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THE EVOLVING RESILIENCE OF GLOBAL METRO NETWORKS

Yun-Hao Dong[1] , Xiao-Wei Luo[2], Fang-Le Peng[3], Wout Broere[4]

Abstract: Metro systems are essential for urban functionality worldwide, and their resilience is a growing concern. While network analysis has offered insights into structural resilience, a comprehensive understanding of dynamic resilience, particularly its temporal evolution in expanding networks and response to multifaceted disruptions, remains underdeveloped. Previous research has often focused on large systems in a few megacities, neglecting smaller networks. This study addresses these gaps by introducing a novel framework to evaluate the dynamic resilience of evolving metro networks. We compiled data for twelve global cities, modeling their metro systems as evolving complex networks, incorporating geographic coordinates, station opening dates, and catchment area population data. A key contribution is a comprehensive resilience metric that integrates network serviceability, based on population-weighted global efficiency, and quantifies vulnerability as the rate of efficiency loss per disrupted node. We formulated three universally applicable disruption scenarios, including critical node, critical region, and critical line disruptions. Each disruption was simulated at both light (10% node removal) and heavy (20% node removal) intensities, reflecting diverse real-world disruption scenarios. These strategies leverage a comprehensive node centrality index derived from degree, closeness, and betweenness centralities, with edge weights based on reciprocal Euclidean geodesic distances. Applying this framework, we analyzed the resilience evolution across the 12 case study cities, uncovering distinct and common patterns. Findings indicate that dynamic resilience provides critical insights complementary to static efficiency measures and that resilience trajectories are highly dependent on disruption size, intensity, and city-specific network characteristics. This study offers a robust methodology for assessing metro network resilience evolution, providing data-driven insights to enhance the robustness of critical public transport systems and inform strategies for developing more resilient cities.

Keywords: evolving resilience, metro network, serviceability, disruption scenarios

1. INTRODUCTION

Over the past century, metro systems have been widely recognized as efficient and environmentally friendly public transportation solutions (Dong et al., 2023; Lin et al., 2021). These systems play a critical role in alleviating transportation pressures in more than 200 large- and medium-sized cities worldwide. The concept of a metro system, however, varies across different contexts. In this study, a metro system is defined as an intra-city (non-intercity) rail transit system operating on a fully grade-separated right of way. With the deepening of global theoretical research and practical applications in transit-oriented development (Singh et al., 2017), the contributions of metro systems extend beyond transportation (Lin et al., 2022). They have become a key driver in the reconfiguration of urban morphology and function through their bidirectional influence on land use along metro corridors (Dong et al., 2022; Zhang, 2020). The morphological characteristics of metro networks play a significant role in shaping this transformative power (Ingvardson & Nielsen, 2018; Lyu et al., 2016). Specifically,

[1] PhD, Dong Yun-Hao, Underground Space, postdoc, Department of Geotechnical Building and Engineering, Tongji University, 1239 Siping Road, P.R. China, Department of Architecture and Civil Engineering, City University of Hong Kong, 83 Tat Chee Avenue, Hong Kong SAR, P.R. China, yunhdong@cityu.edu.hk.

[2] PhD, Luo Xiao-Wei, Construction Management, professor, Department of Architecture and Civil Engineering, City University of Hong Kong, 83 Tat Chee Avenue, Hong Kong SAR, P.R. China, xiaowluo@cityu.edu.hk.

[3] PhD, Peng Fang-Le, Underground Space, professor, head of Tongji University Underground Space Research Center, Department of Geotechnical Building and Engineering, Tongji University, 1239 Siping Road, P.R. China, pengfangle@tongji.edu.cn

[4] PhD, Wout Broere, Underground Space, professor, GeoEngineering Section, Delft University of Technology, Delft, The Netherlands, w.broere@tudelft.nl

a metro network refers to the complex topological configuration formed by the spatial distribution of metro lines and stations as they expand in number and coverage (Gonzalez-Navarro & Turner, 2018).

The continuous evolution of these morphological characteristics not only impacts the operational efficiency and resilience of metro systems but also influences the coupling relationships between metro stations and the surrounding built environment (An et al., 2019; Dong et al., 2021). Among these factors, the resilience of metro networks has garnered increasing attention (Yu et al., 2023). A high-resilience system, capable of withstanding partial failures under specific scenarios, is regarded as essential for reliable public transportation and the development of resilient cities (Derrible & Kennedy, 2010).

While network science's topological analysis has significantly enhanced our understanding of metro network resilience (Pei et al., 2022), a thorough grasp of dynamic resilience in metro systems is still lacking. Despite significant efforts to study metro network growth (Yu et al., 2023), prior research has not sufficiently explored the evolution of resilience in expanding metro networks, particularly their ability to recover from complex and multifaceted disruptions. Additionally, the focus has predominantly been on larger metro systems in a few megacities, overlooking the resilience dynamics of smaller-scale networks. This oversight highlights the need for a more inclusive approach that captures the resilience characteristics of metro networks of varying sizes and complexities.

This gap in understanding prompts two critical research questions: 1) How can we effectively evaluate the dynamic resilience of metro networks? 2) Are there global differences or similarities in the evolution of metro network resilience? To address these questions, we introduced a comprehensive network resilience metric that considers serviceability based on refined network modeling. We also proposed three universally applicable disruption strategies with bi-level disruption intensities. Ultimately, a case study involving 12 global cities was conducted to uncover regular patterns in resilience.

The structure of the remainder of this paper is organized as follows: **Section 2** presents an analytical framework for assessing the resilience of evolving metro networks. **Section 3** delivers analysis results concerning the resilience of metro networks across twelve global cities, highlighting distinct and common patterns. **Section 4** discusses the implications for building more resilient metro systems and outlines the research limitations. Finally, **Section 5** provides the concluding remarks of this study.

2. MATERIAL AND METHODS

2.1. Overview of the metro networks in case study cities

2.1.1 Selection of case study cities and data collection

The selection of case study cities is crucial for identifying patterns in the network resilience. Previous studies often focused on large-scale metro networks in global cities. However, many cities have not yet developed large-scale metro systems, and the performance of medium to large-scale metro networks is also significant for cities that are later developers of such infrastructure. Consequently, we implemented a primary selection strategy based on scale diversity to include metro networks ranging from medium to large scales across the globe. In addition to scale, we also considered the representativeness of the cases globally, considering factors such as the speed of network evolution and socioeconomic status. Ultimately, 12 worldwide cities were selected for case studies, including Shanghai, Beijing, Paris, Chengdu, London, Guangzhou, Moscow, Delhi, Mexico City, Tokyo, Singapore, and Hong Kong.

Data collection relevant to metro systems in the selected cities was based strictly on official data from the respective public transit authorities and Google map, with a cutoff at the end of 2024. The metro-relevant data includes station names, opening dates, geographic coordinates, and topological connections within the metro system. Additionally, we collected population data at a 1km resolution (similar to a metro catchment area with a radius of 800m) from WorldPop (Lloyd et al., 2017) to enhance our computation of network resilience. To eliminate the confusion caused by the multiple definitions of metro, we focused solely on rail transit systems with independent rights-of-way and does not include inter-city rail transit.

2.1.2 Characteristics of the metro networks in case study cities

From a general perspective, the metro networks in the case study cities exhibit diverse characteristics in several aspects. Firstly, in terms of size as illustrated in **Figure 1**, the number of operational stations of the twelve metro networks range from medium to high scales, such as Hong Kong (N=97), to large scales like Moscow (N=252), and even to ultra-large scales such as Shanghai (N=410). Secondly, there is diversity in the evolution time of these networks, including the time-honored metro system in London (operational for 162 years), and the rapidly developed metro system in Chengdu (operational for 15 years). Thirdly, the case study cities generally strike a balance between countries in the Global South (China: Beijing, Shanghai, Guangzhou, Chengdu, Hong Kong; India: Delhi) and the Global North (France: Paris; UK: London; Russia: Moscow; Mexico: Mexico City; Japan: Tokyo; Singapore). Although all selected cities are developed urban areas within their regions, they vary in their socio-economic status.

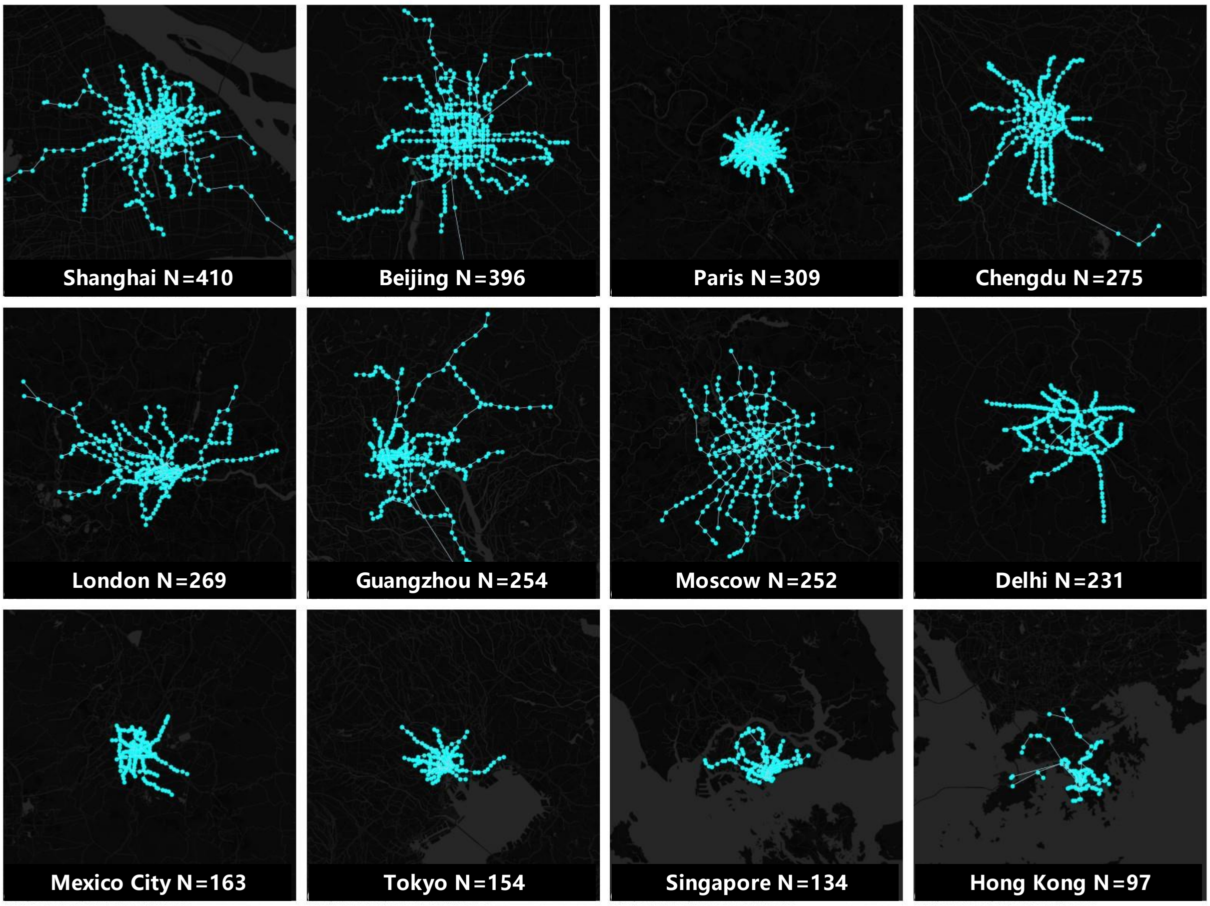

Figure 1. *Metro network of case study cities (N denotes the number of stations)*

2.2. Assessing the resilience of evolving metro networks

Unlike previous studies that focused on the performance of metro networks under deliberate disruptions, this study introduces a resilience analysis framework that incorporates temporal complex networks, universally applicable network disruption scenarios, and resilience metrics that integrate serviceability. The modeling and computation of the network were primarily conducted using NetworkX library in Python (Hagberg et al., 2008). The assessment model is detailed as follows.

2.2.1 Temporal complex networks construction

The network modeling incorporated the metro networks' topological characteristics (Kanwar et al., 2019), real-world geographic position, and temporal development data. Initially, the development progress was quantified by calculating the ratio of the number of metro stations in different years to the number at the end of the period, selecting those years where the development progress exceeded both 5% annually and 30% overall as the temporal cross-sections for analysis. For selected year T, metro stations are denoted as vertices/nodes V_t, and the rail transit connections between them as edges/links E_t (modeled following the L-space approach), thus forming the graph $G_t(V_t, E_t)$. Additionally, each station i records the catchment area population P_{Ti} and geographical coordinates (lon_{Ti}, lat_{Ti}) as necessary attributes in year T. Given that the available population data spans from 2000 to 2020, this study substituted population data for any post-2020 temporal interfaces with the 2020 figures as the proxy, while pre-2000 cross-sections were excluded from consideration.

2.2.2 Targeted disruption strategies formulation

(1) Evaluation of comprehensive node centrality

Assessing the importance of nodes within a network is a prerequisite for formulating specific disruption scenarios. This study focused on the refined topological structure of metro networks, emphasizing the evaluation of node centrality as the importance index. Although many classic centrality measures have been applied in transportation network analysis, they often assess one aspect of node importance. Therefore, we adopted a comprehensive node centrality index that integrates multiple classic centrality indicators to effectively identify critical nodes. Moreover, the weights of all edges are based on the reciprocal of Euclidean geodesic distances to more accurately capture the true distances between station nodes.

Firstly, we measured the degree centrality $C_D(v)$ using expression (1). This metric quantifies the connectivity strength of a metro station by summing the weights of its edges, where $d(u,v)$ denotes the geodesic distance between station u and station v, $N(v)$ denotes the neighborhood of station v.

$$C_D(v) = \sum_{u \in N(v)} \frac{1}{d(u,v)} \tag{1}$$

Secondly, we measured the closeness centrality $C_C(v)$ using expression (2). This metric evaluates how efficiently a station is connected to all other stations in the graph, where N represents the total number of stations.

$$C_C(v) = \frac{N-1}{\sum_{u \neq v} d(u,v)} \tag{2}$$

Thirdly, we measured the betweenness centrality $C_B(v)$ using expression (3). This metric quantifies the extent to which a station acts as a critical junction by computing its occurrence on the shortest paths between other stations. Specifically, it considers the number of these paths that pass through the station in question (station v) $\sigma_{st}(v,$ compared to the total number of shortest paths between all pairs of stations (from station s to station t) σ_{st}.

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{3}$$

Ultimately, we adopted the TOPSIS method (Behzadian et al., 2012; Du et al., 2014) to integrate the aforementioned metrics using expression (4), thus providing a comprehensive indicator to measure the importance of a specific metro station. To capture the importance of network characteristics over time, the weights of the three basic centrality measures in the TOPSIS calculation were determined using the Criteria Importance Through Inter-criteria Correlation (CRITIC) objective weighting method. In other words, the comprehensive centrality index $C_{CP}(v)$ measures the likelihood that a metro station's failure would severely disrupt the network, based on how many connections it has, how easily passengers can reach other destinations through it, and how much passenger traffic flows through it.

$$C_{CP}(v) = F_{topsis}(C_D(v), C_C(v), C_B(v)) \tag{4}$$

(2) Specific disruption scenarios

Specific disruption modelling strategies significantly influence the analysis of metro network resilience. Existing strategies typically involve the sequential removal of nodes based on their importance until the network ceases to function. In contrast, we adopted a single-round disruption approach, where the network is subjected to a single disruption to evaluate its performance before and after the event. This method provides a clearer perspective on the dynamic evolution of network performance across different temporal cross-sections. The disruption scenarios in this study were designed based on network topology configurations, with a focus on disruption scale and scope to approximate various real-world metro incidents and disasters.

For disruption scale, light and heavy disruption were defined in this study to simulate general and severe disturbances in metro networks. Based on metro network performance loss curves, the thresholds for light and heavy disruptions were set at 10% and 20% of the total number of nodes, respectively (Sun et al., 2024).

For disruption scope, three types of specific disruptions are introduced, namely critical node disruptions, critical region disruptions, and critical line disruptions. These strategies were visualized in **Figure 2**, along with pseudocode for selecting affected nodes. Notably, the thresholds for light and heavy disruptions might vary for critical region and line disruptions, particularly for large-scale disruptions such as those on critical metro lines. The proposed specific disruption strategies were further described as follows.

a) **Critical node disruptions**: This scenario considers the most crucial nodes within the metro network to maximize operational disruption. It reflects real-world scenarios such as local power failures, targeted cyberattacks, strategic sabotage, or other catastrophic failures affecting key transit hubs or critical metro stations.

b) **Critical area disruptions**: This scenario simulates disasters or natural events (e.g., flooding, earthquakes) that impact geographically concentrated regions. Stations were selected based on the highest cumulative centrality within a 2 km radius (a general impact zone for disasters regarding metro stations).

c) **Critical line disruptions**: This scenario disrupts entire metro lines by targeting all stations on a line, prioritizing lines with the highest cumulative centrality. It represents scenarios such as systematic failures, large scale power failures, equipment breakdown or other disruptions that disable entire transit lines.

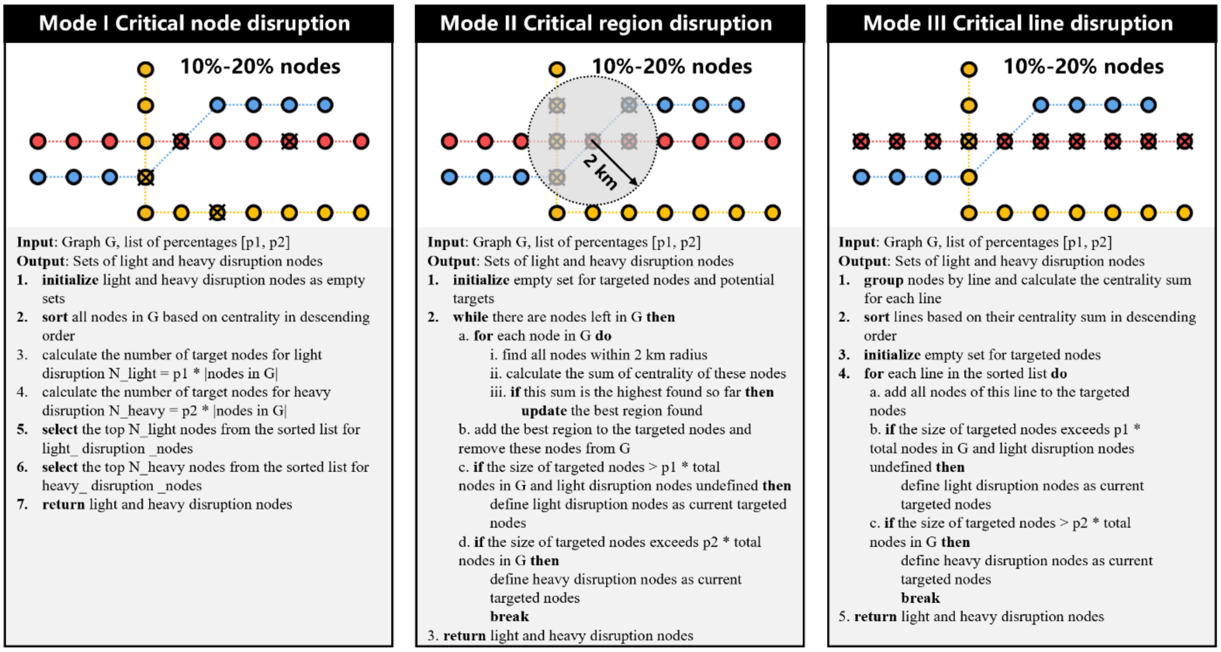

Figure 2. *Graphic representation and pseudocode of specific disruption scenarios*

2.2.3 Evaluation of metro network resilience integrating serviceability

Building on classic network resilience metrics, we introduced the concept of metro serviceability and proposed an improved resilience evaluation metric for metro networks. Global network efficiency is one of the most widely used indicators for resilience assessment of transport and infrastructure networks (Pei et al., 2022). However, global efficiency typically measures distance by considering only topological depth, even when edge weights are adjusted using actual geodesic distances. As a result, it still primarily reflects the topological properties of the network.

Metro networks, as critical components of urban public transportation systems, are deeply embedded within the urban functional systems. The changes in their service capacity under disruptions provide a more accurate reflection of their resilience as transportation networks. To this end, we approximated the service population of a metro station p_i using the average population within a 1km catchment area. Based on this, we proposed a serviceability-integrated global efficiency metric, $E_{service}$, as defined in expression (5).

$$E_{service} = \sum_{i \neq j} \frac{p_i + p_j}{d_{ij}} \qquad (5)$$

Furthermore, we introduced a resilience metric for a temporal state T, denoted as R_T, as shown in Equation (6). P_T denotes the total population within metro-led region at time T. Here, T' represents the post-disruption state. The proposed indicator portrays the resilience metric as a measure of sensitivity to changes in the network state, reflecting the extent to which each disrupted station impacts the overall network resilience. It measures both efficiency loss per capita per failed station. Given that a higher value of this metric indicates lower resilience, this study refers to it as *network vulnerability*.

$$R_T = \frac{E_{service,T} - E_{service,T'}}{(N_T - N_{T'}) \cdot P_T} \qquad (6)$$

3. RESULTS

The comprehensive node centrality is evaluated and visualized (**Figure 3**). Subsequently, the evolution of resilience under three types of critical disruptions across 12 selected cities is depicted in **Figures 4** to **8**. The circles in the figures represent the temporal cross-sectional data analyzed for each city, with the color bars derived from linear interpolation of this cross-sectional data. The color progression from light to dark in the color bars indicates increasing network resilience, aligning with the resilience metric introduced in Section 2.2.3. The variation in color for each city's color bar characterizes the resilience dynamics throughout different stages (the number of stations at a specific cross-section relative to the total number of stations in the final state, which is represented as the *development ratio* on the horizontal axis in the figures). This variation, viewed from the perspective of resilience change rate (network vulnerability), describes the evolutionary process of networks in different cities. Additionally, the size of the circles represents network efficiency combined with serviceability, providing a supplementary portrayal of resilience from the perspective of initial resilience magnitude.

3.1. Comprehensive node centrality evaluation

As shown in **Figure 3**, we could observe the distribution of station importance across 12 selected cities. Overall, the metro networks in these cities generally exhibit a pattern where central areas have higher centrality, while peripheral areas show lower centrality. This primarily reflects the contributions of betweenness centrality and closeness centrality to the comprehensive centrality measure.

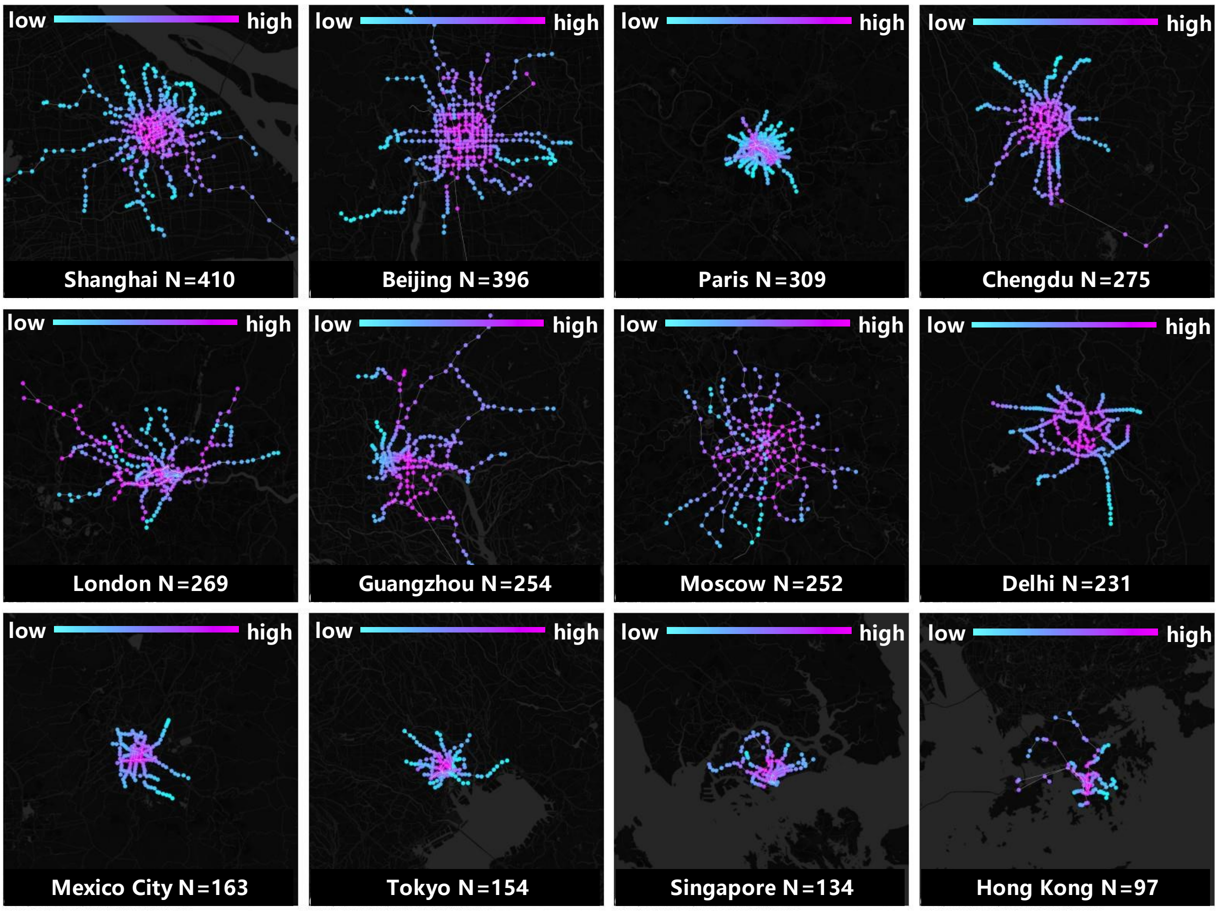

Figure 3. *Comprehensive node centrality*

In some cities (e.g., London and Guangzhou), certain stations located on suburban lines also display slightly higher centrality (though still lower compared to central areas). This phenomenon may be attributed to the influence of degree centrality, and the objective weighting method used to calculate the centrality might have amplified this characteristic to some extent. Notably, our measurement approach is entirely based on the topological configuration of the network and real-world geographic distribution. By designing disruption strategies based on this measure and incorporating the service population reflecting socio-economic development when measuring resilience, our approach aligns with the classic *Natural Movement* concept in Space Syntax studies (Hillier et al., 1993). Essentially, this involves examining how pure topological features influence the composite functionality. In this study, we shifted the focus to the service functionality of metro networks.

3.2. Resilience evolution under critical node disruption

As shown in **Figure 4**, the resilience evolution of metro networks in various cities under light node disruptions shows distinct patterns. The y-axis represents the cities, and the x-axis shows the network development ratio (i.e., the ratio of current to final station count). The resilience evolution for each city is visualized as a color band, where warmer colors indicate higher vulnerability. Circles denote network expansion events, and their size corresponds to the serviceability-integrated global efficiency metric (ranging from 6749.78 to 900203.46). The colors between circles are linearly interpolated. Assuming the metro-led region has a population of 1 million, a network vulnerability value of 0,00050 indicates that each attacked station causes a global efficiency loss of 1000000 × 0,00050 = 500 units on average.

Considering light node disruptions, Hong Kong, Tokyo, Mexico City, Delhi, and Guangzhou demonstrate a continual growth in network resilience, with particularly high resilience levels observed in Guangzhou and Delhi. In contrast, Singapore and Beijing exhibit characteristics of fluctuating resilience. Although the metro networks in Moscow, Chengdu, and Shanghai also continue to grow, the changes in their resilience are less pronounced. London and Paris are unique cases; due to their early established metro systems and the analysis only incorporating demographic data after 2000, only one data point was included for each city. London network shows higher resilience, while the Paris network displays the lowest resilience. It is important to note that this resilience is primarily evaluated based on the rate of efficiency change (network vulnerability). Consequently, while the Paris metro network shows lower resilience, it presents the highest initial network efficiency, which aligns with its highly centralized and dense network distribution. Similarly, the metro networks in Shanghai and Beijing also exhibit high initial network efficiencies.

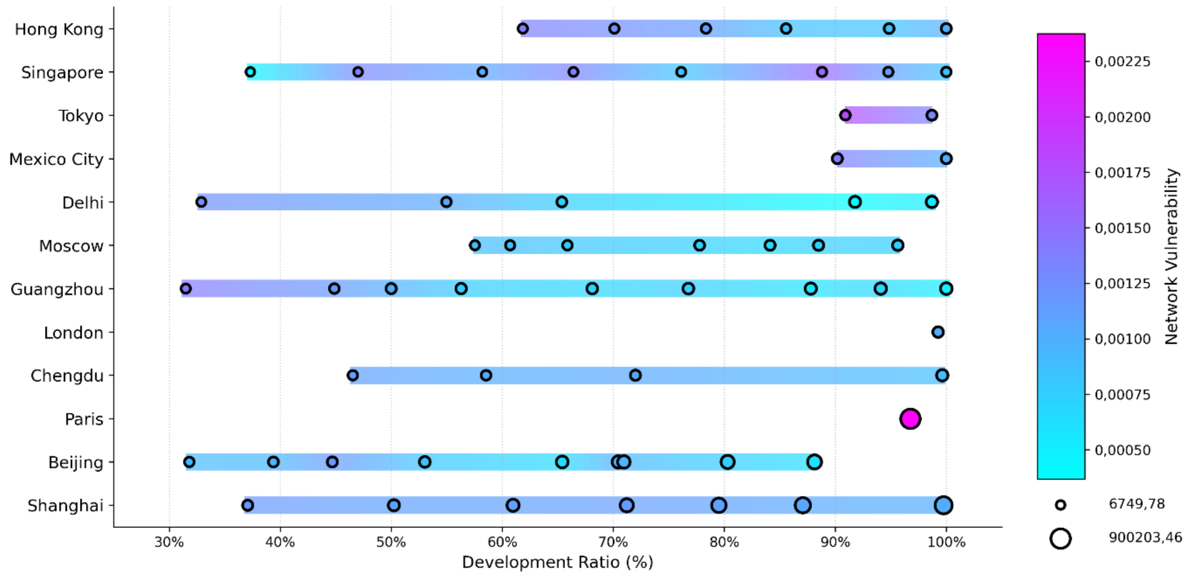

Figure 4. *Resilience evolution under light node disruption*

Figure 5 illustrates the resilience evolution of metro networks under heavy node disruption. Compared to the patterns observed under light disruption scenarios, the general trends in resilience evolution across the cities remain largely consistent, yet there is a noticeable improvement in resilience levels at various stages. Specifically, the change in high resilience levels is minimal, shifting only slightly from 0,0005 to 0,0004. However, the limit of low resilience levels has significantly decreased by approximately 37% (from 0,00225 to 0,0014).

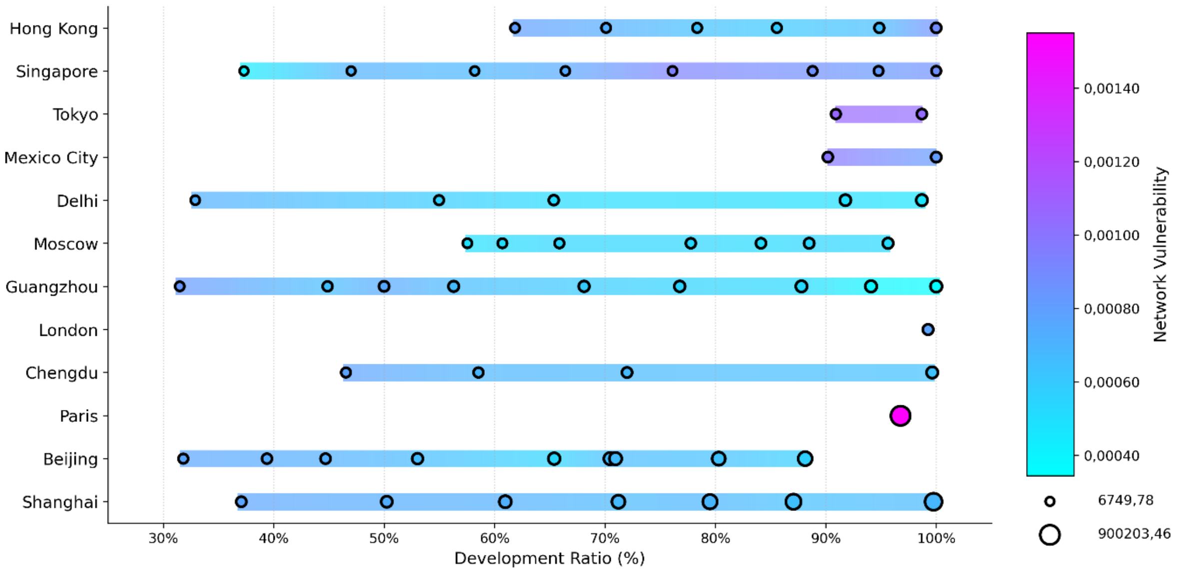

Figure 5. *Resilience evolution under heavy node disruption*

3.3. Resilience evolution under critical region disruption

Figure 6 presents the resilience evolution of metro networks in various cities under a light region disruptions. In this scenario, Hong Kong, Mexico City, Moscow, and Guangzhou exhibit varying degrees of continual resilience improvement. Tokyo and Chengdu show no significant changes in resilience; Singapore, Delhi, Beijing, and Shanghai all demonstrate a pattern where resilience initially decreases and then increases. Paris continues to display the lowest level of resilience, while London's resilience is moderate. Additionally, it is observed that under this disruption mode, the resilience evolution in Singapore, Moscow, and Beijing remains high.

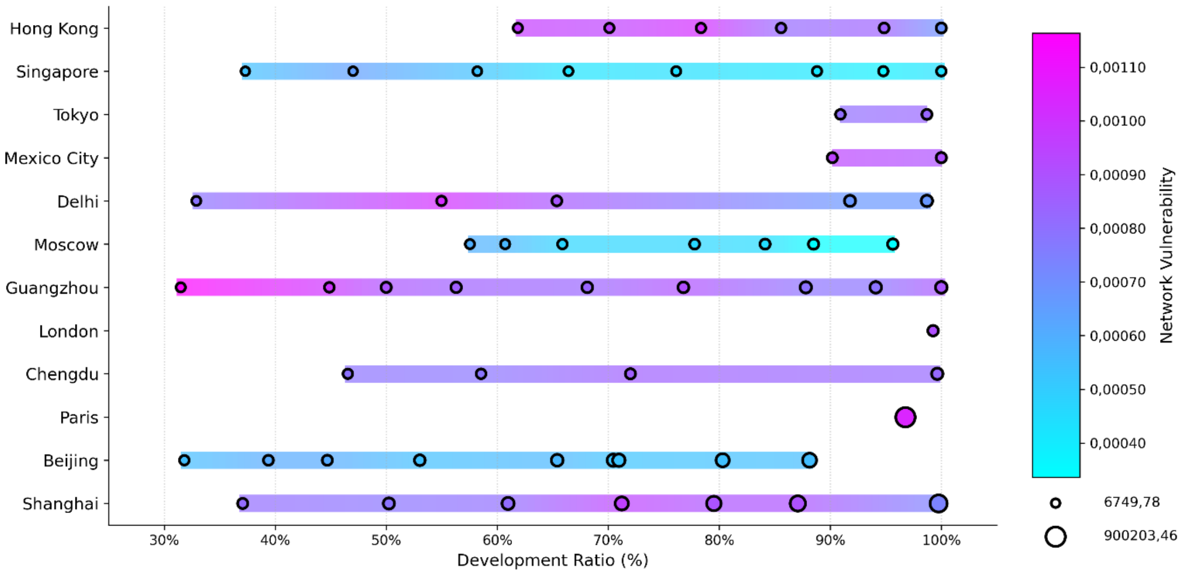

Figure 6. *Resilience evolution under light region disruption*

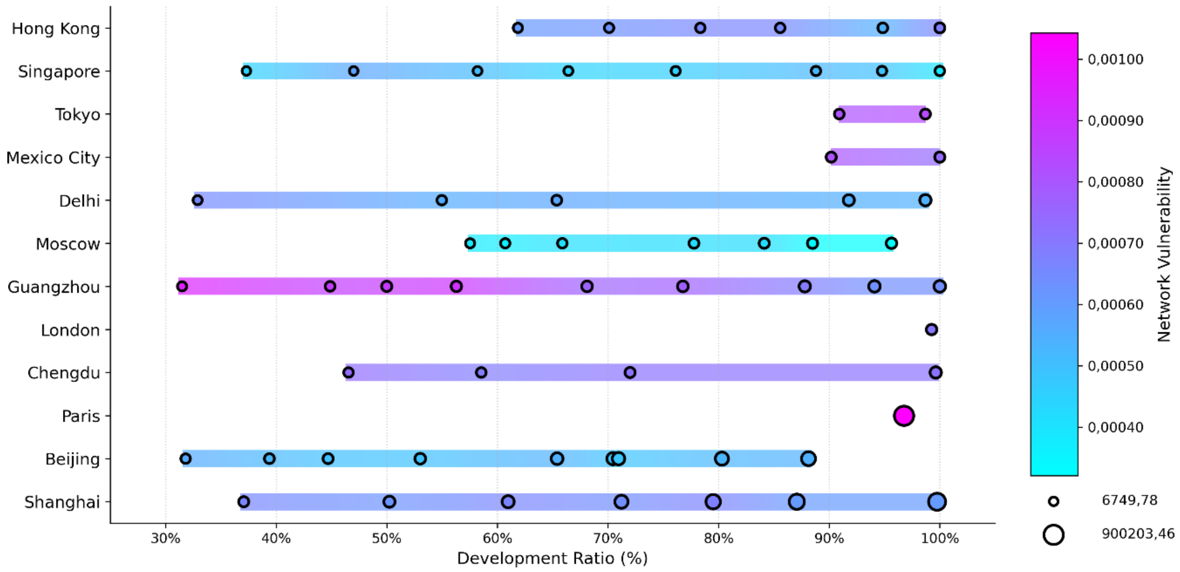

Figure 7. *Resilience evolution under heavy region disruption*

The pattern of metro network resilience evolution under a heavy region disruption differs from that observed under a light region disruption, as depicted in **Figure 7**. Except for Guangzhou, no other cities show significant changes in resilience. Additionally, the range of resilience metrics does not undergo significant alterations (ranging from 0,0004 to 0,0011 in light region disruption versus 0,0004 to 0,0010 in heavy region disruption), suggesting that the scale of the region disruption has a minimal impact on the resilience of metro networks. However, the evolution of resilience in metros appears to be more sensitive to lighter disruptions.

3.4. Resilience evolution under critical line disruptions

As shown in **Figure 8**, under a light line disruption, Hong Kong, Chengdu, and Shanghai exhibit a clear trend of continual network resilience improvement, while Beijing experiences slight fluctuations in network resilience. Other cities do not show dramatic changes in their network resilience. From the perspective of resilience levels, Hong Kong, Singapore, Delhi, Moscow, Guangzhou, and Beijing generally maintain a consistently high state, while the resilience evolution of other networks remains confined to moderate to low values.

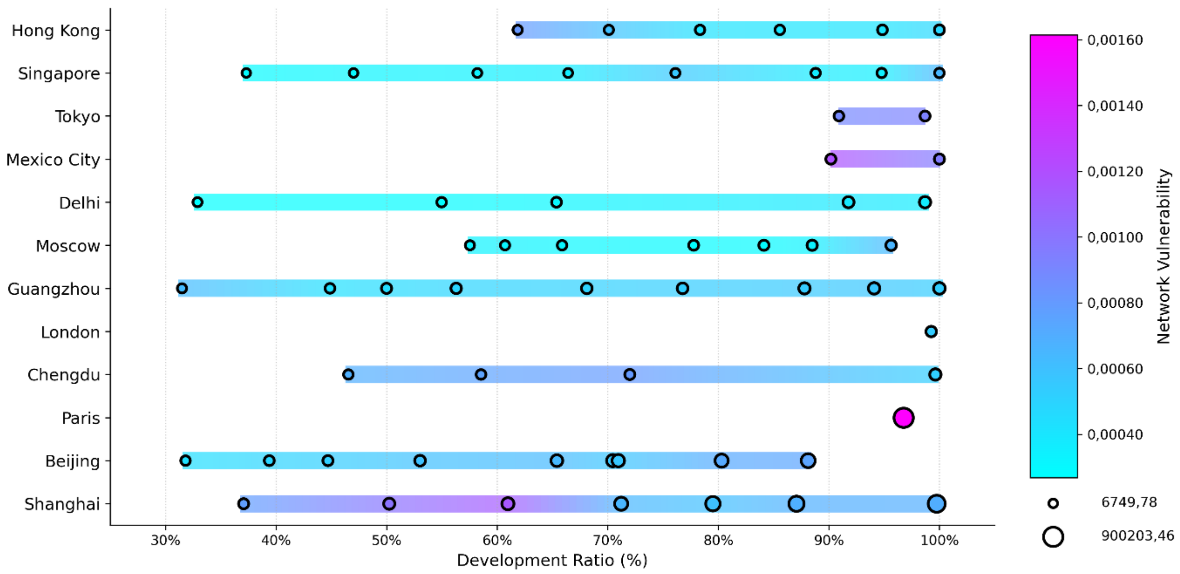

Figure 8. *Resilience evolution under light line disturbance*

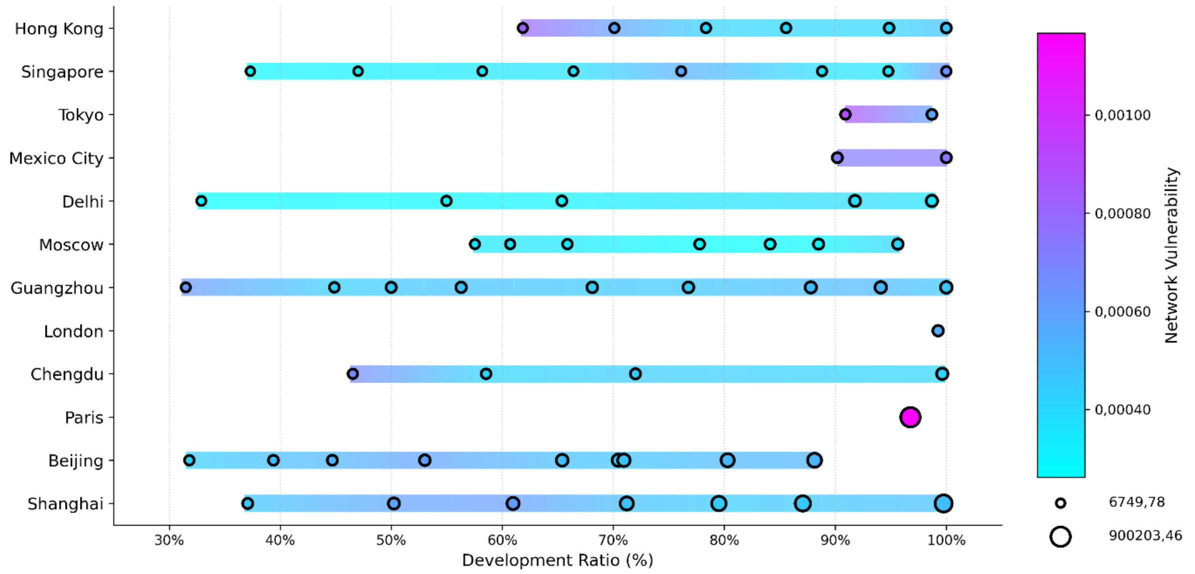

Figure 9. *Resilience evolution under heavy line disturbance*

Figure 9 further delineates the resilience changes under a heavy line disruption. For cities like Hong Kong, Delhi, and Moscow, the pattern of resilience change is consistent with the light line disruption, primarily because a line disruption is a major form of disturbance that can cause significant node removal in smaller-scale networks, regardless of the disturbance's intensity. Moreover, Shanghai's resilience pattern under a heavy disturbance no longer shows continuous improvement but rather a decrease followed by an increase. Changes in other cities are not significantly different, but the high vulnerability values under a light disturbance have decreased by 37,5% (from 0,0016 to 0,0010, similar to the change under critical node disturbance), while the low vulnerability values remain unchanged at 0,0004.

4. DISCUSSION

4.1. Implications on the resilient development of metro networks

This study, based on refined metro network topological modeling, we constructed three disturbance scenarios and integrated a resilience metric that incorporates service levels to examine the characteristics of resilience development during the evolution of metro networks. Analyzing results from 12 global cities, we extracted key findings about changes in metro network resilience, providing significant insights for the development of resilient metro networks.

Firstly, the evaluation of metro network resilience should consider both static and dynamic perspectives. Traditional analyses of transport networks often measure resilience using efficiency metrics. However, this study further examined the rate of resilience change (network vulnerability) under specific disturbance scenarios. The Paris metro system serves as a typical example; it has a relatively concentrated and dense spatial distribution, resulting in high network efficiency. Yet, it exhibits very low network vulnerability across various disturbances, indicating room for improvement in its dynamic resilience. Focusing solely on a static or dynamic perspective during network planning might not adequately capture the characteristics of metro network resilience. In practice, urban planners can combine spatiotemporal population projections with metro network planning to investigate dynamic changes in network resilience over the long term, moving beyond a purely static analysis."

Secondly, the resilience of metro networks exhibits strong differentiation across different disturbance scenarios, intensities, and cities. The driving forces behind this phenomenon are complex, possibly due to the direction and speed of network expansion and the overall network configuration during its evolution. The mismatch between the distribution of the service population in the catchment area and the metro network, where metro transportation is not the dominant mode, might also influence this phenomenon. Therefore, it is imprudent to blindly follow the resilience development patterns of a single case city; a comprehensive evaluation combining specific resilience analysis scenarios and spatial growth patterns is necessary.

Thirdly, resilience evolution trends under different disturbance intensities show similar characteristics within the same disturbance strategy. For critical node and line disturbance, high values of network vulnerability change by about 37% under both light and heavy disturbance intensities. However, critical region disturbances do not significantly affect the distribution of high and low values of network vulnerability. This provides useful insights for planners in designing resilience analysis scenarios.

Finally, despite their vast differences in scale, both the Moscow and Beijing metros demonstrate strong network resilience under various disturbance scenarios, with Beijing's initial network efficiency being higher than Moscow's. These two systems are likely to share similar overall configuration characteristics and expansion patterns, which ensure similar overall resilience evolution. This type of robust metro network system is worth analyzing and emulating by planners. Moreover, the development of graph databases that integrate static network structure with the trajectory and velocity of dynamic growth would enable more effective identification and pattern learning for such resilient networks.

4.2. Limitation and prospects

Despite that this study introduced the concept of resilience evolution to explore the patterns of metro network resilience in global cities, there are still three main areas where the research could be further improved.

Firstly, while this study includes twelve diverse metro networks from around the world as case studies, the sample size is still limited and focused on larger, multi-line networks. Future research should extend this methodology to a broader range of cities, or even conduct a full sample of global comprehensive study, to acquire a more complete understanding of the resilience evolution of metro networks, and should include smaller networks to highlight the impact of lower interconnectivity on network vulnerability.

Secondly, the proposed framework is limited by multisource data collection issues and does not fully consider factors such as the actual operating conditions of metro networks, real impact of disasters and disturbances, the age or type of metro stations (elevated or underground), and the distribution of emergency response resources. For more detailed studies on resilience enhancement, improvements in modeling methods are needed.

Lastly, while the evolving resilience of global metro networks has been studied, the interplay between metro systems and other urban systems requires further exploration. On one hand, metro networks should be analyzed in conjunction with public transport and road networks. On the other hand, the integration of urban development and metro expansion should be further examined to provide deeper insights into comprehensive urban resilience.

5. CONCLUSION

This study has advanced the understanding of metro network resilience by introducing a dynamic evolutionary perspective, moving beyond traditional static assessments. We developed a comprehensive analytical framework that integrates refined network modeling, considering real-world geographic, serviceability, and temporal development data, with universally applicable specific disruption scenarios (critical node, critical region, and critical line disruptions, each simulated at light and heavy intensities). Through a comparative case study of 12 global metro networks, encompassing diverse network scales, evolutionary timelines, and socio-economic contexts, we have identified distinct and common patterns in resilience evolution. The primary findings of this study are summarized as follows.

(1) Dynamic resilience offers crucial insights beyond static efficiency. The Paris metro, for instance, exhibits high initial network efficiency but demonstrates lower dynamic resilience (higher vulnerability) under various disruptions, highlighting the necessity of considering both perspectives in network planning.

(2) Resilience is highly contextual. It varies significantly across different disturbance scenarios, intensities, and individual cities, likely influenced by network expansion patterns, overall configuration, and the alignment between service population distribution and metro network coverage. This underscores the caution against universally applying resilience development patterns from a single case.

(3) Disruption intensity impacts vulnerability consistently within certain strategies. For critical node and line disruptions, an increase in disruption intensity led to a comparable percentage change (approximately 37%) in high network vulnerability values. However, critical region disruptions showed less sensitivity to changes in disruption scale.

(4) Despite differences in scale, both the Moscow and Beijing metro systems demonstrated strong resilience across various scenarios, suggesting that their overall configuration and expansion patterns contribute significantly to this robustness and are worthy of further study for emulation.

This study contributes a novel methodology for evaluating the evolving resilience of metro networks and provides empirical evidence of diverse resilience trajectories. The insights gained can inform urban planners and policymakers in developing more resilient metro systems capable of withstanding multifaceted disruptions, thereby enhancing the reliability of urban public transportation and contributing to the creation of resilient cities.

Future work should aim to expand the sample of cities for a more globally comprehensive understanding and incorporate a richer set of operational and contextual factors to further refine resilience assessment models

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