Research in Transportation Business & Management 56 (2024) 101177

Contents lists available at ScienceDirect

Research in Transportation Business & Management

journal homepage: www.elsevier.com/locate/rtbm

Regional freight accessibility analysis based on truck trajectories—A case study of Hunan Province in China

Jie Li[a], Xinyu Zhang[a,*], Quanjun Zhu[b], Xiangliang Xiao[b], Yun Zhou[a]

[a] *Department of Civil Engineering, Hunan University, Hunan 410082, China*
[b] *Hunan Transportation Research Institute Co., Ltd, Hunan 410015, China*

ARTICLE INFO

Keywords:
Transportation planning
Road freight
Truck trajectory
Regional accessibility
Spatial regression analysis

ABSTRACT

Freight transport is crucial in fostering economic growth and enhancing societal well-being, but it also poses challenges for traffic management and environmental sustainability. For freight planning and policy formulation, it is important to measure and evaluate regional freight accessibility. This paper proposes a novel framework for analyzing regional freight accessibility based on truck trajectory data. The framework is structured around two principal components: extracting freight trip information and constructing a freight accessibility model. It introduces precise and effective methodologies for identifying truck parking zones based on trajectory data, thereby facilitating the extraction of complete freight trip information. Afterward, the framework integrates a distance-weighted topological analysis with multiple relevant indicators to comprehensively assess the freight accessibility of a region. Additionally, it incorporates spatial lag modeling to examine the factors influencing the spatial distribution of freight accessibility within a region. Applied to a case study in Hunan Province, China, the framework demonstrates its efficacy. The analysis reveals that accessibility in Changsha and two other cities stands out significantly higher than in other cities. The study offers valuable insights for strategic freight planning and policy formulation.

1. Introduction

In the past decades, the rapid advancement of economic globalization and e-commerce has accelerated freight demand growth, leading to increased truck volume on road networks. This rise in freight transport may intensify traffic congestion and elevate the potential for vehicular accidents, emphasizing the urgency for transportation authorities to oversee truck traffic effectively. In China, the National Road Freight Vehicle Public Regulation and Service Platform collects trajectory data from heavy-duty trucks exceeding 6 m in length or 12 tons in weight. This regulatory mechanism is designed to refine the dynamic oversight of truck operations and advance road traffic safety management.

Vehicle trajectory data, recording the spatiotemporal information of vehicles, have become a valuable source of information for transportation research. It can reflect the travel behavior (Akter & Hernandez, 2022; Diana, Pirra, & Woodcock, 2020; Yuan, 2022), demand (Demissie & Kattan, 2022; Kinjarapu, Demissie, Kattan, & Duckworth, 2022), and preferences of travelers (Ge & Fukuda, 2016; Xu & González, 2017; Zanjani et al., 2015), as well as the characteristics and performance of transportation systems (Akter & Hernandez, 2023; Akter, Hernandez, & Camargo, 2023; Mjøsund & Hovi, 2022; Nam, Hyun, Kim, Ahn, & Jayakrishnan, 2016). With the rapid development of positioning technologies and intelligent transportation systems, vehicle trajectory data have become more abundant and accessible, enabling more in-depth and comprehensive analysis of various transportation issues. Among different types of vehicle trajectory data, truck trajectory data are particularly important for studying freight transport, which is essential for economic development.

Freight transport is a complex and dynamic process that involves multiple actors, modes, and stages. Various factors related to infrastructure, land use, market, policy, and environment may influence freight transport. Understanding freight transport's spatial and temporal patterns and the factors affecting them is crucial for improving freight efficiency, reducing freight costs, and mitigating negative externalities. However, traditional data sources for freight transport, such as surveys, censuses, and statistics, are often limited in scope, frequency, and accuracy. They are challenging to capture the detailed and dynamic aspects of freight transport, such as the origin, destination, route, duration, and purpose of truck trips. Therefore, truck trajectory data, which can provide rich and timely information on freight movements, has great potential for advancing freight transport research.

* Corresponding author.
E-mail addresses: lijie_civil@hnu.edu.cn (J. Li), xyyh@hnu.edu.cn (X. Zhang), zhouyun05@hnu.edu.cn (Y. Zhou).

https://doi.org/10.1016/j.rtbm.2024.101177
Received 7 January 2024; Received in revised form 14 July 2024; Accepted 25 July 2024
Available online 30 July 2024
2210-5395/

Nomenclature

A_i	Accessibility of region i
A_{ij}	Accessibility
C_{ij}	Distance between freight node and city
$C(V_i)$	Betweenness centrality
D_1	Distances from freight nodes to the administrative center
D_2	Distances between all cities
D_i	Degree centrality value of node i
D_i^+	Positive ideal solutions
D_i^-	Negative ideal solutions
E_j	Entropy value of indicator
M_i	Quality indicator of region i
M_j	Quality indicator of region
N	Number of nodes
P_j	Quality indicator of freight node
P_{jk}	Number of shortest paths
$P_{jk}(i)$	Number of paths pass through node i
Q_j	Quality indicator of regions outside region i
R^2	Goodness of fit
S_i	Comprehensive score
S_t	Distance
V_j^+	Distance from the target to the optimal target
V_j^-	Distance from the target to the worst target
W	Spatial weight matrix
X	Independent variable matrix
Y	Dependent variable
d_{ij}	Travel impedance
f	Travel impedance
i	Region code
j	Region code
k_i	Degree of node i
m	Number of indicators
m_j	Economic quality indicator
p_{ij}	Proportion of indicator
w_j	Weight of indicator
x_{ij}	initial value of indicator
x_{ij}^*	Standardized value of indicator
β	Coefficient of impedance function
ε	Error term
ρ	Spatial lag coefficient

Additionally, analyzing truck trajectory data opens avenues for acquiring a deeper understanding of freight movement patterns and the intricacies of logistic network configurations.

This study aims to propose a framework for assessing regional freight accessibility, using Hunan, China as a case study. Freight accessibility, defined as the ease of reaching destinations for freight activities, is an essential indicator of the performance and quality of freight transport systems. This indicator reflects the spatial distribution of freight demand and supply, as well as the connectivity and efficiency of freight networks (Acheampong & Asabere, 2022; Calatayud, Palacin, Mangan, Jackson, & Ruiz-Rua, 2016; Kocatepe, Ozkul, Ozguven, Sobanjo, & Moses, 2020). It also affects the location choices and competitiveness of businesses and industries (Jiang, Timmermans, & Yu, 2018), as along with regional economic development and social equity (Cascetta, Cartenì, Henke, & Pagliara, 2020). Therefore, measuring and evaluating freight accessibility is essential for understanding the current situation of a freight transport system and guiding freight planning and policy making.

The main contributions of this study are as follows:

a. A methodology is proposed for identifying valid stopping points and parking zones from truck trajectory data, which are the key elements for extracting truck trips and activities.
b. A regional freight accessibility model is developed based on complex network theory, which can capture the structure and dynamics of freight networks and measure freight accessibility at the city level.
c. A spatial regression analysis is conducted to explore the spatial distribution patterns and influencing factors of freight accessibility, using a spatial lag model that accounts for the spatial dependence and heterogeneity of the data.

The rest of this paper is organized as follows: Section 2 reviews the related literature on vehicle trajectory data analysis and accessibility assessment. Section 3 describes the methods used in this study. Section 4 applies the model to the case study of Hunan Province and discusses the results. Section 5 concludes the paper and suggests directions for future research.

2. Literature review

This survey primarily focuses on two key aspects related to trajectory data: the analysis of trajectory data and the assessment of accessibility.

2.1. Trajectory data analysis

Research utilizing collected truck trajectory data has a well-established foundation, as it facilitates the analysis of freight transport demand and the efficiency of transport networks. Researchers identify vehicle stopping points, extract vehicle travel itineraries, and analyze travel characteristics using trajectory data(Hughes, Moreno, Yushimito, & Huerta-Cánepa, 2019; X. Yang, Sun, Ban, & Holguín-Veras, 2014). The development of an algorithm to identify stop points based on these data is particularly crucial.

Previous research on stop points identification algorithms can be categorized into two types. The first type utilizes multisource data for identification, while the second type designs algorithms based on trajectory data alone. Additionally, some research combines both approaches for stop points identification. In methodologies that integrate multiple data sources, the primary data consist of geographical information-related data and the secondary data pertain to driving assistance. Comendador, López-Lambas, and Monzón (2012) developed an analytical framework to identify stop points and extract pertinent travel information by utilizing multiple data sources, such as vehicle observation surveys, GPS data, and vehicle trip diaries. Yang et al. (2022) presented a data-driven framework for identifying stopping points and potential parking zones based on distinct data features. This framework synergizes highway network GIS data with freight-related POI (Points of Interest) data to determine valid stopping points.

Various algorithms employ spatial clustering and threshold techniques to identify parking points from trajectory data. Ma, Wang, McCormack, and Wang (2016) developed a non-hierarchical spatial clustering algorithm, DBSCAN, which leverages spatiotemporal features of trajectory data and incorporates road network information. Other studies have adopted different spatial clustering methods, such as the K-means algorithm (Kuppam et al., 2014), optic algorithms (Ankerst, Breunig, Kriegel, & Sander, 1999), and model-based clustering techniques(Poliziani, Rupi, Mbuga, Schweizer, & Tortora, 2021). In threshold methods, various algorithms have developed based on trajectory data features, including speed (Camargo, Hong, & Livshits, 2017), time (Yanhong & Xiaofa, 2013), and distinct thresholds. Moreover, some studies have suggested hybrid techniques integrating multiple feature thresholds, including speed and time (Liu, Chen, Wei, & Li, 2021; Wei, Chen, Sun, & Li, 2021) or distance and time (Demissie & Kattan, 2022; Laranjeiro et al., 2019; Li et al., 2021; F. Liu et al., 2020; Ye, Zheng, Chen, Feng, & Xie, 2009). Additionally, Chankaew et al. (2018) merged two methodologies to determine potential stop points by using time thresholds and geographic information. However, current approaches to trajectory data processing, often relying on empirical thresholds or spatial clustering, may lead to inaccuracies in identifying stop points. Therefore, more accurate methods and research frameworks are necessary to precisely detect stop points.

2.2. Transport accessibility assessment and modeling

Existing studies on transportation accessibility can be categorized into two main aspects: assessing accessibility and analyzing its influencing factors and evaluating the functionality of transportation networks using accessibility as an essential indicator.

Assessing transportation accessibility and its influencing factors are fundamental in optimizing transportation networks, improving transport efficiency, and achieving sustainable development goals. To this end, various methods have been developed to measure transportation accessibility, including gravity models (Fairthorne, 1964), Huff models (Huff, 1963), and their adaptations. Hansen (1959) initially proposed the definition and calculation method for accessibility, representing the opportunity for interaction between different nodes in a transportation network. Chang, Chen, Li, and Li (2019) elucidated the distinction between absolute and relative accessibility, including their respective calculation methods. By leveraging real-time data from the Google Maps API, they estimated the accessibility of urban parks and employed regression models to assess the influencing factors. Song et al. (2020) introduced the concept of regional potential traffic attraction based on the Huff model. They analyzed the significant relationship between traffic attraction and urban traffic emissions, particularly addressing the imbalance between urban development and traffic accessibility in the city center. Cao et al. (2019) conducted a raster-based accessibility study for the Guangdong-Hong Kong-Macao Greater Bay Area using ArcGIS. They performed accessibility calculations and spatial pattern analyses, exploring spatial connectivity through passenger data from roads, railroads, ports, and airlines. Tome, Santos, and Carvalheira (2019) utilized open-source data alongside the Network Analyst extension of ArcGIS to evaluate the accessibility of both private and public transportation to medium-sized facilities in urban communities. Chen, Ni, Xi, Li, and Wang (2017) proposed a model employing multilevel grid segmentation and multimodal public transportation networks to evaluate the distributional differences in city spatial accessibility. They applied this model to assess the accessibility of public transportation in Nanjing.

Regarding transportation network analysis using accessibility as an indicator, the study primarily integrates complex network theory to analyze the spatial pattern distribution of the network. Deng, Song, Xiao, and Huang (2022) developed a comprehensive model to assess the actual connectivity of ports and logistics in China's Yangtze River Economic Belt. The model utilized an improved gravity model and relevant indicators from complex network theory for intra-port to inland hinterland logistics connectivity analysis. Lu and Lin (2019) emphasized that accessibility assessment is crucial for vulnerability analysis of transportation networks. They proposed an accessibility assessment methodology for multimodal public transport. Dong, Wang, Mostafavi, and Gao (2019) integrated post-disaster network access to critical facilities into network robustness assessment and provided location choices for hospitals and other venues. Previous research has focused on constructing evaluation models and scrutinizing factors influencing accessibility, with a notable concentration on urban infrastructure or critical hubs. However, there has been a gap in studying large-scale road freight transport networks.

3. Methodology

3.1. Research framework

Figure 1 presents an overview of the study, comprising several important steps: (1) Data pre-processing; (2) Stop points detection; (3) Accessibility modeling; and (4) Spatial analysis.

3.2. Data

As depicted in Fig. 1, the data utilized in this study include truck trajectory data, freight node-related data, distance data, and government statistical data. Detailed introduction and processing of truck trajectory data will be provided in the next section. The freight node-related data used in this study comprise geographical information data for national-level and provincial-level freight parks. The dataset encompasses 18 different information fields, such as plot names, development zone names, geographic location, tax revenue, dates of establishment, and others. Of particular note, the tax revenue field serves as the primary indicator of the economic quality of these nodes in this study, as shown in Table 1. Distance data is sourced from the AutoNavi Map API(Amap, 2002), while government statistical data is obtained from government statistical yearbooks websites(HPPGP, 2023).

3.3. Trajectory data processing

3.3.1. Data resources and preprocessing

This study utilized data from the National Road Freight Vehicle Public Regulation and Service Platform(PRC, 2016), encompassing the trajectory information of all heavy trucks in Hunan Province on November 1, 2021. These heavy trucks are defined as those exceeding a length of 6 m or a weight of 12 tons. The dataset comprises approximately 290 million records. Each record consists of 16 distinct fields, classified into two primary categories: GPS specifics and platform-related details. The GPS segment includes essential parameters such as vehicle identification numbers, altitude, longitude, latitude, speed, distance traveled, timestamp, direction, and vehicle status. Table 2 illustrates the data sample, where the vehicle ID is fake data. Moreover, the platform-related segment contains platform access codes. The data were predominantly sampled at 30-s intervals, with a fraction recorded at shorter intervals.

Before starting the trajectory data analysis, it is imperative to thoroughly examine the raw data and eliminate anomalous data records to ensure data consistency and analytical effectiveness. This examination primarily discarded:

(1) Duplicate data.
(2) Outliers, such as those indicating excessively high vehicle speeds.
(3) Data with severe positional discrepancies or abrupt deviations.
(4) Sparse records were instances where a single vehicle's continuous record was fewer than 20 or when the trip duration, even after missing data imputation, was <10 min.

Vehicles meeting these criteria were considered invalid for freight transport analysis and were excluded from further analysis. After eliminating data falling into the above four categories (approximately 16% of the original dataset), 210 million records remain in the dataset. The geographical location map of the study area for the case analysis is shown in Fig. 2. The spatial distribution of preprocessed trajectory data is demonstrated in Fig. 3, which provides valuable insights into the extent of spatial coverage and concentration of GPS data associated with heavy-duty trucks.

3.3.2. Identification of truck stops and parking zones

It is crucial to extract truck trips from GPS trajectory data to study

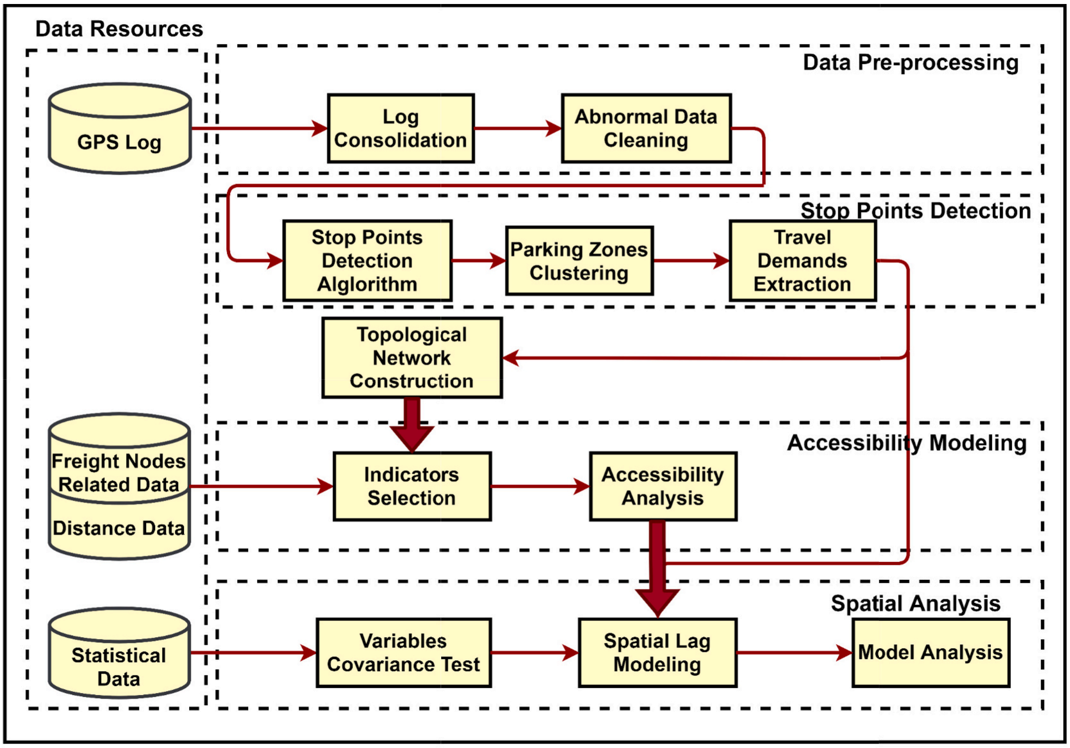

Fig. 1. Overall structure of the study.

Table 1
Example of geographic information data for development zones.

Plot Name	Development Zone Name	Level	Tax Revenue (in 10 thousand yuan)
Area One	Changsha Economic Development Zone	National	47,382
Area Two	Changsha Huanghua Comprehensive Bonded Zone	National	24,732
Area Three	Changsha Lin Kong Industrial Agglomeration Area	Provincial	13,482
Area Four	Yueyang Economic and Technological Development Zone	National	238,193
Area Five	Zhangjiajie Economic Development Zone	Provincial	3479

Table 2
Exemplary GPS data field information.

Index	ID	Latitude	Longitude	Speed	Timestamp	Angle
1	Aa	111.153409	25.318748	0	2021/11/1 12:03:01	308
2	Aa	111.153834	25.318453	30	2021/11/1 12:03:31	190
3	Aa	111.154284	25.318267	25	2021/11/1 12:04:01	0
4	Aa	111.154738	25.318236	44	2021/11/1 12:04:31	313
5	Aa	111.154973	25.317983	64	2021/11/1 12:05:01	76

freight transport based on truck trajectories. This study proposes a method to address the challenge, which primarily involves two steps: (1) accurately identifying stop points, and (2) demarcating parking zones.

3.3.2.1. Identification of valid stop points. Throughout a freight trip, the truck may make various temporary stops, such as waiting at traffic signals or being stuck in traffic jams. To determine valid stop points, such transient stops must be filtered. This study adopts a threshold-driven approach to determine valid stops in truck trajectories and to distinguish them from temporary stops by defining specific time and distance thresholds. The determination of these thresholds was based on previous studies (Camargo et al., 2017; Ma et al., 2016; Y. Yang et al., 2022) and the features of the trajectory dataset. The definitive criteria for identifying valid stopover points are that within consecutive GPS trajectory datasets, GPS coordination should remain within a 500-m buffer area for over 20 min.

3.3.2.2. Identification of freight parking zones. Considering the vast size of the trajectory dataset, multiple stop points are anticipated to be clustered around single locations. This phenomenon indicates that multiple truck trips end at or near this location, resulting in a distribution of different stop points within the area. This study uses Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering algorithm to merge multiple nearby stop points into a single parking zone. This type of density-based clustering algorithm assumes that categories can be determined by the density of sample distribution. By grouping closely connected samples into a single category, a cluster is formed. Therefore, this study employs such an algorithm to define clusters of valid parking spots located in the same area, which are identified as parking zones. Fig. 4 provides a schematic representation of the research methods applied in these two steps.

3.3.3. Extraction of freight trip origin-destination (OD) pairs

Estimating trip distributions and evaluating origin-destination (OD) matrices form the foundation of freight demand modeling and regional transportation planning. Previous analyses of trajectory data have often employed administrative divisions as a reference point. While these divisions have the advantage of providing demographic and socio-economic data, this approach may ignore the detailed trips within each unit, which are critical for understanding freight connectivity. According to Fig. 3, the freight transport hotspots in Hunan Province are

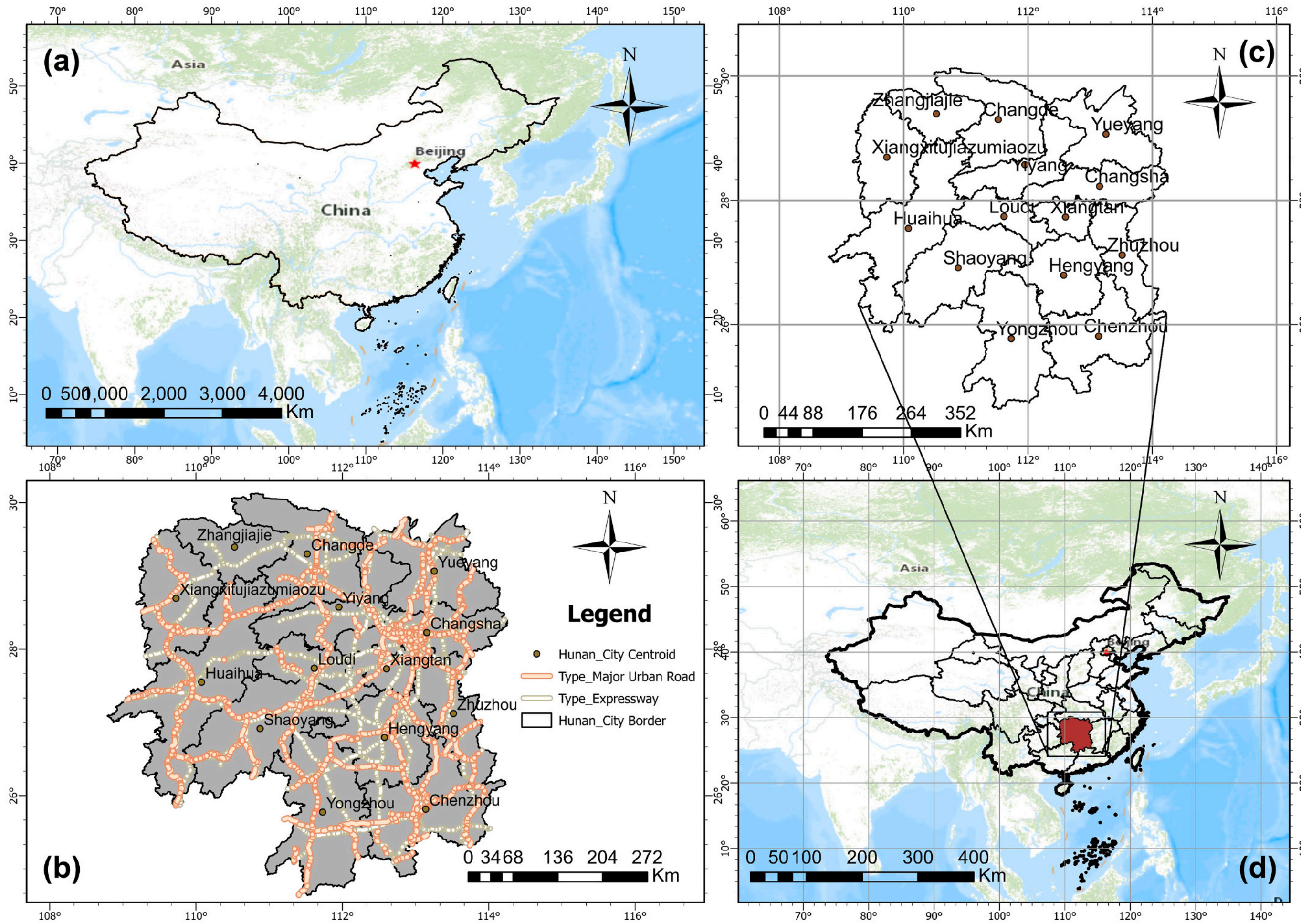

Fig. 2. Geographical Location Maps of the Study Area: (a) the People's Republic of China, (b) the Distribution of Major Roads in Hunan Province, (c) the Administrative Divisions of Hunan Province, and (d) the Locations of Hunan Province within the Administrative Map of China.

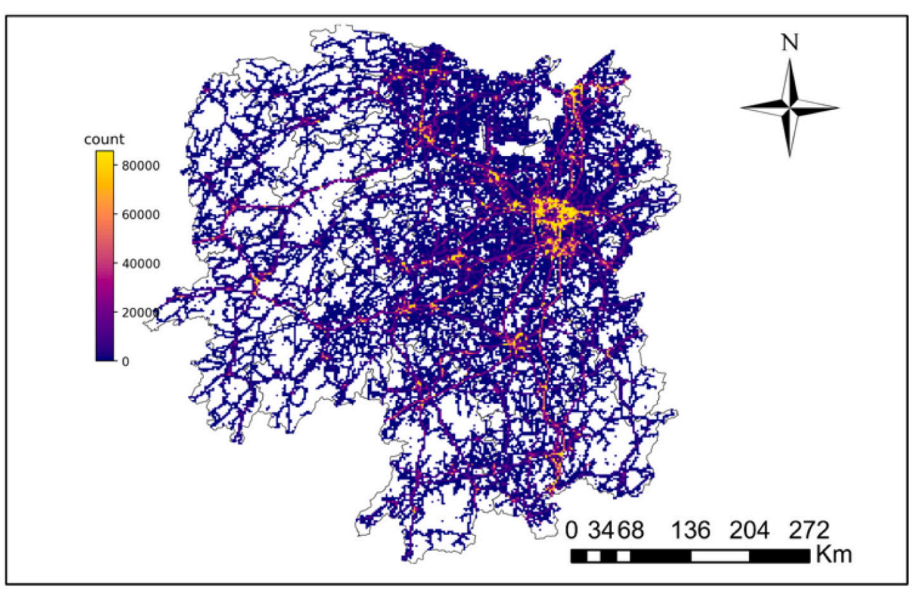

Fig. 3. Heatmap of the trajectory data distribution.

densely distributed, with several hotspots located within cities. It is necessary to consider detailed trip information within these areas.

By dividing the study area into grids through raster segmentation, continuous geographical space can be discretized into discrete grid units, facilitating spatial analysis and processing of vehicle trajectory data. The size and shape of grid units are not fixed; shapes can include

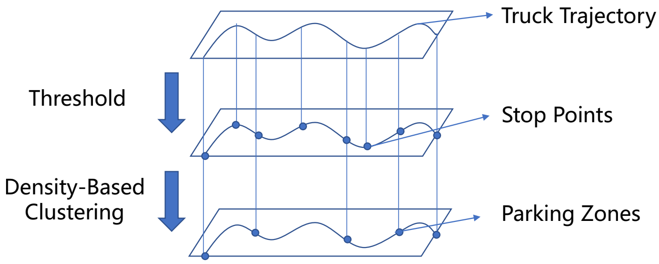

Fig. 4. Method for extracting freight parking zones.

grids, hexagons, rectangles, etc. In this study, grid-shaped raster units are utilized, as depicted in Fig. 5. When selecting grid size, smaller sizes are generally preferred. Choosing an excessively large partition size would similarly fail to effectively capture detailed travel information within the study area. Considering factors such as the size of freight destinations like logistics parks and the lack of necessity to analyze excessively short truck trips, a grid size of 2 km was chosen based on analysis of the dataset.

To perform grid cell partitioning for a specific study area, the latitude and longitude of each grid vertex can be calculated based on the predetermined grid cell size. Subsequently, all grid cells are assigned unique identifiers for indexing and identification purposes. In this study, after identifying parking spots and extracting complete truck trips, the study area was partitioned into 2 km * 2 km grids. Next, the start and end points of truck trips were matched to grids based on latitude and longitude, determining the corresponding grid for each trajectory point and thus obtaining the origin-destination (OD) matrix between grids, as illustrated in Fig. 6.

3.4. Freight accessibility modeling

3.4.1. Method of model design

Analyzing regional accessibility is crucial in transportation network planning. The gravity model, a well-established method for evaluating spatial accessibility, accounts for all areas within the study and considers travel time or distance between regions as travel impedance. This model was initially introduced by Hansen (Hansen, 1959) and is expressed as follows:

$$A_i = \sum_j Q_j d_{ij}^{-\beta} \tag{1}$$

Where: A_i represents the accessibility of region i;Q_j represents the quality indicator of regions outside region i;d_{ij} represents the travel impedance between region i and region j, typically travel time or distance; and β is the coefficient of the impedance function.

The gravity model primarily concentrates on accessibility within a given study region but neglects the competitive dynamics among different regions. Additionally, the model does not account for the probability of regional travel choices. To mitigate these limitations, an enhancement of the gravity model is necessary for a more comprehensive analysis of regional accessibility (Deng et al., 2022):

$$A_i = \sum_j M_i M_j f\left(d_{ij}, \beta\right) \tag{2}$$

Where: A_i represents the accessibility of region i;M_i and M_j represent the quality indicators of the study regions i and j, In the literature, these are economic quality indicators of regions; $f\left(d_{ij}, \beta\right)$ represents the travel impedance between region i and region j;β is the coefficient of the impedance function.

Interregional connectivity is influenced by factors, including the efficiency of the road freight network and the overall strength of the economy. The study takes a comprehensive approach by incorporating the actual road network, important parameters of network nodes, and freight attractiveness indicators of cities and districts. These elements are integrated to calculate regional accessibility, as per the improved Eq. (2). Including major freight-related parks (freight nodes) in the calculation reflects the efficiency of inter-regional freight transport. The specific calculation steps are as follows:

1. The distance matrix D_1 representing the distances from all freight nodes within each city to the administrative center of that city were measured using AutoNavi Map API (Amap, 2002). These distances were then aggregated to determine the total distances S_t within each city t. Additionally, the distance matrix D_2, representing the distances between all cities in Hunan Province, were measured in the same way as D_1.
2. The quality indicator for each freight node was calculated using the provided formula:

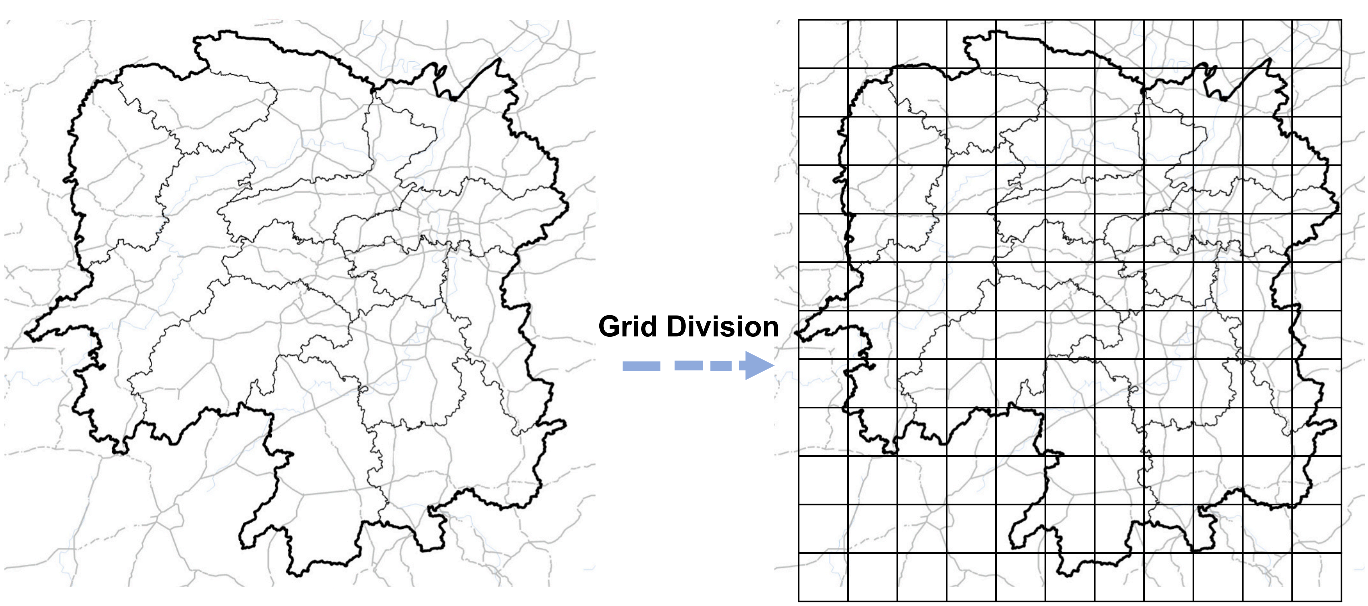

Fig. 5. Grid division schematic.

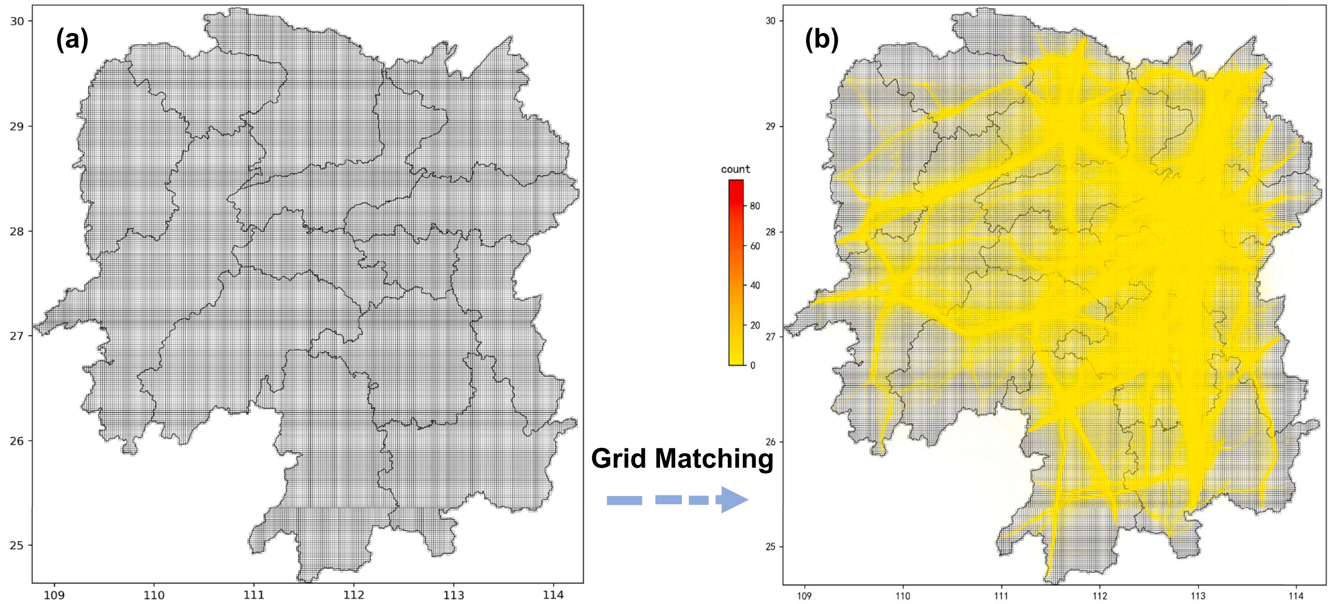

Fig. 6. Freight Trip OD Extraction: (a) Illustration of Grid Division in the Study Area, (b) Freight OD Connectivity Map between Grids.

$$P_j = m_j / (m_j + S_t) \tag{3}$$

where m_j is the economic quality indicator of the node, $P_j$represents the quality indicator of freight node$j$,and normalization is applied to m_j and S_t to eliminate dimensional effects.

3. The attractiveness of each node to other cities was estimated using the following formula

$$A_i = \sum_j M_i P_j f(C_{ij}, \beta) \tag{4}$$

where A_{ij} represents the accessibility of city$i$, M_i represents the quality indicator of city i, C_{ij} is the distance from freight node j to city i calculated based on distance matricesD_1andD_2, and $\beta$is the parameter of the impedance function.

4. The procedures were applied to all cities in Hunan Province to ascertain overall freight accessibility.

3.4.2. Quality indicators of cities

The city's quality indicator is assessed in connection with Eq. (4). The magnitude of this indicator should directly reflect the city's attractiveness to other cities and represent its importance within the overall freight transport network. Therefore, this study adopts topological indicators rooted in complex network theory as the quality indicator.

3.4.2.1. Weighted network construction. As described in Section 3.3.3, at the grid level, origin-destination (OD) truck trips between grid cells within the study area were extracted from the trajectory data. These grids were subsequently aligned with the administrative boundaries of cities, resulting in the calculation of inter-city freight OD trips at a macro level, as visualized in Fig. 7. Further, building on the intercity OD data and utilizing complex network theory, we constructed a flow-weighted network using the Space P method. This method provides an intuitive representation of node connectivity within the network, with its structural representation depicted in Fig. 8.

3.4.2.2. Complex network topological metrics

3.4.2.2.1. Betweenness centrality. Betweenness centrality measures the degree to which a node serves as an intermediary in the shortest paths connecting all pairs of nodes within a network. This metric is primarily a global network attribute, elucidating the importance of a node in facilitating network propagation. The formula for calculating betweenness centrality is as follows:

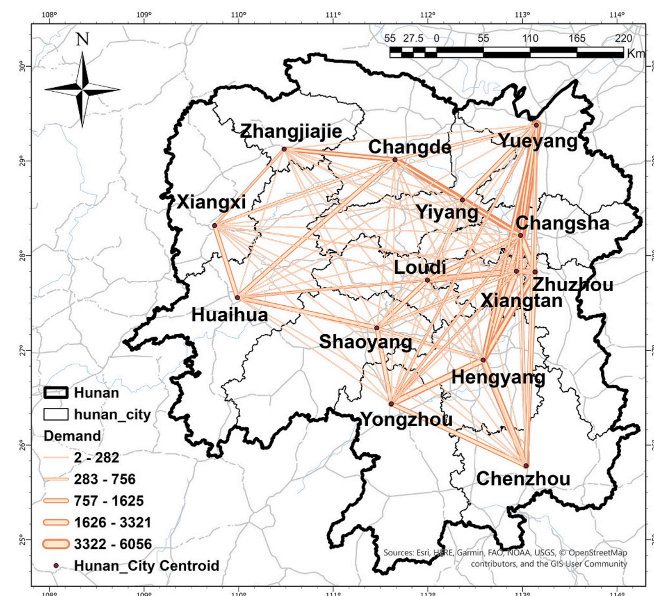

Fig. 7. Freight flow map between cities in Hunan Province.

$$C(V_i) = \sum P_{jk}(i) / P_{jk} \tag{5}$$

Where: $C(V_i)$represents the betweenness centrality value of node i;P_{jk} is the total number of shortest paths between nodes j and k; $P_{jk}(i)$ is the number of those paths that pass through node i.

3.4.2.2.2. Degree centrality. Degree centrality originates from the inherent properties of network nodes and primarily reflects local network characteristics. Nodes with a higher degree of centrality are connected to more neighbors, signifying their greater importance within the network. A node's degree centrality is determined by counting the number of edges connected to it. The formula for calculating degree

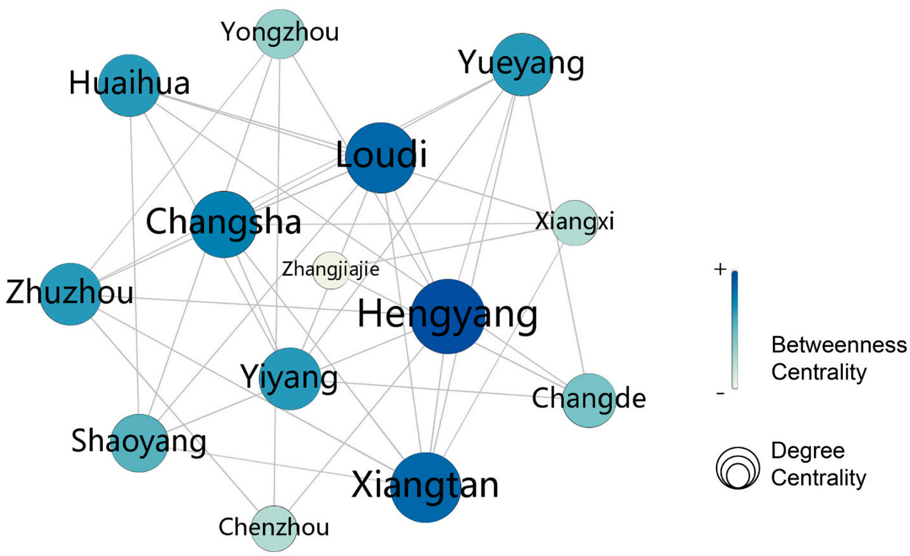

Fig. 8. Topology of major transportation networks in Hunan Province.

centrality is as follows:

$$D_i = k_i/(N-1) \tag{6}$$

Where:D_i represents the degree centrality value of node i;k_i is the degree of node i;N is the total number of nodes in the network.

3.4.2.2.3. PageRank ranking. PageRank is a graph theory-based mathematical algorithm initially developed to evaluate the importance of web pages(Brin & Page, 1998). It treats all web pages on the World Wide Web as nodes and hyperlinks as edges. The weight value of each node indicates the importance of the corresponding page. For example, a page linked by many other pages will have a high weight value (high PageRank). PageRank has now been extended to assess the importance of nodes within a network. In a topological graph, the PageRank value represents the probability of a node being traversed, which depends on the number and importance of other nodes linking to it. Nodes with higher PageRank values are considered more important within the network because they contribute more significantly to the network and have greater influence.

3.4.2.3. TOPSIS model based on entropy weighting. This study employs the TOPSIS model and an entropy-based method, to evaluate the quality indicators of cities and counties in Hunan Province. The essential steps involved are as follows:

1. Decision Matrix: Calculate indicator values for each city in the traffic-weighted network and form a decision matrix, with cities listed in the rows and indicators in the columns.

2. Normalization: Standardize the decision matrix using min-max normalization as per Eq. (7) to eliminate scaling disparities.

$$x_{ij}^* = \frac{x_{ij} - min_{1\le i\le n}x_{ij}}{max_{1\le i\le n}x_{ij} - min_{1\le i\le n}x_{ij}} \tag{7}$$

Where:x_{ij}^* represents the standardized value of the city i in the indicator j;x_{ij}represents the initial value of the city i in the indicator j;n is the total number of cities.

3. Weight Calculation: Employ the entropy-weight technique to calculate weights for the indicators, revealing their impact on the overall results, as outlined in Eqs. (8) and (9):

$$E_j = -\frac{1}{lnn}\sum_{i=1}^{n} p_{ij}lnp_{ij} \tag{8}$$

$$w_j = \frac{1 - E_j}{\sum_{k=1}^{m}(1 - E_k)} \tag{9}$$

Where: E_j represents the entropy value of the indicator j;p_{ij}represents the proportion of the city i in the indicator j;$w_j$represents the weight of the indicator$j$;m is the number of indicators.

5. Ideal Solutions: Determine the highest and lowest values in the decision matrix, indicating the positive and negative ideal solutions.
6. Distance Calculation: Measure the Euclidean distance from every city to these ideal solutions.

$$D_i^+ = \sqrt{\sum_{j=1}^{m}\left(x_{ij}^* - V_j^+\right)^2} D_i^- = \sqrt{\sum_{j=1}^{m}\left(x_{ij}^* - V_j^-\right)^2} \tag{10}$$

Where: $D_i^+$and D_i^- represent the Euclidean distances from the city i to the positive and negative ideal solutions, respectively.

7. Comprehensive scores: calculate comprehensive scores for each city using distance metrics and rank the cities based on these scores to derive final quality indicators

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{11}$$

Where: $S_i$represents the comprehensive score of the city i, which corresponds to the quality index of that city.

3.5. Spatial lag regression analysis

This study employs a spatial lag regression model to conduct spatial regression analysis on the calculated freight traffic accessibility. The spatial lag model is based on the premise that the dependent variable in a region is influenced not only by its inherent factors but also by the factors of neighboring regions. This model accounts for the influence of neighboring regions by introducing a spatial lag term. The expression of the model is as follows:

$$Y = \rho Wy + X\beta + \varepsilon \tag{12}$$

Where:$Y$is the dependent variable, in this study referring to accessibility;$\rho$is the spatial lag coefficient;$W$is the spatial weight matrix, which measures the spatial correlation between regions. Typical weight matrices include binary weights based on adjacency relationships and continuous weight matrices based on distances. This study uses the

"Queen contiguity" matrix, which is based on adjacency relationships; $W$is the spatial lag term; $X$is the independent variable matrix;β is the coefficient of the independent variables;ε is the error term.

4. Results

4.1. Accessibility calculation and analysis

The results indicating the accessibility of 14 cities in Hunan Province, calculated using Eq. (4). It is highlighted that Changsha, Xiangtan, and Hengyang achieved the highest overall accessibility scores among these cities. Yueyang and Zhuzhou, located in the northeastern province, ranked fourth and fifth, respectively. In contrast, cities in the western and southern regions of the province, including Yiyang, Changde, Loudi, Chenzhou, Shaoyang, Huaihua, Yongzhou, Zhangjiajie, and Xiangxi Tujia and Miao Autonomous Prefecture (Xiangxi), took the sixth to fourteenth places. Cities in the central and eastern regions of Hunan Province outperformed their counterparts in the western and southern regions regarding accessibility. Fig. 9 displays the regional disparities in accessibility, divided into five categories ranging from high to low. The areas with the highest levels of accessibility exhibit transport hinterlands within the province, evidenced by the darkest colors in Fig. 9. Other areas with lower accessibility ratings are displayed in progressively lighter shades of color.

Several factors contribute to the variations in accessibility measured throughout Hunan Province, including the characteristics of the freight transport network and geographic features. Cities like Changsha, the provincial capital and a central hub of economic activity, exhibit higher levels of accessibility, likely due to the well-developed transport infrastructure and the convenient transportation options. Similarly, Xiangtan, a key industrial city in the province, also boasts excellent accessibility. The region's stronger economy also contributes to its accessibility.

In contrast, cities such as Zhangjiajie and Xiangxi exhibit limited accessibility. These regions are typically located in remote areas characterized by mountainous terrains or intricate river networks, posing significant challenges to infrastructure development and transportation network improvements. However, Zhuzhou is an exception. Despite its strategic location and substantial economic significance in Hunan Province, its accessibility ranking does not align with conventional expectations, suggesting that factors other than economic prominence and geographic positioning might influence its accessibility.

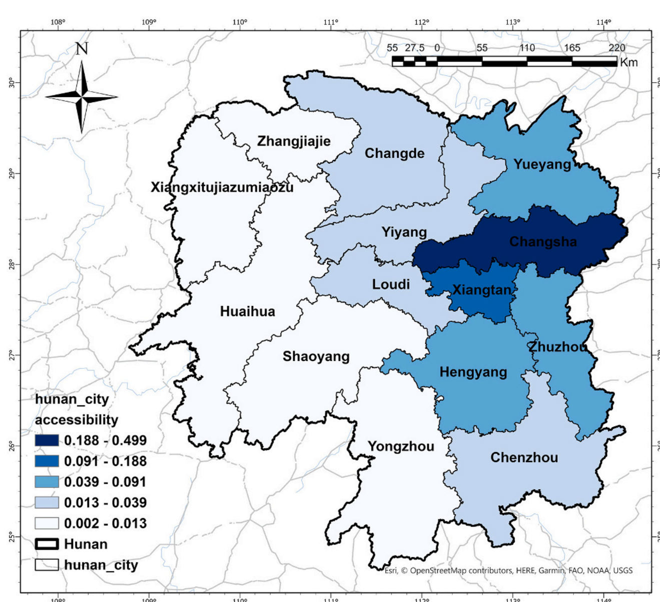

Fig. 9. Spatial distribution of accessibility in Hunan Province.

4.2. nalysis of influencing factors

This section will examine the distribution of spatial accessibility in major cities of Hunan Province and evaluate its relationship with regional freight transport. Two widely used spatial analysis indicators are regional population and regional GDP. A spatial lag model is constructed to assess the influence of regional truck trips, population size, and GDP on freight accessibility. To ensure alignment with the freight data, we acquired population and GDP data from the Hunan Statistical Yearbook (HPPGP, 2023), relating to 2021.

Prior to modeling, it is essential to assess multicollinearity among the three selected independent variables: truck trips, population, and GDP. Multicollinearity may lead to inaccurate parameter estimations, unstable models, and diminished explanatory power. This study calculated the variance inflation factors (VIF) for these independent variables to identify potential multicollinearity. The obtained VIF values are 4.72 for truck trips, 3.42 for population, and 5.87 for GDP, all below the commonly used threshold of 10. The estimation of VIF indicates the absence or presence of weak multicollinearity among these independent variables, which is not expected to affect the fitting results of the model significantly.

The results of the spatial lag model are presented in Table 3.

The spatial lag model applied in this study fits well, as evidenced by the high pseudo R^2 value, which signifies strong explanatory power of the spatial lag effects, and a high log-likelihood value. Furthermore, the precision of the model's regression coefficients is evident from the low standard errors. Additionally, the Akaike Information Criterion (AIC) and Schwarz Criterion (SC) values further confirm the model's aptness in explaining the interrelationships among the variables.

The results presented in Table 3 indicate that GDP and truck trips significantly impact accessibility, while population and the spatial lag term do not ($P > 0.05$). Moreover, an increase in GDP and truck trips correlates with improved accessibility. A higher truck trips may indicate an increase in goods transit, underscoring the significance of inter-city connections. Similarly, regions with higher GDP enjoy larger markets and extensive commercial activities, leading to heightened movement of goods and services via transportation networks.

Population and the spatial lag term have a negative impact on accessibility. An increased transportation demand, often accompanying high population densities, can lead to traffic congestion and added burdens on transportation systems, thereby diminishing accessibility. More vehicles on the road due to high population density can result in traffic congestion and longer commute times, reducing the overall efficiency in reaching destinations. However, the spatial lag term's insignificance indicates that the accessibility in neighboring regions has a negligible or limited impact on the accessibility within the study area.

Table 3
Output results of the spatial lag model.

Variable	Coefficient	Standard Error	*Z*-Score	*P*-Value
Truck Trips	0.0001162	0.0000222	5.2429869	0.000002
GDP	0.0000332	0.0000064	5.2013557	0.000002
Population	−0.0001156	0.0000714	−1.6177391	0.1057188
Constant Term	−0.0353190	0.0208609	−1.6930760	0.0904410
Spatial Lag Term	−0.0196004	0.0359035	−0.5459188	0.5851218
Pseudo R^2		0.9687		
Spatial PseudoR^2		0.9673		
Estimated Standard Error		0.022		
Log Likelihood Value		33.334		
AIC		−56.669		
SC		−53.473		

4.3. Policy implications

Previous research indicates that the spatial distribution of freight traffic accessibility is significantly influenced by inter-city freight flow and GDP. Despite Zhuzhou's advantageous central location in Hunan Province and its relatively high level of economic development, its accessibility ranking is not prominent. This suggests that the transportation network surrounding Zhuzhou is underdeveloped, or that the spatial distribution of the road network in its vicinity requires further optimization to align with Zhuzhou's favorable geographical and economic status. To address this issue, the government can take the following measures:

1. Enhance road network construction. The government should prioritize the development of the transportation network around Zhuzhou, improving both the quantity and quality of the road network to enhance the city's traffic accessibility and logistics efficiency.
2. Promote cross-regional cooperation. The government can facilitate cooperation between Zhuzhou and neighboring cities to jointly build an efficient freight network and promote regional economic development.
3. Implement supportive policies. The government can formulate supportive policies, providing financial support and policy incentives for transportation infrastructure construction, and encouraging enterprises to invest in related fields.

5. Conclusions

Improving regional freight accessibility is crucial for economic development. This study focused on evaluating the accessibility of road freight transport in Hunan Province, China, by analyzing freight trajectory data. A spatial lag model was employed to investigate the relationships between regional freight accessibility and critical factors such as truck trips, population, and GDP.

After identifying stop points, this study developed a process for extracting truck trips from truck trajectory data in Hunan Province. A comprehensive analysis was then conducted to assess the strength of freight connectivity between regions, examining both grid-level and macro-level perspectives. The results reveal a concentration of freight traffic in Changsha, which extends to surrounding cities such as Yueyang, Zhuzhou and Xiangtan. Notably, Changsha emerges as a primary hub for freight connections, especially with Yueyang and Xiangtan.

A comprehensive model was utilized, resulting in accessibility rankings for cities in the province. Changsha, Xiangtan, and Hengyang ranked as the top three cities The accessibility rankings in Hunan Province reflect a pattern where cities in the central and eastern regions generally receive higher ratings, forming a central peak with Changsha as the core, with the notch gradually decreasing towards the outside. Notably, despite its geographical advantages, Zhuzhou did not achieve a high ranking in terms of accessibility.

This study examines the key factors influencing the spatial distribution of freight accessibility in Hunan Province using a spatial lag model. The findings suggest that the spatial lag variable has a negligible impact on accessibility. It can be concluded that the spatial dependence is not a pronounced factor in the distribution of freight accessibility in the province. Instead, the study finds that accessibility is primarily related to the spatial distribution of the road freight network and road truck trips, which are the primary determinants spatial distribution of accessibility.

Improved accessibility can significantly enhance communication and collaboration among cities, expedite the movement of people and goods, and foster economic growth. In regions with limited accessibility, increasing investment in transportation infrastructure, upgrading transport conditions, and improving accessibility are essential for advancing regional economic development and social progress. Although this study proposes a valid model for evaluating accessibility, it still has limitations. One notable limitation is the need to consider differences in freight transport characteristics between intra-provincial and cross-border transport. Future research should aim to distinguish and identify the impacts of various factors on freight accessibility more precisely. Employing additional methods and data to investigate these dynamics thoroughly will be significant. A more profound comprehension of the influencing mechanisms is crucial for enhancing freight accessibility.

CRediT authorship contribution statement

Jie Li: Writing – review & editing, Conceptualization. **Xinyu Zhang:** Writing – original draft, Software, Methodology. **Quanjun Zhu:** Resources, Funding acquisition. **Xiangliang Xiao:** Validation, Software. **Yun Zhou:** Supervision.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be constructed as influencing the position presented in, or the review of, the manuscript entitled.

Data availability

The trajectory data and freight nodes related data were acquired from Hunan Transportation Research Institute Co., Ltd., and they have not given their permission for researchers to share their data. Data requests can be made to Hunan Transportation Research Institute Co., Ltd. via this email: 244023429@qq.com. The distance data were derived from the following resources available in the public domain: https://lbs.amap.com/. The statistical data were derived from the following resources available in the public domain: http://222.240.193.190/2022tjnj/indexch.htm.

Acknowledgment

This work was supported by the Department of Science and Technology of Hunan Province (Grant No. 2022SK2096); the Department of Transportation of Hunan Province (Grant No. 202203); the Department of Transportation of Hunan Province (Grant No. 202322).

References

Acheampong, R. A., & Asabere, S. B. (2022). Urban expansion and differential accessibility by car and public transport in the greater Kumasi city-region, Ghana—A geospatial modelling approach. *Journal of Transport Geography, 98*, Article 103257. https://doi.org/10.1016/j.jtrangeo.2021.103257

Akter, T., & Hernandez, S. (2022). Truck industry classification from anonymous mobile sensor data using machine learning. *International Journal of Transportation Science and Technology, 11*(3), 522–535. https://doi.org/10.1016/j.ijtst.2021.07.001

Akter, T., & Hernandez, S. (2023). Representative truck activity patterns from anonymous mobile sensor data. *International Journal of Transportation Science and Technology, 12*(2), 492–504. https://doi.org/10.1016/j.ijtst.2022.05.002

Akter, T., Hernandez, S., & Camargo, P. V. (2023). Freight operational characteristics mined from anonymous Mobile sensor data. *Transportation Research Record, 2677*(9), 236–247. https://doi.org/10.1177/03611981231158639

Amap. (2002). AutoNavi Open Platform | AutoNavi Map API. https://lbs.amap.com/.

Ankerst, M., Breunig, M. M., Kriegel, H.-P., & Sander, J. (1999). OPTICS: Ordering points to identify the clustering structure. *ACM SIGMOD Record, 28*(2), 49–60. https://doi.org/10.1145/304181.304187

Brin, S., & Page, L. (1998). The anatomy of a large-scale hypertextual web search engine. *Computer Networks and ISDN Systems, 30*(1), 107–117. https://doi.org/10.1016/S0169-7552(98)00110-X

Calatayud, A., Palacin, R., Mangan, J., Jackson, E., & Ruiz-Rua, A. (2016). Understanding connectivity to international markets: A systematic review. *Transport Reviews, 36*(6), 713–736. https://doi.org/10.1080/01441647.2016.1157836

Camargo, P., Hong, S., & Livshits, V. (2017). Expanding the uses of truck GPS data in freight modeling and planning activities. *Transportation Research Record, 2646*(1), 68–76. https://doi.org/10.3141/2646-08

Cao, X., Ouyang, S., Yang, W., Luo, Y., Li, B., & Liu, D. (2019). Transport accessibility and spatial connections of cities in the Guangdong-Hong Kong-Macao Greater Bay Area. *Chinese Geographical Science, 29*(5), 820–833. https://doi.org/10.1007/s11769-019-1034-2

Cascetta, E., Cartenì, A., Henke, I., & Pagliara, F. (2020). Economic growth, transport accessibility and regional equity impacts of high-speed railways in Italy: Ten years ex post evaluation and future perspectives. *Transportation Research Part A: Policy and Practice, 139*, 412–428. https://doi.org/10.1016/j.tra.2020.07.008

Chang, Z., Chen, J., Li, W., & Li, X. (2019). Public transportation and the spatial inequality of urban park accessibility: New evidence from Hong Kong. *Transportation Research Part D: Transport and Environment, 76*, 111–122. https://doi.org/10.1016/j.trd.2019.09.012

Chankaew, N., Sumalee, A., Treerapot, S., Threepak, T., Ho, H. W., & Lam, W. H. K. (2018). Freight traffic analytics from national truck GPS data in Thailand. *Transportation Research Procedia, 34*, 123–130. https://doi.org/10.1016/j.trpro.2018.11.023

Chen, J., Ni, J., Xi, C., Li, S., & Wang, J. (2017). Determining intra-urban spatial accessibility disparities in multimodal public transport networks. *Journal of Transport Geography, 65*, 123–133. https://doi.org/10.1016/j.jtrangeo.2017.10.015

Comendador, J., López-Lambas, M. E., & Monzón, A. (2012). A GPS analysis for urban freight distribution. *Procedia - Social and Behavioral Sciences, 39*, 521–533. https://doi.org/10.1016/j.sbspro.2012.03.127

Demissie, M. G., & Kattan, L. (2022). Estimation of truck origin-destination flows using GPS data. *Transportation Research Part E: Logistics and Transportation Review, 159*, Article 102621. https://doi.org/10.1016/j.tre.2022.102621

Deng, P., Song, L., Xiao, R., & Huang, C. (2022). Evaluation of logistics and port connectivity in the Yangtze River Economic Belt of China. *Transport Policy, 126*, 249–267. https://doi.org/10.1016/j.tranpol.2022.07.019

Diana, M., Pirra, M., & Woodcock, A. (2020). Freight distribution in urban areas: A method to select the most important loading and unloading areas and a survey tool to investigate related demand patterns. *European Transport Research Review, 12*(1), 40. https://doi.org/10.1186/s12544-020-00430-w

Dong, S., Wang, H., Mostafavi, A., & Gao, J. (2019). Robust component: A robustness measure that incorporates access to critical facilities under disruptions. *Journal of the Royal Society Interface, 16*(157), Article 20190149. https://doi.org/10.1098/rsif.2019.0149

Fairthorne, D. B. (1964). Description and shortcomings of some urban road traffic models. *Journal of the Operational Research Society, 15*(1), 17–28. https://doi.org/10.1057/jors.1964.4

Ge, Q., & Fukuda, D. (2016). Updating origin–destination matrices with aggregated data of GPS traces. *Transportation Research Part C: Emerging Technologies, 69*, 291–312. https://doi.org/10.1016/j.trc.2016.06.002

Hansen, W. G. (1959). How accessibility shapes land use. *Journal of the American Institute of Planners, 25*(2), 73–76. https://doi.org/10.1080/01944365908978307

HPPGP. (2023). Hunan Statistical Yearbook 2022. http://222.240.193.190/2022tjnj/indexch.htm.

Huff, D. L. (1963). A probabilistic analysis of shopping center trade areas. *Land Economics, 39*(1), 81–90. https://doi.org/10.2307/3144521

Hughes, S., Moreno, S., Yushimito, W. F., & Huerta-Cánepa, G. (2019). Evaluation of machine learning methodologies to predict stop delivery times from GPS data. *Transportation Research Part C: Emerging Technologies, 109*, 289–304. https://doi.org/10.1016/j.trc.2019.10.018

Jiang, Y., Timmermans, H. J. P., & Yu, B. (2018). Relocation of manufacturing industry from the perspective of transport accessibility – An application of percolation theory. *Transport Policy, 63*, 10–29. https://doi.org/10.1016/j.tranpol.2017.11.003

Kinjarapu, A., Demissie, M. G., Kattan, L., & Duckworth, R. (2022). Applications of passive GPS data to characterize the movement of freight trucks—A case study in the Calgary region of Canada. *IEEE Transactions on Intelligent Transportation Systems, 23*(7), 9210–9225. https://doi.org/10.1109/TITS.2021.3093061

Kocatepe, A., Ozkul, S., Ozguven, E. E., Sobanjo, J. O., & Moses, R. (2020). The value of freight accessibility: A spatial analysis in the Tampa Bay region. *Applied Spatial Analysis and Policy, 13*(2), 527–546. https://doi.org/10.1007/s12061-019-09314-6

Kuppam, A., Lemp, J., Beagan, D., Livshits, V., Vallabhaneni, L., & Nippani, S. (2014). Development of a tour-based truck travel demand model using truck GPS data. https://www.semanticscholar.org/paper/Development-of-a-Tour-Based-Truck-Travel-Demand-GPS-Kuppam-Lemp/f8ad1e6b522acf066d8a57cb64860827be59ab88.

Laranjeiro, P. F., Merchán, D., Godoy, L. A., Giannotti, M., Yoshizaki, H. T. Y., Winkenbach, M., & Cunha, C. B. (2019). Using GPS data to explore speed patterns and temporal fluctuations in urban logistics: The case of São Paulo, Brazil. *Journal of Transport Geography, 76*, 114–129. https://doi.org/10.1016/j.jtrangeo.2019.03.003

Li, J., Pei, X., Wang, X., Yao, D., Zhang, Y., & Yue, Y. (2021). Transportation mode identification with GPS trajectory data and GIS information. *Tsinghua Science and Technology, 26*(4), 403–416. https://doi.org/10.26599/TST.2020.9010014

Liu, F., Andrienko, G., Andrienko, N., Chen, S., Janssens, D., Wets, G., & Theodoridis, Y. (2020). Citywide traffic analysis based on the combination of visual and analytic approaches. *Journal of Geovisualization and Spatial Analysis, 4*(2), 15. https://doi.org/10.1007/s41651-020-00057-4

Liu, S., Chen, G., Wei, L., & Li, G. (2021). A novel compression approach for truck GPS trajectory data. *IET Intelligent Transport Systems, 15*(1), 74–83. https://doi.org/10.1049/itr2.12005

Lu, Q.-C., & Lin, S. (2019). Vulnerability analysis of urban rail transit network within multi-modal public transport networks. *Sustainability, 11*(7). https://doi.org/10.3390/su11072109. Article 7.

Ma, X., Wang, Y., McCormack, E., & Wang, Y. (2016). Understanding freight trip-chaining behavior using a spatial data-mining approach with GPS data. *Transportation Research Record, 2596*(1), 44–54. https://doi.org/10.3141/2596-06

Mjøsund, C. S., & Hovi, I. B. (2022). GPS data as a basis for mapping freight vehicle activities in urban areas – A case study for seven Norwegian cities. *Research in Transportation Business & Management, 45*, Article 100908. https://doi.org/10.1016/j.rtbm.2022.100908

Nam, D., Hyun, K. K., Kim, H., Ahn, K., & Jayakrishnan, R. (2016). Analysis of Grid Cell–based taxi ridership with large-scale GPS data. *Transportation Research Record, 2544*(1), 131–140. https://doi.org/10.3141/2544-15

Poliziani, C., Rupi, F., Mbuga, F., Schweizer, J., & Tortora, C. (2021). Categorizing three active cyclist typologies by exploring patterns on a multitude of GPS crowdsourced data attributes. *Research in Transportation Business & Management, 40*, Article 100572. https://doi.org/10.1016/j.rtbm.2020.100572

PRC. (2016). National road freight vehicle public regulation and service platform. https://www.gghypt.net/.

Song, X., Guo, R., Xia, T., Guo, Z., Long, Y., Zhang, H., Song, X., & Ryosuke, S. (2020). Mining urban sustainable performance: Millions of GPS data reveal high-emission travel attraction in Tokyo. *Journal of Cleaner Production, 242*, Article 118396. https://doi.org/10.1016/j.jclepro.2019.118396

Tome, A., Santos, B., & Carvalheira, C. (2019). GIS-based transport accessibility analysis to community facilities in mid-sized cities. *IOP Conference Series: Materials Science and Engineering, 471*, Article 062034. https://doi.org/10.1088/1757-899X/471/6/062034

Wei, L., Chen, G., Sun, W., & Li, G. (2021). Recognition of operating characteristics of heavy trucks based on the identification of GPS trajectory stay points. *Security and Communication Networks, 2021*, Article e9998405. https://doi.org/10.1155/2021/9998405

Xu, Y., & González, M. C. (2017). Collective benefits in traffic during mega events via the use of information technologies. *Journal of the Royal Society Interface, 14*(129), Article 20161041. https://doi.org/10.1098/rsif.2016.1041

Yang, X., Sun, Z., Ban, X. J., & Holguín-Veras, J. (2014). Urban freight delivery stop identification with GPS data. *Transportation Research Record, 2411*(1), 55–61. https://doi.org/10.3141/2411-07

Yang, Y., Jia, B., Yan, X.-Y., Li, J., Yang, Z., & Gao, Z. (2022). Identifying intercity freight trip ends of heavy trucks from GPS data. *Transportation Research Part E: Logistics and Transportation Review, 157*, Article 102590. https://doi.org/10.1016/j.tre.2021.102590

Yanhong, F., & Xiaofa, S. (2013). Research on freight truck operation characteristics based on GPS data. *Procedia - Social and Behavioral Sciences, 96*, 2320–2331. https://doi.org/10.1016/j.sbspro.2013.08.261

Ye, Y., Zheng, Y., Chen, Y., Feng, J., & Xie, X. (2009). Mining individual life pattern based on location history. In *2009 tenth international conference on Mobile data management: Systems, services and middleware* (pp. 1–10). https://doi.org/10.1109/MDM.2009.11

Yuan, M. (2022). Parking reason inference of trucks based on trajectory data. In *2022 IEEE 7th international conference on intelligent transportation engineering (ICITE)* (pp. 87–92). https://doi.org/10.1109/ICITE56321.2022.10101396

Zanjani, A., Pinjari, A., Kamali, M., Thakur, A., Short, J., Mysore, V., & Tabatabaee, S. (2015). Estimation of Statewide Origin–Destination truck flows from large streams of GPS data. *Transportation Research Record: Journal of the Transportation Research Board, 2*, 87–96. https://doi.org/10.3141/2494-10