, critical paths are prioritized to increase system connectivity and optimize resource utilization. This study proposes a constraint-aware breadth-first search (CA-BFS) algorithm to achieve traversal-based recovery combined with Kruskal's algorithm to obtain the minimum spanning tree (MST) for critical path identification. The method follows a greedy strategy by sorting edge weights and progressively merging connected subgraphs, ultimately constructing an MST with higher repair priorities. The MST portion is restored first, whereas the remaining graph is recovered using a greedy strategy that is based on edge weights. Additionally, the CA-BFS algorithm incorporates time and resource constraints, dynamically adjusting node expansion to ensure efficient recovery progression. For point-based engineering systems, this study proposes a dynamic optimization-based recovery method to maximize system functionality gains. Traditional approaches rely on fixed priorities, which struggle to adapt to dynamic demands. In contrast, the proposed method optimizes the resource allocation at each time step to enhance recovery efficiency. Specifically, the recovery process is formulated as a multistage decision-making problem where, based on the current state and resource constraints, the optimal recovery strategy is dynamically selected through state-transition equations to maximize the increase in functionality. By calculating the contribution of each component's recovery to functionality gains and its resource demands, the optimal resource allocation scheme is determined, thereby achieving efficient recovery of point-based engineering systems through the dynamic optimization-based recovery method. This method generates recovery curves that more accurately reflect actual recovery processes, making it a suitable approach for city resilience assessment.

The outputs of the recovery simulation include the evolving damage states of buildings and infrastructure networks throughout the recovery period. Building damage is translated into reductions in $A_{\text{effective}}$ and Q_{baseline} [15], whereas infrastructure damage is reflected as a loss of service satisfaction that affects $\text{EP}_{\text{unit-area}}$ and r_{SS} [16]. By integrating these effects, the EP and SC recovery curves can be plotted, providing a comprehensive view of the city's recovery trajectory.

3. Calculating urban resilience indexes

The city recovery curves, which use EP and SC as functionality measures, offer policymakers essential insights for disaster preparedness and mitigation planning. In certain situations, a single scalar quantity may be preferable, such as for cost–benefit analyses of disaster-mitigating strategies.

From an economic perspective, the EP recovery curve allows for the calculation of the "total economic loss" (in units of economic value) caused by a disaster (Fig. 1(c)). Since EP is quantified using a hybrid neural network model trained on net profit data, which are derived from total loss, expenditure, and total revenue in social and economic activities, it is important to focus on the revenue and losses of each economic entity within the studied region. This total loss consists of two components: cumulative EP loss and direct repair costs. The cumulative EP loss is quantified as the integral of EP loss (i.e., deviation from the normal level) over the entire recovery period. Direct repair costs, on the other hand, can be estimated using established methodologies that translate damage into financial expenditures [11,13].

From a societal perspective, the SC recovery curve enables the quantification of "cumulative service capacity loss" (measured in person-days), which represents the cumulative unmet needs of people over a specified period (Fig. 1(c)) [17]. The SC can be quantified using the model in Section 1.2, with the needs of living serving as the current demand and accounting for factors such as population redistribution. This indicator is calculated dynamically as the integral of SC loss over the entire recovery period through the relationship between supply and demand.

For example, an urban resilience assessment might quantify results as follows: Under a 1-in-500-year return period earthquake scenario, city A's total economic loss reaches 100 million CNY, and the cumulative service capacity loss is 50 000 person-days. These results provide valuable insights for policymakers, enabling them to design more effective disaster preparedness and mitigation strategies. To ensure the applicability of this framework in practical applications, the calculation of urban resilience indexes can be further normalized by the total building area of the quantified region to compare the resilience of urban areas of different scales.

4. Conclusions

Resilience is an abstract concept that becomes meaningful only when it is quantified using physically significant measures, thus enabling policymakers to make informed disaster mitigation decisions. While buildings and infrastructure networks each have distinct measures of functionality, their combined performance can be aggregated into city-wide functionalities in both economic and social dimensions. This aggregation is achieved by using buildings as proxies for the functionality of associated infrastructure networks, leveraging the graph model structure of the city. To

address uncertainties in recovery strategies and ensure robust resilience assessments, a semiflexible, dynamic optimization recovery strategy can be employed for recovery simulations. Ultimately, the two-dimensional resilience indexes described in this study—total economic loss and cumulative service capacity loss—are derived by integrating a city's functionality loss over the recovery period. These indexes offer critical insights for policymakers looking to design and implement effective disaster mitigation strategies.

CRediT authorship contribution statement

Ying Zhou: Project administration, Conceptualization. **Yi Xiao:** Writing – original draft, Methodology. **Haoran Xu:** Writing – review & editing, Visualization.

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.

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