

Article

Understanding Plum Rain's Effects on Urban Public Bicycle Unavailability Considering Both Place Semantics and Riding Distance

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Abstract: The effect of the plum rain weather event on cycling trips reflects the climate resilience of the public bicycle system. However, quantitative studies regarding the impact of plum rain on public bicycle users and corresponding spatial heterogeneity have not been paid much attention. This paper explores the spatial pattern of affected levels from the perspective of cyclist number, place semantics and riding distance. Corresponding public bicycle trips in normal weather are predicted by spatial-temporal random forest prediction. GIS neighborhood statistics and clustering algorithms are adapted to analyze and visualize the affected levels using origin-destination data of public bicycle trips and point of interest data of city public facilities. It is proved that there is an obvious spatial difference in affected levels by plum rain from three dimensions. In the dimension of the number of cyclists, the docking stations with different affected levels are distributed across the whole urban area. In the place semantic dimension, the docking stations with high affected levels show a clustered zonal distribution in the city center. In the dimension of cycling distance, the docking stations with high affected levels are mainly distributed in the periphery of the central urban area. The study theoretically expands the impact mechanism of environment and active transport. It is beneficial for the early monitoring, warning and assessment of climate change risks for public bicycle planning and management.

Keywords: plum rain; public bicycle; spatial pattern; random forests; place semantics



Citation: Chen, L.; Zhang, H.; Wang, H.; Wu, P. Understanding Plum Rain's Effects on Urban Public Bicycle Unavailability Considering Both Place Semantics and Riding Distance. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 695. <https://doi.org/10.3390/ijgi10100695>

Academic Editor: Wolfgang Kainz

Received: 12 September 2021

Accepted: 12 October 2021

Published: 14 October 2021

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1. Introduction

Climate and environmental problems are challenges for human beings. Climatic conditions undoubtedly have an obvious impact on people's daily travelling behavior [1,2]. Extreme climate events [3,4], such as heavy snow, fog, freezing, intense hurricanes, strong wind, high/low temperature, heavy rain, continuous rain, and rising sea levels, can greatly increase the vulnerability of the transportation system. Different kinds of climatic scenarios and different transit modes result in different responses from transportation sectors and people. Analyzing and studying the influence of weather on residents' transit modes are of great significance in deeply understanding the cognition of the transportation environment. This study will provide guidance to management authorities on coping with the effects of extreme weather events on the transportation system.

The objective of this research is the public bicycle transit in the plum rain season. Plum rain [5] is a unique climate phenomenon in the middle and lower reaches of the Yangtze River in early summer every year. This phenomenon usually starts around June and ends in July, lasting for approximately 20–30 days, with a rainfall of 200–400 mm. The continuous rainy period is called the plum rain season because it is the mature period of plums [6].

This type of climate is very special, with the characteristics of high-temperatures/humidity, a long rainy period and inherent repetitiveness. Acknowledging that public bicycle transit is highly sensitive to these climatic conditions is important. During rainy periods, the availability of public bicycles decreases greatly, resulting in travel inconvenience for residents. Commuters are less sensitive to climatic conditions than non-commuters [2]. Some cyclists would complete their trip given approximately 30 min of respite from the rain. Heavy rains discourage cycling, but other rainy days have no discernable effect on cycling rates [7]. Moreover, spatial inhomogeneity exists in different city locations in terms of the above effect on residents. Since many of the impacts of climate change are already occurring, this study focuses on the plum rain event as to strengthen early monitoring, warning and assessment of climate change risks to public bicycle travelling and corresponding mode shift. Consequently, promoting climate resilience in the public bicycle system remains a most realistic and urgent task.

To date, related research has mainly focused on the effect of weather conditions on travel choices [8–10]. Studies on the relationship between rainfall and transportation are very limited and usually focus on road traffic and railway. Travel time and fuel consumption are reportedly influenced by the intensity of rainfall in Greater Mumbai, India [11]. Freeway traffic flow decreases with the rain, that is, from heavy, moderate, to light rain [12]. Railway operation faces hazards from rainfall-induced flooding, landslides, and debris flow [13]. The continuous rainfall phenomenon is common in many regions and countries (e.g., Monrovia of Liberia, Murmaine of Myanmar, Northeast India, and Bangladesh). However, few studies have been conducted on the effects of such a phenomenon on people's use of certain means of transportation.

To address this research gap, this study aims to explore the spatial pattern of the effects of public bicycle unavailability for residents' transit in the plum rain season. This study is conducted based on the number of cyclists, place semantics, and riding distance. The remainder of this paper is organized as follows. Section 2 provides a summary of earlier studies. Section 3 describes the study area and the data used. In Section 4, the methodology is presented with the research framework. Subsequently, Section 5 presents the analysis results in detail. Finally, Section 6 provides a discussion and the conclusions.

2. Literature Review

Travelers' subjective perception of and response toward weather conditions depends not only on objective weather elements but also on different transit mode characteristics and the severity of weather events. On this basis, a large variety of weather-related assessments of comfort, speed, effort, safety, or aesthetics can be observed under the same weather conditions [14].

2.1. Impact of Weather Elements on Travel Choices

Weather elements, including temperature, wind, precipitation, humidity, and air pressure, have different effects on transport modes. For public transit, a certain degree of transit ridership decrease is associated with the increase in humidity, wind and rainfall. In a case study of subtropical Brisbane, rain/wind speed and the heat index were selected to examine their influence on transit ridership [15]. The optimal riding temperature is 20–25 °C. Lower air temperature intervals have a negative effect on cycling and a positive effect on walking and public transport usage. Strong winds, low temperature, precipitation, and winter months induce a mode shift from cycling to car driving [7,9,16].

For subway transit ridership from a survey on residents in Beijing, long-term temperature change is more important than daily temperature change, and rain has a significant effect on ridership, showing 5.5% and 8% ridership reductions under moderate and heavy rains, respectively [17]. The effect of the weather condition on a passenger waiting inside an underground subway station is different from that on a passenger waiting at outdoor platforms and bus stops [18].

For bicycle transit, temperature and humidity are positively and negatively associated with cycling, respectively, and precipitation has a significant negative impact on cycling flows with a lagged effect [19–22]. Further, rain deters cyclists with lower skills from bicycling 2.5 times more strongly than those with better cycling skills in the case study of the Ithaca campus of Cornell [23]. In particular places (e.g., Australia, Rotterdam Alexander), wind speed has a greater impact on cycling rates than temperature [24].

2.2. Impact of Extreme Climate Events on Travel Choices

Extreme weather events, especially snow, rain, and strong wind, are one of the main reasons for trip cancellation, travel decrease, and travel mode shift [25]. People are generally cautious about travelling during extreme weather events and are inclined to choose the subway [26] or cars rather than buses and bicycles under inclement weather days [27]. For instance, heavy snow increases the transit ridership from private car to rail transport [28].

For public transit, station accessibility as well as proximity and the weather protective features of stations impact transit riders' trip decisions under extreme weather conditions [15]. Bus ridership in low-income areas is more sensitive to extreme weather events than that in wealthy neighborhoods [29]. The impact of extreme weather conditions, namely, high and low temperatures, rain, thunderstorms, and fog, on the travel choices of metro rail users at two stations in Delhi was studied, revealing that adverse weather conditions are likely to disrupt the transport infrastructure and its performance. An interesting conclusion from metro-rail users in Delhi indicates that in all types of extreme weather conditions, approximately 20% of travelers are likely to cancel their trips, 52% are likely to shift modes, and 53% are likely to change their time of travel in the event of thunderstorms [30].

Statistically, severe rainstorms/thunderstorms are the most frequent type of extreme weather event experienced in the U.S.; followed by extreme cold temperatures, high winds, and heat waves. Hurricanes, tropical storms, and storm/tidal surges are rarely experienced [31]. The impact of extreme weather events was measured in an early study mainly through questionnaires given to respondents with at least one extreme event experience, because actual data acquisition was difficult at that time. According to statistics, closed roads, difficult driving conditions, and extreme winds have the main impact on car driving in heavy snow or extreme heat weather events, increasing the average travel times and decreasing variability [4,32]. For Brussels commuters, more than 25% reported that they would change their mode, 60% would change their departure time, and 35% would divert to alternate routes in extreme weather events [33]. Subway travel is considered the least affected by extreme weather, while bus transit is the most susceptible to weather impacts [34].

In general, although much literature has studied the influence of general weather on transport modes in depth, the main focus has been the statistical analysis of weather elements and road traffic/railway. Within this emerging body of literature, few studies have examined the relationship between the plum rain event and public bicycle use in the spatial scale by geographic quantification method. Furthermore, due to the comprehensive influence of multiple factors, such as the number of cyclists, place semantics and cycling distance, the impact which is characterized by complexity and spatial heterogeneity has not been paid much attention by scholars.

3. Study Area and Data Description

3.1. Study Area

The study area is the public bicycle sharing system of Suzhou in the plum rain season in 2015. Suzhou, which is adjacent to Shanghai, has a resident population of 10.75 million and is one of most economically developed cities in China. The plum rain season in Suzhou is from 15 June to 11 July, and the rainfall is 230.9 mm. This season is characterized by high temperature, high humidity, and overcast rain [5]. The plum rain period lasts for

approximately 26 days, and more than half of the days are rainy, as shown in Figure 1. This period is hereafter referred to as the plum rainy season (PRS).

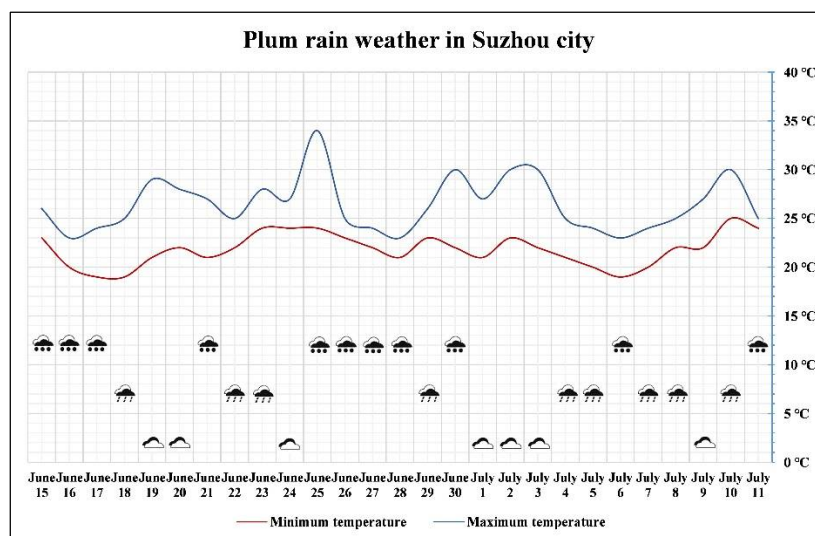


Figure 1. Plum rain weather in Suzhou City (low reaches the Yangtze River of China).

The mixed operation of dockless and docked bicycle sharing systems is common in many cities, and the number of dockless bicycles is generally greater than that of docked bicycles. Uniquely, Suzhou only has a docked bicycle sharing system. The distribution map of the docking stations of Suzhou's public bicycle sharing system is shown in Figure 2. The study area is the city center, including the Gusu, Huqiu, Wuzhong, and Xiangcheng districts.

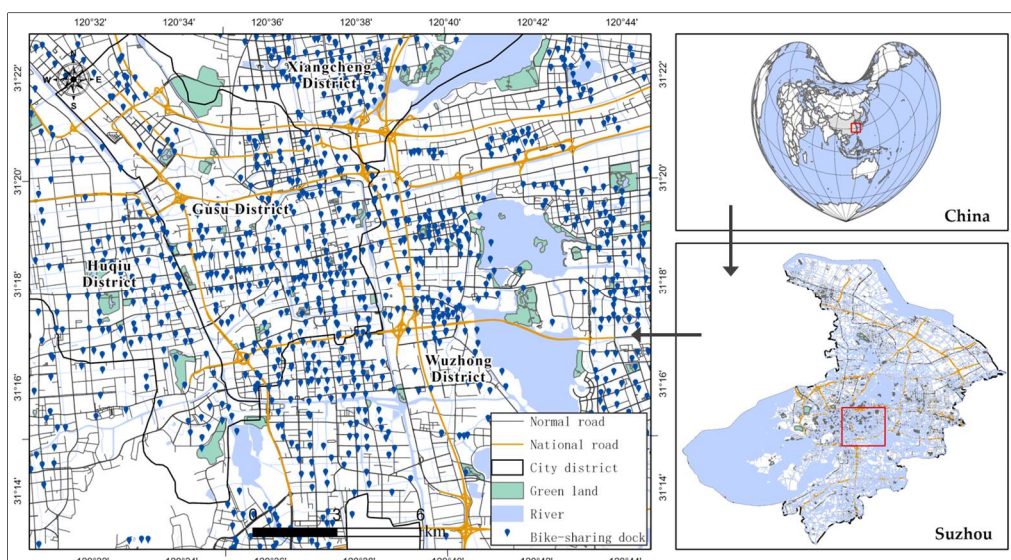


Figure 2. Study area (city center of Suzhou, China).

3.2. Data Description

This study draws on records of 8.21 million trips under the docked public bicycle scheme of Suzhou from May 2015 to July 2015. Each data record contains the OD number of trips, the names and locations of docking stations where the bicycles were borrowed and returned, and the time the bicycles were borrowed and returned. The data include 1031 docking stations with latitude and longitude coordinates. To determine the location

and spatial scope of various facilities, POI data, which include all urban facilities (e.g., shops, restaurants, companies and enterprises, and domain urban transport nodes) and the panel data of school districts and residential blocks with corresponding point data (e.g., egress and access), are collected as auxiliary data. Different types of POI data and their corresponding docking stations are identified separately, especially for the catchment of school districts and residential blocks. In addition, the weather history data of Suzhou from May to July 2015 is prepared to observe the characteristic of the plum rain season.

4. Methodology

This study attempted to analyze the impact and spatial difference of plum rain weather on the unavailability of public bicycles to residents from different dimensions. The research framework of the study is shown in Figure 3. In terms of time, this study was carried out for two periods, namely, workdays and weekends. The corresponding public bicycle trips in normal weather was predicted by the spatial-temporal random forest method. GIS neighborhood statistics and the clustering algorithm were used to analyze and visualize the strength of affected levels, including a reduction in the number of cyclists, difference in place semantic characteristics, and the riding distance.

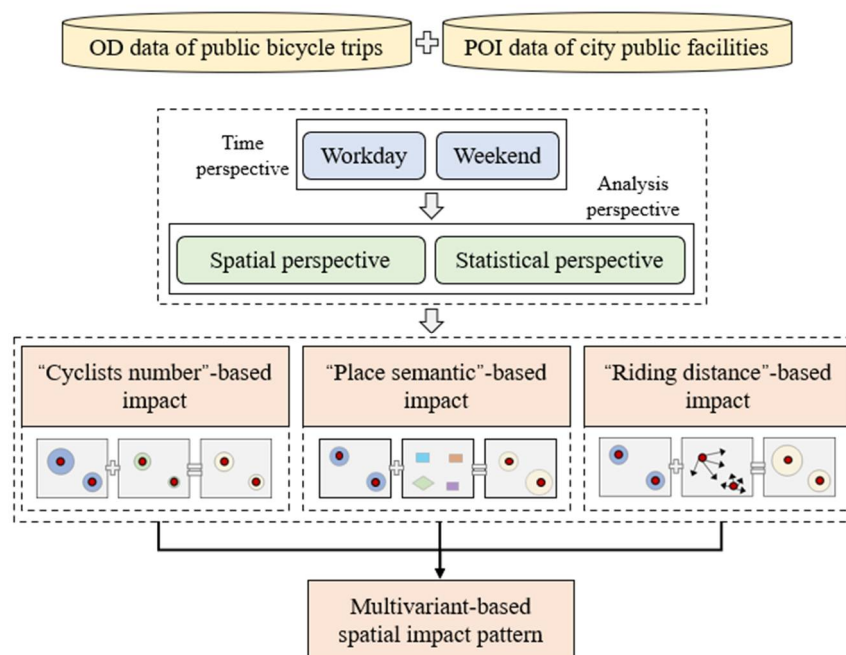


Figure 3. Research framework of the study.

4.1. Inference Method for Impact of Public Bicycle Trips

The day-to-day utilization rate of public bicycles has both temporal heterogeneity and periodicity. In this context, temporal heterogeneity refers to the different utilization rates of public bicycles in different periods and in the same area, and periodic change refers to the relatively stable utilization rate of public bicycles on workdays, which may be random on weekends. That is, this periodicity measure is week-based and takes the day as the basic statistical unit. The utilization rate of public bicycles decreases during the PRS. How many public bicycle trips would have been made if the PRS has no impact? The solution in this study is to predict the public bicycle trips during the PRS that should have been achieved by the corresponding data of the previous month. By comparing the actual data of public bicycles trips during the PRS in 2015, the difference between the predicted and actual values is considered as the number of affected public bicycle trips.

The random forest model was used to predict the public bicycle trips for 16 June to 11 July based on the actual trips data in May in Suzhou. The model is a supervised

classification machine learning method, which predicts the size of the target value in the future period based on the regression of forest [35]. Given the seasonal tendency of the utilization rate of public bicycles, the prediction model is built according to the residual after removing the trend. The predicted value of a position can be expressed by the following formula:

$$\begin{bmatrix} D_{W+1} - \hat{D}_{W+1} \\ D_{W+2} - \hat{D}_{W+1} \\ D_{W+3} - \hat{D}_{W+1} \\ \vdots \\ D_T - \hat{D}_{T+1} \end{bmatrix} = \begin{bmatrix} D_1 & D_2 & D_3 & \cdots & D_W \\ D_2 & D_3 & D_4 & \cdots & D_{W+1} \\ D_3 & D_4 & D_5 & \cdots & D_{W+2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ D_{T-W+1} & D_{T-W+2} & D_{T-W+3} & \cdots & D_{T-1} \end{bmatrix}, \quad (1)$$

where T is the number of time steps in the space-time cube, W is the number of time steps in each time step window, D_T is the value of the time series after de-trending at time T , and $\hat{D}_{T+1}$ is the value estimated at time T according to OLS (Ordinary Least Square) method.

The prediction accuracy of the model must be verified after completing the prediction. Therefore, an evaluation model must be built, excluding part of the final time step of each time series and fitting the forest model to the data included. The forest model can then be used to predict the value of the retained data and compare the predicted and hidden original values. The accuracy of prediction is measured by calculating a validated RMSE statistic equal to the square root of the mean square error between the predicted value of the excluded time step and the original value [36]. The calculation formula is as follows:

$$RMSE = \sqrt{\frac{\sum_{t=T-m+1}^T (c_t - r_t)^2}{m}}, \quad (2)$$

where T is the number of time steps, m is the number of time steps reserved for verification, c_t is the predicted value based on the previous $(T - m)$ time steps, r_t is the original value of the time series reserved for verification at time T . Here the time step is set as 1 day in this study.

4.2. Place Semantic Recognition and Weighted Method

The day-to-day utilization rate of public bicycles also has spatial heterogeneity, which refers to differences in the utilization rate of public bicycles in different areas of the city. The decrease in the utilization rates of public bicycles in different areas is one of the core indicators of the influence of the PRS on different places. In addition, different types of places are considered to have different effects on the utilization rate of public bicycles, due to the difference in convenience of alternative transport modes during the PRS. This study also evaluates the difference in the impacts of the unavailability of public bicycles to residents for transit during the PRS considering the place semantic [37]. Places (e.g., subway stations and residential blocks) are observed with the same declining value of public bicycle utilization. For instance, the unavailability of public bicycles near subway stations during the PRS would result in crowds and queues for bus transfer and taxi services because of the agglomeration of subway passenger flow. By contrast, the unavailability of public bicycles near residential blocks during the PRS may not have a significant effect due to dispersion of people flow and shelter stability.

In view of the above facts, places are divided into five categories, namely, business districts, school districts, residential blocks, employment districts, and urban transport nodes (e.g., subway station, railway station, coach station) [38]. Therefore, the semantic type of places demarcates each docking station that the public bicycles belong to. A schematic of the spatial relationship between docking stations and different types of places is shown in Figure 4, which describes the group affiliation for five types of places and seven docking stations. The place set is defined as $[1, 2, 3, \dots, 11]$, and the docking station set is defined as $[S1, S2, \dots, S7]$. Given that the access and egress data of urban transport

nodes, residential blocks, and schools can be obtained through online electronic maps, the categories of docking stations can be determined directly according to the distance from each other. However, to identify business and employment districts is difficult. For this, the POI data of Suzhou City is collected, including all urban facilities (e.g., shops, restaurants, companies and enterprises). Spatial clustering is adopted to demarcate these two places and then confirm which place semantic the docking stations belong to [39]. Some docking stations may belong to multiple semantic categories of places, that is, located in two or more adjacent places [40]. To solve this problem, calibration is conducted according to the influence degree of multiple place semantics under the unavailability of public bicycles during the PRS. According to the heterogeneity of people flow [41], the convenience of alternative transport modes, and the rigid travel demand, the weight of hypothesis for the five kinds of places are determined qualitatively as 5, 4, 3, 2, and 1, corresponding to urban transport nodes, employment districts, business districts, school districts, and residential blocks, respectively. In this way, the spatial semantics of the public bicycle docking stations can be identified. Then, the influence degree of each lending station based on various place semantics could be observed through the difference between the predicted and actual trips during the PRS. According to the above principles, the semantic type and actual weight of each public bicycle docking station can be determined.

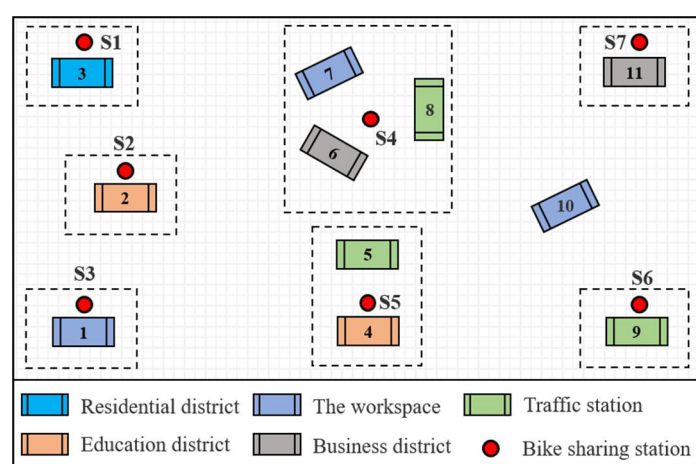


Figure 4. Spatial relationship of various places and docking stations of public bicycle.

4.3. Riding Distance Analysis and Statistics Method

Generally, the riding distances of public bicycles vary in different docking stations. During the PRS, the unavailability of public bicycles may result in individual and holistic differences in impact on cycling distances. From the individual's impact perspective, residents whose riding distance exceeds 3 km may not continue to ride when rain pours, whereas residents whose riding distance is only 500 m may continue to ride. If the average riding distance of all residents cycling at docking station A exceeds 3 km, and the average riding distance of all residents cycling at docking station B is less than 500 m, according to the impact from a holistic perspective, the former has a higher cost than the latter if an alternative transport mode is selected.

Figure 5 shows the schematic of the statistical method based on the riding distance. S_{i_0} represents the lending dock station, and S_{i_j} represents the corresponding returning dock station. The thickness of the arrow indicates the number of trips from the lending dock to the returning dock, whereas the length of the arrow indicates the riding distance. As shown in Figure 5a–c, the riding distance of the docking stations is divided into three types, namely, homogeneous long-distance and heterogeneous trips, heterogeneous distance and heterogeneous trips, homogeneous short-distance and heterogeneous trips. In this paper, the influence index based on the riding distance of each lending station is determined by

the difference between the predicted and actual riding distances during the PRS, and Δd_i denotes the influence index based on the riding distance of each origin dock station.

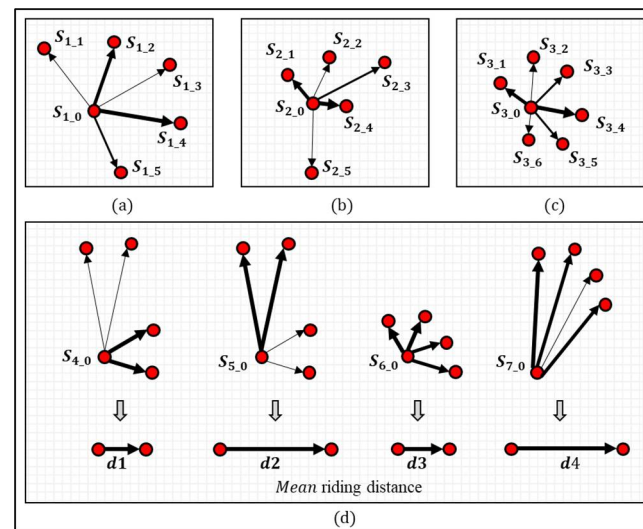


Figure 5. Heterogeneity of riding distance between different docking stations. (a) homogeneous long-distance and heterogeneous trips, (b) heterogeneous distance and heterogeneous trips, (c) homogeneous short-distance and heterogeneous trips, (d) average distance in different composition pattern of origin-destination distance and trips.

As shown in Figure 5d, $S_{4,0}$, $S_{5,0}$, $S_{6,0}$ and $S_{7,0}$ are four types of dock station origin. Among them, most residents who borrow public bicycles from $S_{4,0}$ ride nearby, and only a few residents ride far. Therefore, the average riding distance d_1 is relatively small, which reflects the riding distance of most residents who borrow from this station. Similarly, the average riding distances d_2 , d_3 , and d_4 of $S_{5,0}$, $S_{6,0}$ and $S_{7,0}$ also reflect their corresponding riding distances. The calculation formula of d_i as follows:

$$d_i = \frac{1}{n} \sum_{j=1}^n \sqrt{(X_{i,0} - X_{i,j})^2 + (Y_{i,0} - Y_{i,j})^2}, \quad (3)$$

$$\Delta d_i = d_i^p - d_i^a, \quad (4)$$

where n represents the number of destination dock stations, d_i represents the mean riding distance of the origin dock station as shown in Figure 5d, d_i^p represents the predictive mean riding distance of the origin dock station, d_i^a represents the actual mean riding distance of the origin dock station, and $(X_{i,0}, Y_{i,0})$ and $(X_{i,j}, Y_{i,j})$ represent the corresponding position coordinates of the dock stations.

5. Analysis Results

5.1. Spatial Difference of Reduced Public Bicycle Trips during the PRS

Figure 6 presents the analysis results of the spatial difference in reduced public bicycle trips during the PRS in the entire city area based on the workdays and weekends. The mean value of 19 workdays and 7 weekend days is calculated. This study shows a very obvious decline in public bicycle trips during the PRS, which reduced by 52.86% on workdays and 65.54% on weekend days. The predictive values of workdays and weekends reveal no significant difference in the number of public bicycle trips, with only a gap of 7813 daily trips. The trips are mainly concentrated in the CBD of each district, with the transfer of trips from employment districts to business districts on weekends. However, the semantic difference in the reduced amount of public bicycle trips is obvious during the PRS. During workdays, the trips decreased greatly in residential blocks and school districts, but the

change in urban transport nodes is small. During weekends, the trips decreased greatly in urban transport nodes, school districts, business districts, and employment districts.

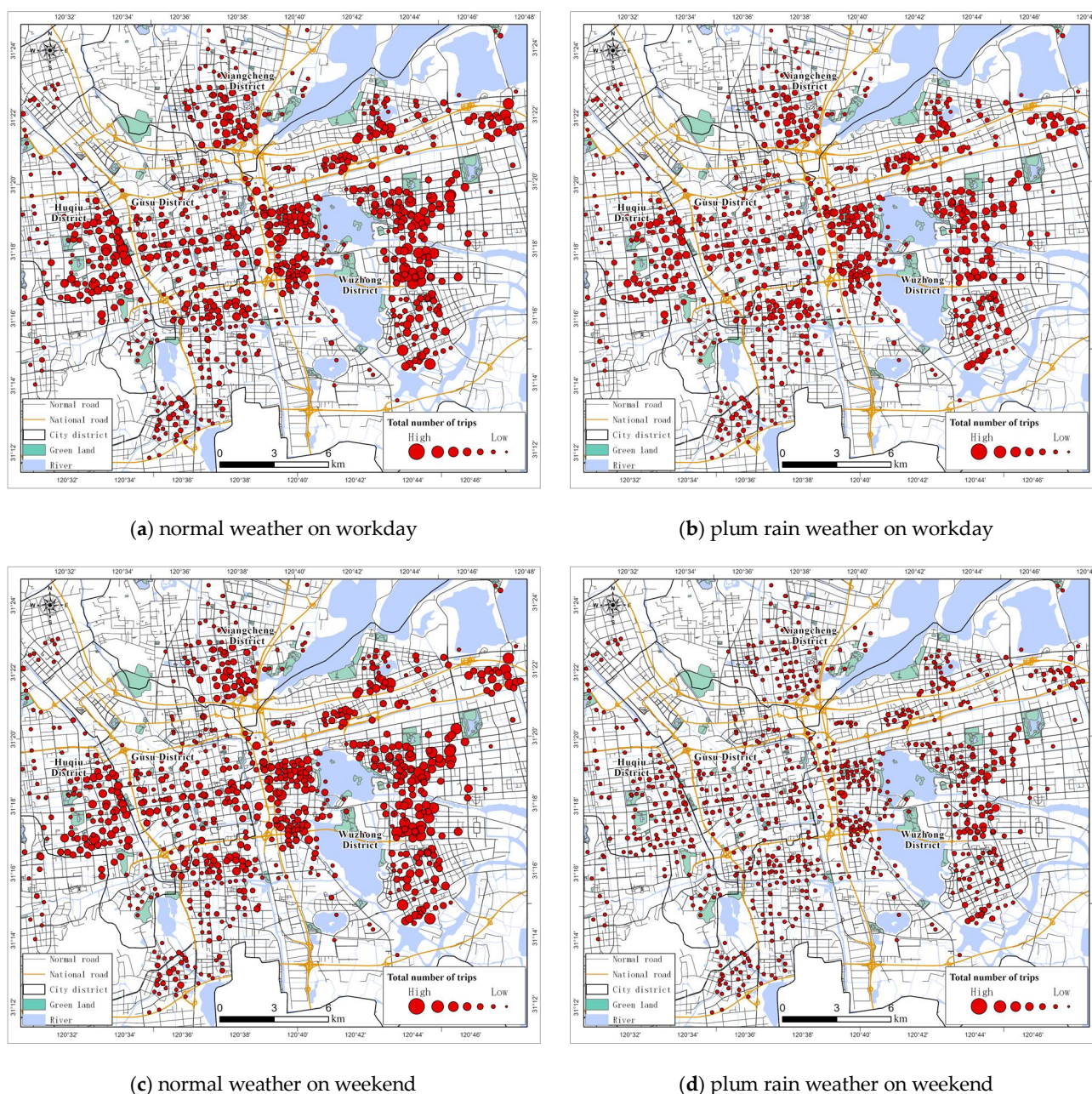


Figure 6. Comparison of public bicycle trips in normal weather and PRS.

The standard deviation reflects the dispersion degree of the number of public bicycle trips. Table 1 shows that the difference in the number of trips between stations during the PRS (42.94) is much smaller than that in normal weather (85.31). During the PRS, the difference in the number of trips between docking stations on weekends (33.00) is much smaller than that on workdays (42.94). The clustering coefficient is used to reflect whether the trips of all docking stations have agglomeration characteristics. The closer the docking stations with large trips are, and the closer the docking stations with small trips are, the greater the spatial clustering coefficient of the docking stations is. However, if the docking stations with large trips are adjacent to those with small trips, the spatial clustering coefficient is relatively low. Table 1 also shows that the clustering coefficients of the four cases are not very different and are slightly higher on weekends than on workdays,

indicating that docking stations with the same number of trips on weekends have slightly greater spatial agglomeration than on workdays.

Table 1. Statistical characteristic of predicted and observed value.

Statistical Characteristic	Workday (Predicted Value)	Workday (Observed Value)	Weekend (Predicted Value)	Weekend (Observed Value)
Total number of trips	106,690	50,283	98,877	34,071
standard deviation	85.31	42.94	84.47	33.00
clustering coefficient	38.17	36.17	40.62	41.39

5.2. Spatial Distribution of Affected Level

5.2.1. Affected Level Analysis Based on the Number of Cyclists

Assuming that each trip record corresponds to a different cyclist, the greater the reduction in trips is, the greater the number of cyclists affected by the plum rain weather is. The spatial distribution of affected level based on the change in the number of cyclists during the PRS is shown in Figure 7. The level of impact is divided into seven groups for the docking stations of public bicycles. Notably, the high- and low-level values are evenly distributed, and the different levels are evenly distributed in the entire city area. The bar chart of grading statistics indicates that the number of each level of workdays is roughly the same as the number of weekends. The affected level of public bicycle docking stations on weekends is larger than that on workdays. During workdays, the public bicycle trips in the CBD with a bundle of residential blocks are more affected than in the CBD with business districts, urban transport nodes, and employment districts. During weekends, the decrease in public bicycle trips in employment districts is large. The high impact level is mainly distributed in the east, middle, and west of the city.

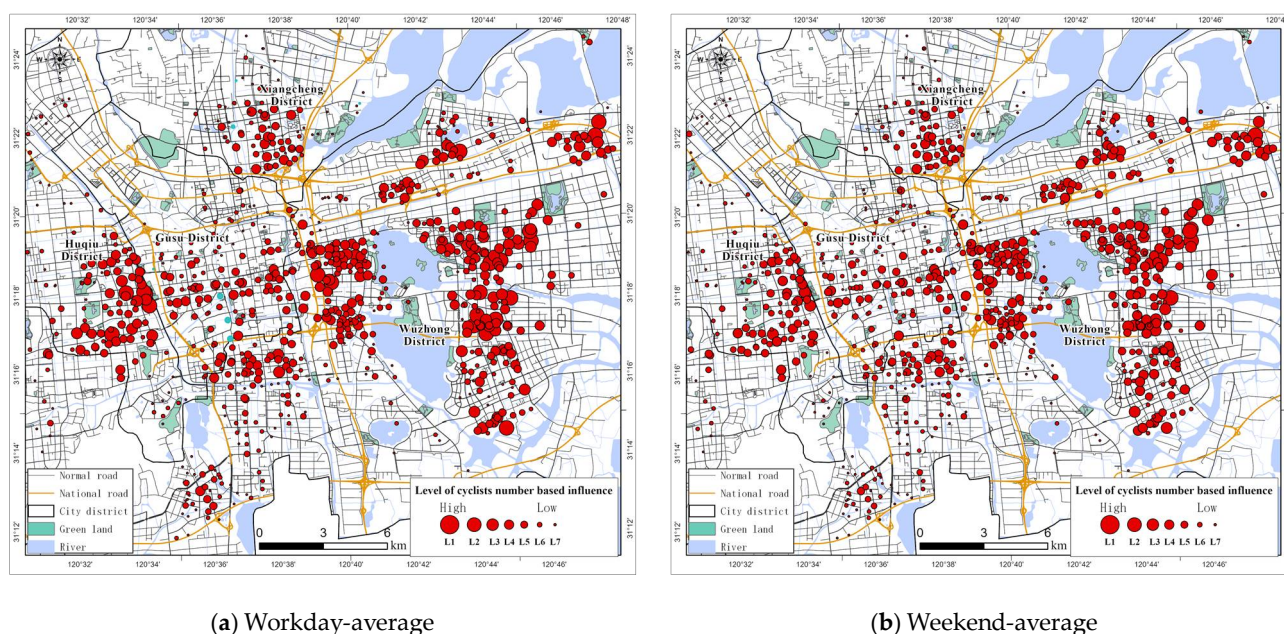


Figure 7. Cyclists number-based impact analysis result.

5.2.2. Affected Level Analysis Based on Place Semantic

The spatial distribution of the affected level based on place semantic characteristics during the PRS is shown in Figure 8. Residents' travel choice by public bicycle is largely related to their travel purpose, and the realization of their travel purpose depends on the nature of the corresponding place. A portion of public bicycle travel demand can be

eliminated or reduced due to the adjustment of travel purpose or travel time during rains, such as staying in the mall or at home and choosing car-hailing services. In the overall city area, the number of docking stations with different affected levels varies greatly. In addition, the proportion of the moderately affected level is also large, accounting for half of the total number. The distribution of the affected level based on place semantic is featured by east-west zonal characteristics, which might be mainly caused by transferring to the subway mode. By contrast, the distribution of affected levels on weekends is relatively wider than that on workdays but with no change in the east-west zonal characteristics. This phenomenon demonstrates that the docking stations in urban transport nodes and employment districts are affected greatly during rains.

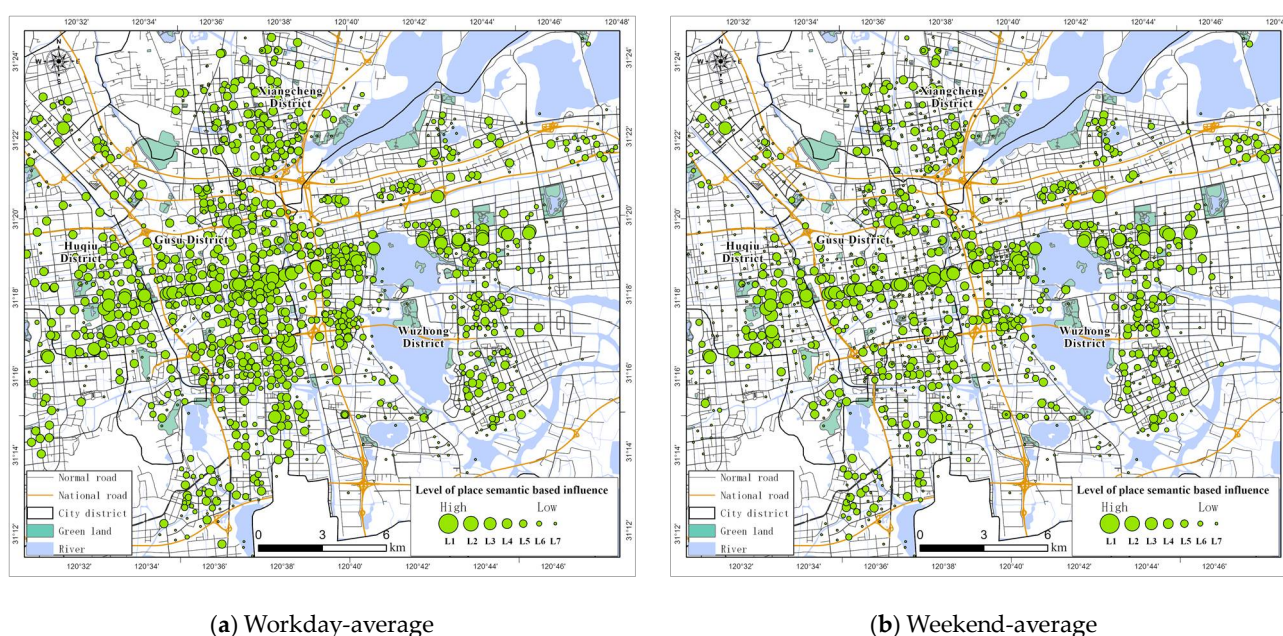
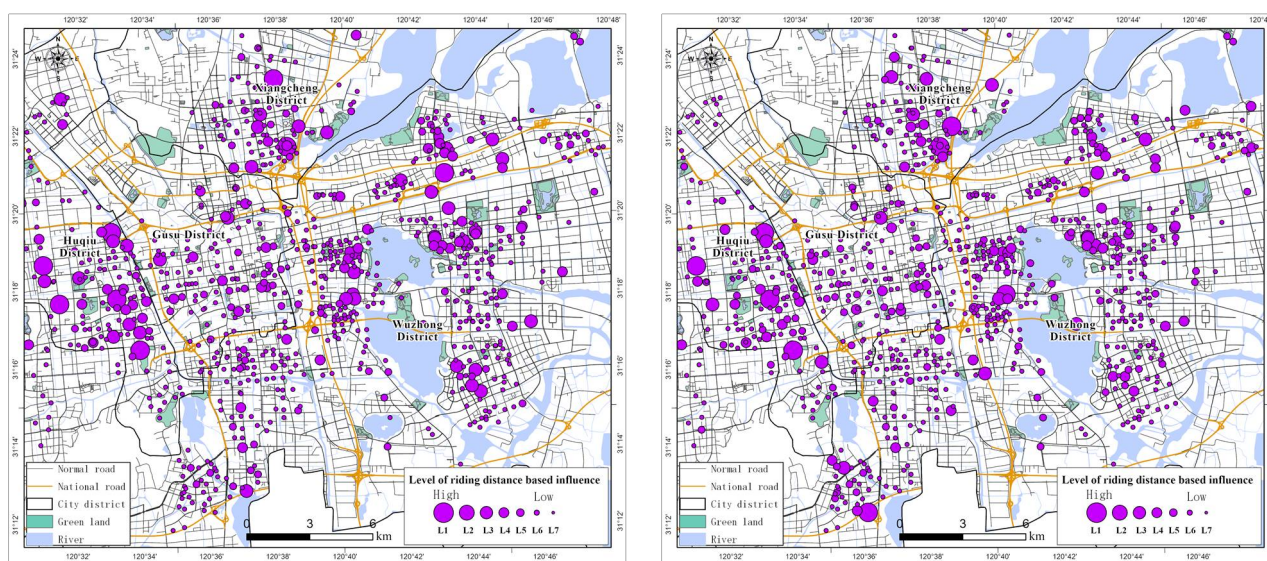


Figure 8. Place semantic-based impact analysis result.

5.2.3. Affected Level Analysis Based on Riding Distance

The spatial distribution of the affected level based on riding distance change during the PRS is shown in Figure 9. The discrete distribution characteristics are obvious according to seven levels, particularly in the city outskirts. Comparison shows that the distribution of affected levels on weekends is relatively wider than that on workdays. To some extent, this phenomenon reflects the fact that residents in the city outskirts rely more on public bicycles for daily travel and cover longer riding distances than residents in the city center. First, two highly affected levels accounted for 81% on workdays and weekends, indicating that during rain, the riding distances would be greatly affected, regardless of the day. This phenomenon might be caused by the halt in the use of public bicycles during rain, or switching from long distance riding to short distance riding.

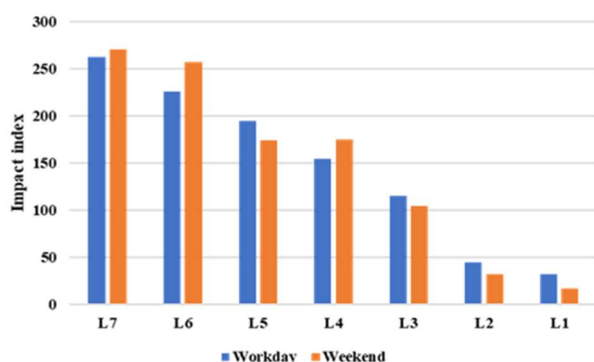
On the whole, docking stations with high affected levels are comparatively less, while docking stations with high affected levels are the majority. The statistical results of the number of docking stations with affected levels is shown in Figure 10 from three perspectives. The level of impact index (L1 to L7) is customized in this study, and the natural discontinuity method is adopted for the grading threshold. The number of corresponding docking stations decreases in a gradient close to each other based on the cyclist number, which is relatively stable. In contrast, there are more docking stations belonging to the low affected level than those belonging to the high affected level based on cycling distance. In addition, the gradient of the number of docking stations based on place semantics decreases between the other two.



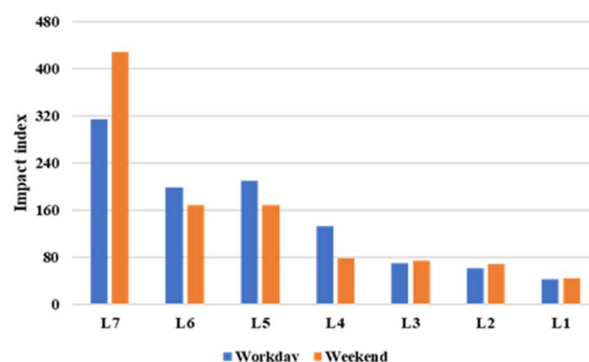
(a) Workday-average

(b) Weekend-average

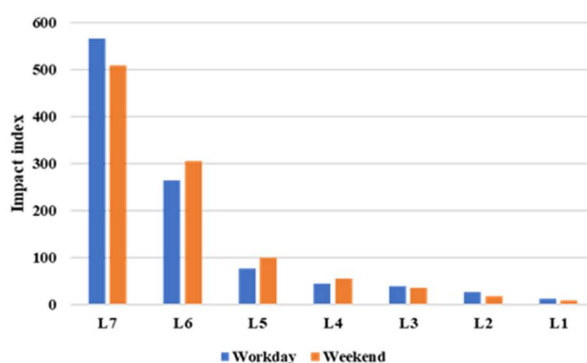
Figure 9. Riding distance-based impact analysis result.



(a) Cyclists number-based impact



(b) Place semantic-based impact



(c) Riding distance-based impact

Figure 10. Statistical results of the number of docking stations with different affected levels from three dimensions.

5.3. Spatial Pattern of Multivariate Impact by Plum Rain

The spatial pattern of the multivariate impact of the PRS on the unavailability of public bicycles to residents is analyzed by the clustering algorithm [38]. Figure 11 shows the impact results of docking stations based on the number of cyclists, place semantic, and

riding distance on workdays and weekends. Tables 2 and 3 show the description of each multivariate impact spatial pattern and the corresponding proportion.

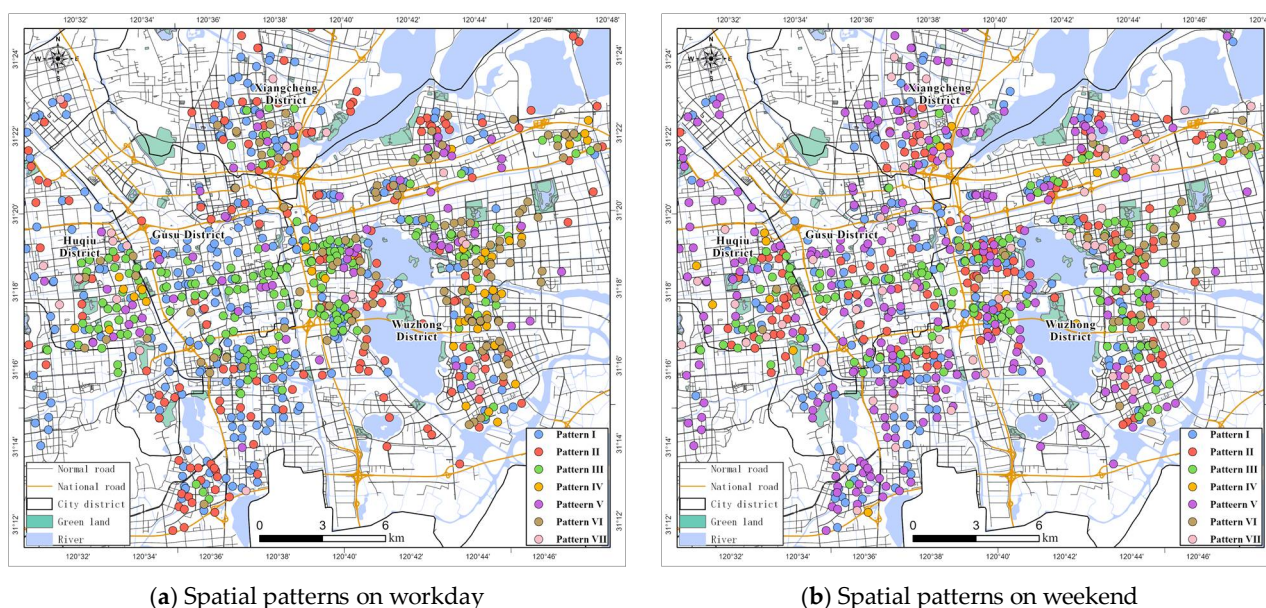


Figure 11. Spatial patterns of impact by multiple factors.

Table 2. Statistical and descriptions for the spatial patterns on workday.

Pattern Name	Proportion	Description of Pattern		
		Riding Distance-Based Impact	Place Semantic-Based Impact	Cyclists Number-Based Impact
Pattern I	29.87%	Moderate	High	Low
Pattern II	26.21%	Moderate	Low	Low
Pattern III	18.40%	Moderate	High	Higher
Pattern IV	4.45%	High	Moderate	Higher
Pattern V	7.12%	Higher	High	High
Pattern VI	11.47%	Moderate	Low	Higher
Pattern VII	2.47%	Higher	Moderate	Moderate

Table 3. Statistical and descriptions for the spatial patterns on weekend.

Pattern Name	Proportion	Description of Pattern		
		Riding Distance-Based Impact	Place Semantic-Based Impact	Cyclists Number-Based Impact
Pattern I	19.56%	Moderate	High	Low
Pattern II	15.27%	Moderate	Low	Higher
Pattern III	16.07%	Moderate	High	Higher
Pattern IV	1.70%	High	Moderate	Moderate
Pattern V	36.23%	Moderate	Low	Low
Pattern VI	4.19%	Higher	High	Higher
Pattern VII	6.99%	Higher	Moderate	Moderate

The workday characteristics during the PRS are shown in Figure 11a. The docking stations belonging to Pattern I accounted for 29.87%, which is the highest proportion, indicating that regardless of the number of cyclists, the place semantic of docking stations

has an obvious influence, with a moderate reduction in riding distance during the PRS. The docking stations belonging to Pattern II accounted for 26.21%, indicating that the riding distance decreased moderately regardless of the number of cyclists and place semantic. The two patterns with blue and red color points are distributed discretely and uniformly in the entire city area. The docking stations belonging to Pattern III accounted for 18.4%, indicating that the riding distance decreased moderately regardless of the number of cyclists and the place semantic. The corresponding points with a green color are mainly distributed in the CBD areas of the *Gusu*, *Xiangcheng*, and *Wuzhong* districts, the Industrial Park, and the High-tech zone. The docking stations belonging to Pattern III accounted for 4.45%, indicating that public bicycle trips decreased greatly with a sharp decline in the number of cyclists, and the riding distance decreased obviously. The corresponding points with an orange color are mainly distributed in the industrial park and sporadically distributed in the CBD area of the *Xiangcheng* district and the High-tech zone. Pattern V, with an obvious impact on the three aspects, only accounts for 7.12% and shows a zonal distribution in the direction of the east-west band. Pattern VI, with an obvious impact on the number of cyclists and a moderate impact on riding distance, accounts for 11.47% and is mainly distributed in the industrial park. Finally, Pattern VII, with the obvious impact on riding distance and a moderate impact on the others, accounts for 2.47%, which is the lowest proportion. Similarly, the weekend characteristics during the PRS are generalized in Table 2. By contrast, the proportions of Patterns I, III, IV, and V declined, whereas those of Patterns II, VI, and VII increased. This phenomenon can be attributed to the decline in users cycling to work on weekends and the increase or decline for other purposes during the PRS. The corresponding spatial distribution is shown in Figure 11b.

6. Discussion and Conclusions

6.1. Discussion

6.1.1. Unfixed Rainy Days and Interannual Variability of the PRS

In this study, the average effect of the unavailability of public bicycles on workdays and weekends is analyzed, rather than the change in the daily utilization of public bicycles. This consideration is related to the special characteristics of plum rain in the Yangtze-Huaihe river basin. Plum rain occurs in the summer, which is the reason that the utilization of public bicycles is still relatively high even if it rains. The PRS has three important indicators, namely the position of the subtropical ridge line, the daily mean temperature, and the discrimination of the number of rainy days during the rainy period. Though proof of rain belt repeatability every year exists, it has great inter-annual variation with substantial differences in the beginning and end times and the strength of rainfall. The rain front is particularly active with frequent rainstorms in some years and not obvious in dry weather. Moreover, some days are rainy and some days are overcast or cloudy during the PRS. In such circumstances, the utilization of public bicycles during the PRS shows corresponding variability and uncertainties inherent from day to day. Thus, such a phenomenon also indicates that in some days during the rainy season, the utilization of public bicycles per day does not decrease greatly. Consequently, selecting the perspective of the average impact on workdays and weekends is more representative than single day.

6.1.2. Perspectives Selection of Affected Dimensions

Congruent with the literature [42,43], public bicycle use is more susceptible to weather than buses, the subway, and taxis given the outdoor exposure. This indicates that meteorological variables have a clear effect on cycling. Suzhou city is located in the subtropical monsoon maritime climate where the temperature does not reach low enough to snow. Thus, the utilization of public bicycles is mainly affected by rainfall, especially continuous rain. Although the numbers of public bicycle trips vary greatly among different docking stations, the relative stability of the number of public bicycle trips for the same docking station can generally be maintained on non-rainy days. Consequently, the difference between the utilization in normal weather and the plum rain weather is the rough impact on the public

bicycle system. Such subjective accounts have been studied by scholars [44,45] through descriptive and inferential statistics for understanding the demographic and socio-economic characteristics of the user. As confirmed by the results of this study, an important issue lies in the selection of the number of cyclists, place semantic, and riding distance as the affected dimensions. The spatial heterogeneity from three perspectives is confirmed and quantified as well. Essentially, the reduction of riding residents causes the reduction in public bicycle trips. The core of the place semantics is the place, while the riding distance refers to the bicycle. That is, the idea of this paper is set out between “cyclists-places-bicycles” and the plum rain weather. Another problem is whether a comprehensive indicator can reflect these three affected aspects. This problem was explored, revealing that completely different units would result in uninterpretable results. Therefore, the spatial clustering algorithm is applied to reflect the comprehensively affected patterns, not only ensuring the spatial combination structure of the perspectives but also the interpretability of the model results.

6.2. Conclusions

This study explores the spatial pattern of the effects of the unavailability of public bicycles for residents’ transit during the plum rain season, based on the number of cyclists, place semantics and riding distance. Plum rain weather definitely has a great impact on residents’ public bicycle trips. In the dimension of the number of cyclists, the docking stations with different affected levels are distributed across the whole urban area. By comparing workdays and weekends, the spatial patterns of the affected level are similar, but the impact of plum rain on weekends is slightly smaller than that of workdays. Although the impacts of plum rain weather on residents at different docking stations are different, the stations with the same affected level do not have spatial agglomeration. In the place semantic dimension, the docking stations with high affected levels show a clustered zonal distribution. For docking stations with high affected levels, the spatial distribution patterns are similar on workdays and weekends. This indicates that the impact of plum rain weather on residents is far greater than that of weekends. In the dimension of cycling distance, the docking stations with high affected levels are mainly distributed in the periphery of the central urban area, and show a cluster-type spatial agglomeration pattern on weekdays and weekends. Other docking stations with low affected levels are randomly distributed on workdays and weekends. Obviously, residents in the suburbs are the most affected group. In addition, the docking stations with high affected levels under all three dimensions are very few both on workdays and weekends, while the docking stations with low affected levels under all three dimensions are much more.

Improving climate resilience is an important means of reducing future risks for the sustainable transportation. This study theoretically expands the impact mechanism of the transport environment (plum rain weather) and active transport mode travel. It is beneficial to the planning and adjustment of public bicycle dispatch and layout optimization in time and region in different perspective in practice. For instance, docking stations should be modestly increased in highly affected locations in suburbs based on riding distance. The spatial correlation perspective is considered to combine the hard environment of the plum rain weather with the soft environment of transportation demand management, which strengthens the connection between travel behavior and urban geography. Since it will take a long time for some climate change mitigation measures to have any real impact, there is no way to minimize negative impacts without adaptation. One possible policy is to push for a mode shift in travel patterns during the plum rain period. For instance, taxi or ride-hailing travel demand derived from public bicycle trip reduction could be enhanced through supply management, especially at the docking stations near the subway. Since the climate phenomenon of plum rain also exists in Taiwan, Liaodong Peninsula, the southernmost part of the Korean Peninsula, and central and southern part of Japan in the subtropical monsoon climate zone. Obviously, public bicycle system in these countries and regions will face the same problems. Consequently, the scientific problem and analytical methods proposed in this paper have general application.

The study is conducted from a geospatial perspective, considering rain rather than the size and duration of rainfall in a day. We also found that the impact on the unavailability of public bicycle transport to residents will also vary under heavy, light, all day rain, and a few hours of rain during the PRS by data mining. The granularity of the study can be further refined. Moreover, the inter-annual variation characteristics of public bicycle unavailability during the PRS can be studied further if consecutive years of relative public bicycle operation data are available. The time dimension of the study could also be expanded. Corresponding work should be carried out systematically in the future.

Author Contributions: Conceptualization, Lijun Chen; methodology, Lijun Chen and Haiping Zhang; software, Haiping Zhang; validation, Lijun Chen; investigation, Lijun Chen, Haoran Wang and Peng Wu; resources, Lijun Chen; writing—original draft preparation, Lijun Chen; writing—review and editing, Lijun Chen and Peng Wu; project administration, Lijun Chen. All authors have read and agreed to the published version of the manuscript.

Funding: This research is supported by the National Natural Science Foundation of China (51408386).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Due to confidentiality agreements, supporting data can only be made available to bona fide researchers subject to a non-disclosure agreement.

Acknowledgments: Special thanks Urban Management Bureau of Suzhou Municipality for data support.

Conflicts of Interest: The authors declare no conflict of interest.

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