Research on the Operation Characteristics of Road Cold Chain Transport Based on Big Data

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Abstract. With the rapid development of big data technology and its support for operational monitoring in the logistics industry, this paper utilizes trajectory data from refrigerated vehicles to analyze the operational characteristics of China's road cold chain transport from three perspectives: scale, spatial distribution, and network structure. The results show that in 2024, the scale of road cold chain transport continues to grow steadily, with cold chain urban distribution services maintaining a dominant role. The demand for road cold chain transport in economically developed regions is relatively active, internal road cold chain transport connections among urban agglomerations such as the Yangtze River Delta, Beijing-Tianjin-Hebei, Chengdu-Chongqing, and the Greater Bay Area are close. In addition, the clustering coefficient indicates that the road cold chain transport network has become more tightly connected, and the hub functions of central cities are further strengthened.

Keywords: Big data, road cold chain transport, operation analysis, spatial distribution

1 Introduction

Cold chain logistics refers to a specialized logistics system that utilizes temperature control, preservation technologies, and dedicated facilities such as cold storage, refrigerated trucks, and containers, to maintain products within specified temperature ranges throughout their entire lifecycle, from initial processing, storage, transportation, circulation, sales, to delivery[1]. Given its wide-ranging applications and critical role in preserving the integrity of fresh agricultural produce and medical goods, high-quality development of cold chain logistics is essential for reducing post-harvest losses, enhancing food quality and safety, and improving the living standards of urban and rural residents. In recent years, the rapid development of emerging business models, such as online fresh food retail and community group buying, has consistently driven demand for cold chain logistics, contributing to steady expansion of the industry. In 2024, the total demand for cold chain logistics in China reached approximately 365 million tons, reflecting a year-on-year increase of 4.3%. During the same period, the annual revenue

H. Li et al. (eds.), *Proceedings of the 2026 5th International Conference on Big Data Economy and Digital Management (BDEDM 2026)*, Advances in Economics, Business and Management Research 383,
https://doi.org/10.2991/978-94-6239-640-1_20

generated by the cold chain logistics sector amounted to 536.1 billion yuan, representing a growth of 3.7% compared to the previous year. Along with market growth, supporting infrastructure and equipment have advanced significantly. By 2024, the national refrigerated vehicle fleet had expanded to 495000 units, representing a year-on-year increase of 14.6%. Over the past five years, the average annual growth rate exceeded 18%. Refrigerated vehicles now constitute 4.3% of all operational freight vehicles nationwide, nearly five times the proportion recorded in 2016, highlighting a substantial and rapid expansion of cold chain capacity.

The Chinese government places high priority on food safety and the development of cold chain logistics. Policy documents such as the Development Plan for Cold Chain Logistics during the 14th Five-Year Plan Period explicitly emphasize strengthening the daily operation monitoring and analysis of the cold chain logistics sector. Consequently, the development status and operational trends of the cold chain logistics have increasingly attracted scholarly attention. Researchers have approached the industry's current conditions and existing challenges from multiple perspectives. Zhang and Hou[2] identified that the spatiotemporal distribution of cold chain logistics facilities exhibits evolutionary characteristics of agglomeration and diffusion. Wang[3] adopted a demand-oriented approach, focusing on the development of cold chain logistics for three major product categories: fresh agricultural products, dairy goods, and pharmaceuticals. From a food safety standpoint, Wang[4] examined existing issues within cold chain logistics sector and proposed corresponding countermeasures. Using hairy crab as a case study, Du[5] analyzed the current status and challenges in the cold chain logistics of aquatic products, offering solutions informed by advanced domestic and international practices. Zhang et al.[6] reviewed the status and existing problems of each development stage of agricultural product cold chain logistics through its embryonic stage and initial growth to its rapid expansion and comprehensive enhancement, and looking forward to the future of agricultural product cold chain logistics.

For the evaluation of cold chain logistics development, Zhang et al.[7] constructed an evaluation index system for evaluating the overall development level of agricultural product cold chain logistics. The analysis revealed that Zhejiang, Jiangsu, and Shandong have the highest levels of cold chain logistics development; Beijing, Shanghai, Tianjin and other major consumption areas exhibit relatively higher development levels in agricultural product cold chain logistics. However, there is a significant deficiency in the development of agricultural product cold chain logistics in production regions located in central and western China. Therefore, it is suggested that modern cold chain logistics systems should be established with metropolitan circles as the core. Zhou et al.[8] conducted a comprehensive measurement of the green development level of fresh agricultural products cold chain logistics in 30 provinces and cities in China, and the study showed that the static green development level of fresh agricultural product cold chain logistics is relatively low, while the total factor productivity for its green development demonstrates an upward trend. Significant disparities were observed both between and within regions regarding the green development level of cold chain logistics. The eastern region exhibited a fluctuating decline, whereas the western and central regions showed a fluctuating upward trajectory. He et al.[9] incorporated carbon emission constraints into a scientific assessment of cold chain logistics efficiency across China's four major urban agglomerations, identified substantial regional variations in efficiency development. Moreover, different influencing factors exerted varying directions and impact across urban agglomerations. However, improvements in economic development levels were found to exert a positive influence across all regions. Furthermore, factors including cold storage capacity, the number of refrigerated vehicles, policy environment, and technological advancement have been shown to exert significant positive effects on cold chain logistics efficiency[10]. Establishing a technology-centric cold chain logistics system, introducing shared models and economies of scale, and achieving full-process informational coordination can enhance overall efficiency and service quality[11]. Liu et al.[12] studied the current state of three specific cold chain logistics sectors—e-commerce, supermarkets, and the catering sector, integrating mathematical modeling and time-window constraint analysis, then developed a joint distribution node model to enhance terminal logistics distribution capability. The rapid growth of the digital economy has also introduced new opportunities for the transformation of cold chain logistics. The application of digital technologies such as big data and artificial intelligence is driving iterative upgrades in management practices. For instance, Du et al.[13] proposed an artificial intelligence-based monitoring, optimization, and decision-making system for agricultural and sideline product cold chains, which enables efficient monitoring and forecasting of environmental data and optimizes transportation routes through dynamic path-planning algorithms.

Although a certain amount of research has been done on the development status and trends of cold chain logistics, primarily focusing on areas such as agricultural product e-commerce logistics, food safety, cold chain distribution optimization, and strategies for cold chain logistics, with key technologies to enhance cold chain logistics efficiency and the development of low-carbon cold chain logistics emerging as new research trends[14]. However, existing studies remain relatively insufficient in utilizing big data to analyze the overall operational dynamics and characteristics of the cold chain logistics sector. Given that road transport dominates cold chain logistics in China, accounting for as high as 90% of the total[15], this study employs trajectory data of refrigerated vehicles to analyze the operational characteristics of China's road cold chain transport (RCCT) from perspectives such as scale, spatial distribution, and network characteristics. The findings aim to provide insights and decision-making references for industry regulatory bodies, upstream and downstream enterprises, and other relevant stakeholders in the cold chain logistics sector.

The remainder of this paper is organized as follows. Section 2 describes the methodology in detail. Section 3 shows the analysis and discussion. Finally, we draw the conclusion in Section 4.

2 Methodology

We use the dynamic data of 2024 refrigerated vehicles on the operation monitoring platform, and use Python language for processing and analysis. In order to ensure the data can reflect the transportation business, this paper defines vehicles with daily mileage exceeding 5 km on the platform as valid vehicles. In 2024, the average daily number of valid vehicles is 49094, and their GPS trajectory data for the whole year were selected and extracted for subsequent analysis. GPS trajectory data mainly records refrigerated vehicle number, license plate number, recording time, latitude and longitude coordinates, instantaneous speed.

2.1 Data Preprocessing

To ensure the quality of GPS trajectory data, a rigorous data preprocessing procedure is employed prior to feature analysis. The preprocessing pipeline encompasses four sequential steps as follows: (1) Elimination of incomplete records: GPS trajectory entries with missing or incomplete attribute information are filtered out to ensure data integrity. (2) Deduplication of temporal attributes: Records featuring duplicate temporal stamps are removed, with the most recently generated GPS trajectory entry retained to preserve the timeliness and validity of the dataset. (3) Detection and removal of spatiotemporal discontinuities: Potential spatiotemporal discontinuity points within the GPS trajectory data are identified primarily through map-matching techniques; entries corresponding to these anomalous points are subsequently excluded to rectify trajectory distortion. (4) Filtering of low-speed records: GPS trajectory entries with speed attributes persistently falling below a predefined threshold are discarded to eliminate invalid or non-representative movement data.

2.2 Trip Information Identification

Stay Point Identification.

Given the presence of noise in the GPS trajectory data of refrigerated vehicles and in combination with the inherent characteristics of GPS data, this study uses a stay point identification method based on the speed and temporal attributes of GPS trajectory points. Specifically, the method first identifies potential stay points by evaluating the speed attributes of individual trajectory points, and then further determines the stay points according to the dwell duration of these potential stay points. Python is employed to conduct the analysis and determination of trip information, with the process grounded in the preprocessed GPS trajectory data of refrigerated vehicles.

First, the instantaneous speed of each trajectory point is calculated. Second, consecutive adjacent trajectory points with instantaneous speeds consistently below a predefined speed threshold are merged into a single candidate stay location. The speed threshold is determined based on the average value of average speed of trajectory points within 5 seconds before and after all trajectory points with a speed of 0 km/h[16,17]. The dwell duration of the candidate stay location is defined as the time interval between the timestamps of the first and the last trajectory points in the merged set.

Subsequently, candidate stay locations adjacent in space and time are clustered to identify stay points. Traverse all candidate stay positions, if the geometric center-to-center distance between any two locations is less than a predefined distance threshold, and classify them into the same cluster. For each cluster, the total time span (the difference between the timestamps of the first and the last trajectory points in the cluster) is calculated. If the total time span exceeds the threshold, the cluster is determined as a stay point.

Route Segmentation.

Arrange all the stay points of the vehicle in chronological order, and define the movement trajectory between adjacent stay points as a travel segment. For each segment, inverse geocoding is performed on stay points to match them with the map, mapping each point's coordinates to its corresponding city. When the starting and ending cities are the same, the route is classified as intra-city delivery; otherwise, it is identified as intercity transport, generating an intercity OD matrix. And vehicle operational status can be further assessed by temperature sensor data. If the cabin remains at low temperature throughout the journey, it can be determined to be in cargo transport mode.

2.3 Network Characteristic Analysis

Transport Network.

The RCCT network can be abstracted as a graph composed of nodes and edges $G = (N, E)$, where N is the node set used to represent each city, and E is the edge set used to represent the communications between two cities. If the number of transport activities between the two cities is greater than 0, an edge is established between them. We define a transport activity of a vehicle from the origin to the destination as a trip. The weight of each edge is assigned as the total number of trips recorded between the corresponding two cities. To accentuate the most significant logistics corridors, a threshold of 200 trips is implemented during the network construction. Specifically, if the number of trips between any two cities falls below this threshold, the connection is deemed weak and is consequently excluded from the final network model. This filtering process helps to streamline the network topology by highlighting the most critical and active freight links. The resulting network is subsequently subjected to structural analysis to identify key nodal cities, major freight pathways, and overall network characteristics.

Degree Centrality.

The degree centrality, D_C measures the ability of a single node to communicate with other nodes, and it refers to the number of nodes connected to other nodes. A higher value indicates greater transport activity, suggesting the node serves as a hub within the network. Essentially, degree centrality represents the total number of direct connections a node has with other nodes. In directed graphs, degree centrality can be further categorized into in-degree centrality and out-degree centrality. In-degree centrality reflects the total number of incoming connections from other nodes to the focal node, embodying a "demand" attribute; out-degree centrality measures the total number of outgoing connections from the focal node to others, representing a "supply" attribute.

$$D_C = \frac{\sum_{j=1}^{n} a_{ij}(i \neq j)}{n-1} \tag{1}$$

Where a_{ij} is the node directly connected to node i and n is the number of city nodes in the network.

Clustering Coefficient.

The clustering coefficient C_v is a transfer function that reflects the local cohesion of the nodes of the network. The clustering coefficient C is the average of the clustering coefficients of all nodes, and it measures the degree of clustering in the vicinity of each node in the graph. It is a coefficient that reflects the degree of aggregation of the entire network, indicating the local cohesiveness of the network. The local clustering coefficients of the nodes are given by the ratio of the connectivity between nodes in the neighborhood divided by the number of possible connected edges between them:

$$\mathrm{C} = \frac{1}{n}\sum_{v_i \in V} C_v = \frac{1}{n}\frac{2|\{a_{ij}:\ v_i, v_j \in N_i, a_{ij} \in A\}|}{k_i(k_i-1)} \tag{2}$$

Where $N_i = \{v_j : a_{ij} \in A\}$ is the set of nodes immediately adjacent to the node i, $k(i)$ is the number of nodes.

3 Analysis and Discussion

This section analyzes the operational characteristics of RCCT from three dimensions: scale, spatial distribution, and network structure. The scale dimension mainly describes changes in the volume of transportation activities. The spatial dimension focuses on the spatial distribution of transportation demand and inter-regional business connections. The network dimension examines changes in the transportation network using two key metrics: node degree centrality and the clustering coefficient.

3.1 Scale Characteristic

In 2024, the scale of RCCT business witness further growth. Refrigerated vehicles completed 54.8 million trips throughout the year, marking a 16.7% increase compared with 2023, as shown in Figure 1. According to the analysis of Cold Chain Logistics Committee of the China Federation of Logistics & Purchasing, in 2024, the continuous increase in cold chain logistics business volume of fresh e-commerce and the growing demand for high-quality agricultural products from consumers have driven the demand for cold chain logistics. The data from the Ministry of Commerce showed that from January to October 2024, sales of Chilean cherries and Malaysian durians on e-commerce platforms increased by 107.8% and 23.6% respectively, creating significant opportunities for industry development and effectively promoting the continuous expansion of the cold chain logistics market. From the perspective of transport business types, the number of trips for all types of transport vehicles increased compare with 2023. Urban distribution accounts for 49.19 million trips, up 16.6% from 2023, while long-distance trunk routes and medium and short distance trunk routes record 1.27 million and 4.35 million trips respectively, representing year-on-year growth of 16.5% and 18.2%. The market composition remains largely unchanged from 2023, with cold chain long-distance trunk vehicles, medium and short distance trunk vehicles, and urban distribution vehicles accounting for 2.3%,7.9% and 89.8%, respectively, confirming urban distribution services as the dominant segment.

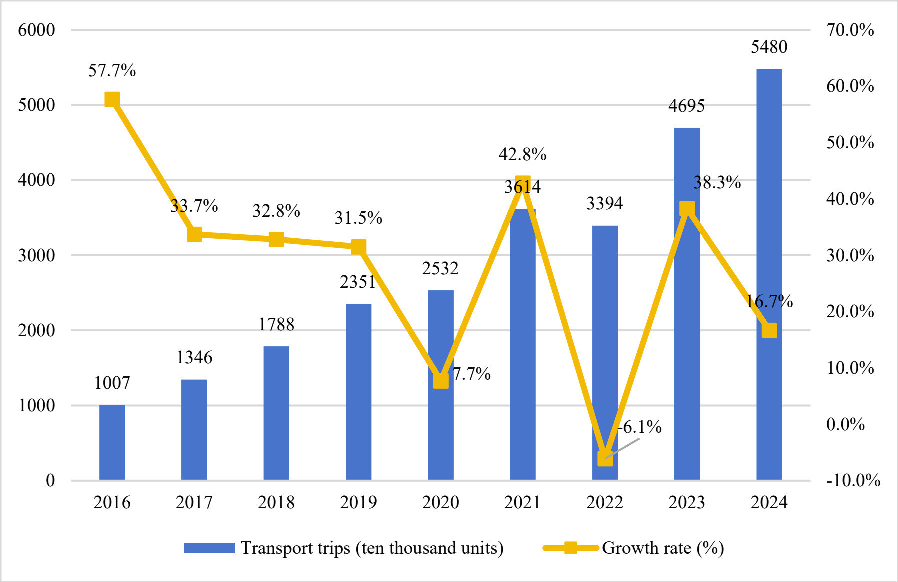


Fig. 1. Changes in RCCT trips scale from 2016 to 2024.

3.2 Spatial Characteristic

Driven by factors such as living standards, consumption capacity and consumption habits, middle-class and younger consumers are willing to pay for high-quality healthy food. Their preference for convenient, efficient and cost-effective consumption channels has also boosted a stronger demand for the scale of RCCT services. Urban distribution services serve as an important guarantee for meeting the demand for a high-quality life in the new consumption era. Figure 2 shows the top 15 cities for cold chain urban distribution trip scale in 2024. The four first-tier cities Shanghai, Beijing, Guangzhou and Shenzhen still rank the top four in terms of the number of cold chain urban distribution trips, followed by new first-tier cities such as Chengdu, Hangzhou, Wuhan, Nanjing, and Chongqing. Among more than 360 prefecture-level cities, the total number of cold chain urban distribution trips of the four first-tier cities accounted for 33.3%, a decrease of 2.8 percentage points from the previous year. The cumulative proportion of the top 15 cities in cold chain urban distribution trips reaches approximately 64.9%, a drop of 1.6 percentage points from the previous year. The proportion of cold chain urban distribution trips in first-tier and new first-tier cities has been declining for two consecutive years, indicating a gradual slowdown in cold chain distribution demand in these cities, while the demand in non-first-tier cities is on the rise.

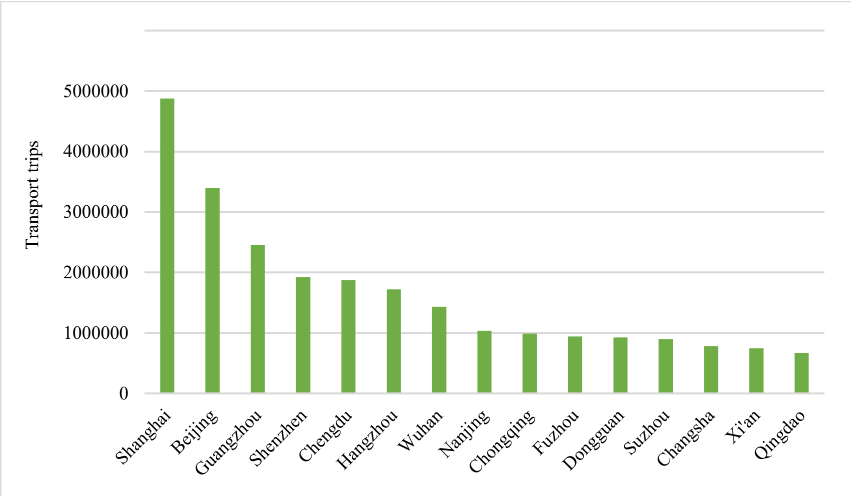


Fig. 2. Top 15 cities for cold chain urban distribution trip scale in 2024.

We counted the number of transport trips between every pair of provinces, regardless of direction. From the perspective of interprovincial transportation scale, coastal regions and economically developed areas in central China rank among the highest in the scale of cold chain interprovincial trips, exhibiting high external connectivity. Jiangsu and Shanghai take the first two place in the number of interprovincial cold chain trips, reaching 1.56 million and 1.45 million respectively, increasing by approximately 70% compared with 2023. The number of trips in Beijing, Zhejiang and Hebei all exceeds 700000, while that in Tianjin, Guangdong and Anhui surpasses 400000.

We also counted the number of transport trips between every pair of cities using the same method. From the perspective of intercity transportation scale, the number of cold chain intercity transportation trips between Dongguan and Shenzhen maintains an overwhelming lead, reaching 1.71 million, as shown in Figure 3. The RCCT trips between Shanghai and Suzhou, Foshan and Guangzhou, as well as Dongguan and Guangzhou, reaches 610000, 580000 and 570000, respectively. The results show that cold chain intercity transportation is mainly dominated by intercity transportation within provinces and intercity transportation within urban agglomerations.

Within the Yangtze River Delta urban agglomeration, the Beijing-Tianjin-Hebei urban agglomeration, the Chengdu-Chongqing economic circle, and the Guangdong-Hong Kong-Macao Greater Bay Area, interprovincial RCCT exhibits close operational connections, reflecting notable achievements in regional integrated development. This trend is particularly pronounced in the Yangtze River Delta and Beijing-Tianjin-Hebei regions. The RCCT volume between Shanghai and Jiangsu ranks the highest, reaching 870000 trips. Meanwhile, the interprovincial transportation volumes between Shanghai and Zhejiang, Beijing and Tianjin, and Beijing and Hebei reach 360000, 350000, and 330000 trips, respectively. From the perspective of source regions, the source regions of RCCT within major economic circles exhibit high concentration and proximity. Figure 4 shows the source location of RCCT for Beijing, Shanghai, Sichuan and Guangdong. In the Beijing-Tianjin-Hebei region, 78.9% of Beijing's interprovincial RCCT originates from Tianjin and Hebei. Within the Yangtze River Delta region, 85.1% of Shanghai's interprovincial cold chain shipments come from Jiangsu and Zhejiang, with 59.0% sourced from Jiangsu alone. In the Chengdu-Chongqing region, Sichuan and Chongqing serve as each other's largest cold chain source regions. For Sichuan, 51.5% of its interprovincial shipments come from Chongqing, and 8.6% from Yunnan. Conversely, 64.2% of Chongqing's interprovincial shipments originate from Sichuan, with another 9.2% from Guizhou. Fujian, Hong Kong, and Guangxi are the main source regions of Guangdong's interprovincial shipments, accounting for 17.4%, 16.8%, and 13.7% of the total cold chain supply respectively.

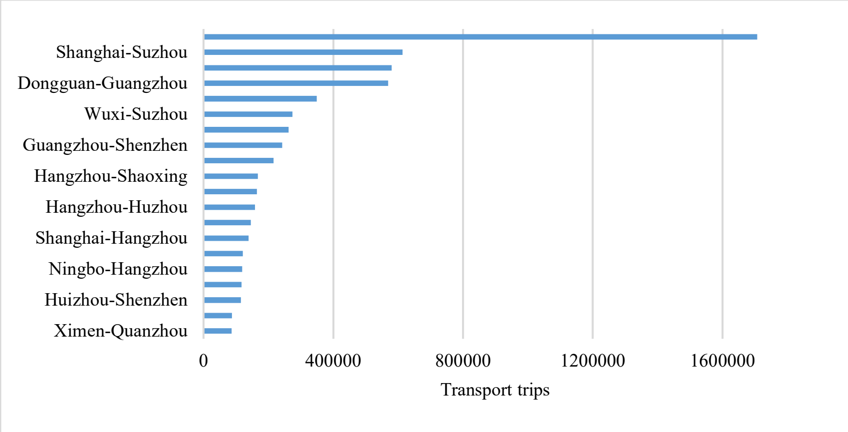
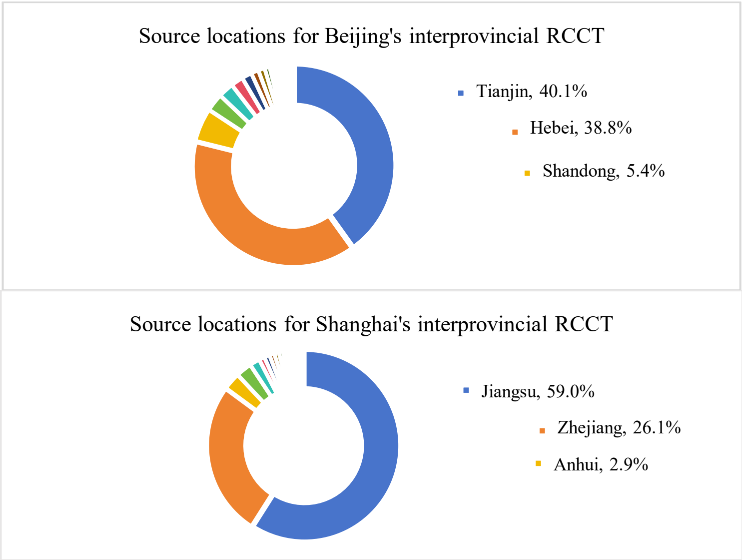


Fig. 3. Top 20 cold chain intercity transport trip scale in 2024.



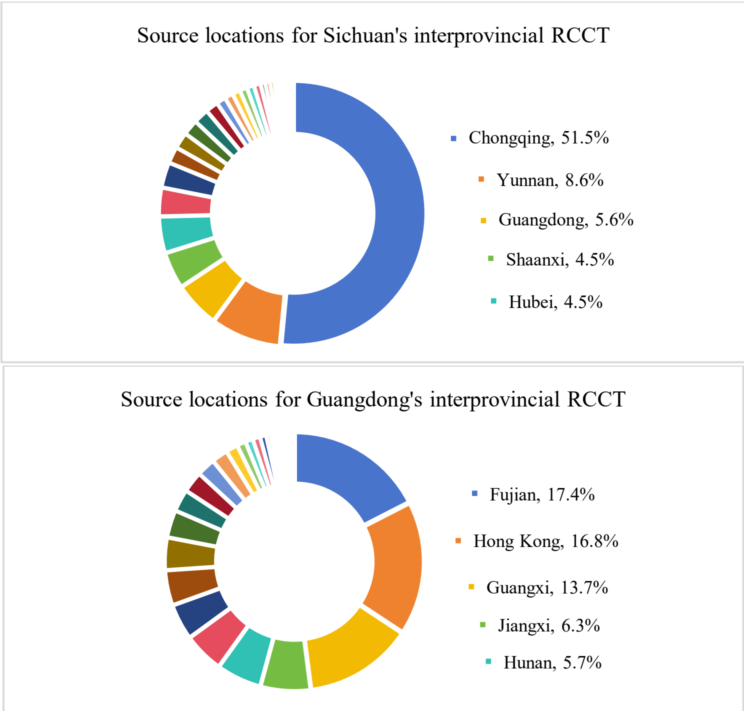


Fig. 4. Distribution of RCCT source regions of major provinces in 2024.

3.3 Network Characteristic

This paper uses Gephi to construct the RCCT undirected network, as shown in Figure 5, in which nodes represent cities and edges represents the communications between two cities, indicating that there is RCCT activity between the two cities. In 2024, the number of nodes in RCCT network reaches 357, with an annual growth rate of 1.1%. The number of network edges reaches to 5061, increasing by 32.3% compared with 2023. The average clustering coefficient of the network rises from 0.584 in 2022 to 0.627. The changes in nodes, edges and clustering coefficient of RCCT network from 2019 to 2024 are shown in Figure 6 and Figure 7, respectively.

Among all network nodes, Shanghai, Beijing, Wuhan, and Guangzhou, as international comprehensive transportation hub cities, play an increasingly prominent core role in the RCCT network. The degree centrality of them has remained firmly among the top four, demonstrating strong distribution and radiation capacity. In 2024, the degree centrality of these four cities further improved, reaching 0.573, 0.444, 0.444, and 0.421 respectively. Meanwhile, the degree centrality of Dongguan and Shenzhen also increases, whereas that of Suzhou, Nanjing, Hangzhou, Jinan, and Tianjin slightly decreases, which are shown in Table 1. However, it is crucial to recognize that while strengthening hub cities within the cold chain transportation network can enhance operational efficiency, it also creates critical single points of failure. These may trigger cascading effects and exacerbate systemic vulnerability. Although multiple paths may exist between any two node cities in the network, network planning must carefully balance efficiency and robustness. Measures such as optimizing the layout of hub nodes and diversifying transportation corridors should be implemented to mitigate risks arising from over-reliance on any single node, thereby improving network resilience. This is also something that needs to be further deepened in future research.

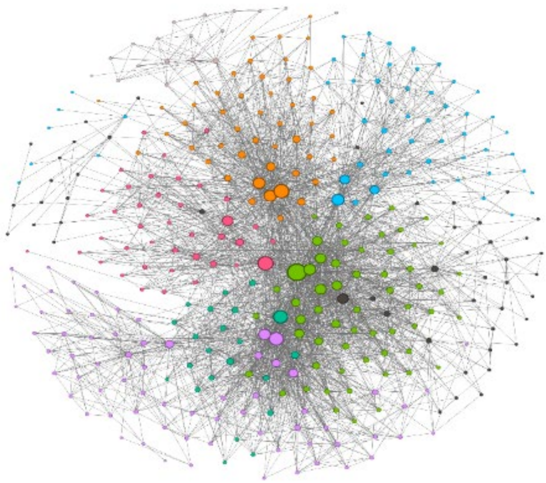


Fig. 5. The RCCT network in 2024.

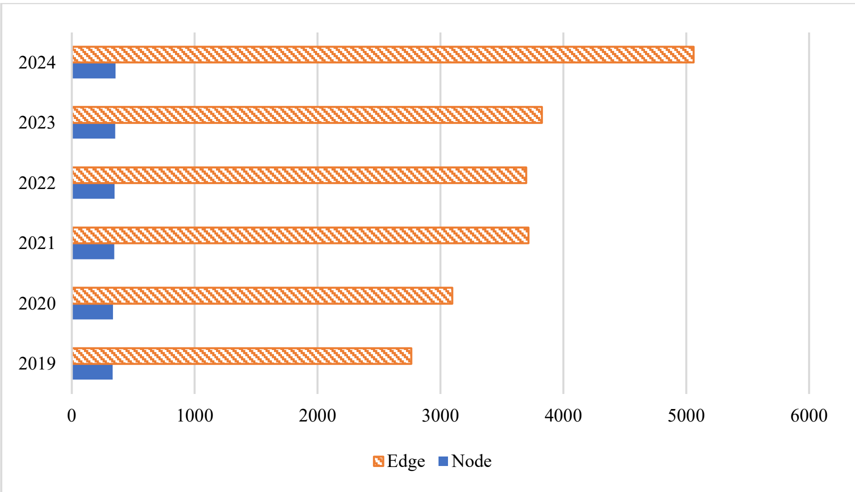


Fig. 6. Changes in nodes and edges of RCCT network from 2019 to 2024.

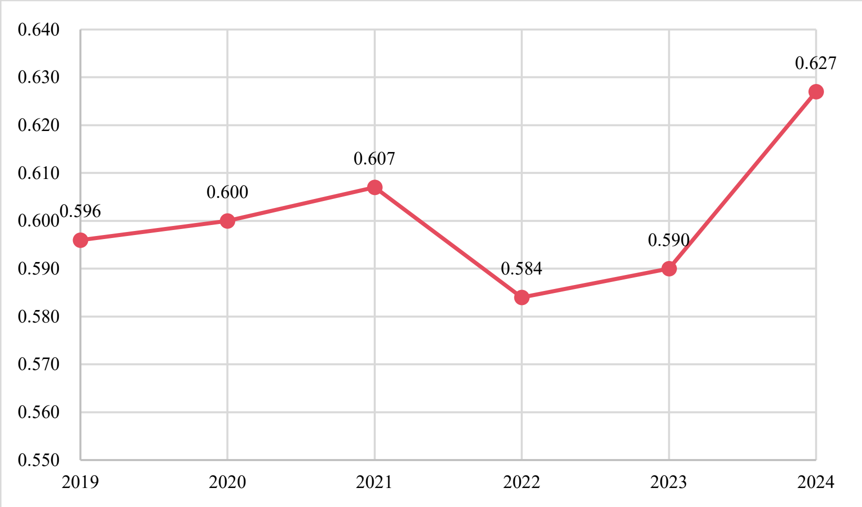


Fig. 7. Changes in clustering coefficient of RCCT network from 2019 to 2024.

Table 1. Changes in degree centrality and its ranking of hub cities in 2024.

City	D_C in 2024	Ranking in 2024	D_C in 2023	Ranking in 2023	Change in ranking
Shanghai	0.573	1	0.489	1	—
Beijing	0.444	2	0.361	2	—
Wuhan	0.444	3	0.361	3	—
Guangzhou	0.421	4	0.341	4	—
Zhengzhou	0.407	5	0.295	6	—
Dongguan	0.368	6	0.250	10	↑ 4
Chengdu	0.360	7	0.270	8	↑ 1
Suzhou	0.334	8	0.298	5	↓ 3
Nanjing	0.326	9	0.276	7	↓ 2
Hangzhou	0.323	10	0.253	9	↓ 1
Shenzhen	0.317	11	0.216	13	↑ 2
Tianjin	0.317	12	0.233	11	↓ 1
Changsha	0.292	13	0.210	14	↑ 1
Hefei	0.281	14	0.202	15	↑ 1
Jinan	0.270	15	0.219	12	↓ 3

4 Conclusion

The rapid development of big data technology has provided strong technical support for enhancing the operational monitoring and analysis of the cold chain logistics sector. This study focuses on the development of the road cold chain sector, utilizing trajectory data from refrigerated vehicles. By identifying vehicle origins and destinations, this paper analyzes the business scale, spatial distribution of demand, and characteristics of the transport network. The results indicate that in 2024, the scale of China's RCCT business maintains steady growth, the demand for RCCT in economically developed regions is relatively active, the internal connections of RCCT business within urban agglomerations are close, the connectivity of RCCT network is continually improving, and the hub functions of central cities are constantly strengthened. The analysis results can provide decision-making support for relevant industry participants.

However, this paper also has certain limitations. Different goods have different temperature and reliability requirements for cold chain transportation, such as frozen food, dairy products, vaccines, etc. However, the data obtained and used in this article cannot distinguish the types of goods. In future research, we will further explore data information. Firstly, we will strengthen analysis from aspects such as operational efficiency and operational quality. Secondly, we will further analyze the evolution of the structural characteristics of the transport network, and the optimization of network resilience. In addition, we will expand data and improve the analysis of RCCT characteristics for different categories of goods.

Acknowledgments

The authors greatly appreciate the reviews' suggestions and the editor's encouragement. This work was supported by the Special Funds Project for Basic Scientific Research Business Expenses of the Central Public Welfare Research Institute (2025-9040).

References

1. General Office of the State Council of the People's Republic of China. 2021. The Development Plan for Cold Chain Logistics during the 14th Five-Year Plan Period.
2. Zhang Q and Hou H. 2021. Analysis on spatial-temporal distribution evolution characteristics of regional cold chain logistics facilities: A case study of BJE. LISS, 433-441. https://doi.org/10.1007/978-981-16-8656-6_39.
3. Wang Y. 2023. Research on the Current situation and trend of the cold chain logistics development in our country. Logistics Sci-Tech 46, 13, 125-126. DOI: 10.13714/j.cnki.1002-3100.2023.13.033.
4. Wang S. 2022. Research on problems and improvement countermeasures of cold chain logistics industry in China. China Food, 14, 127-129. DOI: 10.3969/j.issn.1000-1085.2022.14.054.
5. Du D. 2023. Analysis of current situation and countermeasures of aquatic products cold chain logistics - Taking Chinese mitten crabs as an example. China Storage & Transport, 1, 161-162. DOI: 10.16301/j.cnki.cn12-1204/f.2023.01.080.
6. Zhang M, Li J, Feng W, et al. 2025. Review and prospect on the development of agricultural products cold chain logistics in China. Storage and Process 25, 11, 129-136. DOI: 10.3969/j.issn.1009-6221.2025.11.014.
7. Zhang X and Zhang L. 2018. Evaluation of regional cold chain logistics development of agricultural products in China. Hans Journal of Agricultural Sciences 8, 4, 225-236. DOI: 10.12677/HJAS.2018.84036.

8. Zhou H, Peng W and Zou X. 2025. On the green development level and regional differences of cold chain logistics for fresh agricultural products. Journal of Beijing Jiaotong University (Social Sciences Edition) 24, 2, 62-73. DOI: 10.3969/j.issn.1672-8106.2025.02.007.
9. He M, Yang M, Wu X, et al. 2024. Evaluating and analyzing the efficiency and influencing factors of cold chain logistics in China's major urban agglomerations under carbon constraints. Sustainability 16, 5, 62-73. DOI: 10.3390/su16051997.
10. Xue J and Qian L. 2025. Mechanism analysis of efficiency improvement in agricultural products cold chain logistics. Journal of Commercial Economics, 22, 90-93. DOI: 10.3969/j.issn.2095-9397.2025.22.021.
11. Zhou K. 2025. Optimization strategies for cold chain logistics of fresh agricultural products in China under the background of developing new quality productivity. Journal of Anhui Agricultural Sciences 53, 19, 252-255. DOI: 10.3969/j.issn.0517-6611.2025.19.053.
12. Liu H, Pretorius L and Jiang D. 2018. Optimization of cold chain logistics distribution network terminal. EURASIP Journal on Wireless Communications and Networking, 1, 9. DOI: 10.1186/s13638-018-1168-4.
13. Du B and Liu H. 2025. Artificial intelligence-driven cold chain monitoring optimization and decision-making system. Journal of Yulin University 35, 5, 106-110. DOI: 10.16752/j.cnki.jylu.2025.05.017.
14. Huang H, Xie R, Yang Y, et al. 2024. Hot spots and trends in cold chain logistics at home and abroad explored based on CiteSpace. Packaging Engineering 45, 19, 233-246. DOI: 10.19554/j.cnki.1001-3563.2024.19.023.
15. Li S and Ye J. 2024. Price index system and data collection scheme of road cold chain transportation. China Transportation Review 46, 3, 160-164. DOI: 10.20164/j.cnki.cn11-1197/u.2024.03.026.
16. Liu S, Chen G, Wei L, et al. 2021. A novel compression approach for truck GPS trajectory data. IET Intelligent Transport Systems 15, 1, 74-83. .DOI: 10.1049/itr2.12005.
17. Wei L, Chen G, Sun W, et al. 2021. Recognition of operating characteristics of heavy trucks based on the identification of GPS trajectory stay points. Security and Communication Networks, 1, 1-12. DOI: 10.1155/2021/9998405.