

Research Article

Hotspots Identification and Classification of Dockless Bicycle Sharing Service under Electric Fence Circumstances

Ying Hui, Yingkun Xie , Qing Yu , Xiaolei Liu , and Xinyuan Wang 

The Key Laboratory of Road and Traffic Engineering, Ministry of Education, Tongji University, College of Transportation Engineering, 4800 Cao'an Road, Shanghai 201804, China

Correspondence should be addressed to Qing Yu; 1810514@tongji.edu.cn

Received 18 December 2021; Revised 27 February 2022; Accepted 11 March 2022; Published 31 March 2022

Academic Editor: Linchuan Yang

Copyright © 2022 Ying Hui et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Dockless bicycle sharing is one of the low-carbon transportation modes towards sustainable mobilities. Electric fences, as an effective solution for parking management, may have a high potential in guiding the usage of dockless bicycles at a low operation cost. However, new issues arise with the implementation of electric fences. The location of electric fences in hotspots fails to match the parking demand, leading the parking congestion in urban central areas. In this paper, a novel methodology of bicycle hotspots identification and classification is proposed to support parking management. An evaluation framework for bicycle hotspots is also proposed covering three aspects: demand and supply, unbalance, and land use. The methodology is applied to the case of Xiamen Island by using the trip data covering 53,629 bicycles during morning peak hours. Applying the methodology proposed, 47 pick-up hotspots and 53 return hotspots are identified, respectively. The total parking overload of return hotspots during the morning peak is 12,587 bicycles in Xiamen Island. The 53 return hotspots are classified into three clusters, including (1) hotspots where bicycle sharing is in overload status, (2) hotspots where bicycle sharing service quality needs to be improved, and (3) hotspots where bicycle sharing is in stable status. Based on the demand and land use characteristics, parking management schemes and policy implications are proposed. The result of this paper provides guidance for the layout of dockless bicycle sharing electric fences in different areas.

1. Introduction

Bicycle sharing (BS) is a popular short-distance travel mode all over the world, which promotes the healthy and low-carbon lifestyle of society. In the urban transportation system, it plays a key role in solving “the last-kilometer” problem and connecting to the public transit. Since the birth of the first generation of bike-sharing program “White Bike” in Amsterdam in 1965, BS has undergone several system updates [1]. The original bike-sharing systems were mainly docked ones, which means users need to return the bikes to fixed stations. With the development of information technology and the popularization of smart devices, the dockless bike-sharing system emerged in 2016, especially in China. The bicycle-sharing systems showed an oversupplied situation after a large number of BS operators entered the market, such as Mobike, HelloBike, and DiDiBike [2], and

Xiamen is of no exception [3]. The regulatory authorities mandated in 2020 that the total number of shared bikes in Xiamen should not exceed 150,000 bikes, with 100,000 on Xiamen Island and 50,000 off the island, in order to reconcile the market order. Data shows that the average daily turnover rate of shared bicycles in Xiamen has remained at 3 to 3.5 times.

The dockless BS returning is more unregulated than docked BS, resulting in higher operation and maintenance costs. As a result of human movement patterns, the BS system demonstrated spatiotemporal unbalance, which refers to the gap between inflow and outflow in both time and space dimensions. Rebalance schemes were developed and enhanced with the use of big data models to solve the problem [4]. Rebalance implies redistribution to achieve a state where all stations have roughly equal proportions of bicycles to docks [5].

Hotspots, or places with high BS demand, received extra attention throughout the rebalancing process. In this paper, a BS hotspot is defined as an area where a large number of shared bicycles enter or exit in a short time. For BS operators, peak hour demand in hotspots is a challenge in terms of effective and timely repositioning. For BS users, the hotspots relate to the accessibility of sufficient bikes. For the government, the disordered parking situation has always been a problem. Subdivided region analysis and policy recommendations are required [6].

With the availability of high-precision positioning technology, the electric fence was introduced to BS in Xiamen on April 1, 2020. Electric fences, based on Global Position System (GPS) or Bluetooth, provide a solution for parking management. With the implementation of electric fences, however, new issues related to the BS operation arise. One of the challenges that BS is encountering is electric fence planning and design. While 15,202 electric fences are distributed in urban areas of Xiamen, there is a lack of assessment of the electric fence. For example, does the location of the electric fences matches the parking demand in the corresponding hotspot? Another issue is determining how to design a penalty for illegal parking and user incentives schemes to assist with parking management.

The main contributions of this paper are as follows:

- (i) The methodology of bicycle sharing hotspot identification and classification is proposed
- (ii) The hotspot evaluation framework covering demand & supply, unbalance, and land use is developed
- (iii) A differentiated management strategy for bicycle sharing parking is provided

The graphical abstract is available in the supplementary file (available here). You can get a clear outline of the main findings of this paper by using this visual summary.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of research related to this study. Section 3 presents the methodology framework of hotspots identification and classification. In Section 4, a case study in Xiamen Island is presented. Section 5 summarizes the main conclusions of this paper and proposes future directions.

2. Related Works

Since bicycle sharing systems have grown rapidly in the last two decades, particularly prospered again in the past five years in China, a large number of studies on BS have emerged. Recent researches primarily focus on demand prediction and fleet rebalance.

2.1. Demand Prediction. Accurate estimations for BS travel demands are crucial for successful bike management and fleet rebalance [7]. Generally, the demand prediction can be completed in two steps: the spatial unit setting and prediction algorithm design. Chen et al. [8] proposed a two-phase framework to predict overdemand clusters. In the first

phase, a weighted correlation network was built to support the application of geographically constrained clustering. Feng et al. [9] developed a two-step demand prediction framework where the spectral clustering algorithm was adopted in the first step, station clustering. Similarly, in the research of Huang et al. [10], the Two-Stage Station Clustering algorithm was developed to cluster the central stations and common stations before predicting. In the context of dockless BS, Traffic Analysis Zone (TAZ) was used to predict the gap between inflow and outflow in the work of Xu et al. [11]. Traditional machine learning methods such as Random Forest (RF), Gradient Boosting Decision Tree (GBDT), and Supporting Vector Regression (SVR) were adopted early for demand prediction [9, 12]. With the development and popularization of neural network theory, deep learning methods have widely been used. Qin et al. [13] designed the Spatial-Temporal Bike Flow Prediction (ST-BFP) model, which is a convolutional network based on the residual framework. Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) were used to improve prediction performance [11, 14]. To capture the spatial correlation, Graph Convolutional Network (GCN) was introduced to build a spatiotemporal graph neural network model in work [15]. Another attempt to extract graph-based attributes was made by Yang et al. [7] to enhance short-term prediction. In summary, the spatial unit setting is the basis of demand prediction. Specifically, the spatial unit setting can be divided into three categories: station-based, station-cluster based, TAZ-based.

2.2. Bicycle Fleet Rebalance. Bicycle fleet rebalance refers to the process in which the bicycles are relocated from the oversupply area to the undersupply area. The bicycle rebalance problem (BRP) is crucial to the operation of the system.

Several studies have been devoted to the static BRP (SBRP), which means repositioning bicycles after the whole day's operation [16, 17]. SBRP is abstracted as mixed integer programming (MIP) in previous studies. According to Pal et al. [18], Mixed Integer Linear Program (MILP) could be utilized for solving the SBRP. The proposed MILP formulation can not only handle single and multiple vehicles but also allows for multiple visits to a node by the same vehicle. Liu et al. [19] applied mixed integer nonlinear programming (MINLP) formulation to solve multiple capacitated bike routing problems. Furthermore, an Adaptive Capacity Constrained K-centers Clustering (AdaCCKC) algorithm was proposed to separate outlier stations, reducing the large-scale multiple vehicle routing problems to the inner cluster one vehicle routing problem. Moreover, heuristic algorithms [20, 21] and greedy algorithms [22] have indicated the availability to optimize the rebalance process.

To further optimize the BS system and reduce maintenance costs, dynamic BRP (DBRP) is discussed and studied in depth. DBRP assumes that the whole system is constantly updated, so the rebalancing schemes should be continuously adjusted [23]. Therefore, demand prediction should be involved. Zhang et al. [24] proposed a nonlinear time-space

network flow model to fully integrate the user dissatisfaction estimating, the bicycle repositioning, and the vehicle routing. A more recent study [23] put forward a zone-based two-stage rebalancing method, dividing the research area into two types of zones (zones with deficient bikes (ZDB) and zones with sufficient zones (ZSB)). In the first stage, the ZDB only receives bikes from surrounding ZSB within the initial rebalancing range. In the second stage, based on the result of the previous stage, the remaining ZDB can receive bikes from the rebalancing range that is further away. SBRP and DBRP could be integrated for an advanced rebalance scheme. Tian et al. [25] designed a new framework to solve the rebalancing problem, which contains two aspects: dynamic rebalancing within each station and static rebalancing among stations.

User incentives-based BS fleet rebalance refers to optimizing the bike circulation by leading users to shift bikes between highly active stations and inactive ones [26]. With the interaction of sharing bicycles, users, and the environment, reinforcement learning could be adopted to determine the optimal incentive scheme [27, 28]. Otherwise, worker recruiting showed more cost-efficient compared with traditional truck-based rebalance [29].

2.3. Summary of Related Works. BS electric fences have been implemented in several cities in China. However, up to now, few works have studied electric fence planning, design, and operation. Zhang [30] firstly proposed a methodology framework to support electric fence planning. However, the study result remains at the assumption level, not under implementation. Xie et al. [31] combined the location-based electric fence and image-based bicycle parking place identification to verify the users' parking behavior. Yuan et al. [32] developed high precision virtual electric fence technology based on GNSS, intelligent terminal, and precision orientation algorithm, which achieved submeter positioning precision.

To summarize, as BS advances to a new stage of development, the variety and efficiency of system optimization methods have been improved. For both demand prediction and fleet rebalance, there is a need for accurate division and classification of the operation area, particularly the hotspots. The emergence of the electric fence shows the potential for regulating users' parking behavior. The user incentive scheme provides new ideas for user-based fleet rebalance.

However, to the best of our knowledge, there is little literature integrating the identification and classification of bicycle sharing hotspots with consideration of the electric fence. Policy guidance on the electric fence planning and parking management scheme remains unclear in response to the demands of various stakeholders.

Therefore, in this paper, a novel methodology framework for identifying and classifying BS hotspots is proposed. For the first time, electric fence data, regarded as a parking supply, is used in hotspots analysis. In addition, recommendations on the electric planning and design are given based on the hotspots classification results. The penalty for illegal parking is discussed, as well as user incentive schemes.

3. Methods

3.1. Methodology Framework. The methodology framework of this study is shown in Figure 1. Multisource data including BS trip data, electric fence data, and POI data is collected in this paper to support BS hotspots identification and classification. The methodology framework is as follows.

Task 1: BS hotspots identification. The origin (O) and destination (D) of each trip are extracted from BS trip data. To achieve high-precision recognition, the spatial resolution is set to $50\text{ m} \times 50\text{ m}$ grids. The longitude and latitude of each grid center and the O/D number of each grid are packed as the input of DBSCAN. The determination of neighbor parameters of DBSCAN is done using the KNN method. Finally, the pick-up hotspot (PH) and return hotspot (RH) are identified separately.

Task 2: BS hotspots classification. The return hotspots (RHs) are the critical areas for rebalancing the BS fleet. Meanwhile, the government also pays great attention to the bicycle parking order in RHs. Therefore, the RHs obtained from Task 1 are chosen as the study subject of Task 2's research. To measure the RHs in BS parking demand, parking supply, unbalance, and land use, nine indicators are extracted from the collected data. RHs are classified using the Gaussian mixture clustering method based on the 9 indicators. The classification result is used to provide guidance on parking management schemes and policy recommendations.

3.2. Identification of BS Hotspots. A BS hotspot is defined here as an area where a large number of shared bicycles flow in or out in a short time. The main challenge faced by BS operators and regulators is the hotspot identification and corresponding management strategy. In this paper, we attempt to answer two questions through hotspots identification: How are hotspots distributed in space? Is there a connection between the spatial distribution of hotspots and urban structure?

The key characteristics of hotspots can be listed as follows:

- (1) Closed and continuous in space
- (2) High level of demand
- (3) Temporal dynamic change in demand

Based on the characteristics above, the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) method is adopted with O/D (origin/destination) demand as a clustering feature to identify BS hotspots.

DBSCAN is an unsupervised machine learning algorithm. It is a density-based clustering nonparametric algorithm. The algorithm uses a simple minimum density level estimation based on a threshold for the number of neighbors, minPts, within the radius ϵ (with an arbitrary distance measure) [33]. Compared with the traditional kernel density estimation method, DBSCAN can help identify the boundary of the hotspot area accurately according to the neighbor parameters. The accuracy of identification results

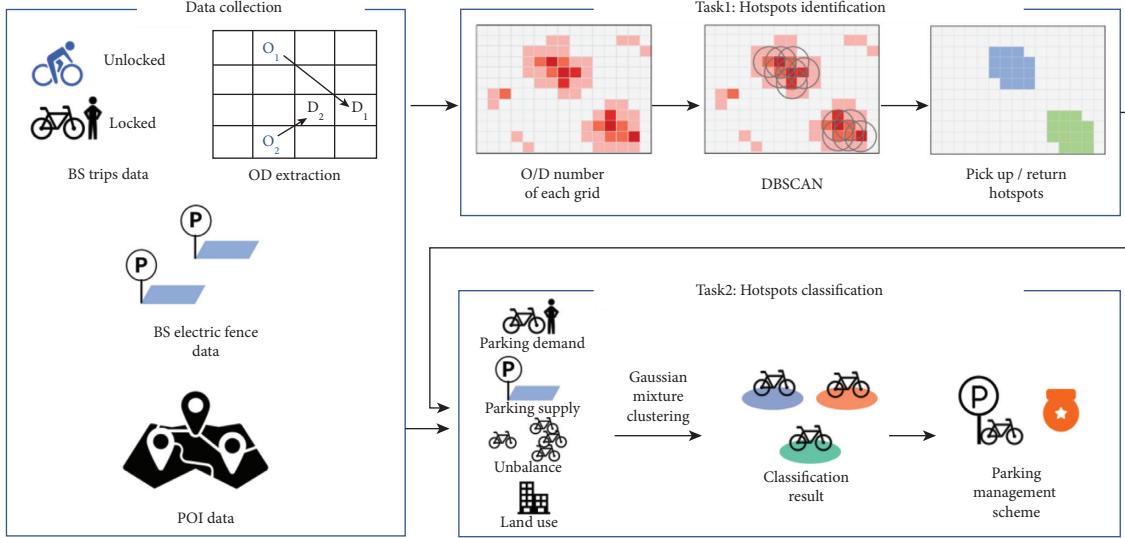


FIGURE 1: Methodology framework.

depends on the two neighbor parameters: the radius ϵ and the number of neighbors (or total weight), minPts.

The longitude and latitude of each grid center are packed as the training instances X , with the BS O/D (origin/destination) demand of each grid being the sample weight. For parameter estimation, firstly, the number of neighbors minPts should be given according to domain knowledge. Then the radius could be determined using the k-distance plot. The average distance corresponding to the elbow point (with the largest slope) is the optimal radius ϵ .

3.3. Evaluation Framework of BS Return Hotspots. In previous sections, BS return hotspots (RHs) could be identified with high precision. In this section, we develop an evaluation framework covering three aspects (supply and demand, unbalance, and land use) to assess the characteristics of RHs and take it as the basis for classification, as shown in Table 1. The following paragraphs explain why certain aspects are chosen.

For supply and demand, it is a crucial independent input in many BS planning problems, such as bicycle relocation, demand management [34]. Çelebi et al. [35] concluded that one of the key motivating factors for bicycle use is the convenience that the service is not interrupted because of the unavailability of empty slots for returns, emphasizing the importance of evaluating the parking supply for shared bicycles. Furthermore, demand level analysis could support the layout planning of electric fences [30].

In terms of unbalance, while BS facilitates people's first/last-mile travel, it can also have negative effects such as infringing on pedestrian rights, blocking bike paths, and impeding metro user flows [36–38], which is caused by spatial-temporal unbalance.

Regarding land use, previous studies have shown that land use factors have an effect on bicycle sharing demand [2, 39–42]. Xing et al. [43] discovered that the bike-sharing trip origin and destination could be divided into five typical groups, i.e., dining, transportation, shopping, work, and

residential places on weekdays. In this paper, we choose three travel purposes from five categories: residential, work, and shopping places.

3.3.1. Demand and Supply. BS parking supply is an important index for RHs assessment. Compared with docked BS, the parking of dockless BS tends to be more dispersed. Bicycle returning has become more restricted since the implementation of electric fences in the real world. The electric fences that specify where the bikes can be returned can be regarded as the parking supply. According to *Planning Standard for Urban Pedestrian and Bicycle Transportation System* published by the Ministry of House and Urban-Rural Development (MOHURD) of China in 2021, it was suggested that the width and length of a single bicycle parking space should be 0.6–0.8 m and 2.0 m, respectively, equivalent to the area of 1.2–1.6 m². In this paper, we determine that the parking area for each bicycle should be 1.5 m². Using the area of electric fences in certain RH and the parking area for one single bicycle, the parking capacity P_c can be calculated.

BS demand is not only the basis for hotspots identification but is also a key index of classification. Although hotspots represent areas with high demand, the demand among these hotspots is still uneven. The BS demand is calculated as follows. Taking a record of OD data (bikeid, origin, destination, stime, etime) as an example, it will generate a departure demand at origin, and an arrival demand at destination. Given a time window Δt , the end of the time window t , and a hotspot H with r bikes inside, there are F_{out} BS trips departing from H , and F_{in} trips arriving in H . The parking demand P_d of hotspot H at time t can be calculated as follows:

$$P_d = r + F_{\text{in}} - F_{\text{out}}. \quad (1)$$

Then, the parking overload of hotspot H at time t can be calculated by the following equation:

TABLE 1: The evaluation indexes of RHs.

Aspect	Indicators	Name of indicators	Description
Supply	P_c	Parking capacity	The maximum number of bicycles that can be parked in this area
	A_d	Arrival demand	The total number of trips whose destination is in this area
	D_d	Departure demand	The total number of trips whose origin is in this area
Demand	P_o	Parking overload	The maximum difference between the number of parking bicycles and the parking capacity
	R_m	Min-max ratio	The ratio between the minimum and the maximum of parking bicycles
Unbalance	P_N	Peak time no.	The no. of the time when the number of parking bicycles reaches its peak
	L_R	Residential POI	The number of residential POIs in this area
	L_O	Office POI	The number of office POIs in this area
Land use	L_C	Commercial POI	The number of commercial POIs in this area

$$P_o = P_d - P_c, \quad (2)$$

where P_d , P_c , and P_o denote the parking demand, parking capacity, and parking overload, respectively, F_{in} , F_{out} represent BS trips arriving in hotspot H and trips departing from hotspot H , and r is the number of existing bicycles of hotspot H .

3.3.2. Unbalance. The spatial-temporal heterogeneity of BS demand and supply leads to the problem of unbalance. Peak time is defined here as the time when the number of parking bicycles reaches a maximum. Min-max ratio represents the ratio between the minimum and the maximum of parking bicycles.

To obtain a better understanding of the unbalance in hotspots during the morning peak, there is a need to study the peak time P_N and min-max ratio R_m . Given time series T_i and hotspot H , the number of parking bicycles P_d varies over time. Suppose its maximum and minimum in T_i are P_{dmax} and P_{dmin} , the min-max ratio R_m can be calculated as follows:

$$R_m = \frac{P_{dmin}}{P_{dmax}}. \quad (3)$$

3.3.3. Land Use. BS trips, like the other modes of transportation, are activity-based. The diversity and intensity of activities may be influenced by land use factors. Previous studies have shown that the frequencies of POIs can disclose and classify urban land use [43, 44]. Therefore, incorporating land use indicators into the evaluation framework makes sense. Here, we used the number of residential POI L_R , office POI L_O , and commercial POI L_C to describe land use attributes.

3.4. Classification of BS Return Hotspots. The Gaussian mixture model (GMM) is used to classify the RHs after extracting nine indicators from multisource data. The choice of GMM clustering is motivated by two considerations. On the one hand, we preliminary investigated the performance of GMM-based classification methods on the classification problems in many application scenarios [45, 46]. Under complex data, GMM has a wider fitter range and the advantage of high generalization ability. On the other hand,

inspired by traffic status classification in Liu et al.'s work [47], we chose GMM to cluster the RHs.

GMM is a common algorithm of prototype clustering in machine learning. GMM uses the Gaussian probability model as a clustering prototype. The definition of the multivariate Gaussian distribution is as follows [48]: Given random variable \mathbf{x} in n -dimensional sample space χ , if \mathbf{x} obeys Gaussian distribution, its probability density function is shown in the following equation:

$$p(\mathbf{x}) = \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} e^{-1/2(\mathbf{x}-\boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x}-\boldsymbol{\mu})}, \quad (4)$$

where $\boldsymbol{\mu}$ is an n -dimensional mean vector and Σ is $n \times n$ covariance matrix. To clearly show the dependence of Gaussian distribution on corresponding parameters, the probability density function is denoted as $p(\mathbf{x}|\boldsymbol{\mu}, \Sigma)$. Then the Gaussian mixture distribution can be defined as follows:

$$p_{\mathcal{M}}(\mathbf{x}) = \sum_{i=1}^k \alpha_i \cdot p(\mathbf{x}|\boldsymbol{\mu}_i, \Sigma_i). \quad (5)$$

The distribution consists of k mixture components, and each mixture component corresponds to a Gaussian distribution. In equation (5), $\boldsymbol{\mu}_i$ and Σ_i are the parameters of the i th Gaussian mixture component, and $\alpha_i > 0$ is the corresponding mixture coefficient. It should be noted that $\sum_{i=1}^k \alpha_i = 1$.

The indicators of RHs are all calculated as the input of the algorithm. The RHs with nine indexes are regarded as the training set $D = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_m\}$. The random variable $z_j \in \{1, 2, \dots, k\}$ represents the Gaussian mixture component of the sample \mathbf{x}_j . The objective of GMM is to divide the set D into k clusters $C = \{C_1, C_2, \dots, C_k\}$. The cluster label λ_j of each sample \mathbf{x}_j is determined as follows:

$$\lambda_j = \operatorname{argmax}_{i \in \{1, 2, \dots, k\}} \gamma_{ji}, \quad (6)$$

where γ_{ji} ($i = 1, 2, \dots, k$) denotes the posterior probability generated by Gaussian mixture components $p_{\mathcal{M}}(z_j = i | \mathbf{x}_j)$.

4. Results and Discussion

4.1. Case Study and Datasets. In this paper, the BS system on Xiamen Island (Xiamen, China) is selected as the study object. In December 2016, the bike-sharing service entered Xiamen and began operations. In 2017, the oversupply of

shared bikes had caused widespread concern in society. Until now, with the promulgation of legislative documents, the amount of shared bicycles has been limited to 150,000. The Xiamen Island, surrounded by the sea, can be considered as a closed area for sharing bicycle operation (Figure 2).

Multisource data including BS trip data, BS electric fence data, and POI data were used for subsequent modeling and analysis. The BS trip data and electric fence data were obtained from the Digital China Innovation Contest (DCIC 2021) official websites. A record of trip data contains the bicycle ID, latitude, longitude, lock status, and update time. When a user picks up or returns the bicycle, a record with time and location status is generated and sent to the server. The dataset includes 198,382 trips during the morning peak (6:00–10:00) of five consecutive weekdays from December 21 to 25, 2020. Although it is winter, the local average maximum temperature is around 20°C, which is suitable for cycling. Furthermore, most of the data processing in this paper is supported by the Python package TransBigData [49].

The descriptive analysis was conducted, and results showed a sharp decline in the number of orders on 2020/12/23 (Figure 3(a)), which was influenced by the moderate rain that was not suitable for cycling. Therefore, the OD data of the other four weekdays will be used for subsequent analysis. The number of orders reaches its peak at 08:10–08:20 (Figure 3(b)). 3/4 of the BS travel distances are within 1,200 meters (Figure 3(c)), which shows that BS is indeed the mode of transportation for the first/last mile. Besides, as shown in Figure 3(d), while some trips last 20 minutes or more, the majority (3/4) of trip duration is within 10 minutes.

The BS electric fence data includes the geographic boundaries of 10,471 electric fences, and each electric fence is a closed quadrilateral connected by five points (Figure 4).

Point of interest (POI) data was obtained from the Baidu web API service. The residential area and commercial & office area are the two most important factors influencing the BS usage frequency [41]. These areas are populated areas with high activity intensity. Therefore, in this paper, three types of POI, residential, commercial, and office, are used as the land use attributes of hotspots.

4.2. Results of Hotspots Identification. A BS hotspot, as defined in methods, is an area where shared bicycles flow in and out in large numbers over a specific time. We define two types of hotspots in this paper: pick-up hotspots (PHs) and return hotspots (RHs), which refer to areas with high pick-up demand and areas with high return demand, respectively.

Prior to identifying hotspots, OD pairs were assigned to the corresponding space unit, with spatial resolution set to 50 m × 50 m grids. The average number of bicycles picked up and returned in each grid was then calculated for the entire morning peak (6:00–9:59) of each weekday.

To identify BS hotspots, the two parameters of DBSCAN, epsilon (ϵ) and minimum samples (minPts), may highly affect the number and the size of hotspots, which should be determined in advance. For selecting minimum samples,

there is no automatic approach. Based on domain knowledge in urban traffic, minPts was set to 150. K nearest neighbors (KNN) method was applied then to find the best ϵ value. By plotting the average k-distances (where $k = \text{minPts} = 150$) in ascending order (Figure 5), the distance corresponding to the elbow of the curve was the best epsilon, that is $\epsilon = 2.5$.

After DBSCAN parameter estimation, the longitude and latitude of the grids are packed as the input of the clustering algorithm. Then, pick-up and return demand are set as sample weights, respectively, to identify the BS hotspots in both situations. It reported 47 pick-up hotspots and 53 return hotspots on Xiamen Island, with different centers indicated by different colors (Figure 6).

There are some interesting findings. Figure 6 shows that 48.8 percent of pick-up hotspots and 37.7 percent of return hotspots are located near metro lines, indicating that BS plays an important role in connecting to the metro transit system and that bicycle trips beginning at metro stations are more frequent. Figure 7 shows, for example, that demand for pick-up and return is high at metro stations during the morning peak on weekdays.

While the demand for bicycle pick-up and the return has reached equilibrium in some areas, which appear in Figures 6(a) and 6(b) simultaneously, there are still some other areas with one-way bicycles inflow or outflow. For example, Figure 8(a) shows that the pick-up hotspot near *Dianqian Road 1st Road*, surrounded by multiple residential districts, failed to become a return hotspot. However, there are two return hotspots on Huli Avenue, where numerous office buildings are located nearby. One possible explanation for this phenomenon might be the separation of work and residence. During morning rush hours, a considerable number of BS users begin their journey from home to work. If the number of job opportunities mismatches the number of employed people in a certain area, the population flow may show one-way inflows or outflows, resulting in the phenomenon mentioned above. Figures 8(b) and 8(c) also present the one-way inflow and outflow in the hotspots, respectively. The observed result could explain the spatial heterogeneity to a certain extent.

4.3. Result of Hotspots Classification. Return hotspots represent the places where a substantial proportion of BS users return shared bicycles. The total parking overload of 53 RHs during the morning peak is 12,587 bicycles, while the total parking demand is 82,677 bicycles, indicating an insufficient parking supply in return hotspots. Further investigation of destination (return behavior) distribution could aid in gaining a better understanding of human mobility during morning peak hours and the role of the BS in the transportation system.

53 RHs are classified into three clusters using the Gaussian-mixture clustering algorithm. The spatial distribution of three types of hotspots is depicted in Figure 9(a). The average normalized scores of multiple indexes for the three clusters are shown in Figure 9(b). The result, depicted in Figure 9(b), indicates the heterogeneity of parking

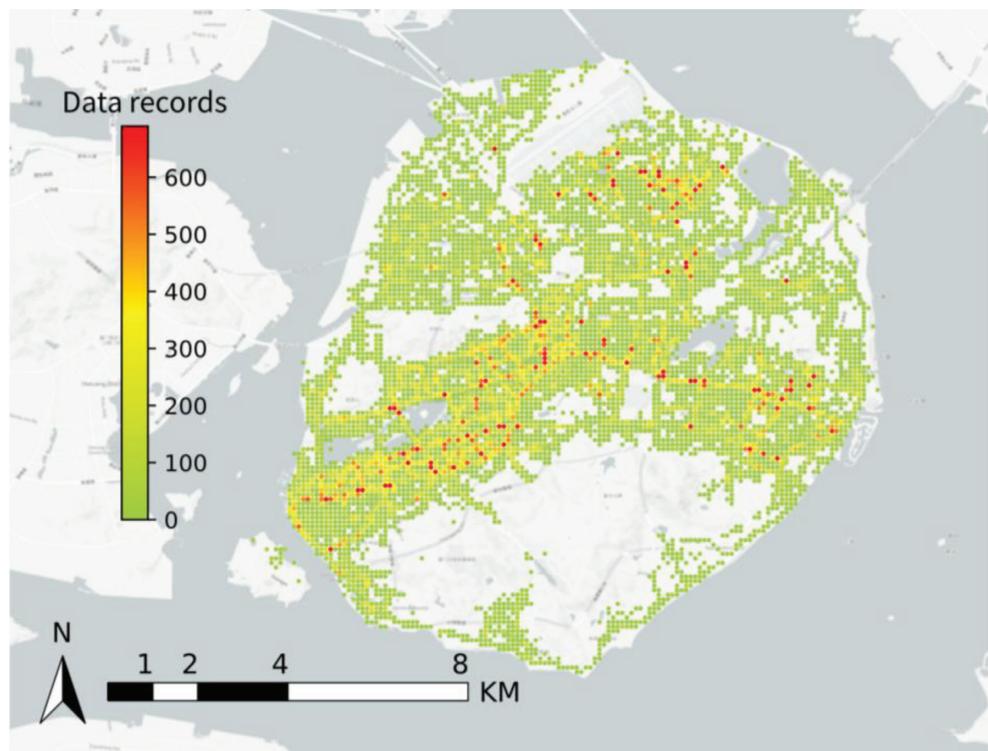


FIGURE 2: BS spatial distribution in Xiamen Island.

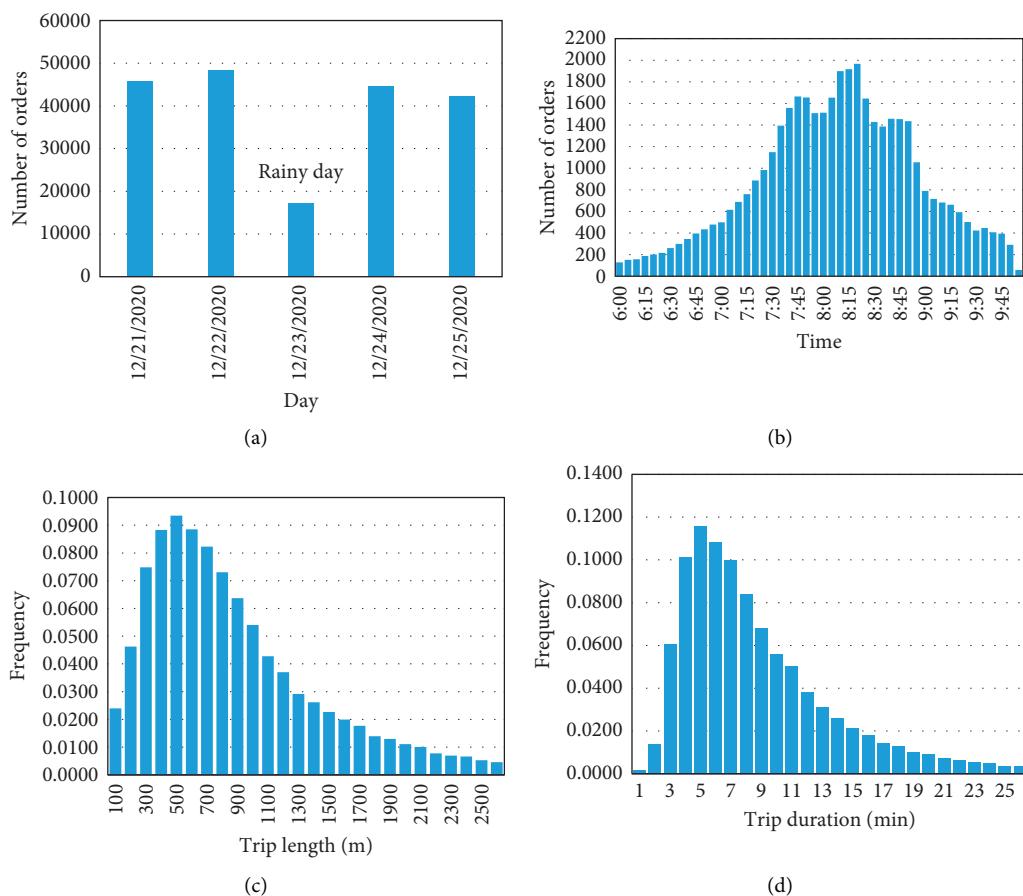


FIGURE 3: BS trip characteristics. (a) Daily distribution. (b) Temporal distribution. (c) Travel distance distribution. (d) Trip duration distribution.

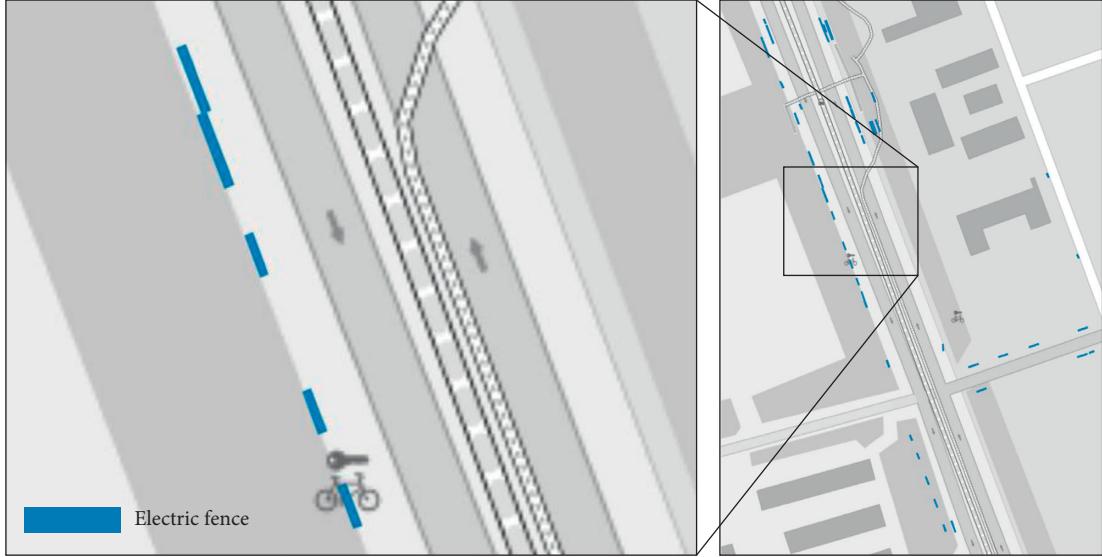
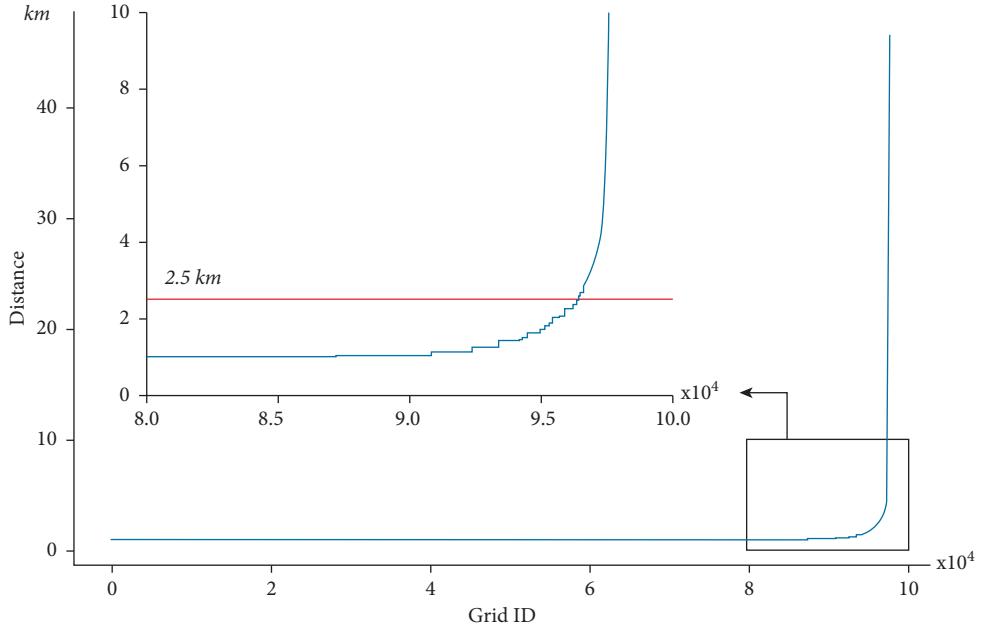


FIGURE 4: BS electric fence geographic data.

FIGURE 5: Points sorted by distance to the k th nearest neighbor.

demand, supply, and land use in the three return hotspot clusters. The unbalance characteristics (minmaxratio, peaktimeno) of the three clusters, on the other hand, show little variation. The gaps between the minimum and maximum BS demand during the morning peak hours, in particular, are nearly the same for the three clusters. Parking bicycles is at a high level in RHs labeled as Cluster 1 or Cluster 2, as shown in Figure 9(c), indicating that more regulatory attention should be paid to the two clusters.

4.3.1. Cluster 1: Hotspots Where BS Is in Overload Status. Cluster 1 accounts for 3.8% (2/53) of all return hotspots. These are typically areas with a high demand for BS service.

Despite having a relatively large parking capacity, it is unable to meet the demand for bike-sharing. In other words, there is a great gap between parking demand and supply in these hotspots. In terms of land utilization, this category has more POI than the other two, indicating that these areas are more developed. At the same time, the proportion of office POI accounts for more than that of residential and commercial POI, resulting in high demand for the last mile to work. For example, Huli Innovation Park is home to numerous high-tech enterprises, and bike-sharing is used as the main mode for employees to enter the park.

In general, the centralized distribution of office POI, such as office buildings, and the undiversified traffic mode structure have resulted in the situation described above.

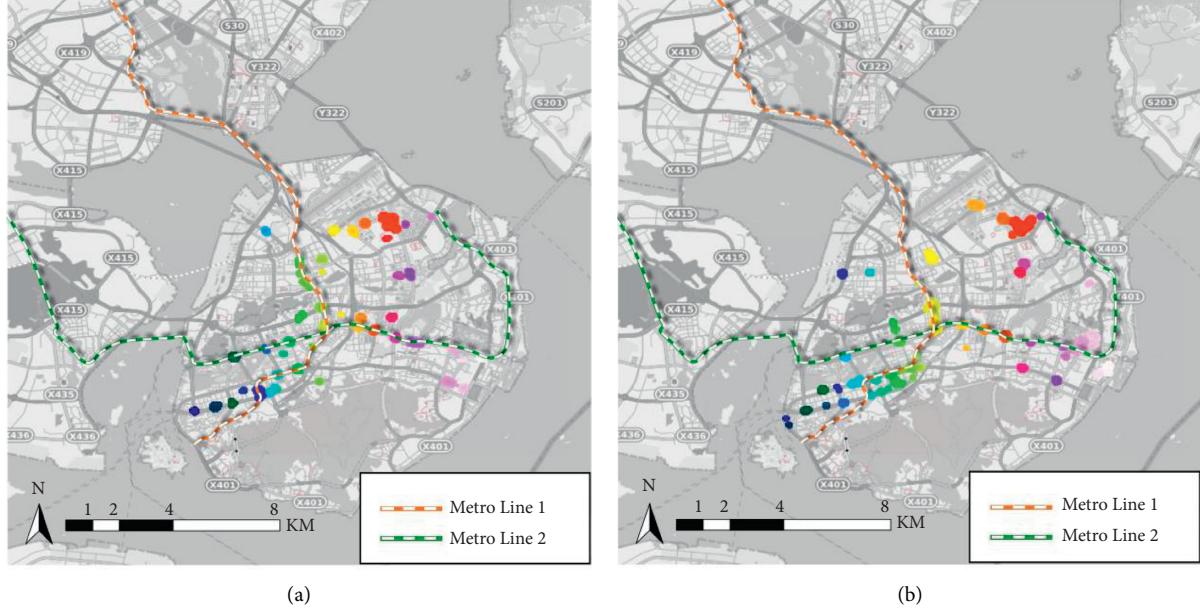


FIGURE 6: Pick-up hotspots and return hotspots. (a) Pick-up. (b) Return.

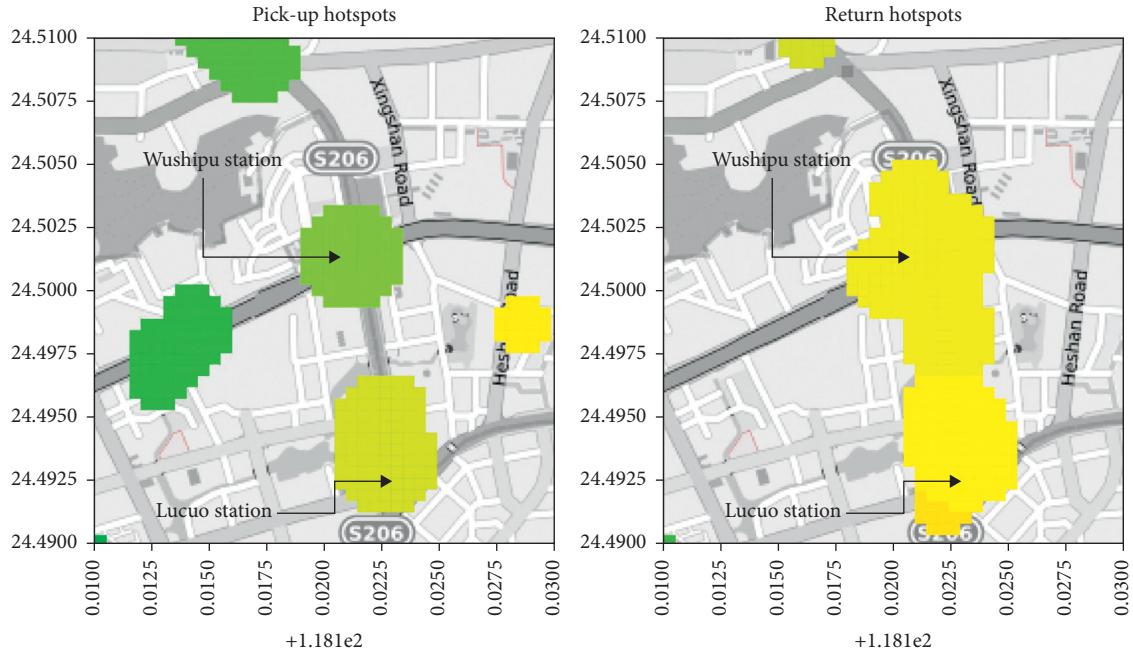


FIGURE 7: Hotspots near the metro station.

The BS is in overload status at this type of hotspot. It appears difficult to solve the problem solely from the perspective of BS.

4.3.2. Cluster 2: Hotspots Where BS Service Quality Needs to Be Improved. 18.9% (10/53) of return hotspots are labeled as Cluster 2. The demand for bike-sharing is medium in these return hotspots. Parking overload is also at a medium level due to a lack of electric fences (parking capacity). For

example, Lücuo metro station, located in the city center, is a transfer hub with ten entrances for Lines 1 and 2. People can reach any metro station on Xiamen Island without making any stops from this metro station. As a result, a large number of BS orders were terminated at this location. On average, land use is fairly balanced. The proportion of residential POI is similar to that of commercial POI but slightly higher than that of office POI.

To summarize, the designated electric fence in Cluster 2 cannot meet the parking demand due to limited roadside

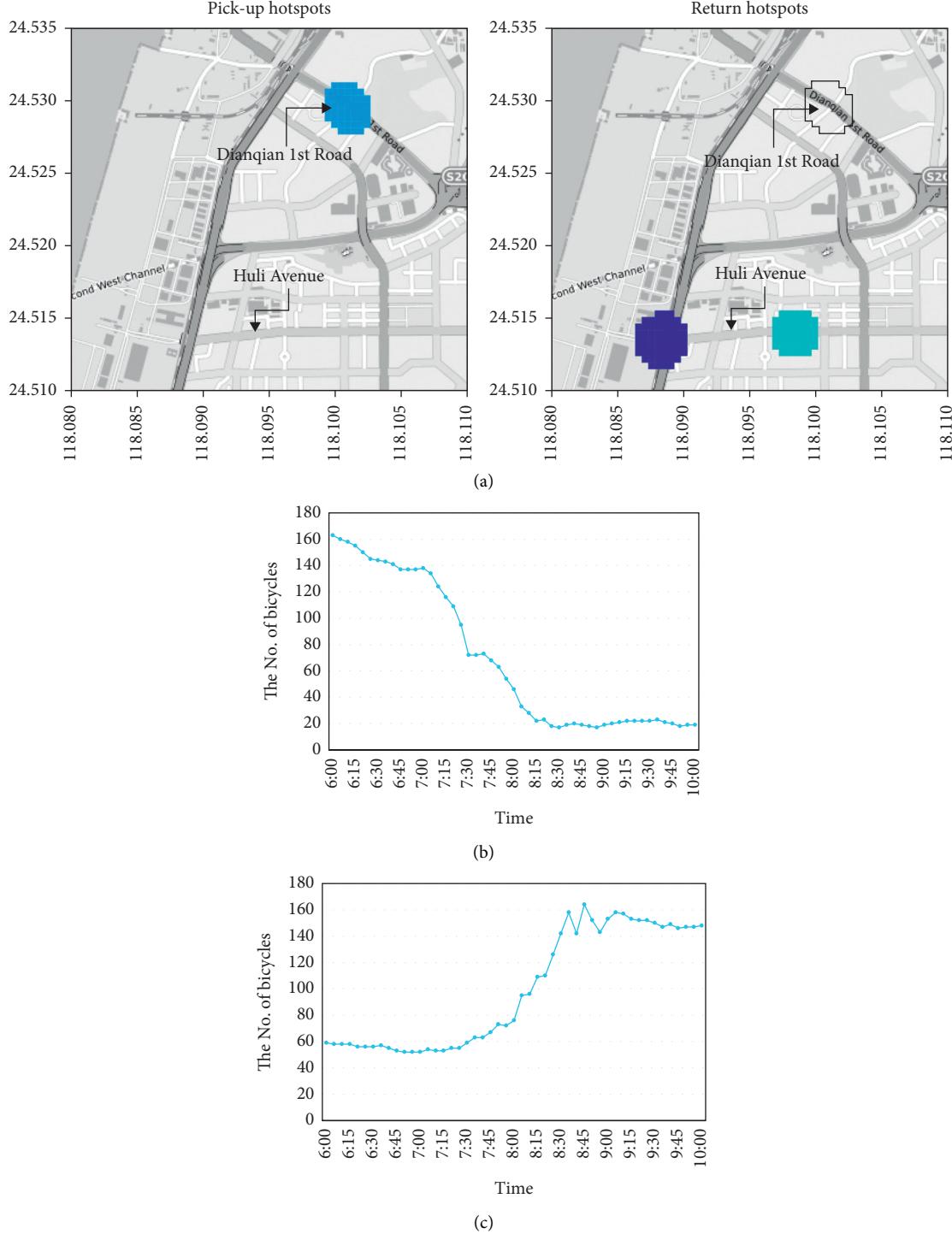


FIGURE 8: Outflow and inflow of shared bicycles in Dianqian 1st Road and Huli Avenue. (a) Hotspots near Dianqian 1st Road and Huli Avenue. (b) The no. of bicycles near Dianqian 1st Road. (c) The no. of bicycles near Huli Avenue.

space. This type of hotspot is the most vulnerable to BS electric fence supply. In other words, if more or larger electric fences could be assigned to the hotspot, parking congestion would be significantly reduced. BS service quality should be improved in Cluster 2 return hotspots by increasing parking supply and strengthening parking management. Otherwise, if users are unable to return their bikes

to the electric fences, there is a risk that shared bicycles will occupy the pedestrian space.

4.3.3. Cluster 3: Hotspots Where BS Is in Stable Status. 77.3% (41/53) of return hotspots are classified into Cluster 3. In such areas, the demand level for bike-sharing is relatively low. Although the parking capacity is insufficient, the

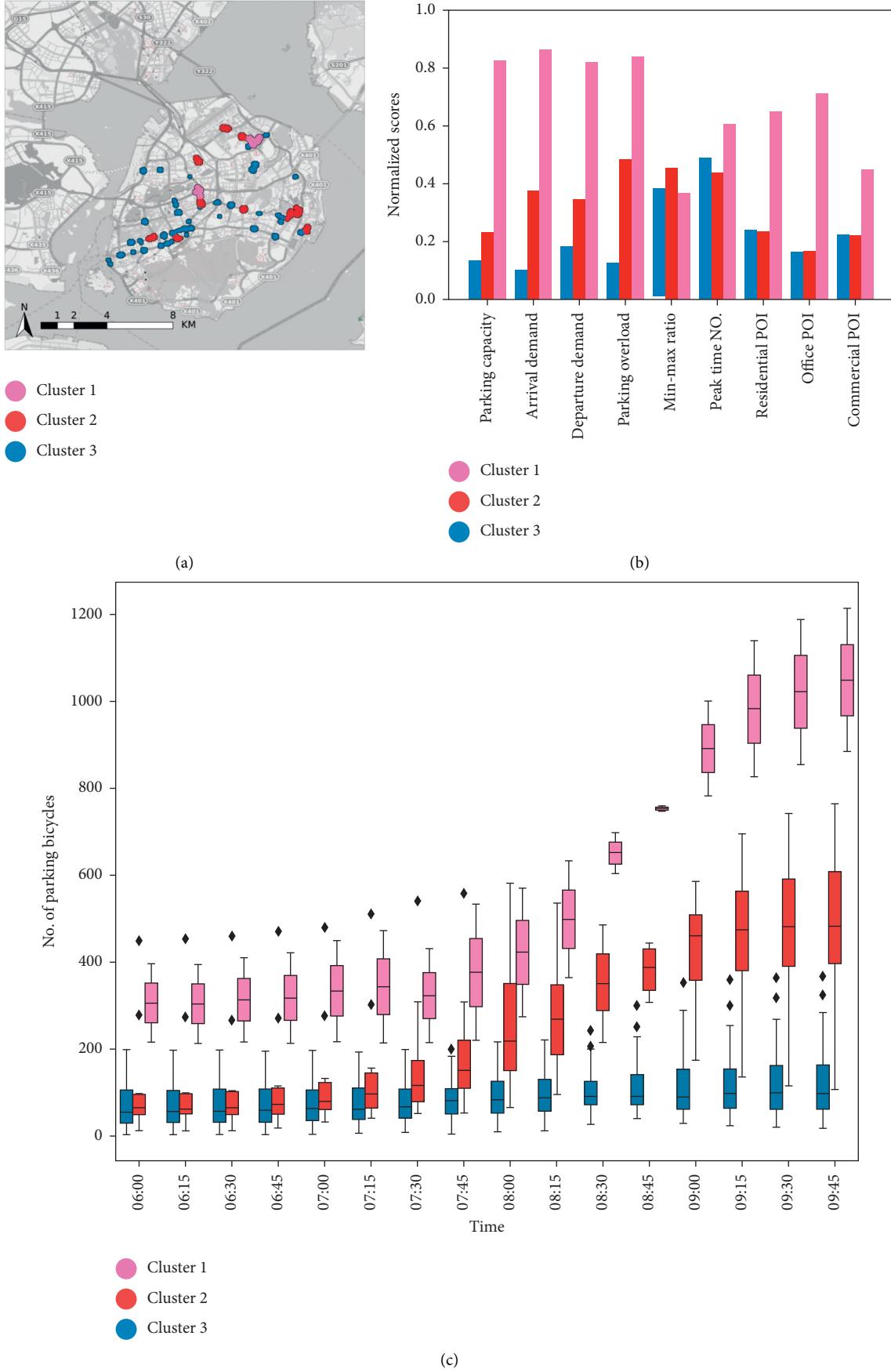


FIGURE 9: Hotspots classification result. (a) Spatial distribution of different types of hotspots. (b) Average normalized scores of indexes. (c) No. of parking bicycles in RHs.

parking gap is still small. As shown in Figure 9(a), the size of this type of hotspot is rather smaller than the other two. The average hotspot in this category is equivalent to a circle with a radius of 185 m. In addition, the land use of hotspots is nearly balanced, similar to Cluster 2.

Overall, in Cluster 3 hotspots, the BS is in stable status with little parking overload. However, the dispersion of return hotspots tends to increase potential operation and maintenance costs.

4.4. Discussion of Parking Management Schemes and Policy Implications. The emergence of electric fences shows the potential for regulating parking behavior among users. At the moment, the shape of electric fences is uniform, with each fence being a closed quadrilateral connected by five points. The planning and designing of electric fences need to be optimized in combination with the supply and demand characteristics of hotspots.

Here, according to the demand intensity and management requirement, we propose three recommended electric fence layouts (Figure 10): the first type is a large continuous block, the second is a continuously banded area, and the third is a dispersed banded area.

Parking management schemes are classified into two types: illegal parking penalties and user incentives. The penalty for illegal parking means that if a user fails to return the bicycle to the electric fence, the BS App will notify the user. If the user continues to park outside the electric fence, a fine will be imposed. User incentives imply that, prior to a bicycle-sharing trip, the app can recommend an electric fence with adequate parking ability near the destination, supplemented by certain incentive rewards (such as free tickets, coupons, etc.). It should be noted that parking management schemes should be integrated with the design of electric fences.

The recommended electric fence layout and parking management schemes for three clusters of RHs will be described in the below sections.

4.4.1. Cluster 1: Hotspots Where BS Is in Overload Status. For BS operators, the electric fences could be designed as large continuous areas to deal with parking demand during morning peak hours. On the other hand, the inelastic demand for bicycle sharing may lead to the failure of parking management schemes. It's worth noting that there are more office POIs in this type of hotspot, which may cause the tidal-flow phenomenon. Considering the bicycles stuck here may affect the sidewalk, it is recommended to move the bicycles out of the area after the morning peak to avoid high parking overload.

For the government, considering the great demand for short-distance travel in this area, in addition to bicycle-sharing, alternative modes of transportation such as shuttle buses could be introduced to serve the residents in this type of area.

4.4.2. Cluster 2: Hotspots Where BS Service Quality Needs to Be Improved. Due to the concentrated parking of bike-sharing in such areas, it is more appropriate to set up a

continuously banded area of electric fences according to the roadside environment. In terms of parking management, a parking incentive scheme (coupons, free of charge, etc.) could be used to guide users to park bicycles to the adjacent areas where electric fences are still available. For operators, this type of area is suitable for the development of sharing bicycle services. Therefore, it is necessary to strengthen the dispatching management and match the travel demand in this type of area.

For the government, the active traffic environment in such areas should be further improved, such as expanding the width of bicycle lanes. Furthermore, the bicycle-riding space should be isolated from the vehicle space for safety.

4.4.3. Cluster 3: Hotspots Where BS Is in Stable Status. Given the dispersed nature of shared bicycle parking in this area, the location of electric fences should be integrated with the bus station and metro station. Furthermore, electric fences should be set as a dispersed band along the roadside, where maintenance personnel can easily collect bicycles. It is also recommended that parking penalty schemes be implemented to regulate users' parking behavior, particularly parking outside the electric fence, which can be considered illegal parking behavior.

Despite the demand level of this type of area being low, the peak hours and demand valley-peak ratio are similar to the other two types. As far as the government is concerned, this kind of hotspot is the vast area where the "the first/last mile" problem exists. The government should supervise BS enterprises to launch appropriate bicycles in these places to ensure the public's short-distance travel.

4.5. A Case Study of BS Return Hotspot Parking Management Scheme. The classification of return hotspots based on supply-demand relationships, unbalanced characteristics, and land use attributes offer the potential for more precise parking management schemes. Take Huli Innovation Park as an example, which houses 6,869 businesses and provides 66,000 jobs. The total number of bicycles parked in this area is 1802. Figure 11(a) depicts the spatial distribution of parking congestion.

As shown in Figure 11(b), there are three clusters of RHs in this park. In the hotspot labeled as Cluster 1 inside the park, commuters return shared bicycles here, resulting in a sharp increase in the number of parking bicycles after 8:00 AM (Figure 11(c)). It should be noted that this trend is opposite to the hotspot near the Xiamen Air Bike Lane entrance. This case might reveal the phenomenon that the shared bicycles flow in the office park during the morning peak. Moreover, as can be seen in Figure 11(a), the parking overload appears to be higher at the gate of office buildings. This finding is likely to be related to the closed management of office buildings. Xiamen Air Bike Lane entrance, marked as Cluster 2, is located at the edge of the park. In this hotspot, people can get access to bicycle service through the Air Bike Lane, which is an elevated road only for bicycles. Therefore, the availability of shared bicycles leads to a growth of parking bicycles before 8:00 AM. However, the number of

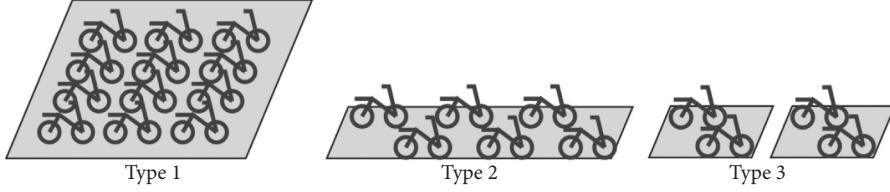


FIGURE 10: Recommended electric fence layout.

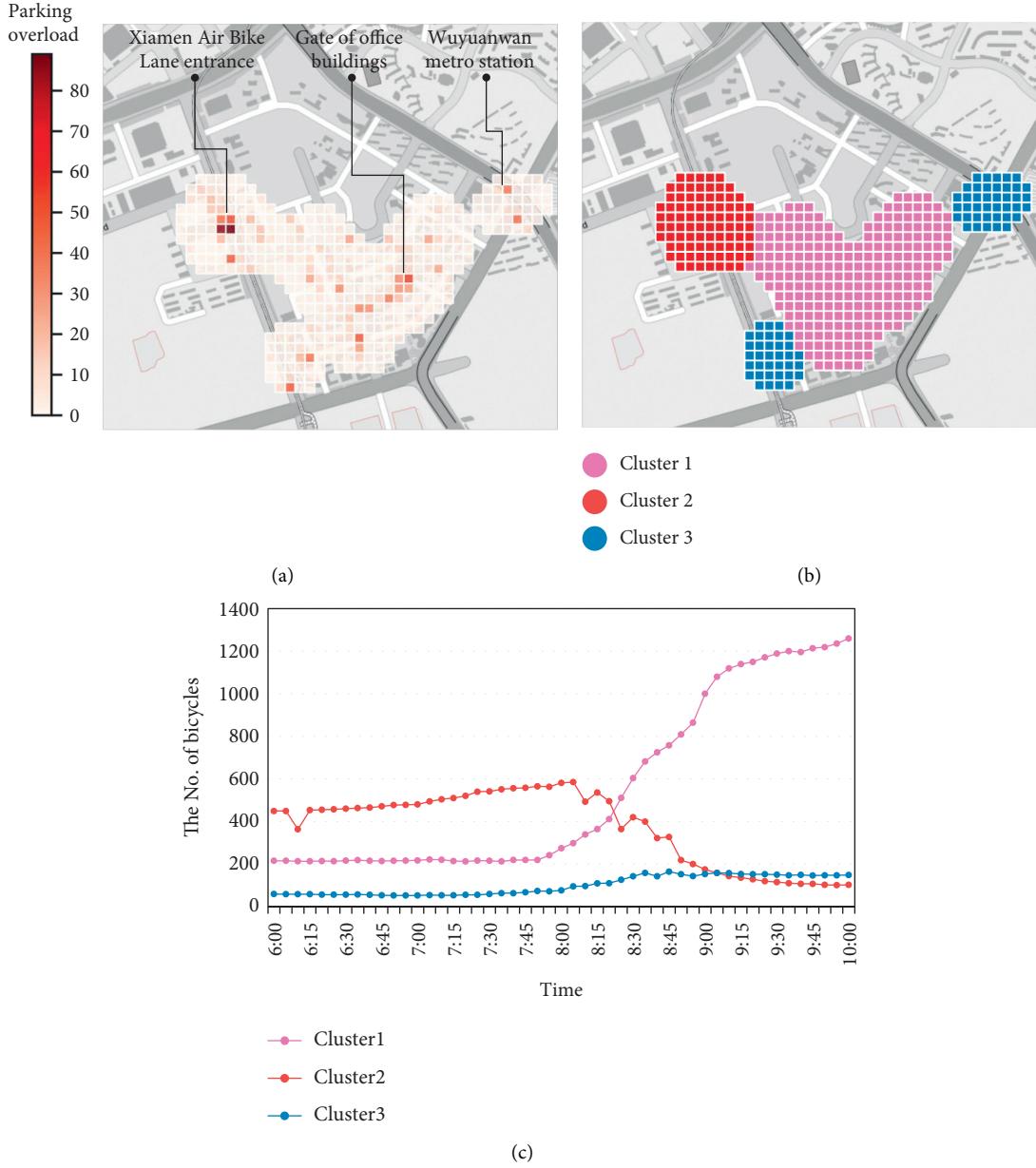


FIGURE 11: Hotspots in Huli Innovation Park. (a) Parking overload. (b) RHs classification result. (c) Parking bicycles.

bicycles decreased sharply from 585 to 102 until 10:00 AM, as shown in Figure 11(c). Two hotspots classified into Cluster 3 are also at the edge of the park. Considering the time-varying characteristics of parking bicycles, the BS is in stable status without much parking overload. The number of bicycles parked in these two hotspots reached its peak at 8:45 AM (Figure 11(c)), then remained at around 150 bicycles.

In the hotspot labeled as Cluster 1 inside the park, there is a need to design large continuous areas as electric fences in such hotspots to facilitate commuters' parking. Particularly at the gate of office buildings, the real-world double-layer bicycle rack could be introduced to expand the capacity of the electric fences. Moreover, based on the phenomenon that parking bicycles continue to increase during the morning peak, BS

enterprises could transfer bicycles out of the hotspot to reduce the parking overload. For the hotspot labeled as Cluster 2, the availability of the Air Bike Lane enhances the usage frequency of shared bicycles. To avoid high parking overload, the electric fences here should be expanded in combination with the location of the entrance of the Air Bike Lane. Besides, some bicycles could be supplemented to the hotspot to meet the needs of commuters to enter the park by bike. In the two hotspots classified into Cluster 3, it is not necessary to greatly expand electric fences. Instead, the electric fence should be placed near the bus station and the metro station to promote transfer connection with public transit. In addition, part of the electric fences in the hotspot could be set closed so that bicycles would be returned in a few opened electric fences.

5. Conclusions and Future Directions

In this paper, a novel framework for integrating multisource data is proposed to support BS parking system design and management. The definition of a BS hotspot is given. DBSCAN method is adopted with O/D (origin/destination) demand as a clustering feature to identify BS hotspots. In particular, we identify 47 pick-up hotspots (PHs) and 53 return hotspots (RHs), respectively, and conduct a comparative analysis. An evaluation framework covering three aspects (demand and supply, unbalance, and land use) is developed to assess the characteristics of RHs. The evaluation framework consists of 9 indexes derived from multisource data. Furthermore, for the first time, real-world bicycle-sharing electric fence data is used as a parking supply. The investigation of demand and supply in return hotspots shows that the total parking overload of 53 RHs during the morning peak is 12,587 bicycles. Using the Gaussian-mixture clustering algorithm, 53 RHs are classified into three clusters, including hotspots where BS is in overload status, hotspots where BS service quality needs to be improved, and hotspots where BS is in stable status. Overall, there is a lack of parking capacity in RHs on Xiamen Island. Based on the demand&supply pattern, the land utilization, and the unbalance feature, parking management schemes and policy implications are proposed.

The main findings of this paper are as follows:

- (i) The study has found that bicycle sharing hotspots do exist from the perspective of bicycle pick-up and bicycle return.
- (ii) The results of hotspots identification have revealed that bicycle sharing plays an important role in the connection to the metro transit. Additionally, bicycle trips starting from metro stations are more frequent.
- (iii) The difference in the spatial distribution between pick-up hotspots and return hotspots provides insights into the one-way bicycle inflow or outflow phenomenon. An analysis of return hotspots reveals that the parking supply is insufficient.
- (iv) The classification result of 53 return hotspots has found that the supply and demand patterns in hotspots are heterogeneous.

The findings in hotspots identification are consistent with previous studies, such as the spatial feature of hotspots [2, 50]. The findings of this study provide recommendations for the placement of BS electric fences in various areas. Some limitations, however, should be acknowledged. BS trip data only include weekday morning peak trips. As a result, the extraction of BS's temporal dynamics is unavailable. Parking management schemes only take into account illegal parking penalties and user incentives. The effect of parking management schemes on BS service should be studied further in future studies using multiscenario simulation. The real-world survey data should be used to calibrate the users' attitudes toward the electric fence and the corresponding penalty schemes.

Data Availability

BS trip data and electric fence geographic data were obtained from Digital China Innovation Contest, DCIC 2021 (https://data.xm.gov.cn/contest-series/digit-china-2021/#/3/competition_data).

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors' Contributions

Study conception and design were contributed by Yingkun Xie, Qing Yu, Xiaolei Liu, and Xinyuan Wang. Data collection, analysis and interpretation of results, and draft manuscript preparation were done by Yingkun Xie and Qing Yu. Review and editing were performed by Ying Hui and Qing Yu. All authors reviewed the results and approved the final version of the manuscript.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant no. 51978475).

Supplementary Materials

Illustration of graphical abstract: (1) Origin/destination events in each grid extracted from the bicycle-sharing trip dataset are packed as the input of the DBSCAN cluster algorithm. (2) It reported 47 pick-up hotspots and 53 return hotspots on Xiamen Island. (3) Using electric fence data and point of interest (POI) data, an evaluation framework covering three aspects (supply and demand, unbalance, and land use) are developed to assess the characteristics of return hotspots. (4) Using the Gaussian-mixture clustering algorithm. 53 return hotspots are classified into three clusters, including hotspots where BS is in overload status, hotspots where BS service quality needs to be improved, and hotspots where BS is in stable status. (5) Parking management schemes and policy implications are proposed based on the classification result. (*Supplementary Materials*)

References

- [1] H. Si, J.-g. Shi, G. Wu, J. Chen, and X. Zhao, "Mapping the bike sharing research published from 2010 to 2018: a scientometric review," *Journal of Cleaner Production*, vol. 213, pp. 415–427, 2019.
- [2] Y. Zhang, D. Lin, and X. C. Liu, "Biking islands in cities: an analysis combining bike trajectory and percolation theory," *Journal of Transport Geography*, vol. 80, Article ID 102497, 2019.
- [3] H. Luo, F. Zhao, W.-Q. Chen, and H. Cai, "Optimizing bike sharing systems from the life cycle greenhouse gas emissions perspective," *Transportation Research Part C: Emerging Technologies*, vol. 117, Article ID 102705, 2020.
- [4] J. Wu, "Challenges and opportunities in algorithmic solutions for rebalancing in bike sharing systems," *Tsinghua Science and Technology*, vol. 25, no. 6, pp. 721–733, 2020.
- [5] C. Médard de Chardon, G. Caruso, and I. Thomas, "Bike-share rebalancing strategies, patterns, and purpose," *Journal of Transport Geography*, vol. 55, pp. 22–39, 2016.
- [6] Q. Yu, W. Li, D. Yang, and Y. Xie, "Policy zoning for efficient land utilization based on spatio-temporal integration between the bicycle-sharing service and the metro transit," *Sustainability*, vol. 13, no. 1, p. 141, 2020.
- [7] Y. Yang, A. Heppenstall, A. Turner, and A. Comber, "Using graph structural information about flows to enhance short-term demand prediction in bike-sharing systems," *Computers, Environment and Urban Systems*, vol. 83, Article ID 101521, 2020.
- [8] L. Chen, D. Zhang, L. Wang et al., "Dynamic cluster-based over-demand prediction in bike sharing systems," in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 841–852, New York, NY, USA, September 2016.
- [9] S. Feng, H. Chen, C. Du, J. Li, and N. Jing, "A hierarchical demand prediction method with station clustering for bike sharing system," in *Proceedings of the 2018 IEEE Third International Conference on Data Science in Cyberspace (DSC)*, pp. 829–836, Guangzhou, China, June 2018.
- [10] J. Huang, X. Wang, and H. Sun, "Central station based demand prediction in a bike sharing system," in *Proceedings of the 2019 20th IEEE International Conference on Mobile Data Management (MDM)*, pp. 346–348, Hong Kong, China, June 2019.
- [11] C. Xu, J. Ji, and P. Liu, "The station-free sharing bike demand forecasting with a deep learning approach and large-scale datasets," *Transportation Research Part C: Emerging Technologies*, vol. 95, pp. 47–60, 2018.
- [12] T. Xu, G. Han, X. Qi, J. Du, C. Lin, and L. Shu, "A hybrid machine learning model for demand prediction of edge-computing-based bike-sharing system using internet of things," *IEEE Internet of Things Journal*, vol. 7, no. 8, pp. 7345–7356, 2020.
- [13] R. Qin, L. Kong, M. Guo, B. Yao, and M. Guizani, "Rebalance modern bike sharing system: spatio-temporal data prediction and path planning for multiple carriers," in *Proceedings of the 2018 IEEE 24th International Conference on Parallel and Distributed Systems (ICPADS)*, pp. 1–6, Singapore, December 2018.
- [14] B. Wang and I. Kim, "Short-term prediction for bike-sharing service using machine learning," *Transportation Research Procedia*, vol. 34, pp. 171–178, 2018.
- [15] R. Guo, Z. Jiang, J. Huang et al., "BikeNet: accurate bike demand prediction using graph neural networks for station rebalancing," in *Proceedings of the 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, pp. 686–693, Leicester, UK, August 2019.
- [16] M. Liu and X. Xu, "Dockless bike-sharing reallocation based on data analysis: solving complex problem with simple method," in *Proceedings of the 2018 IEEE Third International Conference on Data Science in Cyberspace (DSC)*, pp. 445–450, Guangzhou, China, June 2018.
- [17] P. Leclaire and F. Couffin, "Method for static rebalancing of a bike sharing system," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1561–1566, 2018.
- [18] A. Pal and Y. Zhang, "Free-floating bike sharing: solving real-life large-scale static rebalancing problems," *Transportation Research Part C: Emerging Technologies*, vol. 80, pp. 92–116, 2017.
- [19] J. Liu, L. Sun, W. Chen, and H. Xiong, "Rebalancing bike sharing systems," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 1005–1014, New York, NY, USA, August 2016.
- [20] J. Schuijbroek, R. C. Hampshire, and W.-J. van Hoeve, "Inventory rebalancing and vehicle routing in bike sharing systems," *European Journal of Operational Research*, vol. 257, no. 3, pp. 992–1004, 2017.
- [21] L. Shi, Y. Zhang, W. Rui, and X. Yang, "Study on the bike-sharing inventory rebalancing and vehicle routing for bike-sharing system," *Transportation Research Procedia*, vol. 39, pp. 624–633, 2019.
- [22] Y. Duan, J. Wu, and H. Zheng, "A greedy approach for vehicle routing when rebalancing bike sharing systems," in *Proceedings of the 2018 IEEE Global Communications Conference (globecon)*, Abu Dhabi, United Arab Emirates, December 2018.
- [23] X. Zhang, H. Yang, R. Zheng, Z. Jin, and B. Zhou, "A dynamic shared bikes rebalancing method based on demand prediction," in *Proceedings of the 2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, pp. 238–244, Auckland, New Zealand, October 2019.
- [24] D. Zhang, C. Yu, J. Desai, H. Y. K. Lau, and S. Srivathsan, "A time-space network flow approach to dynamic repositioning in bicycle sharing systems," *Transportation Research Part B: Methodological*, vol. 103, pp. 188–207, 2017.
- [25] Z. Tian, J. Zhou, W. Y. Szeto, L. Tian, and W. Zhang, "The rebalancing of bike-sharing system under flow-type task window," *Transportation Research Part C: Emerging Technologies*, vol. 112, pp. 1–27, 2020.
- [26] J. Hu, Z. Yang, Y. Shu, P. Cheng, and J. Chen, "Data-driven utilization-aware trip advisor for bike-sharing systems," in *Proceedings of the 2017 IEEE International Conference on Data Mining (ICDM)*, V. Raghavan, S. Aluru, G. Karypis, L. Miele, and X. Wu, Eds., pp. 167–176, New Orleans, LA, USA, November 2017.
- [27] Y. Duan and J. Wu, "Optimizing rebalance scheme for dockless bike sharing systems with adaptive user incentive," in *Proceedings of the 2019 20th IEEE International Conference on Mobile Data Management (MDM)*, pp. 176–181, Hong Kong, China, June 2019.
- [28] L. Pan, Q. Cai, Z. Fang, P. Tang, and L. Huang, "A deep reinforcement learning framework for rebalancing dockless bike sharing systems," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, pp. 1393–1400, 2019.

- [29] Y. Duan and J. Wu, "Spatial-temporal inventory rebalancing for bike sharing systems with worker recruitment," *IEEE Transactions on Mobile Computing*, vol. 21, no. 3, pp. 1081–1095, 2022.
- [30] Y. Zhang, D. Lin, and Z. Mi, "Electric fence planning for dockless bike-sharing services," *Journal of Cleaner Production*, vol. 206, pp. 383–393, 2019.
- [31] S. Xie, Y. Li, Q. Xu, F. Fang, and L. Li, "Image-based parking place identification for regulating shared bicycle parking," in *Proceedings of the 2018 15th International Conference On Control, Automation, Robotics And Vision (ICARCV)*, pp. 1709–1714, Singapore, November. 2018.
- [32] X. Yuan, J. Senlin, Z. Chongxia, L. Wei, H. Yan, and Y. Hejun, "High accuracy virtual electronic fence management technique based on GNSS," in *Proceedings of the 2017 13th IEEE International Conference on Electronic Measurement Instruments (ICEMI)*, pp. 79–83, Yangzhou, China, October. 2017.
- [33] E. Schubert, J. Sander, M. Ester, H. P. Kriegel, and X. Xu, "DBSCAN revisited, revisited," *ACM Transactions on Database Systems*, vol. 42, no. 3, p. 19, 2017.
- [34] C. S. Shui and W. Y. Szeto, "A review of bicycle-sharing service planning problems," *Transportation Research Part C: Emerging Technologies*, vol. 117, Article ID 102648, 2020.
- [35] D. Çelebi, A. Yörüşün, and H. Işık, "Bicycle sharing system design with capacity allocations," *Transportation Research Part B: Methodological*, vol. 114, pp. 86–98, 2018.
- [36] S. Chang, R. Song, S. He, and G. Qiu, "Innovative bike-sharing in China: solving faulty bike-sharing recycling problem," *Journal of Advanced Transportation*, vol. 2018, pp. 1–10, 2018.
- [37] Z. Chen, D. van Lierop, and D. Ettema, "Dockless bike-sharing systems: what are the implications?" *Transport Reviews*, vol. 40, no. 3, pp. 333–353, 2020.
- [38] J.-g. Shi, H. Si, G. Wu, Y. Su, and J. Lan, "Critical factors to achieve dockless bike-sharing sustainability in China: a stakeholder-oriented network perspective," *Sustainability*, vol. 10, no. 6, p. 2090, 2018.
- [39] E. Eren and V. E. Uz, "A review on bike-sharing: the factors affecting bike-sharing demand," *Sustainable Cities and Society*, vol. 54, Article ID 101882, 2020.
- [40] A. Li, P. Zhao, Y. Huang, K. Gao, and K. W. Axhausen, "An empirical analysis of dockless bike-sharing utilization and its explanatory factors: case study from Shanghai, China," *Journal of Transport Geography*, vol. 88, Article ID 102828, 2020.
- [41] Y. Du, F. Deng, and F. Liao, "A model framework for discovering the spatio-temporal usage patterns of public free-floating bike-sharing system," *Transportation Research Part C: Emerging Technologies*, vol. 103, pp. 39–55, 2019.
- [42] Y. Shen, X. Zhang, and J. Zhao, "Understanding the usage of dockless bike sharing in Singapore," *International Journal of Sustainable Transportation*, vol. 12, no. 9, pp. 686–700, 2018.
- [43] J. Bao, C. Xu, P. Liu, and W. Wang, "Exploring bikesharing travel patterns and trip purposes using smart card data and online point of interests," *Networks and Spatial Economics*, vol. 17, no. 4, pp. 1231–1253, 2017.
- [44] Y. Xing, K. Wang, and J. J. Lu, "Exploring travel patterns and trip purposes of dockless bike-sharing by analyzing massive bike-sharing data in Shanghai, China," *Journal of Transport Geography*, vol. 87, Article ID 102787, 2020.
- [45] H. Alizadeh, A. Khoshrou, and A. Zuquete, "Traffic classification and verification using unsupervised learning of Gaussian Mixture Models," *2015 IEEE International Workshop on Measurements & Networking (M&N)*, in *Proceedings of the 2015 IEEE International Workshop on Measurements & Networking (M&N)*, pp. 1–6, Coimbra, Portugal, October 2015.
- [46] H. Alizadeh, H. Vranken, A. Zuquete, and A. Miri, "Timely classification and verification of network traffic using Gaussian mixture models," *IEEE Access*, vol. 8, Article ID 91287, 2020.
- [47] X. Liu, L. Pan, and X. Sun, "Real-time traffic status classification based on Gaussian mixture model," in *Proceedings of the 2016 IEEE First International Conference on Data Science in Cyberspace (DSC)*, pp. 573–578, Changsha, China, June. 2016.
- [48] Z. Zhou, *Machine Learning*, Tsinghua University Press, Beijing, China, 2016.
- [49] Q. Yu and J. Yuan, "TransBigData: a Python package for transportation spatio-temporal big data processing, analysis and visualization," *Journal of Open Source Software*, vol. 7, no. 71, p. 4021, 2022.
- [50] Z. Liu, Y. Shen, and Y. Zhu, "Where will dockless shared bikes be stacked?" in *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pp. 566–575, New York, NY, USA, July 2018.