Wiley
Journal of Advanced Transportation
Volume 2024, Article ID 1404168, 18 pages
https://doi.org/10.1155/2024/1404168

WILEY

Research Article

The Association between Rainfall and Taxi Travel Activities: A Case Study from Wuhan, China

Rong Chen,[1] **Lingjia Liu**,[1] **and Yongping Gao**[2]

[1]*School of Geography and Environment, Jiangxi Normal University, Nanchang 330022, China*
[2]*School of Geography, Nanjing Normal University, Nanjing 210023, China*

Correspondence should be addressed to Lingjia Liu; liulingjia_office@jxnu.edu.cn

Received 25 October 2023; Revised 13 March 2024; Accepted 28 March 2024; Published 23 May 2024

Academic Editor: Chung-Cheng Lu

Rainfall has a significant impact on urban population mobility, posing great challenges to traffic management and urban planning. An understanding of this influence from multiple perspectives is urgently needed. In this study, we devised a multiscale comparative research framework to explore the spatiotemporal effects of rainfall on taxi travel patterns, aiming to provide a new perspective on the investigation of rainfall's impact on urban human mobility. More specifically, at the macroscopic scale, we computed taxi travel indicators across the entire study area and used kernel density estimates to observe the spatiotemporal distribution patterns influenced by rainfall. Subsequently, complex traffic networks were constructed by considering urban road intersections as nodes and combined with visualization methods to understand changes in taxi travel patterns visually at the microscopic level. We selected Wuhan City, a typical urban area in southern China with frequent rainfall, as the study area and used meteorological data along with a large volume of taxi spatiotemporal trajectory data for investigation. Results indicated a 4.16% decrease in weekly travel volume due to rainfall, with a 3.96% decrease on workdays and a 4.64% decrease on weekends. However, nighttime rainfall between 19:00 and 22:00 on weekdays increased the demand for taxi travel. Furthermore, the impact of rainfall on weekends exceeded that on workdays, restricting people's mobility and leisure activities, resulting in reduced travel to recreational tourist spots and commercial pedestrian streets. Rainfall altered residents' travel preferences to some extent, with more residents choosing taxis during rainy weather, which led to decreased transportation efficiency and increased traffic congestion. These findings contribute to a deeper understanding of the complex relationship between population mobility patterns and the urban ecological environment, providing valuable insights for planning resident travel and taxi dispatching under adverse weather conditions.

1. Introduction

The city embodies a complex system where humans navigate, interact with urban infrastructure, and generate a myriad of flows that reflect their trajectories [1]. Understanding the nature of these flows offers invaluable perspectives and insights for addressing socioeconomic issues such as urban planning, transportation forecasting, and epidemic prevention and control [2–6]. Traditional methods for analysing population mobility often rely on costly, subjective, and spatially limited questionnaire surveys [7–9]. In recent years, the development and widespread adoption of location services and communication technologies have presented new opportunities for the timely collection and analysis of large-scale mobility data [8, 10]. Technologies like smart cards, shared bicycles, mobile phone signals, social media check-ins, and taxi trajectories contribute substantial urban population mobility big data, offering rich location and activity information at the individual level [1, 11–13]. In comparison to traditional approaches, big data are more accurate, objective, comprehensive, cost-effective, and easily accessible [14, 15]. It has emerged as the primary dataset for trajectory data research and applications, providing abundant information for studying dynamic urban changes [6].

Taxis, serving as a door-to-door, round-the-clock mode of transportation, fulfil the dense and recurrent daily travel needs within cities, playing a crucial role in urban public transportation systems [16]. According to statistical data from 2022, taxi passenger volume in China reached approximately 20.82 billion trips, constituting 27.6% of the total urban passenger transportation and ranking as one of the primary choices for residents' travel [17]. Presently, taxis are equipped with GPS recording devices that promptly collect more precise spatiotemporal information, including passenger boarding and alighting locations, during journeys [11]. Differing from buses and rail transit, taxis operate without constraints of routes and schedules, offering the most flexible and extensive trajectory data based on passenger preferences [18, 19]. Taxi trajectory data exhibit higher accuracy and involves fewer privacy concerns compared to other modes of transportation. This characteristic aligns taxi trajectory data more closely with the genuine intentions of passenger travel, allowing it to authentically portray the spatiotemporal characteristics of residents' mobility and the travel patterns of taxis.

Weather conditions, as an integral part of the urban ecosystem, exert a significant influence on the daily travel patterns of residents and population movements [20–24]. Therefore, comprehending how adverse weather affects human travel patterns contributes to enhancing public transportation services and better meeting passengers' travel needs under diverse weather conditions. Various meteorological factors have been well researched in the transportation domain, including rainfall [25, 26], snowfall [22], temperature [27], and wind [28], either individually or in combinations [29–31]. Existing studies primarily employ exploratory and descriptive methods, such as statistical charts, graphs, and summaries, to analyse and describe data characteristics under different weather conditions [32]. For instance, Liu et al. quantified the impact of weather on ride-hailing taxi passenger volume, finding that a 1 mm increase in precipitation led to a 0.39% rise in traffic volume, while a 1 m/s increase in wind speed resulted in a 1.04% decrease in traffic volume [22]. Autoregressive Distributed Lag models, built on statistically summarized data, are used for quantitative analysis of the sustained effects of snowfall on taxi operations [33]. While these methods provide overall statistical characteristics of the dataset, aiding in uncovering spatiotemporal distribution patterns of taxi activities and population mobility under weather influences [34], simple quantitative analyses of travel features and large-scale fuzzy analyses fall short in addressing the current complexity of human mobility dynamics. A comparative analysis of taxi travel activities and population mobility spatiotemporal distribution characteristics under different weather conditions, especially through a multiscale and multidimensional approach, is lacking.

Therefore, we utilized taxi trajectory data to construct a complex geographic spatial network at the street level. Graphs and network characteristics extracted from the trajectory data were investigated for their structural properties and the interactions between these properties using graph theory and complex network-related methods. Spatial statistical analysis methods were combined to analyse taxi travel metrics, establishing a multiscale, multidimensional analytical framework. This framework was applied to investigate the impact of rainfall on taxi travel activities and population mobility patterns, providing a bottom-up perspective for studying population mobility patterns under the influence of rainfall. Subsequently, we applied our comparative research framework to the rain-prone city of Wuhan, collecting taxi trajectory data and meteorological data within the study area. The taxi data were categorized into four scenarios: weekdays with clear weather, weekdays with rain, weekends with clear weather, and weekends with rain. We aimed to explore the feasibility of using taxi trajectory data to investigate the impact of rainfall on population mobility. To scrutinize and dissect the spatial disparities of fundamental taxi travel metrics on a macroscopic level, and subsequently, to assemble a comprehensive traffic network on a microscopic scale, a meticulous examination and comparative analysis of the alterations in network configuration induced by rainfall which is achieved through a fusion of network attribute metrics and visualization techniques, is involved.

2. Literature Review

2.1. Application of Taxi Trajectory Data. In recent years, the widespread development of location services and communication technologies has made the collection and study of taxi trajectory data possible. Many studies use this information to identify traffic congestion [35, 36] and estimate traffic flows [37], which helps to understand urban mobility patterns from a social perception perspective, improve traffic, and assist managers in taking emergency measures [38]. Furthermore, the unique advantages of taxi trajectory data in studying urban population travel patterns and population mobility have garnered significant attention. Researchers explore crowd movement patterns [39] and employ mathematical and statistical methods to focus on collective mobility patterns at the urban scale by mining traffic hotspots and tracking traffic trajectories between key areas [35]. It is noteworthy that the application of taxi trajectory data extends beyond the realm of intelligent transportation, gradually seeking comprehensive integration with other professional fields, such as extracting urban functional structures [38, 40, 41]. For instance, Hu et al. established a geographical semantic analysis framework to extract traffic interaction information from taxi data, delineating urban functional zones at the road level [40]. They analysed the respective strengths and interactions between taxis and other modes of transportation. Combining Point of Interest (POI) data and road network data, taxi trajectory data have been used to investigate taxi demand travel patterns and associated influencing factors using grid partitioning and geographic weighted regression models [11].

Spatial statistical methods provide an intuitive means for researchers to comprehend the overall distribution characteristics of datasets, commonly employed in the analysis of taxi trajectory data [42, 43]. Exploratory and descriptive techniques, such as statistical charts, graphs, and summaries, are utilized to analyse and depict data features. Additionally, point clustering analysis on taxi origin and destination locations aids in identifying popular areas, enabling the recommendation of optimal passenger origin points to taxi drivers [44]. Chen et al. proposed a two-stage clustering algorithm to identify candidate areas in urban space, integrating taxi trajectory data to estimate taxi travel routes and destinations [21]. Various regression models are employed in studies predicting the fitting of taxi trajectories to passenger mobility [45, 46]. By fitting the distribution of passenger boarding points, these models forecast spatiotemporal changes and waiting times for passengers in hotspot areas [47]. When facing unknown overall data characteristics in taxi trajectory data, spatial statistical methods effectively capture the dataset's overall statistical features, revealing spatiotemporal distribution patterns of taxi activities and population mobility [34]. In addition, Zhang employed machine learning methods, training graph convolutional networks on road network information and taxi trajectory data [48]. This approach extracted spatiotemporal features of roads and accurately predicted taxi flow at city intersections using the TaxiInt prediction model. Nonnegative matrix factorization methods were used to study the spatial supply patterns of taxis in Wuhan, reflecting the impact of taxis' self-organized operational behaviour on urban residents' travel characteristics [33]. Liu et al. introduced community detection methods, utilizing collective travel data extracted from taxi GPS trajectory data to explore urban travel patterns and city structure [49]. It is evident that taxi trajectory data, through diverse methodologies, significantly contributes to the study of population mobility patterns, providing robust support for urban transportation.

2.2. Impact of Weather on Transportation Systems. As a crucial component of environmental factors, weather significantly influences transportation activities and urban population mobility [50]. In comparison to localized events such as road construction and traffic accidents that affect travel, weather variations have a broader impact on the entire urban transportation network, compelling individuals to change their travel plans or even cancel them [20, 51]. Given the intricate and variable nature of weather factors, current research predominantly focuses on the impact of various weather elements on taxi travel activities and crowd mobility patterns [52]. For instance, Li et al. investigated the lag effects of snowfall on taxi operations using GPS data, revealing substantial delayed effects induced by snowfall [22]. Caceres et al. developed an effective probability model utilizing ETC toll data to estimate the distribution of travel times on highways under different weather conditions [53]. Disastrous weather events like typhoons and storm surges bring destructive impacts to transportation [22, 54–56]. Additionally, rainfall exerts a more pronounced effect on residents' daily travel patterns [23, 57], causing delays during normal travel times and influencing drivers' moods, resulting in changes to the spatiotemporal distribution of traffic demand [58–60]. Smith's observations of traffic sequencing on the Hampton Highway found that light rain led to a 4%–10% reduction in highway capacity, while this figure is 25%~30% in heavy rain [59]. Lam incorporated rainfall intensity as a parameter into generalized speed-flow and speed-density models to analyse its impact on the flow-speed-density relationship on urban roads in Hong Kong [60]. Sun quantitatively studied the effects of rainfall on taxi calling and operations in Shanghai using taxi GPS data [24]. They attempted to identify the two most significant factors influencing these effects through a multiple regression model: passenger numbers and taxi availability. Most studies have examined the influence of weather factors on various transportation modes concerning travel frequency, travel methods, travel speed, and travel time [42, 43]. However, there is a deficiency in research on the spatiotemporal distribution characteristics of taxi travel activities under different weather conditions from a multiscale, multidimensional perspective.

2.3. Research on Complex Networks. A substantial volume of traffic flow enables researchers to simulate entire cities within a spatially embedded transportation network, offering a bottom-up and objective perspective for studying population mobility patterns [61]. By integrating mathematical statistical analysis [62] with spatial visualization of network attribute characteristics [63], geospatial complex networks provide a more intuitive understanding of subtle variations in traffic flow. For instance, Xin et al. studied the impact of the COVID-19 pandemic on the bike-sharing system and population mobility in New York City at different scales based on geospatial network analysis [1]. Yang et al. utilized geographic spatial complex networks to study the changes in shared bicycle systems resulting from the operation of a new subway line in Nanchang [6]. In the aviation sector, Dai et al. examined the evolving structure of the complex air transportation network in Southeast Asia from 1972 to 2012, considering both topological and spatial changes [64]. Geospatial complex networks have also been applied to maritime transport, shedding new light on the factors affecting port and shipping development [65].

Supported by taxi GPS trajectory data, complex networks can conduct in-depth analyses of taxi transportation processes and activity networks at a more refined spatiotemporal scale. Some studies have recognized the value of exploring the complex characteristics of networks formed by taxi activities using GPS trajectory data [33, 66, 67]. Fu et al. constructed a type of urban travel complex network based on taxi operational GPS trajectory data. They employed directed weighted complex network metrics to analyse the complexity of the taxi travel trajectory network structure and spatial analytical features [66]. Kang et al. systematically studied the spatial supply patterns of taxis using complex networks and nonnegative matrix factorization methods [33]. Peng et al. utilized taxi data and traffic nodes to build a complex transportation network, analysing the impact of rainfall on urban population movement under different modes [67]. However, previous research has exhibited arbitrary spatial unit division, posing challenges in defining nodes and edges due to significant differences in unit scales. Additionally, the nonuniform distribution of taxi trajectory data across urban areas may lead to insufficient understanding of characteristics and connectivity in certain regions during network analysis.

3. Study Area and Data

3.1. Study Area. The analysis for this study utilized taxi track data for June and July 2014 from Wuhan City, which is the most populous in Central China and is affected by frequent rainfall. There are thirteen administrative regions in Wuhan City, including Jiang'an, Jianghan, Qiaokou, Hanyang, Wuchang, Qingshan, Hongshan, Dongxihu, Hannan, Caidian, Jiangxia, Huangpi, and Xinzhou. Since the majority of taxi trajectory data is concentrated within the Third Ring Road area of Wuhan City, we selected this region as our study area, which also serves as the city centre. Figure 1 shows the study area. As of 2014, the city of Wuhan, where the sharing economy and online taxis were not yet widespread, relied mainly on buses, taxis, and rail transport to move people, with 16,597 taxis operating in the city at the time.

3.2. Data Description. Three datasets were used in this study: the taxi GPS trajectory dataset, the road network dataset, and the daily rainfall dataset; all datasets were selected from Wuhan City for June and July 2014. Every few seconds, 16,597 taxis uploaded a status data entry to the database through their GPS devices. Each data entry consists of 12 fields, including taxi ID, time, longitude, latitude, operational status, instantaneous speed, and direction. The road network dataset, obtained from the official website of OpenStreetMap (OSM), provided the required transport network and road intersection data to align with our trajectory data on the map. The daily rainfall dataset was acquired by the Wuhan City Meteorological Bureau and effectively reflects the city's rainfall conditions. Following the classification of daily rainfall by the China Meteorological Administration, rainfall below 10 millimetres was defined as light rain, which has minimal impact on traffic and human activities [68]. Therefore, for this study, we prioritized selecting rainfall data ranging from moderate rain to heavy rain. To facilitate comparative analysis under similar conditions, we selected two complete weeks of data from the available dataset—one with clear weather and the other with rainy weather. The selected dates may not be consecutive but must include a full workweek and weekend. The chosen dates are presented in Table 1.

3.3. Data Preprocessing and Matching. The richness of trajectory data does not eliminate the scarcity of activity information. The original dataset contains personal behavioural data of taxi drivers, but only a small portion of it is useful for our study [19]. Therefore, a simple and effective data preprocessing step is necessary to ensure the accuracy of research results. First, the 12 fields of each status data entry will be reduced to five fields for efficient data processing. These five fields include vehicle ID, latitude, longitude, UTC, and taxi operating status. The vehicle ID, latitude, and longitude determine the vehicle information and real-time location, while UTC records the duration of the trip. The operating status is used to differentiate between the driving and passenger-carrying states of the vehicle. All these elements are crucial for identifying each trip route. Based on this, the taxi trajectory data are extracted. We arrange all vehicle IDs for the same day in chronological order, and based on the sorted taxi operating status data, we extract the vehicle's travel trajectory and origin/destination points. Identification of origin/destination points relies on the continuous changes in different states. When the operating status changes from 0 to a continuous 1, it is recorded as the origin point (O point), and when the continuous status changes from 1 to 0, it represents the destination point (D point) of the trip. Travel time is the time difference between the O point and the D point, while the travel distance is the cumulative distance from the O point to each waypoint and the D point. These steps are repeated until all taxi travel trajectories are extracted, and the number of passengers carried by the vehicles on that day is recorded. Finally, to maintain data quality and ensure result accuracy, it is necessary to clean erroneous travel trajectory data, excluding data loss or redundancy caused by GPS device malfunctions, building obstructions, and similar situations during taxi journeys. Three types of data should be cleaned: (1) travel time less than 2 minutes; (2) average speed exceeding 120 km per hour; and (3) travel distance outside the range of 1 to 100 kilometres. After data preprocessing, approximately 30,000 trajectory data entries are obtained on average per day for the study. Each trajectory data entry represents a complete trip, containing information such as the taxi's origin/destination locations, travel time, and travel distance.

The accuracy error of GPS devices can lead to taxi trajectory points deviating from the urban road network, impacting data quality, and this type of error cannot be eliminated through data preprocessing. The purpose of map matching is to accurately align taxi trajectory points with the urban road network. Currently, map matching algorithms involve two crucial processes: finding target features and projecting target points onto these features. Commonly used matching algorithms include projection algorithms, geometry-based algorithms, probability statistical algorithms, and fuzzy logic algorithms. The "point-to-line shortest path" method employed in this paper belongs to the category of geometry-based algorithms, specifically point-to-line matching. The principle involves calculating the projection distance of GPS location points onto all candidate routes, comparing it with the actual distance of the matching road segment, and selecting the candidate route with the shortest distance as the target route. The mathematical point-to-line model is illustrated in Figure 2.

In practical implementation, to reduce data processing, we designate the O point of travel trajectories as the reference dataset for map matching, with the following specific steps: (1) set a 500-meter maximum buffer distance as the minimum projection distance to eliminate some mismatched points; (2) vertically project trajectory points onto all target road segments within the defined range; and (3) match the target road segment with the smallest projection distance and record the position information of the projected point on the target road segment. Finally, the position of the projected point is obtained as the matching point corresponding to the trajectory point.

FIGURE 1: Overview of the study area. (a) Location of the study area in Wuhan City. (b) Study area.

TABLE 1: Selection of weather data.

Weather	Mon	Tues	Wed	Thurs	Fri	Sat	Sun
Rainy day	June 30th	July 1st	July 16th	June 26th	July 18th	July 12th	June 1st
Clear day	July 14th	July 15th	July 23rd	June 12th	July 25th	July 26th	June 22nd

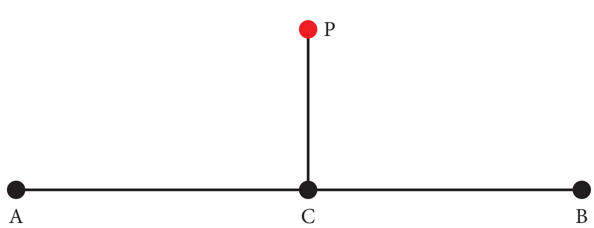


FIGURE 2: Point-to-line matching.

4. Methods

4.1. Comparative Analysis Framework. Our comparative analysis framework consists of three general steps, as depicted in Figure 3. Firstly, we conduct data processing on taxi GPS trajectory data, OSM road network data, and meteorological rainfall data. This involves tasks such as field simplification, extraction of taxi trajectories, and cleaning trajectory data. Subsequently, we employ the "point-to-line shortest path" map matching method to align taxi trajectory points with road network data. Secondly, we perform spatiotemporal data analysis at both macro and microscales. At the macroscale, our emphasis lies on the overall statistical analysis of the data. Spatial statistical methods are utilized to statistically analyse taxi travel volume, travel time, and travel distance, with the visualization of data clustering characteristics through kernel density. At the microscale, we construct a complex geographic spatial network using road intersections as nodes. We analyse the differences in relevant network metrics at the street level during nonrainy periods, detect network communities, analyse the spatiotemporal distribution of detected communities, and conduct spatial visualization analysis of community metrics using Graph. Finally, through multiscale spatiotemporal and network analyses, we compare the differences between sunny and

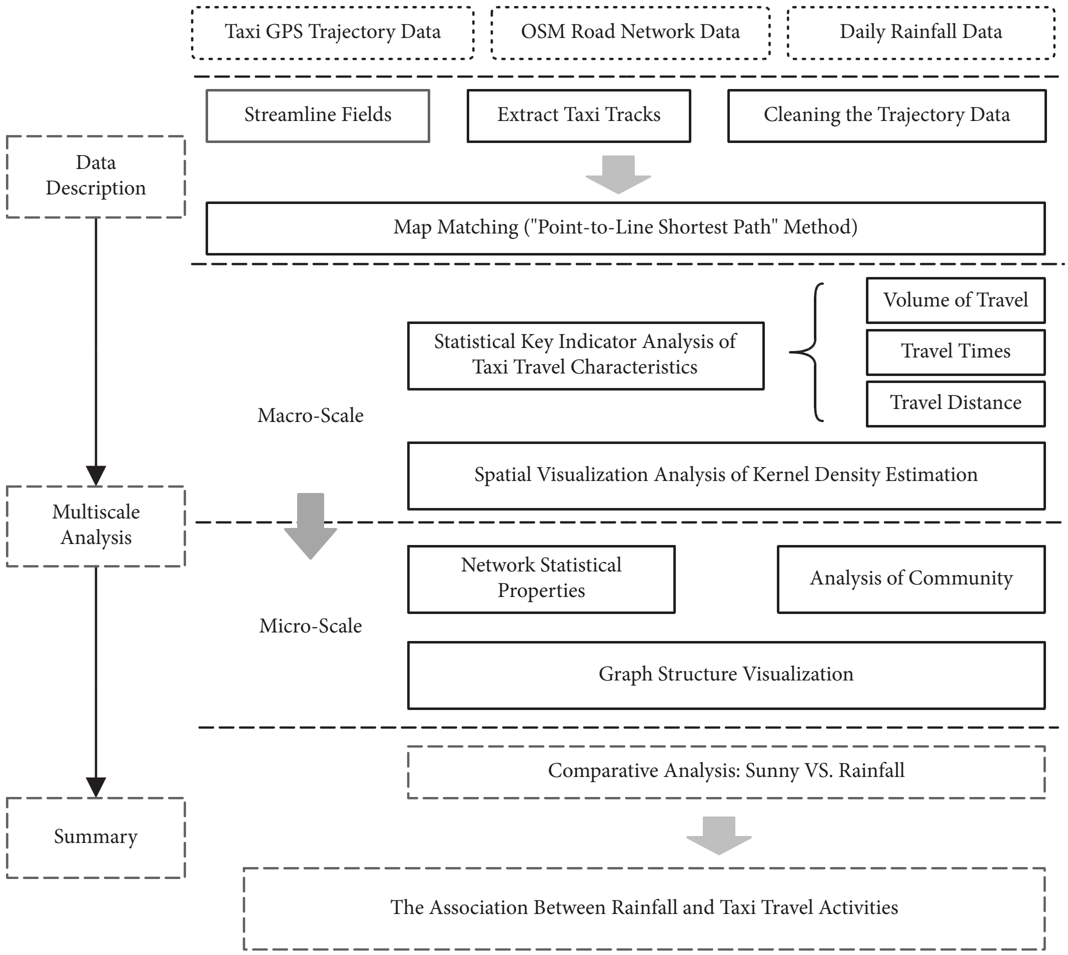


Figure 3: The work flow of our comparative analysis framework.

rainy days across different time ranges, aiding in the study of the impact of rainfall on taxi travel activities and urban population mobility.

4.2. Macroscale Analysis. At the macroscale, we initially conduct spatial statistical analysis of indicators related to taxi travel characteristics in the form of visualizations through charts. Subsequently, the spatial distribution and clustering features of O and D points are visualized using kernel density estimation methods.

4.2.1. Spatial Statistical Analysis. Spatial statistical analysis provides an intuitive means for researchers to comprehend the overall distribution characteristics of the dataset, aiding in the selection of appropriate analytical models for subsequent trajectory data analysis [66]. The crucial indicators reflecting the patterns of taxi travel include trip volume, travel time, and travel distance. The trip volume serves as a tangible metric for assessing urban population mobility, exhibiting temporal variability. High trip volumes to some extent reflect the high fluidity of the urban population, with significant susceptibility to influencing factors, rendering it of considerable research value. Travel time is an indicator capable of reflecting different travel purposes, as diverse purposes lead to varied spatiotemporal distribution patterns of travel behaviour. Additionally, travel distance stands as one of the primary factors influencing residents' choice of travel modes. For instance, residents typically opt for eco-friendly modes such as bicycles or public buses for short-distance travel, while for long-distance journeys, ideal scenarios often involve minimizing travel time, leading to choices like taxis or subways. Metrics such as average trip volume and average usage duration not only facilitate the analysis of passenger travel behaviour patterns and population mobility but also assist taxi companies in dispatch planning to meet the operational needs of daily taxi services.

4.2.2. Kernel Density Analysis. The kernel density analysis method is employed to assess the spatial clustering of elements throughout the entire study area. This method utilizes discrete points to generate continuous surfaces, revealing regions where elements are more concentrated [34]. The kernel density analysis facilitates the extraction of hotspots in taxi aggregation [69] and the analysis of the spatiotemporal distribution patterns of taxi behaviour [70]. In comparison to commonly used point density calculation methods that ignore spatial distribution heterogeneity or spatial continuity (such as sampling methods, Voronoi diagram methods, etc.), the kernel density analysis method considers both spatiality and the decay effect of continuity [4, 71]. It yields smoother and more reasonable boundaries for the extracted areas. The formula for kernel density analysis is

$$f(x) = \frac{1}{h^2} \sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right), \tag{1}$$

where $k(x)$ is the kernel function, h is bandwidth, and n is the number of discrete points in the bandwidth range. Previous studies have shown that the selection of bandwidth is generally positively correlated with the dispersion of the points and is related to the scale of the analysis [72]. Generally, larger values of h correspond to the analysis at the macroscale that reflects the trend distribution, whereas smaller values of h help find local characteristics. In practice, therefore, h must be adjusted to suit the demands of the analysis and the actual results.

4.3. Microscale Analysis. At the microscale, we constructed a complex geographic spatial network at the street level, focusing on analysing network statistical metrics related to complex networks. Subsequently, the changes in community structures under different conditions were examined.

4.3.1. Construction of Complex Transportation Networks. Complex networks represent an abstraction model for understanding complex systems, where entities are abstracted into nodes and relationships between entities into edges. This model provides a closer approximation to the real spatial distribution and natural structure of road networks in urban spaces. In the context of taxi transportation, the vast amount of trajectory data form a taxi traffic network, where the spatial positions of nodes are defined by origin and destination locations, and edge weights reflect the strength of connections between nodes [62, 66]. This spatial network, constituted by the travel behaviours of taxis, falls into the category of typical transportation complex networks [73]. Analysing its structural and topological interactions using graph theory and methods related to complex networks can reveal intricate relationships within the transportation system.

The uneven distribution of road intersections in the road network does not align with the actual origin and destination points of taxis. Therefore, to construct a more realistic complex network, road intersections need to be extracted based on general patterns of residents' travel. The methodology involves extracting all road intersections in the Wuhan road network, clustering intersections on road segments shorter than 300 meters into a single intersection, and equally dividing road segments longer than 1000 meters into smaller sections to maintain lengths between 300 and 1000 meters. Taxis' origin and destination points are then clustered onto the corresponding road intersections. Each taxi trip from O to D represents a connection, resulting in a directed and weighted complex transportation network. In this network, road intersections serve as nodes (N), and each taxi trip between two intersections is an edge. The weight of each edge represents the number of taxi connections between the intersections, providing insight into the total volume of trips for each node. The final step involves visualizing network characteristics using graph theory and complex network methods. By examining the dynamic changes in network attributes, we can reveal how rainfall influences taxi travel activities and population mobility.

4.3.2. Community Detection. Community detection is an algorithm used to identify structural communities within complex networks. A community represents a subset of nodes in a complex network, and the entire network can be considered composed of multiple communities. Nodes within the same community exhibit tighter connections, while connections between communities are relatively sparse. In this study, a community's node set corresponds to a set of road intersections with higher frequencies of travel connections in the taxi traffic network. Community detection relies on high-strength connections between nodes rather than spatial proximity. In this context, it identifies subsets of road intersections with frequent travel connections. The detected communities are then analysed for their spatial distribution through spatial visualization. Analysing the dynamic changes in community structure under different weather conditions and periods provides valuable insights into the impact of rainfall on taxi travel activities and population mobility. This approach is particularly crucial for understanding the influence of rainfall on taxi travel and population mobility.

5. Results and Analysis

5.1. Statistical Analysis of Travel Data. In this study, the analysis is conducted on an hourly basis to compare the travel volumes during weekdays, weekends, and different periods of sunny and rainy days within a week (Figure 4). The abbreviations used in the figure are as follows: SAWE and RAWE represent sunny weekend days and rainy weekend days, SAWD and RAWD represent sunny weekdays and rainy weekdays, and SDAW and RDAW represent the sunny week and rainy weeks, respectively. These abbreviations have the same meanings in the following charts.

From Figure 4, it can be observed that rainfall reduces the taxi travel volume, with a more pronounced impact on weekends. Rainfall not only decreases the taxi travel volume but also delays the peak travel time, leading to a certain degree of traffic congestion. Specifically, rainfall causes a 3.96% reduction in taxi travel volume on weekdays (Figure 4(a)) and a 4.64% reduction on weekends (Figure 4(b)), resulting in a weekly decrease of 4.16% (Figure 4(c)). During weekdays, commuting and work-related travel constitute a significant portion, and rainfall primarily affects the timing of people's travel. For example, on sunny days, the travel peak occurs between 7 a.m. and 2 p.m., while on rainy days, the peak shifts to between 8 a.m. and 1 p.m. Unlike the continuous rise on sunny days, rainy days exhibit noticeable fluctuations in travel volume, reaching a higher

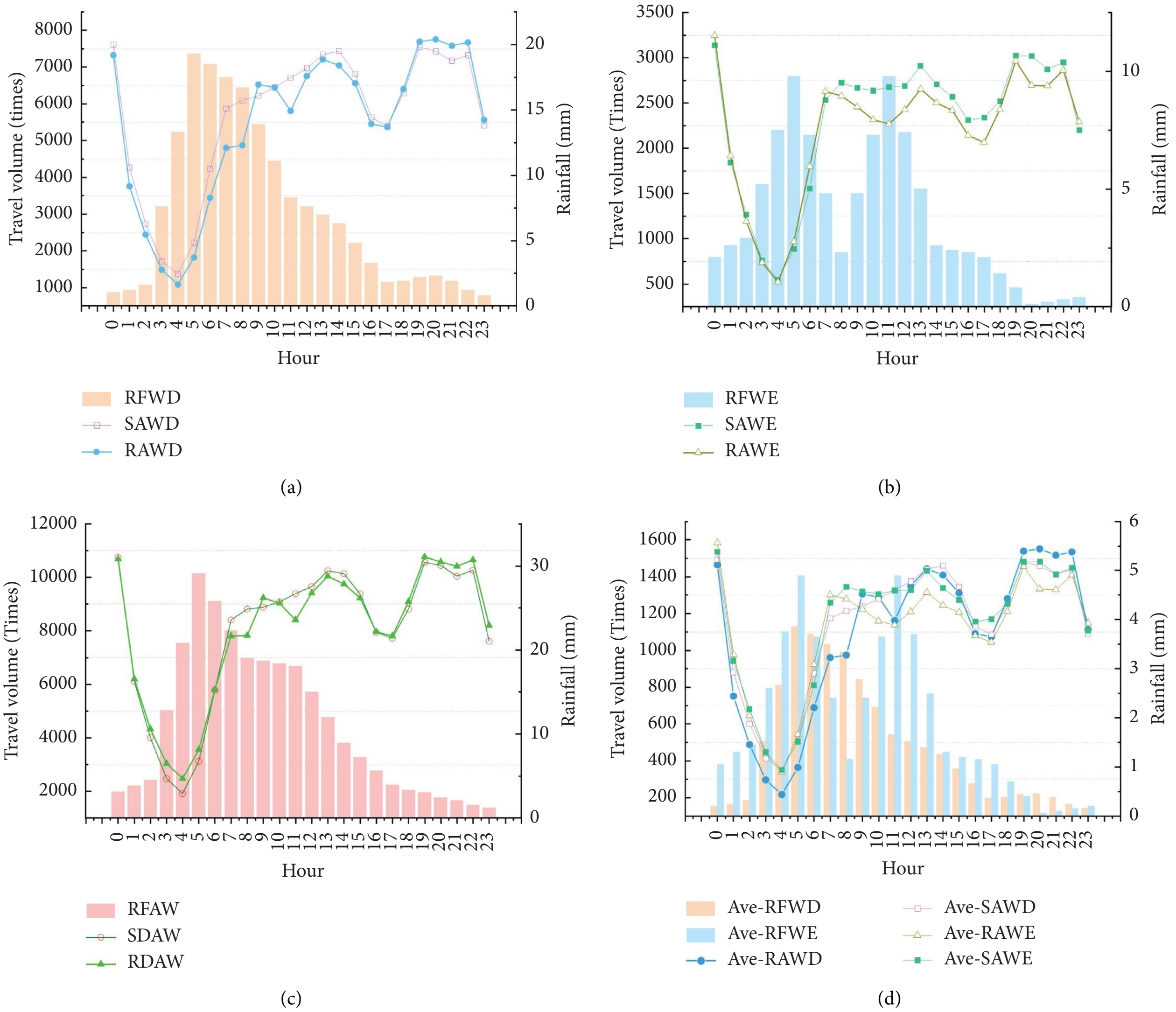


Figure 4: The relationship between rainfall and travel volume. (a) Sunny and rainy travel volume on weekdays. (b) Sunny and rainy travel volume on weekends. (c) A week of sunny and rainy travel. (d) The average sunny and rainy travel volume on weekdays and weekends.

level than sunny days at 9 a.m. This is closely related to the concentration of rainfall between 7 a.m. and 8 a.m. People often choose to delay their travel during heavy rainfall, resulting in a higher taxi demand during necessary commuting hours to minimize the impact of rainfall. With decreasing rainfall, there is minimal impact on residents' travel between 2 p.m. and 7 p.m. However, rainfall significantly influences the choice of nighttime transportation.

On weekdays with rainfall, more people opt for taxis between 7 p.m. and 10 p.m., resulting in a 4.17% increase in taxi travel volume. In contrast, rainfall considerably diminishes people's desire to travel on weekends, particularly between 7 a.m. and 10 p.m. The travel volume on rainy days is significantly lower than on sunny days, with low peaks at 11 a.m. and 5 p.m. Notably, 11 a.m. coincides with the peak rainfall, and after 5 p.m., as rainfall decreases, travel volume increases, showing no significant difference from sunny days. Additionally, between 7 p.m. and 10 p.m. on weekends, taxi travel volume decreases by 5.47%. This could be attributed to people engaging in leisure activities on weekends, with the flexibility to choose travel times and destinations. Rainfall limits people's travel options, making them more inclined to choose cost-effective means like walking, especially when rainfall is minimal. On sunny days, people are more likely to engage in long-distance recreational activities, resulting in higher demand for taxis. Therefore, with the average travel volume on weekends exceeding that on weekdays (Figure 4(d)), we can understand that rainfall leads to a lower attenuation rate of travel volume on weekdays than on weekends, indicating a more pronounced impact on weekends.

Building upon that, we further conduct a statistical analysis of travel duration frequency (Figure 5). It is evident that taxi trips predominantly exhibit short durations, and rainfall extends the travel time, leading to an increase in the frequency of short-duration trips. As depicted in Figure 5, the travel frequency for all conditions peaks within 6 minutes and gradually decreases over time. During weekdays, the total frequency within 30 minutes for both sunny and rainy days accounts for 87.75% and 87.34%, respectively, which is higher than the respective percentages of 87.58% and 85.73% for weekends during the same period. This indicates that short-duration trips dominate taxi travel, and more people choose taxi travel during weekdays, with rainfall having a greater impact on weekends. Additionally, rainfall increases the frequency of travel durations by 6 minutes, particularly during weekdays. This suggests that rainfall to some extent increases the number of long-duration trips and alters people's travel modes, such as switching from cycling to taking a taxi. The traffic congestion issues introduced by rainfall may also be a significant factor contributing to the prolonged travel times.

Moreover, we analysed the travel distances of taxis in kilometres (Figure 6). We defined trips with a distance exceeding 10 kilometres as long-distance travel. Overall, regardless of weather conditions (sunny or rainy) or weekdays/weekends, the travel frequency decreases as the travel distance increases, and the rate of change becomes smaller. During weekdays, the total frequency of trips within 10 kilometres for sunny and rainy days is 81.53% and 81.3%, respectively. Rainy days have a lower travel frequency than sunny days for distances up to 7 kilometres, but as the travel distance increases, the frequency of rainy days gradually surpasses that of sunny days. The results for weekends are similar to weekdays, with total frequencies within 10 kilometres being 81.36% and 79.47% for sunny and rainy days, respectively. However, it is only after 9 kilometres that the frequency of rainy days surpasses that of sunny days. This indicates that short-distance trips dominate taxi travel, and rainfall increases the frequency of long-distance travel. Due to the impact of rainfall, the frequency of short-distance travel decreases, especially on weekends.

5.2. Analysis of Spatial and Temporal Distribution. The spatial distribution of OD points exhibits variations, prompting an investigation into the spatiotemporal distribution patterns of passenger flow at O point and D point locations. A kernel density interpolation analysis was conducted on the quantity of OD points during both rainy and nonrainy weather conditions across weekends, weekdays, and the entire week (Figure 7).

As depicted in Figure 7, the hotspots of taxi origin and destination points in Wuhan City are primarily concentrated around the train station, central business district, commercial streets, Optics Valley Square, and some small scenic spots. The variations in hotspot areas across the series of maps are not very pronounced. However, differences emerge during rainy weekends, where the hotspot areas for D points (Figure 7(b)) exhibit a more diffuse pattern compared to O points (Figure 7(a)) in larger areas. In smaller hotspot areas, the kernel density values for D points are lower than those for O points, and the range is slightly reduced. This conclusion holds for other temporal dimensions and weather conditions. For instance, on rainy weekends, the comparison between O points in rainy and nonrainy conditions reveals that in larger dense areas, the rainy day O points' hotspot areas are more dispersed than those on sunny days. In smaller dense areas, the kernel density values for rainy days are enhanced compared to sunny days, leading to a contraction in the region.

Upon this foundation, we subtracted the number of taxi trips on rainy days from that on sunny days within the same road intersections, followed by conducting kernel density interpolation analysis. Negative values indicate a reduction in trips on rainy days, whereas positive values signify an increase in trips. As illustrated in Figure 8, rainfall exhibits distinct spatial variations in its impact on weekends and weekdays. Rainfall does not extinguish residents' desire to travel on weekends, with a preference for taxi rides to comprehensive shopping malls or other city attractions. Consequently, high-density regions for O and D points on weekends (Figures 8(a) and 8(d), highlighted in red) are mainly distributed near the train station and residential areas. Simultaneously, taxi trips originating and terminating in business districts, such as Wangjiawan and Xudong, experience a minor increase on rainy days. Notably, on weekdays, high-density regions for O and D points (Figures 8(b) and 8(e), highlighted in red) are also concentrated near the train station and business districts. However, the increase in the vicinity of the train station and residential areas is significantly lower than that on weekends. Conversely, there is a sharp increase in taxi trips near business districts, particularly around the Xudong business district. This is attributed to the densely populated residential areas nearby and the absence of a subway in this area in 2014. Rainfall has heightened the demand for taxis in this region, especially for essential commuting or work-related activities.

Furthermore, regardless of weekdays or weekends, there is a decrease in taxi trips near leisure and entertainment attractions and commercial pedestrian streets due to rainfall. For instance, the commercial pedestrian street in Jianghan District consistently registers as a low-density area. Near the South Lake College Town, the impact of rainfall remains optimistic, with minimal changes in travel volume. The areas around Wuhan University and Huazhong University of Science and Technology experience noticeable fluctuations only on weekdays. In summary, rainfall increases taxi travel near train stations, business districts, and residential areas while decreasing residents' inclination to visit leisure tourist spots and commercial pedestrian streets. Additionally, rainfall prompts more residents to choose taxi rides, particularly on weekends. On weekdays, apart from essential commuting or work-related activities, people prefer alternative modes of transportation or staying at home during rainy weather. Consequently, during rainfall, transportation authorities should focus on traffic management near the train station, business districts, and densely populated residential areas to prevent congestion. Simultaneously, attention should be given to taxi dispatching during weekday commuting hours to meet residents' travel needs.

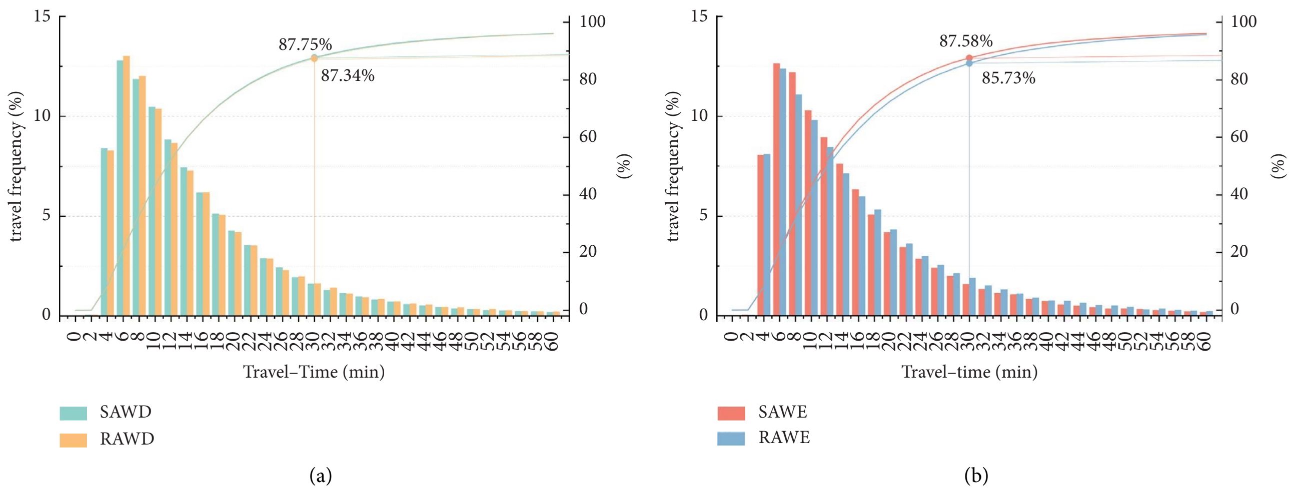


Figure 5: Travel time-frequency distribution map. (a) Distribution of rainy and sunny weekdays. (b) Distribution of rainy and sunny weekends.

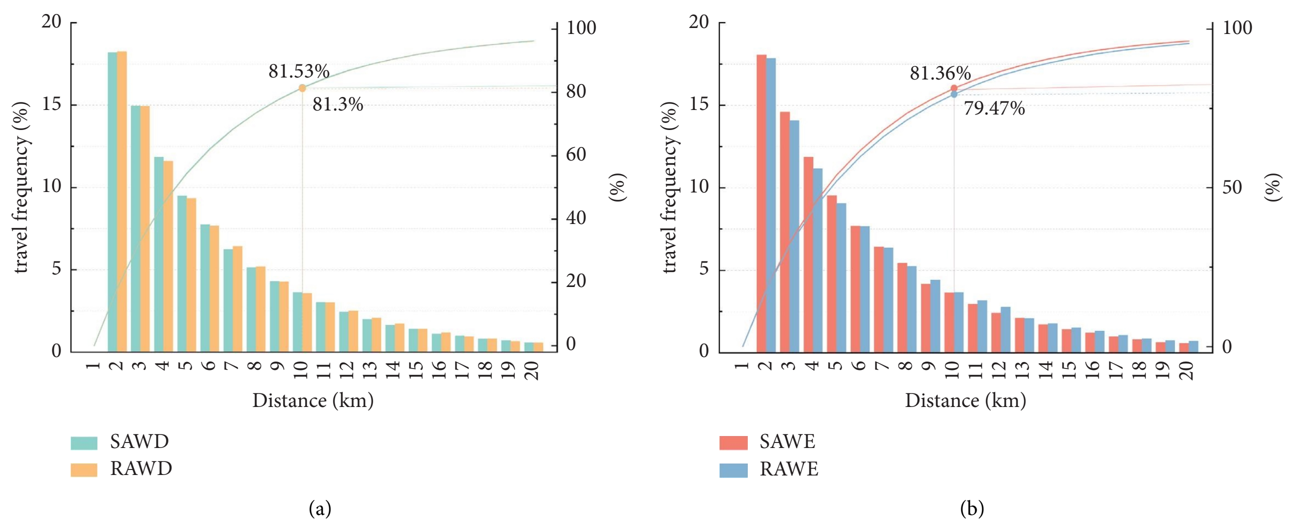


Figure 6: Travel distance frequency distribution map. (a) Distribution of rainy and sunny weekdays. (b) Distribution of rainy and sunny weekends.

5.3. Network Statistical Properties. In this section, we constructed complex taxi traffic networks under different conditions using the methods outlined in Section 4.3.1. We calculated the network attributes for taxi traffic networks on rainy and sunny days during weekdays, weekends, and the entire week. The computed results are presented in Table 2, where a series of changes articulate the impact of rainfall on taxi traffic networks under various conditions. On rainy weekends, the number of edges decreased from 43,166 to 41,824, representing a reduction of 3.21%. Meanwhile, the number of nodes remained relatively constant, resulting in a decrease in travel connections within the taxi traffic network on rainy days. Changes in the number of network edges affect the average node degree, which signifies the number of links connected to a node in the network, aiding in assessing the connectivity and accessibility of destination nodes in a mobile graph [63]. On rainy weekends, the average node degree declined from 62.79 to 59.88, and the node degree variance reduced from 4,271.82 to 3,999.64. This indicates a decrease in interactivity within the taxi traffic network during rainfall, with increased heterogeneity in connections between nodes, resulting in an overall reduction in external contacts for taxis.

Additionally, node traffic represents the total volume of trips starting or ending at a node. The total node traffic and average node traffic on rainy days were both lower than those on sunny days, suggesting that rainfall reduced residents' demand for taxis while leading to a more uneven distribution of traffic flow between nodes, thereby diminishing interactivity. Simultaneously, rainfall caused a slight decrease in the network connectivity of the taxi traffic network, falling below the level observed on sunny days under similar conditions. The average clustering coefficient, indicative of the degree of clustering among network nodes,

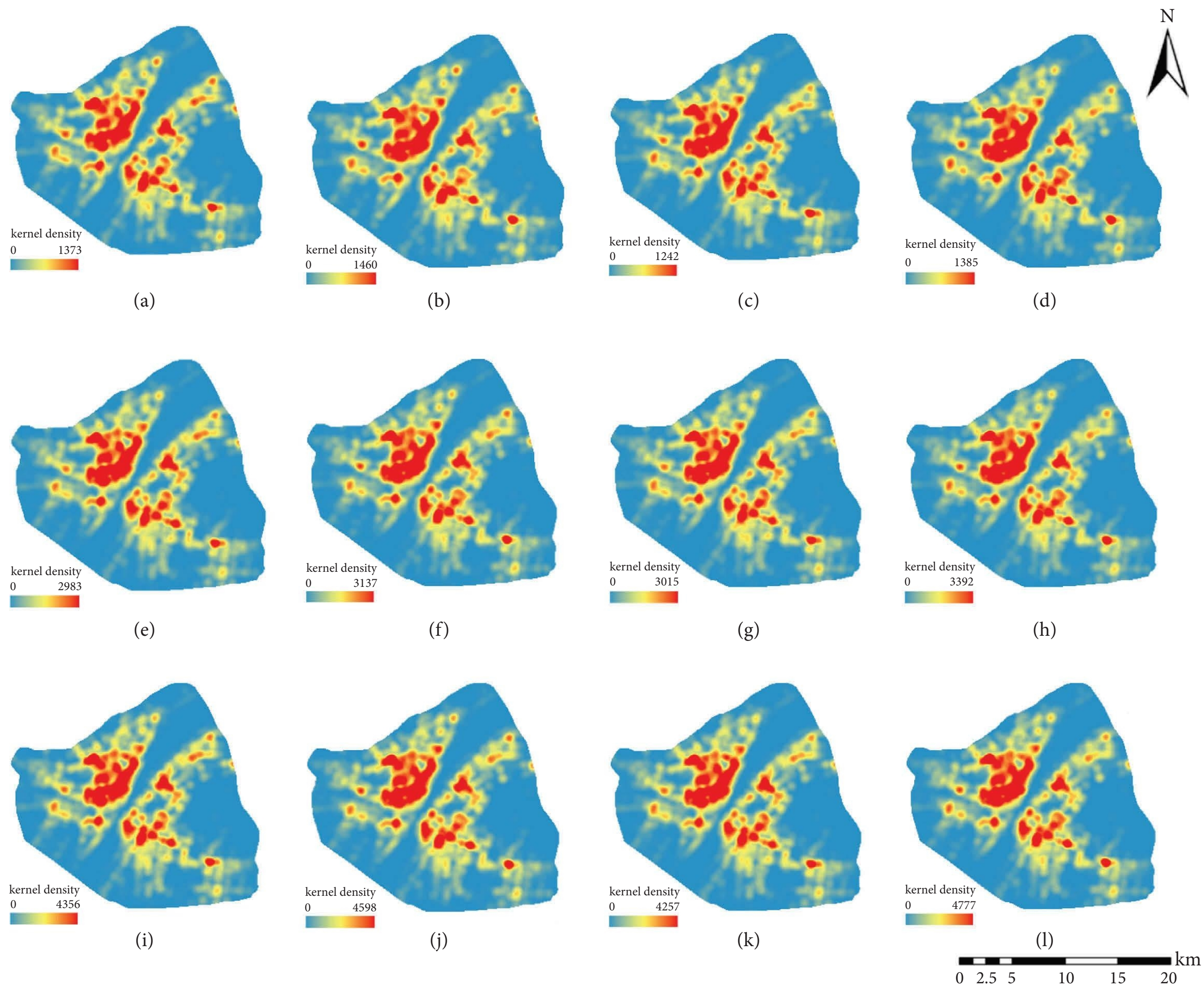


Figure 7: Kernel density distribution of OD points under different conditions. (a) O point of rainy weekends. (b) D point of rainy weekends. (c) O point of sunny weekends. (d) D point of sunny weekends. (e) O point of rainy weekdays. (f) D point of rainy weekdays. (g) O point of sunny weekdays. (h) D point of sunny weekdays. (i) O point of rainy weeks. (j) D point of rainy weeks. (k) O point of sunny weeks. (l) D point of sunny weeks.

also exhibited a minor decrease. This suggests that rainfall led to a reduction in the density of connections between nodes, weakening the clustering connections between taxi road intersections and diminishing the strength of cyclical networks, thereby increasing the probability of node failures (such as traffic congestion or accidents). In summary, across the same time dimensions during weekdays and the entire week, various parameters on rainy days were lower than those on sunny days. This implies that rainfall diminishes the cohesion of taxi traffic networks, reducing connectivity and accessibility and potentially leading to traffic congestion or accidents.

In contrast to some biological or technological networks, transportation networks exhibit a pronounced spatial dimension. Figure 9 illustrates the spatial distribution of node degrees on sunny and rainy weekends. The spatial distribution of node degrees follows a heterogeneous pattern, with high node degree values concentrated in areas with significant population mobility, such as train stations and commercial streets, including Hankou Railway Station, Wuchang Railway Station, Jianghan Road Commercial Street, and Optics Valley Square. Simultaneously, as the radial distance from high node degree areas increases, the node degree values experience a slight decline. Temporally, changes in node degrees are not very pronounced, with both sunny and rainy weekends showing higher node degrees in areas like train stations and commercial streets. Minor variations include a subtle increase in node degree at Wuhan Railway Station on rainy weekends and slight decreases near commercial streets and the CBD. By integrating these observations with the documented phenomenon of diminished graph density and heightened average path length during rainfall, as delineated in Table 2, it is evident that the taxi traffic network experiences heightened isolation in local connections on rainy days. This could be attributed to the fact that, in the absence of navigation devices at the time, taxi drivers relied on experience to choose routes, and rainfall made route selection more challenging and relatively centralized.

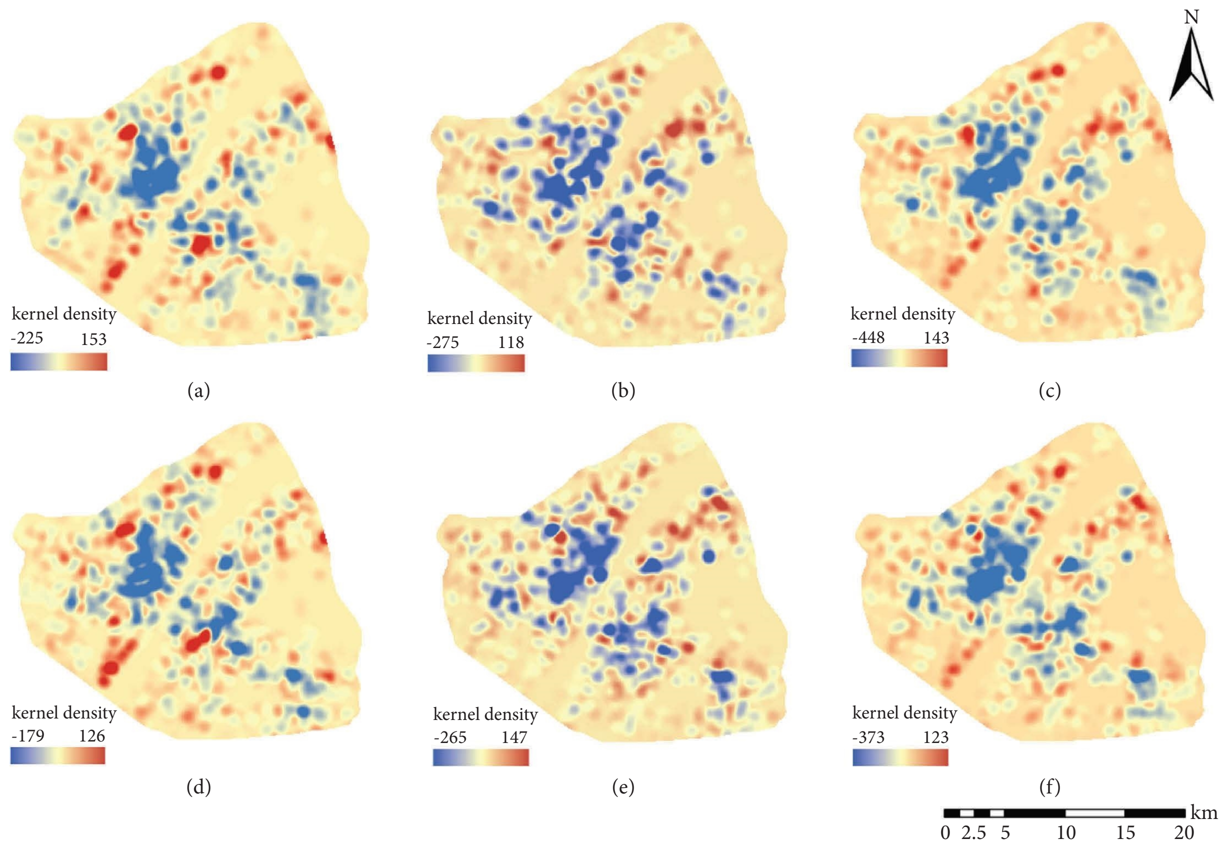


Figure 8: Kernel density analysis of the difference in OD point distribution under two weather conditions. (a) O point of weekends. (b) O point of weekdays. (c) O point of a week. (d) D point of weekends. (e) D point of weekdays. (f) D point of a week.

Table 2: Comparison of network properties under different conditions.

Properties	Weather	Workdays	Weekend	A week
Number of nodes (N)	Rainy	1424	1397	1439
	Sunny	1434	1375	1441
Number of edges (L)	Rainy	84176	41824	107537
	Sunny	86409	43166	109979
Network connectivity ($\delta = 2L/N^2$)	Rainy	0.08302	0.04286	0.10386
	Sunny	0.08404	0.04566	0.10593
Node average degree	Rainy	118.22	59.88	149.46
	Sunny	120.51	62.79	152.64
Node variance degree	Rainy	13753.11	3999.64	20816.63
	Sunny	14420.21	4271.82	21735.49
Total flow	Rainy	130842	52774	183616
	Sunny	136244	55343	191587
Node average flow	Rainy	183.77	75.55	255.19
	Sunny	189.91	80.49	265.79
Node variance flow	Rainy	52846.44	9021.28	104271.29
	Sunny	58020.71	9747.79	114307.99
Coefficient average clustering	Rainy	0.264	0.171	0.298
	Sunny	0.274	0.18	0.309
Graph density	Rainy	0.041	0.021	0.052
	Sunny	0.042	0.023	0.053
Length average path	Rainy	2.409	2.7	2.309
	Sunny	2.411	2.672	2.311
Modularity	Rainy	0.404	0.395	0.39
	Sunny	0.408	0.428	0.41

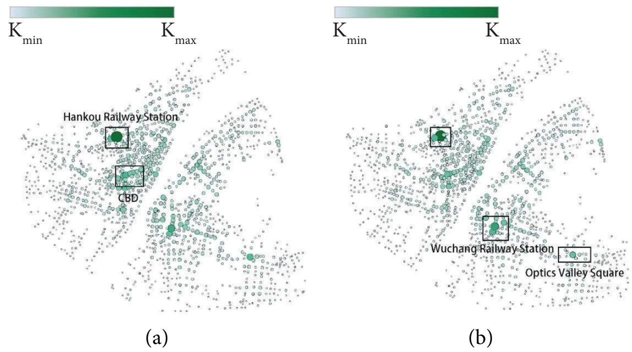


Figure 9: Spatial distribution of node degree. (a) Sunny rest day. (b) Rainy day off.

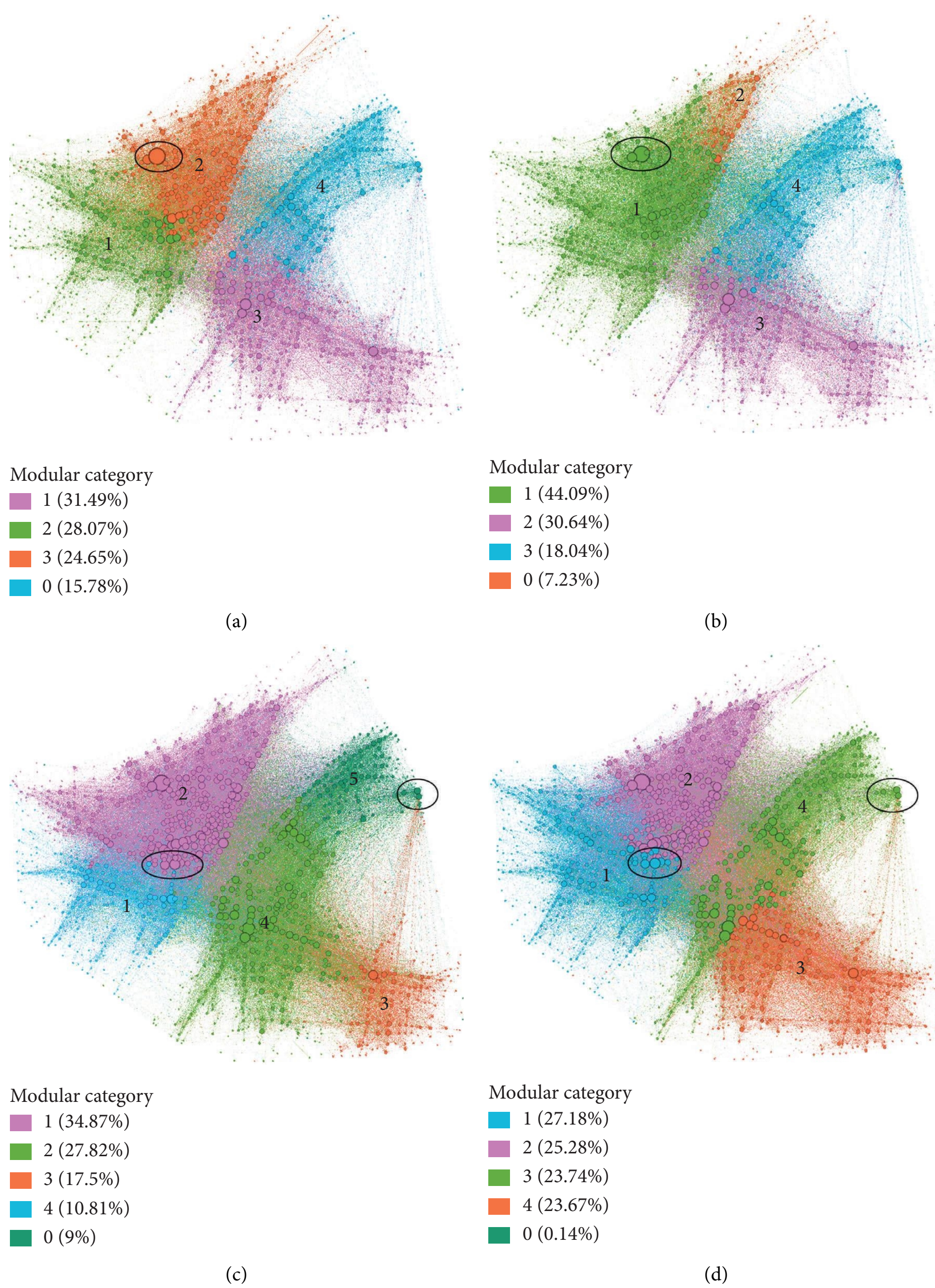
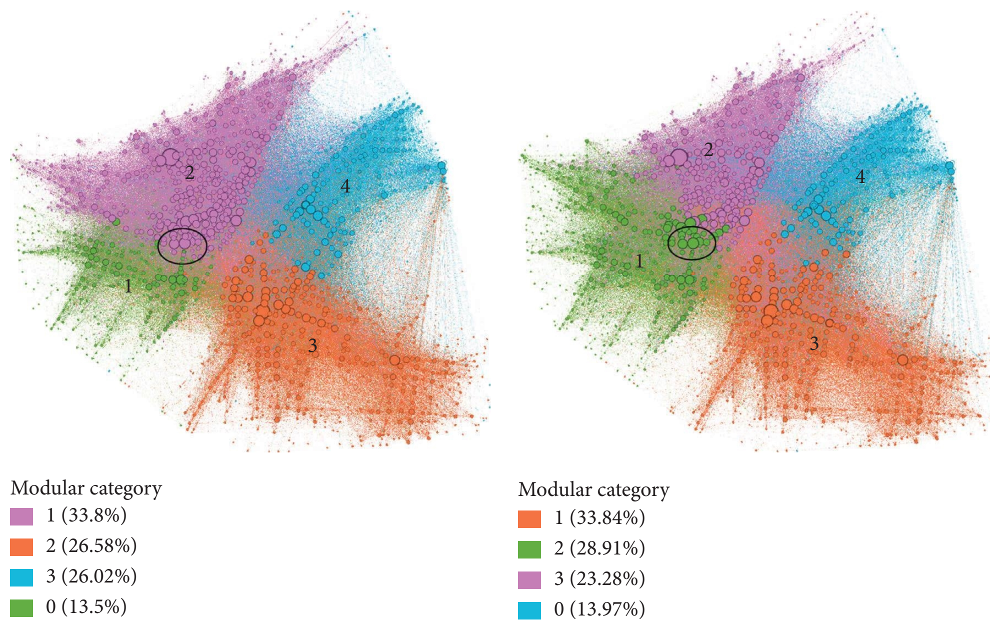


Figure 10: Continued.



(e) (f)

Figure 10: Community structure. (a) Sunny weekends. (b) Rainy weekends. (c) Sunny weekdays. (d) Rainy weekdays. (e) Sunny week. (f) Rainy week.

5.4. Community Detection and Graph Structure. Community detection in transportation networks is a technique employed to unveil clustering behaviour within the network. A community can be understood as a set of nodes in the taxi traffic network sharing similar characteristics. The distinction between internal and external communities is determined by modularity, where a higher modularity value indicates a more reasonable community division with tighter connections among nodes. Conversely, a lower modularity value implies a more ambiguous community division and sparser connections among community nodes. Taxi activities are impacted by rainfall, diminishing the efficiency of taxi travel in the network, elevating the probability of traffic congestion, and rendering community delineation more ambiguous. The modularity decreases from 0.41 to 0.39 over the week, with a more pronounced reduction observed on weekends. Detected community structures are illustrated in Figure 10, with numbers representing distinct community structures. Under different weather conditions, four communities on weekends and five communities on weekdays are identified, exhibiting similar structures in terms of partition form and geographical coverage. Rainfall induces changes in community structures, causing the expansion of the 1st community on weekends northward, absorbing much of the 2nd community's area (Figure 10(b)). Similarly, rainfall causes the northward expansion of the 1st community on weekdays, albeit to a lesser extent than on weekends. The 3rd community extends northwestward towards Wuchang Station, and the 5th community is nearly engulfed and merged into the 4th community (Figure 10(d)). Rainfall facilitates community merging, resulting in a reduction in the number of communities and an expansion of geographical coverage. Community merging is somewhat related to node degrees, as residents alter travel destinations during rainfall, reducing high-degree nodes and leading to community transitions. Regions with high node degrees, marked by circles in the figure, exhibit significant community transition phenomena. It can be seen that rainfall broadens the mobility range of taxis, with residents choosing taxis for long-distance travel, thereby increasing the use of medium and long-distance passenger taxis and replacing some of the services normally provided by buses and subways. Compared to weekends, weekdays witness large-scale mobility due to necessary commuting and work-related travel, enlarging community coverage and aligning with the current imbalance in residence and work areas in major cities.

6. Conclusions

To capture the impact of rainfall on taxi travel patterns and population mobility, this study employed geostatistical analysis and geographic spatial complex network methods to construct a comparative analytical framework for investigating the effects of rainfall on taxi services in Wuhan City at different scales. In this research, taxi travel data were utilized to extract passenger trajectory information. Road intersections were designated as nodes, and taxi movements between road intersections served as edges, with the frequency of taxi connections between two road intersections as the weight, thereby constructing a complex taxi traffic network. The study integrated geostatistical analysis methods and spatial visualization techniques to present the association between rainfall and taxi activities at various scales. The conclusions are as follows:

(1) Rainfall reduced taxi travel volume during different time intervals (a 3.96% decrease on weekdays, a 4.46% decrease on weekends, and a 4.16% decrease over the week). However, rainfall increased taxi travel demand during specific periods (a 4.17% increase between 19:00 and 22:00 on weekdays). Taxi journeys primarily involve short durations and distances, and rainfall extends residents' travel times, delaying the occurrence of travel peaks. It increased the frequency of short-duration and long-distance trips, a phenomenon more pronounced on weekends.

(2) Hotspots for taxi OD points in Wuhan City were concentrated around train stations, CBD areas, commercial streets, Optics Valley Square, and some smaller attractions. Rainfall increased taxi travel in areas near train stations, business districts, and residential areas but decreased travel to leisure tourist spots and commercial pedestrian streets.

(3) Rainfall had a greater impact on weekends than on weekdays. It restricted residents' travel range and entertainment activities on weekends, while the large-scale migration on weekdays was mainly due to necessary commuting or work-related activities resulting from a residence-work imbalance. Simultaneously, rainfall altered residents' travel modes to some extent, with more residents opting for taxis during rainy weather.

(4) Rainfall expanded the mobility range of taxis, causing changes in community structures. Residents with distant destinations increasingly chose taxis, leading to higher usage rates for mid- to long-distance trips. However, the connectivity and accessibility of the taxi traffic network decreased due to rainfall, resulting in reduced transportation efficiency and an increased risk of traffic congestion or accidents.

The practicality of our multiscale comparative analysis framework has been effectively demonstrated in this study, further affirming the feasibility of taxi trajectory data in the examination of population mobility. Through our conclusion analysis, we offer some recommendations for urban policymaking and transportation planning. Firstly, during rainfall, traffic managers should pay attention to traffic guidance at various times near train stations, commercial areas, and densely populated areas, especially during working days, to avoid traffic congestion. Secondly, taxi companies should consider rain-related taxi dispatching. More taxis should be deployed near essential transportation hubs, such as train stations and traffic nodes, during rainy weather. Conversely, the allocation of taxis near scenic spots and entertainment facilities should be reduced on rainy days to ensure residents' travel needs.

Several limitations exist in this study. Firstly, research on big data is constrained by computational performance, demanding significant time for data processing. Moreover, this study analysed data for a limited number of days and solely relied on taxi trajectory data to discuss the impact of rainfall on taxi travel patterns and population mobility. The limited data may weaken the significance of the impact of rainfall on population mobility, and a more comprehensive investigation of the effects of rainfall on residents' travel could be achieved by integrating multiple data sources such as smart card transportation data, mobile signalling data, and Weibo check-in data. Secondly, this study focuses solely on the impact of rainfall on population mobility, without considering the influence of other factors such as temperature, humidity, and wind speed, which can affect residents' travel patterns. Additionally, the psychological impact of prolonged rainy weather in the summer monsoon region is not considered, which is an essential factor influencing residents' travel. In future research, we can extend the multiscale comparative analysis framework to different cities, incorporating various data sources to further investigate the impact of different or combined factors on transportation and population mobility patterns. This will contribute valuable insights to the universality study of the multiscale comparative analysis framework.

Data Availability

The taxi GPS trajectory dataset used to support the findings of this study has not been made available because of participant privacy and commercial confidentiality. The road network dataset was obtained from the official OpenStreetMap website (https://www.openstreetmap.org). The daily rainfall dataset was obtained from publicly available data from the Wuhan Meteorological Bureau.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

We would like to thank the Wuhan Traffic Management Bureau for providing the geospatial data used in this study. This research was supported by the National Natural Science Foundation of China (nos. 42361069 and 42001344), Jiangxi Provincial Water Conservancy Science and Technology Project (nos. 202325ZDKT12 and 2023SKTR03), Jiangxi Provincial Postdoctoral Research Project Merit Funding Programme (grant no. 2021KY40), and GDAS Project of Science and Technology Development (grant no. 2021GDASYL-20210103001).

References

[1] R. Xin, T. Ai, L. Ding, R. Zhu, and L. Meng, "Impact of the COVID-19 pandemic on urban human mobility-A multiscale geospatial network analysis using New York bike-sharing data," *Cities*, vol. 126, Article ID 103677, 2022.

[2] C. Borrego, H. Martins, O. Tchepel, L. Salmim, A. Monteiro, and A. Miranda, "How urban structure can affect city sustainability from an air quality perspective," *Environmental Modelling & Software*, vol. 21, no. 4, pp. 461–467, 2006.

[3] K. Desouza and T. Flanery, "Designing, planning, and managing resilient cities: a conceptual framework," *Cities*, vol. 35, pp. 89–99, 2013.

[4] G. Nian, B. Peng, D. Sun, W. Ma, B. Peng, and T. Huang, "Impact of COVID-19 on urban mobility during post-epidemic period in megacities: from the perspectives of taxi travel and social vitality," *Sustainability*, vol. 12, no. 19, p. 7954, 2020.

[5] S. Sabrin, M. Karimi, R. Nazari, M. Fahad, R. Peters, and A. Uddin, "The impact of stay-at-home orders on air-quality and COVID-19 mortality rate in the United States," *Urban Climate*, vol. 39, Article ID 100946, 2021.

[6] Y. Yang, A. Heppenstall, A. Turner, and A. Comber, "A spatiotemporal and graph-based analysis of dockless bike sharing patterns to understand urban flows over the last mile," *Computers, Environment and Urban Systems*, vol. 77, Article ID 101361, 2019.

[7] M. Cools, E. Moons, L. Creemers, and G. Wets, "Changes in travel behavior in response to weather conditions do type of weather and trip purpose matter?" *Transportation Research Record*, vol. 2157, no. 1, pp. 22–28, 2010.

[8] S. Gong, J. Cartlidge, R. Bai, Y. Yue, Q. Li, and G. Qiu, "Extracting activity patterns from taxi trajectory data: a two-layer framework using spatio-temporal clustering, bayesian probability and Monte Carlo simulation," *International Journal of Geographical Information Science*, vol. 34, no. 6, pp. 1210–1234, 2020.

[9] Y. Jia, J. Wu, and M. Xu, "Traffic flow prediction with rainfall impact using a deep learning method," *Journal of Advanced Transportation*, vol. 2017, pp. 1–10, 2017.

[10] Y. Liu, X. Liu, S. Gao et al., "Social sensing: a new approach to understanding our socioeconomic environments," *Annals of the Association of American Geographers*, vol. 105, no. 3, pp. 512–530, 2015.

[11] X. Qian and S. Ukkusuri, "Spatial variation of the urban taxi ridership using GPS data," *Applied Geography*, vol. 59, pp. 31–42, 2015.

[12] W. Tu, R. Cao, Y. Yue, B. Zhou, Q. Li, and Q. Li, "Spatial variations in urban public ridership derived from GPS trajectories and smart card data," *Journal of Transport Geography*, vol. 69, pp. 45–57, 2018.

[13] Y. Yuan, M. Raubal, and Y. Liu, "Correlating mobile phone usage and travel behavior- A case study of harbin, China," *Computers, Environment and Urban Systems*, vol. 36, no. 2, pp. 118–130, 2012.

[14] C. Chen, L. Bian, and J. Ma, "From traces to trajectories: how well can we guess activity locations from mobile phone traces?" *Transportation Research Part C: Emerging Technologies*, vol. 46, pp. 326–337, 2014.

[15] Y. Lu and Y. Liu, "Pervasive location acquisition technologies: opportunities and challenges for geospatial studies," *Computers, Environment and Urban Systems*, vol. 36, no. 2, pp. 105–108, 2012.

[16] X. Liu, L. Sun, Q. Sun, and G. Gao, "Spatial variation of taxi demand using GPS trajectories and POI data," *Journal of Advanced Transportation*, vol. 2020, Article ID 7621576, 20 pages, 2020.

[17] China Highway, "Statistical bulletin of the development of the transportation industry in 2022," 2022, http://www.chinahighway.com/article/65400150.html.

[18] J. Choi, W. No, M. Park, and Y. Kim, "Inferring land use from spatialtemporal taxi ride data," *Applied Geography*, vol. 142, Article ID 102688, 2022.

[19] L. Gong, X. Liu, L. Wu, and Y. Liu, "Inferring trip purposes and uncovering travel patterns from taxi trajectory data," *Cartography and Geographic Information Science*, vol. 43, no. 2, pp. 103–114, 2016.

[20] H. Bi, Z. Ye, and H. Zhu, "Data-driven analysis of weather impacts on urban traffic conditions at the city level," *Urban Climate*, vol. 41, Article ID 101065, 2022.

[21] H. Lu, M. Chen, and W. Kuang, "The impacts of abnormal weather and natural disasters on transport and strategies for enhancing ability for disaster prevention and mitigation," *Transport Policy*, vol. 98, pp. 2–9, 2020.

[22] B. Li, H. Cai, and D. Xiao, "How snowfalls affect the operation of taxi fleets? A case study from harbin, China," *Journal of Advanced Transportation*, vol. 2022, Article ID 3215435, 14 pages, 2022.

[23] M. Elhenawy, H. Rakha, and H. Ashqar, "Joint impact of rain and incidents on traffic stream speeds," *Journal of Advanced Transportation*, vol. 2021, Article ID 8812740, 12 pages, 2021.

[24] J. Sun, H. Dong, G. Qin, and Y. Tian, "Quantifying the impact of rainfall on taxi hailing and operation," *Journal of Advanced Transportation*, vol. 2020, Article ID 7081628, 14 pages, 2020.

[25] D. Jaroszweski and T. McNamara, "The influence of rainfall on road accidents in urban areas: a weather radar approach," *Travel Behaviour and Society*, vol. 1, pp. 15–21, 2014.

[26] D. Chen, Y. Zhang, L. Gao, N. Geng, and X. Li, "The impact of rainfall on the temporal and spatial distribution of taxi passengers," *PLoS One*, vol. 12, no. 9, p. e0183574, 2017.

[27] J. Corcoran and S. Tao, "Mapping spatial patterns of bus usage under varying local temperature conditions," *Journal of Maps*, vol. 13, no. 1, pp. 74–81, 2017.

[28] P. Thaker and S. Gokhale, "The impact of traffic-flow patterns on air quality in urban street canyons," *Environmental Pollution*, vol. 208, pp. 161–169, 2016.

[29] J. Zhao, C. Guo, R. Zhang, D. Guo, and M. Palmer, "Impacts of weather on cycling and walking on twin trails in seattle," *Transportation Research Part D: Transport and Environment*, vol. 77, pp. 573–588, 2019.

[30] A. Singhal, C. Kamga, and A. Yazici, "Impact of weather on urban transit ridership," *Transportation Research Part A: Policy and Practice*, vol. 69, pp. 379–391, 2014.

[31] L. Ma, H. Xiong, Z. Wang, and K. Xie, "Impact of weather conditions on middle school students' commute mode choices: empirical findings from Beijing, China," *Transportation Research Part D: Transport and Environment*, vol. 68, pp. 39–51, 2019.

[32] W. A. N. G. Yuanfei, *HE Honglin Spatial Data Analysis Method*, Science Press, Beijing, China, 2007.

[33] C. Kang and K. Qin, "Understanding operation behaviors of taxicabs in cities by matrix factorization," *Computers, Environment and Urban Systems*, vol. 60, pp. 79–88, 2016.

[34] W. U. Huayi and R. Huang, "YOU lan recent progress in taxi trajectory data mining," *Acta Geodaetica et Cartographica Sinica*, vol. 48, pp. 1341–1356.

[35] T. Erdelic, T. Caric, M. Erdelic, L. Tisljaric, A. Turkovic, and N. Jelusic, "Estimating congestion zones and travel time indexes based on the floating car data," *Computers, Environment and Urban Systems*, vol. 87, Article ID 101604, 2021.

[36] Z. Kan, L. Tang, M. Kwan, C. Ren, D. Liu, and Q. Li, "Traffic congestion analysis at the turn level using taxis' GPS trajectory data," *Computers, Environment and Urban Systems*, vol. 74, pp. 229–243, 2019.

[37] H. Luan and S. Zhang, "Jointly modeling bus and taxi ridership: a bayesian multivariate spatial analysis accounting for

cross-ridership correlation," *Transactions in GIS*, vol. 26, no. 4, pp. 2099–2119, 2022.
[38] D. Zhu, N. Wang, L. Wu, and Y. Liu, "Street as a big geo-data assembly and analysis unit in urban studies: a case study using Beijing taxi data," *Applied Geography*, vol. 86, pp. 152–164, 2017.
[39] Y. Zhang, X. Li, A. Wang, T. Bao, and S. Tian, "Density and diversity of OpenStreetMap road networks in China," *Journal of Urban Management*, vol. 4, no. 2, pp. 135–146, 2015.
[40] S. Hu, S. Gao, L. Wu et al., "Urban function classification at road segment level using taxi trajectory data: a graph convolutional neural network approach," *Computers, Environment and Urban Systems*, vol. 87, Article ID 101619, 2021.
[41] J. Xu, J. Liu, Y. Xu et al., "Identification of spatial and functional interactions in Beijing based on trajectory data," *Applied Geography*, vol. 145, Article ID 102744, 2022.
[42] K. Bo, J. Teng, C. Zhang, and D. Han, "Commuting in the storm: adaptation of transit riders and measures for transit operator-A case in Shanghai," *Journal of Advanced Transportation*, vol. 2021, Article ID 6622461, 15 pages, 2021.
[43] T. Maze, M. Agarwal, and G. Burchett, "Trb whether weather matters to traffic demand, traffic safety, and traffic operations and flow," *Management And Deliveryof Maintenance and Operations Services*, vol. 52, 2006.
[44] M. Zhang, J. Liu, Y. Liu, Z. Hu, and L. Yi, "Recommending pick-up points for taxi-drivers based on spatio-temporal clustering," in *Proceedings of the 2012 Second International Conference on Cloud and Green Computing*, Washington, DC, USA, June 2012.
[45] C. Yang, E. J. Gonzales, and P. Thakuriah, "Modeling taxi demand and supply in New York city using large-scale taxi GPS data," in *Seeing Cities through Big Data: Research, Methods and Applications in Urban Informatics*, N. Tilahun and M. Zellner, Eds., pp. 405–425, Springer International Publishing, New York, NY, USA, 2017.
[46] M. Al Duhayyim, A. Abdulrahman Albraikan, F. N Al-Wesabi et al., "Modeling of artificial intelligence based traffic flow prediction with weather conditions," *Computers, Materials & Continua*, vol. 71, no. 2, pp. 3953–3968, 2022.
[47] X. Li, G. Pan, Z. Wu et al., "Prediction of urban human mobility using large-scale taxi traces and its applications," *Frontiers of Computer Science*, vol. 6, no. 1, pp. 111–121, 2012.
[48] J. Zhang, H. Chen, and Y. T.I. Fang, "TaxiInt: predicting the taxi flow at urban traffic hotspots using graph convolutional networks and the trajectory data," *Journal of Electrical and Computer Engineering*, vol. 2021, Article ID 9956406, 9 pages, 2021.
[49] X. Liu, L. Gong, Y. Gong, and Y. Liu, "Revealing travel patterns and city structure with taxi trip data," *Journal of Transport Geography*, vol. 43, pp. 78–90, 2015.
[50] Z. Guo, N. Wilson, and A. Rahbee, "Impact of weather on transit ridership in Chicago, Illinois," *Transportation Research Record*, vol. 2034, no. 1, pp. 3–10, 2007.
[51] M. Zhou, D. Wang, Q. Li, Y. Yue, W. Tu, and R. Cao, "Impacts of weather on public transport ridership: results from mining data from different sources," *Transportation Research Part C: Emerging Technologies*, vol. 75, pp. 17–29, 2017.
[52] G. Zhang, K. Yau, and G. Chen, "Risk factors associated with traffic violations and accident severity in China," *Accident Analysis & Prevention*, vol. 59, pp. 18–25, 2013.
[53] H. Caceres, H. Hwang, and Q. He, "Estimating freeway route travel time distributions with consideration to time-of-day, inclement weather, and traffic incidents," *Journal of Advanced Transportation*, vol. 50, no. 6, pp. 967–987, 2016.
[54] Z. Fang, Y. Wu, H. Zhong, J. Liang, and X. Song, "Revealing the impact of storm surge on taxi operations: evidence from taxi and typhoon trajectory data," *Environment and Planning B: Urban Analytics and City Science*, vol. 48, no. 6, pp. 1463–1477, 2021.
[55] Y. Jiang, N. Zhang, A. Li, H. Wu, R. Li, and J. Yang, "Effects of weather on highway traffic capacity in China: characteristics and causes of roadblocks due to fog events," *Pure and Applied Geophysics*, vol. 177, no. 10, pp. 5027–5040, 2020.
[56] Q. Miao, E. Welch, and P. Sriraj, "Extreme weather, public transport ridership and moderating effect of bus stop shelters," *Journal of Transport Geography*, vol. 74, pp. 125–133, 2019.
[57] D. Eisenberg, "The mixed effects of precipitation on traffic crashes," *Accident Analysis & Prevention*, vol. 36, no. 4, pp. 637–647, 2004.
[58] S. Guo, R. Wu, Q. Tong et al., "Is city traffic damaged by torrential rain?" *Physica A: Statistical Mechanics and its Applications*, vol. 503, pp. 1073–1080, 2018.
[59] B. Smith and J. Conklin, "TRB use of local lane distribution patterns to estimate missing data values from traffic monitoring systems," *Advanced Traffic Management Systems for Freeways And Traffic Signal Systems 2002: Highway Operations, Capacity, and Traffic Control*, vol. 56, pp. 50–56, 2002.
[60] W. Lam, M. Tam, X. Cao, and X. Li, "Modeling the effects of rainfall intensity on traffic speed, flow, and density relationships for urban roads," *Journal of Transportation Engineering*, vol. 139, no. 7, pp. 758–770, 2013.
[61] M. Batty, *The New Science of Cities*, The MIT Press, Cambridge, UK, 2013.
[62] M. Saberi, H. Mahmassani, D. Brockmann, and A. Hosseini, "A complex network perspective for characterizing urban travel demand patterns: graph theoretical analysis of large-scale origin-destination demand networks," *Transportation*, vol. 44, no. 6, pp. 1383–1402, 2017.
[63] C. Zhong, S. Arisona, X. Huang, M. Batty, and G. Schmitt, "Detecting the dynamics of urban structure through spatial network analysis," *International Journal of Geographical Information Science*, vol. 28, no. 11, pp. 2178–2199, 2014.
[64] L. Dai, B. Derudder, and X. Liu, "The evolving structure of the Southeast Asian air transport network through the lens of complex networks, 1979–2012," *Journal of Transport Geography*, vol. 68, pp. 67–77, 2018.
[65] C. Ducruet, "Multilayer dynamics of complex spatial networks: the case of global maritime flows (1977-2008)," *Journal of Transport Geography*, vol. 60, pp. 47–58, 2017.
[66] X. Fu, Y. Yang, and H. Sun, "Structural complexity and spatial differentiation characteristics of taxi trip trajectory network," *Journal of Traffic and Transportation Engineering*, vol. 17, pp. 106–116.
[67] P. Guo, Y. Sun, Q. Chen, J. Li, and Z. Liu, "The impact of rainfall on urban human mobility from taxi GPS data," *Sustainability*, vol. 14, no. 15, p. 9355, 2022.
[68] I. Tsapakis, T. Cheng, and A. Bolbol, "Impact of weather conditions on macroscopic urban travel times," *Journal of Transport Geography*, vol. 28, pp. 204–211, 2013.
[69] Y. Hu, H. Miller, and X. Li, "Detecting and analyzing mobility hotspots using surface networks," *Transactions in GIS*, vol. 18, no. 6, pp. 911–935, 2014.
[70] D. Zhang, J. Wan, Z. He et al., "Identifying region-wide functions using urban taxicab trajectories," *ACM Transactions on Embedded Computing Systems*, vol. 15, no. 2, pp. 1–19, 2016.

[71] E. Parzen, "Emanuel parzen on estimation of a probability density function and mode," *The Annals of Mathematical Statistics*, vol. 33, pp. 1065–1076.

[72] C. Wu, X. Ye, F. Ren, and Q. Du, "Check-in behaviour and spatio-temporal vibrancy: an exploratory analysis in shenzhen, China," *Cities*, vol. 77, pp. 104–116, 2018.

[73] J. I. A. O. Long and Y. Liu, "SI ruochen role of distance constraint in the structure of taxi passenger flow network," *Acta Scientiarum Nauralium Universitaties Pekinensis*, vol. 50, pp. 880–886.