



# Discovering Spatiotemporal Patterns and Urban Facilities Determinants of Cycling Activities in Beijing

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## Abstract

The new generation of dockless bike sharing systems has been deployed on a large scale around the world, successfully promoting cycling activities. Analyzing cycling activity patterns can reveal people's travel behavior and urban dynamics with fine granularity. This paper aims to discover the spatiotemporal patterns and urban facilities determining cycling activities based on dockless bike sharing data in the downtown area of Beijing. We collected approximately 1.5 million cycling trip records for seven consecutive days. In urban spaces, roads are basic spatial elements for human movement. Thus, this study shifts the analysis perspective to a road network perspective. We use network kernel density estimation (NKDE) to analyze the spatio-temporal distribution of cycling activities. In the NKDE, the road unit is the analysis unit. The road unit is an approximate decomposition of a block and can minimize the effect of the modifiable areal unit problem (MAUP). We then apply a colocation mining method, network-distance-based global colocation quotient (GCLQ), which does not need to divide the study area into analysis units and is not affected by the MAUP, to examine the association between cycling activities and four categories of urban facilities, including transportation facilities, company and business facilities, residences, and scenic spots. Finally, taking spatial heterogeneity into consideration, we apply network-distance-based local colocation quotient (LCLQ) to capture the variability of association across areas. The result shows that cycling activity hot spot areas are within the Fourth Ring Road or near subway line one and the Batong Line. In addition to exhibiting obvious morning and evening peaks, cycling activities exhibit a small peak at noon on weekdays. On weekends, cycling activities show a relatively uniform temporal distribution. LCLQ performs better than GCLQ. The results of LCLQ show the spatial variance of the association and identify the areas where cycling activities are associated with different urban facilities at different times.

**Keywords** Bike sharing · Spatiotemporal analysis · Colocation · Urban facilities

## Introduction

Bike sharing is a means of sustainable transportation. Since the first public bike sharing system (BSS) was implemented in 1965, public bike sharing systems have developed rapidly. The new generation of dockless BSSs (e.g., Ofo and Mobike) originated in 2015 in China with the development of information technology and the sharing economy (Xu et al. 2019) and has been deployed on a large scale around the world. A user can unlock a shared bike through a mobile application and then begin a trip. Once the trip is finished, the user parks the shared bike on any suitable public city space and pays for the trip through the mobile application. Without docking stations, the new generation of dockless BSSs enables users to use shared bikes anytime and anywhere, fully unleashing the potential of shared bikes. Furthermore, BSSs have positive social, environmental, and economic effects, such as relieving traffic congestion (Wang and Zhou 2017),

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reducing public transportation travel times (Jäppinen et al. 2013), producing little air and noise pollution (Shaheen et al. 2010), solving the “last mile” problem (Garcia-Gutierrez et al. 2014; Yang et al. 2019), reducing energy consumption (Zhang and Mi 2018), and increasing public transit use (Caulfield et al. 2017). Because of its flexibility and various benefits, the dockless BSS has been deployed on a large scale around the world. As travel data describe people’s movement, they can be used as proxies for urban flows. Compared with travel card or taxi data, which are characterized by medium-long distance travel, dockless bike sharing data record short-distance travel and can reflect people’s micro-mobility (Yang et al. 2019). Analysis of the spatiotemporal pattern of bike sharing can help reveal people’s travel behavior and urban dynamics at a fine granularity. Additionally, knowledge of the spatiotemporal pattern of bike sharing can help improve the performance of BSSs (Alvarez-Valdes et al. 2016; Du et al. 2019).

This study aims to analyze the spatiotemporal pattern and urban facilities determinants of cycling activities in Beijing from a road network perspective. Through data analysis, we seek to describe the characteristics of people’s travel behavior and the spatial-temporal distribution characteristics of shared bikes, which can provide a reference for the optimization of BSSs. First, we use network kernel density estimation (NKDE) to analyze the spatiotemporal distribution of the origins and destinations of dockless bike trips. Then, noting that bike sharing activities are more flexible than other transportation modes, we explore the spatial-temporal characteristics of bike sharing activities and their correlation with urban facilities from a micro perspective. We use the network-distance-based global colocation quotient (GCLQ) to examine the association between dockless bike usage and urban facilities and use the network-distance-based local colocation quotient (LCLQ) to analyze the changes in the strength of association in different places. We hope that the two approaches adopted in this paper and the results can provide new ideas for other bike sharing system-related researches.

## Related Work

### Discovering the Spatiotemporal Pattern of Shared Bike Usage

Cluster methods are popular tools for analyzing the spatiotemporal pattern of bike sharing. For station-based BSS, cluster methods can be used to group docking stations according to usage patterns and to understand spatiotemporal causes of imbalances (Vogel et al. 2011; Jiménez et al. 2016; Lathia et al. 2012; Zhou 2015; Zhang et al. 2017a). For dockless BSS, cluster methods can be used to group concerned areas

or shared bike usage hotspots based on time-series usage patterns (Du et al. 2019).

In addition to cluster methods, other methods are also used. For station-based BSS, Austwick et al. (2013) used community detection tools to identify network subregions within bikeshare flow networks. Zhou (2015) built a similarity graph of cycling flows and used community detection algorithms to find the spatial communities of cycling flows. Bordagaray et al. (2016) proposed a data mining algorithm to classify cycling trips into different usage types in Santander’s BSS. Zhang et al. (2018) combined trip chain and transition activity matrices to indicate bike usage patterns and potential bike usage purposes and analyzed bike sharing users’ travel behavior. For dockless BSS, Zhang et al. (2019) used percolation theory to identify geographical areas of interest with a high concentration of bike usage. Yang et al. (2019) used kernel density estimation and graph-based analyses to examine travel behavior, mobility patterns, and flows of bike usage over the last mile before and after a new subway line was put into operation.

Visualization methods can also help to understand the usage of shared bike systems, and flow maps are commonly used. Flow maps have been used to analyze the spatial and temporal patterns of bike sharing activities, as well as the influence of weather conditions and calendar events on bike usage (Du et al. 2019; Wood et al. 2014; Corcoran et al. 2014; Zhao et al. 2015). In addition to flow maps, Oliveira et al. (2016) coordinated pixel-oriented timelines with maps to identify temporal and spatial patterns of bike usage. Yan et al. (2018) designed a visual analytics system to extract potential activity patterns of bike users based on tensor factorization. Du et al. (2019) used a sliced spatial heatmap to visualize the spatial distribution pattern of bike trip origins and destinations and used a space-time cube to reveal the imbalance usage pattern of BSSs.

To analyze and understand socioeconomic environments from geospatial data at the individual level, spatial assembly operations are needed (Liu et al. 2015). When analyzing the cycling activities from dockless bike sharing data, existing studies usually map individual bike usage data onto administrative areal or regular areal units. The assembly step may affect the final analysis results, and this problem is referred to as the modifiable areal unit problem (MAUP). In urban spaces, human movement is usually constrained by roads, and roads are basic spatial elements for human movement. Shen and Karimi (2016) analyzed social media check-in data from a street network perspective and proposed that urban roads connect urban functions at physical and cognitive levels. Zhu et al. (2017) suggested that the street unit is a promising substitute for areal units and can help us uncover hidden knowledge concealed under areas. Yu et al. (2017) proposed a spatial colocation pattern mining method containing the network-constrained neighborhood and compared it

with the traditional plane-space-based method through the network cross k-function (Okabe and Yamada 2001). The results showed that the network-constrained approach is more effective than the traditional approach in a network-structured space. As bike sharing activities are also constrained by the street network, we need to take the above results into account. Thus, this study shifts the analysis perspective to a road network perspective. We use network kernel density estimation (NKDE) to analyze the spatiotemporal distribution of the origins and destinations of dockless bike trips. In the NKDE, the road segment is used as the analysis unit. Compared with traditional areal units, the road unit is an approximate decomposition of a block and can minimize the effect of the MAUP (Zhu et al. 2017).

### Determinants of Cycling Activities

Some studies have focused on examining the correlation between shared bike usage patterns and factors that may affect bike sharing (e.g., the built environment and weather conditions). For station-based BSS, regression analysis is commonly used to examine the potential influencing factors. Mateo-Babiano et al. (2016) employed Spearman's correlation coefficient and linear regression analysis to determine the influence of cycling infrastructure, land use, and topography on bike sharing. Zhang et al. (2017b) used a multiple linear regression model to analyze the influence of the built environment on bike use demand and the ratio of demand to supply at bike stations. Rixey (2013) used a regression model to examine the influence of demographic and built environment characteristics near docking stations on ridership levels. In addition to regression analysis, Wang and Lindsey (2019) used linear mixed-effects models and multinomial logistic models to examine the association between sociodemographic characteristics and bike sharing behavior. Faghih-Imani et al. (2014) employed a multilevel linear model to analyze the impact of meteorological conditions, bicycle infrastructure, temporal characteristics, built environment, and land use on arrival and departure flows at docking stations.

For dockless BSS, researchers usually divide a study area into regular grid cells to assemble individual bike usage data and then use appropriate methods to analyze the potential influencing factors. Shen et al. (2018) used spatial autoregressive models to explore the influence of access to public transportation, bike fleet size, built environment, weather conditions, and bicycle infrastructure on bike usage. Du et al. (2019) used random forests to evaluate the contribution of land use, sociodemographic characteristics, number of POIs, and cycling environment on bike usage. Xu et al. (2019) used the eigendecomposition approach to find the built environment indicators that are correlated with bike usage.

In existing studies, the spatial assembly process may cause the MAUP. To eliminate the impact of the MAUP, we apply a colocation mining method, network-distance-based colocation quotient, to examine the association between cycling activities and urban facilities, as colocation quotient method does not need to divide the study area into analysis units. Many existing studies have used colocation quotient method to analyze the association of spatiotemporal behavior with urban facilities. Leslie and Kronenfeld (2011) first proposed a new metric labeled the colocation quotient (CLQ), a measurement designed to quantify (potentially asymmetrical) spatial associations between categories of a population that may itself exhibit spatial autocorrelation. Wang et al. (2017) developed a simulation-based statistical test for the local indicator of colocation quotient (LCLQ) to examine the association of land use facilities with crime patterns. Chen et al. (2020) mined the colocation patterns (CPs) of urban activities with point-of-interest (POI) data and identified nearly a thousand unique POI CPs for 25 cities. Different from these existing studies, this paper applies the network-distance-based colocation quotient and takes the shared bike as the research object. Compared with other modes of transportation, shared bikes exhibit more microscopic travel behaviors. The network-distance-based colocation quotient method takes the network road, which better reflects reality, as the entry point and can not only detail the overall characteristics of shared bike travel from a global perspective, but also consider the spatial heterogeneity and use LCLQ to capture the variability of association across areas within the overall trend.

### Study Area and Data Sources

Beijing is the capital of China. The study area is downtown Beijing, including Chaoyang, Dongcheng, Xicheng, Haidian, Shijingshan, and Fengtai Districts, and its total area is approximately 1378 km<sup>2</sup>. The dockless bike usage data were from Mobike, which include approximately 1,500,000 trips from May 10th to May 16th in 2017 in the downtown area of Beijing. The weather was sunny or cloudy with temperatures of 15 to 30 °C, and the air quality was excellent or good in that period; therefore, cycling activities were likely not affected by extreme weather conditions and air quality. Each trip records the following attributes: order ID, bike ID, bike type, start time, start longitude, start latitude, end longitude, and end latitude. Road network data were obtained from OpenStreetMap. Dockless bike usage data reflect people's micro-mobility, so the road data must be detailed. The main road in Beijing is shown in Fig. 1.

POI data came from Gaode Maps and can be found in the Peking University Open Research Data Platform. The publication time of POI data was June or August 2017. In terms of

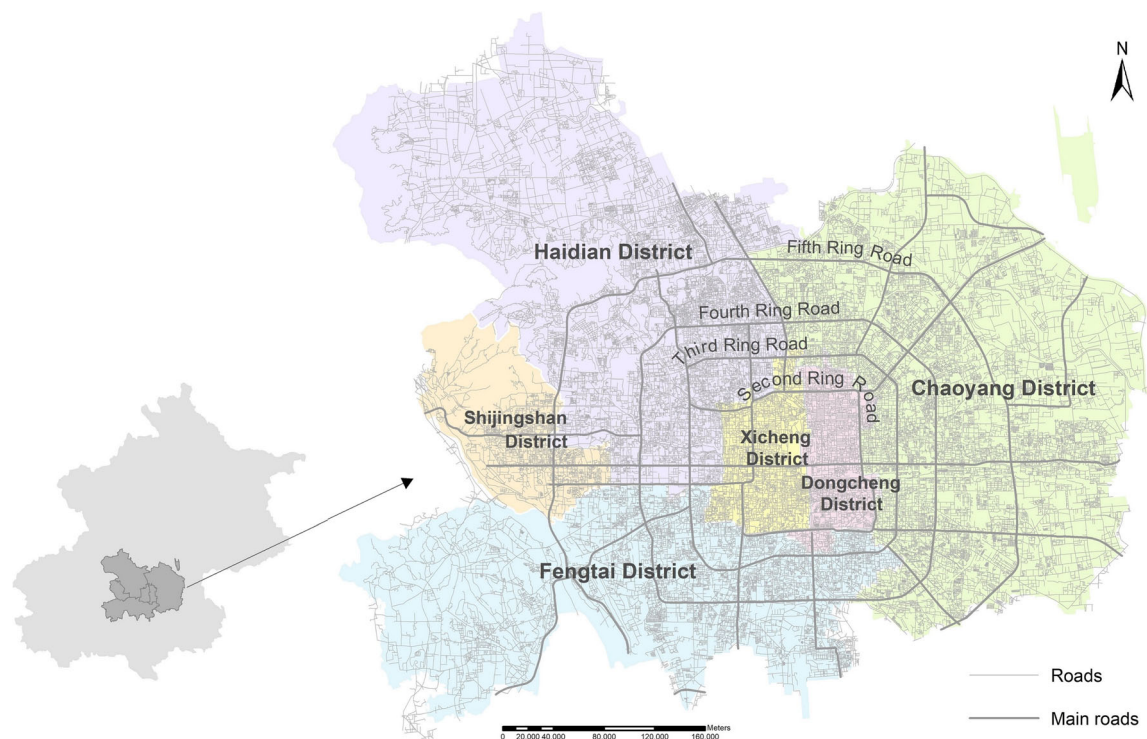


Fig. 1 Study area

the division and selection of POIs of urban facilities, we preliminarily referred to the selection criteria of many existing relevant studies. We combined the findings of several studies on the influencing factors of shared bikes (Faghih-Imani et al. 2017; Zhang et al. 2017b; Du and Cheng 2018; Xu et al. 2019) and finally extracted six types of urban facilities that are used the most frequently: company and business, entertainment, shopping, restaurant, transportation, and residence. These types of urban facilities cover almost all aspects of the city's functions. Later, considering the excessive number of entertainment, shopping, and restaurant POIs, parks were chosen to represent entertainment places. In addition, in order to better analyze the connection problem of the “last mile” of shared bikes, we extracted and divided the transportation facilities into two categories: bus station and subway station. However, dockless bike usage data record short-distance travel, while the distance between a subway station entrance and the center point of the subway station may be relatively long. Moreover, shared bikes are not allowed to be ridden in many residential quarters and parks. Thus, we used subway station entrances, residential quarter entrances, and park entrances to represent subway stations, residential quarters, and parks, respectively. Finally, the classification adopted is as follows: bus station, subway station entrance, park entrance, residential quarter entrance, and office building entrance.

## Methodology

### Network Kernel Density Estimation (NKDE)

KDE is commonly used to analyze the spatial distribution of points (Bailey and T.C.G 1995; Silverman 1986). KDE takes the distance decay impact of points into consideration and can produce a comprehensible density surface of input points. Based on the characteristics of road networks and road network events, KDE is extended to NKDE (Xie and Yan 2008; Okabe et al. 2009; Yu et al. 2015). We use NKDE to analyze the spatial pattern of bike trip origins and destinations in different time periods. NKDE is defined as follows:

$$f(s) = \sum_{i=1}^n \frac{1}{\tau^2} k\left(\frac{s-s_i}{\tau}\right) \quad (1)$$

where  $f(s)$  denotes the density value at location  $s$ ,  $n$  represents the number of point events, and  $s_1, \dots, s_n$  represent the corresponding locations of the point events.  $s-s_i$  represents the network distance between  $s$  and  $s_i$ , and  $\tau$  denotes the bandwidth.  $k()$  denotes the kernel function.

NKDE has two parameters:  $k()$  and  $\tau$ . Existing studies have found that  $k()$  has little impact on the results (Xie and Yan 2008; Yu et al. 2015). In this study, we selected the quartic kernel function (Eq. (2)).  $\tau$  is a critical parameter (Xie and Yan 2008). A larger  $\tau$  produces a smoother density surface, whereas a smaller  $\tau$  produces a “spikier” density surface.

$$k\left(\frac{s-s_i}{\tau}\right) = \frac{3}{4} \left(1 - \frac{(s-s_i)^2}{\tau^2}\right) \tag{2}$$

NKDE differs from traditional KDE in three aspects: (1) the analysis context is network space instead of planar space, (2) network distance rather than Euclidean distance is used in the kernel function and bandwidth, (3) the analysis unit is linear unit rather than area unit.

### Colocation Quotient

#### Global Colocation Quotient (GCLQ)

GCLQ is a global point-based colocation metric (Leslie and Kronenfeld 2011). In the realm of human geography, the spatial patterns of the origin and destination of bike trips and different types of POIs may be controlled by the overall population distribution and transportation infrastructure and tend to be located in varying degrees of proximity to other human activity centers. GCLQ can eliminate the effect of clustering of a joint population on the results. Thus, we use network-distance-based GCLQ to detect the association between bike usage and the urban facilities of the city. The GCLQ is defined as

$$CLQ_{A \rightarrow B} = \frac{N_{A \rightarrow B} / N_A}{N_B / (N-1)} \tag{3}$$

where  $N_A$  represents the number of  $A$  points (bike trips origins or destinations),  $N_B$  represents the number of  $B$  points (different types of POIs, e.g., bus stations),  $N$  denotes the total number of  $A$  and  $B$  points, and  $N_{A \rightarrow B}$  represents the number of  $A$  points where a  $B$  point is the nearest neighbor of the  $A$  point. In defining neighborhoods, road network distance is used rather than Euclidean distance (Wang et al. 2017).

The expectation of GCLQ is 1 if different types of points are randomly located given a fixed distribution pattern of points (Leslie and Kronenfeld 2011). A  $CLQ_{A \rightarrow B}$  value greater than 1 suggests that  $A$  points are collocated with  $B$  points. The larger the  $CLQ_{A \rightarrow B}$  value is, the stronger the colocation pattern is. In contrast, a  $CLQ_{A \rightarrow B}$  value less than 1 indicates a dispersed pattern between  $A$  points and  $B$  points. Monte Carlo simulation is used for the significance test (Leslie and Kronenfeld 2011).

Furthermore, Cromley et al. (2014) broadened the definition of neighborhood and proposed geographically weighted CLQ. A point could have more than one neighbor within a bandwidth.  $N_{A \rightarrow B}$  is calculated as

$$N_{A \rightarrow B} = \frac{\sum_{i=1}^{N_A} \sum_{j=1}^{m_i(j \neq i)} w_{ij} x_j}{\sum_{i=1}^{N_A} \sum_{j=1}^{m_i(j \neq i)} w_{ij}} \tag{4}$$

where  $m_i$  denotes the number of nearest neighbors of the  $i$ th  $A$  point and  $x_j$  is a binary variable indicating whether the  $j$ th point is type  $B$  (1 indicates yes and 0 otherwise).  $w_{ij}$  can be different types of kernel density functions, such as the box kernel density weighting function or Gaussian kernel density weighting function.

#### Local Colocation Quotient (LCLQ)

GCLQ implicitly assumes that the association relationship stays stationary over space and thus cannot detect changes in the strength of association over space. Therefore, LCLQ was proposed to address this limitation (Cromley et al. 2014). We used LCLQ to reveal the spatial variability of the association between bike usage and the urban facilities. The LCLQ is formulated as

$$LCLQ_{A_i \rightarrow B} = \frac{N_{A_i \rightarrow B}}{N_B / (N-1)} \tag{5}$$

$$N_{A_i \rightarrow B} = \sum_{j=1}^N (j \neq i) \left( \frac{w_{ij} x_j}{\sum_{j=1}^N (j \neq i) w_{ij}} \right) \tag{6}$$

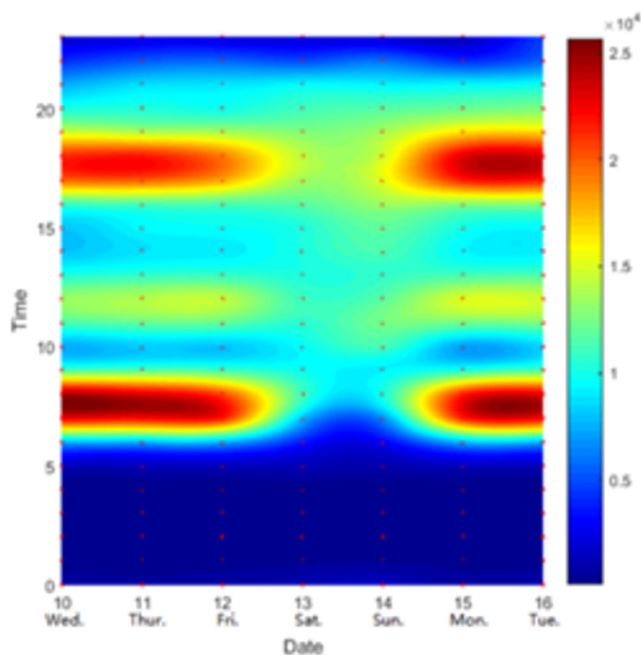
where  $A_i$  represents the  $i$ th  $A$  points. In defining neighborhoods, we also use road network distance rather than the Euclidean distance. Additionally, Monte Carlo simulation is used for the significance test of LCLQ (Wang et al. 2017).

## Results, Discussion, and Implications

### Spatiotemporal Distribution of Bike Trip Origins and Destinations




We used a heatmap to visualize the number of trips per hour during the week, as shown in Fig. 2. Obvious bike usage differences between weekdays and weekends can be observed in Fig. 2. Bike usage is generally higher on weekdays. Moreover, clear travel peaks can be observed at approximately 7 a.m.–9 a.m. and 5 p.m.–7 p.m. on weekdays, and small travel peaks can be observed at approximately 12 a.m. on weekdays, whereas there are no obvious travel peaks on weekends. The differences may be related to residents’ travel purpose. On weekdays, shared bikes may be mainly used for commuting; on weekends, commuting is not the main purpose for residents, and the choice of travel time and space is flexible.



We used NKDE to visualize the spatial pattern of trip origins and destinations per hour on May 11 (Thursday) and 13 (Saturday). The bandwidth is set to 1000 m, and the results are shown in Appendix S1. On May 11 (Thursday), from 10 p.m. to 5 a.m., the city is relatively “silent,” and only sporadic “points of light” are observed in the maps, which is consistent



**Fig. 2** Heatmap representing the number of trips per hour during the week


with the general sleeping time of people. After 5 a.m., the city gradually wakes up. The first “hot” area occurs in Muxiyuan, Liujiayao, and Shiliuzhuang at 5 a.m.–6 a.m., as shown in Fig. 3. The reason could be that wholesale markets gather in these locations and open at 6 a.m. or 7 a.m.

The spatial distribution patterns of bike trip origins and destinations are similar in the kernel density maps on May 11 (Thursday). From 7 a.m. to 10 p.m., especially in the morning and evening peak hours, people’s bike usage patterns show distinct spatial distribution characteristics. Bike usage hot spot areas have the shape of “”. The bike usage hot spot areas are within the Fourth Ring Road (“”) or near subway line 1 and the Batong Line, which run east and west through the central city (“”). Some cold spots are observed within the Fourth Ring Road. These areas have very low kernel density, which is quite different from the surrounding areas. The cold spots are near ancient buildings and gardens, such as Tian’anmen Square, Jingshan Park, the Forbidden City, Beihai Park, Temple of Heaven, and Longtan Park, and this observation may be related to the strict control measures of historical and cultural heritage and buffer areas (Figs. 4 and 5).

Outside the “”, there are large areas with kernel densities of zero or close to zero. Factors such as being far from the city center, having a relatively low population density, and having a relatively sparse road network affect the use frequency of shared bicycles. Outside the “”, there are also some hot spots, as shown in Fig. 6. A large hot spot is observed in the Wangjing-Jiuxianqiao business district (E in Fig. 6), which may be related to the many Internet companies

gathered here. Taking the Beijing Olympic Games as an opportunity, the Ya’ao business circle (D in Fig. 6), which includes the low kernel density of Olympic Forest Park (e in Fig. 6), has attracted a large number of permanent residents. With the completion of large residential areas and metro lines, the Ya’ao business circle moved northward, and the Beiyuan-Lishuiqiao area (C in Fig. 6) became the new core area of the Ya’ao business circle. There are also some small hot spot areas, such as Shangdi, Zhongguancun Dongsheng Science and Technology Park, Fengtaiyuan of Zhongguancun Science Park, and Wanyuan Road (A, B, F, G in Fig. 6). These hot spot areas are other high-tech industrial cluster areas.

During morning peak hours, the number of bike trips increases sharply. After 9 a.m., the intensity of trip origins and destinations substantially and then begins to increase at 11 a.m. At noon (11 a.m.–1 p.m.), there is a small peak in bike usage: the hot spots are concentrated and the range is small, as shown in Fig. 7. This peak may be related to the lunch break, and the hotspots may reflect the employment concentration area to some extent, such as Zhongguancun, Wukesong, Financial Street, Guomao, Muxiyuan, and Fengtaiyuan of Zhongguancun Science Park.

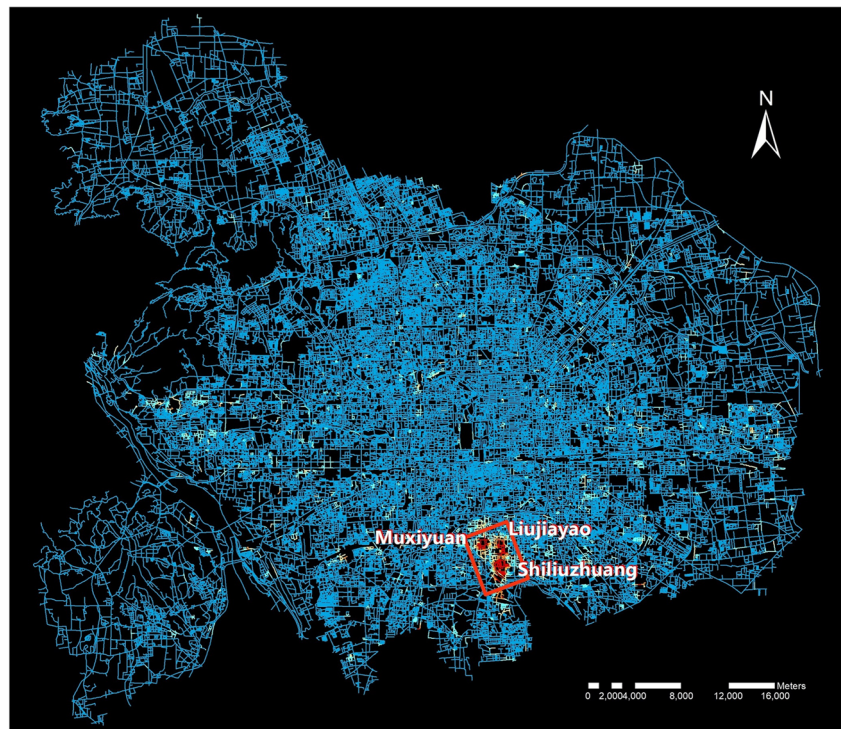
Compared to that of weekdays, overall usage is reduced on weekends, and bike trip origins/destinations show a relatively uniform spatial distribution pattern in different periods (7 a.m.–10 p.m.) on weekends. From 7 a.m. to 10 p.m., bike usage hot spot areas still have the shape of “”. Compared to weekdays, the active time for bike usage on weekends is postponed. The first “hot” area still occurs in Muxiyuan, Liujiayao, and Shiliuzhuang from 5 a.m. to 6 a.m. No obvious travel peaks occur on weekends, and only a small travel peak is observed at dusk (5 p.m.–7 p.m.).

## The Association Between Cycling Activities and Urban Facilities

By analyzing the colocation quotient results from May 10 to May 16, we found that there were obvious differences between the spatial patterns of weekdays and weekends, but the patterns of each day were basically the same. Therefore, we decided to take the results of May 11 (Thursday) and May 13 (Saturday) as the representatives of weekdays and weekends to analyze the relationship between bike sharing trips and urban facilities.

We used GCLQ to analyze bike trip origin/destination and different types of POIs per half hour during the morning and evening peak hours on May 11 (Thursday) and the same time period on May 13 (Saturday), and the bandwidth is set to the ten nearest neighbors. The results are shown in Tables 1 and 2. Many GCLQ values are below one, and the results show that bike trip origins/destinations were significantly (at the 0.05 level) isolated from any of the POI types. GCLQ values for

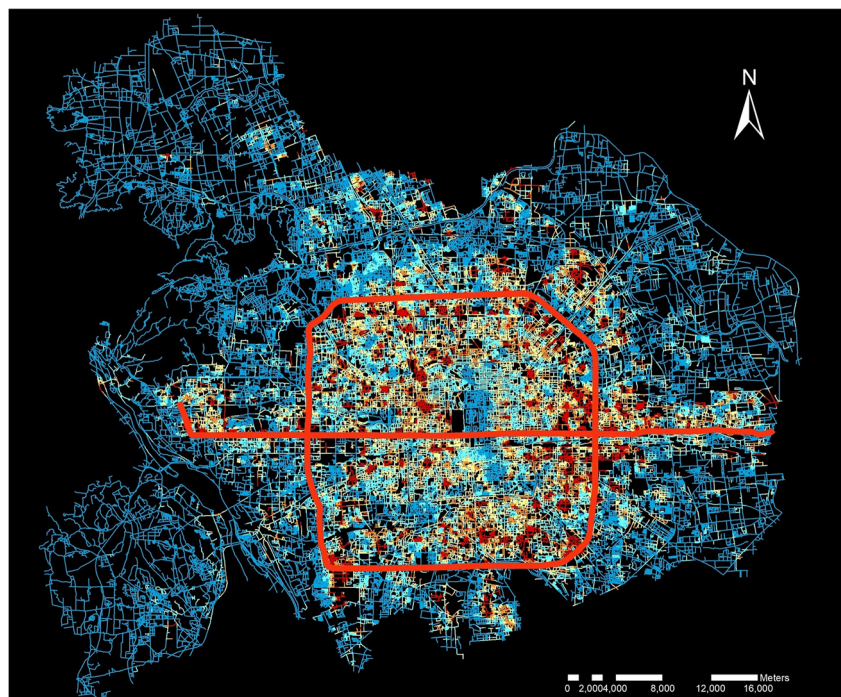
**Fig. 3** First “hot” areas on weekdays



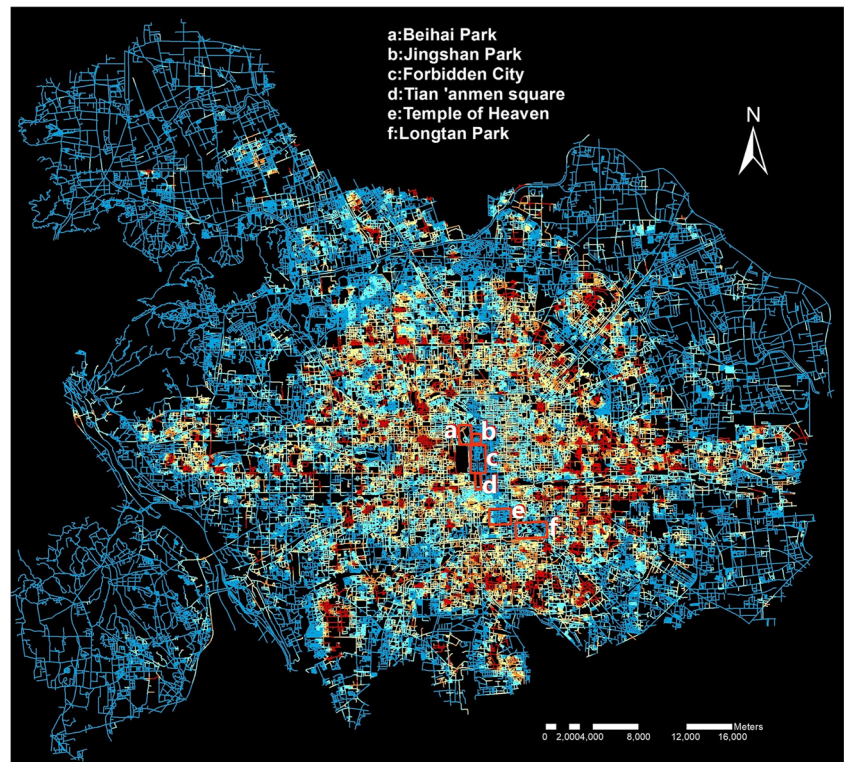
trip destinations versus subway stations at 8 a.m.–8:30 a.m. and 5 p.m.–5:30 p.m. on May 11 and 9 a.m.–9:30 a.m. on May 13 are larger than 1, indicating that trip destinations and subway stations were spatially collocated during these periods. Some GCLQ values for bus station and subway

stations are not significant on May 13. In general, GCLQ values for residential quarters on May 11 (Thursday) are smaller than those on May 13 (Saturday). On May 11 and 13, GCLQ values for trip origins versus residential quarters are larger than those for trip destinations during the morning

**Fig. 4** Basic pattern of bike usage hot spot areas during the morning and evening peak hours on weekdays



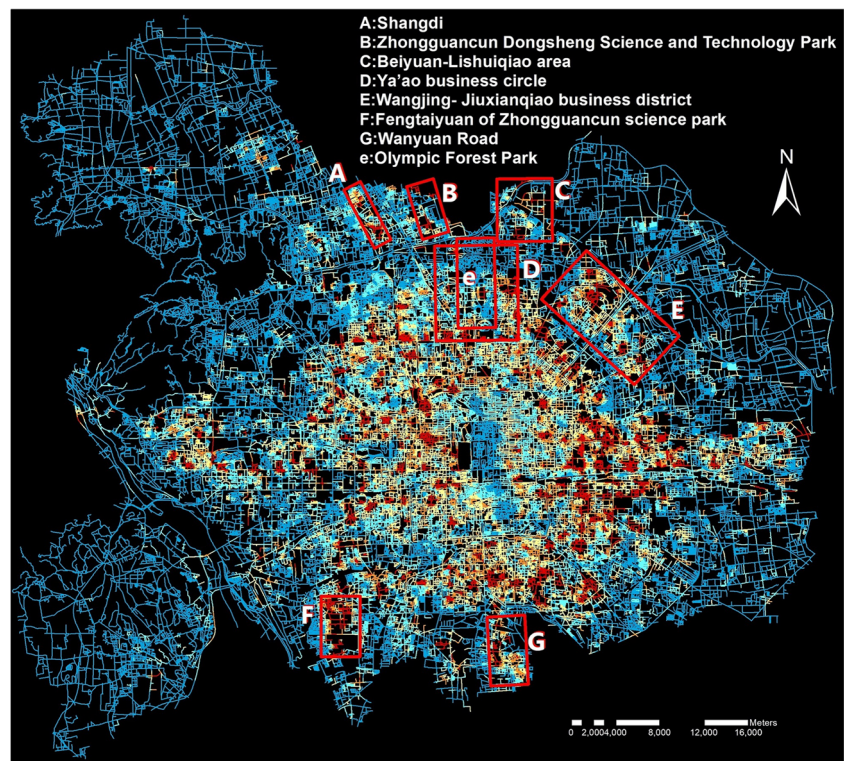
**Fig. 5** Cold spots inside the Fourth Ring Road during the morning and evening peak hours



peak, indicating a spatial association of less dispersion between trip origins and residential quarters. In the evening peak, the situation is reversed. GCLQ values for office buildings on May 11 (Thursday) are larger than those on May 13

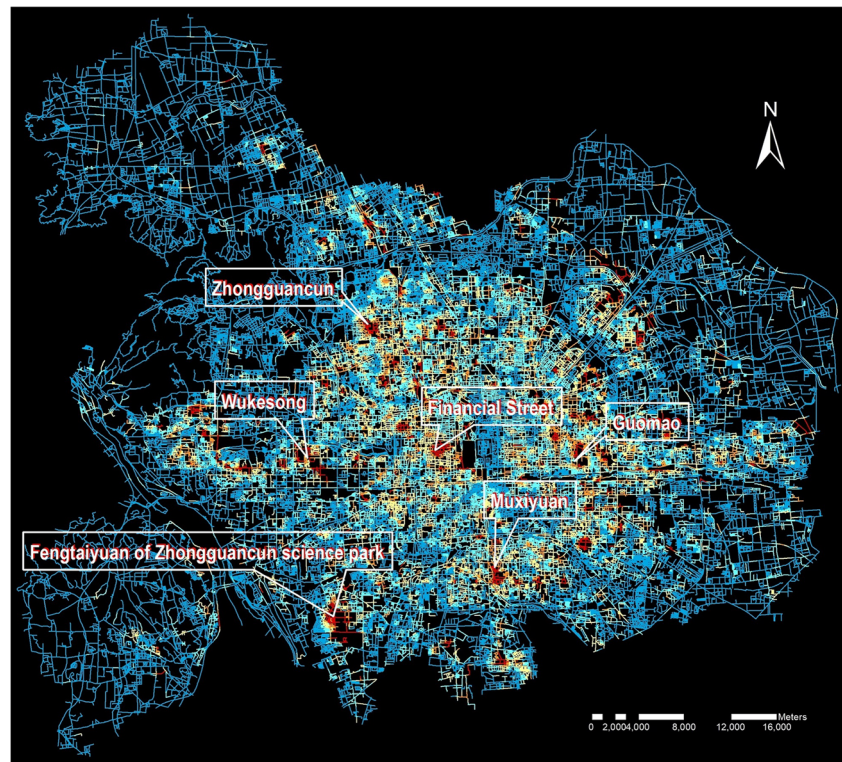
(Saturday). This may be related to the difference between travel purposes on weekdays and weekends, where travel for commuting accounts for a larger proportion on weekdays than on weekends.

**Fig. 6** Hot spots outside the Fourth Ring Road during the morning and evening peak hours





**Fig. 7** Spatial pattern of trip origins and destinations during the small peak at noon



GCLQ assumes that the association relationship remains stationary over space and hides the local association relationship. For a complex geographic environment, LCLQ is more useful. Over the course of a day, we chose several periods of the most representative spatial pattern visualization results for analysis of LCLQ. Some of these periods are the most typical periods of the day in terms of spatial patterns. Others are periods in which there is a significant difference in spatial patterns between the weekday and the weekend or the periods of the same day in which the spatial pattern is distinct. The LCLQ results based on the bandwidth of 1000 m are shown in Appendix S2.

**Bus Stations**

In general, half of the trip origin/destination points were significant at the 0.05 level on the two days. Origin/destination points with an LCLQ greater than 2 are scattered outside the Fourth Ring Road, indicating a strong colocation pattern between origin/destination points and bus stations, as shown in Fig. 8. The reason for the strong colocation pattern could be as follows: (1) since road traffic congestion is serious within the Fourth Ring Road, especially during rush hour, subways have an advantage over buses in terms of travel time; (2) traffic pressure outside the Fourth Ring Road is alleviated.

**Table 1** Global colocation quotient of five kinds of POI on May 11

Time slot	Bus stations		Subway stations		Parks		Residential quarters		Office buildings	
	Origin	Destination	Origin	Destination	Origin	Destination	Origin	Destination	Origin	Destination
7:00–7:30	*0.929	*0.846	*0.857	*0.868	*0.795	*0.719	*0.940	*0.803	*0.840	*0.814
7:30–8:00	*0.947	*0.892	*0.909	*0.957	*0.811	*0.770	*0.882	*0.832	*0.931	*0.895
8:00–8:30	*0.930	*0.946	*0.925	*1.051	*0.981	*0.880	*0.893	*0.735	*0.884	*1.052
8:30–9:00	*0.895	*0.812	*0.943	1.010	*0.807	*0.808	*0.870	*0.848	*0.915	*0.947
17:00–17:30	*0.958	*0.976	*0.985	*1.017	*0.840	*0.869	*0.900	*0.924	*0.962	*0.971
17:30–18:00	*0.948	*0.980	*0.854	0.987	*0.847	*0.861	*0.896	*0.927	*0.951	*0.964
18:00–18:30	*0.940	*0.972	*0.946	*0.886	*0.821	*0.838	*0.868	*0.918	*0.914	*0.919
18:30–19:00	*0.944	*0.977	*0.953	*0.980	*0.831	*0.849	*0.869	*0.921	*0.873	*0.888

Colocation quotient values with \* are significant at the 0.05 level

**Table 2** Global colocation quotient of five kinds of POI on May 13

Time slot	Bus stations		Subway stations		Parks		Residential quarters		Office buildings	
	Origin	Destination	Origin	Destination	Origin	Destination	Origin	Destination	Origin	Destination
7:00–7:30	0.993	*0.982	*0.908	*0.944	*0.785	*0.785	*0.949	*0.888	*0.760	*0.814
7:30–8:00	1.007	1.001	*0.939	1.004	*0.838	*0.831	*0.942	*0.903	*0.821	*0.842
8:00–8:30	*0.987	0.989	*0.968	1.008	*0.798	*0.800	*0.930	*0.914	*0.848	*0.869
8:30–9:00	0.990	0.991	*0.980	1.008	*0.797	*0.799	*0.943	*0.918	*0.854	*0.886
17:00–17:30	0.993	1.000	1.010	1.007	*0.849	*0.818	*0.912	*0.927	*0.880	*0.870
17:30–18:00	1.005	0.993	0.990	1.008	*0.840	*0.836	*0.928	*0.937	*0.874	*0.875
18:00–18:30	0.994	0.990	*0.976	*0.936	*0.843	*0.828	*0.910	*0.932	*0.858	*0.867
18:30–19:00	0.999	0.994	1.002	0.986	*0.876	*0.829	*0.910	*0.983	*0.867	*0.857

Colocation quotient values with \* are significant at the 0.05 level

Meanwhile, the number of bus stations is much larger than the number of subway stations.

There are also obvious differences in the spatial distribution patterns of LCLQ between May 11 (weekend) and May 13 (weekday). On May 11, inside the Fourth Ring Road, almost all the significant origin/destination points have an LCLQ less than 1, indicating a significant dispersion relationship between trip origins/destinations and bus stations in these areas (Fig. 8(a)). On May 13, most of the significant origin/destination points are collocated with bus stations, and they are concentrated in Pinganli, Wukesong business district, Qianmen business district, Jiuxianqiao business district, Lincui business district, and Qinghe business district, as shown in Fig. 8(b). However, on May 13, the proportion of points that have an LCLQ less than 1 near the Muxiyuan business district is increased significantly in the evening compared with the daytime. This may be related to the recreational cycling behavior in the evening that has been observed in previous studies.

### Subway Stations

LCLQs detect areas where trip origins/destinations are collocated with subway stations, and the areas are near the subway stations on both 2 days, as shown in Appendix S2. In general, the spatial distribution patterns of LCLQs are similar on May 11 (weekday) and May 13 (weekend), as shown in Fig. 9, except there are strong colocations between trip origins/destinations and subway stations near subway interchange stations on May 11 (weekday), such as Xidan Station and Guomao station (Fig. 9(a)). The difference in the strength of colocation between trip origins/destinations and subway stations on weekdays and weekends may be related to commuting behavior. The need for subways during commuting may strengthen the colocation, and shared bikes are likely to serve as a connecting vehicle for commuting.

### Parks

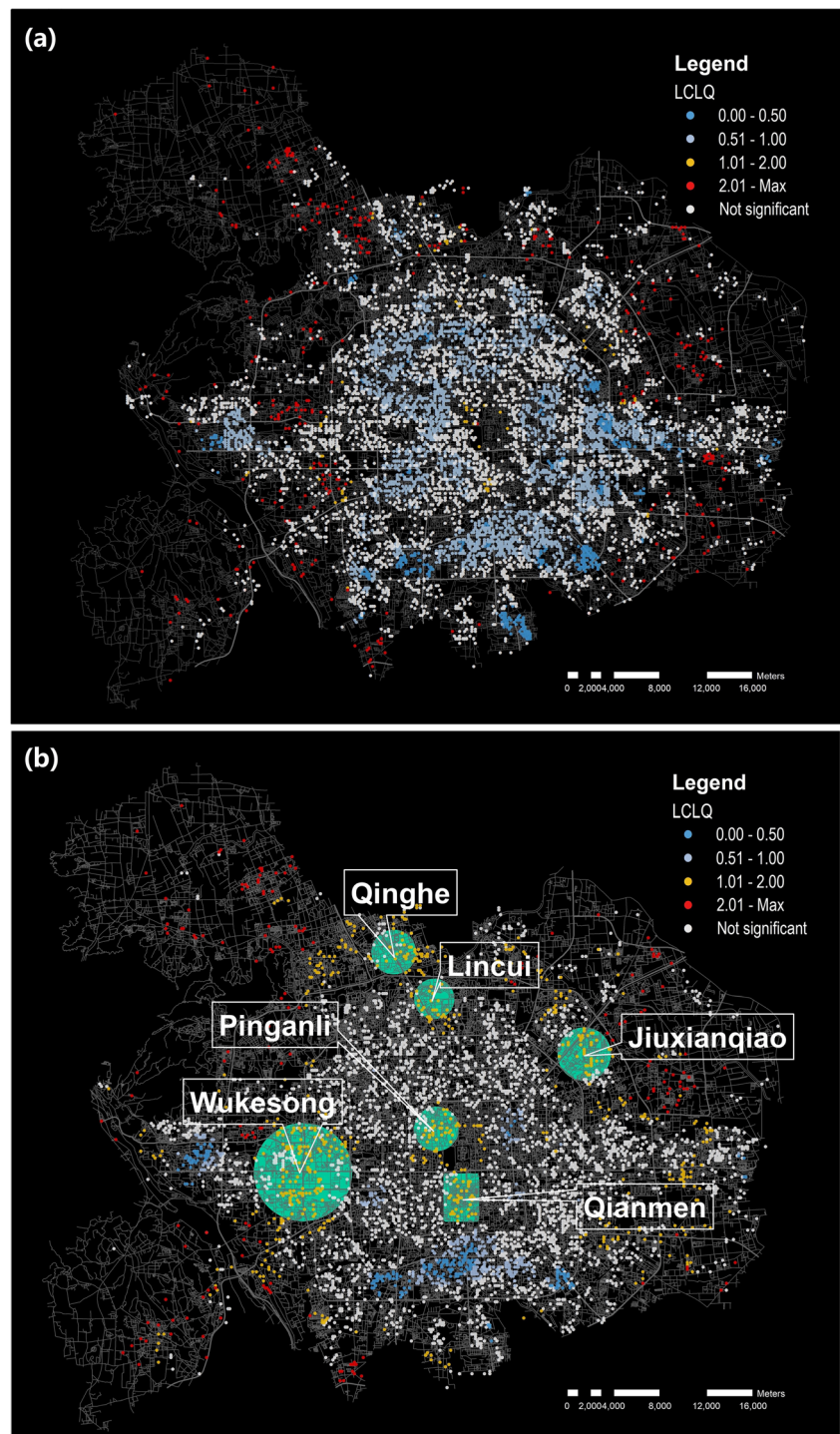
In general, the spatial distribution patterns of LCLQ values in different study periods on weekdays and weekends are similar. There are several areas where the LCLQs are greater than 2 in the result maps, indicating that trip origins/destinations are highly collocated with parks in these areas. Among the highly collocated areas, the area between the North Fourth Ring Road and the North Second Ring Road is the largest (a in Fig. 10(a)), likely because there are not only many large parks, such as Olympic Park and Shichahai Park, but also many small and micro urban parks. Another large area (b in Fig. 10(a)) is in Shijingshan District, which has the largest per capita public green space in Beijing. The other highly collocated areas are distributed around the Temple of Heaven, Chaoyang Park, Xinglong Country Park, and many other medium-sized parks as shown in Fig. 10(a).

### Residential Quarters

In general, among the significant trip origin/destination points, almost all have an LCLQ value greater than 1. The significant trip origin/destination points with an LCLQ smaller than 1 are concentrated in the southeast of the study region, indicating a significant dispersion pattern here. Points collocated with residential quarters are distributed in the central and western regions. From a single-day perspective, there was little difference among the study periods.

Although the overall distributions of LCLQ on the two days were consistent, more points on May 11 had an LCLQ greater than 2, and they were concentrated in Shijingshan District, around Guangqumen and near several small residential quarters, as shown in Fig. 11. Considering that the residences in Shijingshan District are far from the center of the city, people may use shared bikes as

**Fig. 8** LCLQ values for trip origins versus bus stations. (a) 8:00–8:30 on May 11. (b) 8:00–8:30 on May 13



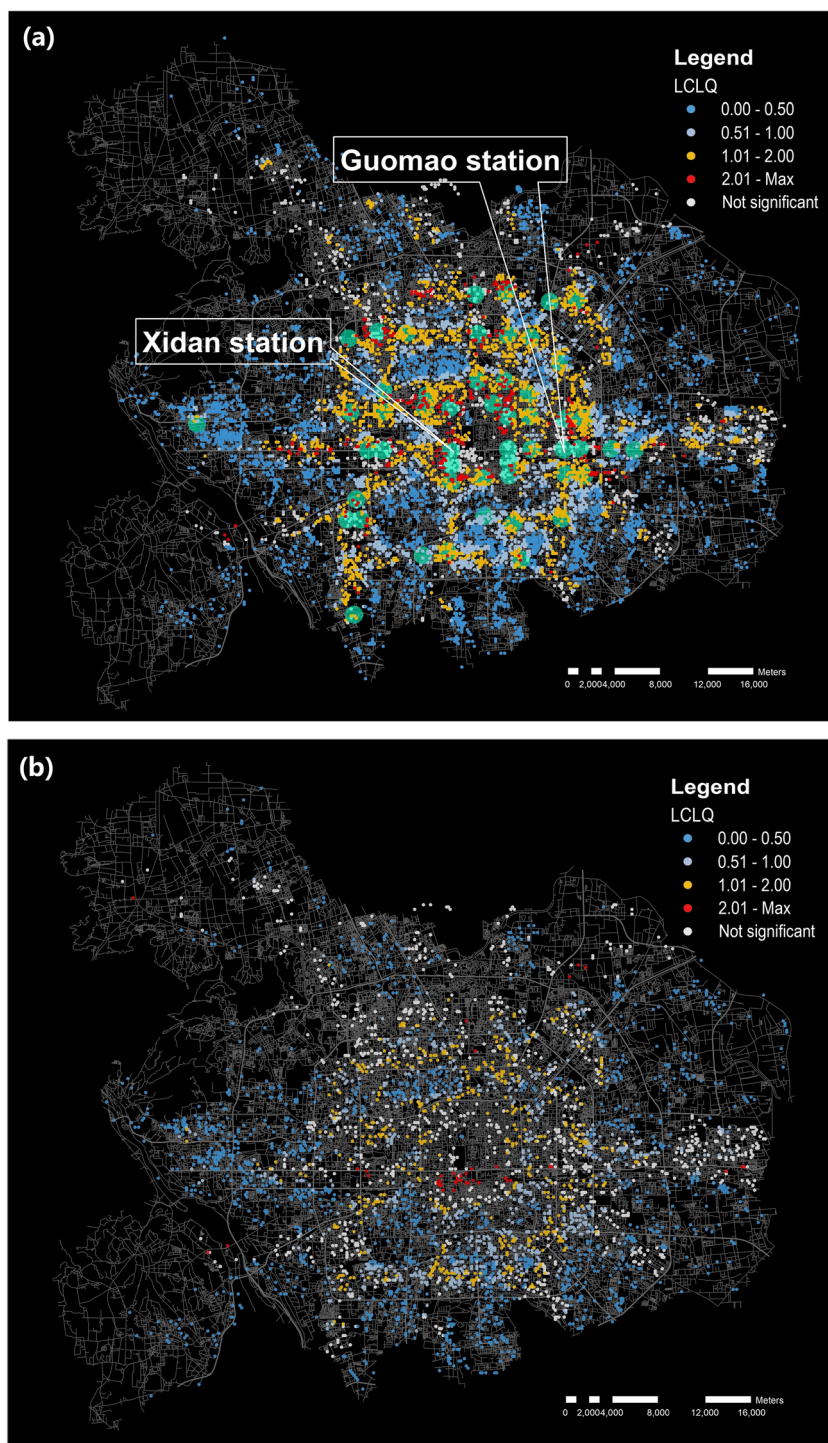
connecting vehicles from their homes to subways or bus stations, which could lead to a high LCLQ value of bike sharing origin/destination.

**Office Buildings**

As shown in Appendix S2, trip origins/destinations are collocated with office buildings inside the Third Ring Road

and near the Fourth North Ring Road on both May 11 and May 13. The spatial distribution of LCLQ varies greatly over the two days. Compared with May 11, the proportion of points that have an LCLQ between 1 and 2 on May 13 is considerably reduced. On May 11, the strong collocation patterns (an LCLQ value larger than 2) are scattered (Fig. 12(a)). However, on May 13, a strong collocation pattern (an LCLQ value larger than 2) between trip

**Fig. 9** LCLQ values for trip origins versus subway stations. (a) 7:30–8:00 on May 11. (b) 7:30–8:00 on May 13

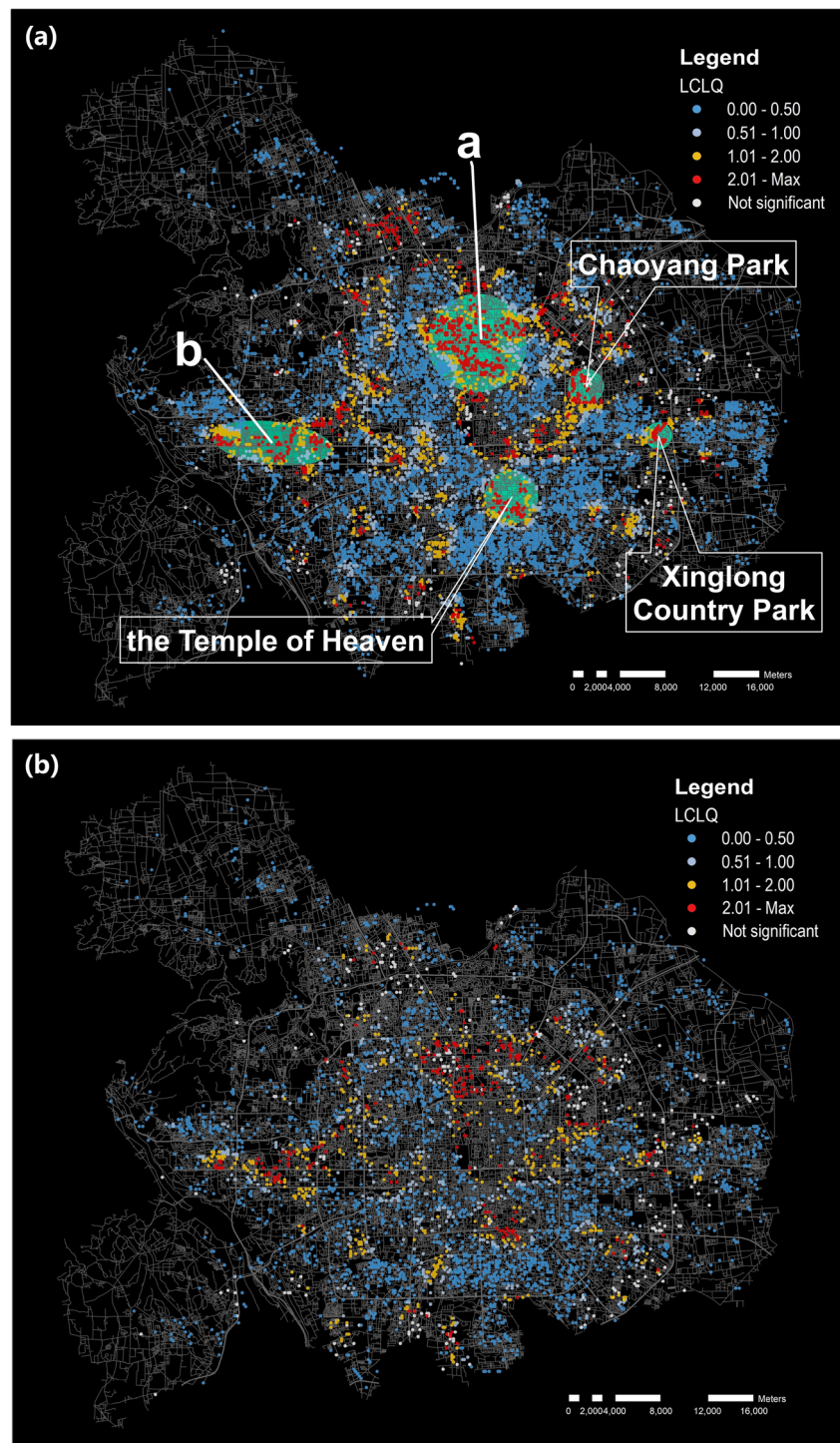


origins/destinations and office buildings is concentrated around the north of the East Second Ring Road, in Financial Street of Xicheng District and Zhongguancun Software Park (Fig. 12(b)). Meanwhile, the proportion of points that have an LCLQ between 1 and 2 slightly increased in the evening on May 13 (Fig. 13).

## Conclusions

The boom in BSSs has been driven by the development of information technology and the sharing economy in recent years. This paper analyzes the spatiotemporal pattern and urban facilities determinants of cycling activities in the

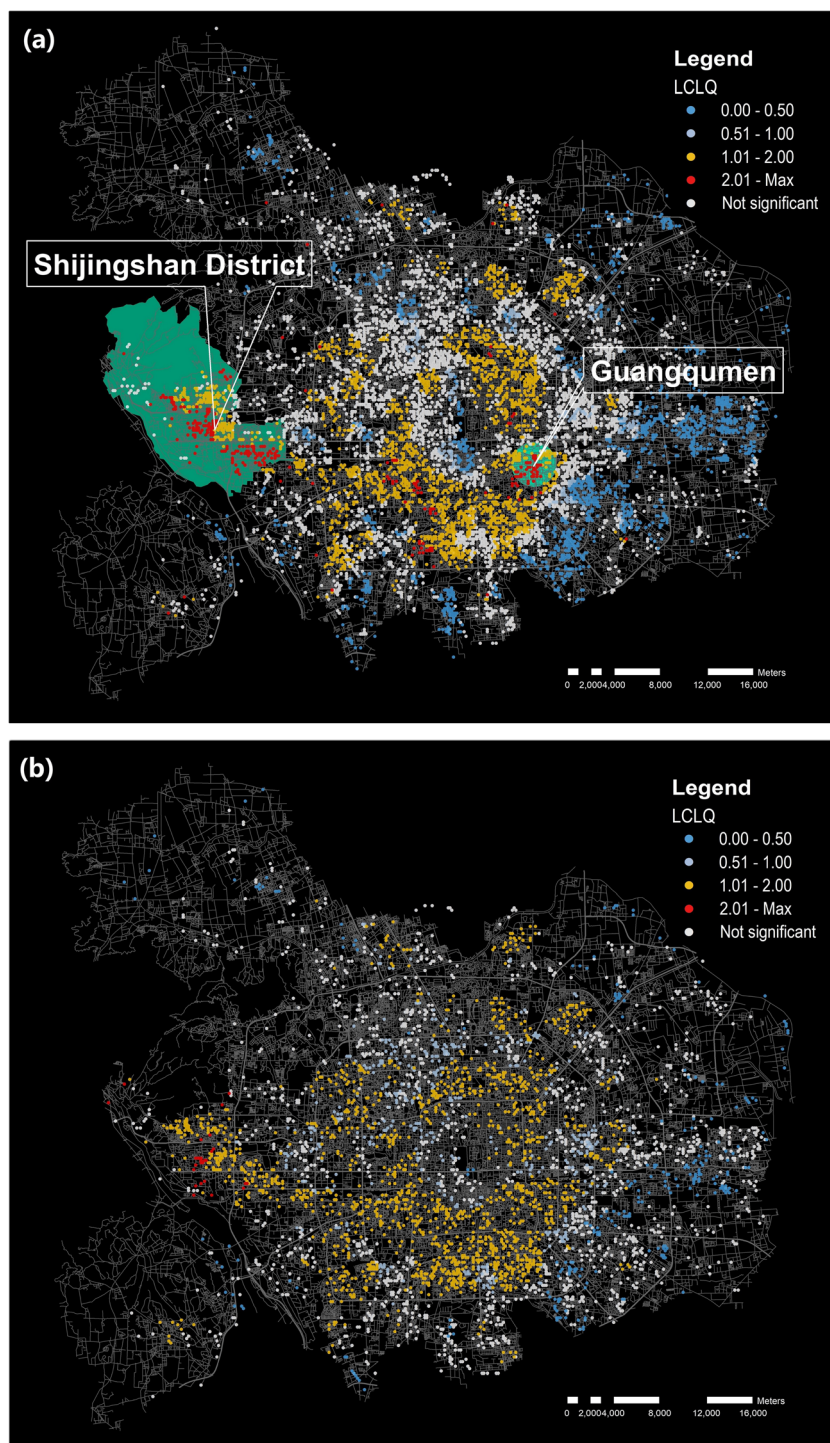
**Fig. 10** LCLQ values for trip origins versus parks. (a) 7:30–8:00 on May 11. (b) 7:30–8:00 on May 13



downtown area of Beijing. To the best of our knowledge, our work distinguishes itself from existing studies in terms of the analysis perspective and method. First, the analysis perspective is a road network. This perspective is highly suitable for analyzing human movement, as human movement is usually constrained by roads (Yu et al. 2017; Zhu et al. 2017) and roads connect urban functions at physical and cognitive levels (Shen and Karimi 2016). Furthermore, the analysis

perspective may minimize the effect of MAUP (Zhu et al. 2017). Second, different methods are used to examine the determinants of cycling activities. Shared bike riding is a relatively microscopic human activity in the city. Therefore, this paper applies network-distance-based GCLQ and LCLQ to reveal the spatial variability of the association between cycling activities and urban facilities from the macro and micro perspectives. These methods are not affected by the MAUP. The

**Fig. 11** LCLQ values for trip origins versus residential quarters.  
(a) 7:30–8:00 on May 11. (b) 7:30–8:00 on May 13

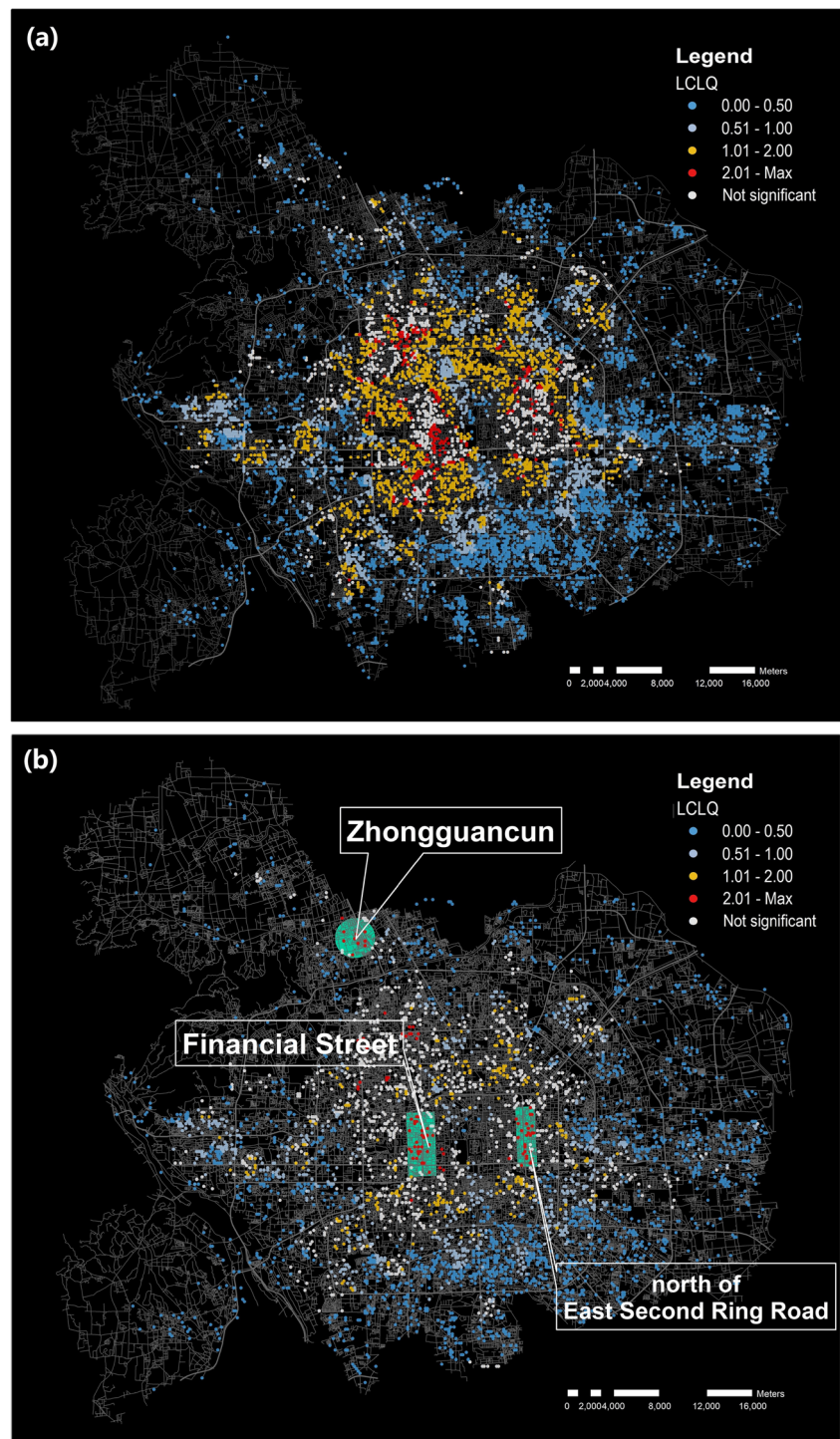


spatial and temporal characteristics of bike sharing trips and the spatial and temporal patterns of the connection between bike sharing trips and different urban facilities in Beijing represented by the research results can provide a reference for future studies on bike sharing trip characteristics in big cities.

There are several implications for policy and planning that arise from this study. First, the results show obvious temporal differences in bike usage between weekdays and weekends

and during different periods of a single day: (1) Bike usage is generally higher on weekdays. (2) Based on the differences in travel peaks, we speculate that bike sharing may be mainly used for commuting on weekdays, whereas on weekends, travel time and space options are more flexible. Therefore, these differences should be considered when scheduling bicycles. Weekends are more suitable for the maintenance of shared bikes, while on weekdays during peak hours, more

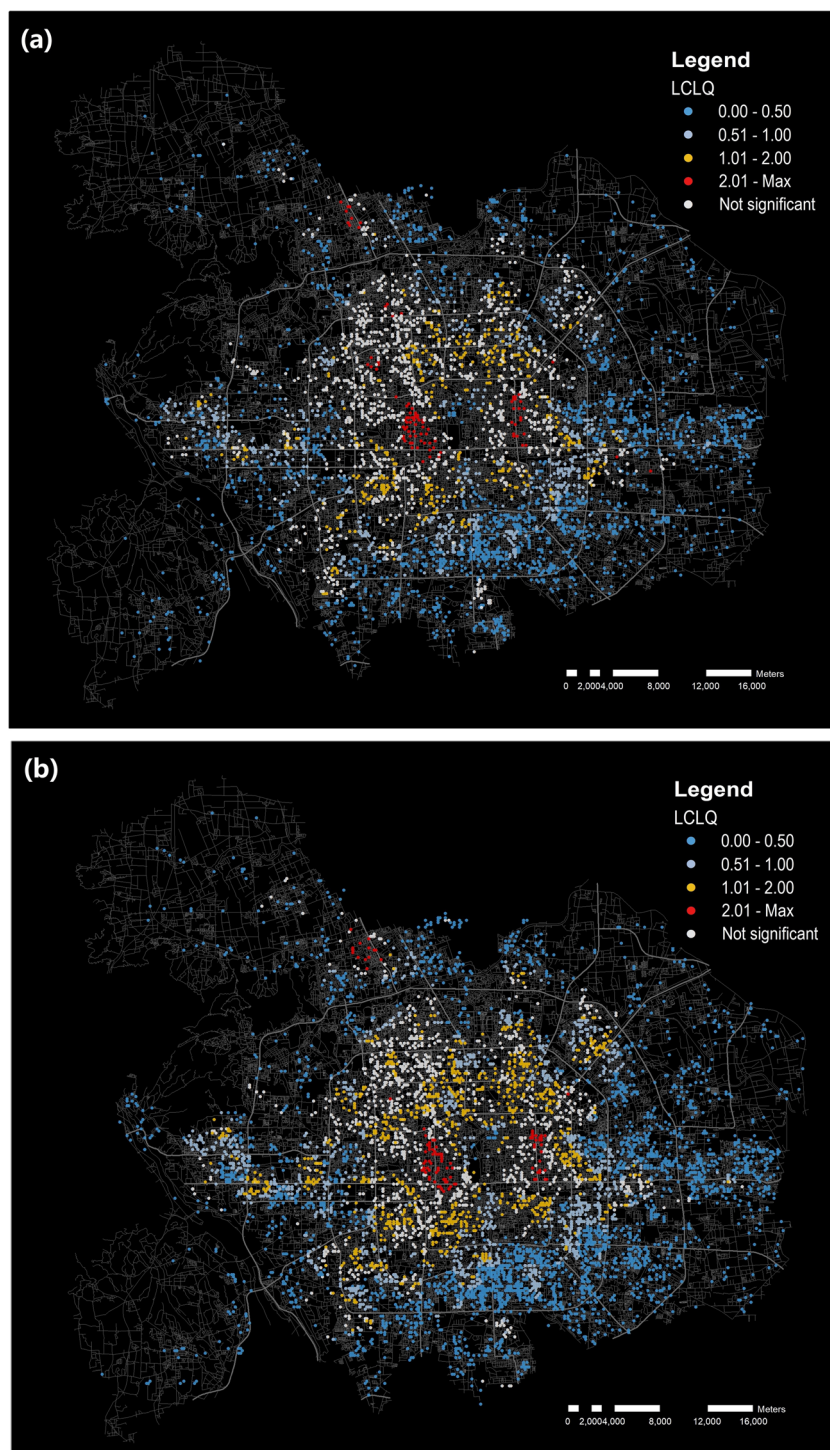
**Fig. 12** LCLQ values for trip origins versus office buildings. (a) 7:30–8:00 on May 11. (b) 7:30–8:00 on May 13



shared bikes should be set up along popular commuting roads. Second, the NKDE results of the origins and destinations of bike trips reveal popular roads for cycling: (1) Roads in the Muxiyuan, Liujiayao, and Shiliuzhuang regions have a large number of shared bike trips between 5 a.m. and 6 a.m. (2) During the morning and evening peak hours on weekdays and from 7 a.m. to 10 a.m. on weekends, the bike usage hot spot areas are within the Fourth Ring Road (“□”) or near

subway line 1 and the Batong Line, which run east and west through the central city (“—”). (3) Outside the Fourth Ring Road, there are also popular streets for bike sharing in the Wangjing-Jiuxianqiao business district, Ya’ao business circle except the Olympic Forest Park, and other small hot spot areas. Thus, in the blocks with active bike sharing activities mentioned above, relevant personnel can consider adding parking areas and planning bike paths to regulate cycling

**Fig. 13** LCLQ values for trip destinations versus office buildings on May 13. (a) 8:00–8:30. (b) 18:00–18:30



behavior and alleviate the road pressure. Third, network-distance-based LCLQ detects changes in the association between trip origins/destinations and different types of POIs in different regions: (1) During weekdays, there is a strong colocation between trip origins/destinations and bus stations outside the Fourth Ring Road, and there are strong colocations between trip origins/destinations and subway stations near multiple subway interchange stations within the Fourth Ring

Road. Taking this finding as a reference, we can increase the number of shared bikes around the subway interchange stations within the Fourth Ring Road and provide more shared bikes around the bus stations outside the Fourth Ring Road, which can give full play to the role of shared bikes in the “last mile.” (2) On weekdays, there are many trip origins/destinations in Shijingshan District that are strongly related to residential quarters. It is speculated that shared bikes may



serve as one of the transportation tools for residents to commute long distances. This finding can be applied to design bike fleet rebalancing strategies. Relevant personnel should responsively adjust the number of shared bikes around residential communities that are slightly farther from bus and subway stations.

There are also some limitations in this study, and several issues should be explored further. (1) The work covers only a 7-day period, and calendar events and different weather conditions are not captured. Future work will analyze the relative long-term spatiotemporal patterns of bike sharing and the influence of calendar events and weather conditions. (2) In our study, the analysis time period is sliced into subperiods, and NKDE and network-distance-based CLQ are applied to each subperiod. When analyzing the spatiotemporal pattern of shared bike usage, we need to compare the results of different periods. Moreover, the spatial and temporal dimensions are not well integrated. Future work will seek more effective methods that can integrate the spatial and temporal dimensions, such as geographically and temporally weighted regression (Wu et al. 2019).

**Author contribution** All authors contributed to the study conception and design. Material preparation and data collection and analysis were performed by Mengjie Zhou, Yuli Gu, Qinyue Yu, and Siyuan Yang. The first draft of the manuscript was written by Mengjie Zhou and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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**Data availability** The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Competing interests** The authors declare no competing interests.

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