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Impacts of COVID-19 pandemic on user behaviors and environmental benefits of bike sharing: A big-data analysis

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HIGHLIGHTS

- We quantitatively explore the impacts of COVID-19 on the usage of bike sharing.
- A novel method is proposed to estimate trip distances and trajectories of bike sharing.
- Complex network theory is employed to explore the transformation of user behaviors.
- COVID-19 impacts the user behaviors and environmental benefits of bike sharing significantly.

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ABSTRACT

The COVID-19 pandemic spreads rapidly around the world, and has given rise to huge impacts on all aspects of human society. This study utilizes big data techniques to analyze the impacts of COVID-19 on the user behaviors and environmental benefits of bike sharing. In this study, a novel method is proposed to calculate the trip distances and trajectories via a python package OSMnx so as to accurately estimate the environmental benefits of bike sharing. In addition, we employ the topological indices arising from complex network theory to quantitatively analyze the transformation of user behavior pattern of bike sharing during the COVID-19 pandemic. The results show that this pandemic has impacted the user behaviors and environmental benefits of bike sharing in Beijing significantly. During the pandemic, the estimated reductions of energy consumption and emissions on 6th Feb decreased to approximately 1 in 17 of those on a normal day, and the environmental benefits at most recovered to 70% of those in normal days. The impacts of COVID-19 on the environmental benefits in different districts are different. Furthermore, the decline of average strength and strength distribution obeying exponential distribution but with different slope rates suggests that people are less likely to take bike sharing to the places where were popular before. The pandemic has also increased the average trip time of bike sharing. Our research may facilitate the understanding of the impacts of COVID-19 pandemic on our society and environment, and also provide clues to adapt to this unprecedented pandemic so as to respond to similar events in the future.

1. Introduction

The rapid spreading of coronavirus disease 2019 (COVID-19) pandemic has brought unprecedented challenges and threatens to the normal life of human beings and global public health [1]. Since the first case of COVID-19 was identified in December 2019 in Wuhan city [2], there had been more than 31.3 million confirmed cases across 188 countries and territories, and the COVID-19 had resulted in more than

965,000 deaths by 22nd September 2020 [3]. In addition, this unprecedented disease has caused the huge impacts on global economy [4], global energy markets [5], geopolitics [6], environment and climate [7], and so forth. Due to high infectivity and destructiveness of COVID-19, and the suddenness of its outbreak, Chinese government has taken strong measures to stop the spreading of this new disease, such as national-wide lockdown and isolation of people at high risk areas [8]. However, COVID-19 is able to spread from human to human, while

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public transport tends to contain many people in one shared space, which implies people probably change their attitudes and behaviors to public transport [9], although it is a primary travelling mode for most of people [1].

Meanwhile, in recent years, as the rapid growth of the number of private vehicles, shortage of urban land resources, and deterioration of air quality in cities, city administrations have realized the importance of sustainable public transport. As a green and low-carbon transport mode, bike sharing has become increasingly popular in many cities across the world, and has been regarded as an important way to integrate public and sustainable transport due to its significant advantages in energy conservations, alleviation of traffic congestion, mitigation of environment pollution [10,11]. In general, bike sharing refers to a service which allows shared use of bicycles to public for a short term, and serves as a form of public transportation [12]. As the innovation of Internet of Things (IoT) technology and the extensive use of smart phones, dockless bike sharing emerges to solve the “first mile” and “last mile” problems and connects the users with public transits, which provides convenience for users [13,14]. The benefits generated by dockless bike sharing include reduced congestion, emissions, and fuel use [15]. Compared to the traditional docked bike-sharing systems, the dockless bike sharing is able to provide flexible mobility [16,17]. Under this severe COVID-19 pandemic, people’s lifestyle and travelling modes have been drastically changed because of the pandemic panic and strict restriction measures such as city lockdown and traffic control. It is expected that bike sharing is also affected by such unprecedented COVID-19 pandemic. However, owing to the better ventilation, convenient disinfection, and avoidance of close contact between travellers, people have more positive attitude to use bike sharing for travelling than public transport during the pandemic [18]. Although COVID-19 impacts the total demand of bike sharing, it shows better resilience than subway to the pandemic [19].

Although bike sharing has existed for about 50 years, its popularity has been significantly increasing in recent years owing to the advance of IoT technology. There are some studies analyzing the development history [20,21], and business models of bike sharing [22]. They deem that bike sharing has four generations so far, and dockless bike sharing belongs to one type of the fourth generation. Compared to the traditional docked bike sharing, the dockless one may provide much greater convenience to users [23]. In addition, existing research concerning bike sharing mainly focuses on three areas [24], which is slightly different from Médard and Caruso [25]. The first area refers to bike sharing rebalance problem (BRP) [26], which was first proposed by Benchimol et al. [27]. BRP can be divided into dynamic and static rebalancing [28]. Dynamic BRP takes into account daytime operations and real-time demand variations, and such problems have complex dynamic nature [29,30]. For example, Shui and Szeto [31] adopt a rolling horizon method to handle the complexity caused by the routes and demand variations of bikes over a multi-period operational horizon. Most of BRP studies concentrate on static rebalancing, which only considers night-time operations and the station demand of bikes is assumed to be constant [27,32]. The static rebalancing problem of bike sharing can be described as one redistributing one commodity among vertices in order to reach a target distribution with a minimum cost [33,34], while Kadri, Kacem, et al. [35] regard such problem as travelling salesman problem with additional constraints. Following this, Pal and Zhang [36] propose a Novel Mixed Integer Linear Program (NMILP) to solve the static complete rebalancing problem, which can handle single and multiple vehicles, and allow the same vehicle visiting the same node multi-times. Many heuristic algorithms are proposed to solve static BRP. For example, Li, Szeto, et al. [37] utilize a combined hybrid genetic algorithm to solve the static bike repositioning problem, which can be formulated as a mixed-integer linear programming problem. The second area includes demand prediction and location optimization of bike sharing [38,39]. Reasonable demand prediction and location optimization of bike sharing are able to directly impact the service quality of

bike-sharing systems. Vogel, Greiser, et al. [40] utilize data mining methods to derive bike activity pattern based on extensive operational data of bike-sharing systems. Following this, Kaltenbrunner, Meza, et al. [41] and Chen, Ma, et al. [42] also propose the methods based on data mining to infer spatial-temporal bike trip patterns. In addition, many methods are utilized to predict the demand of bike sharing. Zeng, Yu, et al. [43] adopt the gradient boosting decision tree (GBDT) and neural network (NN) techniques to extract the global features of bike-sharing systems so as to improve the demand prediction. To achieve the sustainable development of dockless bike sharing, Hua, Chen, et al. [44] employ clustering analysis to identify the virtual stations of shared bikes in Nanjing, and parking demand is estimated based on trip data of Mobike and bike-sharing survey. Kaspi, Raviv, et al. [45] leverage a Bayesian model to detect the station demand of bike sharing based on trip transaction data. As well as this, machine learning methods combining with big data are used for forecasting demand of dockless bike-sharing systems [46,47].

As for the third area, it mainly involves the evaluation of bike sharing from economic, social and environmental perspectives [48]. Air pollution reduction caused by bike sharing is presented by Shaheen, Guzman, et al. [20], while Brand, Goodman, et al. [49] argue that the CO₂ emission reduction requires a supportive built environment. Wang and Zhou [50] investigate the evidence that bike sharing can effectively reduce the congestion during rush-hour time by studying cases of cities in the US. Following this, Li, Zhu, et al. [51] have confirmed that the dockless bike sharing in China may improve the users’ first mile and last mile connections with public transit. In addition, a framework of sustainable business model is proposed by Gao and Li [22] to address the social-environmental benefits by analyzing Mobike, the largest dockless bike-sharing operator in China. Sun, Wang, et al. [52] evaluate the feasibility and adaptation of shared transportation including shared bikes from five perspectives: resource, environment, convenience, economy and governance. Based on their research, bike sharing is regarded as an important way to alleviate the traffic and environment problem in Beijing. As well as this, Zhang and Mi [14] investigate the environmental benefits of bike-sharing systems in Shanghai by using big data analysis, and bike sharing of Mobike is used as example to estimate the reduction of energy consumption and emissions for the whole city. The results show that the more developed districts in Shanghai have higher environmental benefits, and environmental benefits at the evening peaks are more significant than those at morning peaks. Teixeira and Lopes [19] find the transfer mode from some subway users to bike sharing during the COVID-19 pandemic in New York city, and they emphasize that bike-sharing system is more resilient than subway to disruptive events.

The existing studies related to bike sharing are very abundant, however, to date, limited studies explore the impacts of COVID-19 on the bike-sharing systems, although it is an important sustainable transport mode. Particularly, to some extent, the transformation of user travelling behaviors and environmental benefits is able to reflect the emergency response patterns of people in cities when suffering from the pandemic, which facilitates the further understanding of impacts caused by COVID-19 on our society, so as to help adapt to the ongoing pandemic. Therefore, this study mainly explores the environmental benefits and user behaviors of bike sharing during the pandemic, which has definitely changed lifestyle of human beings.

In this paper, we have made three main contributions. Firstly, we propose a novel method to estimate trip distances and trajectories of bike sharing with the longitudes and latitudes of origins and destinations via a free open python package OSMnx, which apparently provides a feasible way to estimate environmental benefits without detailed time sequential GPS track data. Secondly, we set up novel complex networks based on bike-sharing trips and the topology of the road network, and the topological indices arising from complex network theory, strength and its distribution, are employed to explore user behavior pattern in terms of statistical characteristics during the pandemic. Thirdly, the dockless bike-sharing data of three main operators (accounting for more

than 95% of total average daily orders) in Beijing are utilized to investigate the transformation of user behaviors and environmental benefits of bike sharing under COVID-19, and such dataset can provide more accurate estimations compared to the one with only one bike-sharing operator's data.

The remaining of this study is organized as follows. Section 2 introduces data source and the methods used in this study, including the proposed method to estimate the trip distances with limited trip information, and the topological indices arising from complex network theory. In Section 3, we show the results and discussions related to bike-sharing trip analysis, environmental benefits, and user behaviors for bike sharing. Finally, Section 4 presents the conclusions.

2. Data and methods

2.1. Study area and data source

As the capital of China, Beijing is one of the most populous cities around the world with more than 21.54 million residents within an area of 16,410 km² (Fig. 1)¹. Beijing is the political, cultural and educational center of China, its Gross Domestic Product (GDP) was 458 billion dollars in 2018, approximately 3.45% of China's total GDP. Its nominal GDP per capital was 21,261 dollars, and ranked No.1 in China². Beijing is located in the north of China, and consists of 16 districts, such as Haidian, Chaoyang, Changping and Fengtai districts. In addition, Beijing owns multiple ring roads, which are all expressways and cover the majority parts of the city. The Central Business District (CBD) of Beijing is located in the east of the city and between the 3rd and 4th ring roads. In this study, most of bike-sharing trip data fall within the 6th ring road, and nearly all of the trips are within the red box, which marks the study area, as shown in Fig. 1. By the end of 2019, Beijing possessed 900,000 dockless shared bikes [53], and the number declined greatly compared to 2.35 million in 2017 due to the cleaning up and rectification of the city administrations³.

The data used in this study are obtained from the Traffic Information Center of Beijing Municipal Commission of Transport (BMCT), where is in charge of managing and regulating the operations of bike-sharing operators in Beijing. Compared to the bike-sharing data used in other studies [14], the dataset here includes trip data of three main dockless bike-sharing operators in Beijing: Mobike, Hello bike and Qingju bike, which account for the 95.7% of the average daily orders. The dataset covers the main periods during the outbreak of the COVID-19 pandemic (from 14th Jan to 10th Mar 2020). By the end of 2019, average daily orders of bike sharing was up to 1.23 million, and Mobike was most frequently used with 839,000 daily orders [54]. The dataset provided by BMCT includes 17,761,557 valid orders, and contains the basic trip information including bike ID, start time, end time, the longitudes and latitudes of origin and destination points. It is noteworthy that the dataset does not include any user information and GPS track data due to the protection of user privacy and business secrets. Therefore, we cannot know the real bike trip trajectories of the users. In Section 2.2, a novel method is proposed to solve this problem.

The spatial distributions of origins and destinations from 14th Jan to 10th Mar for all bike-sharing trips are presented in Fig. 2 by Geographical Information System (GIS) software. As can be observed, most of trips take place in Beijing's central areas, such as Dongcheng, Xicheng, Chaoyang and Haidian districts.

¹ Beijing Municipal Bureau of Statistics and Survey Office of the National Bureau of Statistics in Beijing 2018: <http://tjj.beijing.gov.cn/>

² National Bureau of Statistics of the People's Republic of China: <http://www.stats.gov.cn/tjsj/>

³ <http://www.mnw.cn/news/shehui/1844556.html>

2.2. Estimation of environmental benefits of bike sharing

2.2.1. Trip distance estimation

The estimation of environmental benefits is based on the trip distances of bike sharing [14]. In most of cases, in order to satisfy the security and privacy concerns, the data concerning bike sharing do not include the GPS track with temporal information, which is necessary for the calculation of the accurate trip distances. Here the obtained bike-sharing data just contain the longitudes and latitudes of trip origins and destinations. In the traditional way, the trip distances are calculated based on the straight lines between origins and destinations, namely, Euclidean distance, which tends to underestimate the realistic distances of trips. Given this, we propose a novel method to calculate the trip distances with limited trip information. This method assumes that all users of bike sharing are very rational and always choose the shortest paths between origins and destinations as their routes. Therefore, the main idea of this method is to calculate the shortest paths between origins and destinations based on urban bikeable road networks extracted by OSMnx, which is an open python package to extract, model, visualize, and analyze road networks from OpenStreetMap [55]. In the extracted road network, nodes refer to the intersections or junctions of roads, and links represent the road segments between nodes. The calculation procedures of the proposed method are shown in Table 1:

2.2.2. Estimation of energy conservation and emission reduction

In this study, the environmental benefits refer to the energy conservation and emission reduction (ECER) potentially caused by using bike sharing. Here we adopt the method developed by Zhang and Mi [14] to estimate the ECER, and bike sharing is assumed to be able to replace the travelling by vehicles if the distances between origins and destinations are reasonable. In other words, if the distance exceeds a threshold, people consider to take taxi or private cars for travelling. The energy consumption of a vehicle can be calculated as follows:

$$E = \begin{cases} 0, & \text{if } d < \theta \\ \frac{d' \cdot \rho_1 \cdot \rho_2}{1000 \cdot e_1 \cdot e_2} & \text{if } d \geq \theta \end{cases} \quad (1)$$

where E is the energy consumption of a vehicle, and θ is the threshold (unit: m) which determines people's travelling mode, d is the distance of bike sharing obtained from Table 1 (unit: m), d' is the distance of potential vehicle usage, which can be derived from Table 2, ρ_1 is the density of petroleum (unit: kg/m³), and we take 745.2 in the study (from Energy Statistics Handbook [56]); ρ_2 is the petroleum consumption per km (unit: m³/km), here we take 7.2×10^{-5} (from IEA [57]); since the efficiency of petroleum exploitation and transportation is considered, here e_1 and e_2 represent the exploitation efficiency and distribution efficiency separately, and take 87% and 95%, respectively [58].

According to Intergovernmental Panel on Climate Change (IPCC) [59], CO₂, NO_x, and CO are main pollutants emitted by road transport, so in this study we mainly focus on the estimation of CO₂ and NO_x emissions. Eq. (2) is used to calculate the emissions generated by vehicle fuel consumption.

$$M_i = \begin{cases} 0, & \text{if } d < \theta \\ \frac{d' \cdot \rho_1 \cdot \rho_2 \cdot c_i}{1000}, & \text{if } d \geq \theta \end{cases} \quad (2)$$

where M_i is emissions generated by fuel consumption, and c_i is emission factors for different types of greenhouse gas pollution generated by driving vehicles, which are obtained from EPA [60]. The calculation procedures for environmental benefits of bike sharing are presented in Table 2.

As can be seen from Table 2, if the trip distance of bike sharing exceeds the threshold, the distance of potential vehicle usage is calculated according to step (3)-(5) based on the road network for vehicles G_r . This

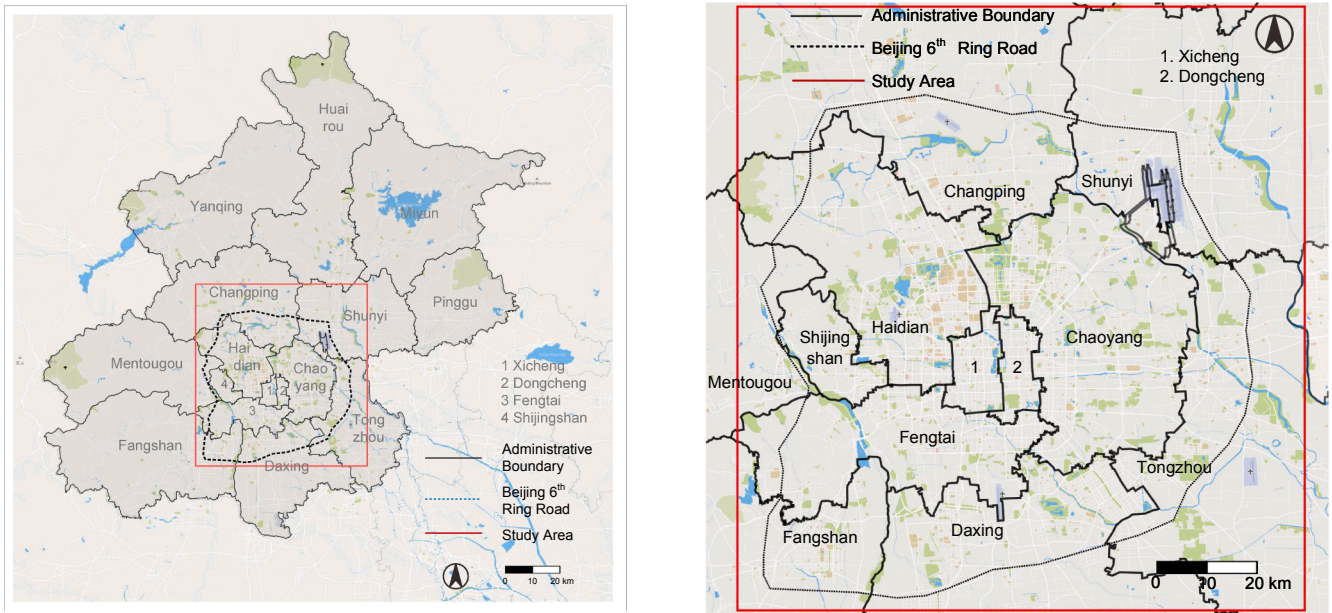
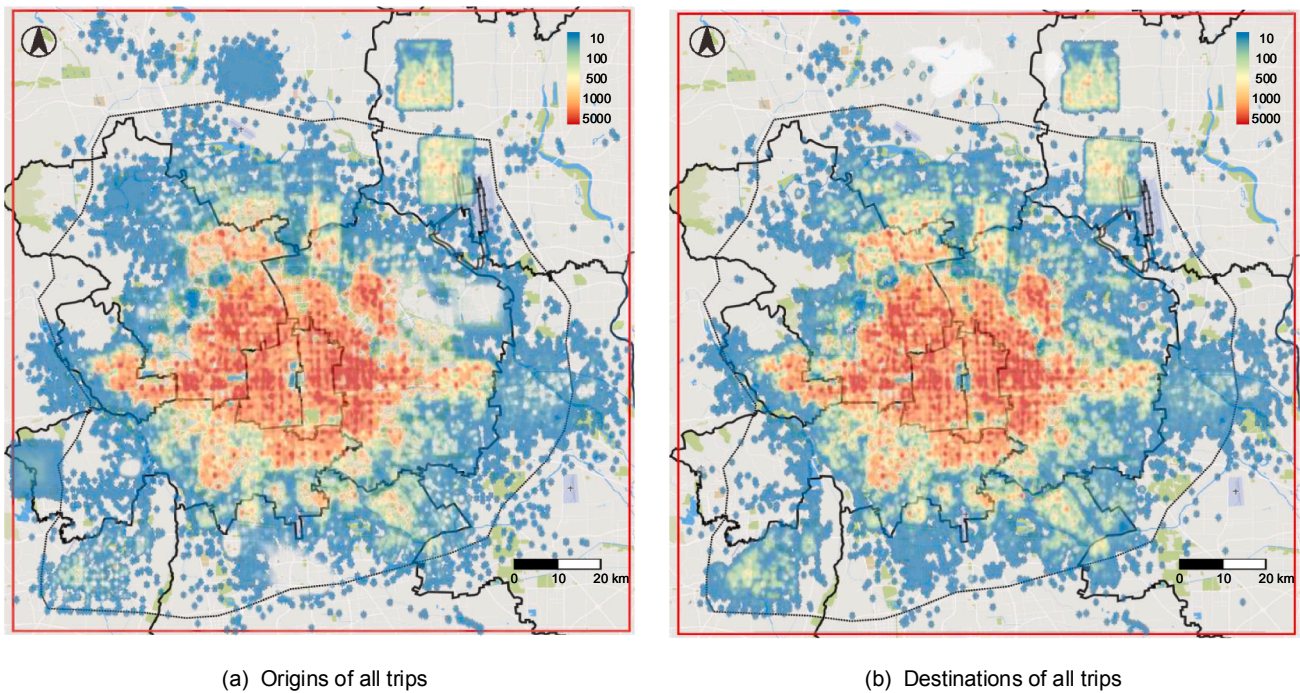


Fig. 1. Study area of Beijing.



(a) Origins of all trips

(b) Destinations of all trips

Fig. 2. The distribution of origins and destinations of all bike-sharing trips.

Table 1

The calculation procedures for the distances of all bike-sharing trips.

- 1 Extract the bikeable road network in Beijing with OSMnx, which is denoted as $G(N, L)$, where N is the set of nodes, and L is the set of links.
- 2 Define the sets of longitudes and latitudes of origins and destinations for bike sharing as (O_{lon}, O_{lat}) and (D_{lon}, D_{lat}) , respectively.
- 3 Find the nearest point locations of (O_{lon}, O_{lat}) and (D_{lon}, D_{lat}) from G , denoted as (O'_{lon}, O'_{lat}) and (D'_{lon}, D'_{lat}) .
- 4 Input (O'_{lon}, O'_{lat}) , (D'_{lon}, D'_{lat}) and G , utilizing *Dijkstra* algorithm to calculate the shortest paths of all bike-sharing trips.
- 5 Save the length of the shortest paths as R .

calculation process is similar with distance calculation of bike sharing, but it is worth noting that we utilize the network of vehicles G_v rather than the bikeable network G . Given that bicycle roads often cannot share with vehicles, for example, bicycles are not allowed on highways, so using G_v to calculate the environment benefits can achieve more accurate and realistic estimation. Following this, we can calculate the potential fuel consumption and emissions based on Eqs. (1) and (2), respectively.

More detailed interpretations concerning the method to estimate the energy consumption and emissions can be referred to Zhang and Mi [14]'s work. In this study, θ also takes 1 km, which implies that bike-sharing trips with distances larger than 1 km have potential for ECER.

Table 2

The calculation procedures for environmental benefits of all bike-sharing trips.

1	Extract the road network for vehicles in Beijing with OSMnx, which is denoted as $G_v(N_v, L_v)$, where N_v and L_v is the set of nodes and links of the road network for vehicles.
2	When trip distance d of bike sharing is larger than the threshold θ , step (3)-(6) are conducted repeatedly:
3	Find the nearest point locations of (O_{lon}, O_{lat}) and (D_{lon}, D_{lat}) from G_v , denoted as $(O_v'_{lon}, O_v'_{lat})$ and $(D_v'_{lon}, D_v'_{lat})$.
4	Input $(D_v'_{lon}, D_v'_{lat})$, $(O_v'_{lon}, O_v'_{lat})$ and G_v , utilizing <i>Dijkstra</i> algorithm to calculate the shortest paths of all potential vehicle trips.
5	Save the distance length d of the shortest paths of potential vehicle usage as R_v .
6	Based on Eqs. (1) and (2), calculate the potential fuel consumption E and emission M_i , namely, environmental benefits of one bike-sharing trip.
7	Add up potential fuel consumption E and emission M_i of all bike-sharing trips, and environmental benefits of bike sharing are obtained.

To accurately estimate the environmental benefits of bike sharing in Beijing during COVID-19 pandemic, the estimated results are divided by 95.7%, the average daily orders share of three bike-sharing operators. Here we need to emphasize that the method used in the study can effectively handle huge amount of bike-sharing data despite not considering realistic factors such as scheduling and different travel modes, so it can be employed to explore the impacts of COVID-19 on environmental benefits and user behaviors of bike sharing. Although the proposed method can effectively estimate the trip distances with limited trip information, it still requires extensive computation time due to repeat calculation of the shortest paths. In the future, more sophisticated methods which consider many realistic factors can be further explored, and the efficiency of calculation and the complexity of models should be balanced when handling a massive amount of data.

2.3. User behavior pattern analysis based on complex network theory

The number of studies regarding user behaviors of bike sharing is considerable, and the methods are diverse, such as spatial agent-based model [61], user surveys [62], a video-based observation method [63], data mining [64], and theory of planned behaviors [65]. However, there are limited studies and methods to explore the impacts of COVID-19 on user behaviors based on GPS data of bike sharing. In this study, in order to observe the transformation of user behaviors for bike sharing in Beijing under unprecedented COVID-19 pandemic from the perspective of statistical mechanics, we propose to set up novel complex networks based on the realistic road network and trip data of bike sharing (as shown in Fig. 6), and topological indices arising from complex network theory: strength and strength distribution, are utilized to quantify such transformation. These indices are first proposed by Barrat, Barthelemy, et al. [66] to quantify the strength of nodes in terms of the total weight of their connections. To build the network, firstly we divide the study area into small lattices with size of $1 \text{ km} \times 1 \text{ km}$; following this, these lattices are defined as the nodes of the network, the links exist if there are bike-sharing trips between two nodes, and the number of trips within the lattices is the weight of the links. Based on this novel complex network, the strength of each node s_i can be calculated as:

$$s_i = \sum_{j=1}^N w_{ij} \cdot a_{ij} \quad (3)$$

where a_{ij} denotes the connection between node i and node j ; if i and j are connected a_{ij} is 1 otherwise it is 0, and N is the number of the network nodes; w_{ij} is the weight of the link between node i and node j .

The strength distribution of the network $P(s)$ is very important in studying real networks, which is very similar with degree distribution [67]. $p(s)$ is defined as a ratio of the number of nodes with strength $s(N_s)$ to the number of all nodes (N), that is, N_s/N . $P(s)$ represents the cumulative strength distribution [68], as shown below.

$$P(s) = \sum_{s'=s}^{\infty} p(s') \quad (4)$$

The mean strength of a network is the average of the strength of all nodes, denoted as $\langle s \rangle$ [69]. In this study, strength and strength distribution are used to measure the impact of COVID-19 on user behaviors of bike sharing from the perspective of complex network theory.

3. Results and discussions

3.1. Bike-sharing trips during the COVID-19

The data of bike-sharing trips used in this study are from 14th Jan to 10th Mar 2020, 57 days in total, which covers the dates of important events during the outbreak of COVID-19 pandemic, including the date when Prof. Nanshan Zhong announced COVID-19 was human-to-human transmission (20th Jan, red vertical line in Fig. 3), the date of Wuhan lockdown (23rd Jan, purple vertical line), and the end date of extended Spring Festival Holiday (2nd Feb, blue vertical line), which all have impacts on the activities and mobility of people. During this period, the minimal number of bike-sharing trips is 48,516 (6th Feb), and the maximal trip number is 912,761 (15th Jan). Compare to 1.27 million average daily usage in 2019⁴, the average number of trips during the COVID-19 pandemic drops to 311,606. In this study, in order to explore the transformation of environmental benefits and user behaviors of bike sharing in Beijing during the COVID-19 pandemic, we attempt to utilize these landmark events to distinguish the different stages of the pandemic. Although the first COVID-19 case can be traced back to November 2019 [70], there was no panic when people were not aware of this virus, and all social and economic activities ran normally. Until human-to-human transmission of COVID-19 was reported by media and the lockdown of Wuhan city was officially announced, the panic spread across the country immediately, which greatly impacted all aspects of our society. Following this, the end of extended holiday, which was officially announced, represents an attempt for work resumption. The landmark events used in the study are all known to public and widely reported by media, which can effectively distinguish the different stages of the COVID-19 outbreak in China.

In this study, invalid trip orders of bike sharing mainly refer to ones with zero values of longitudes and latitudes of origins/destinations, which are probably caused by malfunctions of bike sharing. After removing invalid orders, we plot the number of bike-sharing trips during COVID-19 in Fig. 3. As we can see, overall the number of bike-sharing trips decreased significantly after 20th Jan and 23rd Jan, which was probably caused by the panics of people. Afterwards, the number of bike-sharing trips stayed at a low level. The number of trips gradually increased after the holiday, but still remained a lower level compared to that before Wuhan lockdown, which shows that the COVID-19 outbreak has significantly negative impacts on the utilization of bike sharing. In order to observe the relationship between trip numbers of bike sharing in Beijing and the development of COVID-19 pandemic in China, we present the trips, total confirmed cases, active cases and new cases in Fig. 3.

As can be seen from Fig. 3, as the pandemic evolves, the utilization of bike sharing approximately is divided into several different stages. Before the announcement of human-to-human transmission on 20th Jan, the number of bike-sharing trips was above 700,000 except that on Saturday (18th Jan). Thereafter, the number of trips decreased greatly due to the panic to this new disease, the event of Wuhan lockdown exacerbated the COVID-19 panic, the trip number continued a quick downward trend until the day of Spring Festival. During this period, the

⁴ <http://global.chinadaily.com.cn/a/202002/26/WS5e55e4bca31012821727a76c.html>.

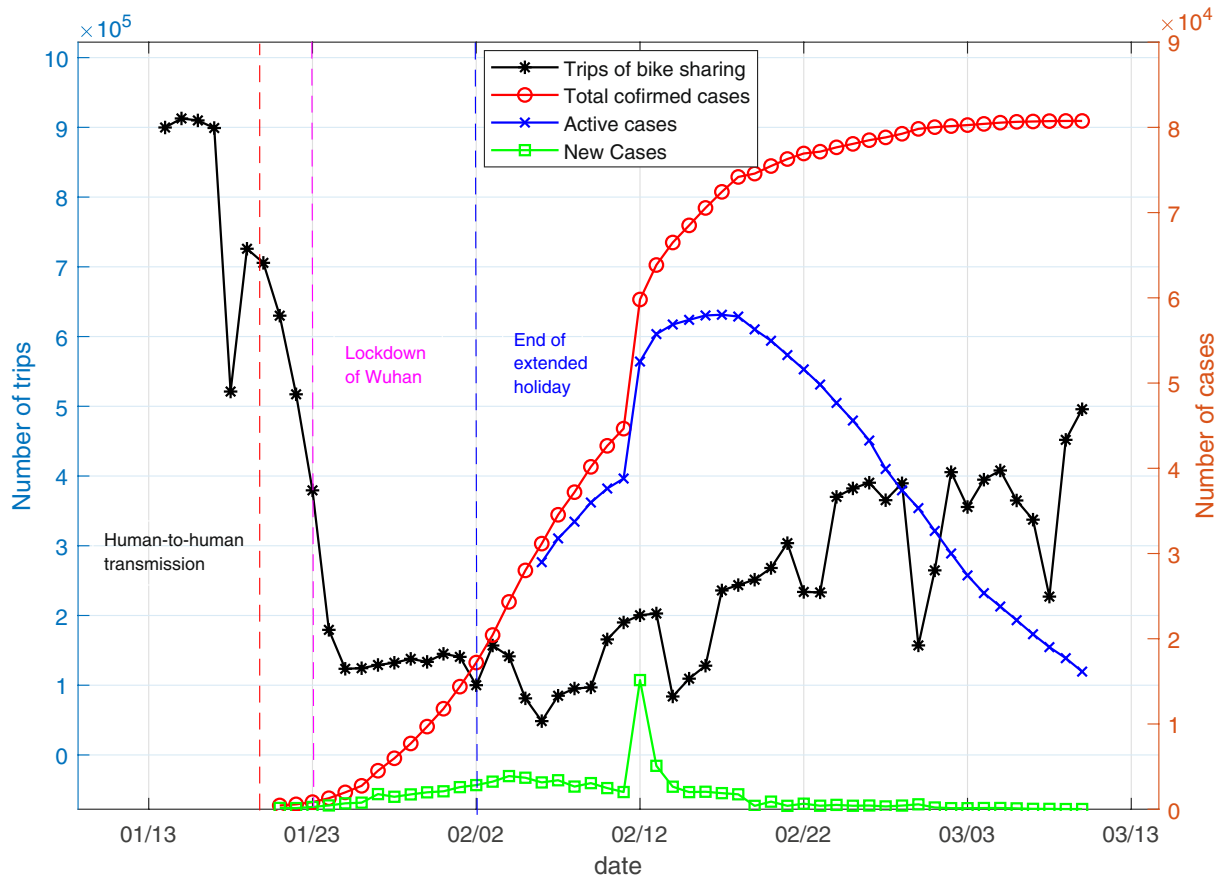


Fig. 3. Number of trips of bike sharing in Beijing and the number of confirmed cases of COVID-19 in China.

number of new cases for COVID-19 had been increasing steadily, and the government called on people to reduce travelling. Here we would like to say that the migration of population during the Spring Festival in Beijing also caused the drop of bike-sharing orders, but apparently COVID-19 pandemic had greater impacts on bike-sharing trips (the explanations are presented in the following paragraph). We may see that even after 2nd Feb, the end of extended holiday, the trips of bike sharing still went down since the panic was difficult to vanish within a short time. As the decrease of new cases and active cases, the number of trips grew very slowly despite the end of the holiday and work resumption, and during this period people tended to less use bike sharing on Saturday, for example, the trip number reduced by nearly 50% on 29th Feb compared to that on the previous weekday. In addition, we notice that the abrupt growth of COVID-19 new cases on 12th Feb clearly hinders the increasing use of bike sharing within a short term.

Here we need to emphasize that weather and the Spring Festival are also important factors to affect travelling, but the impacts of these factors on the analysis of bike sharing in the study are very limited. Firstly, the highest amount of bike-sharing trips in the dataset occurred in January, approximately 0.91million, when was the coldest time before the outbreak of the pandemic (average temperature in Jan was -1°C)⁵, and the Spring Festival travel season had already started for one week. However, in February and March, when the temperature rose gradually, the orders of bike sharing were still far less than the minimum usage before the pandemic. Secondly, according to the statistics from BMCT, the population of Beijing decreased by approximately 40% during the Spring Festival⁶. Assuming that the usage of bike sharing reduced with

the same proportion, and the number of orders decreased to approximately 0.76–0.95 million per day during the Spring Festival, which was consistent with the trend before 20th Jan shown in Fig. 3. However, the orders of bike sharing declined rapidly after the outbreak of the pandemic, and remained at a low level after 30 days of the end of the holiday, which fully demonstrated the overwhelming impacts of the pandemic on the usage of bike sharing, and such impacts exceeded temperature and the Spring Festival. In the future, if necessary datasets are available, we can further explore the heterogeneous impacts caused by different factors on the bike-sharing system.

In order to visually observe the variations of spatial distribution of origins and destinations for bike-sharing trips during the COVID-19 pandemic, we select 4 different typical days to exhibit the trip distribution of bike sharing at different stages of COVID-19 outbreak, as shown in Fig. 4.

On 17th Jan, Spring Festival travel season had begun, but there were still many trip orders of bike sharing in Beijing. As can be seen from Fig. 4, most of trip origins and destinations are distributed in central areas of Beijing, such as Dongcheng, Xicheng, the parts of Haidian and Chaoyang districts. It is expected that people's behaviors remain normal state before announcement of human-to-human transmission and Wuhan lockdown. Thereafter, the COVID-19 panic widely spread in China, the government extended the holiday to 2nd Feb accordingly, so the users of bike sharing in Beijing decreased greatly after 20th Jan. At the stage of pandemic spreading, we select the distribution of origins and destinations on 25th Jan to demonstrate the decline of bike-sharing orders in Beijing, and the trips at the city center were significantly reduced, as observed in graphs (c) and (d) of Fig. 4. Due to the strong measures taken by Chinese government, such as restrictions on public transport, quarantining infected cases and promoting wearing masks, this COVID-19 pandemic was effectively and quickly controlled.

⁵ <https://www.timeanddate.com/weather/china/beijing/historic>

⁶ https://www.sohu.com/a/125402812_457595

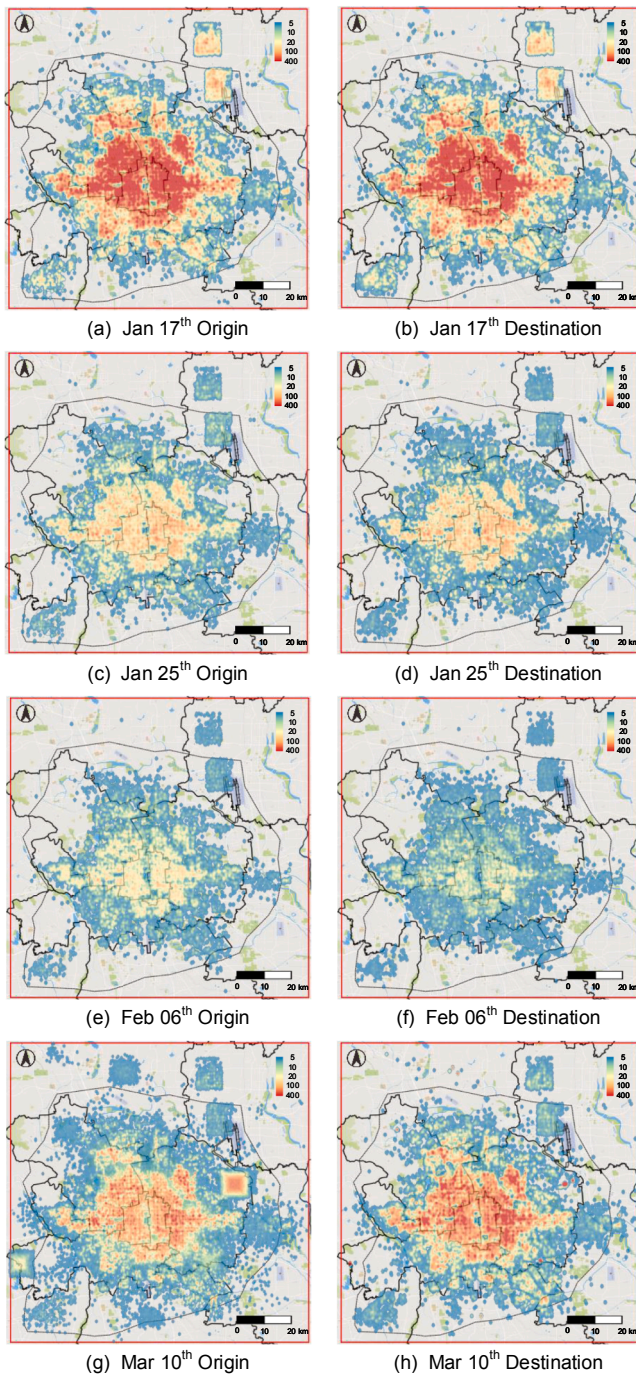


Fig. 4. Spatial distribution of origins and destinations for bike sharing under COVID-19 pandemic.

However, the number of bike-sharing trips did not recover but decreased to a lower level even after the end of the holiday on 2nd Feb. At the early stage of work resumption, the impact of pandemic panic still existed, as can be observed from graphs (e) and (f) of Fig. 4, the trip number for bike sharing kept going down. Afterwards, the number of bike-sharing trips slowly climbed along with fluctuations, which showed people were reluctant to increase their travelling due to shocks of the pandemic, and the distribution of origins and destinations on 10th Mar shown in graphs (g) and (h) of Fig. 4 had confirmed this point.

3.2. Impact of COVID-19 on the environmental benefits of bike sharing

In this section, we adopt the method introduced in Section 2.2 to estimate the environmental benefits of bike sharing in Beijing during the COVID-19 pandemic, so as to explore the impacts of this pandemic on the bike-sharing systems. It is widely accepted that bike sharing has considerable potential to reduce energy consumption and emissions. The spatial distribution of environmental benefits for bike sharing under COVID-19 pandemic is shown in Fig. 5. We can see that the environmental benefits are more significant in more central areas, where includes many business centers, shopping malls and places of interests, and population density is relatively higher. Before the pandemic panic spread, bike sharing led to a reduction of 99.06 tonnes of petroleum consumption, 252.69 tonnes of CO₂ and 2.21 tonnes of NO_x on 17th Jan, a typical normal day at this stage. As shown in the graphs (a), (b) and (c) of Fig. 5, the environmental benefits are mainly distributed in Dongcheng, Xicheng, west of Chaoyang and southeast of Haidian districts. After the Wuhan lockdown, bike-sharing orders significantly reduced, so the environmental benefits went down accordingly. On 25th Jan, a reduction of 13.49 tonnes of petroleum, 34.4 tonnes of CO₂ and 0.3 tonnes of NO_x was caused by bike sharing, and environmental benefits apparently decreased compare to 17th Jan, which demonstrated the COVID-19 pandemic had severe impacts on the environmental benefits of bike sharing. At early stage of work resumption, the environmental benefits unexpectedly continued to decline. On 6th Feb, environmental benefits caused by bike sharing reduced to 5.72 tonnes of petroleum, 14.59 tonnes of CO₂ and 0.13 tonnes of NO_x, which was approximately 1 in 17 of those on 17th Jan. As the pandemic was put under control, the environmental benefits grew up to a reduction of 70.14 tonnes of petroleum, 178.93 tonnes of CO₂ and 1.57 tonnes of NO_x, and accounted for approximately 70% of those on 17th Jan. As can be observed from the graphs (j), (k) and (l) of Fig. 5, the distribution of environmental benefits demonstrates that the use of bike sharing gradually recovered from the COVID-19 pandemic, and the central areas such as business centers, transportation hubs and other important public places started recovery earlier. In addition, detailed quantitative environmental benefits can be shown in Table 3.

Although Ricci [71] argues that no evidence shows the significant reductions of carbon emissions and pollution caused by bike sharing, in this section, we employ the proposed method to prove that the bike sharing has potential to achieve significant environmental benefits, and also reveal that the impacts of this severe COVID-19 pandemic on the environmental benefits of bike sharing cannot be ignored.

In this study, the study area covers nearly all of bike-sharing trips in Beijing, and excludes four districts (Miyun, Pinggu, Yanqing and Huairou) due to few bike-sharing orders. As can be seen from Table 3, the environmental benefits are apparently higher in the districts with larger size of populations. For example, Chaoyang and Haidian districts, where population density is larger, have the highest and second highest environmental benefits before and after the outbreak of the pandemic, respectively, while the environmental benefits of Mentougou district are the lowest due to the least population in Beijing. It can be observed that this pandemic greatly impacts the environmental benefits of bike sharing in all districts, and the environmental benefits of the districts on 6th Feb decreased to 4%-9% of those on 17th Jan, except the Xicheng district where reduced to 14%. In addition, it also can be observed that the recovery of environmental benefits in different districts was also different in more than 30 days after the end of the holiday. Most of districts are able to recover to 60%-80%, such as Dongcheng, Fengtai and Changping districts, but Shunyi and Xicheng districts can only recover to 25% and 48%, respectively. Furthermore, the environmental benefits in some districts were even higher than those on 17th Jan, for example, Mentougou, Tongzhou and Daxing increased by 132%, 78% and 21%, respectively, which apparently shows that people within these areas more frequently use bike sharing than before. A reasonable explanation for this phenomenon is that people in these districts started

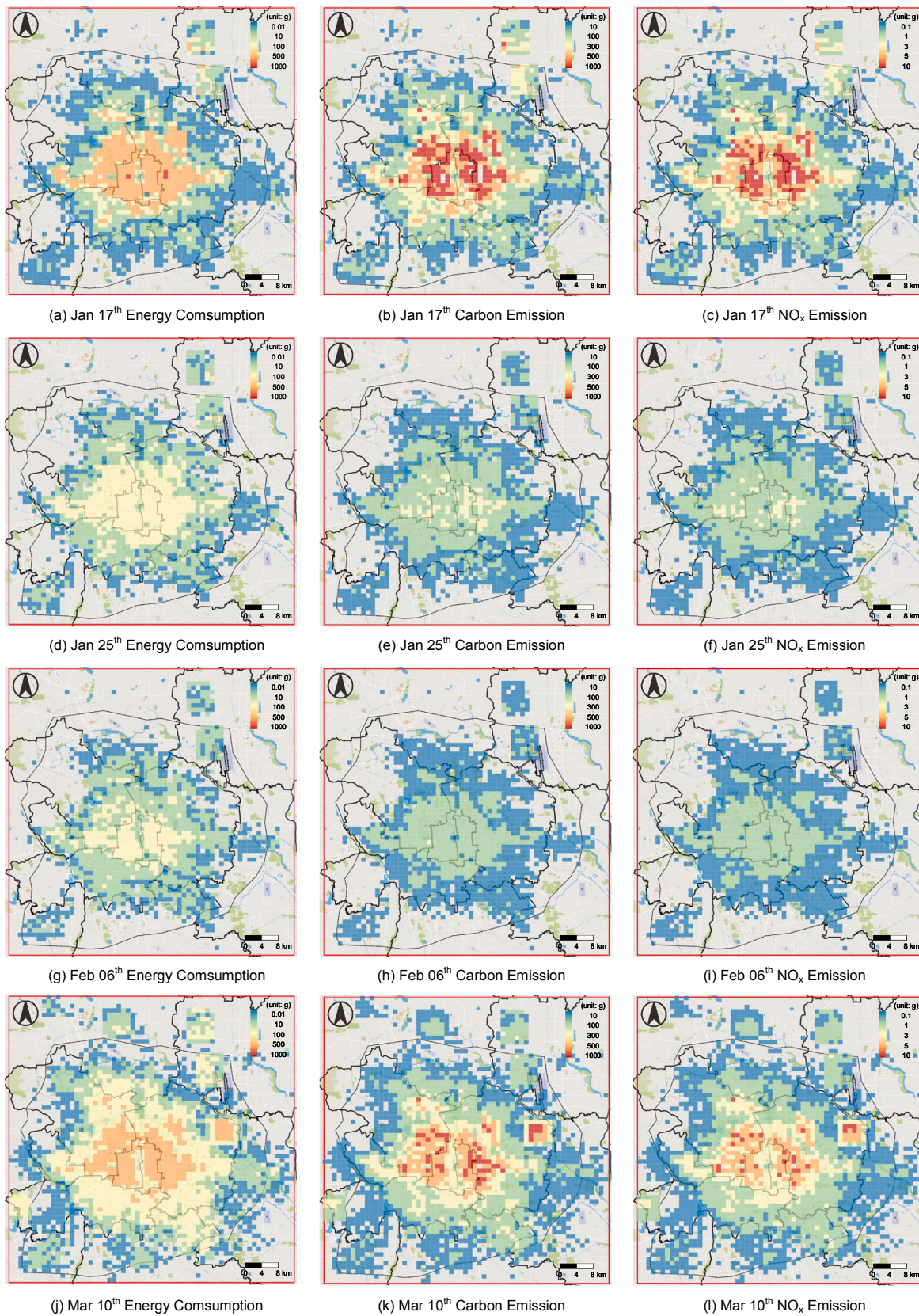


Fig. 5. Spatial distribution of environmental benefits of bike sharing in Beijing.

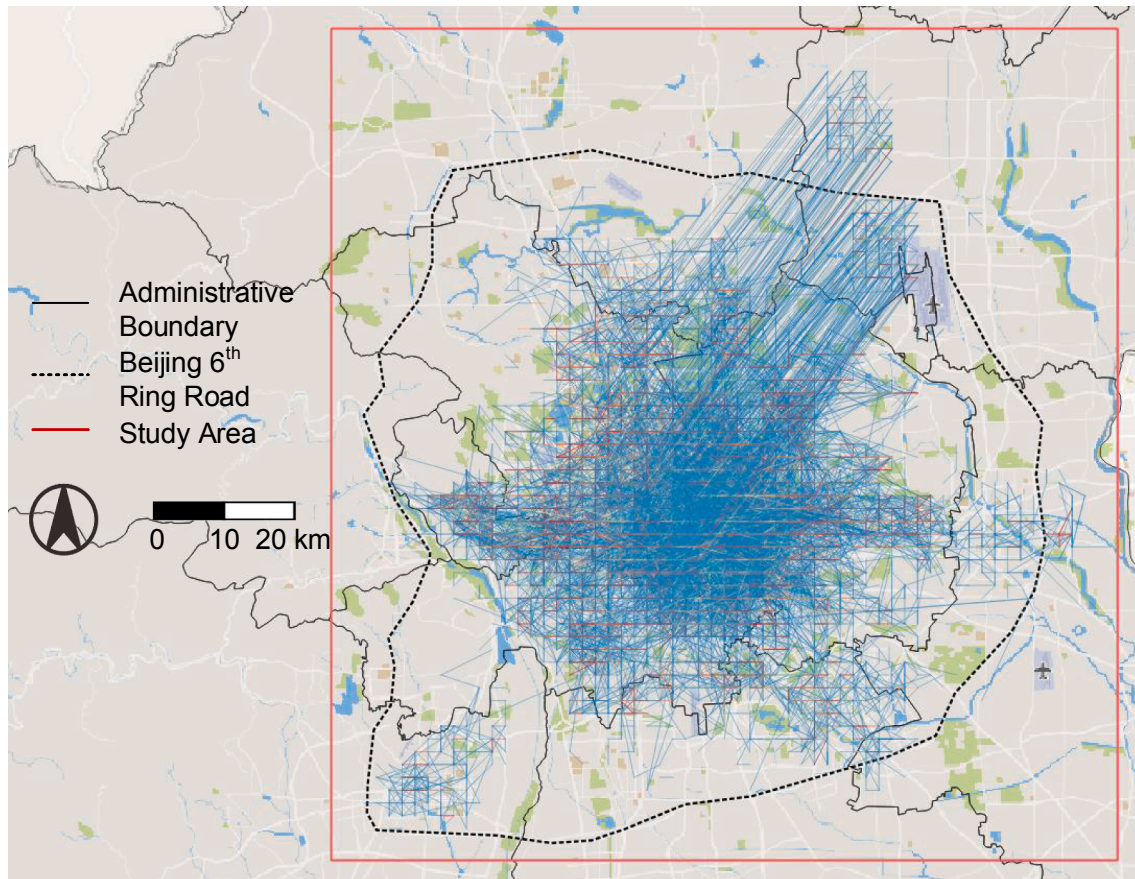


Fig. 6. Topology of the complex network based on bike-sharing trips in Beijing.

for work resumption earlier compared to other districts, and they were more likely to utilize bike sharing to replace public transits for daily travelling due to the impact of COVID-19. In the future, we may explore this point further if job-housing data in Beijing are available.

3.3. Impact of COVID-19 on user behaviors of bike sharing

In this section, we utilize complex network theory to explore the impacts of the pandemic on the user behaviors of dockless bike sharing in Beijing. As introduced in Section 2.3, the complex networks based on bike-sharing trips are built, as shown in Fig. 6. We attempt to present the trip distributions in the proposed complex network by using links with different colors, but it does not work very well. Therefore, here we use node heatmap to exhibit the trip distribution of bike sharing in Beijing from the perspective of complex network theory, which is presented in Fig. 7.

In Fig. 7, we can see that the trip distributions in the proposed complex networks are significantly different at different stages as COVID-19 pandemic evolves in China. At the stage before announcement of human-to-human transmission (20th Jan), the nodes with higher strength, namely, more trips, were mainly located in Xicheng, Dongcheng, southeast of Haidian and west of Chaoyang districts, which covers major business centers, transportation hubs, education institutions, places of interests and so on, as shown in the graph (a) of Fig. 7. The trip distribution on 17th Jan represents the one of a typical normal day at this stage, which demonstrates the normal state that people adopted bike sharing for daily travelling before 20th Jan, and the average strength on this day was 40.38, which implies that each node (1 km × 1 km lattice) had more than 40 user orders before pandemic panic began. At the stage after Wuhan lockdown (23rd Jan), as shown in the graph (b) of Fig. 7, nodes' strength significantly decreased due to the

reduction of users caused by the pandemic. The average strength on 25th Jan had reduced to 13.07, and the distribution of nodes with relatively high strength were still located in four central districts, but the coverage extent reduced greatly. When the extended holiday ended on 2nd Feb, it was expected that user number of bike sharing would have gradually recovered to the normal state. However, at early stage of work resumption, the average strength on 6th Feb had dropped to 7.41, even much smaller than that on 25th Jan. The distribution shown in the graph (c) of Fig. 7 displays that the trips in the central districts of Beijing were very low as well. In 37 days after work resumption, the bike-sharing orders had increased, and the average strength on 10th March rose to 18.31, which was still much lower than that before 20th Jan. As can be observed from the graph (d) of Fig. 7, there are only a few nodes with high strength, and these nodes are mainly distributed around the hospitals, CBD and transportation hubs.

In order to clearly show the most important nodes in the complex networks during the pandemic, the top 10 nodes with largest strength at different stage are summarized in Table 4. We can see that most of nodes with high strength are distributed within Haidian, Chaoyang, Dongcheng districts. In addition, it can be observed that node #1912 was the most popular place in the normal days (17th Jan) before the outbreak of the pandemic, but this node was not top 10 locations with largest strength anymore for bike sharing after the outbreak of the pandemic, even more than one month after the holiday, it did not appear in Table 5 again. Other nodes, such as #2034, #1741 and #1494, were not top 10 locations with largest strength either. In addition, although some nodes such as #2033 and #1680 still existed in Table 5 after the outbreak of the pandemic, their rankings were significantly lower than those before the pandemic. Therefore, we draw a conclusion that the popularity of the places where people usually take bike sharing to visit has been changed by the pandemic, even after the end of the holiday more than

Table 3
Environmental benefits of bike sharing in administrative districts in Beijing.

No.	District	17th Jan			25th Jan			6th Feb			10th Mar		
		Fuel (kg)	CO ₂ (kg)	NOx(kg)	Fuel (kg)	CO ₂ (kg)	NOx(kg)	Fuel (kg)	CO ₂ (kg)	NOx(kg)	Fuel (kg)	CO ₂ (kg)	NOx(kg)
1	Dongcheng	7912.68	20184.67	176.58	1489.22	3798.88	33.23	537.36	1370.77	11.99	5323.22	13579.15	118.79
2	Fengtai	8050.86	20537.14	179.66	1546.63	3945.34	34.51	696.72	1777.27	15.55	6756.29	17234.80	150.77
3	Daxing	1241.69	3167.46	27.71	236.20	602.53	5.27	123.31	314.54	2.75	1763.21	4497.82	39.35
4	Fangshan	287.79	734.12	6.42	61.31	156.39	1.37	21.93	55.95	0.49	302.70	772.16	6.75
5	Changping	1444.50	3684.81	32.23	195.67	499.15	4.37	83.53	213.08	1.86	1302.60	3322.83	29.07
6	Chaoyang	30864.79	78733.78	688.76	3944.17	10061.28	88.02	1571.53	4008.87	35.07	26821.67	68420.08	598.54
7	Haidian	18866.79	48127.78	421.02	3365.50	8585.14	75.10	1397.34	3564.52	31.18	17407.23	44404.54	388.45
8	Shijingshan	2812.04	7173.31	62.75	554.13	1413.54	12.37	269.96	688.65	6.02	1891.64	4825.44	42.21
9	Xicheng	11015.57	28099.91	245.82	1554.32	3964.96	34.69	743.96	1897.78	16.60	6346.93	16190.55	141.63
10	Tongzhou	407.69	1039.98	9.10	99.14	252.91	2.21	66.01	168.40	1.47	1064.83	2716.30	23.76
11	Mentougou	8.60	21.94	0.19	1.36	3.46	0.03	0.64	1.63	0.01	19.45	49.62	0.43
12	Shunyi	3559.89	9081.02	79.44	439.39	1120.84	9.81	205.76	524.88	4.59	1142.71	2914.98	25.50
	Total	99059.10	252692.42	2210.55	13487.03	34404.42	300.97	5718.06	14586.36	127.60	70142.48	178928.28	1565.26

30 days, most of these places cannot become popular again to bike-sharing users. This point is also verified by the analyses for Fig. 8.

To observe the transformation of user behaviors of bike sharing in Beijing from macroscopic perspective, the strength distributions of bike-sharing trips in log-log scale are illustrated in Fig. 8.

As can be seen from Fig. 8, the y-axis represents logarithm of the complementary cumulative probability $P(S \geq s)$, which is the probability that a randomly chosen node has strength equal to or larger than s . The slope of the distribution curves in Fig. 8 describes the speed of descent of the strength distribution curves, which reflects whether the majority of nodes of the proposed complex networks have frequent bike-sharing orders. Before the pandemic panic spreads, strength distribution on 17th Jan shows a smaller slope rate, which implies that the ratio of nodes with fewer trips is smaller, while the nodes with high strength account for a larger proportion. After the declaration of human-to-human transmission and Wuhan lockdown, the slope of strength distribution on 25th Jan becomes smaller, and the slope on 6th Feb decreases further even after holiday has ended for 4 days. The slope of strength distribution on 10th Mar shows that bike-sharing trips are gradually recovering, but still far from the normal state. The COVID-19 has caused huge impacts on people's behaviors and lifestyle, and user behaviors of bike sharing in Beijing have also been inevitably changed. The slope of the strength distribution used here plainly shows the change of bike-sharing use, in order to quantify such change, the fitted strength distributions are summarized in Table 5.

As can be observed from Table 5, although these four distributions all follow exponential distribution well, the slopes are different, which can reflect the transformation of bike-sharing use pattern to some extent. Compared to before COVID-19 outbreak, people are less likely to take dockless bike sharing to places where bike-sharing users used to go, even though the pandemic is under control and work resumption has begun for a period of time.

In order to further observe the travel behaviors of bike-sharing users, we plot the average trip time during the outbreak of the pandemic in Fig. 9. It can be observed that the average trip time of bike sharing was approximately 1330–1360 s before the pandemic. However, since human-to-human transmission of COVID-19 and the lockdown of Wuhan city were announced, the average trip time began to increase gradually, and then reached the highest on 6th Feb, approximately 1600 s. Thereafter, the average trip time decreased to a relatively stable level, which was still higher than that before the pandemic, even though the temperature had risen significantly and the pandemic had been under control. The possible explanation is that people tend to use bike sharing for longer trips due to the impacts of COVID-19, which used to be done by using public transits.

4. Conclusions

In the time of COVID-19 pandemic, our study has a special value and significance. Exploring the transformation of user behaviors and environmental benefits of bike sharing will help to comprehend how the severe pandemic caused by COVID-19 influences people's life, behaviors, and our society and environment, and also provide some clues to adapt this pandemic.

This study focuses on the user behaviors and environmental benefits of bike sharing during the pandemic. Firstly, a novel method is proposed to calculate trip distances and trajectories of bike sharing with limited information via an open python package OSMnx. Following this, we utilize the complex network theory to capture the transformation of user behavior pattern of bike sharing at the different stages of COVID-19 outbreak. In addition, more complete bike-sharing data from three main operators in Beijing are obtained to explore the impacts of COVID-19 on bike-sharing systems. This study fills the gap on the research of transformation of user behaviors and environmental benefits of dockless bike sharing under COVID-19 pandemic.

The results show that the average daily trips of bike sharing in

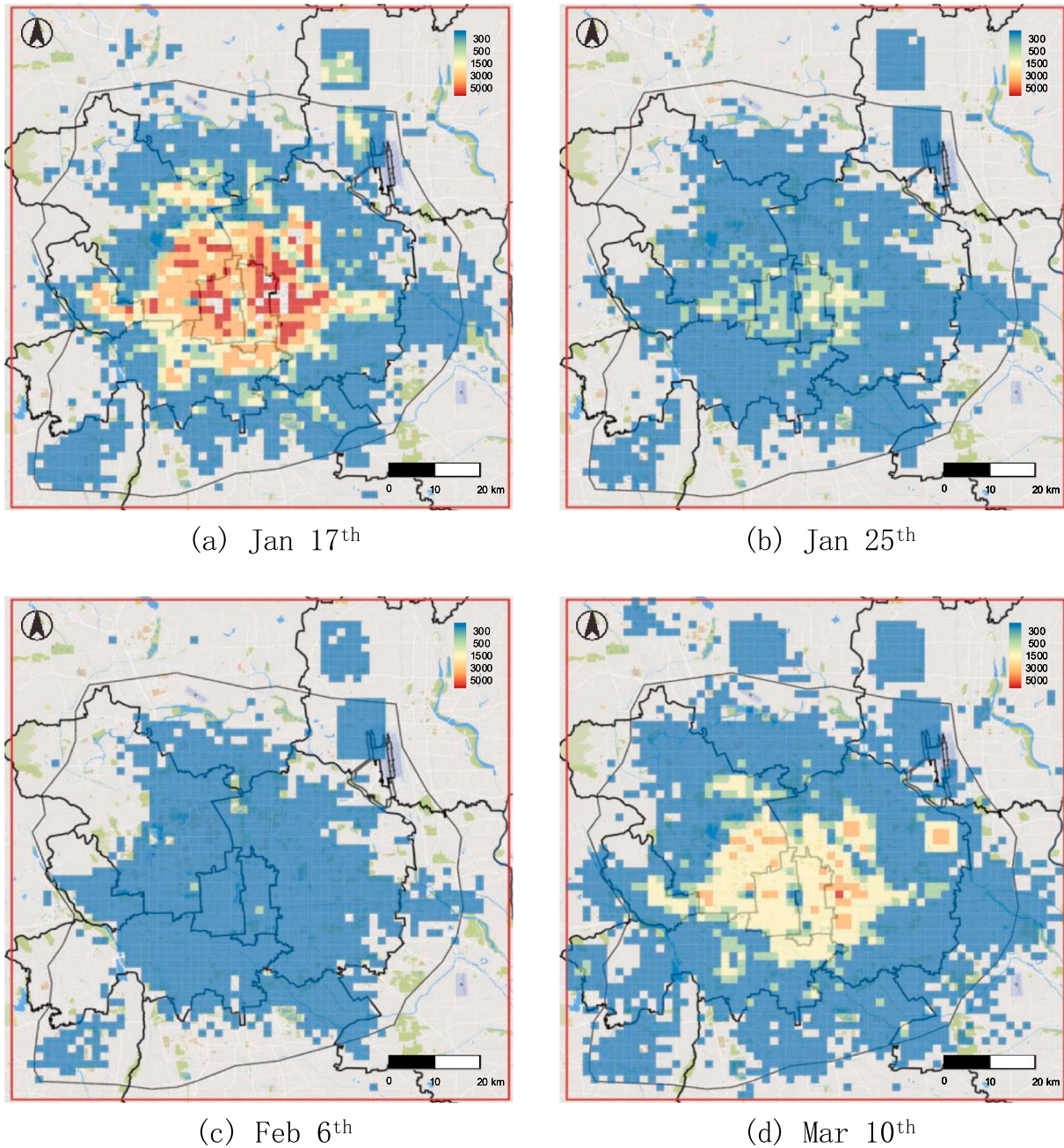


Fig. 7. Trip distribution of bike sharing in the complex networks.

Beijing reduce to approximately 0.3 million during the period of COVID-19 outbreak (from 14th Jan to 10th Mar), and the origins and destinations of bike-sharing trips are distributed in central areas of Beijing, such as Dongcheng, Xicheng, the parts of Haidian and Chaoyang districts. Since the announcement of human-to-human transmission and Wuhan lockdown, the number of bike-sharing trips decreased greatly and did not recover to the normal state even at the early stage of work resumption. In addition, bike sharing has potential to achieve significant environmental benefits, and the ongoing pandemic causes huge impacts on the environmental benefits of bike sharing. The estimated reductions of energy consumption, CO₂ emission and NO_x emission on 6th Feb reduced to approximately 1 in 17 of those on a normal day (17th Jan), and the environmental benefits on 10th Mar recovered to 70% of those in normal days, even though holiday had ended for more than one month. There are higher environmental benefits in the districts with larger size of population, and Chaoyang and Mentougou districts, where have the

largest and least size of population in Beijing, achieve the highest and lowest environmental benefits of bike sharing before and after the pandemic outbreak, respectively. The impacts of COVID-19 on the environmental benefits of bike sharing in different districts vary, and the environmental benefits on 10th Mar in some districts are even higher than those on 17th Jan. The results also suggest that the travel behaviors of bike sharing can be impacted by the COVID-19 greatly. The nodes with high strength are mainly distributed in Xicheng, Dongcheng, southeast of Haidian and west of Chaoyang districts in normal days, and the average strength, which represents the trips within local areas, dropped from 40.38 (on 17th Jan) to 13.07 (on 25th Jan), and further reduced to 7.41 (on 6th Feb) due to the pandemic panic. Even after the end of the holiday more than one month, most of these places in Beijing cannot become popular again to bike-sharing users. The slopes of strength distribution of the proposed complex networks have also confirmed such change. The average trip time of bike sharing after the

Table 4
Top 10 locations of bike-sharing trip distribution.

Days No.	17 th Jan		25 th Jan		6 th Feb		10 th Mar	
	Node ID	Location	Node ID	Location	Node ID	Location	Node ID	Location
1	1912	Haidian	1542	Haidian	1494	Dongcheng	1542	Haidian
2	2033	Haidian	1741	Chaoyang	1375	Chaoyang	2119	Chaoyang
3	1542	Haidian	1494	Dongcheng	1669	Haidian	1619	Chaoyang
4	1619	Chaoyang	1375	Chaoyang	1682	Chaoyang	1603	Haidian
5	1680	Chaoyang	1682	Chaoyang	1621	Chaoyang	1375	Chaoyang
6	2034	Haidian	1680	Chaoyang	1542	Haidian	2033	Haidian
7	1682	Chaoyang	1677	Dongcheng	1428	Xicheng	2119	Chaoyang
8	1741	Chaoyang	1669	Haidian	1376	Chaoyang	1680	Chaoyang
9	1494	Dongcheng	1437	Chaoyang	2038	Haidian	2120	Chaoyang
10	2097	Haidian	1616	Dongcheng	1677	Dongcheng	1682	Chaoyang

Table 5
Strength distribution type of bike-sharing trips.

Days	17th Jan		25th Jan		6th Feb		10th Mar	
Strength distribution	Exponential		Exponential		Exponential		Exponential	
	$P(S \geq s) \propto e^{-\gamma s}$		$P(S \geq s) \propto e^{-\gamma s}$		$P(S \geq s) \propto e^{-\gamma s}$		$P(S \geq s) \propto e^{-\gamma s}$	
	γ	R^2	γ	R^2	γ	R^2	γ	R^2
	0.3352	0.8833	0.4754	0.8713	0.5453	0.8956	0.3865	0.8966

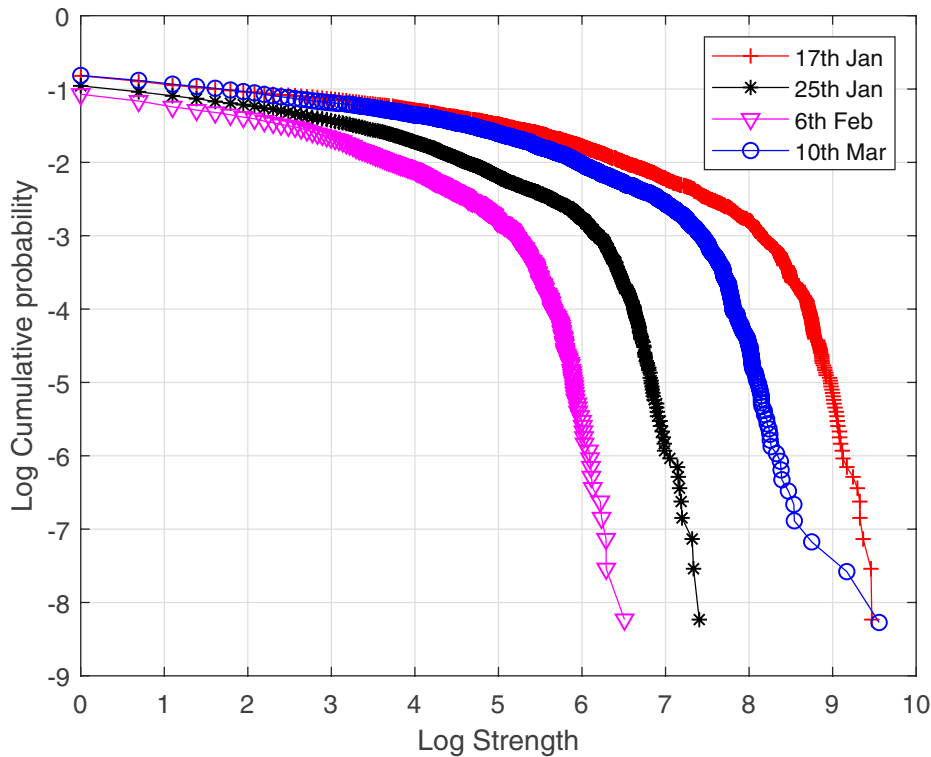


Fig. 8. Strength distribution of bike-sharing trips in log–log scale.

outbreak of the pandemic was higher than that before the pandemic, even though the temperature had risen significantly and the pandemic had been under control. To summarize, the user travelling behaviors and environmental benefits for bike sharing have been transformed significantly, and the impacts caused by COVID-19 are difficult to disappear within a short term.

Although this study provides the innovative methods to quantitatively analyze the impacts of the COVID-19 pandemic on the

environmental benefits and user behaviors of bike sharing, there are several limitations in this study. Firstly, due to the sensitivity of data during the pandemic, only bike-sharing data from 14th Jan to 10th Mar can be provided, which restricts further in-depth analysis. In addition, the proposed method to calculate the trip distances is time-consuming since it relies on the extensive computations of shortest paths. In the future, high performance computing including parallel/distributed computing and Graphics Processing Unit (GPU) can be employed.

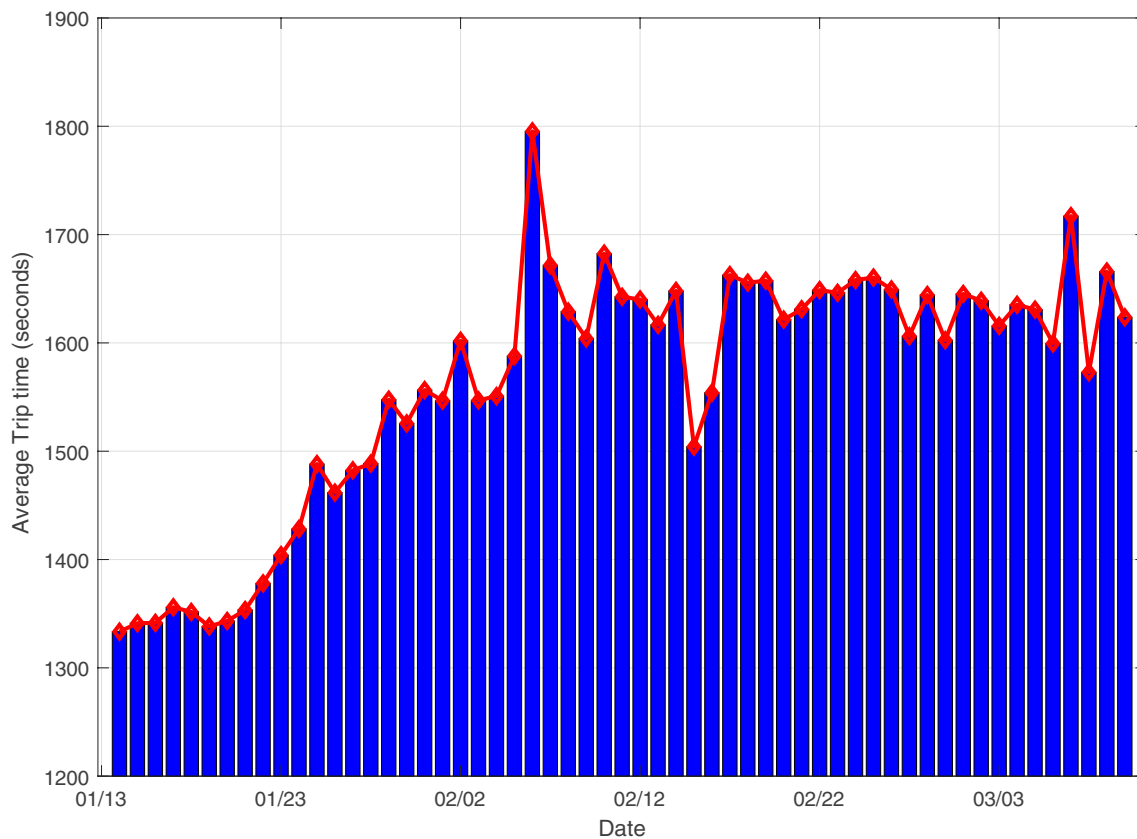


Fig. 9. Average trip time of bike sharing in Beijing during the outbreak of the pandemic.

Thirdly, it will be more meaningful to explore the impacts of the pandemic on all types of public transport, such as subway, bus and bike sharing, and the user transfer between different travel modes will disclose more realistic transformation of travel behavior patterns of people in cities under this severe pandemic. These explorations may facilitate the further understanding of impacts of COVID-19 pandemic on our society and environment.

CRedit authorship contribution statement

Wen-Long Shang: Conceptualization, Methodology, Software, Formal analysis, Validation, Writing - original draft, Writing - review & editing. **Jinyu Chen:** Software, Visualization. **Huibo Bi:** Software, Validation, Supervision. **Yi Sui:** Writing - review & editing. **Yanyan Chen:** Resources, Project administration. **Haitao Yu:** Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- [1] Shen J, Duan H, Zhang B, Wang J, Ji J, Wang J, et al. Prevention and control of COVID-19 in public transportation: Experience from China. *Environ Pollut* 2020; 266: 115291.
- [2] Novel Coronavirus – China. World Health Organization (WHO), 2020. <https://www.who.int/csr/don/12-january-2020-novel-coronavirus-china/en/>.
- [3] COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU). Johns Hopkins University, 2020. <https://gisanddata.maps.arcgis.com/apps/opsdashboard/index.html#/bda7594740fd40299423467b48e9ecf6>.
- [4] Times 2020.
- [5] Reed S. OPEC scrambles to react to falling oil demand from China. *The New York Times* 2020.
- [6] Mackinnon A, Palder D. Coronavirus in the corridors of power. *Foreign Policy* 2020.
- [7] Venter ZS, Aunan K, Chowdhury S, Lelieveld J. COVID-19 lockdowns cause global air pollution declines. *Proc Natl Acad Sci USA* 2020;117(32):18984–90.
- [8] Lin Q, Zhao S, Gao D, Lou Y, Yang S, Musa S, et al. A conceptual model for the coronavirus disease 2019 (COVID-19) outbreak in Wuhan, China with individual reaction and governmental action. *Int J Infect Dis* 2020;93:211–6.
- [9] Sui Y, Zhang H, Shang WL, Sun R, Wang C, Ji J, et al. Mining urban sustainable performance: spatial-temporal emission analysis and potential changes in post-COVID-19 future. *Appl Energy* 2020;20: 115966.
- [10] Fishman E, Washington S, Haworth N. Bikeshare's impact on active travel: Evidence from the United States, Great Britain, and Australia. *J Transport & Health* 2015;2.
- [11] Martin E, Shaheen S. Evaluating public transit modal shift dynamics in response to bikesharing: A tale of two U.S. Cities. *J Transport Geography* 2014;41.
- [12] Parkes SD, Marsden G, Shaheen SA, Cohen AP. Understanding the diffusion of public bikesharing systems: Evidence from Europe and North America. *J Transp Geogr* 2013;31:94–103.
- [13] Liu Z, Jia X, Cheng W. Solving the last mile problem: ensure the success of public bicycle system in Beijing. *Procedia - Social and Behav Sci* 2012;43:73–8.
- [14] Zhang Y, Mi Z. Environmental benefits of bike sharing: A big data-based analysis. *Appl Energy* 2018;220:296–301.
- [15] Fishman E, Washington S, Haworth N. Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia. *Transp Res Part D* 2014;31: 13–20.
- [16] Hauf A, Douma F. Governing dockless bike share: Early lessons for Nice Ride Minnesota. *Transp Res Rec* 2019;2673(9):419–42.
- [17] Ma Y, Lan J, Thornton T, Mangalagu D, Zhu D. Challenges of collaborative governance in the sharing economy: the case of free-floating bike sharing in Shanghai. *J Cleaner Prod* 2018;197(Part 1):356–65.
- [18] Nikiforiadis A, Ayfantopoulou G, Stamelou A. Assessing the impact of COVID-19 on bike-sharing usage: The Case of Thessaloniki, Greece. *Sustainability* 2020;12(19): 8215.

- [19] Teixeira JF, Lopes M. The link between bike sharing and subway use during the COVID-19 pandemic: The case-study of New York's Citi Bike. *Transportation Res Interdisciplinary Perspect* 2020;6: 100166.
- [20] Shaheen S, Guzman S, Zhang H. *Bikesharing in Europe, the Americas, and Asia: Past, Present, and Future*. Institute of Transportation Studies, UC Davis, Institute of Transportation Studies, Working Paper Series. 2010;2143.
- [21] DeMaio P. Bike-sharing: History, impacts, models of provision, and future. *J Public Transportation*, 2009, 12.
- [22] Gao P, Li J. Understanding sustainable business model: A framework and a case study of the bike-sharing industry. *J Cleaner Prod* 2020;267(10).
- [23] Zhang L, Zhang J, Duan Z-Y, Bryde D. Sustainable bike-sharing systems: Characteristics and commonalities across cases in urban China. *J Cleaner Prod* 2015;97.
- [24] Li M. Operation and management optimization model and mechanism research of free-floating bike sharing system. PhD Thesis of Beijing Jiaotong University; 2019.
- [25] Médard dCC, Caruso G. Estimating bike-share trips using station level data. *Transp Res Part B: Methodol*, 2015. 78: p. 260–279.
- [26] Lin JH, Chou TC. A geo-aware and VRP-based public bicycle redistribution system. *Int J Vehicular Technol* 2012;2012:14.
- [27] Benchimol M, Benchimol P, Chappert B, Taille A, Laroche F, Meunier F, et al. Balancing the stations of a self service "bike hire" system. *RAIRO - Operations Res* 2011;45:37–61.
- [28] Tian Z, Zhou J, Szeto WY, Tian L, Zhang W. The rebalancing of bike-sharing system under flow-type task window. *Transp Res Part C: Emerging Technol* 2020;112: 1–27.
- [29] Caggiani L, Ottomanelli M. A modular soft computing based method for vehicles repositioning in bike-sharing systems. *Procedia - Social and Behav Sci* 2012;54: 675–84.
- [30] Contardo C, Morency C, Rousseau L. Balancing a dynamic public bike-sharing system; 2012.
- [31] Shui C, Szeto W. Dynamic green bike repositioning problem – A hybrid rolling horizon artificial bee colony algorithm approach. *Transp Res Part D: Transport and Environ* 2017;60.
- [32] Nair R, Miller-Hooks E. Fleet management for vehicle sharing operations. *Transportation Sci* 2011;45(4):524–40.
- [33] Chemla D, Meunier F, Calvo R. Bike sharing systems: Solving the static rebalancing problem. *Discrete Optimization* 2013;10:120–46.
- [34] Erdogan G, Battarra M, Calvo R. An exact algorithm for the static rebalancing problem arising in bicycle sharing systems. *Eur J Oper Res* 2015;245.
- [35] Kadri AA, Kacem I, Labadi K. A branch-and-bound algorithm for solving the static rebalancing problem in bicycle-sharing systems. *Comput Ind Eng* 2016;95.
- [36] Pal A, Zhang Y. Free-floating bike sharing: Solving real-life large-scale static rebalancing problems. *Transp Res Part C: Emerging Technol* 2017;80:92–116.
- [37] Li Y, Szeto W, Long J, Shui C. A multiple type bike repositioning problem. *Transp Res Part B: Methodol* 2016;90:263–78.
- [38] Zhang H, Song X, Long Y, Xia T, Zheng J, Huang D, et al. Mobile phone GPS data in urban bicycle-sharing: Layout optimization and emissions reduction analysis. *Appl Energy* 2019.
- [39] Yuan M, Zhang Q, Wang B, Liang Y, Zhang H. A mixed integer linear programming model for optimal planning of bicycle sharing systems: A case study in Beijing. *Sustain Cities Soc* 2019;47.
- [40] Vogel P, Greiser T, Mattfeld D. Understanding bike-sharing systems using data mining: exploring activity patterns. *Procedia - social and behavioral sciences. Procedia - Social and Behav Sci* 2011;20:514–23.
- [41] Kaltenbrunner A, Meza R, Grivolla J, Codina J, Banchs REJPMC. Urban cycles and mobility patterns: Exploring and predicting trends in a bicycle-based public transport system. 2010. 6: p. 455–466.
- [42] Chen L, Ma X, Thi Mai Trang N, Pan G, Jakubowicz J. Understanding bike trip patterns leveraging bike sharing system open data. *Front Comput Sci* 2016;11(10).
- [43] Zeng M, Yu T, Wang X, Su V, Nguyen LT, Mengshoel O. Improving demand prediction in bike sharing system by learning global features. in *KDD* 2016; 2016.
- [44] Hua M, Chen X, Zheng S, Cheng L, Chen J. Estimating the parking demand of free-floating bike sharing: A journey-data-based study of Nanjing, China. *J Cleaner Prod* 2020;244: 118764.
- [45] Kaspi M, Raviv T, Tzur M. Detection of unusable bicycles in bike-sharing systems. *Omega* 2016;65:10–6.
- [46] Ai Y, Li Z, Gan M, Zhang Y, Yu D, Chen W, et al. A deep learning approach on short-term spatiotemporal distribution forecasting of dockless bike-sharing system. 2018. 31: p. 1665–1677.
- [47] Liu Z, Shen Y, Zhu YJPotEAIcOWS, Mining D. Inferring dockless shared bike distribution in new cities; 2018.
- [48] Yu Q, Zhang H, Li W, Sui Y, Song X, Yang D, et al. Mobile phone data in urban bicycle-sharing: Market-oriented sub-area division and spatial analysis on emission reduction potentials. *J Cleaner Prod* 2020;254.
- [49] Brand C, Goodman A, Ogilvie D. Evaluating the impacts of new walking and cycling infrastructure on carbon dioxide emissions from motorized travel: A controlled longitudinal study. *Appl Energy* 2014;128:284–95.
- [50] Wang M, Zhou X. Bike-sharing systems and congestion: Evidence from US cities. *J Transp Geogr* 2017;65:147–54.
- [51] Li Y, Zhu Z, Guo X. Operating characteristics of dockless bike-sharing systems near metro stations: Case study in Nanjing City, China. *Sustainability* 2019;11:2256.
- [52] Sun L, Wang S, Liu S, Yao L, Luo W, Shukla A. A comparative research on the feasibility and adaptation of shared transportation in mega-cities – A case study in Beijing. 2018. 230: p. 1014–1033.
- [53] Beijing News. By the end of 2019, 900000 shared bicycles exist in Beijing 2019 (<http://auto.sina.com.cn/news/hy/2020-02-25/detail-iimxyqvz5614347.shtml?hpid=00041>).
- [54] The total number of shared bicycles in Beijing reduces to 900000. *China Economic Net*. 2019. http://district.ce.cn/newarea/roll/202002/26/t20200226_34351286.shtml.
- [55] Boeing G. OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Comput Environ Urban Syst* 2017;65:126–39.
- [56] Energy statistics handbook. <https://www150.statcan.gc.ca/n1/pub/57-601-x/00105/4173282-eng.htm>.
- [57] IEA. Fuel Consumption of Cars and Vans. 2018. <https://www.iea.org/reports/fuel-consumption-of-cars-and-vans>.
- [58] Yu B, Ma Y, Xue M, Tang B, Wang B, Yan J, et al. Environmental benefits from ridesharing: a case of Beijing. *Appl Energy* 2017;191:141–52.
- [59] IPCC, Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2019). 2019 https://www.ipcc-nggip.iges.or.jp/public/gp/bgp/2_3_Road_Transport.pdf.
- [60] Greenhouse Gas Emissions from a Typical Passenger Vehicle. United States Environmental Protection Agency (EPA), 2018. <https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle>.
- [61] Lu M, An K, Hsu S-C, Zhu R. Considering user behavior in free-floating bike sharing system design: a data informed spatial agent-based model. *Sustainable Cities and Society* 2019;49.
- [62] Link C, Strasser C, Hinterreiter M. Free-floating bikesharing in Vienna—A user behaviour analysis. *Transp Res Part A: Policy Practice* 2020;135:168–82.
- [63] Gao Y, Schwebel DC, Zhang L, Xiao W, Hu G. Unsafe bicycling behavior in Changsha, China: A video-based observational study. *Int J Environ Res Public Health* 2020;17:3256.
- [64] Vogel P, Mattfeld DC. Strategic and operational planning of bike-sharing systems by data mining -a case study. Paper presented at the Computational Logistics: Second International Conference, Hamburg, Germany; 2011.
- [65] Si H, Shi J-G, Tang D, Wu G, Lan J. Understanding intention and behavior towards sustainable usage of bike sharing by extending the theory of planned behavior. *Resour Conserv Recycl* 2020;152: 104513.
- [66] Barrat A, Barthelemy M, Pastor-Satorras R, Vespignani A. The architecture of complex weighted networks. *Proc Natl Acad Sci USA* 2004;101(11):3747–52.
- [67] Shang W, Pien K-C, Han K, Majumdar A, Ochieng W. Robustness and topology analysis of european air traffic network using complex network theory. 94th Transportation Research Board annual meeting in Washington, D.C. 2014.
- [68] Shang W-L, Chen Y, Bi H, Zhang H, Ma C, Ochieng YW. Statistical characteristics and community analysis of urban road networks. 2020 *Complexity* 2000.
- [69] Shang W-L, Chen Y, Song C, Ochieng YW. Robustness analysis of urban road networks from topological and operational perspectives. *Mathematical Problems in Engineering* 2020.
- [70] Ma J. China's first confirmed Covid-19 case traced back to November 17, in *South China Morning Post*; 2020.
- [71] Ricci M. Bike sharing: a review of evidence on impacts and processes of implementation and operation. *Res Transp Business & Manage* 2015;15:28–38.