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Structure and dynamics of urban freight truck movements: A complex network theory perspective

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ABSTRACT

Knowledge of the core structure and inherent dynamics of urban freight transport systems is important for the development of policies, aimed at improving the livability and sustainability of cities. The past decade has witnessed a great deal of efforts into analyzing the geographic structure of urban freight transport systems. However, in-depth studies on the system core structure and underlying dynamics are still absent. This study contributes to the field by analyzing large scale freight truck trip data from Chinese cities, using complex network analysis. We empirically reconstruct and characterize the urban freight truck mobility networks and reveal the underlying spatial interaction patterns. We develop a spatial network growth model which explains how hub-and-spoke core structure of urban freight transport systems are formed. The developed model captures the essential interaction dynamics of freight locations, and explains the effects of spatial distance, economic size and business pattern replication. Inspired by the model, we provide policy implications for land-use planning, transportation planning and sustainable urban development.

1. Introduction

Efficient and effective urban freight transport systems are vital to ensure that the supply chain operates smoothly and that goods are distributed promptly to businesses and residents (Guerrero et al., 2022a; Machado et al., 2023). The structure of urban freight transport system can be defined as the physical and organizational arrangements of freight locations with various functions (e.g., production, distribution or transshipment). Urban freight vehicles are a critical component of this system, playing a pivotal role in the seamless movement of goods within cities. Especially, large trucks undertake high-volume transport tasks between functional locations, e.g., industrial companies, logistics warehouses and comprehensive markets, establishing their spatial interactions between different urban regions (Rodrigue, 2020). The analysis of large-scale freight trucks movements can give the necessary insights into the core structure and inherent dynamics of urban freight transport systems, which are of vital importance for policymakers to assess and

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develop freight policies, and to improve the livability and sustainability of cities (Kutty et al., 2023).

The past decade has witnessed a great deal of efforts into revealing the structure of urban freight transport system. Previous studies have highlighted the importance of infrastructure and facilities required to support efficient and sustainable freight movements (Bombelli et al., 2020; Brettmo and Browne, 2020; de Oliveira et al., 2021; Fulzele and Shankar, 2022; Gupta and Dhar, 2022), and have identified opportunities for optimizing their use through the development of new technologies and policies (Aljohani and Thompson, 2021; Janjevic et al., 2019; Mohri and Thompson, 2022) However, in-depth studies on understanding the underlying interaction patterns and dynamics of these freight locations are still scarce. The research gaps limit our potential to manage and regulate urban freight transport systems. In the era of big data, however, massive urban freight truck mobility data are becoming available, providing the possibility to fill these gaps.

To this end, our study explores the core structure of urban freight transport system and underlying interaction dynamics using large-scale truck trip data, from the perspective of complex networks. We employ data on freight truck flows between urban functional locations using GPS trajectory and freight Point-of-Interest (POI) data, and construct urban freight truck mobility networks. We uncover the core structure of urban freight transport systems and the interaction patterns between locations by characterizing the properties of freight truck mobility networks. To study interaction dynamics of freight locations, we propose a spatial network growth model. The results show that our model is able to reproduce a wide range of core structure features of urban freight transport system and can capture essential growth mechanisms that produce this end state. Finally, we discuss the practical implications inspired by our model for regulating urban freight transport system, and discuss the potential applications.

The contributions to the literature of our study are threefold: (1) We construct urban freight truck mobility networks by obtaining large scale freight truck flow data between functional locations. (2) We reveal the spatial core structure of urban freight transport systems and the interaction patterns between freight locations by using a complex network characterization. (3) We develop a spatial network growth model to explain the interaction dynamics of freight locations that lead to the observed structures, and provide policy implications for sustainable urban planning and management.

The remainder of this paper is organized as follows: **Section 2** gives the literature review. **Section 3** provides the methods of constructing urban freight truck mobility networks, characterizing network structure and developing the spatial network growth model. **Section 4** describes the empirical and model results. **Section 5** discusses policy implications inspired by the model and its practical applications. **Section 6** at the end, offers concluding insights.

2. Literature review

Our work can be positioned in relation to two streams of literature: the first explores the structure of urban freight transport systems, the second captures interaction dynamics between locations. We discuss these below.

The structure of urban truck transport systems can be interpreted as the geographic distributions of freight facilities and their spatial interactions (Rodrigue, 2020). Research has paid much attention to the spatial attributes of freight facilities across countries (Renhao, 2019; Wang and Zhang, 2014; Yang et al., 2022b) or at the city level (Chen et al., 2008; Guo et al., 2023; Li et al., 2017). They revealed that the location patterns of freight facilities can be featured by sprawling, polarization, and recentralization (Yang et al., 2022c). In addition, they also linked transport accessibility, market demand, logistics facility agglomeration, and local policy to the spatial locations of freight facilities (Aljohani and Thompson, 2016; Heitz et al., 2020). The empirical results suggest that due to various factors related to land use control and operational environments, freight facilities are currently located primarily in logistics clusters in the periphery of metropolitan areas, close to highway networks, major airports and seaports (Allen and Browne, 2010; Allen et al., 2012; Cidell, 2011; Leigh and Hoelzel, 2012). Several studies have found that the dense roadway network in Europe allows companies to construct large warehouses in more centralized locations. Some studies (Jacobs et al., 2011; Mullen and Marsden, 2015) also explored the links between urban transport nodes and regional development. They suggested that freight gateways increasingly serve distant and dispersed carriers, shippers and customers and consequently, a decreasing share of the hubs' benefits may materialize locally. In short, these studies have improved our understanding of the geographic structure of urban freight transport systems. However, they have been unable to connect these structures to the underlying spatial interactions, which shape the structure and dynamics of freight transport systems. In-depth studies on understanding urban freight transport system by integrating the interactions characterized by massive freight truck flows between functional locations are still absent.

The use of complex networks theory (Barbosa et al., 2018; Barthelemy, 2011; Guerrero et al., 2022b; Louail et al., 2015; Murali et al., 2016; Truong Van et al., 2020) to study the interaction dynamics between locations has become widespread. The common research approach here is to develop evolving network models which are able to reproduce observed structural properties of the real-world system and to explain the underlying dynamical mechanisms (Cimini et al., 2019). Early studies mainly concentrated on unweighted evolving network models, the most representative one being the Barabasi-Albert (BA) model (Barabasi and Albert, 1999). The BA model proposes a preference attachment rule and reproduces the scale-free property of real-world systems, providing a theoretical explanation for the richer-get-richer phenomenon (Colizza et al., 2006). Other unweighted evolving network models (Dorogovtsev et al., 2001; Zheng et al., 2021) have subsequently been developed. While these typically consider network topology growth, they ignore network edge weights. In urban freight truck mobility networks, edge weights indicate the interaction strength between locations and, therefore, are essential to be considered. Previous studies also developed weighted evolving network models (Barrat et al., 2004; Pan et al., 2006; Wang et al., 2006) from different perspectives, with as most representative the Barrat-Barthelemy-Vespignani (BBV) model (Barrat et al., 2004). The nodes of many real-world networks, including urban freight truck mobility networks, are located in geographic space, implying that the interactions of locations are constrained by the cost associated with space (Barthelemy, 2011). To this end, more recent studies (Allard et al., 2017; Barrat et al., 2005; Louf et al., 2013; Popovic et al., 2012) have proposed evolving network models based on the network growth rule of preference attachment with a spatial constraint.

Taken together, the above evolving network models have aided our understanding of the underlying growth mechanisms of many real-world systems. However, these still do not adequately explain the interaction dynamics between locations in an urban freight transport system. While it is known that the establishment of a new freight location, for example for production, is usually accompanied by replicating the successful business patterns of existing companies (Bishop, 2012; Dunford et al., 2010; Piacentino et al., 2017), current models do not take this into account. More realistic network models are needed to account for such factors that drive the formation and growth of the core structure of urban freight transport systems.

3. Methodology and data

In this work, we aim to uncover the core structure of urban freight transport system and explore the underlying interaction dynamics from the perspective of complex networks. We first construct urban freight truck mobility networks by using massive freight truck flows, and then characterize their properties to uncover the core structure of urban freight transport systems. Finally, we develop a spatial network growth model to explain the interaction dynamics between freight locations and provide policy implications inspired by the model.

3.1. Construction of urban freight truck mobility networks

The datasets we used to construct urban freight truck mobility networks consist of freight truck GPS trajectory data and urban freight-related POI data.

Freight truck GPS trajectory data were collected from the China Road Freight Supervision and Service Platform (https://www.gghypt.net/). This platform is used to record the real-time geographic locations of all freight trucks with a load exceeding 12 tons in China and monitor their traffic violations. Our GPS trajectory data contains 41 billion trajectory records of 2.6 million freight trucks in China from May 18, 2018 to May 31, 2018. The attributes of trajectory records include truck ID, timestamp, longitude, latitude, speed and direction angle. Urban freight-related POI data were crawled from Amap (https://lbs.amap.com/), which is a leading map application in China. POI data provide the names and geographical coordinates of urban freight locations, including freight companies,

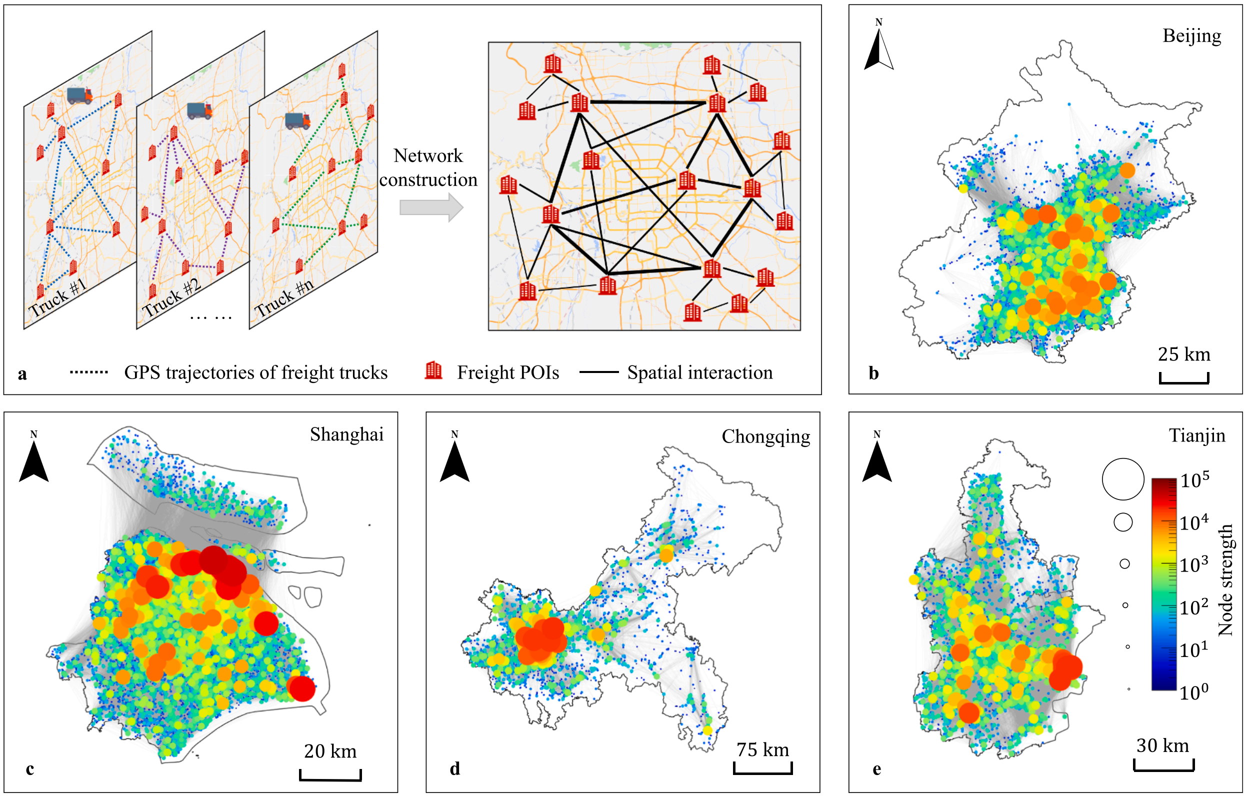

Fig. 1. Construction and illustration of urban freight truck mobility networks. **a** Network construction by using freight truck GPS trajectory data and urban freight-related POI data. Individual mobility network of each freight truck (left panels) is first constructed, and then the urban freight truck mobility network (right panel) is constructed. **b-e** Illustration of empirical urban freight truck mobility networks of four cities in China. Size and color of each node indicate its strength.

markets, logistics facilities and transport terminals.

To construct urban freight truck mobility networks (as shown in Fig. 1**a**), we need to obtain the truck flows between urban freight locations from freight truck GPS trajectories. We first use the urban freight truck trip origin–destination (OD) identification algorithm (Yang et al., 2022a) to identify the trip chains of each freight truck from its GPS trajectory. The algorithm identifies truck trip ODs by dynamically selecting dwell time thresholds to hierarchically segment continuous GPS trajectories, and the identified ODs are linked to freight-related POIs according to geographic proximity. Subsequently, we proceed to construct the trip chains for each individual freight truck. This involved organizing the identified trip OD pairs into sequences, effectively representing the chronological order of movements made by each truck. Subsequently, we leverage the constructed trip chains to create the individual mobility network for each freight truck. The network nodes represent freight-related POIs visited by the truck, and network edges depict the truck movements between these locations. Moving to the collective level, we aggregate the truck flows between freight-related POIs based on the collective movements of all freight trucks in the dataset, and construct the urban freight truck mobility networks. The urban freight truck mobility network is a weighted network $G(\boldsymbol{N}, \boldsymbol{E}, \boldsymbol{W})$, where $\boldsymbol{N}$ is the set of nodes coordinated by longitude and latitude; $\boldsymbol{E}$ is the set of edges and $\boldsymbol{W}$ is the set of edge weights, i.e., number of truck trips.

We choose four typical Chinese cities, i.e., Beijing, Shanghai, Chongqing and Tianjin, as case studies considering their diverse socio-economic profiles, population sizes, industrial activities, and transportation infrastructures. The schematics of urban freight truck mobility networks of these four Chinese cities are shown in Fig. 1**b-e**, and the characteristics of four cities and corresponding networks are shown in Table 1. We can find that Chongqing is a very big city with a geographic area of 82,403 km^2; Shanghai is a relatively smaller city compared to other three case cities, but its economic activities are the most vibrant with the highest Gross Domestic Product (GDP); Beijing, as the capital, has both a large geographic area and high economic activity. Meanwhile, Tianjin has relatively lower population, GDP, and total road length. These four cities represent distinct urban environments in China.

3.2. Characterization of the spatial distribution of network nodes

To commence, we aim to characterize the spatial distribution of network nodes for two primary objectives. The first objective is to elucidate the relationships between freight-related locations and the urban road infrastructure. The second objective is to uncover spatial patterns of aggregation or dispersion among freight-related locations.

For the first objective, we assess how the characteristics of road networks vary in proximity to different types of locations within the city, and to provide insights into the relationships between locations and transportation infrastructure. To this end, we begin by retrieving urban road data from OpenStreetMap (https://www.openstreetmap.org/), and extract four types of road categories, including motorways, primary roads, secondary roads and tertiary roads, based on their relevance to trucking activities, as shown in Fig. 2**a**. Subsequently, we create Voronoi polygons for all network nodes (see Fig. 2**b**). Voronoi polygons can divide a city into areas, where each area is closer to a specific location than any other, providing a representation of the spatial influence for each location. Within each Voronoi polygon (see Fig. 2**c**), we calculate the density of each types of roads, which is defined as the ratio of the total road length encompassed by the polygon area (km^2). This road density metric provides a quantitative measure of how concentrated or sparse road infrastructure is around each freight-related location. Finally, we use Pearson correlation coefficient (Pearson and Lee, 1903) to examine the statistical relationships between truck flows of each location and the calculated road densities within their respective Voronoi polygon. We aim to unveil patterns and correlations that shed light on how road infrastructure influences the activity and accessibility of locations within the context of freight transportation.

For the second objective, we use two metrics, i.e., *Moran's I* (Moran, 1950) and *Geary's C* (Geary, 1954), to analyze and quantify the degree of spatial autocorrelation within the distribution of freight-related locations. *Moran's I* measures the degree of spatial autocorrelation by assessing whether similar values (in our case, truck flows generated and attracted by locations) tend to cluster together or disperse across space. A positive *Moran's I* value suggests clustering, indicating that nearby locations exhibit similar characteristics, while a negative value suggests dispersion, meaning dissimilar locations tend to be close to each other. *Geary's C* is another metric that evaluates spatial autocorrelation. *Geary's C* considers the spatial proximity of locations. It looks at pairs of neighboring locations and examines whether the values in these pairs are similar or dissimilar. It compares the observed differences in values between neighboring locations to what would be expected if the values were randomly distributed across the space. If *Geary's C* is close to 1, it suggests that there is no significant spatial pattern, and values are randomly distributed or spatially homogeneous. If *Geary's C* is significantly less than 1, it indicates spatial clustering, meaning that similar values tend to occur in nearby locations. If *Geary's C* is significantly greater than 1, it indicates spatial dispersion, implying that dissimilar values tend to occur in neighboring locations. Moreover, we incorporate *Ripley's F* functions (Ripley, 1976) for the examination of clustering or dispersion tendencies of locations in

Table 1
Characteristics of four case cities and their freight truck mobility networks. City geographic area *GA*; population *POP*; Gross Domestic Product *GDP*; total road length *RL*; number of network nodes *N*; number of network edges *E*. *Moran's I* and *Geary's C* are two metrics used to examine the aggregation or dispersion tendencies of truck flows into and out of locations.

City	*GA*	*POP*	*GDP*	*RL*	*N*	*E*	*Moran's I*	*Geary's C*
Beijing	16,410	2,154	30,320	22,256	15,983	207,264	0.43	0.39
Shanghai	6,341	2,424	32,680	13,106	16,094	436,172	0.52	0.23
Chongqing	82,403	3,102	20,363	157,483	10,629	203,203	0.71	0.15
Tianjin	11,920	1,560	18,810	16,257	10,697	216,724	0.65	0.18

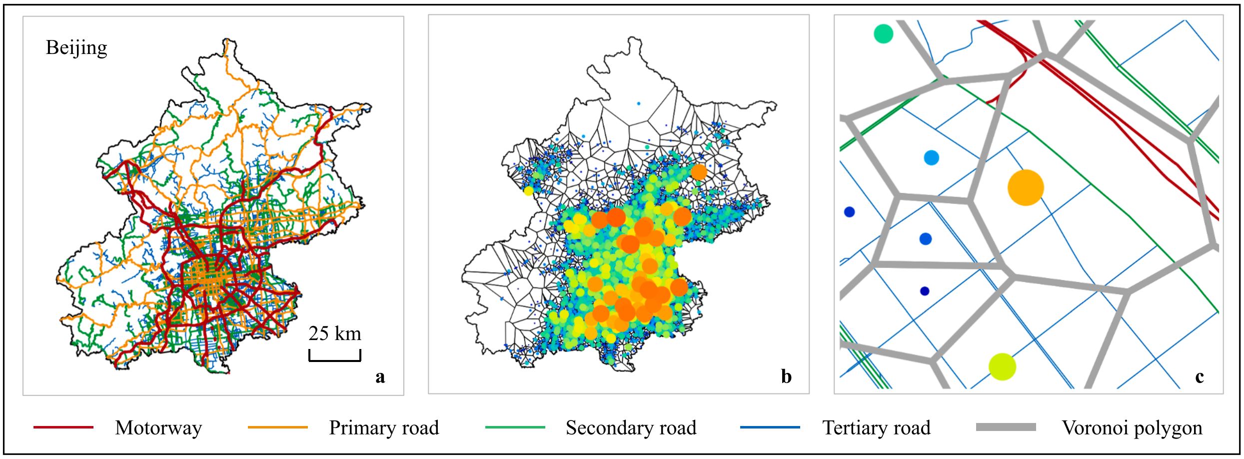

Fig. 2. Illustration of spatial relationships between network nodes and urban roads. **a** Hierarchical structure of the four types of urban roads in Beijing. **b** Voronoi polygons for all network nodes. **c** Magnification of network nodes and urban roads within Voronoi polygons.

relation to distances from a random spatial Poisson point process. *Ripley's F* function, denoted as $F(r)$, quantifies the cumulative distribution function of distances between pairs of points within a distance r. It is a measure used to analyze spatial point patterns and evaluate whether points are clustered, dispersed, or randomly distributed within a specific range of distances. Mathematically, $F(r)$ is defined as:

$$F(r) = \hat{\lambda}^{-1} \sum_{i} \sum_{j \neq i} \frac{\mathscr{H}(d_{ij} < r)}{N} \tag{1}$$

where $\hat{\lambda}$ is the average density of points (generally estimated as N/A, where A is the area of the region containing all points with number of N), d_{ij} is the distance between the ith and jth points, and $\mathscr{H}(\hat{A}\cdot)$ is the indicator function (1 if its operand is true, 0 otherwise). If the points are approximately homogeneous, $F(r)$ could be approximately equal to πr^2.

3.3. Measures for characterizing network structure

Next, we use the measures of network science (Barthelemy, 2011; Newman, 2003) to characterize the properties of urban freight truck mobility networks, and to uncover the core structure of urban freight transport system.

Network property measures we use include: node degree, edge distance, rich-club coefficient, average degree of nearest neighbors, clustering coefficient and Jaccard similarity coefficient. The degree of a node i is the number of its neighbors and is then given by $k_i = \sum_j A_{ij}$. When i and j are connected, $A_{ij} = 1$; and vice versa, $A_{ij} = 0$. Freight locations with high node degree are more likely to serve as hubs, due to their high level of connectivity with other locations. They are likely to receive a higher volume of freight flows and serve as key nodes for the consolidation and distribution of goods.

The distance d_{ij} of edge (i,j) is the Euclidean distance between freight locations i and j. Spatial distance and transport costs are closely related in freight transport. Generally, longer spatial distance between two locations results in higher transport costs, since longer distances require more fuel, labor and equipment to transport goods. Rich-club coefficient is a metric used to measure the extent to which highly connected nodes in a network are interconnected with one another, given by

$$RC(k) = E_{>k}/(N_{>K}(N_{>K} - 1)/2) \tag{2}$$

where $E_{>k}$ denotes the number of edges between nodes with degree greater than k and $N_{>K}$ denotes the number of nodes with degree greater than k. When the rich-club coefficient $RC(k)$ has higher values in higher degree level k, it suggests that there is a strong level of interdependence among the highly connected freight locations, and that they are more likely to collaborate and exchange goods or services among themselves.

The weighted and unweighted average degree of nearest neighbors, i.e., $\langle k_{nn}\rangle_i^w$ and $\langle k_{nn}\rangle_i$, of node i are metrics used to describe the local structure of a network. They are calculated by averaging the degree of the neighbors of a node in a network. If edges with larger weights tend to connect neighbors with larger degrees, then $\langle k_{nn}\rangle_i^w > \langle k_{nn}\rangle_i$; and vice versa, then $\langle k_{nn}\rangle_i^w < \langle k_{nn}\rangle_i$. If the interaction strengths between node i and all its neighbors are identical, then $\langle k_{nn}\rangle_i^w = \langle k_{nn}\rangle_i$. The weighted and unweighted average degree of nearest neighbors per degree class, i.e., $\langle k_{nn}\rangle(k)$ and $\langle k_{nn}\rangle^w(k)$, can be used to analyze the interaction patterns between locations with different connectivity.

The weighted and unweighted clustering coefficient, i.e., C_i and C_i^w, of node i are metrics used to describe the degree to which nodes in a network tend to cluster or form local clusters, as well as the extent to which the neighbors of a node are also connected to each other. If the interaction strength between node i and its two neighbors that form a closed cluster tend to be higher, then $C_i^w > C_i$; and vice versa, then $C_i^w < C_i$. If the interaction strengths between node i and all neighbors are identical, then $C_i^w = C_i$. The weighted and unweighted average clustering coefficient per degree class, i.e., $C^w(k)$ and $C(k)$, indicate the distribution of network weights between nodes of different degree classes.

The Jaccard similarity coefficient $Jac_{i,j}$ measure the similarity between nodes i and j based on their connectivity patterns, given by

$$Jac_{ij} = \frac{|\Gamma(i) \cap \Gamma(j)|}{|\Gamma(i) \cup \Gamma(j)|} \tag{3}$$

where $\Gamma(i)$ denotes the set of neighbors of node i, the numerator denotes the number of common neighbors between the two nodes, and the denominator denotes the number of distinct neighbors of the two nodes. Two freight locations with a high Jaccard similarity coefficient may serve similar industries, operate on similar transport routes or collaborate with each other.

3.4. A spatial network growth model

We develop a spatial network growth model with the aim to explain how the core structure properties of urban freight transport systems are formed, and to understand the interaction dynamics of urban freight locations. In the model, nodes are added to the initial network one by one over time. This process is equivalent to the emergence and development of new freight location functions, e.g., production. New established companies often take inspiration from existing companies and try to replicate their successful business patterns. This can include their product offerings, marketing strategies, pricing models and distribution channels (Bishop, 2012; Dunford et al., 2010; Piacentino et al., 2017). Therefore, in the model, we consider the mechanism of system element replication (Chung et al., 2003) and integrate the effects of spatial distance and economic size in the process of network growth. The details of the model are as follows.

Our model starts with an initial fully connected seed network containing N_0 nodes (see Fig. 3**a**), which are randomly selected from among the freight locations in city. Each edge in this seed network is given a weight w_0. For simplicity, we set $N_0 = 5$ and $w_0 = 1$ both to constants. At each step, we randomly select a point from the remaining urban freight locations as the new added node n (see Fig. 3**b**). Next, we assume this new freight location n tries to replicate the business patterns of one existing location i, i.e., the new location n tends to share the partners of the replicated existing location i. According to spatial interaction theory (Fotheringham and O'Kelly, 1989; Roy and Thill, 2003), the model assumes that a new company tends to replicate the business patterns of spatially adjacent and

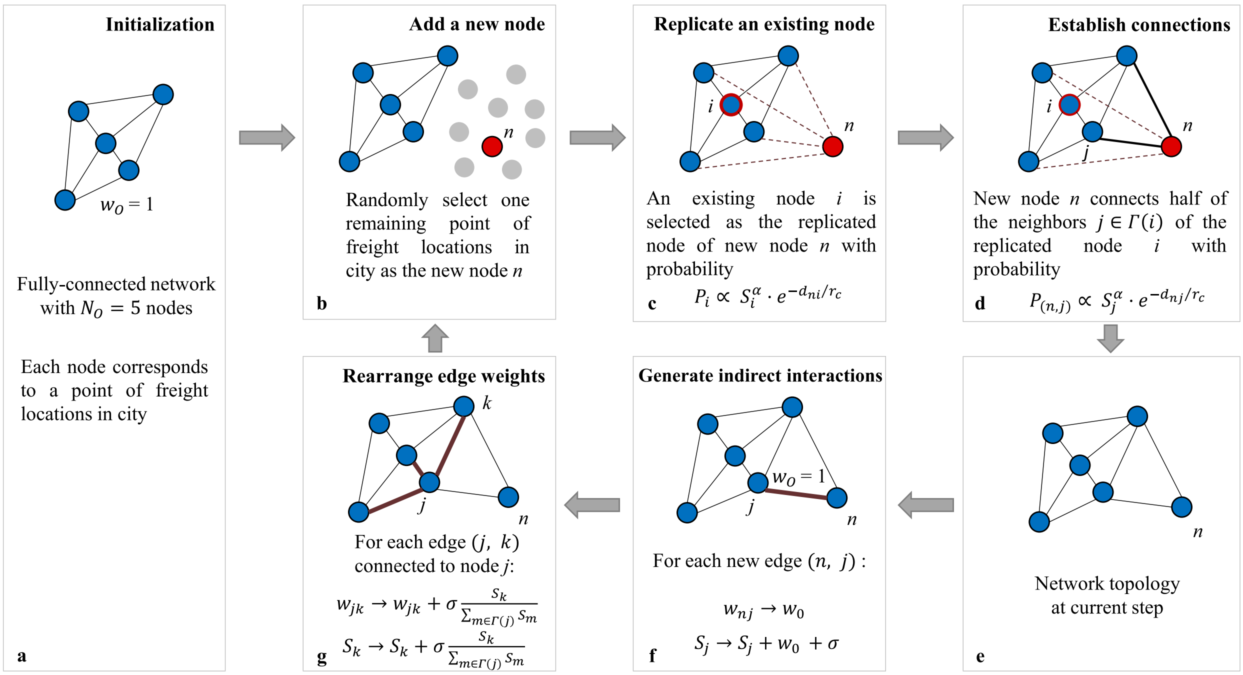

Fig. 3. Model illustration. The growth of network at each step consists of two processes, i.e., topology growth (panel **b-d**) and weight updates (panel **e-g**). In the topology growth, a new node n is first added (panel **b**) and selects its replicated node i (panel **c**). The neighbors of replicated node i are the potential connecting nodes of the new node n, as indicated as by four dotted lines. **d** New node n connects to half of the neighbors $\Gamma(i)$ of replicated node i, as indicated as by two bolded solid lines. In weight update process starting from the current topology (panel **e**), the establishment of a new edge of weight w_0 to the node j generates a total indirect interaction σ between new node n and the neighbors of node j (panel **f**), and σ is proportionally distributed among the edges departing from the node j according to the strengths of neighbors $\Gamma(j)$ (panel **g**).

attractive or successful existing companies. In the network, all neighbors $\Gamma(i)$ of the replicated node i are considered as potential interacting nodes of new node i (see Fig. 3**c**). Each existing location i is randomly selected as the replicated node according to the probability

$$P_i \propto s_i^{\alpha} \cdot e^{-d_{ni}/r_c} \tag{4}$$

where s_i is the strength of node i,α is the attractiveness parameter, d_{ni} is the Euclidean distance between nodes n and i, and r_c is the typical scale. Node strength s_i captures the generated and attracted truck flows of location i in the current network, measures the economic size of location i and is calculated as the sum of weights of the edges connecting node i. The spatial proximity of two locations is measured by the variable e^{-d_{ni}/r_c}, in which the typical scale r_c controls the effects of trade, logistics and transaction costs associated with spatial distance on the spatial interaction.

Next, we assume the connection rule that new node n connects to some but not all the neighbors $\Gamma(i)$ of replicated node i, considering that commonly a new company would not have as many cooperation partners as the existing successful companies. For simplicity, we assume that new node n connects to half of the neighbors $\Gamma(i)$ of duplicate node i (see Fig. 3**d**). Also considering the effects of spatial distance and economic size, we assume each node $j \in \Gamma(i)$ is randomly connected by the new node n according to the probability

$$P_{(n,j)} \propto s_j^{\alpha} \cdot e^{-d_{nj}/r_c} \tag{5}$$

where s_j is the strength of node j, d_{nj} is the Euclidean distance between nodes n and j, α and r_c are identical to equation (4). After establishing new edges, we can obtain the topology of the current network at this step (see Fig. 3**e**).

Finally, we update edge weights after new edges have been established. In the real world, when a new location establishes interaction with an existing location, it may also establish indirect interactions with other existing locations through this connected location. For example, a logistics company could transport more goods to other companies in a city through a new established connection with a freight hub, leading to the indirect interactions between this logistics company and other companies. Therefore, we update weights using the traffic increment rule (Barrat et al., 2004). We assume that the direct interaction strength of new node n with connected node j is $w_0 = 1$ (equal to the edge weights of initial network) and the indirect interaction strength of new node n with other nodes via connected node j is σ. The strength s_j of the connected node j is updated according to the rule (see Fig. 3**f**)

$$s_j \rightarrow s_j + w_0 + \sigma \tag{6}$$

where the indirect interaction strength σ is assigned to the edges between the new node n and the other nodes. Here we assume that new node n only interacts indirectly with all neighbors $\Gamma(j)$ of the connected node j, and the indirect interaction strength of the new node n with each node $k \in \Gamma(j)$ is proportional to the strength of node k. The weight w_{jk} of each existing edge (j,k) is rearranged according to the rule (see Fig. 3**g**)

$$w_{jk} \rightarrow w_{jk} + \sigma \frac{s_k}{\sum_{m \in \Gamma(j)} s_m} \tag{7}$$

The strength s_k of node $k \in \Gamma(j)$ is updated according to the rule (also see Fig. 3**g**)

$$s_k \rightarrow s_k + \sigma \frac{s_k}{\sum_{m \in \Gamma(j)} s_m} \tag{8}$$

In the next step, another new node is added from the remaining urban freight-related POIs, and the topology and weights of current network are updated according to the above rules. The network growth process ends when the network size reaches the set value.

The model contains three key parameters, i.e., the attractiveness parameter α, typical scale r_c and indirect interaction strength σ. We estimate the model parameters by using a graph similarity-based method (Sala et al., 2010) to reproduce the structure properties of real networks as well as possible.

4. Results and discussion

We construct freight truck mobility networks of four cities, i.e., Beijing, Shanghai, Chongqing and Tianjin, for analysis. We characterize the structure of the mobility networks to uncover the distribution patterns of network nodes (see **Section 4.1**), the spatial structure of truck mobility networks (see **Section 4.2**) and interaction patterns between urban locations (see **Section 4.3**). Moreover, we estimate the optimal parameters of spatial network growth model for each city, and generate corresponding model networks. We compare the properties of model networks with those of empirical networks, and give explanations for how the core structure features of urban freight transport system are formed (see **Section 4.4**).

4.1. Distribution patterns of network nodes

To characterize the distribution patterns of network nodes, we conduct two distinct analyses. (1) Urban road infrastructure relationship analysis: elucidating the spatial relationships between freight-related locations and the urban road infrastructure; (2) spatial distribution analysis: unveiling the spatial distributions of aggregation or dispersion among locations relevant to freight activities.

4.1.1. Urban road infrastructure relationship analysis

For the urban road infrastructure relationship analysis, we first calculate the densities of four types of roads, i.e., motorway, primary road, secondary road and tertiary road, within the Voronoi polygons corresponding to locations, and then examine the statistical relationships between truck flows into and out of locations and surrounding road densities. Taking Beijing as an example, the analysis results are shown in Fig. 4. The results can shed light on how the hierarchy of roadways impacts freight transportation patterns. Firstly, the positive Pearson correlation coefficient ($r = 0.1521$, p-value $= 0.1669$) between motorway density and locations truck flows suggests a modest positive relationship. This indicates that higher motorway density is associated with slightly increased truck flows. Motorways, known for their efficiency and connectivity, seem to play a role in facilitating freight activities within the city. Secondly, the correlation between primary road density and truck flows ($r = 0.2038$, p-value $= 0.0627$) demonstrates a stronger positive association. This may due to that primary roads typically play a crucial role in connecting key economic centers and industrial zones, providing more direct and accessible routes for freight movements than motorways. Motorways, while efficient for long-distance travel, may have limited accessibility within the city and may not serve as primary routes for urban logistics. On the other hand, the negative correlations for secondary and tertiary road density implies a weak and inverse relationship with location truck flows. This suggests the presence of secondary and tertiary roads, typically characterized by lower capacity or less strategic importance, may have limited influence on the volume of truck flows in the context of freight transportation.

In addition, Fig. 4 also indicates that for locations characterized by low truck flows, there is a tendency for the densities of motorways and primary roads in the vicinity to be lower, while the densities of secondary roads and tertiary roads tend to be higher. Conversely, for locations with high levels of truck flows, there is a trend toward higher densities of motorways and primary roads in the surrounding area, accompanied by lower densities of secondary roads and tertiary roads. The road infrastructure in urban areas is often tailored to the specific needs and activities of different locations (Adugbila et al., 2023). Locations with low truck flows prioritize local accessibility and reduced congestion, leading to denser networks of secondary and tertiary roads. In contrast, locations with high truck flows require efficient, long-distance transportation options, which are provided by motorways and primary roads. These findings not only underscore the significance of road hierarchy in shaping freight transportation patterns, but also highlight the multifaceted nature of urban logistics (Allen et al., 2012; Pirra et al., 2022). Urban planners and transportation authority should carefully consider these factors to balance the freight demands of various areas within a city.

4.1.2. Spatial distribution analysis

For the spatial distribution analysis, we first calculate the metrics of *Moran's I* and *Geary's C* for the nodes of freight truck mobility networks in four cities, as shown in Table. 1. The results suggest that the spatial distribution patterns of network nodes in these four cities exhibit varying degrees of spatial autocorrelation and heterogeneity in relation to freight truck mobility. Chongqing, characterized by a vast geographic area, exhibits a remarkably high *Moran's I* value of 0.71 and a low *Geary's C* value of 0.15, indicating a

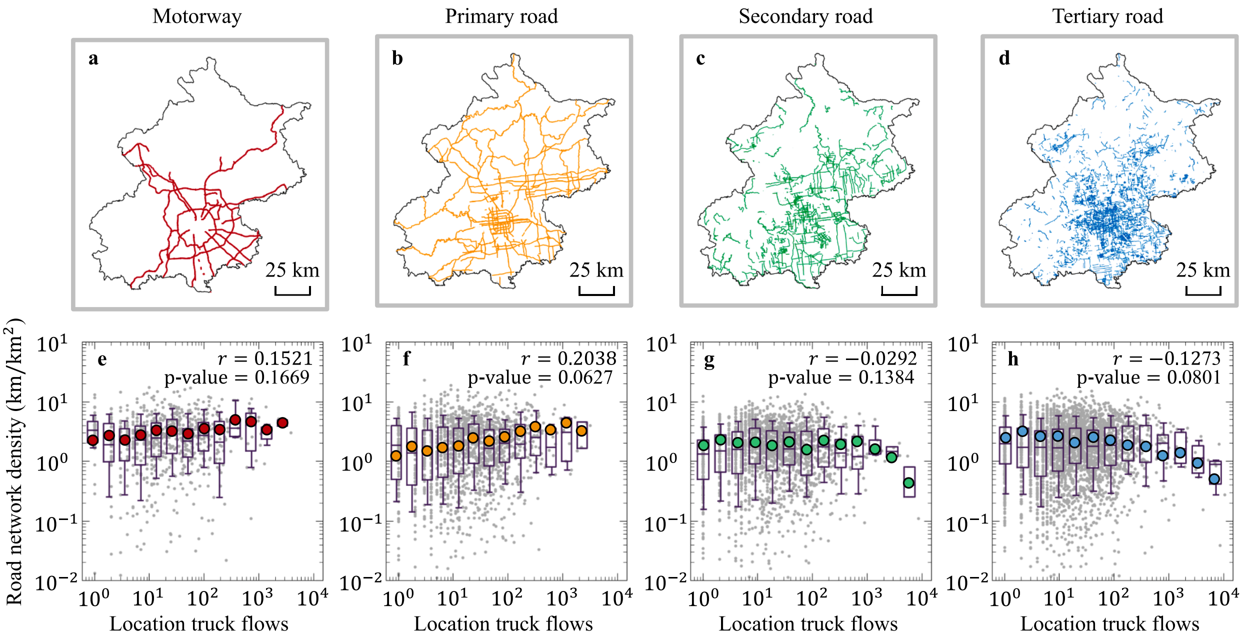

Fig. 4. Statistical relationships between location truck flows and road densities of surrounding areas. **a-b** Geographical distribution of four types of roads in Beijing. **e-h** Boxplots of road density with respect to location truck flows. The grey points are scatter plot for each location. The points in boxes represent the average road density in the bins. The boxplots represent the distribution of road density in different bins of location truck flows.

substantial clustering tendency among freight-related nodes. This suggests that in Chongqing, freight activities tend to concentrate in specific regions. Tianjin, with its relatively lower population, GDP, and total road length, still demonstrates a substantial *Moran's I* value of 0.65 and *Geary's C* value of 0.18, indicating a clustering tendency among its freight-related nodes. In contrast, Shanghai (with *Moran's I* value of 0.52 and *Geary's C* value of 0.23) and Beijing (with *Moran's I* value of 0.43 and *Geary's C* value of 0.39) exhibit weaker location clustering tendencies despite their high levels of economic activity.

Moreover, the incorporation of *Ripley's F* function $F(r)$ for spatial analysis corroborates above observations (see Fig. 5). Initially, the curves of $F(r)$ surpass the random pattern (πr^2), suggesting an aggregation of locations within certain distances. There may be factors that promote the clustering or aggregation of locations within relatively short distances. These factors could include economic activities, infrastructure development, and urban planning policies that encourage the concentration of businesses or services in certain areas (Adeniyi et al., 2023). Beyond certain critical distances, the $F(r)$ curves dip below the random pattern, indicating locations within the cities tend to spread out or become more evenly distributed as distances increase. This dispersion could be due to factors like suburbanization or geographical barriers that encourage the scattering of locations over a larger area (Lundman and Kymalainen, 2023). In addition, the intersections of $F(r)$ curves with the random pattern (πr^2) are at distances of 65 km, 69 km, 41 km, and 42 km for Beijing, Shanghai, Chongqing, and Tianjin, respectively. We can find that Chongqing and Tianjin have stronger location clustering tendencies, but these clusters are more concentrated within shorter distances. Beijing and Shanghai have weaker location clustering tendencies, and the clusters extend over larger areas. These findings not only provide insights into the unique location distribution patterns in these cities, but also offer a foundation for urban planning tailored to each city's distinct urban environment profile.

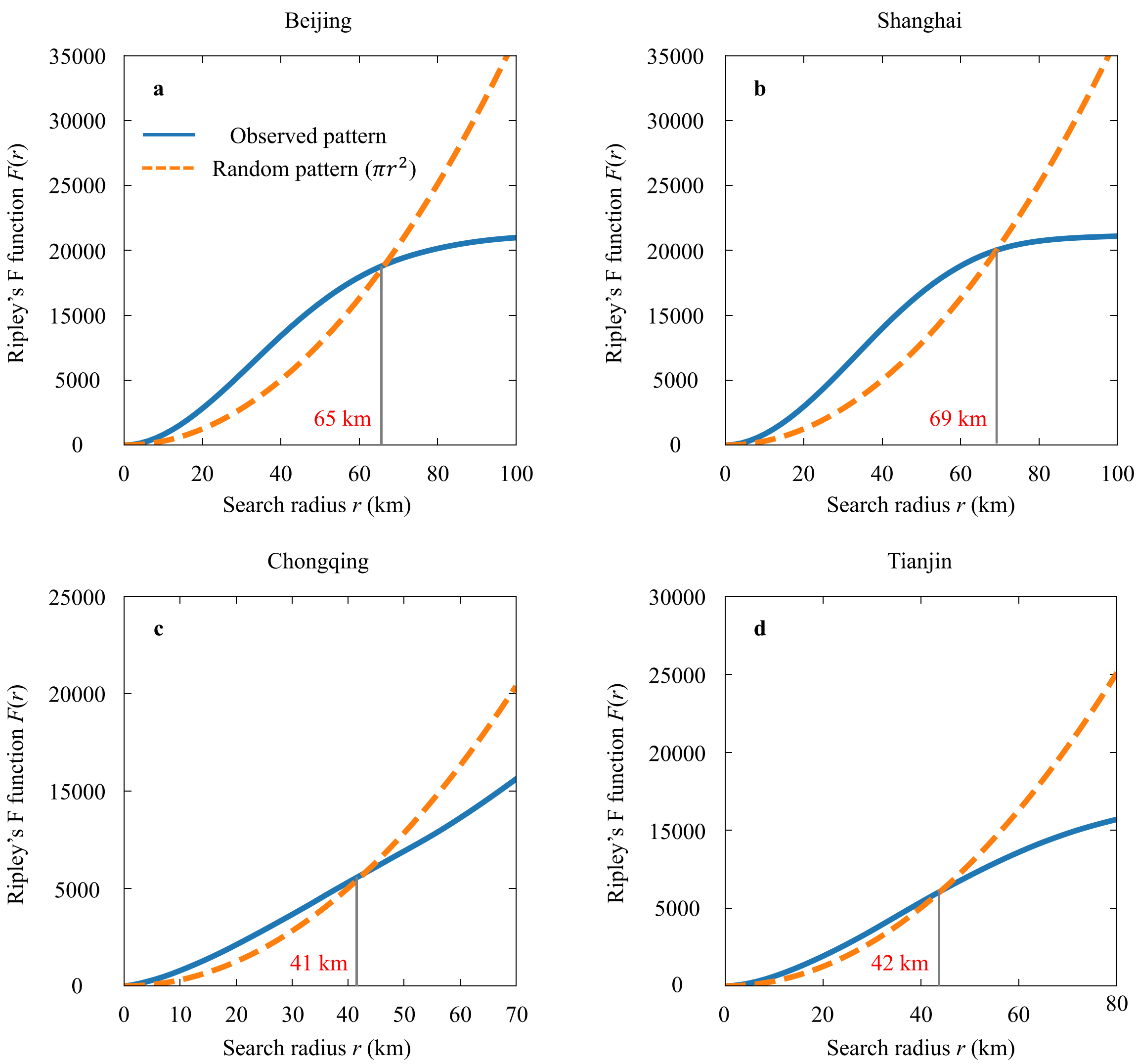

Fig. 5. Distributions of *Ripley's F* functions $F(r)$ with respect to search radius r in four cities.

4.2. Spatial structures of truck mobility networks

We use the measures of node degree, edge distance and rich-club coefficient to characterize the urban freight truck mobility networks of four cities, and to uncover their spatial structure.

We first calculate the degree of each node and obtain the degree distributions $p(k)$ of urban freight truck mobility networks (see Fig. 6**a-d**). The degree distributions $p(k)$ obey the cut-off power-law distribution, i.e., $p(k)\ (k+\Delta k)^{-\gamma}e^{-k/k_x}$, where γ is the power exponent and k_x is the cutoff value. These results suggest that urban freight truck mobility networks have a scale-free property (Barabasi and Albert, 1999), indicating that a few key locations (such as distribution centers or warehouses) are highly connected to many other locations (such as retail stores or manufacturing facilities), while most other locations have relatively few connections. These highly connected locations, also known as 'hubs', are critical for the overall functioning of the urban truck transport system and for efficient freight movements (Combes and Tavasszy, 2016).

Next, we calculate Euclidean distances between connected pairs of locations and obtain the distance distributions $p(d)$ of urban freight truck mobility networks (see Fig. 6**e-h**). The distance distributions $p(d)$ decay exponentially, i.e., $P(d)\ e^{-d/r_d}$, where r_d is the typical scale. The results indicate that most freight movements occur over short distances, while long-distance movements are relatively rare. This is a reflection of supply chain regionalization (Silva et al., 2021) where many manufacturing, retail, and distribution centers located within close proximity to each other and are located closer to the end consumers. This has led to more feasible and cost-effective localized freight movements and a decrease in long-distance movements.

Moreover, we calculate the rich-club coefficient $RC(k)$ at different degree levels k (see Fig. 6**i-l**), which is an increasing function of k

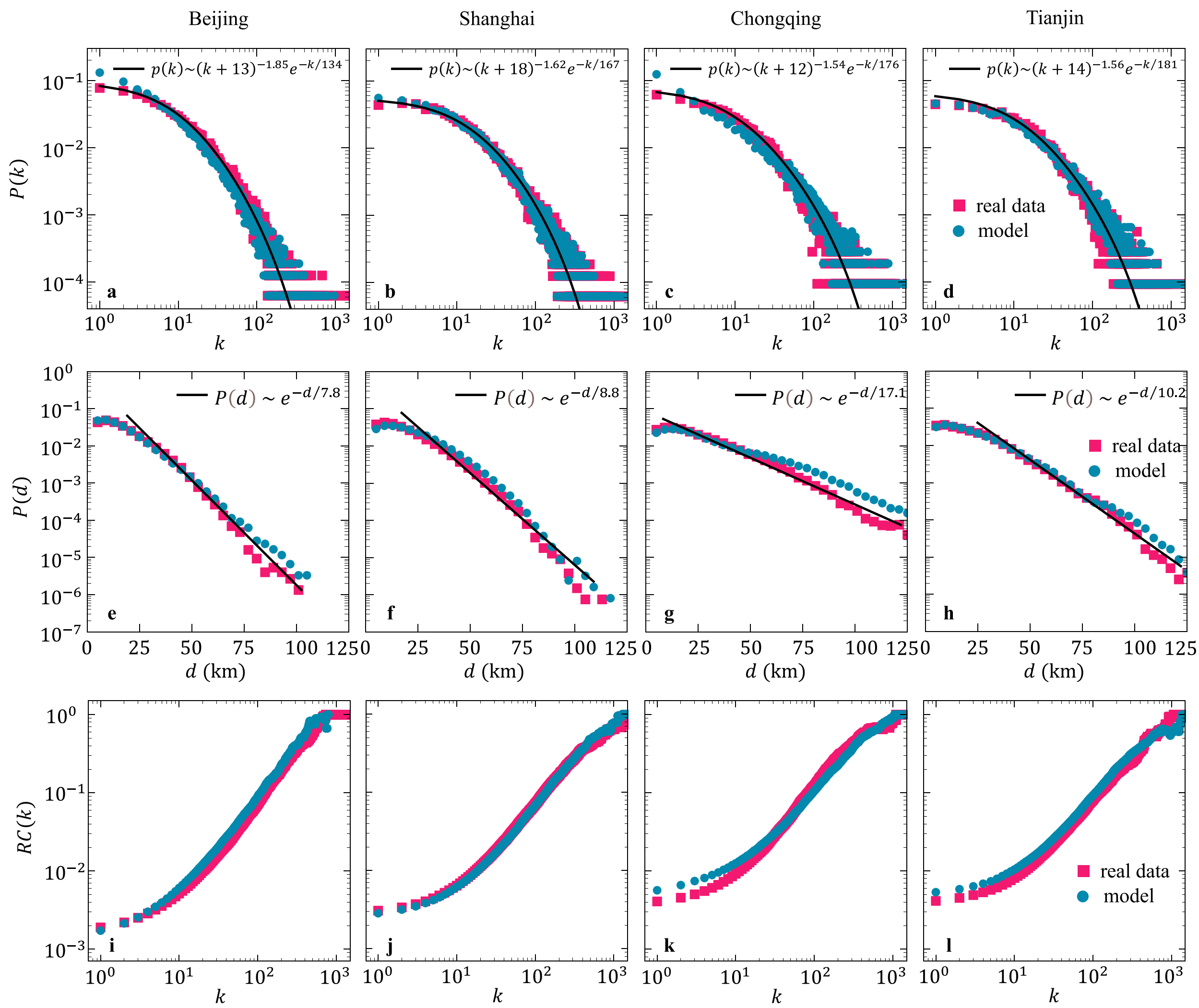

Fig. 6. Spatial structure properties observed from freight truck mobility networks of four cities and reproduced by the developed spatial network growth model. **a-d** Node degree distributions $p(k)$. The line represents the fitted cut-off power-law distribution $p(k)\sim(k+\Delta k)^{-\gamma}e^{-k/k_x}$. **e-h** Edge distance distributions $p(d)$. The line represents the fitted exponential distribution $P(d)\sim e^{-d/r_d}$. **i-l** Rich-club coefficient distributions $RC(k)$.

and closed to 1 for sufficiently large k. The results imply that freight locations with few connections tend to distribute locally, while major freight hubs or distribution centers tend to be strongly connected with one another. This is a reflection of spatial concentration of economic activity and transport infrastructure (Hui et al., 2020). These hubs often serve as crucial nodes in urban freight transport systems, facilitating the movement of goods between various locations within the city, and dominating the network. Nodes located in less central or less accessible areas remain relatively isolated.

To further understand the core structure of urban freight transport system, we explore how locations with different connectivity are organized in space. For each connected pair of nodes, we calculate the maximum degree of the two nodes and the distance between them. We obtain the two-dimensional probability distributions of the maximum degree and distance for all node pairs in freight truck mobility networks of four cities, as shown in Fig. 6**b-e**. The results indicate that the data of the maximum degrees of node pairs are concentrated in large values, contrasting with the scale-free degree distributions $p(k)$ shown in Fig. 6**a-d**. These results suggest that a large number of locations have low connectivity, but they tend to establish interactions with high-connectivity nodes, i.e., preferential attachment (Barabasi and Albert, 1999). Well-connected locations are typically easily accessible, making them attractive locations for businesses and freight operations to set up new facilities. This can save time, reduce transportation costs and benefit from economies of scale. Fig. 7**b-e** show that long-distance interactions always involve high-connectivity nodes, reflecting the hub-and-spoke core structure of urban freight transport systems (see Fig. 7**a**), where hubs serve as the primary transfer points for goods moving between different regions in city.

Based on the above analysis, we can also observe variations in the spatial structure of heavy truck mobility networks among different cities. For example, a higher power exponent γ (1.85) in degree distribution $p(k)$, as observed in Beijing (see Fig. 6**a**), suggests that it has a more centralized or hub-like network structure, with specific locations serving as major connectivity hubs. In contrast, the lower power exponents in Shanghai (1.62) (see Fig. 6**b**), Chongqing (1.54) (see Fig. 6**c**), and Tianjin (1.56) (see Fig. 6**d**) suggest more distributed network connectivity. Moreover, the variations in the typical scales r_d of distance distributions signify differences in the spatial reach of freight truck interactions. Chongqing's larger typical scale (17.1) (see Fig. 6**g**) implies that freight locations are more widely dispersed, likely due to its extensive geographic area. Conversely, Shanghai's smaller typical scale (8.8) (see Fig. 6**f**) suggests localized freight interactions, reflecting its compact urban layout. In addition, the distributions of maximum degree and distance of node pairs offer insights into network characteristics. In Chongqing, where maximum degree values are concentrated at higher levels and node pair distances are relatively large (see Fig. 7**d**), indicating that certain locations in the city serve as major hubs for freight activities, leading to longer-distance interactions. In Tianjin, the concentration of node pair distances at smaller values (see Fig. 7**e**) signifies that freight interactions are primarily local, with shorter distances between locations. In Beijing and Shanghai, the more even distribution of maximum degree values (see Fig. 7**b-c**) suggests a balanced mix of both central and peripheral locations in their freight systems.

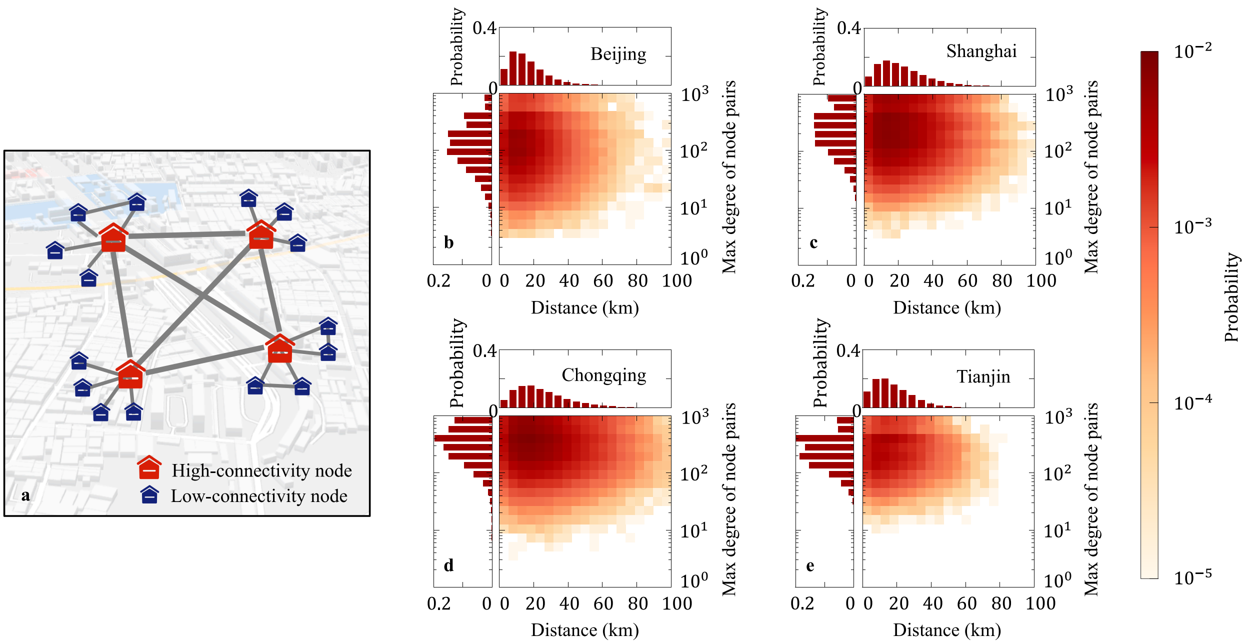

Fig. 7. Spatial organization of nodes with different connectivity. **a** Illustration of hub-and-spoke core structure of urban freight transport systems. **b-e** Distributions of the maximum degree and distance of node pairs in freight truck mobility networks of four cities. The histograms on the left and above the figure represent the probability distributions of the maximum degree and distance respectively.

4.3. Interaction patterns between locations

Here we use measures of degree of nearest neighbors, clustering coefficient and the Jaccard similarity coefficient to uncover the interaction patterns between urban freight locations.

We first calculate the weighted and unweighted average degree of nearest neighbors per degree class k, i.e., $\langle k_{nn}\rangle(k)$ and $\langle k_{nn}\rangle^{w}(k)$. The results show that $\langle k_{nn}\rangle^{w}(k) \geq \langle k_{nn}\rangle(k)$ at different values of k and the ratio of $\langle k_{nn}\rangle^{w}(k)$ to $\langle k_{nn}\rangle(k)$, i.e., $\langle k_{nn}\rangle^{w}(k)/\langle k_{nn}\rangle(k)$, is an increasing function of k (see Fig. 8**a-d**), suggesting the distribution of edge weights in the network is heterogeneous, especially for high-connectivity nodes. The interaction strength between locations is typically positively correlated with their connectivity, as shown in Fig. 9**b-c**. Locations with better connectivity, such as well-developed distribution centers or airports, can facilitate the movement of freight more efficiently. This leads to an increase in the volume of goods being transported between these locations, thus enhancing the interaction strength. Locations with high connectivity often benefit from agglomeration economies (Li et al., 2022), promoting more freight movement between connected locations, leading to stronger interactions.

Next, we calculate the weighted and unweighted clustering coefficient per degree class k, i.e., $C^{w}(k)$ and $C(k)$. The results show that

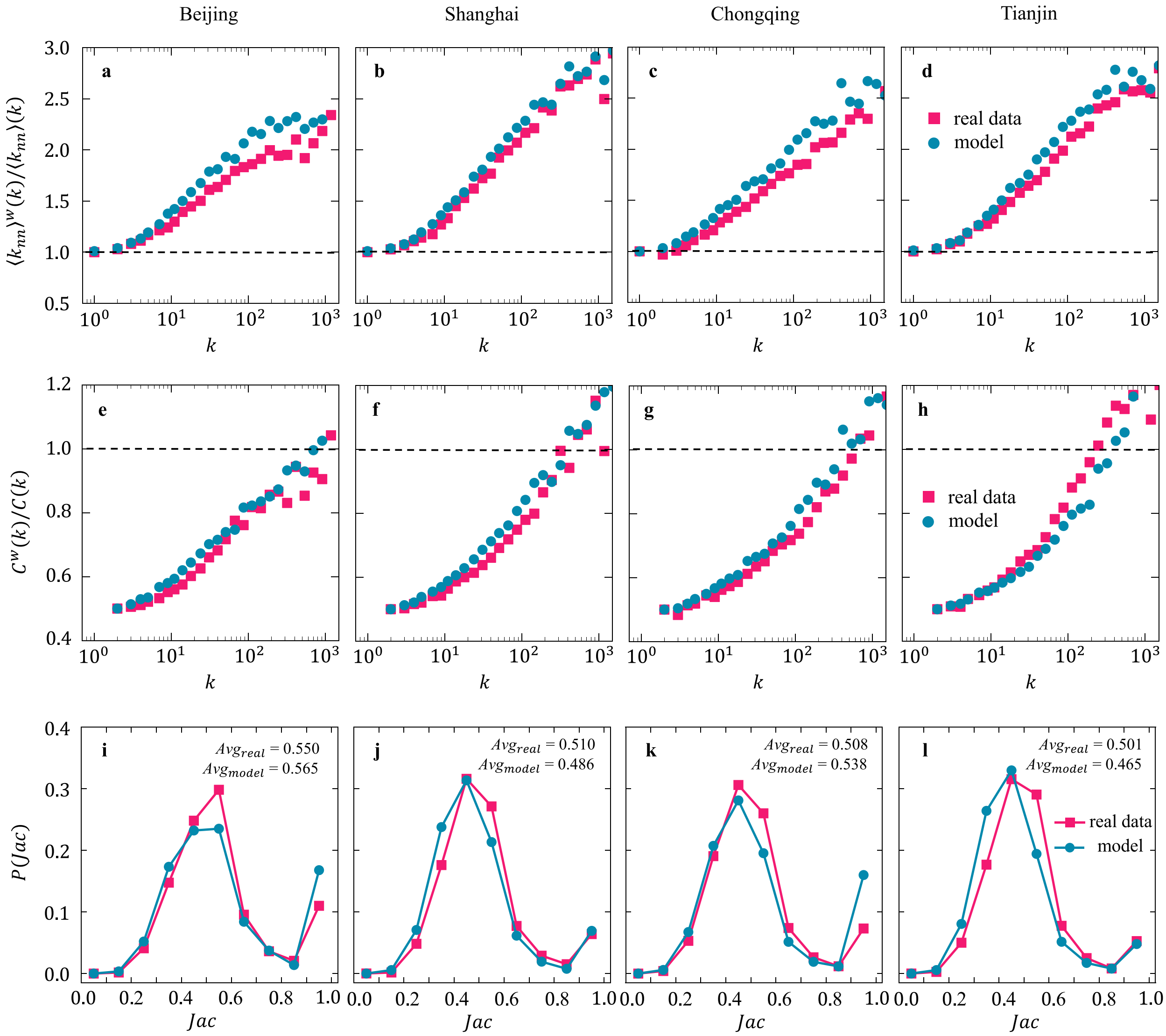

Fig. 8. Interaction patterns between urban freight locations observed from freight truck mobility networks of four cities and reproduced by the developed spatial network growth model. **a-d** Distributions of the ratio of weighted average degree of nearest neighbors per degree class $\langle k_{nn}\rangle^{w}(k)$ to unweighted one $\langle k_{nn}\rangle(k)$, i.e., $\langle k_{nn}\rangle^{w}(k)/\langle k_{nn}\rangle(k)$. Each dashed line indicates $\langle k_{nn}\rangle^{w}(k)/\langle k_{nn}\rangle(k) = 1$. **e-h** Distributions of the ratio of weighted clustering coefficient per degree class $C^{w}(k)$ to unweighted one $C(k)$, i.e., $C^{w}(k)/C(k)$. Each dashed line indicates $C^{w}(k)/C(k) = 1$. **i-l** Distributions of Jaccard similarity coefficient $p(Jac)$ for all node pairs. Avg$_{real}$ and Avg$_{model}$ indicate the average values of the data of Jaccard similarity coefficients for all node pairs in real networks and model networks respectively.

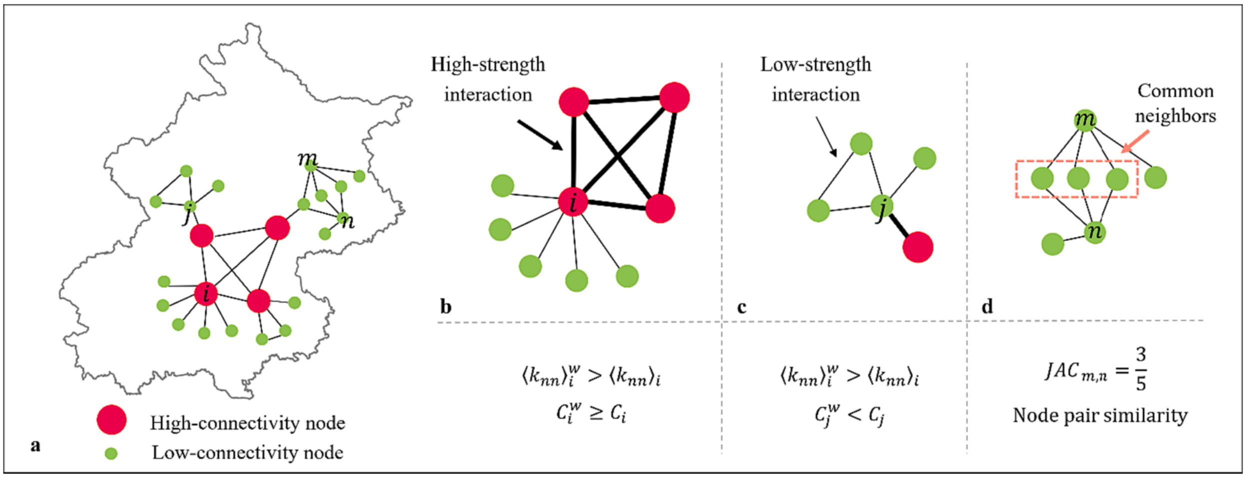

Fig. 9. Illustration of interaction patterns between urban freight locations. **a** Diagram of spatial structure of urban freight truck mobility networks. **b** Sub-structure consisting of high-connectivity node i and its neighbors. The thickness of connection between two nodes indicates the high or low interaction strength. $\langle k_{nn}\rangle_i^w$ and $\langle k_{nn}\rangle_i$ indicate the weighted and unweighted average degree of nearest neighbors of node i. C_i^w and C_i indicate the weighted and unweighted clustering coefficient of node i. **c** Sub-structure consisting of low-connectivity node j and its neighbors. **d** Similarity of interaction patterns of two nodes. $JAC_{m,n}$ indicates the Jaccard similarity coefficient between nodes m and n.

the ratio of $C^w(k)$ to $C(k)$, i.e., $C^w(k)/C(k)$, is an increasing function of k (see Fig. 8**e-h**); $C^w(k) \geq C(k)$ at large k, while $C^w(k) < C(k)$ at small k. This indicates that high-connectivity nodes tend to form tightly-knit clusters within the network and they are connected by strong connections, as shown in Fig. 9**b**. In contrast, the interaction strength within local clusters consisting of low-connectivity locations is usually low, as shown in Fig. 9**c**. Due to distance and logistics operations issues, many low-connectivity locations, such as last-mile delivery locations (Abualola et al., 2023), may have weaker connections with each other, while have stronger connections with major transport hubs. Furthermore, we calculate the Jaccard similarity coefficient $Jac_{i,j}$ to measure the similarity of interaction pattern between locations i and j. The distribution of Jaccard similarity Jac and average value Avg_{real} for all node pairs in the urban freight truck mobility networks of four cities are shown in Fig. 8**i-l**, which indicate that $p(Jac)$ peaks around value of 0.5 and Avg_{real} is also significantly high for large-scale networks.

The above results suggest that the interaction patterns of many location pairs are similar, i.e., they tend to transport cargo or provide products to the same client or there is a significant overlap between their service areas, as shown in Fig. 9**d**. As highlighted in the literature, freight locations located within the same market area tend to serve the same clients because they are well-suited to handle the specific needs of those clients, or required to meet specific supply chain requirements, such as just-in-time delivery (Carvalho et al., 2022). In addition, the above results also reveal disparities in the interaction patterns between locations among different cities. Specifically, we can observe both slower growth rates and lower maximum values of $\langle k_{nn}\rangle^w(k)/\langle k_{nn}\rangle(k)$ and $C^w(k)/C(k)$ in Beijing compared to other three cities. This could indicate a more dispersed or less tightly connected urban freight network in Beijing, where certain locations have fewer strong connections with other locations. Beijing's economic activities may be more diversified compared to other cities, including a mix of industrial, commercial, and administrative functions. This economic heterogeneity can lead to disparities in the types of urban freight activities and the spatial distribution of freight locations, potentially resulting in different interaction patterns. Furthermore, historical and cultural factors may also impact how goods are transported and distributed, potentially shaping the interaction patterns between locations in Beijing.

4.4. Formation of structures and interaction patterns

Here we provide an explanation for how the core structure characteristics of urban freight transport systems and the interaction patterns between locations are formed. The developed spatial network growth model contains three key parameters, i.e., the attractiveness parameter α, typical scale r_c and indirect interaction strength σ. We first estimate the parameters by using a graph similarity-based method (Sala et al., 2010) by using the data of real urban freight truck mobility networks, and generate the model network for each city.

The obtained degree distributions $p(k)$ of model networks (see Fig. 6**a-d**), are in excellent agreement with the real results. This shows that the model can reproduce the scale-free property of real networks, mainly attributed to the connection rule that considers the effects of economic size on the interactions between locations. The model clarifies that when new locations are established, they often interact with locations that have large economies of scale. These existing well-developed locations have already built significant infrastructure and resources that make them attractive to businesses and consumers. For example, a new factory might locate near a port or transport hub that is already well-connected to national and international markets. Similarly, a new retail store might locate in a shopping mall or commercial district that already has a large customer base and established supply chains. Therefore, as the city grows, these well-developed locations are getting larger and larger, resulting in the scale-free characteristics of urban freight transport systems.

Next, we obtain the distance distributions $p(d)$ of model networks (see Fig. 6**e-h**), and they are again in excellent agreement with real results. This is mainly attributed to the connection rule that considers the effects of spatial distance on the interactions between locations. The model clarifies that when a new location is established, it is often more practical to make connections with nearby locations. These physically closer locations are easier to reach and interact with for reducing transportation costs or improving access to resources. Therefore, the interaction distance between locations is typically short in the urban freight transport systems. In addition, our model is able to reproduce the rich-club property of real networks (see Fig. 6**i-l**). This is often referred to as the replication rule, which states that the establishment of a new location is often accompanied by the replication of the successful business patterns of existing locations. Here, under the effects of economic size on spatial interactions, well-developed locations are increasingly connected to each other as an urban freight system sprawl.

Importantly, our model suggests an explanation for the sprawl patterns between urban freight locations. The model shows that when a new location establishes interaction with an existing location, it may also establish indirect interactions with other existing locations through this connected location. For example, a new factory that establishes a supply chain relationship with an existing supplier may indirectly benefit other suppliers who are connected to the existing supplier through their own supply chains. This spillover effect (Tang et al., 2023) becomes more significant as more connections are established to well-developed locations. Therefore, the $\langle k_{nn}\rangle^{w}(k)/\langle k_{nn}\rangle(k)$ and $C^{w}(k)/C(k)$ are both increasing functions of k (see Fig. 8**a-d** and Fig. 8**e-h**). Due to this spillover effect, the interaction patterns between locations with different connectivity differ: high-connectivity locations tend to form the backbone of the network and are connected by strong connections, while the interaction strength within local clusters consisting of low-connectivity locations is usually low.

Finally, our model explains the similarity of connection patterns of locations (Fig. 8**i-l**), i.e., a large number of location pairs share many common neighbors. The replication rule in the model clarifies that new established companies often take inspiration from existing companies and try to replicate their successful business patterns. Many successful companies have developed proven business models, strategies, and practices that have helped them achieve their goals and grow their businesses. By taking inspiration from existing companies, new companies hope to reduce the risks associated with starting a new business and increase their chances of success. Therefore, many locations tend to transport cargo or provide products to the same client and there is a significant overlap between their service areas in the urban freight transport systems.

5. Practical implications

With the above analyses, we have revealed the prevalent core structure properties and interaction patterns of urban freight systems. To explain the underlying interaction dynamics, we have developed a spatial network growth model. It improves our qualitative understanding of structural, functional and dynamic properties of urban freight mobility networks. In addition, the models provide quantitative spatial metrics. The developed model captures the essential interaction dynamics of freight locations, and explains the effects of spatial distance, economic size and business pattern replication on the development of urban freight transport systems. We discuss the relevant insights and implications for urban planning and management practice below.

Firstly, the model empirically confirms that the clustering of freight locations enhances the efficiency of the urban freight transport system, by reducing the spatial distance between locations and facilitating interactions between them. By improving the efficiency of urban freight transport systems, the negative impacts of freight activities on the environment and public health can be reduced, and make urban development more sustainable. To promote clustering, policies can provide incentives for businesses to locate near existing freight clusters, such as tax breaks or reduced land costs. Urban planners can create zoning regulations that encourage the clustering of businesses and freight locations. Transportation planners can also focus on improving access to existing freight clusters by developing transportation infrastructure, such as roads and highways, that facilitate interactions between locations.

Secondly, our model results show that new businesses often take inspiration from existing successful companies and try to replicate their business patterns. To achieve sustainable urban freight, policies can support collaboration and knowledge sharing in the sustainable freight industry, helping businesses to adopt sustainable practices and technologies more quickly and accelerating the industry's transition to a more sustainable future. These policies may include government-supported sustainable freight development programs (Touratier-Muller and Ortas, 2021) or tax incentives and grants for businesses to invest in sustainable infrastructure (Wangsa et al., 2023).

Thirdly, our model highlights the potential for new freight locations to establish indirect interactions with other existing locations through their connected location. Based on the model's observation, businesses and government agencies can promote the development of intermodal facilities and the integration of different modes of transportation, to improve the significance of the spillover effects on urban freight economy (Marinos et al., 2022). The specific initiatives may include building intermodal facilities, dividing freight-friendly zones and optimizing freight movement. These initiatives also have the potentials to enhance traffic safety (Song et al., 2023a; Song et al., 2023b; Su et al., 2023) and improve the overall efficiency of urban freight systems (Jia et al., 2023; Lin et al., 2023).

In addition to the policy relevant insights from the model application, the developed models also have potential to be applied in practice for predictions and policy evaluations. Where large-scale freight truck mobility data are available, these can be used to construct urban freight truck mobility networks and estimate the parameters of the spatial network growth model. As we discussed in the model construction, the values of the model parameters α and r_c reflect the roles of location attractiveness and space in the spatial interaction pattern between locations. The value of the model parameter σ reflects the indirect interaction strength between locations. The variations in model parameters across cities reveal the distinct characteristics of urban truck transport systems. This helps us to understand the current situation of economic development in specific cities and provide guidance for freight policy development. For cities where large-scale freight truck mobility data are not available, we can approximate the model parameters by referring to the real networks of comparable cities in terms of land use, city size, economic development level, etc. Finally, our model can also be used to predict the future growth of urban freight transport system, providing directions for a more sustainable logistics sprawl (Aljohani and Thompson, 2016).

6. Conclusion

Urban freight transport systems play a crucial role in the functioning of cities and their economies. This work presents methods to uncover the core structure of urban freight transport system and reveal the underlying interaction dynamics, aiming to provide support for urban planning and management. To this end, we obtained a large amount of truck flow data between urban freight locations. We characterized the properties of freight truck mobility networks by using complex networks measures, and to uncover the core structure of urban freight transport systems and interaction patterns between urban locations. To explain the underlying interaction dynamics, we developed a spatial network growth model that consider the effects of spatial distance, economic size and business pattern replication on the growth of urban freight transport systems. Our model captures the essential dynamics of locations, and provide several policy insights for urban land-use planning, transportation planning and sustainable development.

The above leads to a number of new research opportunities. For example, the socio-economic attributes, such as size, industries served, geographic area covered and employment practices of the freight locations can be considered. An analysis that provides a more comprehensive understanding of urban freight transport system could be further studied. Also, the trip purposes of freight trucks can be identified from massive mobility data. In this way, we can obtain the directional flow of goods carried by freight trucks between different types of locations, and analyze in-depth the spatial interaction patterns between freight locations. In addition, while we have opted for the Euclidean distance in our current analysis due to its simplicity and computational efficiency, we acknowledge that it represents a simplification of the intricate urban environment. Future research could explore the differences and trade-offs between various distance metrics, such as real distances or travel times. Investigating these aspects would contribute to a more comprehensive understanding of the factors influencing urban freight mobility and network dynamics.

Moreover, our research primarily focuses on large freight trucks, typically those with a loading capacity exceeding 12 tons. Urban freight systems encompass a diverse fleet of vehicles, including smaller trucks, cargo-bikes, and small vans. These smaller vehicles play a crucial role in the last-mile delivery process within cities and have their unique operational characteristics and spatial patterns. Future research could explore a more comprehensive analysis by including these smaller vehicles, aiming to provide a more holistic understanding of the urban freight transport system. Our proposed network model could also be adapted, e.g., specifically designing new parameters, connection rules and interaction dynamics, to capture the intricacies of last-mile logistics. The universality of the network model could be further validated across a spectrum of urban contexts, including cities of varying scales and diverse regions globally.

Furthermore, our research aims to uncover the broader structural aspects of urban freight truck mobility networks and their formation mechanisms over the long term. In the future, there is potential for conducting more granular temporal analyses that delve deeper into the understanding of urban freight truck movements. This temporal analysis could encompass factors such as rush hour periods and high-traffic days, unveiling distinct congestion patterns, bottleneck occurrences, and operational inefficiencies specific to various times of the day. Such insights would contribute to tackling congestion challenges and enhancing the efficiency of daily freight operations.

CRediT authorship contribution statement

Yitao Yang: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft. **Bin Jia:** Conceptualization, Supervision, Funding acquisition, Project administration. **Xiao-Yong Yan:** Conceptualization, Supervision, Funding acquisition, Methodology, Writing – review & editing. **Yan Chen:** Methodology, Writing – review & editing. **Lóránt Tavasszy:** Writing – review & editing, Supervision. **Michiel de Bok:** Writing – review & editing, Supervision. **Zhuotong Bai:** Writing – review & editing. **Erjian Liu:** Writing – review & editing. **Ziyou Gao:** Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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