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Assessing the resilience of urban truck transport networks under the COVID-19 pandemic: A case study of China

Abstract

The COVID-19 pandemic underscores the critical role of urban truck transport networks in maintaining essential supply chains amidst crises. However, existing research on the resilience of these networks is limited, often relying on aggregated socio-economic data to provide an overview of broader trends. This study addresses the gap by utilizing a large-scale GPS dataset of individual trucks from Chinese cities, enabling a micro-level analysis of urban truck transport network resilience under pandemic. First, we examine how pandemic-induced disruptions reshaped the spatial distribution of freight activities, identifying demand pattern shifts in the city. Second, we introduce two key resilience metrics—handling efficiency and transport efficiency—to determine whether truck transport networks could adapt to fluctuating demand and maintain reliable service across regions, freight hubs, and industry-specific supply chains. The findings reveal significant variations in network resilience across cities, with suburban hubs and critical industries demonstrating higher adaptability, while urban hubs and non-essential sectors faced greater challenges. By providing a micro-level perspective and quantifiable resilience metrics, this study advances the understanding of urban logistics resilience and provides practical insights for policymakers to enhance supply chain reliability in the face of future disruptions.

Keywords: Truck transport networks; COVID-19 resilience; Logistics efficiency; Supply chain disruptions

1. Introduction

During the past years, the coronavirus disease 2019 (COVID-19) emerged as a public health crisis (Benita, 2021; Gibbs et al., 2020). Governments worldwide responded with lockdowns and stringent control measures to curb the spread of the virus, leading to disruptions in economic activities and altering the dynamics of urban systems (Santana et al., 2023; Yabe et al., 2023). After COVID-19 outbreak, urban trucks have played a crucial role in ensuring the uninterrupted functioning of supply chains, supporting healthcare systems, and meeting the evolving needs of urban populations (Lemke et al., 2020; Wu et al., 2022). Especially, trucks were heavily utilized for the distribution of medical supplies, including personal protective equipment and vaccines. This was particularly crucial during the early stages of the pandemic when demand for these items surged dramatically (Cui et al., 2022). Moreover, with lockdowns in place and restrictions on movement, the demand for home deliveries of essential goods such as food and household supplies also increased. Trucks facilitated the timely delivery of these items to both urban and rural areas, ensuring people could adhere to stay-at-home orders while still having access to necessary provisions (Singh et al., 2021). The fluctuating demand for certain products, coupled with workforce shortages and health and safety concerns due to COVID-19 outbreak posed significant challenges to the reliability of urban truck transport networks. Assessing network resilience under the COVID-19 pandemic is crucial for developing effective strategies to address current challenges and prepare for future crises.

The concept of resilience has evolved across diverse disciplines, each offering unique

1 perspectives relevant to urban truck transport networks. In engineering, resilience is often defined as
2 the ability of a system to withstand shocks and return to its original equilibrium, emphasizing
3 robustness and resistance to disturbances (Holling, 1996). This “engineering resilience” perspective
4 highlights the importance of infrastructure robustness in withstanding disruptions. Ecological
5 resilience, in contrast, focuses on the capacity of a system to absorb disturbance and reorganize
6 while undergoing change, emphasizing adaptability and persistence in the face of shocks (Holling,
7 1973). This “ecological resilience” view is particularly pertinent to complex systems like urban freight
8 networks, where adaptability is crucial for navigating unpredictable disruptions. Building upon these
9 foundations, social-ecological resilience theory recognizes the interconnectedness of human and
10 natural systems, emphasizing the adaptive capacity of complex socio-technical systems to navigate
11 change and maintain essential functions (Gunderson, 2000; Walker et al., 2004). Furthermore, in the
12 context of supply chains, resilience is often conceptualized as the ability to anticipate, prepare for,
13 respond to, and recover from disruptions, encompassing dimensions like visibility, agility,
14 diversification, and risk management (Christopher and Peck, 2004; Ponomarev and Holcomb, 2009).
15 These theoretical frameworks collectively underscore that resilience in urban truck transport networks
16 is not merely about resisting shocks but fundamentally about adaptability, learning, and maintaining
17 functionality within a dynamic and uncertain environment.

18 Urban truck transport networks ensure that products are delivered within the expected
19 timeframes, minimizing disruptions to supply chains and meeting the demands of consumers and
20 businesses. The performance of these networks is fundamentally reflected in their efficiency, which
21 can be measured in two aspects: the loading/unloading operations, and the transportation process
22 itself (Pang et al., 2025). However, the COVID-19 pandemic severely impacted this efficiency.
23 Workforce shortages and movement restrictions disrupted loading/unloading and transportation,
24 exacerbating pre-existing urban mobility challenges (Broaddus et al., 2015; Du et al., 2021).
25 Integrating theoretical perspectives and recognizing the centrality of freight systems’ functions, we
26 define the resilience of urban truck transport networks as *“the ability to maintain operational efficiency
27 during disruptions, ensuring the continuous functioning of essential supply chains and the timely delivery
28 of goods.”* This conceptualization positions resilience as a dynamic interplay between maintaining
29 core functions and adapting to unforeseen challenges, providing a robust framework for analyzing
30 and enhancing the performance of urban truck transport networks in crisis scenarios.

31 In the resilience assessment of urban freight transportation systems, previous studies mainly
32 focused on the structural resilience related to natural disasters (such as flooding, earthquake, or
33 hurricane) (Bell and Bristow, 2022; Ding and Wu, 2023; Fialkoff et al., 2017; Gabela and Sarmiento,
34 2020; Rowell and Goodchild, 2017) and human-made events (such as operational shutdowns, attacks,
35 or road crashes) (Chen and Miller-Hooks, 2012; Cox et al., 2011; Loo and Leung, 2017; Song et al.,
36 2023a; Song et al., 2023b; Su et al., 2023; Vani and Maoh, 2023; Wang et al., 2024a) on infrastructure.
37 In the context of pandemic research, most previous studies relied on aggregated socio-economic data
38 to offer a broad understanding of pandemic-induced impacts on supply chain operations at company
39 levels (Cai et al., 2023; Castillo et al., 2022; Fandreyewska et al., 2022; Kaur et al., 2020; Koleva and
40 Chankov, 2022; Settey et al., 2021; Suguna et al., 2021; Sulkowski et al., 2022; Theodorou et al., 2023).
41 Limited attention has been given to how urban truck transport systems maintain operational
42 efficiency and service reliability during disruptions triggered by the pandemic. A comprehensive
43 analysis integrating new fine-grained datasets is needed to further explore the resilience of truck
44 transport networks.

1 To fill in the previous gaps, in the paper, we provide a new data source of individual truck
2 movements in cities before and during COVID-19 pandemic, aiming to assess the resilience of urban
3 truck transport networks from a micro-level perspective. First, we use data fusion techniques to
4 extract truck flows between locations from large-scale GPS data, capturing changes in freight
5 demand across different locations and industries due to the outbreak of the pandemic. We analyze
6 how the demand for goods shifted due to pandemic-related disruptions and to identify which
7 locations and industries experienced the most significant changes. Next, based on individual truck
8 operational data, we define two quantifiable metrics, i.e., company handling efficiency and truck
9 transport efficiency, to measure the resilience of truck transport networks. By analyzing the resilience
10 metrics, we examine the specific impacts of the COVID-19 pandemic across geographic regions
11 (including urban and rural areas), freight hubs and industries (including essential and non-essential
12 sectors) and assess network resilience. Finally, based on the findings, we offer insights for
13 policymakers seeking to enhance network resilience in future crises.

14 Our study makes three key contributions to literature. (1) By utilizing individual truck movement
15 data, we offer a micro-level analysis of urban truck transport network resilience during the COVID-19
16 pandemic. This approach provides a deeper understanding of how disruptions affected specific
17 locations and industries, moving beyond general socio-economic trends. (2) We introduce a set of
18 quantifiable indicators that assess the resilience of urban truck transport networks. These indicators
19 allow for a comprehensive evaluation of how disruptions, such as labor shortages and transportation
20 restrictions, impacted network performance. (3) Our findings offer practical insights for policymakers,
21 helping develop targeted strategies to enhance the resilience of urban truck transport systems. By
22 identifying the varying impacts of the pandemic across different regions and industries, we provide
23 guidance for strengthening the resilience of these systems in future crises.

24 The remainder of this paper is organized as follows: **Section 2** gives the literature review. **Section**
25 **3** provides data sources and network resilience assessment. **Section 4** analyzes the research results.
26 **Section 5** discusses practical implications derived from research findings. **Section 6** at the end, offers
27 concluding insights.

28 **2. Literature Review**

29 The resilience of urban truck transport networks has been a growing area of research in recent
30 years, particularly in light of disruptions caused by unforeseen events, such as natural disasters (Bell
31 and Bristow, 2022; Ding and Wu, 2023; Fialkoff et al., 2017; Gabela and Sarmiento, 2020; Rowell and
32 Goodchild, 2017), human-made events (Chen and Miller-Hooks, 2012; Cox et al., 2011; Loo and Leung,
33 2017; Vani and Maoh, 2023; Wu et al., 2023). Scholars have explored different dimensions of
34 resilience (Gauthier et al., 2018; Jansuwan et al., 2021; Pant et al., 2014; Testa et al., 2015), ranging
35 from the ability of transport systems to adapt to shocks to the efficiency with which they recover from
36 disruptions (Chen and Miller-Hooks, 2012).

37 Urban truck transport system resilience is commonly analyzed through two dimensions:
38 structural resilience and functional resilience. Structural resilience (Achillopoulou et al., 2020;
39 Argyroudis et al., 2019; Chen et al., 2015) pertains to the physical infrastructure that supports urban
40 truck transport systems, encompassing roads, bridges, tunnels, warehouses and intermodal facilities.
41 This dimension emphasizes robustness, durability, and the ability of infrastructure to withstand
42 external shocks. Research highlights that resilient infrastructure is crucial in mitigating disruptions,
43 such as road closures or infrastructure damage, caused by natural disasters or high-demand periods.

1 For instance, Khademi et al. (2015) examined the aftermath of earthquakes in urban areas,
2 demonstrating how structural vulnerabilities in key facilities can amplify logistical challenges.
3 Similarly, Hao and Wang (2022) identified the role of urban planning in reinforcing the physical
4 resilience of road networks to withstand extreme weather events.

5 Functional resilience (Akyuz et al., 2023; Kulkarni et al., 2022; Mahmud et al., 2021; Pahwa and
6 Jaller, 2023), in contrast, examines the operational performance of urban truck transport systems
7 during disruptions. It evaluates the capacity of the network to maintain service reliability, timely
8 deliveries, and overall efficiency under adverse conditions. Unlike structural resilience, functional
9 resilience focuses on adaptive responses to external shocks, such as re-routing deliveries, adjusting
10 schedules, or prioritizing critical shipments (Akyuz et al., 2023). This perspective of functional
11 resilience aligns with our definition of resilience in this study, which is the ability to maintain
12 operational efficiency during disruptions, ensuring the continuous functioning of essential supply
13 chains and the timely delivery of goods. Previous studies (Beer et al., 2022; Ferreira et al., 2017; Potter
14 et al., 2022; Solomon et al., 2019; Trotter and Ivory, 2019) have highlighted that regulatory measures,
15 such as traffic restrictions and emissions controls, pose significant challenges to the functional
16 resilience of urban truck transport systems. These regulations can create operational difficulties that
17 affect the ability of truck networks to maintain efficiency, especially during disruptions. For instance,
18 studies (Broaddus et al., 2015; Du et al., 2021) have shown that in cities with strict congestion
19 charges or emission limits, freight operators must frequently adjust their routes or schedules to avoid
20 restricted areas, leading to longer travel times and reduced reliability in meeting delivery deadlines.

21 The resilience of urban truck transport networks builds on a foundation shaped by pre-pandemic
22 regulatory and structural conditions, which influenced their capacity to respond to disruptions like the
23 COVID-19 crisis. Prior to the pandemic, urban freight systems operated under diverse regulatory
24 frameworks, such as congestion pricing, emission zones, and time-of-day restrictions, which
25 constrained truck mobility and operational flexibility (Cui et al., 2015). For example, cities with
26 established low-emission zones required logistics operators to adopt cleaner fleets or adjust
27 schedules, potentially enhancing adaptability to later restrictions but also increasing operational
28 costs. Structurally, the resilience of transport networks depended on the robustness of physical
29 infrastructure—roads, bridges, and warehouses—which varied widely across urban areas
30 (Holguín-Veras et al., 2020). In some regions, well-developed intermodal facilities and road networks
31 provided a buffer against disruptions, while in others, aging infrastructure posed vulnerabilities (Dey et
32 al., 2015). These pre-existing conditions set the stage for the functional resilience observed during the
33 pandemic, as networks with stronger baselines could leverage prior investments in adaptive
34 strategies (e.g., route optimization) or infrastructure durability to mitigate new challenges.
35 Furthermore, research beyond freight transport also emphasizes the importance of pre-existing
36 conditions, as seen in studies of airline passenger responses to uncertainty (Huderek-Glapska and
37 Antczak, 2025), urban rail proximity dynamics (Tsai, 2024), carbon and freight market (Tsai, 2025; Xu
38 et al., 2024; Xu et al., 2022a), which collectively highlight how prior contexts shape resilience across
39 transport sectors.

40 The COVID-19 pandemic has brought functional resilience into sharp focus, as maintaining
41 supply chain efficiency became critical in the face of widespread disruptions (Li et al., 2022). The
42 existing literature primarily relied on aggregated socio-economic data to offer a broad understanding
43 of pandemic-induced impacts on supply chain operations at company levels. For example, research
44 (Belbag, 2022; Burlea-Schiopoiu et al., 2022; Cai et al., 2023; Fandreyewska et al., 2022; Gu et al., 2021;

1 Hoda et al., 2020; Koleva and Chankov, 2022; Roggeveen and Sethuraman, 2020; Theodorou et al.,
2 2023) has been the examination of how changes in consumer behavior, driven by lockdowns and
3 social distancing measures, have influenced the demand for goods within urban areas. The surge in
4 online shopping and home deliveries during the pandemic has prompted a reevaluation of last-mile
5 delivery strategies of logistics companies. Studies (Chowdhury et al., 2021; Hohenstein, 2022; Pahwa
6 and Jaller, 2023; Xu et al., 2022b; Yang et al., 2021b; Zhang et al., 2023; Zhao et al., 2022; Zheng et al.,
7 2021) have explored how logistics operators adapted to increased demand, addressing challenges
8 related to delivery speed, efficiency, and the optimization of routes to meet the evolving needs of
9 urban consumers. Moreover, research has explored how urban freight stakeholders navigated these
10 disruptions, highlighting strategies such as diversification of suppliers, inventory management, and
11 contingency planning to ensure a steady flow of goods (Dablanc et al., 2022; Puram et al., 2022;
12 Suguna et al., 2021; Sulkowski et al., 2022).

13 In summary, although existing research has enhanced our understanding of the impact of
14 COVID-19 on demand patterns and the strategic responses of supply chain companies, there is a
15 notable gap in the literature regarding the resilience of truck transport networks. Specifically, limited
16 attention has been given to how these systems maintain operational efficiency and service reliability
17 during disruptions triggered by the pandemic. The specific urban truck mobility challenges
18 exacerbated by the pandemic remain also underexplored. This limitation hinders the development of
19 more effective policies and solutions for maintaining supply chain efficiency in future crises.

20 **3. Methodology and data**

21 In the paper, we first construct urban truck transport networks before and during COVID-19
22 pandemic by obtaining truck flows between locations (see **Section 3.1**), and then define resilience
23 metrics with a focus on network efficiency (see **Section 3.2**). Next, using the metrics, we assess
24 network resilience across geographic regions, freight hubs and industries (see **Section 3.3**). The
25 methodology framework is shown in **Fig. 1**.

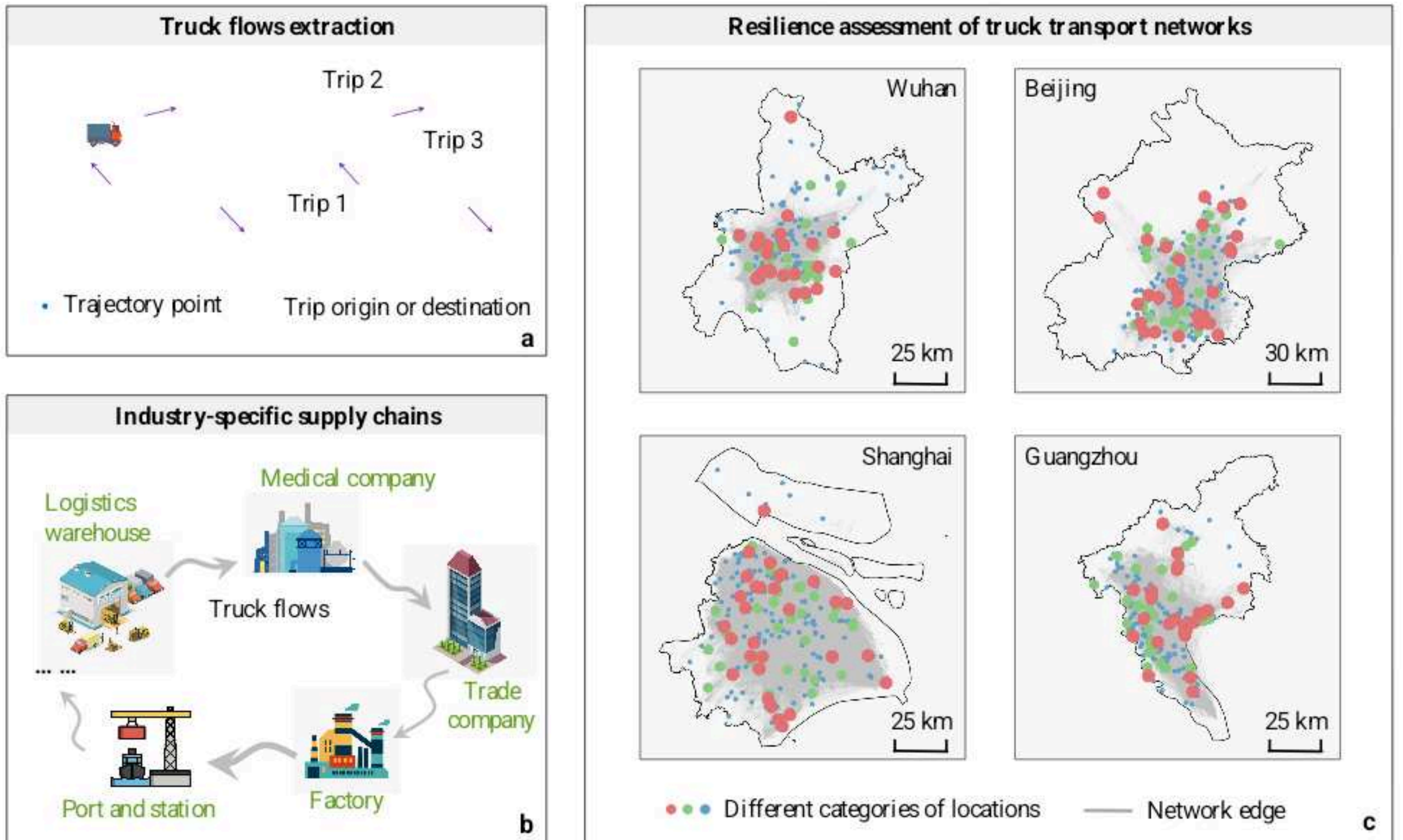


Fig. 1. Methodology framework. **a** The extraction of truck flows between locations from truck GPS data. A truck origin-destination (OD) identification method is employed to obtain the trips of each truck from its trajectory points. **b** The analysis of industry-specific supply chains by quantifying the truck flows between locations. Each location is labelled by industrial category provided by urban point-of-interest (POI) dataset. **c** The assessment of resilience of urban truck transport networks by using the truck flows before and after the COVID-19 pandemic outbreak.

3.1. Data

We use two datasets, i.e., truck GPS data and freight-related POI data, to obtain the truck flows between locations before and after the COVID-19 outbreak, and to construct urban truck transport networks.

3.1.1. Truck GPS data

The purpose of collecting GPS data for trucks was to capture the immediate impact of the COVID-19 pandemic on urban truck transport networks. The initial outbreak of COVID-19 was identified in Wuhan, China, leading to the official lockdown of the city on January 23, 2020. The lockdown of Wuhan marked a significant turning point, as it was the first city to implement strict measures to contain the virus. In response to Wuhan's lockdown, other cities across China quickly adopted similar restrictions, leading to nationwide limitations on movement and economic activities. To capture the immediate effects of these unprecedented measures, we selected a time span of one week before and one week after the Wuhan lockdown, specifically from January 16, 2020, to January 30, 2020. This period allows us to observe the initial shock to the truck transport network and its rapid adjustments in the face of new constraints. By selecting this specific timeframe, we ensure that our analysis captures the direct impact of the initial lockdown measures during the early stages of the COVID-19 pandemic.

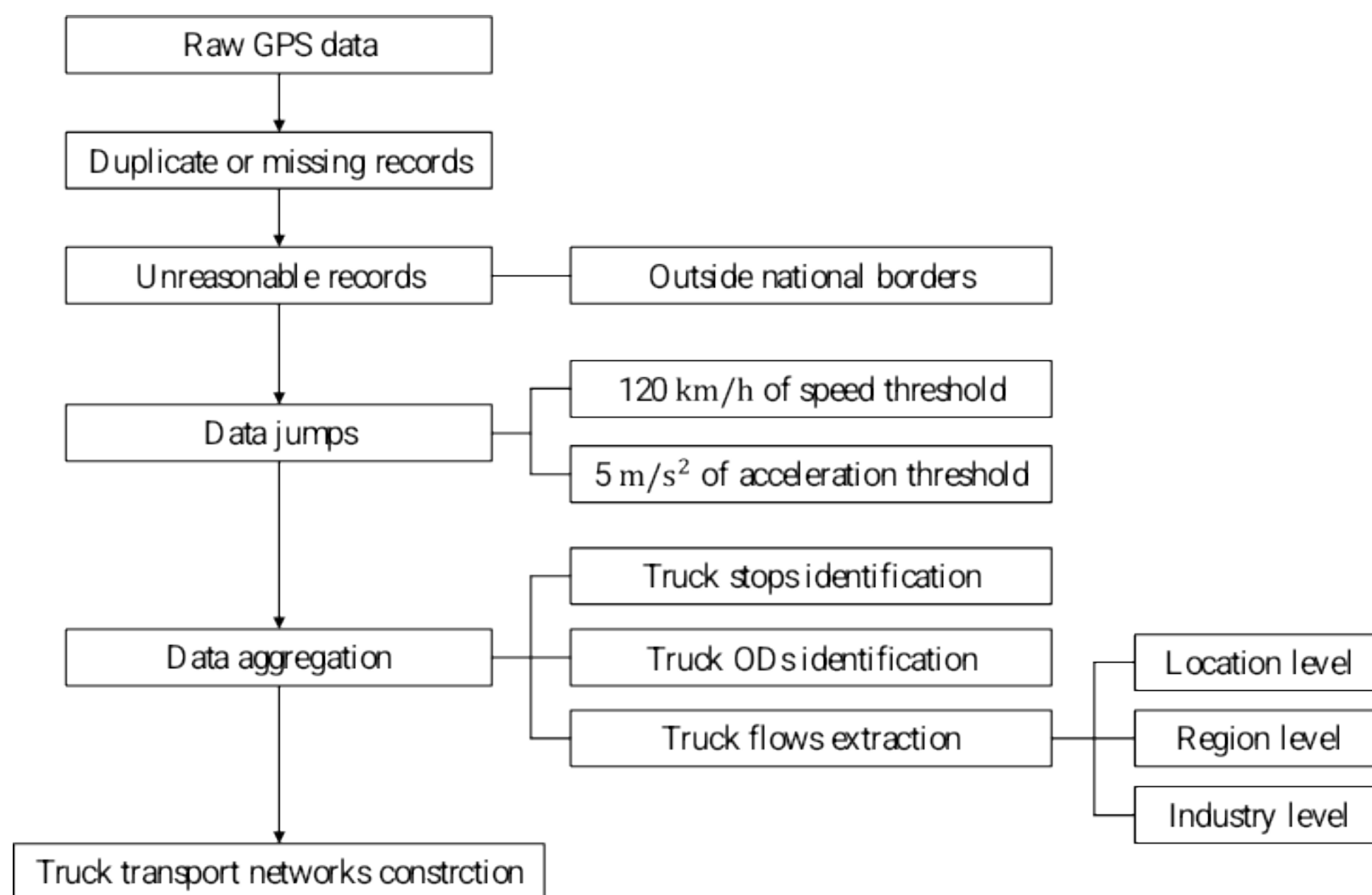
1 GPS dataset was sourced from the China Road Freight Supervision and Service Platform, an
2 integrated system dedicated to monitoring and improving the efficiency of road freight operations
3 nationwide. Functioning as a centralized platform, it utilizes technology, data, and logistics to
4 supervise, manage, and optimize the transportation of goods via road networks across the country.
5 The platform records the real-time geographic locations of all activated freight trucks in China. The
6 GPS records are uploaded to the platform every 30 seconds. The number of GPS records is greater
7 than 30 billion. The data attributes include identifier, geographic coordinates, speed, activation status,
8 and timestamps.

9 3.1.2. Freight-related POI data

10 The freight-related POI data were obtained through web crawling from Amap utilizing the
11 provided application programming interface (API). Within the Amap application, developers organize
12 POIs in a hierarchical structure based on industry categories. We choose three categories of POIs.
13 Category one encompasses freight companies involved in metallurgy, medicine, telecommunication,
14 construction, networking, trade, decoration, machinery, minerals, and factories. The second category
15 comprises freight markets such as supermarkets, building material markets, home appliance markets,
16 integrated markets, industrial parks, and agricultural bases. The third category includes freight
17 facilities like transportation terminals (e.g., train stations, airports, and ports) and logistics nodes (e.g.,
18 warehouses and distribution centers). These different categories of locations are used to construct
19 truck transport networks, and to analyze industry-specific supply chains within urban areas.

20 3.1.3. Data processing and aggregation

21 GPS data often contain errors and redundant information, especially in challenging urban
22 environments like city canyons or tunnels where signal reflection and obstruction occur. To ensure
23 data accuracy and reliability, preprocessing steps are essential. Three main types of abnormal data
24 are considered: duplicate or missing records, unreasonable data points (e.g., those outside national
25 borders), and data jumps, as shown in **Fig. 2**.



26
27 **Fig. 2.** Flowchart of data processing and aggregation.

1 Duplicate or missing records are straightforwardly removed to maintain data integrity. Similarly,
2 unreasonable data points are eliminated, such as those beyond national borders. For data jumps, we
3 calculate average speed and acceleration between successive GPS points, removing records
4 exceeding 120 km/h or 5 m/s². These thresholds are justified by freight vehicle operational realities:
5 120 km/h aligns with maximum legal highway speed limits (typically 100–110 km/h) and exceeds
6 typical freight truck capabilities, ensuring only erroneous jumps are excluded; 5 m/s² reflects the
7 upper limit of heavy vehicle acceleration (normally < 3 m/s²), accommodating extreme cases like
8 emergency braking while filtering implausible GPS errors, as supported by vehicle dynamics studies
9 (Jiang et al., 2023; Reyes et al., 2022). To confirm robustness, we conducted a sensitivity analysis,
10 testing speed thresholds from 100 km/h to 150 km/h, acceleration from 3 m/s² to 7 m/s². **Table 1**
11 presents the percentage of data removed at each threshold setting. The results demonstrate that
12 across a reasonable range of threshold values for both speed and acceleration, the variation of
13 percentage of retained data remains minimal. This limited sensitivity to threshold adjustments
14 confirms the robustness of our preprocessing, ensuring that minor alterations to these thresholds
15 would not significantly affect the volume of data available for analysis. Preprocessing may result in
16 large time intervals between successive GPS points due to signal loss. To ensure the usefulness of
17 the data, we adopt a threshold of 1 hour between successive records, following prior research (Ma et
18 al., 2011; Yang et al., 2022c). Freight trips with intervals exceeding this threshold are discarded to
19 mitigate the limitations imposed by excessively long gaps in data availability.

20 **Table 1.** Sensitivity Analysis Results for Threshold Selection

Parameter	Test Range	Retained Data (%)	Selected Threshold	Retained at Selected (%)
Speed	100–150 km/h	96.2–98.7	120 km/h	98.1
Acceleration	3–7 m/s ²	94.1–95.4	5 m/s ²	94.7

21 After the preprocessing steps, the cleaned GPS data are ready for further analysis. In this study,
22 we use GPS data to measure the changes in freight demand due to the outbreak of COVID-19
23 pandemic, and to assess resilience of truck transport networks. To this end, we conduct a data
24 aggregation process to obtain truck flows from GPS data on different levels. First, we use a
25 data-driven method (Yang et al., 2022b) to identify truck stops from GPS trajectories. In this method, a
26 city-specific speed threshold is defined by capturing the characteristics of the speed distribution for
27 all trucks. This speed threshold is used to ascertain whether a truck is stationary. Second, we employ
28 a cutting-edge nonparametric iterative technique known as the Loubar method (Bassolas et al., 2019;
29 Louail et al., 2014) to determine the multilevel time thresholds, which are dynamically selected to
30 identify truck ODs from stops according to the circuitous degree of travel routes. More details can be
31 found in the work of Yang et al. (2022b). Third, we extract aggregated truck flows across locations,
32 regions and industries for two periods, i.e., before pandemic and during pandemic. At the location
33 level, we analyze freight demand by calculating the total number of truck trips associated with
34 specific locations during both the pre-pandemic and pandemic periods. This allows us to analyze how
35 freight activity has changed at key locations. At the region level, we aggregate truck trips to assess
36 freight demand within urban areas, within suburban areas, and between urban and suburban areas for
37 both periods. This regional segmentation aims to identify freight patterns shifted across different
38 geographic contexts. At the industry level, we map the truck trips to specific industries, calculating the
39 freight demand for various sectors for both periods. This enables us to assess how different
40 industries have been affected.

After the data aggregation, we can obtain the freight demand (i.e., number of truck trips) between different categories of locations, as shown in **Fig. 1b**. we construct urban truck transport networks according to the obtaining truck flows, as shown in **Fig. 1c**. The network is a directed weighted network $G(N, E, W)$, where N is the set of nodes coordinated by longitude and latitude; E is the set of edges and W is the set of edge weights, i.e., number of truck trips. The node represents freight-related location or POI with industrial category attribute. The edge represents spatial interactions between locations. We construct two truck transport networks of a city, i.e., the first one G_1 before pandemic, and the second one G_2 during pandemic, based on the truck flows in these two periods.

3.2. Definition of network resilience metrics

During the pandemic, demand for goods fluctuated unpredictably, with surges in certain sectors and sharp declines in others. In the face of such volatility, a key characteristic of a resilient truck transport network is its adaptability – its capacity to effectively respond to these fluctuating demands from businesses and populations while maintaining timely and reliable delivery services. This adaptability is intrinsically linked to operational efficiency (Choudhry and Qian, 2024; Yang et al., 2023b), which reflect how effectively truck transport networks adjust to sudden changes in demand and disruptions, serves as a critical manifestation of network adaptability. Therefore, in this study, we define network resilience metrics specifically related to operational efficiency at the location, region, and industry levels. By focusing on these efficiency metrics, we aim to quantify and assess the network's adaptability, and thus its overall resilience, in the face of pandemic-related disruptions and beyond.

3.2.1. Location-level metrics

At the location level, we introduce two dimensions of operational efficiency, i.e., handling efficiency at loading or unloading locations, and truck transport efficiency between locations. These two dimensions collectively address the full scope of a truck's journey within urban logistics system, from the moment goods are loaded to their delivery to end-users. First, handling efficiency reflects the speed and effectiveness of loading and unloading operations at distribution centers, warehouses, and other delivery points. During the COVID-19 pandemic, handling efficiency might be impacted by workforce shortages and social distancing measures in logistics companies, leading to slower loading and unloading processes (Nguyen and Kim, 2024). This posed challenges to network resilience by increasing truck wait times, thereby hindering the timely delivery of goods. The handling efficiency H_i of specific location i is defined as

$$H_i = \frac{1}{DT_i} , \quad (1)$$

where DT_i represents the average dwell time for trucks loading or unloading at location i . A higher H_i indicates a more efficient handling process, where trucks spend less time waiting to load or unload.

Second, truck transport efficiency between locations reflects the ability of trucks to navigate urban road networks swiftly and reliably, delivering goods to their destinations within the expected timeframe. This dimension is particularly sensitive to external factors, including road closures and

1 government-imposed movement restrictions during pandemic crises. These factors challenge
 2 network resilience by hindering timely deliveries. The transport efficiency Γ_{ij} between location i and
 3 j is defined as

$$4 \quad \Gamma_{ij} = \frac{1}{TT_{ij}}, \quad (2)$$

5 where TT_{ij} represents the average transport time for trucks traveling from location i to j . A higher
 6 Γ_{ij} indicates that trucks are able to travel between locations efficiently, with shorter transport times.

7 **3.2.2. Region-level metrics**

8 At the region level, network resilience metrics expand to encompass the operational efficiency of
 9 truck transport systems within specific regions, including both urban and suburban areas. This
 10 involves the average handling efficiency H_{region} within urban and suburban areas, as well as the
 11 average truck transport efficiency Γ_{region} for routes within urban areas, within suburban areas, and
 12 between urban and suburban areas. Specifically, the region-level handling efficiency H_{region} can be
 13 expressed as inversely proportional to the average dwell time across all locations within the region

$$14 \quad H_{\text{region}} = \frac{N}{\sum_{i \in R} DT_i}, \quad (3)$$

15 where N is the total number of locations in the region R (urban or suburban). A higher H_{region}
 16 indicates better handling efficiency, as trucks spend less time waiting at logistics facilities across the
 17 region. The region-level transport efficiency Γ_{region} reflects the ability of trucks to move efficiently
 18 within and between regions. This metric evaluates transport times across all relevant location pairs
 19 and is defined as

$$20 \quad \Gamma_{\text{region}} = \frac{M}{\sum_{(i,j) \in R} TT_{ij}}, \quad (4)$$

21 where M is the total number of location pairs within the region or between regions R . A higher
 22 Γ_{region} signifies more efficient transport, with shorter travel times across the region's routes.

23 **3.2.3. Industry-level metrics**

24 At the industry level, network resilience metrics evaluate the operational efficiency of truck
 25 transport systems within specific industry sectors. These metrics provide a focused perspective on
 26 how well logistics networks serve the unique needs of industries during disruptions like the COVID-19
 27 pandemic. The industry-level handling efficiency H_{industry} reflects the average effectiveness of
 28 loading and unloading operations at locations serving a particular industry, defined as

$$29 \quad H_{\text{industry}} = \frac{N}{\sum_{i \in I} DT_i}, \quad (5)$$

30 where N is the total number of locations serving the industry I . A higher H_{industry} indicates greater
 31 handling efficiency, essential for industries requiring time-sensitive logistics. The industry-level
 32 transport efficiency Γ_{industry} measures the effectiveness of goods movement within the supply chain
 33 of a specific industry or between industries. The metric is defined as

$$\Gamma_{\text{industry}} = \frac{M}{\sum_{(i,j) \in I} TT_{ij}}, \quad (6)$$

where M is the total number of location pairs within the specific industry or between industries I . A higher Γ_{industry} indicates more efficient transport operations, which is critical for maintaining the flow of goods within an industry's supply chain or in inter-industry collaboration.

3.3. Assessment of truck transport networks resilience

To assess the resilience of urban truck transport networks under the COVID-19 pandemic, we employ a two-step approach. In the first step, truck movement data derived from large-scale GPS records is analyzed to quantify changes in freight flows and spatial interactions across the network. This involves mapping the volume and direction of truck movements to identify shifts in freight demand, the emergence of new freight hubs, and the decline of existing ones. By comparing patterns from the pre-pandemic and pandemic periods, we aim to uncover significant changes in the spatial distribution of freight activities. Particular attention is paid to variations in truck movements to and from essential service locations, urban centers, and suburban areas to understand how demand evolved in response to the crisis. The second step focuses on evaluating the operational efficiency of the truck transport network using the resilience metrics defined in **Section 3.2**. This step examines whether the network could adapt to the fluctuating demand and maintain reliable service during the pandemic across locations, regions and industries.

Specifically, at the location level, the analysis examines handling efficiency and transport efficiency metrics to understand how facilities and routes adapted to fluctuating demand. Handling efficiency is measured by the throughput of goods at specific locations compared to pre-pandemic levels, highlighting facilities that maintained or increased output despite constraints. Transport efficiency is evaluated by monitoring the consistency of travel times for trucks between origin-destination pairs. Locations minimizing disruptions and maintaining reliable delivery times under restrictions demonstrate logistical resilience.

At the region level, resilience is analyzed through regional handling efficiency and regional transport efficiency metrics, focusing on geographic zones like urban centers and suburbs. Regional handling efficiency evaluates the cumulative throughput of goods across all facilities in a region, identifying areas sustaining operations despite challenges. Regional transport efficiency measures the reliability and speed of truck movements within and between regions. This metric highlights resilient urban-suburban connections that should ensure supply chain continuity for essential goods during the pandemic.

At the industry level, the analysis focuses on industry handling efficiency and industry transport efficiency to assess sector-specific performance. Industry handling efficiency measures the ability of logistics facilities within a sector to maintain throughput under pandemic conditions, focusing on sectors like healthcare and food with increased demand. Industry transport efficiency evaluates the reliability of truck movements supporting a sector's supply chain. Sectors achieving stable transport times despite disruptions demonstrate greater resilience.

4. Results and analysis

In this section, we assess network resilience, defined as the ability to maintain operational efficiency during disruptions, by examining whether truck transport networks were able to meet the evolving demands of freight hubs and industry-specific supply chains during the pandemic. We select

1 four typical cities in China, i.e., Wuhan, Beijing, Shanghai, and Guangzhou, for case studies. For each
2 city, we construct two truck transport networks for pre-pandemic (i.e., network G_1) and
3 post-pandemic (i.e., network G_2) periods respectively. We analyze the changes in freight demand by
4 comparing the truck flows between these two networks in a city, focusing on shifts in key locations
5 and sectors. Next, based on resilience metrics, we assess the operational efficiency of truck transport
6 networks, identifying the capacity to adapt to demand fluctuations and maintain reliable service
7 across urban regions (see **Section 4.1**), freight hubs (see **Section 4.2**) and industry-specific supply
8 chains (see **Section 4.3**).

9 **4.1. Network resilience across regions**

10 To visualize the spatial distribution of freight demand and its changes due to the pandemic, we
11 present the constructed truck transport networks of the four case cities in **Fig. 3** for both
12 pre-pandemic (panels a-d) and post-pandemic (panels e-h) periods. We first calculate the node freight
13 demand, i.e., sum of truck inflows and outflows of each node, and utilize the Gini coefficient (Gini,
14 1997) to quantify the inequality of freight demand among nodes in these two networks. The size and
15 color of each node in **Fig. 3** represent its freight demand, allowing for a visual comparison of demand
16 intensity across locations and time periods. The boundaries delineate urban and suburban areas,
17 providing a geographic context for demand distribution. The results indicate that the Gini coefficient
18 of pre-pandemic network G_1 is significantly larger than that of post-pandemic network G_2 . This
19 change suggests that, before the COVID-19 pandemic, freight demand was more unevenly distributed
20 across the truck transport networks, with certain regions (particularly urban areas) shouldering a
21 disproportionate share of the total freight traffic (Cidell, 2010; Lv et al., 2024; Yang et al., 2024c).
22 However, during the COVID-19 pandemic, both urban and suburban areas experienced a decline in
23 freight demand due to the disruptions. The decrease in freight demand was more pronounced in
24 urban areas, where the slowdown of economic activity led to a significant reduction in freight flows.
25 Although suburban areas also saw a drop in freight traffic, the impact was less severe, leading to a
26 relative increase in freight demand in these regions (Jia et al., 2023; Lin et al., 2023). As a result, the
27 freight flows across regions became more evenly distributed, with suburban areas experiencing a
28 smaller decline in demand compared to the urban areas. This shift is reflected in the reduced Gini
29 coefficient in G_2 . This spatial rebalancing of freight demand underscores a critical lesson for urban
30 logistics systems: over-reliance on centralized urban hubs amplifies systemic risks during crises. The
31 pandemic-induced decentralization highlights the need for diversified logistics networks that integrate
32 suburban areas as complementary nodes. Such a strategy could enhance resilience by redistributing
33 pressure from overburdened urban cores, aligning with global trends in sustainable urban freight
34 planning (Pan et al., 2021).

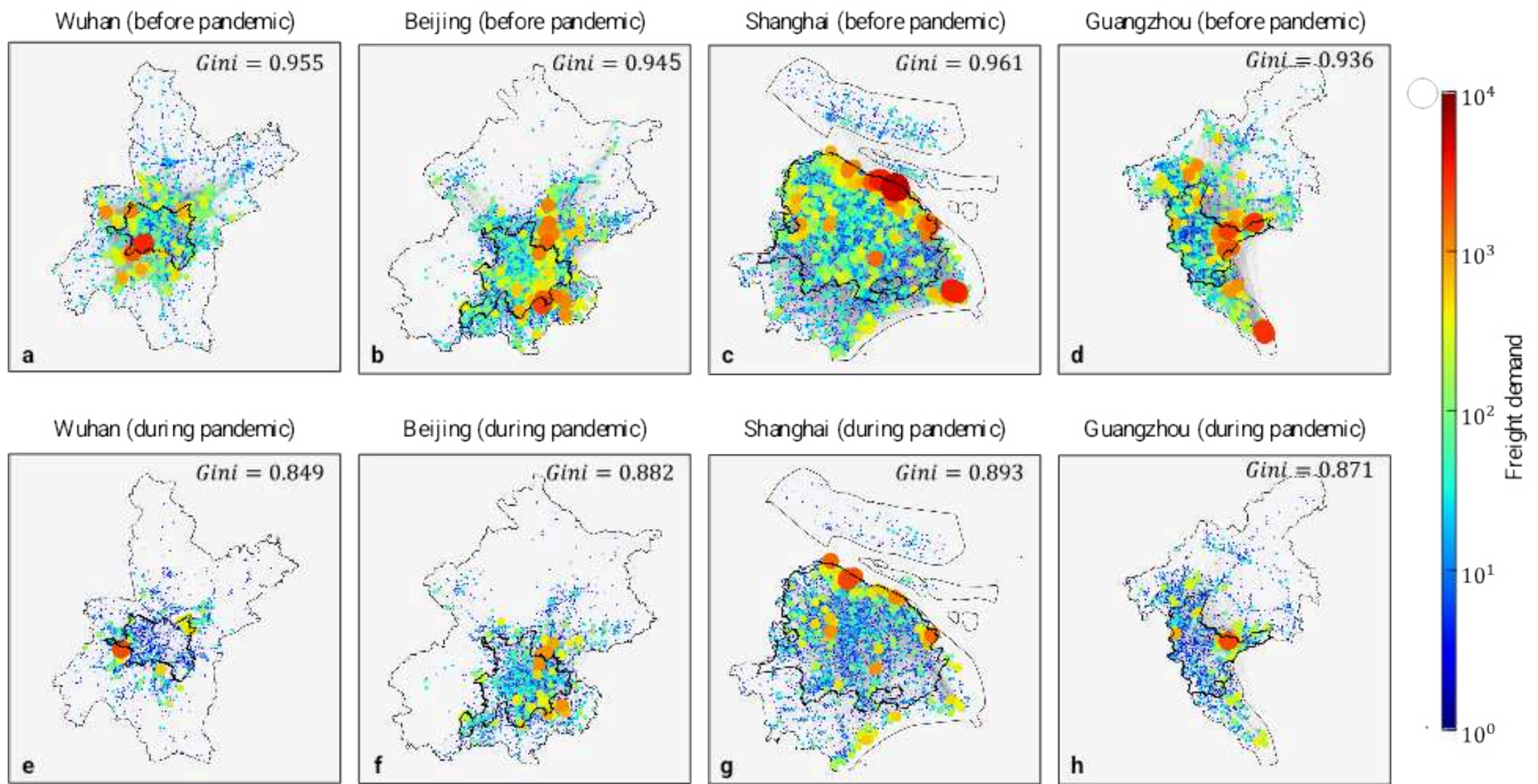


Fig. 3. Illustration of truck transport networks of four case cities during the pre-pandemic (panels **a-d**) and post-pandemic (panels **e-h**) periods. The point and line represent network node and edge. Size and color of each node indicate its freight demand, i.e., sum of truck inflow and outflow. The boundary within each city denote the urban areas, while the remaining regions represent the suburban areas. The Gini coefficient is calculated for the freight demand across all locations in the city.

To understand how effectively the networks adapted to fluctuating demand across different geographic areas, we calculate region-level resilience metrics to assess the operational efficiency of truck transport networks in both urban and suburban areas, as shown in **Fig. 4**, which visualizes changes in region-level operational efficiency for urban and suburban areas within each city. **Fig. 4a** illustrates handling efficiency changes, with bars showing pre- and post-pandemic values for urban and suburban areas across the four cities. In Wuhan and Beijing, suburban areas exhibited higher handling efficiency both before and during the pandemic, while urban areas experienced a more substantial decline. This suggests that urban regions, with their higher traffic density and logistics complexity, were more vulnerable to disruptions (Yang et al., 2024b). In Shanghai, however, urban areas demonstrated greater resilience, likely due to more adaptive logistics systems and better infrastructure, which helped mitigate the pandemic's impact on handling efficiency. In contrast, Guangzhou saw urban areas maintaining higher handling efficiency overall, but suburban regions experienced a larger drop. This indicates that suburban areas in Guangzhou were more susceptible to pandemic-related disruptions, possibly due to limited resources or logistical challenges in these regions (Zhi et al., 2024b). Higher handling efficiency is associated with reduced truck wait times at logistics facilities, ensuring more timely deliveries. The regional disparities highlight the greater vulnerability of urban areas to disruptions during the pandemic, while suburban areas, with fewer bottlenecks and lower traffic volumes, exhibited relative stability. These findings challenge the conventional wisdom that urban-centric logistics systems inherently maximize efficiency. Instead, they reveal a trade-off between pre-pandemic efficiency and crisis resilience, emphasizing the value of suburban buffer zones in absorbing demand shocks—a concept aligned with the 15-minute city

1 framework for decentralized urban logistics (Teixeira et al., 2024).

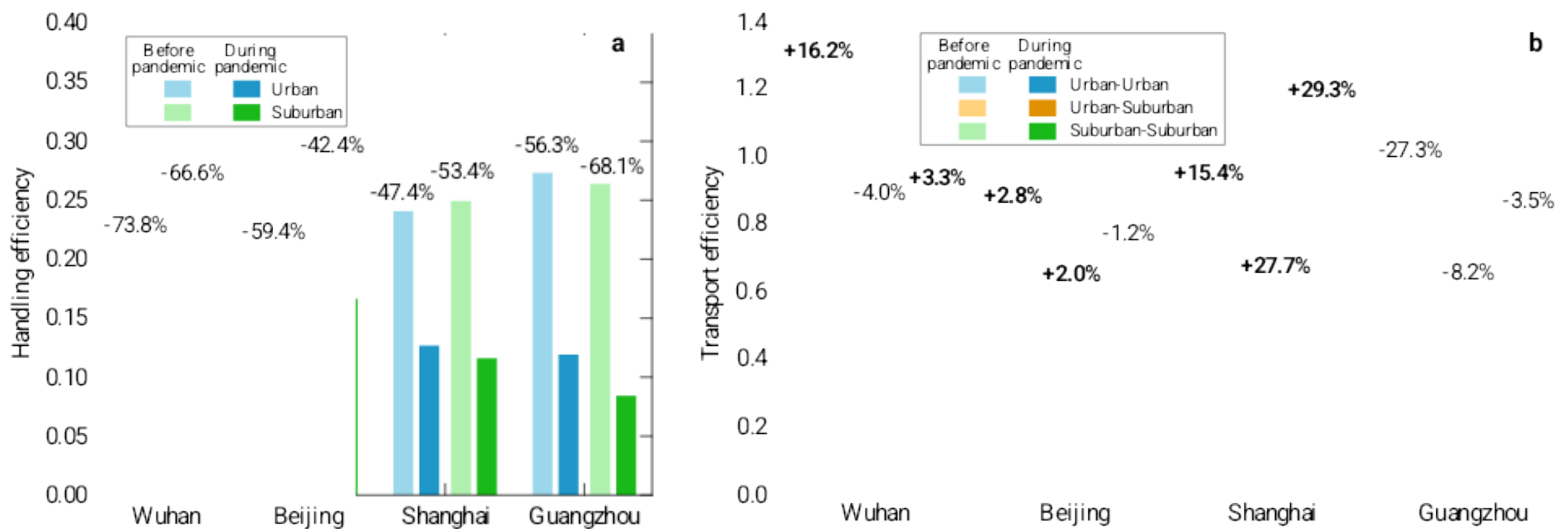


Fig. 4. Changes in region-level operational efficiency of truck transport networks.

In contrast, transport efficiency across regions showed a more varied response to the pandemic, as shown in **Fig. 4b**. Transport efficiency trends emerge: upward bars in Shanghai (e.g., 15.4% urban, 29.3% suburban, 27.7% inter-regional) highlight significant improvements, depicted as taller post-pandemic bars. These improvements in Shanghai reflect a high level of network resilience, where the logistics system leveraged the lower congestion levels to enhance operational efficiency across all regions (Yang et al., 2024a). However, cities like Guangzhou saw a significant decline in transport efficiency, particularly in urban areas, where efficiency dropped by 27.3%. Stricter mobility restrictions, less adaptive logistics infrastructure or delays in addressing pandemic-induced disruptions could have contributed to these inefficiencies (Gonzalez et al., 2022). The contrasting outcomes in Shanghai and Guangzhou illustrate the pivotal role of governance and infrastructure preparedness. Shanghai's success in maintaining transport efficiency aligns with its status as a global logistics hub with advanced digital tracking systems and flexible routing protocols (Lyu et al., 2023), whereas Guangzhou's struggles reflect gaps in crisis-responsive infrastructure—a cautionary tale for cities prioritizing short-term efficiency over long-term adaptability.

Overall, the findings highlight varying levels of network resilience across cities and regions during the pandemic. Urban areas, with their higher logistical complexity, dense traffic, and greater exposure to mobility restrictions, were generally more vulnerable to disruptions in maintaining operational efficiency, thus exhibiting lower resilience based on our definition. Suburban regions demonstrated greater stability, benefiting from lower traffic volumes and less congestion, indicating higher resilience in terms of maintaining operational efficiency.

4.2. Network resilience across freight hubs

Building upon the regional analysis, this section delves into the resilience of truck transport networks specifically at key freight hubs within the four case cities. We first explore the transformation of freight hubs due to the outbreak of pandemic through network structure analysis, and second assess network resilience by examining whether truck transport networks were able to meet the evolving demands of these freight hubs.

To explore the first aspect of freight hubs transformation, we analyze the changes in truck flows along the edges connected to network nodes between pre-pandemic network G_1 and post-pandemic network G_2 . Specifically, we define the node j that is directly linked to a specific node i as its

1 interacting node $j \in \Gamma(i)$. For each node i , the truck flows between this node and some of its
 2 interacting nodes may increase, while those between this node and other interacting nodes may
 3 decrease due to the pandemic. We calculate the total increased and decreased truck flows between
 4 nodes and their interacting nodes. For simplicity and representativeness, we select the top 10 nodes
 5 in networks G_1 and G_2 with the highest freight demand as hub nodes respectively, and the
 6 distributions are shown in **Fig. 5**, which presents a scatter plot illustrating the shift in hub node roles in
 7 each city between the pre-pandemic (panels a-d) and post-pandemic (panels e-h) periods. the
 8 horizontal axis represents the total increase in truck flows for each node, while the vertical axis shows
 9 the total decrease. Nodes located away from the diagonal indicate significant shifts in their hub roles.
 10 The results suggest different cities exhibit distinct patterns of freight hub transformations. In Wuhan
 11 (**Fig. 5ae**), a significant decrease in truck flows between hub nodes in G_1 and their interacting nodes
 12 led to these nodes losing their hub roles in G_2 , while some nodes saw a surge in demand, becoming
 13 new hubs. In Beijing (**Fig. 5bf**) and Guangzhou (**Fig. 5dh**), the freight hubs in G_2 are distributed around
 14 the diagonal, showing decreased flows with some nodes and increased flows with others. This
 15 asymmetric change reflects a reconfiguration of freight distribution, where some nodes experienced
 16 reduced demand due to supply chain disruptions, while others adapted by strengthening connections
 17 to meet new logistical needs (Castillo et al., 2022; Sulkowski et al., 2022; Yang et al., 2023a). In
 18 Shanghai (**Fig. 5cg**), while some hubs underwent changes, others continued to play central roles in
 19 both networks, indicating a relatively stable overall network structure despite pandemic disruptions.
 20 The hub reconfiguration patterns observed—particularly the emergence of new suburban hubs in
 21 Wuhan and asymmetric flow redistribution in Beijing—mirror the "adaptive multiplex networks"
 22 concept in supply chain resilience (Wang et al., 2024b). These shifts suggest that resilience during
 23 crises depends not only on infrastructure robustness but also on the dynamic rewiring of connections,
 24 which enables systems to bypass disrupted nodes—a mechanism critical for maintaining continuity in
 25 essential goods delivery.

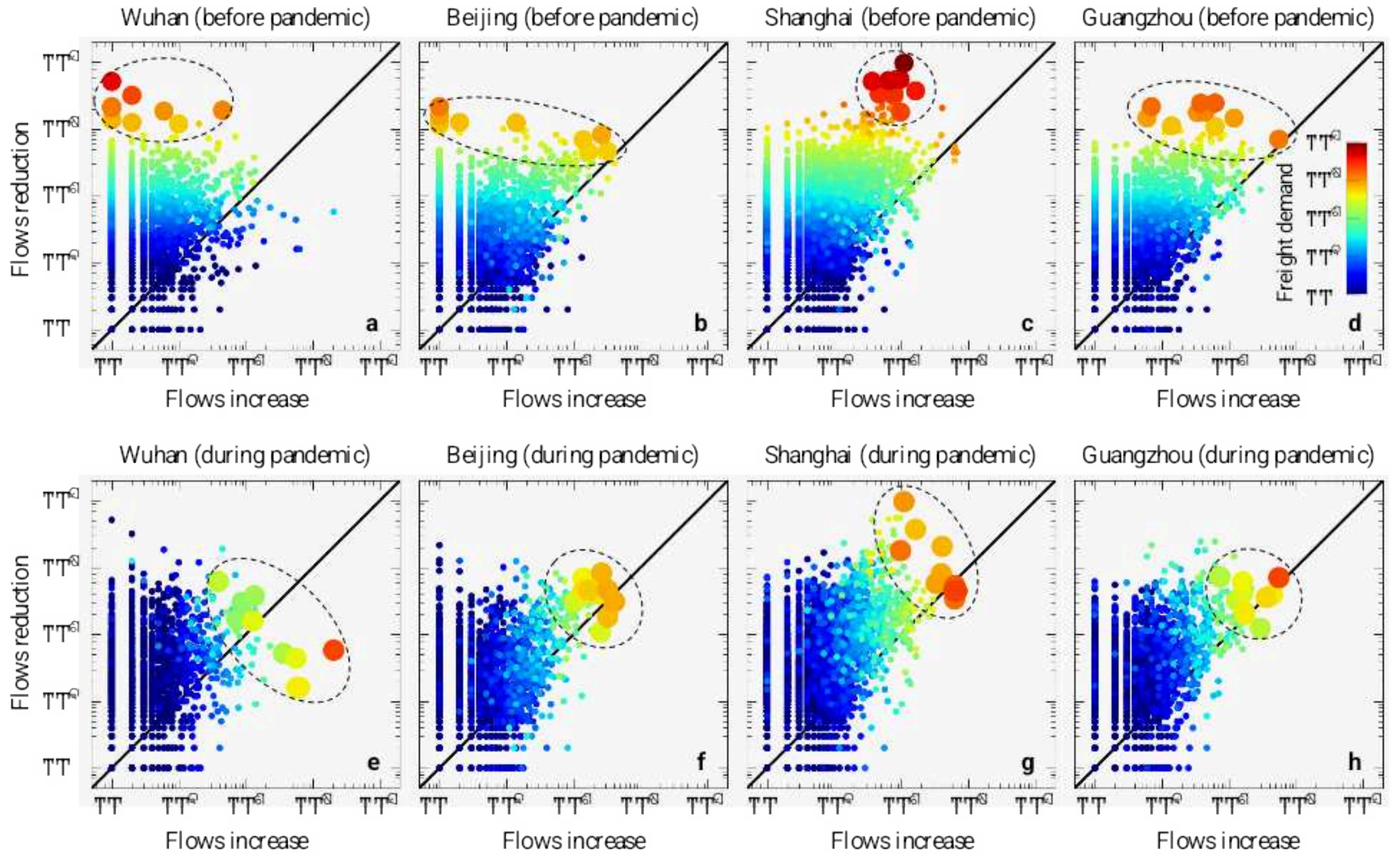
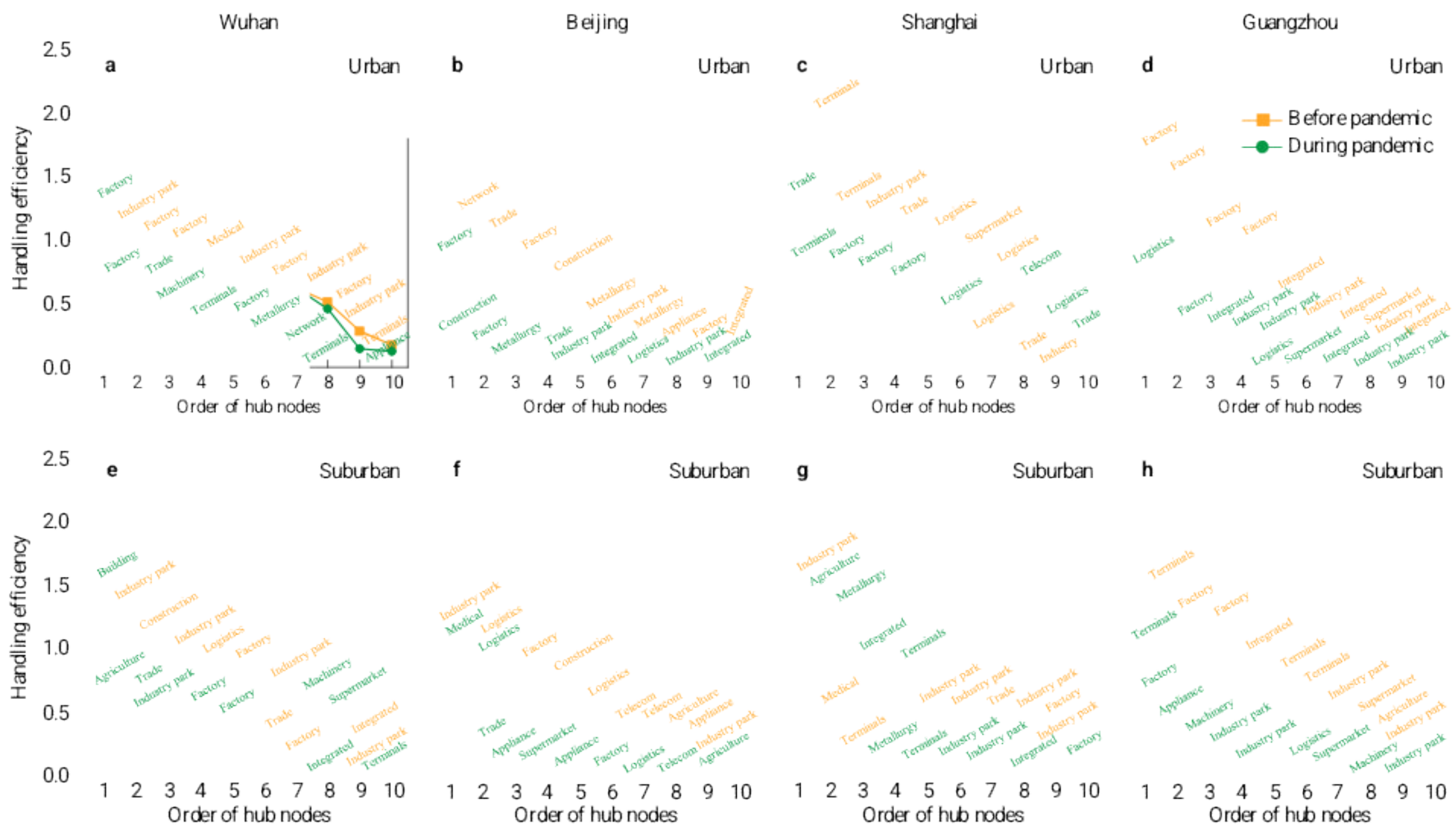


Fig. 5. Hub nodes shift in truck transport networks of four case cities during the pre-pandemic (panels **a-d**) and post-pandemic (panels **e-h**) periods. The points represent nodes, which are identical in both networks of a city. The horizontal axis represents the total increase in truck flows on some edges connected to a node after the COVID-19 outbreak, and the vertical axis represents the total reduction in truck flows on other edges connected to this node after the COVID-19 outbreak. For a given city, the points are in the same position in the figures (e.g., panel **a** and **e**) before and during pandemic. Size and color of each node indicate its freight demand during pre-pandemic or post-pandemic periods. The dashed circle indicates the top 10 largest nodes in the network.

To assess network resilience across freight hubs, we calculate the location-level handling efficiency of the top 10 freight hub nodes with the highest demand within urban and suburban areas before and during the pandemic respectively, as shown in **Fig. 6**. Here, handling efficiency is used as a metric to evaluate resilience, reflecting the ability to maintain operational efficiency at freight hubs. In **Fig. 6**, hub nodes are ordered by handling efficiency for both periods, allowing for a direct comparison of performance changes. The results suggest that in cities like Beijing (see **Fig. 6bf**) and Shanghai (see **Fig. 6cg**), suburban freight hubs demonstrated greater resilience by efficiently adapting to emerging demands, especially in essential sectors like healthcare and agriculture. These essential sectors experienced a surge in demand due to the increased need for medical supplies, food, and other essential goods during the crisis. Suburban freight hubs in cities like Beijing and Shanghai demonstrated higher resilience during the pandemic, especially in essential sectors like healthcare and agriculture, which saw a surge in demand for medical supplies, food, and other critical goods. This higher handling efficiency can be largely attributed to government prioritization and policy support (Abduljabbar et al., 2022; Pahwa and Jaller, 2023). During the crisis, the government implemented measures to ensure the uninterrupted flow of essential goods, including fast-tracking shipments of medical equipment, vaccines, and food products, and providing preferential treatment to

1 trucks carrying these supplies. Suburban hubs benefited from these policies as they typically faced
2 fewer logistical constraints and less congestion than urban hubs (Yang et al., 2022a). This allowed
3 them to process goods more efficiently, even as demand surged. In Wuhan (see **Fig. 6ae**), the
4 handling efficiency of freight hub nodes remained relatively stable during the pandemic, due to
5 balanced demand and effective adaptation by the city's logistics infrastructure. However, in
6 Guangzhou (see **Fig. 6dh**), both urban and suburban hub nodes saw a significant decline in handling
7 efficiency. The resilience of suburban hubs in Beijing and Shanghai underscores the importance of
8 policy-driven prioritization. For instance, the Chinese government's "green channel" policy, which
9 expedited medical supply logistics (Chen et al., 2019), likely amplified the handling efficiency gains in
10 suburban hubs. Conversely, Guangzhou's decline highlights systemic vulnerabilities in cities where
11 logistics policies are less integrated with regional supply chain strategies—a gap increasingly
12 addressed in post-pandemic urban freight planning.

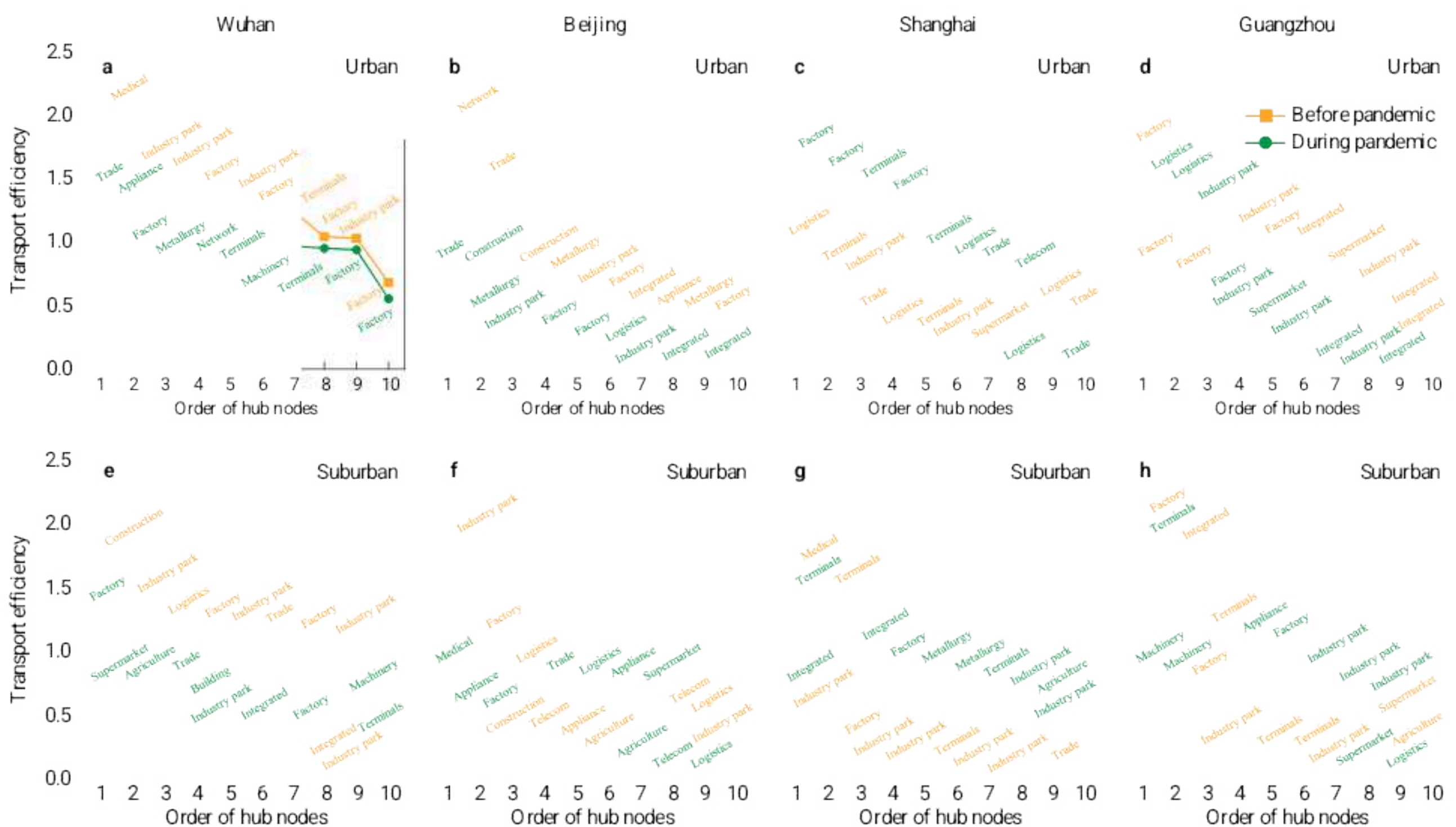


13
14 **Fig. 6.** Handling efficiency of freight hubs within urban areas (panels **a-d**) and suburban areas (panels **e-h**). The
15 point represents hub node, and the industry category of each hub node is marked beside the point. Hub nodes
16 are ordered in descending order of handling efficiency for both periods.

17 **Figure 7** complements the handling efficiency analysis by presenting transport efficiency
18 changes across freight hubs in urban and suburban areas. The results present the results of transport
19 efficiency across freight hubs in the four case cities. In Shanghai (see **Fig. 7cg**), transport efficiency
20 improved significantly at both urban and suburban hubs, particularly at factories and terminals. This
21 improvement can be attributed to reduced congestion and more efficient logistics operations (Zhang
22 et al., 2023), which allowed for quicker and more reliable movement of trucks, especially in essential
23 sectors. In contrast, Wuhan saw a notable decline in transport efficiency at both urban and suburban
24 hubs, as shown in **Fig. 7ae**. The pandemic-induced disruptions, combined with increased mobility
25 restrictions, caused delays and slower truck movements across the city, highlighting the challenges
26 Wuhan faced in maintaining transport efficiency during the crisis. Beijing (see **Fig. 7bf**) and
27 Guangzhou (see **Fig. 7dh**) exhibited a relatively neutral pattern, with transport efficiency either

1 remaining stable or showing moderate fluctuations, indicating that their freight hubs were less
2 affected by the pandemic compared to Wuhan, but did not experience the same level of improvement
3 seen in Shanghai.

4 Overall, the analysis shows that suburban hubs were more resilient in general, especially in
5 essential sectors, demonstrating a greater ability to maintain operational efficiency under pandemic
6 disruptions. Urban hubs struggled more, facing challenges like congestion and mobility restrictions,
7 which reduced handling and transport efficiency, indicating lower resilience in maintaining operational
8 efficiency. Some cities, e.g., Shanghai, with strong infrastructure and government support showed
9 improvements in operational efficiency, highlighting the importance of adaptive logistics and policy
10 interventions in maintaining resilience during crises. Shanghai's improvements demonstrate a higher
11 level of network resilience in maintaining and even enhancing operational efficiency.



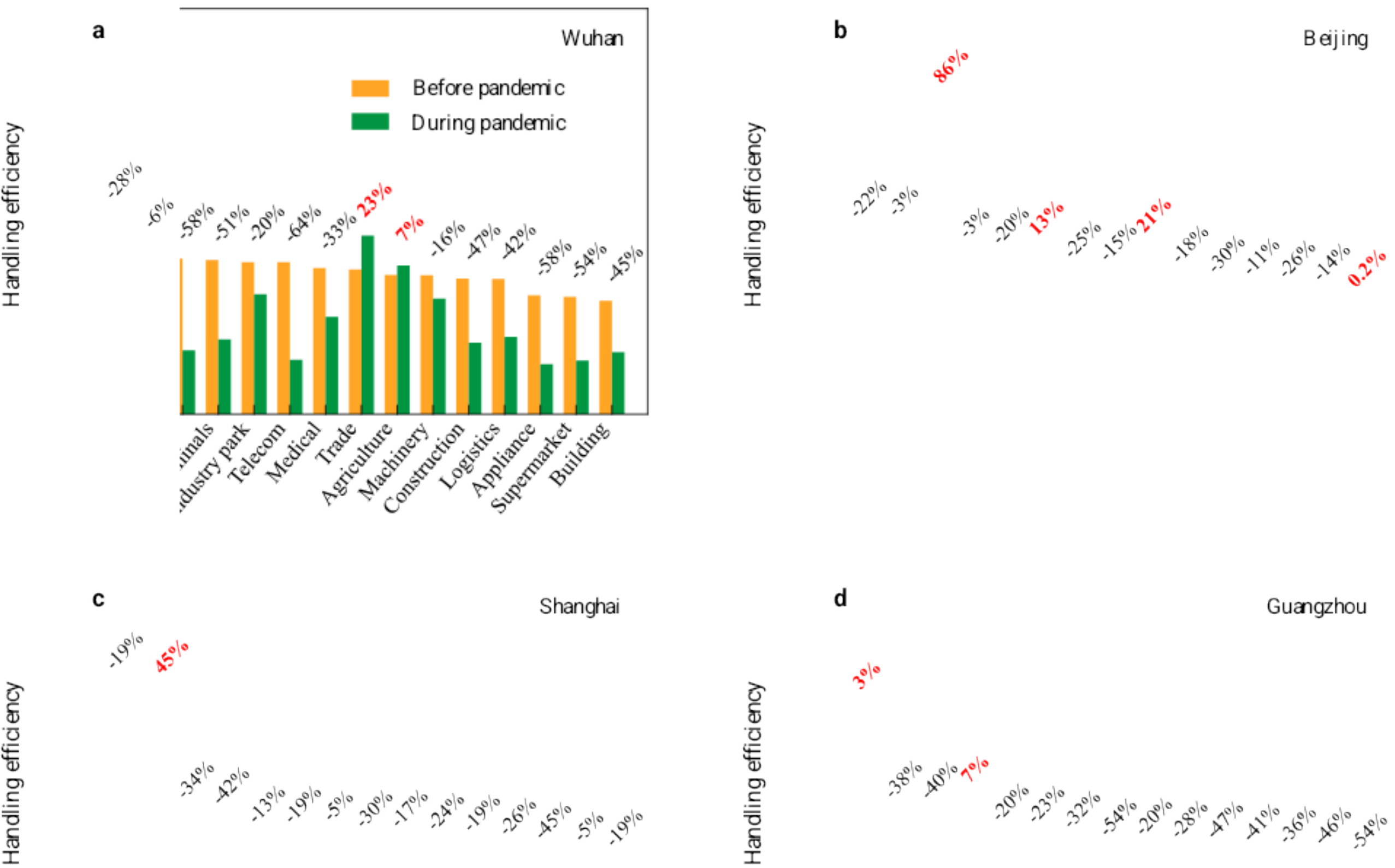
12
13 **Fig. 7.** Transport efficiency of freight hubs within urban areas (panels a-d) and suburban areas (panels e-h). The
14 point represents hub node, and the industry category of each hub node is marked beside the point. Hub nodes
15 are ordered in descending order of transport efficiency for both periods.

16 4.3. Network resilience across industry-specific supply chains

17 In this section, we analyze the resilience of truck transport networks, defined as the ability to
18 maintain operational efficiency, at the industry-specific supply chain level. The focus is on how
19 effectively the networks maintained reliable operations across key industries during the pandemic.
20 We also assess two dimensions of resilience: handling efficiency at facilities serving specific
21 industries and transport efficiency within and between industry supply chains. These efficiency
22 metrics serve as proxies to quantify resilience, reflecting the degree to which operational efficiency is
23 maintained during disruptions.

24 To examine industry-level handling efficiency, we present **Fig. 8**, which compares handling
25 efficiency across 15 industry categories with the highest freight demand for pre-pandemic and
26 post-pandemic periods. For the first dimension, we calculate industry-level handling efficiency before

1 and during pandemic, which reflects the average effectiveness of loading and unloading operations at
 2 locations serving a particular industry. As shown in **Fig. 8**, handling efficiency across industries was
 3 relatively high and consistent before the pandemic. However, post-pandemic results indicate a decline
 4 in overall handling efficiency with notable variations between industries, particularly between critical
 5 and non-critical sectors. Key industries such as agriculture and healthcare demonstrated improved
 6 handling efficiency during the pandemic, driven by increased demand and targeted prioritization in
 7 specific cities (Di Porto et al., 2022; Ivanov, 2021; Sabouhi et al., 2020). For instance, In Wuhan, trade
 8 companies and agriculture bases saw handling efficiency increase by 23% and 7%, respectively. This
 9 improvement reflects the city's prioritization of essential goods and food supply chains, ensuring swift
 10 operations at these critical facilities (Fu et al., 2022). In Beijing, medical companies exhibited an 86%
 11 increase in handling efficiency, highlighting the importance of prioritizing healthcare-related logistics
 12 during the pandemic to ensure timely delivery of medical supplies and equipment. In Shanghai,
 13 telecom companies experienced a 45% improvement, likely due to the surging demand for
 14 communication technology to support remote work and online education during lockdowns. In
 15 Guangzhou, terminals and metallurgy facilities achieved modest increases of 3% and 7%, respectively,
 16 indicating a degree of stability in sectors crucial to regional and industrial operations. Conversely,
 17 non-essential industries, such as network companies in Wuhan, experienced significant declines in
 18 handling efficiency due to resource reallocation and disruptions in operations.



19
 20 **Fig. 8.** Handling efficiency of industries during the pre-pandemic and post-pandemic periods. The horizontal axis

1 represents the 15 industry categories with the highest freight demand, sorted in descending order of
2 pre-pandemic handling efficiency. The percentage above the bar indicates the ratio of efficiency change.

3 Finally, to analyze industry-level transport efficiency, we present **Fig. 9**, which visualizes the
4 changes in transport efficiency within and between industries for the pre- and post-pandemic periods.
5 We calculate industry-level transport efficiency before and during pandemic, which reflects the speed
6 and reliability of goods movement within and between specific industry supply chains. The results
7 suggest distinct patterns across the four case cities. In Wuhan, transport efficiency improved for
8 industries such as logistics and medical supply chains (see **Fig. 9a**), driven by prioritization of
9 essential goods and streamlined transport operations during the pandemic. This reflects the city's
10 efforts to ensure the timely delivery of critical supplies, supported by policy measures that facilitated
11 smoother movement of trucks serving these sectors (Belbag, 2022). However, transport efficiency for
12 factories and all other non-essential industries declined significantly, primarily due to disruptions in
13 supply chain continuity, restricted movement of non-essential goods, and reduced demand during
14 lockdown periods (Castillo et al., 2022; Dablanc et al., 2022). In Beijing, transport efficiency between
15 terminals saw a significant increase (see **Fig. 9b**). This improvement was likely due to optimized
16 intra-terminal operations for faster and more reliable movement of goods to support residential and
17 business needs. In Guangzhou, despite a significant decline in handling efficiency for telecom
18 companies (see **Fig. 8d**), transport efficiency between telecom companies and other industries
19 improved substantially (see **Fig. 9d**). During the pandemic, telecom infrastructure became
20 increasingly critical to support remote work, leading to prioritization in logistics operations. However,
21 In Shanghai, changes in transport efficiency across industries were less pronounced (see **Fig. 9c**),
22 reflecting a relatively stable logistics system that effectively maintained operational consistency
23 despite the challenges posed by the pandemic.

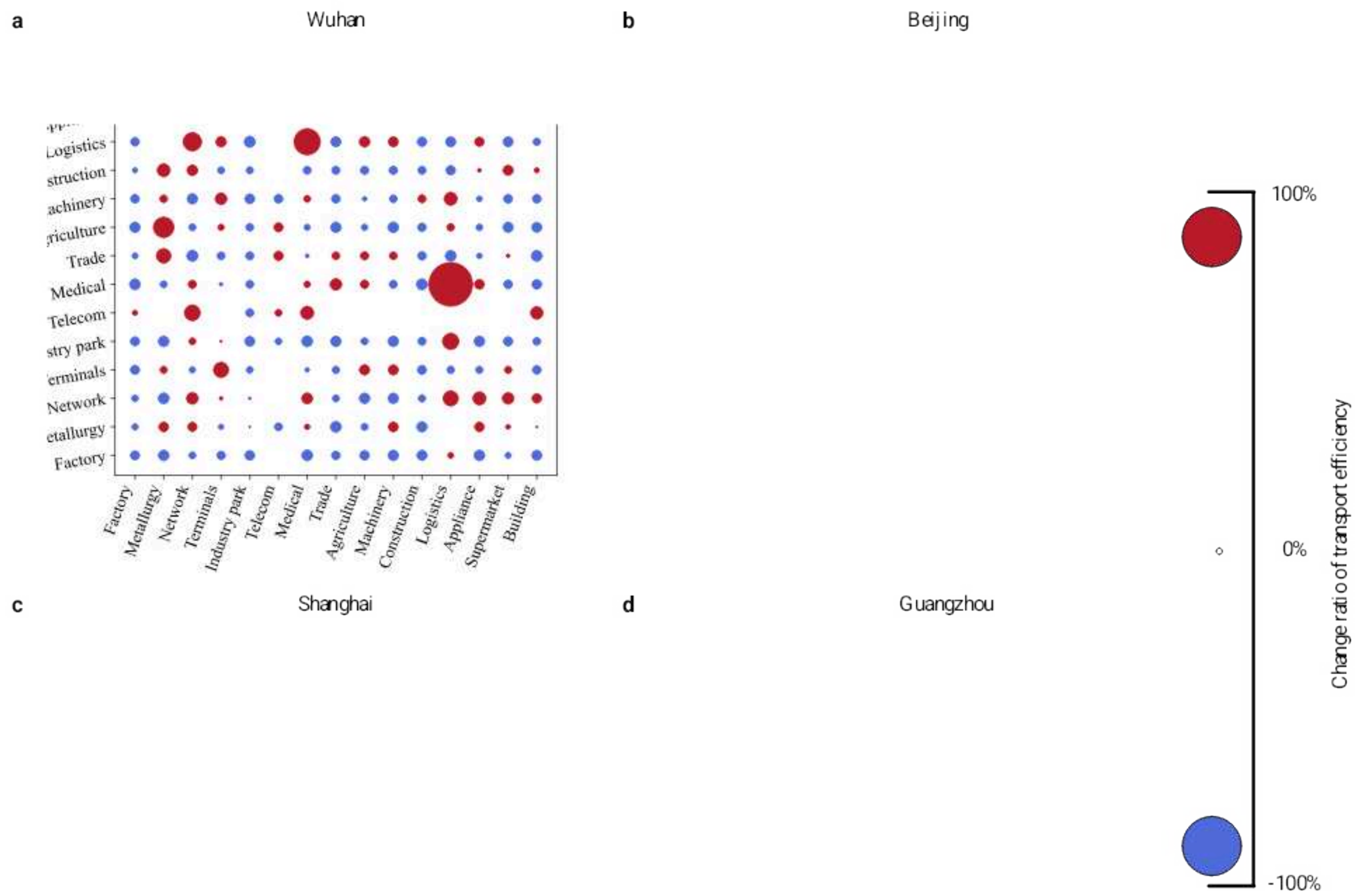


Fig. 9. Transport efficiency between and within industries during the pre-pandemic and post-pandemic periods. The point represents industry pair (from the industry on the vertical axis to the industry on the horizontal axis), and the size of each point indicates the ratio of change in transport efficiency.

The bifurcation between critical and non-critical sectors reveals a broader paradigm shift in supply chain management: the pandemic accelerated the transition from "just-in-time" to "just-in-case" logistics models (Yang et al., 2021a). The improved resilience of essential sectors demonstrates the effectiveness of strategic stockpiling and multi-tier supplier networks, while the decline in non-essential sectors reflects the inherent risks of lean, highly optimized systems during systemic shocks. These insights align with global calls for supply chain legislation mandating redundancy in critical industries (Ekanayake et al., 2021).

Overall, the analysis of network resilience across industry-specific supply chains highlights differences in how critical and non-critical sectors adapted to pandemic disruptions in terms of maintaining operational efficiency. Critical industries, such as agriculture, healthcare, and telecom, demonstrated greater resilience, with improved handling and transport efficiency due to increased demand, indicating lower resilience in maintaining operational efficiency during the pandemic. These efforts ensured the timely delivery of essential goods. In contrast, non-essential industries faced declines in efficiency, affected by resource reallocation, restricted operations, and reduced demand.

1 The findings emphasize the importance of strategic prioritization, adaptive infrastructure, and robust
2 logistics in maintaining supply chain resilience during crises (Borca et al., 2021).

3 **5. Discussion**

4 This study provides a detailed analysis of urban truck transport network resilience during the
5 COVID-19 pandemic, focusing on operational efficiency at the regional, freight hub, and
6 industry-specific levels. By leveraging fine-grained truck movement data, the research offers a
7 micro-level perspective on how disruptions affected specific locations and industries, moving beyond
8 traditional macroeconomic and structural analyses. A key finding is the critical role of adaptability in
9 sustaining network performance amidst unprecedented challenges. The observed variations in
10 handling efficiency and transport efficiency highlight how the network adapted to disruptions—such
11 as workforce shortages and traffic restrictions—through real-time adjustments like optimized loading
12 schedules or alternative routing. The results reveal that critical industries such as healthcare,
13 agriculture, and telecom demonstrated higher resilience, supported by government prioritization and
14 adaptive logistics operations, while non-essential industries faced significant declines due to reduced
15 demand and resource reallocation. This adaptability enabled the system to maintain delivery
16 timeliness despite fluctuating demand and operational constraints, underscoring its importance as a
17 cornerstone of resilience. These insights reveal that resilience is not merely a static property but a
18 dynamic process, driven by the network's capacity to flexibly respond to evolving conditions at
19 multiple scales. This dynamic and adaptive capacity is central to our definition of resilience, which
20 focuses on the ability to maintain operational efficiency during disruptions.

21 This understanding of resilience as a dynamic and adaptive process directly aligns with the
22 ecological and social-ecological resilience theories, which emphasizes a system's capacity to absorb
23 disturbances and reorganize while maintaining essential functions (Gunderson, 2000; Holling, 1973;
24 Walker et al., 2004). Our operational efficiency metrics serve as quantifiable indicators of this
25 adaptability in action. Specifically, the fluctuations in handling and transport efficiency across
26 locations, regions, and industries during the pandemic provide empirical evidence of the network's
27 capacity to absorb disturbance and reorganize its functions to maintain a degree of operational
28 stability. By grounding our analysis in these theoretical frameworks and empirically demonstrating the
29 adaptive capacity of urban truck transport networks through efficiency metrics, this study contributes
30 to a more theoretically informed and practically relevant understanding of resilience in urban logistics
31 systems.

32 The challenges faced by urban truck transport networks during the pandemic were not solely
33 driven by COVID-19 but were also a result of pre-existing trends that were exacerbated by the crisis.
34 For instance, increasing urban congestion and logistical complexity, which had already been growing
35 in densely populated cities, made urban freight hubs particularly vulnerable to disruptions (Labarthe et
36 al., 2024). The pandemic amplified these vulnerabilities through mobility restrictions and surges in
37 demand for essential goods, further straining already burdened urban hubs. Suburban freight hubs, by
38 contrast, benefited from pre-existing conditions such as lower traffic volumes and fewer logistical
39 bottlenecks, which supported their greater resilience during the pandemic. The study's resilience
40 metrics reveal that while suburban hubs maintained or improved handling and transport efficiency,
41 urban hubs experienced significant declines, reflecting their inherent challenges in coping with
42 sudden disruptions. For instance, handling efficiency in urban hubs decreased significantly due to
43 congestion and workforce shortages, whereas suburban hubs were better able to adapt due to their

1 simpler logistical frameworks and government prioritization of essential supply chains.

2 At the industry level, pre-existing trends such as the growing reliance on e-commerce and digital
3 infrastructure in sectors like telecom were accelerated by the pandemic. This shift not only increased
4 demand but also placed pressure on transport networks to adapt quickly (Wang et al., 2019). Our
5 findings indicate that telecom supply chains exhibited improvements in transport efficiency, partly
6 due to pre-existing investments in logistics digitization (Kaur et al., 2020), which enabled better
7 coordination and prioritization during the crisis. For instance, in Guangzhou, despite a significant
8 decline in handling efficiency for telecom companies, transport efficiency between telecom and other
9 industries improved substantially, reflecting the prioritization of critical infrastructure to support
10 remote work and online communication needs.

11 Based on these observations, this study provides several actionable insights for policymakers,
12 tailored to the unique challenges and resilience patterns observed in different cities during the
13 pandemic. The first key finding is the resilience of suburban areas and hubs, which consistently
14 outperformed urban counterparts during the pandemic, as seen in Beijing and Shanghai (see **Sections**
15 **4.1** and **4.2**). This suburban advantage, driven by lower congestion and adaptability to surging
16 demands in critical sectors like healthcare and agriculture, suggests a clear policy priority: invest in
17 suburban logistics infrastructure to bolster urban supply chain resilience. Policymakers should
18 allocate resources to develop modern suburban distribution centers equipped with automation and
19 real-time tracking technologies (Sudan and Taggar, 2021), enhancing handling efficiency and
20 reducing wait times. Improved road connectivity between suburban and urban areas, such as
21 expanding freight-specific lanes or upgrading inter-regional highways (Fang and Guo, 2022; Zhi et al.,
22 2024a), would further facilitate efficient goods movement, mitigating urban bottlenecks. Additionally,
23 integrating digital logistics platforms—e.g., GPS-enabled routing systems—can optimize
24 suburban-urban flows, ensuring timely last-mile deliveries even under disruptive conditions. This
25 suburban focus decentralizes logistics reliance on urban cores, a strategy validated by Shanghai’s
26 high transport efficiency gains (see **Section 4.1**), offering a scalable model for crisis preparedness.

27 The second insight emerges from the resilience of critical industries—healthcare, agriculture, and
28 telecom—which maintained or improved efficiency due to government prioritization (see **Section 4.3**).
29 To institutionalize this resilience, policymakers must implement targeted policies that ensure supply
30 chain continuity for essential goods during disruptions. This includes establishing dedicated freight
31 corridors for critical industries (Bosona, 2020), streamlining permitting processes for trucks carrying
32 medical supplies or food, and granting exemptions from mobility restrictions, as seen in Beijing’s
33 medical sector efficiency surge (see **Section 4.3**). Contingency plans should also prioritize resource
34 allocation, such as redeploying workers to essential hubs or reserving storage for critical goods
35 (Srinivas and Marathe, 2021), preventing shortages like those avoided in Wuhan’s agriculture sector
36 (see **Section 4.3**). These measures, inspired by the study’s findings, not only address immediate
37 crises but also build long-term resilience by embedding adaptability into urban logistics systems,
38 ensuring essential services remain robust under pressure.

39 A third actionable recommendation, informed by urban areas’ vulnerability and non-essential
40 industry declines, is to enhance urban logistics flexibility through adaptive infrastructure and
41 regulatory frameworks. Urban areas, with their dense traffic and complex logistics, struggled with
42 handling and transport efficiency drops (e.g., Guangzhou’s 27.3% urban transport decline), while
43 non-essential sectors faced resource reallocation challenges. Policymakers should invest in urban
44 micro-hubs—small, strategically located facilities—to alleviate congestion and improve last-mile

1 delivery efficiency (Narassima et al., 2024). Dynamic regulatory adjustments, such as temporary
2 suspension of congestion charges or time-of-day restrictions during crises (Rahman et al., 2024), can
3 further support urban truck mobility. Shanghai's urban resilience demonstrates the efficacy of
4 adaptive infrastructure, suggesting a blueprint for other cities. Additionally, creating flexible
5 resource-sharing mechanisms—e.g., public-private partnerships to redistribute logistics assets to
6 struggling sectors—can mitigate non-essential industry declines, ensuring equitable service across
7 urban economies.

8 **6. Conclusion**

9 This study provides a comprehensive analysis of the resilience of urban truck transport networks
10 during the COVID-19 pandemic, offering insights into how disruptions affected operational efficiency
11 across regions, freight hubs, and industry-specific supply chains. By leveraging individual truck
12 movement data and defining quantifiable metrics for handling and transport efficiency, we were able
13 to capture the nuanced impacts of the pandemic on different geographic locations and industries.
14 The findings highlight significant variations in resilience, with suburban hubs and critical industries
15 demonstrating greater adaptability due to fewer logistical constraints and targeted policy support,
16 while urban hubs and non-essential sectors faced more pronounced challenges. This study
17 contributes to the existing literature by providing a micro-level perspective on network resilience,
18 moving beyond aggregated socio-economic analyses to examine the specific impacts of disruptions
19 on truck transport networks. The proposed metrics offer a robust framework for evaluating resilience,
20 providing actionable insights for policymakers and industry stakeholders.

21 Despite our comprehensive analysis of the impact of the COVID-19 pandemic on urban truck
22 transport networks, this study has several limitations and points to future research opportunities.
23 Firstly, while our analysis offers a lens into adaptability and its manifestation in maintained
24 operational efficiency during the COVID-19 pandemic, we recognize that it primarily captures
25 immediate responses rather than the recovery phase, which necessitates longitudinal data beyond our
26 current scope. Future longitudinal research could expand beyond operational efficiency to incorporate
27 broader dimensions of resilience including recovery, robustness, redundancy and resourcefulness.
28 Secondly, This study focuses on selected cities in China, where dense urban populations, advanced
29 logistics networks, and stringent regulatory measures during the COVID-19 pandemic provide a
30 distinct context for assessing truck transport resilience. While the resilience metrics offer a flexible
31 framework for evaluating adaptability to disruptions, the generalizability of our findings may be
32 constrained by China's unique logistical, regulatory, and economic environment. These conditions
33 may differ significantly from those in other regions. Future research could address this limitation by
34 conducting comparative studies across multiple regions and countries, examining how cultural,
35 regulatory, and economic differences shape transport network resilience. Such studies could
36 elucidate universal principles of resilience while identifying region-specific factors, ultimately
37 providing more globally applicable recommendations for enhancing logistics resilience. Thirdly, we
38 simplified the analysis by not considering the trucks' loading status, focusing instead on movement
39 and interaction patterns. Integrating data on laden versus empty trips could uncover specific
40 vulnerabilities and optimize strategies, as laden trips may require different prioritization during
41 disruptions. Finally, we did not classify nodes into categories like supply, transient, and demand
42 nodes. Node classification could provide insights into critical points, bottlenecks, and network
43 interactions, enabling targeted strategies to improve resilience. Future research addressing these

1 limitations would refine our understanding of network dynamics and enhance strategic planning for
2 robust urban transport systems.

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