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RESEARCH ARTICLE

A Spatio-Temporal Perspective on Commercial Vehicle Travel Patterns in Urban Environments

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ABSTRACT The relationship between commercial vehicle travel patterns and urban functional areas reveals potential connections between urban form and human geographic flows, which provides critical information for optimizing urban transportation systems. Benefiting from the large-scale trajectory datasets, it would be possible to investigate deeper research by modeling the implied urban travel patterns. This study designs a framework to reveal the collective movement patterns of commercial vehicle trajectories inside the urban environment, focusing on their spatiotemporal variations within functional areas. Stopping behaviors of trajectories were identified to construct spatiotemporal origin-destination (OD) matrices, representing time-varying human geographic flows. The singular value decomposition (SVD) method was employed to quantify spatio-temporal OD matrice to obtain time and space travel features. Travel patterns' dynamics and spatial interactions within functional areas were then analyzed. The experimental results obtained with real-life datasets from Changsha, China, uncovered three typical travel patterns depicting commercial vehicle activities in urban environment shifts from work-related locations on weekdays to leisure destinations on weekends, with central areas experiencing more short and medium-range trips. The findings provide scientific references for optimizing spatio-temporal travel patterns and functional distribution to meet the demands of urban development and traffic management strategies.

INDEX TERMS Urban functional area interaction, vehicle travel patterns, spatio-temporal data analysis, singular value decomposition (SVD).

I. INTRODUCTION

Understanding urban travel demand is crucial for transportation planning and management in cities [1], [2]. Rapid urbanization in China has led to increasing city sizes, populations, and daily travel volumes, causing frequent traffic congestion [3], [4], [5]. Cities are complex entities comprising space, function, and human activities [6], [7]. The daily travel patterns of residents are vital for optimizing urban spatial structure [8], enhancing planning and management [9], and improving overall city service quality [10]. The amelioration of urban service quality serves as a catalyst for the deployment of autonomous driving technology, which in turn augments the efficacy of traffic management systems [11], [12]. Embedded within this technology are sophisticated learning algorithms designed to discern and analyze travel patterns [13], [14]. These algorithms are capable of adapting to the commuting behaviors of the populace, thereby enabling a strategic enhancement in routing protocols and decision-making processes, which ultimately elevates the caliber of urban services. Thus, analyzing these patterns is key to effective traffic management and fostering high-quality urban development.

Investigating the travel patterns of urban vehicles and exploring the spatial interactions among individuals, cities, and functions, as well as optimizing urban spatial structures [15], [16], has long been of interest to urban researchers and planners. When people move within cities, both functional interactions and spatial interactions undergo changes. Understanding the reasons behind urban spatial structures

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through functional interactions allows us to analyze the interdependence between spatial and functional dynamics, revealing the mutual relationship between urban structures and functions. However, previous research has predominantly focused on static analysis of spatial interactions [17], [18], overlooking the dynamic variations in functional dynamics of urban travel.

With the advancement of positioning technology, acquiring real-time mobility data has become increasingly convenient. Commercial vehicle trajectory data offers advantages such as diverse vehicle types, large sample sizes, extensive spatial and temporal coverage, and high dimensionality, making it crucial for studying urban travel patterns and structural characteristics. This data provides detailed descriptions of vehicle movements in space [19], [20], [21], and reveals the travel patterns of vehicles. Simultaneously, the trajectory data generated by a multitude of human activities encapsulates the functional aspects of urban land, allowing for the extraction of the dynamic functionalities of urban spaces. This, in turn, enables the revelation of the dynamic characteristics of the interaction between urban space and functionality.

The large amount of operational vehicle trajectory data enables us to uncover the travel patterns of vehicles and reveal the dynamic changes in urban functional areas [22], [23]. However, dealing with such a large amount of data presents significant challenges in discovering the underlying spatiotemporal patterns. Traditional origin-destination (OD) matrices, manually collected and updated [24], [25], suffer from low dimensionality, high cost, and slow updates. Previously used for trip number analysis, time series models and variation factors fail to capture the intrinsic structure of travel demand and the daily variation of all OD pairs. The spatiotemporal OD matrix provides a detailed framework for studying continuous trips, with higher accuracy and dimensionality [26], [27].

Nevertheless, the richness of information in the matrix can potentially obscure the inherent spatiotemporal patterns [28], [29], [30]. As a solution, dimensionality reduction techniques have emerged, including matrix decomposition based on Principal Component Analysis, feature decomposition, and non-negative matrix factorization [31], [32], [33]. These methods extract significant features for OD clustering and spatial distribution analysis [34]. However, spatiotemporal OD matrices are typically of arbitrary shape with complex data structures. Singular Value Decomposition (SVD) excels in extracting the intrinsic properties of data through eigenvalues and is commonly used for micro-level pattern analysis [35], [36], [37], [38]. SVD has garnered widespread attention in traffic pattern analysis and forecasting [34], [39], [40]. Despite its potential, the direct application of SVD in OD data mining and extraction is limited.

The spatio-temporal OD matrix constructed based on running vehicle trajectory data contains travel information in both time and space dimensions. Based on this, after SVD decomposition, the travel pattern can be further explained from both time and space. The time aspect involves identifying active time periods for vehicles, duration of activity, and temporal variations. By analyzing time characteristics, different travel patterns can be delineated. On the other hand, the spatial aspect pertains to the distribution characteristics of travel trajectories, spatial range, and the dynamic changes in functional areas. In this paper, addressing the abovementioned challenges, we utilize GPS trajectory and POI data to derive OD pairs enriched with semantic information. We construct a spatio-temporal OD matrix model and apply SVD to discern residents' travel patterns. Our study further conducts cluster analysis on semantically enhanced OD flows, aiming to elucidate the spatio-temporal dynamics of urban functional areas. By clustering OD flows with similar semantic attributes, we identify distinct travel patterns, facilitating the exploration of temporal and spatial shifts in urban functional areas. This research is geared towards analyzing and understanding the travel patterns of commercial vehicles within the city and their interplay with functional areas, providing a theoretical foundation for optimizing spatial structures and public resource allocation in urban settings.

The remainder of this paper is structured as follows: Section II presents the study area and data. Section III outlines the research methodology. Section IV delves into analyzing the results of SVD and discussing the spatio-temporal patterns of commercial vehicle distribution. Finally, Section V concludes the paper and suggests avenues for future research.

II. STUDY AREA AND MATERIALS

A. STUDY AREA

Changsha, the political, economic, cultural, and transportation hub of Hunan Province and a key city along the middle Yangtze River, serves as our study area. It encompasses Furong, Tianxin, Yuelu, Kaifu, Yuhua, and Wangcheng Districts, along with Changsha County, Liuyang City, and Ningxiang City. Spanning 11,816 square kilometers with a population density of approximately 643.23 people per square kilometer, Changsha extends from N27°51′-N28°40′ latitude and E111°53′-E114°15′ longitude (refer to Figure 1). The city's predominantly tertiary economy contributes about 57.2% to its GDP, with the service and transportation industries accounting for 27.1% and 3.3%, respectively. As of 2021, Changsha housed 165,658 commercial vehicles. The city's rapid urbanization emphasizes optimizing its spatial structure, especially given the traffic congestion. Notably, Changsha's road network facilitates north-south traffic but lacks adequate east-west connections, impacting regional development. This study aims to understand Changsha's travel demands and characteristics to support informed decision-making and congestion alleviation. Moreover, the insights gained here could benefit other emerging first-tier cities in China's midlands, which are also predominantly reliant on the tertiary sector.

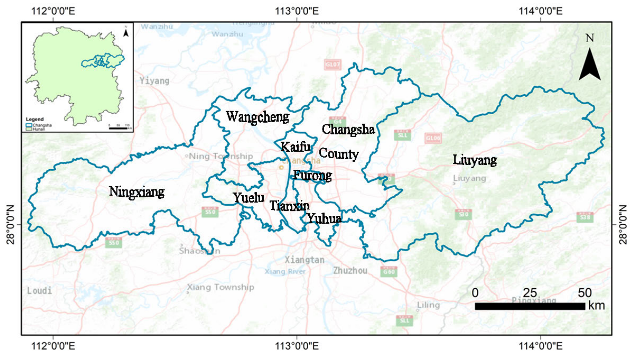


FIGURE 1. Study area.

TABLE 1. The original commercial vehicle GPS records in changsha.

ID	Time	Lng	Lat	Name
Xiang****	2015-01-01 00:23:04	112.997420	28.095979	Changsha
Xiang****	2015-01-01 00:24:25	112.997338	28.095915	Changsha
Xiang****	2015-01-01 00:25:25	112.997364	28.095906	Changsha
...	...	...	...	...
Xiang****	2015-01-01 23:04:45	112.132336	25.377642	Yongzhou
Xiang****	2015-01-01 23:05:43	112.132195	25.377748	Yongzhou

B. DATA

The CV data used in this case study was provided by Data management platform under the Ministry of Transport and contains trip records from December 26, 2014, to January 9, 2015. The dataset includes GPS records of commercial vehicles like taxis, buses, and trucks. It necessitates extracting and removing duplicate and incomplete entries (missing latitude or longitude). Focusing on Changsha, we conducted a topological overlay operation to isolate the city's commercial vehicle trajectories. This process yielded over 100,000 daily records for Changsha's commercial vehicles. As illustrated in Table 1, each record comprises the vehicle ID (ID), GPS sampling time (Time), latitude (Lng) and longitude (Lat) coordinates, and city name (Name).

In the commercial vehicles, buses, taxis, and trucks play a major role. They are categorized based on the vehicle's travel time, OD duration, and license plate number. For buses, three conditions need to be met: 1) The license plate number starts with "Xiang A"; 2) The journey takes place between 6:00 and 24:00; 3) The average duration of each OD trip of a bus is within 10 minutes. Typically, the distance between two adjacent bus stops in a city is not greater than 1 km, and even in traffic congestion, the travel time does not exceed 10 minutes. Taxis are identified as vehicles with license plate numbers starting with "Xiang A" and an average OD trip duration within 45 minutes. Trucks are characterized by an average OD trip duration exceeding 45 minutes.

TABLE 2. POI types and detailed descriptions.

Type	Description
Accommodations	Hotels, guest houses, and accommodation services
Finances	Banks, ATMs, credit unions, investment and finances.
Entertainments	Sports stadiums, fitness centers, resorts, farmhouses, cinemas, KTVs, theaters, dance halls, and game places
Transport Facilities	Airports, train stations, subway stations, bus stations, and bus stops
Educations	Schools, kindergartens, libraries, science and technology museums, art museums, exhibition halls and cultural palaces
Living services	Communication business hall, post office, logistics company, ticket office, laundry, graphic express store, real estate agency, public utilities, maintenance points, and domestic services,
Commercial Residences	Office buildings, residential areas and dormitories
Shopping Malls	Shopping centers, department stores, supermarkets, convenience stores, and home building materials
Restaurants	Restaurants, snack and fast food restaurants, cake and dessert stores, cafes, and bars
Governments and Corporate Organizations	Governments, administrative units, foreign-related agencies, party groups, welfare agencies, and political and educational institutions

Additionally, the study requires POI data inside Changsha, sourced from Baidu Map's open platform. This data is essential for identifying the city's various functional areas. Each POI entry includes the name, location coordinates, address, ID, and business hours. To align with Changsha's functional area characteristics and residents' stay behavior, we categorized the POI data into ten types: accommodations, finances, entertainment, transport facilities, education, living services, commercial residences, shopping malls, restaurants, and governmental and corporate organizations (refer to Table 2).

III. METHODOLOGY

We propose a flowchart (see Figure 2) for analyzing and identifying travel patterns from commercial vehicle trajectory data. The flowchart consists of two main phases: Spatio-temporal OD matrix construction and Urban travel pattern identification. In the Spatio-temporal OD matrix construction phase, POI data is incorporated to obtain the functional area attributes of blocks. This information is then used to determine the semantic attributes of the origin and destination of each OD trip, leading to the construction of the final matrix. To identify travel patterns, the study utilizes SVD to decompose the spatio-temporal OD matrix. Through this decomposition, the temporal, spatial, and functional area interactions of commercial vehicle travel patterns within the city are explored.

A. SPATIO-TEMPORAL OD MATRIX CONSTRUCTION

This phase begins with processing GPS trajectory data of commercial vehicles to generate OD pairs. The stopping

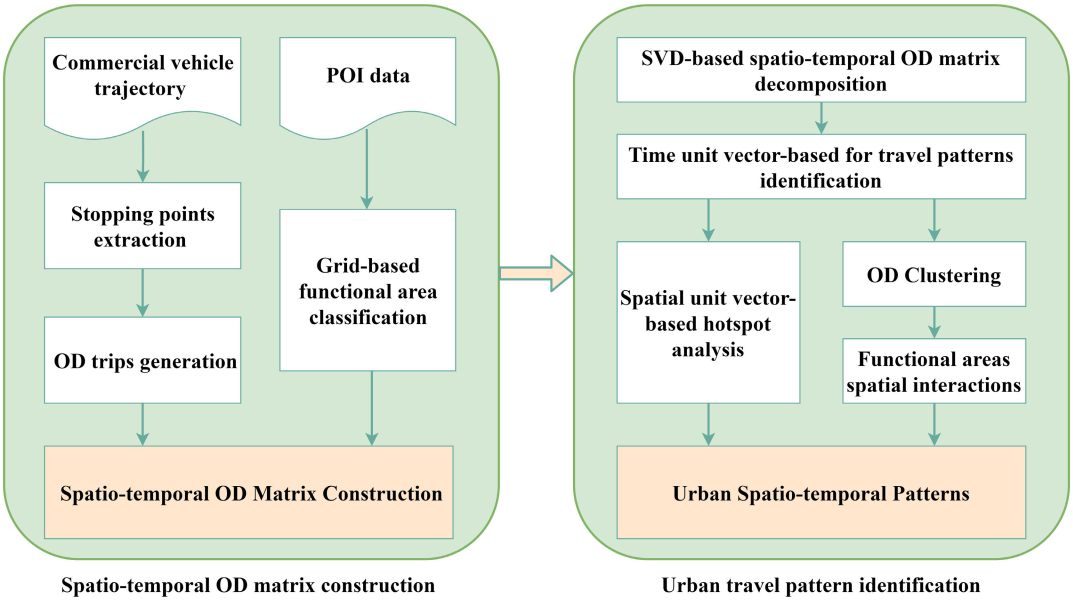


FIGURE 2. **Analysis flowcharts.**

points from this data are extracted using a time-distance-speed threshold method. The next step involves integrating POI data, which assigns functional area attributes to each OD pair. This integration results in a high-dimensional spatio-temporal OD matrix, encapsulating temporal and spatial elements. The time dimension is segmented into one-hour intervals based on the distribution characteristics of commercial vehicles, leading to 24 time slices for each day.

B. URBAN TRAVEL PATTERN IDENTIFICATION

This phase employs SVD to decompose the spatio-temporal OD matrix and unearth the underlying travel patterns of commercial vehicles. The temporal vectors from the SVD decomposition are analyzed to discern distinct travel patterns. Conversely, the spatial vectors are scrutinized to pinpoint urban hotspot areas, indicating regions with significant commercial vehicle activity. Moreover, the study clusters the OD flows according to the enhanced semantic attributes of the commercial vehicle travels. This clustering effectively captures the spatio-temporal dynamics in urban functional areas, providing insights into the varying utilizations of different areas by commercial vehicles over time.

C. STOPPING POINTS EXTRACTION

In this study, a stopping point is taken as the starting point, which can also be understood as the end point of the previous OD trip; the latter stopping point is taken as the end point, which is also the starting point of the next OD trip to construct the OD trip. Therefore, we first need to extract the stopping points from the commercial vehicle trajectory points. First, according to the trajectory time threshold, distance threshold, and speed threshold, the set of candidate stopping points of the trajectory is filtered. After that, the distance between adjacent clusters is calculated and compared with the distance threshold, and the clusters that meet the threshold range are merged. Finally, the first point in each cluster is selected as the stopping point to get the final cluster of stop points.

The traditional stopping point identification method mostly uses the empirical speed value or stopping time to determine whether the vehicle is stopping. Researchers typically determine the identification method for stay points based on different research purposes [41], [42]. However, the GPS data used in this paper includes the data of the whole of Changsha city, which involves a wide range and a large period. Commercial vehicles may have traffic jams, traffic accidents, temporary driver breaks, and other events during the driving process. The uncertainty and diversity of these special events lead to the impossibility of using empirical speed value or stopping time to determine whether a vehicle is stopped or not. Therefore, this paper innovatively proposes an identification method based on time-distance-speed thresholds to determine the stopping points. A segment of commercial vehicle trajectory Traj $= \{p_1, p_2, \ldots, p_i\}$, trajectory point $P_i = \{T_i, \text{lon}_i, \text{lat}_i\}$, where i={0,1,2, …, n} and $T_0 < T_1 <, \ldots, < T_n$. After the stop extraction, we get the set of candidate stops $C = \{c_1, c_2, \ldots, c_n\}, c_n = (T_n, lon_n, lat_n, Dis_n, V_n)$. The distance and speed is calculated as follows:

$$Dis_{ij} = r \times 2 \arcsin \sqrt{\sin(\Delta lat/2)^2 + \cos(lat_i) \times \cos\left(lat_j\right) \times \sin(\Delta \lg/2)^2} \tag{1}$$

$$\mathrm{V}_{ij} = \frac{Dis\left(P_i, P_j\right)}{T_j - T_i} \tag{2}$$

where r is the radius of the Earth 6378.137 km, Δlat is the difference in latitude between the two points, and Δlng is the difference in longitude between the two points. $Dis(P_i, P_j$ is the distance between the trajectory points P_i and P_j, $T_j - T_i$ is the time between the two points.

First, calculate the speed of the trajectory points. Trajectory points with speed greater than 100 km/h are considered as error points and are eliminated [43]. Second, in past studies, the threshold value for determining stopping is usually set below 1 m/s. Use the distance formula to calculate the distance between the two points, if the distance between the two points is less than 100 m; then filter by time threshold, the time distance between trajectory point P_i and P_j is more than 120 s are extracted to form candidate stop sequences. Next, extracting environmental trajectory features, an SVM-based classifier is employed to further discriminate against actual stops [44], thus reducing the error rate of recognition of stops in the trajectory. Then, consecutive candidate stop sequences that are close in space are likely to represent the same stopping behavior. In this paper, a constraint is introduced to merge consecutive time and adjacent spatial stop sub-OD travel flows. If the distance between two stop sub-OD travel flows is less than 100 m, the two stop sequences are merged. Finally, the first trajectory point from each candidate stop sequence is extracted as the stopping point.

D. PATTERN RECOGNITION BASED ON SPATIO-TEMPORAL OD MATRIX

The space-time OD matrix is a high-dimensional matrix containing both time and space. It can represent the movement of people geographically within a certain time. Decomposing the spatio-temporal OD matrix, the spatio-temporal characteristics of human activities can be obtained. The spatial information of the spatio-temporal OD matrix in previous studies is generally at city scale and the temporal information is at the daily scale. In this study, a more fine-grained spatio-temporal OD matrix will be constructed. For this, the study area must be divided into suitable grids for being rasterized to construct the OD matrix. The research on the impact of spatial grid division on the layout analysis of urban functional areas confirmed that 500 m × 500 m grid can effectively identify single functional areas [45]. Therefore, we use a 500 m × 500 m fishing net to divide the study area and divide Changsha city into 48578 grids. It makes the number of streets within each grid smaller and the OD travel flows of commercial vehicles evenly distributed. At the same time, the POI distribution within each grid can be evaluated, and the functional areas are more carefully classified. If the grid division is too large, individual functional areas will be difficult to identify; if it is too small, the fragmentation of functional areas increases and reduces the clustering effect. Figure 3 shows the grid division results and shows the distribution of the restaurants in the grid with the example of the restaurant category. The OD pairs are topologically overlaid with the functional areas

TABLE 3. A sample of spatio-temporal OD matrix.

	Restaurants-Shopping Malls	Restaurants-Living services	Restaurants-Educations	...	Shopping Malls-Restaurants
0	87	72	4	...	54
1	21	4	6	...	11
2	2	2	12	...	8
...	...	...	...	...	...
22	195	254	51	...	121
23	165	69	8	...	124

to get the semantic information of the OD pairs in order to construct the spatio-temporal OD matrix. Table 3 shows a sample spatio-temporal OD matrix. The columns of the matrix represent the space, such as, the first column is the OD between the restaurant class and the shopping class. The rows of the matrix represent the time, for example, the first row is the time slice ordinal number of the first hour.

The spatio-temporal OD matrix constructed in this paper is a one-day unit, composed of one-hour time slices. SVD has better performance in fine-grained feature extraction than other matrix decomposition methods. The SVD decomposition of the obtained spatio-temporal OD matrix can be decomposed into a superposition of n matrices of rank 1 as follows:

$$\begin{aligned} X &= U\Sigma V^T = \sum_{i=1}^{r} s_i u_i v_i^T \\ U &= (u_1, u_2, \ldots, u_r), V = (v_1, v_2, \ldots, v_r) \\ S &= diag\{s_1, s_2, \ldots s_r\}\,(s_1 \geq s_2, \ldots s_r) \end{aligned} \tag{3}$$

where X is the $m \times n$ matrix with rank r, U is the $n \times r$ matrix, u_i is the i-th column of U, and U^T is the transposition matrix of U set matrix. V is an $m \times r$ matrix, v_i is the i-th column of V, V^T is the transpose matrix of V. U and V satisfy $U^T U = E$ and $V^T V = E$, u_i and v_i are unit vectors, E is a unit matrix. S is a diagonal matrix, the i-th diagonal element is s_i, which is the decomposed singular value, and the singular value s_i denotes the importance of $u_i v_i^T$ in X. The larger the s_i, the more significant the travel pattern represented.

E. OD TRAVEL FLOW CLUSTERING

OD flow clustering is the clustering of complete trajectory flows, taking into account the temporal relationships and continuity of all points. In contrast to traditional point clustering methods, the objective of clustering OD flows is to classify the complete flow into different clusters to recognize different flow patterns. When the functions of the OD grid of an OD flow are specified, the OD travel flows is given semantic meaning. The OD travel flows are then clustered to specify the spatial and functional interactions in Changsha. We merge OD travel flows with the following constraints based on spatial and semantic information [30]:

1) The origin grids of the OD travel flows must be spatially adjacent, as do the destination grids of the OD travel flows. In Figure 4(b), a grid is spatially adjacent

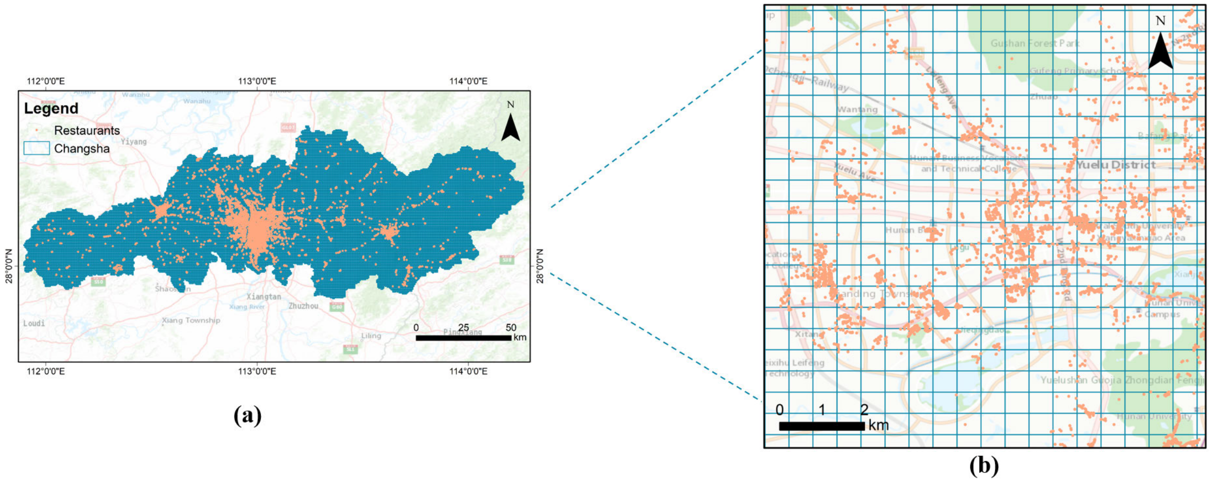


FIGURE 3. The result of Changsha grid division: (a) The overall distribution of Restaurants in the grid; (b) Detailed distribution.

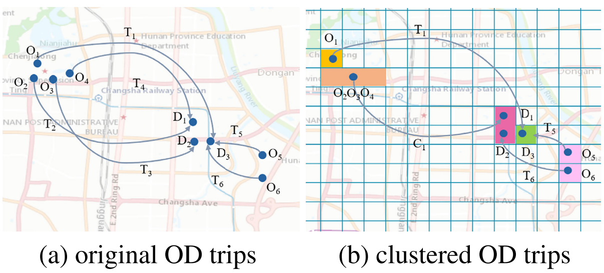


FIGURE 4. OD travel flow clustering.

to eight surrounding grids, and spatially neighboring O/D points can be brought together by clustering;

2) Clustering flows with similar semantics can enhance our perception of the changing characteristics of functional areas, as well as to understand the interaction characteristics of functional areas. The origin grids of the OD travel flows have the same function, as do the destination grids of the OD travel flows.

OD travel flows will be clustered into one group if they meet constraints. Figure 4 shows the clustering of OD flows. Figure 4(a) shows all OD travel flows whose starting and ending points are mapped to the grid in Figure 4(b), where the colors represent the functions of the grids. The grids corresponding to O_2, O_3 and O_4 are spatially adjacent and have the same function, and the regions corresponding to D_1 and D_2 are also spatially adjacent and have the same function, so OD travel flows T_2, T_3 and T_4 are grouped into C_1. However, O_1 has different functions than O_2 and O_3; therefore, trajectory T_1 is not clustered into the same group, although it has the same destination as T_5 and T_6.

IV. RESULTS AND DISCUSSION

According to the general characteristics of people's travel, we could roughly divide travel time scales into three situations: weekend, holiday and workday. To represent these situations, we randomly chose three days to represent these situations, December 27, 2014 (Weekend), January 1, 2015 (Holiday) and January 8, 2015 (Workday) respectively. The spatio-temporal OD matrices for each time scales were decomposed to identify the travel demand and spatio-temporal patterns in Changsha. The singular value represents the importance of each demand mode in the commercial vehicle transportation spatiotemporal OD matrix. A larger singular value indicates that the demand mode represents more raw information of the spatiotemporal OD matrix. Based on Figure 5, the maximum singular value is much larger than the other singular values, and the singular value decreases rapidly. By considering the top three singular values, it is possible to represent 80% of the original information of the spatiotemporal OD matrix and identify three representative travel demands.

Based on the three columns of time unit vectors of commercial vehicle travel modes, the study identified three travel patterns. Among the three situations (weekend, holiday, and workday), the fluctuation of the workday pattern roughly follows the working hours. The fluctuation of the weekend and holiday patterns does not resemble the workday pattern, with the holiday pattern showing greater fluctuations than the weekend pattern. This indicates that there is a higher number of commercial vehicle trips during holidays compared to weekends. According to Figure 6, the positive and negative values of the time unit vector values correspond to the direction of fluctuation of the travel pattern in the time dimension, and the absolute magnitude corresponds to the degree of fluctuation. As shown in Figure 6(a-c), the first pattern has a long peak duration, lasting from 8:00 to 16:00. This pattern represents the commercial vehicles driving in the daytime, regarded as the daytime pattern. Figure 6(d-f) shows the time unit vectors in the second mode, all of them have a clear peak in the morning, called it morning peak pattern.

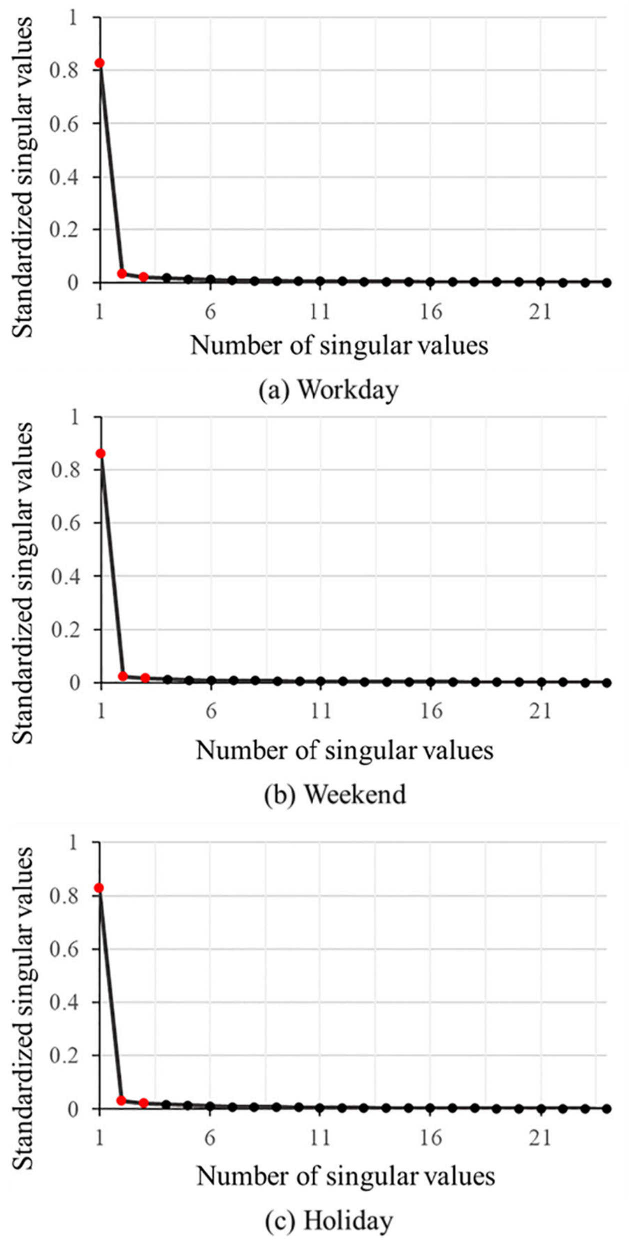


FIGURE 5. Singular value normalization diagram in three situations.

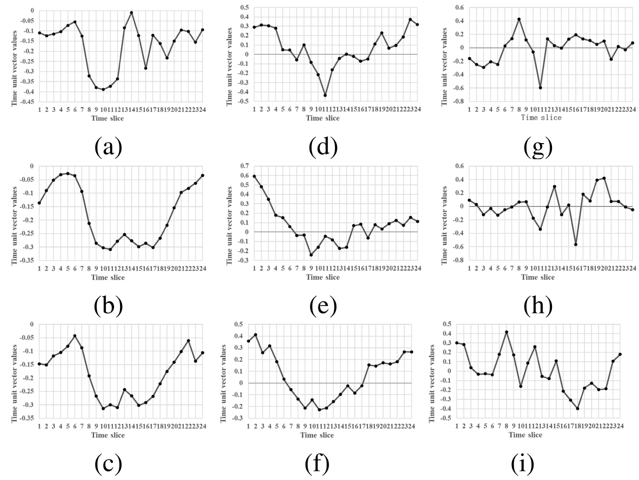


FIGURE 6. The distribution of normalized singular values:(a),(b) and (c) represent the first column of workday, weekend and holiday respectively; (d),(e) and (f) represent the second column of workday, weekend and holiday respectively; (g),(h) and (i) represent the third column of workday, weekend and holiday respectively.

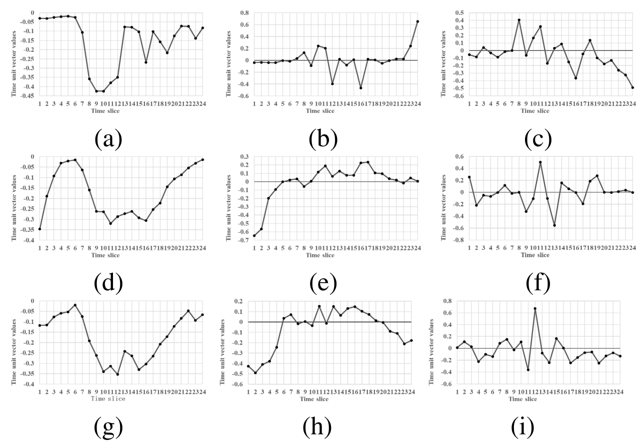


FIGURE 7. The distribution of normalized singular values of taxis:(a),(b) and (c) represent the travel patterns of workdays; (d),(e) and (f) represent the travel patterns of weekends; (g),(h) and (i) represent the travel patterns of holidays.

The third travel pattern has peaks at midday and evening in Figure 6(g-i), and is inferred to be the evening peak pattern.

The travel patterns of buses, taxis, and trucks during workdays, weekends, and holidays have been further refined. Overall, the travel patterns of these three types of vehicles are broadly similar. However, due to differences in the nature of work and working hours for each type of vehicle, their travel patterns also exhibit distinct characteristics, as detailed in V. Buses exhibit the highest travel demand on weekdays, typically between 7:00 and 18:00. Taxis supplement bus services on weekdays, with occasional demand fluctuations during the day, peaking between 20:00 and 2:00, coinciding with the return-to-home rest periods for some overtime workers or leisure individuals. As for trucks, their travel demand displays significant fluctuations with no clear regular. Taking taxis as an example, Figure 7 illustrates the time unit vectors for workdays, weekends, and holidays. As shown in the Figure 7(a-c), on workdays, taxis demand is concentrated between 19:00 and early 2:00, as well as during peak commuting hours. while on weekends and holidays(Figure 7(d-i)), the peak demand for taxis extends throughout the day and from 1:00 to 4:00 in the early morning. This indicates that taxis assist people with travel on workdays, and there is a higher demand for taxi services during holidays and weekends.

The three columns of time unit vectors correspond to three columns of spatial unit vectors, and their spatial dimensions also have three travel patterns, which correspond to the original point data (Figure 8) and the destination point data (Figure 9). People travel for different purposes at different times of the day, and there are differences in the spatial locations they go to, leading to differences in the hotspot areas for each travel mode. People usually focus on commuting, with increased areas to corporate institutions such as Wuyi Square, Meixi Lake International Culture and Art Center, Hunan Steel Market, Hunan Radio and Television Station, Provincial People's Government, and Xiangya Hospital. Irrespective of the travel mode, the trips of commercial vehicles are predominantly concentrated in the central area of Changsha. The areas with higher concentration include the Wuyi business district, Meixi Lake business district, BBK Star City Tiandi, Gaoqiao Market, and other business and financial centers, along with major transportation hubs such as Changsha's four major bus stations, railway station, and Changsha South Station.

Furthermore, the different patterns of commercial vehicles we analyzed can contribute to the intelligent transportation system. On the one hand, traffic planning and traffic control can be managed, according to specific patterns, and then improve the capacity coordination of the transportation system. For example, during the morning peak hours of commuting, there is an increase in commercial vehicles in hotspot areas such as Wuyi Square, Lugu Park, and Hunan Radio and Television Station. During peak hours, prioritize traffic flow in key areas by optimizing traffic signals and expanding lanes to improve the efficiency and capacity of the transportation system, thereby alleviating congestion. On the other hand, it can contribute to the operation of commercial vehicles in terms of picking up and dropping off guests, thereby increasing turnover. Putting in more public transportation in areas where travel is concentrated not only meets people's travel demand but also reduces urban problems such as traffic congestion and supports green travel. In rural areas, it is necessary to put in public transportation such as buses and other commercial vehicles, such as cabs, can also be arranged.

A. FUNCTIONAL INTERACTIONS

We analyze the spatial-temporal functional interactions in the urban environment through Sankey diagrams, as described in Figures 10 - 12. The flow of each functional area in the Sankey diagram represented the magnitude of the spatial vector values, with larger values representing more pronounced spatial fluctuations. We use the term 'outflux' to denote the movement of commercial vehicles away from a particular area, and 'influx' to denote the movement of vehicles towards a particular area.

The Sankey diagram (Figure 10(a)) predominantly highlights the high outflux and influx from the restaurant areas during workday daytime, implying a considerable demand for dining out during midday hours. A part of the commercial vehicles flowed from the restaurant areas to the finance areas, implying that people would return to work after dining and confirming that most people chose to dine out during working hours. Additionally, the spatial fluctuations in areas with transportation facilities and educational institutions were also more notable, potentially due to people's daytime travel and daily commutes. As shown in Figure 10(b), during the morning peak on workdays, the commercial residential areas have the highest outflux and the restaurant areas have the highest influx, with trips dominated by dining and commuting. A larger portion of the commercial vehicles departing from the commercial residential areas went to the government and corporate organization areas, while the rest went to areas such as restaurant areas and living service areas. Figure 10(c) shows the workday evening peak travel pattern, the highest travel volume is for shopping, followed by outflux from government and corporate organization areas, and higher influx from the finance areas, government and corporate organization areas and living service areas.

Different from workdays, people usually choose to engage in recreational activities on weekends. Figure 11(a) shows that the increase in demand for commercial vehicle trips on weekends is caused by people's dining activities, shopping and recreational activities, and learning activities. The largest number of trips is accounted for by interactions within the restaurant areas during the daytime on weekends, and a portion of the commercial vehicles departing from restaurant areas flow to the shopping mall areas and the education areas. The outflux from the education areas are greatest during the weekend morning peak hours, with a rich variety of destinations (Figure 11(b)). The most internal interaction is mainly with the education areas, with the most significant spatial fluctuations, which indicates that going to the education areas is the main reason for the increased travel demand. The outflux from the government and corporate organization areas are the next largest, going to the education areas, the shopping mall areas, and the entertainment areas, respectively. As shown in Figure 11(c), commercial vehicles significantly flow from the shopping mall areas and restaurant areas to the transport facility areas and the accommodation areas, respectively. It suggesting that many out-of-town visitors head to the station or return to their hotels to rest after their recreational activities.

The morning peak pattern during New Year's Day has significant interactions of various functional areas and people's trips show diverse characteristics. In Figure 12(a), the functional area interaction of the daytime pattern on New Year's Day was similar to weekends, with the highest outflux and influx in the restaurant areas and the rest going to the shopping mall areas and the finance areas, respectively. The interaction between the shopping mall areas and the finance areas is also more obvious. In Figure 12(b), the interaction between the accommodation areas and the restaurant areas is the highest, with the largest spatial fluctuations and a significant increase in travel demand. This may be a result of visitors staying in hotels on holidays and dining out in the morning to start the day's activities. As shown in Figure 12(c), in the evening peak pattern, the government and corporate organization areas have the highest spatial

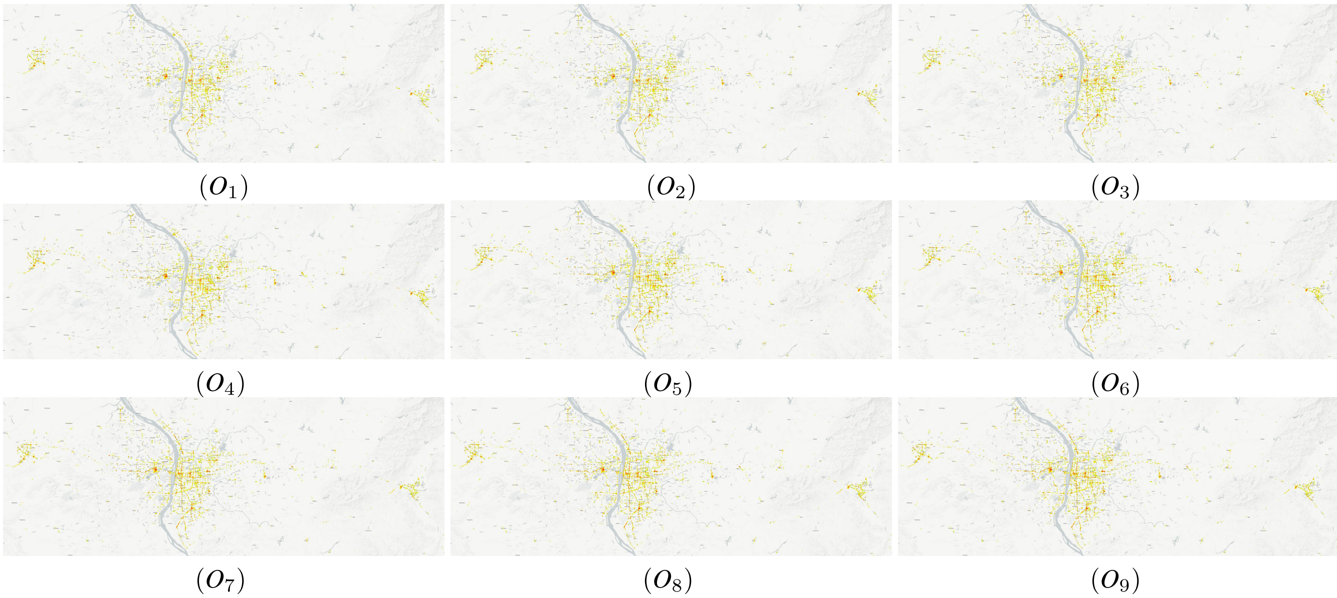


FIGURE 8. Spatial patterns of origins.

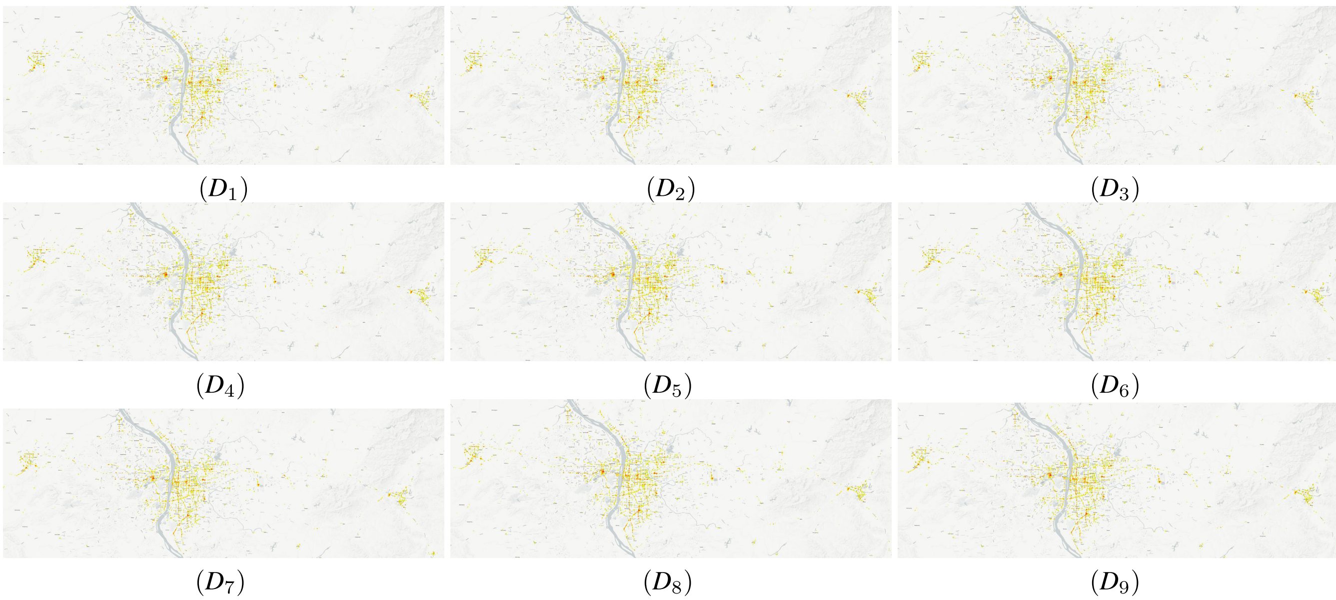
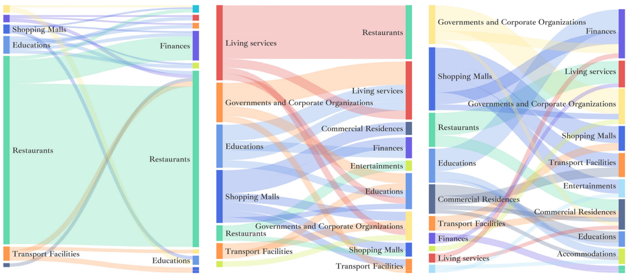


FIGURE 9. Spatial patterns of destinations.

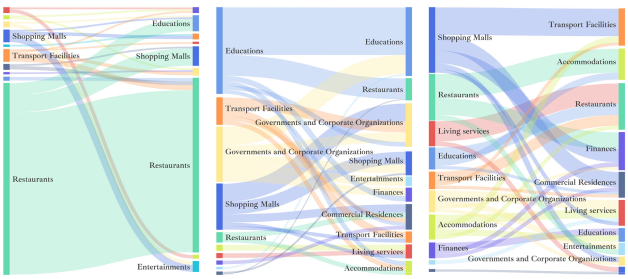
fluctuation, flowing to a variety of functional areas such as transport facility areas, accommodation areas, and living service areas.

In summary, the analysis of commercial vehicle movements during workdays, weekends, and holidays reveals distinct patterns in terms of dining, commuting, shopping, accommodation, and education activities. During the daytime on workdays, people's activities are dominated by dining and commuting. Therefore, restaurant areas, finance areas and government and corporate organisation areas have highly active. In the weekend patterns, the fluctuations in commercial vehicle movements associated with dining out and education are more prominent during the day and shopping and accommodation activities are significant in the evening. As for the holiday pattern, similar to the weekend, the areas of high spatial fluctuation in commercial vehicle movements are dining, shopping, and lodging, but the areas of holiday commercial vehicle activity are more complex. These findings could be crucial for urban planners and businesses, especially those in the restaurants and shopping malls, to better understand and cater behaviors during weekends and holidays. To accommodate the increased



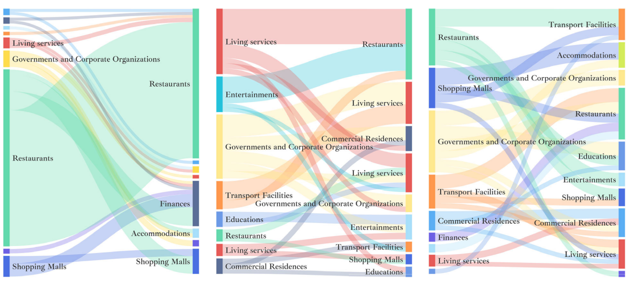
(a) Daytime (b) Morning peak (c) Evening peak

FIGURE 10. Different travel patterns on workday.



(a) Daytime (b) Morning peak (c) Evening peak

FIGURE 11. Different travel patterns on weekend.



(a) Daytime (b) Morning peak (c) Evening peak

FIGURE 12. Different travel patterns on holiday.

demand during these peak periods, urban planners should focus on optimizing the city's transportation system by providing convenient public transportation and sufficient parking facilities, facilitating easier access to shopping malls and entertainment areas.

B. SPATIAL INTERACTIONS AT DIFFERENT TIMES

We reveal the spatial interactions of functional areas by clustering OD travel flows, and the clustering algorithm is described in Section III-E. Then the OD travel flows with significant functional area changes were selected and classified by travel distance into short trips within 5 km, medium trips within 15 km and long trips over 15 km.

On workdays, the main purposes of commercial vehicle trips are dining, schooling and commuting. In terms of spatial distribution, development is higher in the south and east of the city, where vehicle activity is concentrated. In Figure 13(a), during the day, short-distance commercial vehicle trips form three distinct clusters in the city, one to the south and east of the main city and two others in the city centers of Liuyang and Ningxiang. The main purposes of the trips are dining out and commuting. Medium-distance commercial vehicle trips are concentrated in the main city of Changsha, spreading from the center to the edges. Active restaurant areas are found in the center of Changsha, education areas are distributed in the suburbs, and transport facility areas are concentrated in the north and south ends of the main urban area and on the edge of Ningxiang. Long-distance commercial vehicle trips effectively connect the east and west parts of Changsha. The transport facility along Ningxiang are more active than in Liuyang and more closely connected to Changsha. In the morning, Figure 13(b) shows that short-distance commercial vehicle trips are concentrated in the southern part of the city, with the southern Tianxin District being the core area of the Chang-Zhu-Tan Integration City. Trips in the south are mainly concentrated in the finance areas. Mid-distance travel maintains a similar spatial pattern to that of daytime hours, with weak connections to the cities of Ningxiang and Liuyang. The western part of the city becomes active in the government and corporate organization areas and commercial residential areas, making effective connections with the eastern of the city. Long-distance commercial vehicle trips are similar to daytime, but with less travel demand. In Figure 13(c), in the evening, short-distance commercial vehicle trips form a circular trip structure along the periphery of the main city, and travel demand gradually increases in the west. Commercial vehicles in the western part of the city are mainly concentrated in the vicinity of University City and Meixi Lake in Yuelu District, interacting between the restaurant areas, education areas and commercial residential area. Medium-distance vehicles tend to travel north-south, with east-west trips connected at the Yinpenling Bridge, Sanchaji Bridge, and Monkey Stone Bridge. Long-distance vehicle trips increase in the north, occurring mainly in government and corporate organization areas and commercial residential area.

On weekends, long-distance travel patterns are similar, with short- and medium-distance trips varying with time. In Figure 14(a), during the daytime, short-distance trips are largely distributed in the southern and eastern portions of the main urban area of Changsha, with small concentrations in the north and Liuyang. Trips in the south and west are concentrated between restaurant areas and transport facility areas, while trips in the north and Liuyang city center are dominated by shopping mall areas and transport facility areas, respectively. Mid-distance trips are similar to weekday mornings, but travel demand decreases in the restaurant areas and increases in the shopping mall areas. The two districts with large spatial fluctuations in the restaurant areas are Yuelu and Furong districts. Long-distance trips are dominated by the interaction of the Long Town Center with Ningxiang and

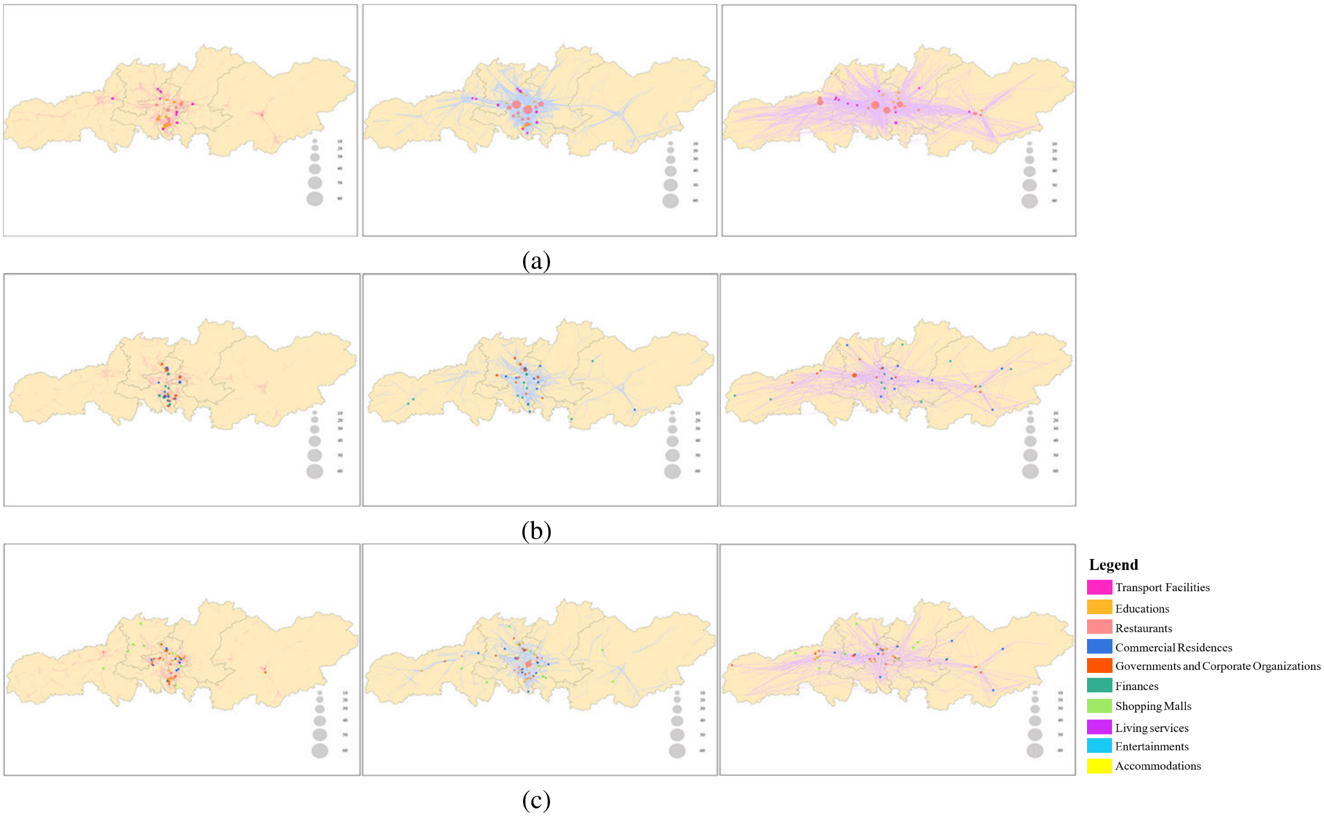


FIGURE 13. Spatial interactions between regions on workday: (a) daytime hour; (b) morning rush hour; (c) evening rush hour. The color of the nodes denotes the function.

Liuyang. As shown in Figure 14(b), short-distance trips are distributed in the south and north of Changsha, dominated by activities in the education areas and the government and corporate organization areas in the morning. Medium-distance trips in the education areas and government and corporate organization areas are still distributed in the north and south of Changsha, and trips in the shopping mall areas increase in the east and west. In the evening, short-distance trips are primarily basically distributed in Tianxin, Yuhua and Furong districts, with functional area interactions dominated by restaurant areas, living service areas and shopping mall areas(In Figure 14(c)). Medium-distance trips exhibit a travel pattern radiating from the Wuyi business district of Changsha to the surrounding area, and commercial vehicles mainly move between the living services area and shopping mall areas.

During on holidays, when the number of foreign tourists increases, the functional areas that are most frequently active are the accommodation areas and are located along the major stations of the city. In Figure 15(a), during the daytime, short trips are mainly distributed in the eastern part of the Xiangjiang River, as well as in the eastern and southern parts of the main city. The travel demand is mainly concentrated in shopping mall areas, restaurant areas and government and corporate organization areas. Medium-distance trips cover the north and south ends of the city and connect with Liuyang and Ningxiang. Fluctuations in the restaurant area are evident, mainly around the Wuyi shopping district, Changsha University City and Datuo. Long-distance commercial vehicle trips have similarities to weekend and workday travel patterns. On holiday mornings, Figure 15(b) shows short-distance trips form an arc-shaped structure in the eastern part of the main city, connecting Changsha Station-Changsha South Station-Dongjing Station, implying increased travel demand near these stations. In addition, travel demand near Changsha Huanghua Airport increases significantly. Commercial vehicle trips are concentrated between accommodation areas. Mid-distance trips spread from south to north and from east to west, showing three distinct sub-clusters. Trips to the south and east are concentrated between lodging areas, trips to the west are concentrated between entertainment areas, and trips to the north are dominated by government and corporate organization areas. In Figure 15(c), on holiday evenings, short-distance travel patterns are similar to those on weekends and are concentrated in the Yuelu, Tianxin and Furong districts, as well as in the northern part of the Kaifu district. Medium-distance trips are concentrated between the restaurant areas and the government and organization areas and are concentrated in the central part of the city. Long-distance trips connect the city east-west, but the functional area changes continue to be concentrated in the main part of the city.

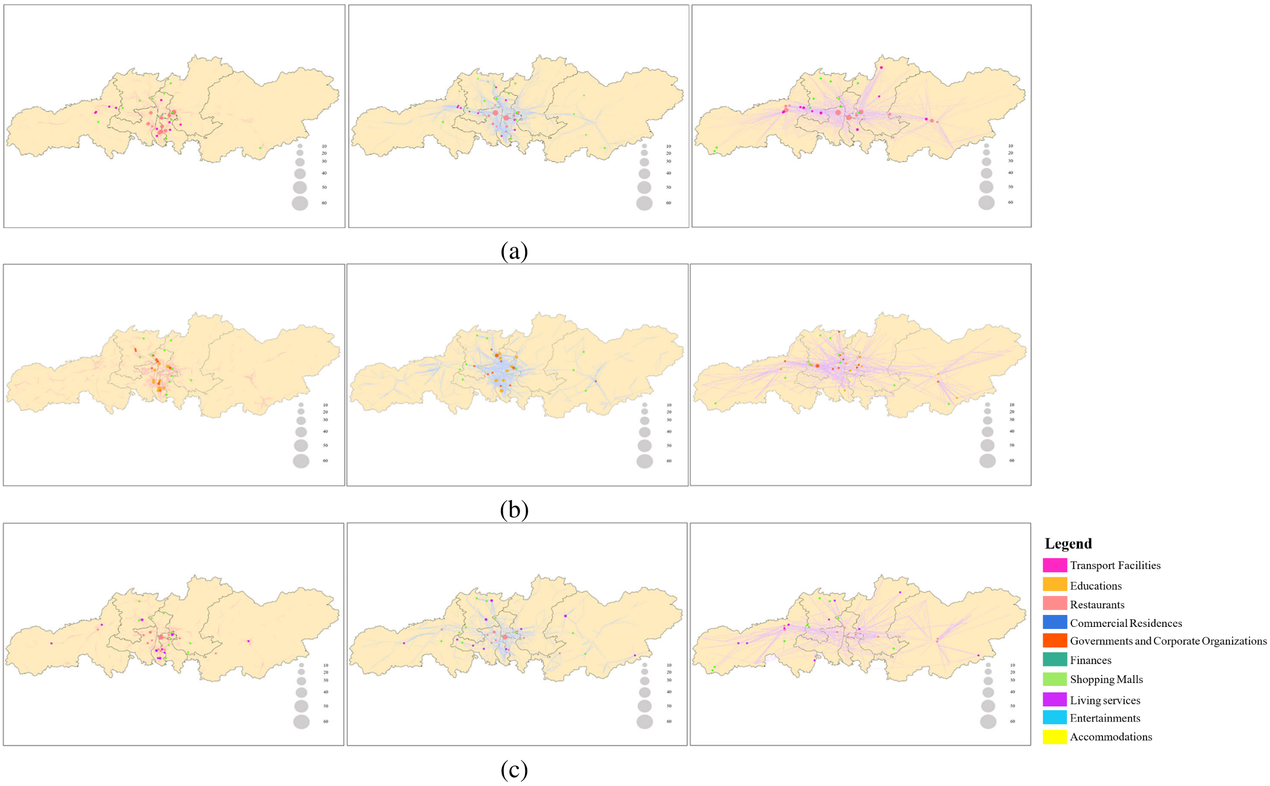


FIGURE 14. Spatial interactions between regions on weekend: (a) daytime hour; (b) morning rush hour; (c) evening rush hour. The color of the nodes denotes the function.

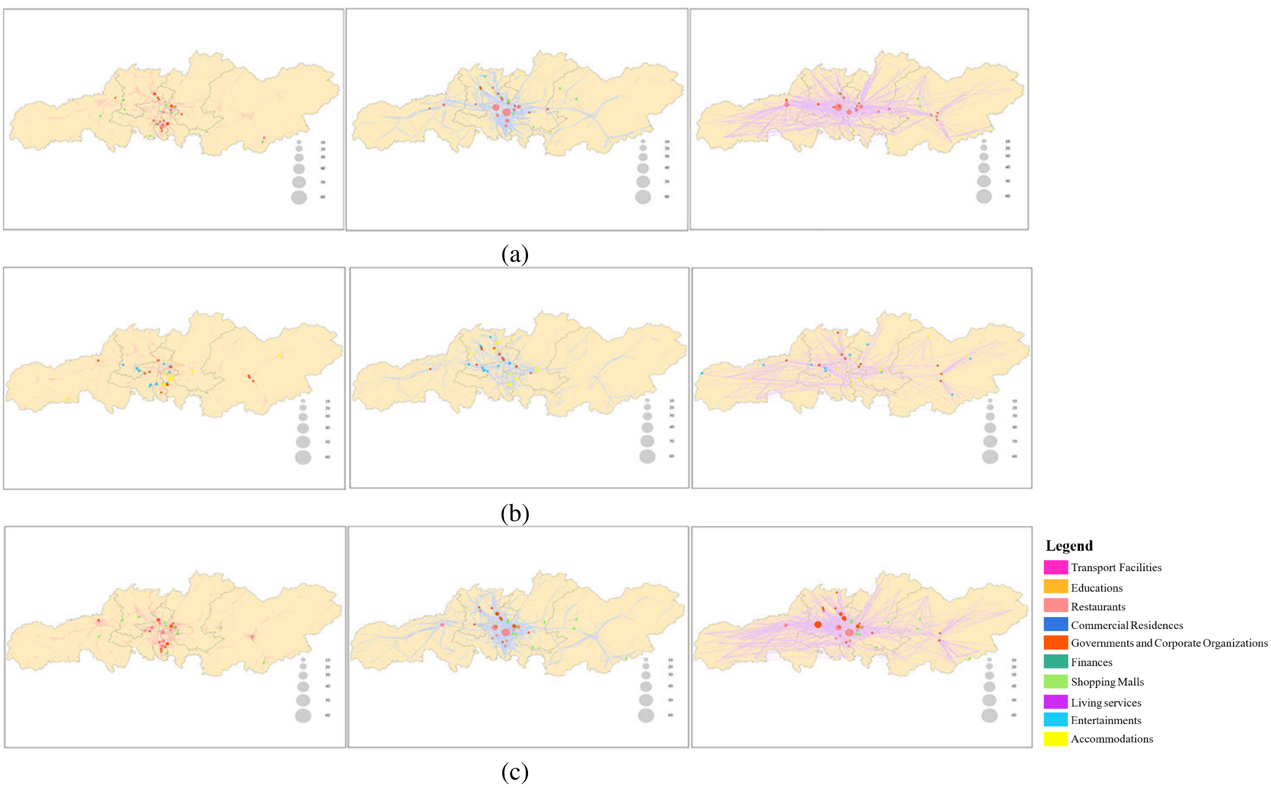


FIGURE 15. Spatial interactions between regions on holiday: (a) daytime hour; (b) morning rush hour; (c) evening rush hour. The color of the nodes denotes the function.

Overall, The three different distances of the workday pattern indicate that the spatial interaction in Changsha city is more clustered than in other regions, as well as, with the increase of the distance of the travel flow, there is more spatial interaction in the east-west direction. As for the weekend pattern, whatever the distance and time scale, all of them illustrate a significant feature of multicentricity. In addition, the travel flow increase in the shopping mall which is assembled with dining and shopping. The holiday pattern is roughly similar to the weekend pattern, but the spatial interaction is more frequent among these regions. Furthermore, the medium-distance and the long-distance are even more obvious in the east-west direction. Together these results provide important insights into people's travel behavior which is analyzed by the spatial interaction among the different functional areas. Understanding the purpose and mode of it helps us to better improve the operation system of commercial vehicles, provide better services to users, and then assist in the rational allocation of transportation resources.

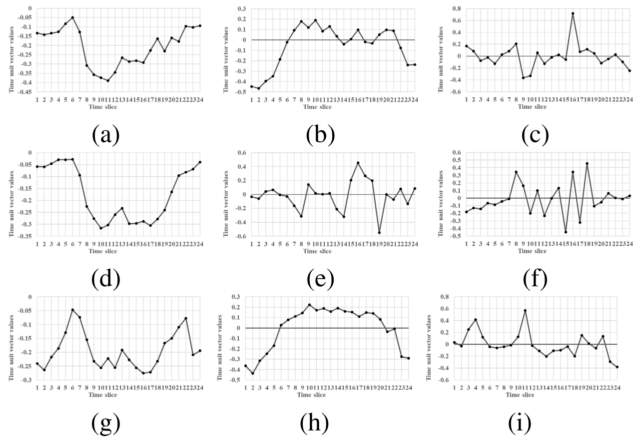


FIGURE 16. **The distribution of normalized singular values of buses:(a),(b) and (c) represent the travel patterns of workdays; (d),(e) and (f) represent the travel patterns of weekends; (g),(h) and (i) represent the travel patterns of holidays.**

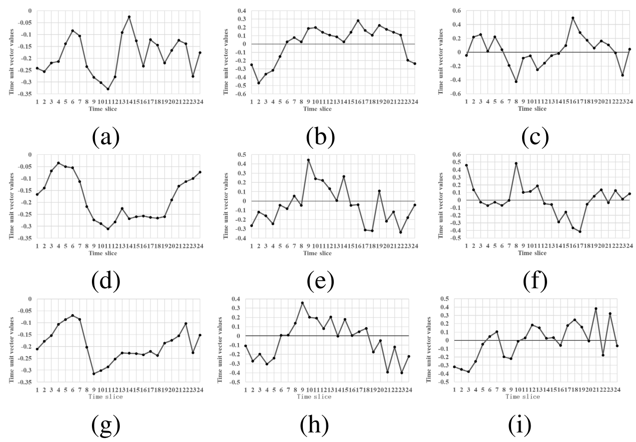


FIGURE 17. **The distribution of normalized singular values of trucks:(a),(b) and (c) represent the travel patterns of workdays; (d),(e) and (f) represent the travel patterns of weekends; (g),(h) and (i) represent the travel patterns of holidays.**

V. CONCLUSION

Human activity in cities has a pattern of change, and exploring travel patterns is useful for understanding the spatial interactions of cities. Human activities in cities also result in dynamic changes in urban land functions and spatial interactions. Therefore, it is necessary to take into account the changes in urban land functions and their interactions when studying spatial dynamics. Our study leveraged commercial vehicle trajectory and POI data to construct a spatio-temporal OD matrix, employing SVD to analyze urban travel patterns in Changsha City. The OD flows for each travel mode are clustered and analyzed to uncover the spatial and functional interactions among urban functional areas in Changsha City.

Regarding the analysis of travel modes, We discerned three primary traffic patterns: daytime, morning peak, and evening peak. Notably, the prolonged morning peak, persisting until 9:00 on weekdays and extending to 11:00 on weekends, indicates substantial traffic congestion in Changsha, underscoring the pressing need to optimize the urban transport network for efficient peak demand management. Our comparative analysis of trajectory data from taxis, buses, and trucks revealed distinct travel patterns. Buses show the highest demand on weekdays, from 7:00 to 18:00. Taxis supplement bus services, with demand peaking between 20:00 and 2:00, aligning with the commute of night workers and late-night individuals returning home. Conversely, truck demand fluctuates significantly, influenced more by time-of-day factors. Spatially, commercial vehicle activity in Changsha is concentrated in the central urban areas, such as the Wuyi, Meixi Lake, and Datuo Business Districts, major transit hubs, and educational institutions. This distribution suggests an east-west development disparity across the Xiangjiang River, with the eastern bank being more advanced. To promote balanced urban growth, we recommend developing the cultural tourism sector on the west bank, capitalizing on attractions like the Yuelu Mountain Scenic Area.

By examining spatial variations in travel patterns, we enhance the semantic understanding of OD flows for commercial vehicles, allowing for a deeper exploration of the interplay between spatial distribution and functionality. On workdays, commercial vehicle movements are primarily driven by dining, education, and commuting needs, with a notable increase in visits to shopping centers in the evenings. Restaurants are predominantly centralized in the urban core, while educational institutions are situated more on the periphery. During weekends, significant spatial shifts are observed in educational areas during the morning peak. Concurrently, there is heightened demand for travel to restaurants and shopping malls throughout the day and evening, with a noticeable expansion from east to west. On holidays, pronounced interactions are noted between accommodation and dining zones, especially in proximity to major transit hubs such as Changsha Railway Station, Changsha South Railway Station, and Huanghua Airport. This trend indicates a preference among tourists for lodging in areas with convenient citywide accessibility.

Our study's categorization of functional areas was based on POIs, revealing a data gap in Changsha's suburbs. Future research should incorporate additional data like road networks, population density, or remote sensing to classify these areas better. Furthermore, constructing the OD matrix with varied dimensions such as time, distance, or duration could provide more nuanced insights.

APPENDIX

See Figures 16 and 17.

REFERENCES

[1] Q. Wang, B. Guo, Y. Ouyang, L. Cheng, L. Wang, Z. Yu, and H. Liu, "Learning shared mobility-aware knowledge for multiple urban travel demands," *IEEE Internet Things J.*, vol. 9, no. 9, pp. 7025–7035, May 2022.

[2] R. Wang, X. Zhang, and N. Li, "Zooming into mobility to understand cities: A review of mobility-driven urban studies," *Cities*, vol. 130, Nov. 2022, Art. no. 103939.

[3] G. Bryan, E. Glaeser, and N. Tsivanidis, "Cities in the developing world," *Annu. Rev. Econ.*, vol. 12, no. 1, pp. 273–297, 2020.

[4] C. Li, W. Yue, G. Mao, and Z. Xu, "Congestion propagation based bottleneck identification in urban road networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 5, pp. 4827–4841, May 2020.

[5] T. Shen, Y. Hong, M. M. Thompson, J. Liu, X. Huo, and L. Wu, "How does parking availability interplay with the land use and affect traffic congestion in urban areas? The case study of Xi'an, China," *Sustain. Cities Soc.*, vol. 57, Jun. 2020, Art. no. 102126.

[6] U. Ammara, K. Rasheed, A. Mansoor, A. Al-Fuqaha, and J. Qadir, "Smart cities from the perspective of systems," *Systems*, vol. 10, no. 3, p. 77, Jun. 2022.

[7] D.-G. Wang, Y. Niu, and J. Qian, "Evolution and optimization of China's urban tourism spatial structure: A high speed rail perspective," *Tourism Manage.*, vol. 64, pp. 218–232, Feb. 2018.

[8] X. Liu, L. Gong, Y. Gong, and Y. Liu, "Revealing travel patterns and city structure with taxi trip data," *J. Transp. Geography*, vol. 43, pp. 78–90, Feb. 2015.

[9] L. Zhang, J. Zhang, Z.-Y. Duan, and D. Bryde, "Sustainable bike-sharing systems: Characteristics and commonalities across cases in urban China," *J. Cleaner Prod.*, vol. 97, pp. 124–133, Jun. 2015.

[10] I. Paulino, S. Lozano, and L. Prats, "Identifying tourism destinations from tourists' travel patterns," *J. Destination Marketing Manage.*, vol. 19, Mar. 2021, Art. no. 100508.

[11] D. Baek, S. Kim, S.-W. Seo, and S.-H. Lee, "Results and lessons learned from autonomous driving transportation services in airfield, crowded indoor, and urban environments," 2024, *arXiv:2403.01233*.

[12] V. Sadrani and G. V. V. J. Rao, "Design of an efficient mathematical optimization engine for solving autonomous driving performance for urban traffic conditions," in *Proc. 10th IEEE Uttar Pradesh Sect. Int. Conf. Electr., Electron. Comput. Eng. (UPCON)*, Dec. 2023, pp. 950–958.

[13] L. Chen, P. Wu, K. Chitta, B. Jaeger, A. Geiger, and H. Li, "End-to-end autonomous driving: Challenges and frontiers," 2023, *arXiv:2306.16927*.

[14] L. Anzalone, P. Barra, S. Barra, A. Castiglione, and M. Nappi, "An end-to-end curriculum learning approach for autonomous driving scenarios," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 10, pp. 19817–19826, Oct. 2022.

[15] S. Zhang, X. Liu, J. Tang, S. Cheng, and Y. Wang, "Urban spatial structure and travel patterns: Analysis of workday and holiday travel using inhomogeneous Poisson point process models," *Comput., Environ. Urban Syst.*, vol. 73, pp. 68–84, Jan. 2019.

[16] Z. Zhong, E. E. Lee, M. Nejad, and J. Lee, "Influence of CAV clustering strategies on mixed traffic flow characteristics: An analysis of vehicle trajectory data," *Transp. Res. C, Emerg. Technol.*, vol. 115, Jun. 2020, Art. no. 102611.

[17] Y. Deng, J. Wang, C. Gao, X. Li, Z. Wang, and X. Li, "Assessing temporal–spatial characteristics of urban travel behaviors from multiday smart-card data," *Phys. A, Stat. Mech. Appl.*, vol. 576, Aug. 2021, Art. no. 126058.

[18] H. Wang, H. Huang, X. Ni, and W. Zeng, "Revealing spatial-temporal characteristics and patterns of urban travel: A large-scale analysis and visualization study with taxi GPS data," *ISPRS Int. J. Geo-Information*, vol. 8, no. 6, p. 257, May 2019.

[19] C. H. V. Cooper, "Using spatial network analysis to model pedal cycle flows, risk and mode choice," *J. Transp. Geography*, vol. 58, pp. 157–165, Jan. 2017.

[20] M. Fekih, T. Bellemans, Z. Smoreda, P. Bonnel, A. Furno, and S. Galland, "A data-driven approach for origin–destination matrix construction from cellular network signalling data: A case study of Lyon region (France)," *Transportation*, vol. 48, no. 4, pp. 1671–1702, Aug. 2021.

[21] M. Shengdong, X. Zhengxian, and T. Yixiang, "Intelligent traffic control system based on cloud computing and big data mining," *IEEE Trans. Ind. Informat.*, vol. 15, no. 12, pp. 6583–6592, Dec. 2019.

[22] D. Sun, C. Zhang, L. Zhang, F. Chen, and Z.-R. Peng, "Urban travel behavior analyses and route prediction based on floating car data," *Transp. Lett.*, vol. 6, no. 3, pp. 118–125, Jul. 2014.

[23] D. J. Sun, Y. Zheng, and R. Duan, "Energy consumption simulation and economic benefit analysis for urban electric commercial-vehicles," *Transp. Res. D, Transp. Environ.*, vol. 101, Dec. 2021, Art. no. 103083.

[24] P. Gordon and Q. Pan, "Assembling and processing freight shipment data: Developing a GIS-based origin-destination matrix for Southern California freight flows," METRANS Transp. Center (California), Los Angeles, CA, USA, Tech. Rep. REPT-99-25-2000-6, 2001.

[25] K. W. Axhausen, M. Löchl, R. Schlich, T. Buhl, and P. Widmer, "Fatigue in long-duration travel diaries," *Transportation*, vol. 34, no. 2, pp. 143–160, Jan. 2007.

[26] M. Lippi, M. Bertini, and P. Frasconi, "Short-term traffic flow forecasting: An experimental comparison of time-series analysis and supervised learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 2, pp. 871–882, Jun. 2013.

[27] Z. Wang, W. Nie, and T. Lin, "Analysis of the spatio-temporal characteristics of intercity travel based on SVD and complex network: Take Bohai rim city group as an example," in *Proc. Int. Conf. Intell. Traffic Syst. Smart City (ITSSC)*, Mar. 2022, pp. 357–365.

[28] W. Rao, Y.-J. Wu, J. Xia, J. Ou, and R. Kluger, "Origin-destination pattern estimation based on trajectory reconstruction using automatic license plate recognition data," *Transp. Res. C, Emerg. Technol.*, vol. 95, pp. 29–46, Oct. 2018.

[29] H. Chen, C. Yang, and X. Xu, "Clustering vehicle temporal and spatial travel behavior using license plate recognition data," *J. Adv. Transp.*, vol. 2017, pp. 1–14, 2017.

[30] J. Xu, J. Liu, Y. Xu, Y. Lv, T. Pei, Y. Du, and C. Zhou, "Identification of spatial and functional interactions in Beijing based on trajectory data," *Appl. Geography*, vol. 145, Aug. 2022, Art. no. 102744.

[31] T. Djukic, G. Flötteröd, H. van Lint, and S. Hoogendoorn, "Efficient real time OD matrix estimation based on principal component analysis," in *Proc. 15th Int. IEEE Conf. Intell. Transp. Syst.*, Sep. 2012, pp. 115–121.

[32] Y. Zhi, H. Li, D. Wang, M. Deng, S. Wang, J. Gao, Z. Duan, and Y. Liu, "Latent spatio-temporal activity structures: A new approach to inferring intra-urban functional regions via social media check-in data," *Geo-Spatial Inf. Sci.*, vol. 19, no. 2, pp. 94–105, Apr. 2016.

[33] Y. Yin, Q. Wu, and M. Li, "Characterizing intercity mobility patterns for the greater bay area in China," *ISPRS Int. J. Geo-Information*, vol. 12, no. 1, p. 5, Dec. 2022.

[34] M. Cao, B. Cai, S. Ma, G. Lü, and M. Chen, "Analysis of the cycling flow between origin and destination for dockless shared bicycles based on singular value decomposition," *ISPRS Int. J. Geo-Information*, vol. 8, no. 12, p. 573, Dec. 2019.

[35] M. Chan, W. Yang, P. Yan, and H. Shi, "Two-dimensional spatial data fusion method based on SVD decomposition," *Prog. Geophys.*, vol. 35, no. 3, pp. 940–949, 2020.

[36] R. Kulkarni, P. Pal, and E. Banoth, "Spatio-temporal analysis of dynamic speckle patterns using singular value decomposition," *Opt. Lasers Eng.*, vol. 142, Jul. 2021, Art. no. 106588.

[37] T. Anwar, V. Uma, and G. Srivastava, "Rec-CFSVD++: Implementing recommendation system using collaborative filtering and singular value decomposition (SVD)++," *Int. J. Inf. Technol. Decis. Making*, vol. 20, no. 04, pp. 1075–1093, Jul. 2021.

[38] N. Hashemipour, J. Aghaei, A. Kavousi-fard, T. Niknam, L. Salimi, P. Crespo del Granado, M. Shafie-Khah, F. Wang, and J. P. S. Catalão, "Optimal singular value decomposition based big data compression approach in smart grids," *IEEE Trans. Ind. Appl.*, vol. 57, no. 4, pp. 3296–3305, Jul. 2021.
[39] C. Yang, F. F. Yan, and X. D. Xu, "Clustering daily metro origin-destination matrix in Shenzhen China," *Appl. Mech. Mater.*, vol. 743, pp. 422–432, Mar. 2015.
[40] X. He, Y. Cao, and C. Zhou, "Evaluation of polycentric spatial structure in the urban agglomeration of the pearl river delta (PRD) based on multi-source big data fusion," *Remote Sens.*, vol. 13, no. 18, p. 3639, Sep. 2021.
[41] R. Guidotti, A. Monreale, S. Rinzivillo, D. Pedreschi, and F. Giannotti, "Retrieving points of interest from human systematic movements," in *Software Engineering and Formal Methods: SEFM 2014 CollocatedWorkshops: HOFM, SAFOME, OpenCert, MoKMaSD, WS-FMDS*. Grenoble, France: Springer, 2014, pp. 294–308.
[42] S. Dutta, A. Das, and B. K. Patra, "CLUSTMOSA: Clustering for GPS trajectory data based on multi-objective simulated annealing to develop mobility application," *Appl. Soft Comput.*, vol. 130, Nov. 2022, Art. no. 109655.
[43] Z. Kan, M.-P. Kwan, D. Liu, L. Tang, Y. Chen, and M. Fang, "Assessing individual activity-related exposures to traffic congestion using GPS trajectory data," *J. Transp. Geography*, vol. 98, Jan. 2022, Art. no. 103240.
[44] T. Wu, H. Shen, J. Qin, and L. Xiang, "Extracting stops from spatio-temporal trajectories within dynamic contextual features," *Sustainability*, vol. 13, no. 2, p. 690, Jan. 2021.
[45] S. Luo, Y. Liu, M. Du, S. Gao, P. Wang, and X. Liu, "The influence of spatial grid division on the layout analysis of urban functional areas," *ISPRS Int. J. Geo-Information*, vol. 10, no. 3, p. 189, Mar. 2021.

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