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Impact of the COVID-19 pandemic on urban human mobility - A multiscale geospatial network analysis using New York bike-sharing data

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ABSTRACT

The COVID-19 pandemic breaking out at the end of 2019 has seriously impacted urban human mobility and poses great challenges for traffic management and urban planning. An understanding of this influence from multiple perspectives is urgently needed. In this study, we propose a multiscale geospatial network framework for the analysis of bike-sharing data, aiming to provide a new perspective for the exploration of the pandemic impact on urban human mobility. More specifically, we organize the bike-sharing data into a network representation, and divide the network into a three-scale structure, ranging from the whole bike system at the macroscale, to the network community at the mesoscale and then to the bicycle station at the microscale. The spatiotemporal analysis of bike-sharing data at each scale is combined with visualization methods for an intuitive understanding of the patterns. We select New York City, one of the most seriously influenced city by the pandemic, as the study area, and used Citi Bike bike-sharing data from January to April in 2019 and 2020 in this area for the investigation. The analysis results show that with the development of the pandemic, the riding flow and its spatiotemporal distribution pattern changed significantly, which had a series of effects on the use and management of bikes in the city. These findings may provide useful references during the pandemic for various stakeholders, e.g., citizens for their travel planning, bike-sharing companies for bicycle dispatching and bicycle disinfection management, and governments for traffic management.

1. Introduction

Cities are complex systems where human move around, interact with urban facilities, and produce a variety of flows that reflect their mobility traces. The study of human mobility can help capture the spatiotemporal movement patterns in cities and is crucial for applications such as migratory flow estimation, traffic forecasting, urban planning, and pandemic modeling (Barbosa et al., 2018). Traditional methods for the detection and analysis of human flow mainly use questionnaire methods. In recent years, the advancement of the positioning and information and communication technologies (ICTs) provides new opportunities with timely collected large-scale movement data for analysing human mobility (Ding et al., 2015; Yuan et al., 2012). For instance, in the context of the boom of the sharing economy, biking-sharing has become prevalent over the last years (Si et al., 2019).

As a low-carbon, environment-friendly and healthy travel mode

(Pucher et al., 2010), bike-sharing is effective in satisfying the needs of entertainment, leisure, and multimodal transport commuting connection in the last/first mile. After several generations of development, bike-sharing have been spreading rapidly around the world (Eren & Uz, 2020). There are nearly 2000 open bike-sharing systems in the world at the time of the publication of Meddin et al. (2021). The wide usage of bike-sharing has promoted the population movement in the city and increased the diversity of people's travel modes. Research from China shows that a large number of users (about 80%) would choose to walk, use public transport or travel on their own bicycle if the bike-sharing program is not available (Fishman et al., 2013). According to whether there is a dock, it can be divided into dock-based bike-sharing and dockless bike-sharing. For the dock-based bike-sharing concerned in this study, users pick up bicycles from the stations near their starting point and return them at the stations near their destinations. Currently these shared bicycles are generally equipped with position recording devices,

and large amounts of data could be collected from these devices, which enables a convenient city sensing, and provide rich information for the study of urban dynamic changes (Xu et al., 2019).

The outbreak of COVID-19 at the end of 2019 has posed a great challenge for the world. Many cities were locked down, and people had to isolate themselves at home, which affected the operation of cities (Zhang et al., 2020). In the pandemic, human behaviors and their mobility patterns in the city may change either due to the intention of avoiding risks, or the restrictions imposed by the pandemic policy (Liu et al., 2020). To support better decision-making under these changes, the study of the pandemic impact on urban mobility requires a comprehensive analysis of large relevant data from different perspectives. Bike-sharing data as an emerging type of data could serve for this purpose in understanding urban riding patterns during the pandemic, e. g., how the daily riding behavior changed before and during the pandemic, and what are the current riding flow distributions in the downtown area.

Extensive studies have applied complex network methods to construct geospatial networks from traffic data and explore network structures and characteristics in various transportation domains, e.g., railway transportation (Cats, 2017), bus transportation (Wang et al., 2020), aviation (Wang et al., 2011), and maritime transport (Ducruet, 2017). In this study, we propose a framework to combine geospatial complex network and multi-scale geospatial analysis for the investigation of urban human mobility using bike-sharing data during the pandemic. To the best of our knowledge, there has been no prior study to analyze the impact of the COVID-19 on the bike-sharing system from the perspective of urban human mobility. Using this framework, we aim to: (1) Explore the feasibility of using the bike-sharing data to investigate urban human mobility during the pandemic; (2) Combine the multiscale geospatial analysis with the complex network methods to explore the riding behaviors based on the bike-sharing data at different scales; and (3) Visually analyze the spatiotemporal factors and the abstract network indicators for the bike-sharing system.

More specifically, in this framework, we organize the bike-sharing data by a network representation. We further divide the network into a three-scale structure, ranging from the whole bike system at the macroscale, to local network communities at the mesoscale and then to the individual bicycle stations at the microscale. At the macroscale, we focus on the analysis of the overall characteristics and distribution trends from the trip data using network indicator statistics and kernel density estimation visualization. At the mesoscale, we first detect network communities and construct the subnetworks based on the detected communities and then visually analyze these subnetwork indicators. At the microscale, we take the bicycle station which is the basic element of the network as the research object to study the differences of relevant network indicators in different periods. Using the above methods, we try to answer the following research questions: Overall, does the pandemic have an impact on urban mobility represented by shared bicycle riding? Specifically, what changes have taken place in the spatiotemporal patterns of riding behavior during the pandemic? Furthermore, how has the characteristics of the bike-sharing network changed in the pandemic, such as community structure, network topology and network flow?

We apply our framework to the origin-destination (OD) bike-sharing data collected from the study area of New York City, USA from January to April in 2019 and 2020. The multi-scale visualization and analysis results reveal a series of spatiotemporal changes of riding behaviors during the pandemic. The network structure also changes significantly. Our framework can be adopted or extended to similar topics in other cities in the world to help people understand the impact of the pandemic on urban life, and support relevant companies and governments for their decision-making. There are differences in pandemic severity and pandemic prevention policies in different regions. The comparison of different results around the world is also helpful for a comprehensive understanding of the spatiotemporal similarities and differences of the impact of the pandemic. The remainder of this paper is organized as follows. Section 2 describes the relevant research background. The study area and data are shown in Section 3. Section 4 introduces the research framework and relevant method in detail. Section 5 presents the experiment and analysis. Section 6 introduces the implications of the case study results, and discusses the limitations of the study and the future work. Finally, Section 7 concludes the paper.

2. Research background

The emergence of multiple new types of data sources in recent years provides a broader perspective for the study of urban mobility. For instance, check-in data (Wu et al., 2018), GPS data (Molloy et al., 2021), sports and health data (Braun & Malizia, 2015) are used to assist the analysis of dynamic human flows. With the popularity of the sharing economy in recent years, bike-sharing data has been increasingly examined (Fishman et al., 2013; Si et al., 2019). As a type of spatiotemporal data, bike-sharing data contain the bike use information of a large number of users that reflects the riding activities in the city. This rich information helps understand the urban flow patterns from the perspective of social sensing (Liu et al., 2015). A number of research has employed riding data to study the usage characteristics of shared bicycles and discover different travel patterns (Du & Cheng, 2018; Zhang et al., 2018). Bike-sharing data have been also widely used for estimation purposes, e.g., travel destination choice analysis (Faghih-Imani & Eluru, 2015) and bike-sharing demand estimation (Faghih-Imani & Eluru, 2016), which are helpful in improving bicycle scheduling scheme by bicycle companies and enhancing user experiences. In addition, there have been comparative studies conducted to analyze the respective advantages of shared bicycles and other transport modes (e.g., ride-hailing services and taxis) and their interactions to help a deep understanding of the transport connections in the city (Faghih-Imani et al., 2017; McKenzie, 2020). Moreover, many research work have conducted spatiotemporal analysis by combining bike-sharing data with other sources of data. For instance, Li et al. (2020) investigated shared bicycle trajectories together with transportation network data to explore the human mobility in the city.

The study of urban human mobility patterns requires dedicated methods from different disciplines. Many research works have applied complex network theory (Newman, 2018) in various spatial fields and constructed geospatial networks by combining complex networks and spatial locations. Barthélemy (2011) conducted a comprehensive survey of geospatial networks and reviewed important spatial network models. The survey also explained how the spatial constraints affect the network structure and properties and discussed various processes taking place on these spatial networks. Lin and Ban (2013) reviewed research works on transport networks from a complex network perspective and summarized network expression and construction methods of various transportation systems. In terms of specific transportation networks research, Wang et al. (2020) built networks for urban bus data at different scales to analyze the spatial configuration of urban bus networks based on geospatial network analysis methods. In terms of railway network, Cats (2017) made a longitudinal analysis of the topological evolution of multimodal railway network by investigating its topology dynamics using data collected from Stockholm. In the field of aviation, Wang et al. (2011) used geospatial complex network to explore the network structure and node centrality of various cities in China's air transport network, and compared the characteristics of air transport network in China with those in other countries. Dai et al. (2018) investigated the evolving structure of the Southeast Asian air transport network over the period 1979–2012 to captures the main topological and spatial changes. Geospatial complex networks were also applied to maritime transport to allow a new understanding of the factors affecting the development of ports and shipping (Ducruet, 2017).

For the studies on bike-sharing data, some research models and statistically analyzes the influence of various spatiotemporal variables

and factors (e.g., weather) on daily bike-riding and bike demand (Faghih-Imani & Eluru, 2016; Kutela & Teng, 2019). Other research focuses on the spatial mining of bike-sharing data, such as using spatial clustering methods to explore the riding purpose (Wang & Lindsey, 2019) or analyze the mobility patterns in urban environments (Keler et al., 2019). Geospatial complex networks can combine statistical and spatial analysis for network indicators based statistical analysis (Saberi et al., 2017) and spatial visualization of network features (Zhong et al., 2014). So it is suitable to use the complex networks to study the bike-sharing data. Although there are many transportation network researches in the field of traditional transportation, there is still insufficient research on bike-sharing data analysis using complex network at present. Austwick et al. (2013) were among the few who applied complex networks to bike-sharing data, and pointed out that spatial analysis of complex networks has not been fully explored. The main reason is that traditional complex network analysis methods, such as indicator calculation, need to be extended for bike-sharing data with inherent spatial characteristics. Some researchers have used complex networks to analyze the influence of interference factors on the bike-sharing system. For instance, Saberi et al. (2018) studied the impact of the London Metro strike on the bike-sharing system based on complex network indicators. Yang et al. (2019) studied the changes in the bike-sharing system caused by the operation of the new metro line. Bike-sharing data can strongly support the study of urban human mobility by combining with methods from complex network, spatial analysis and other domains. However, many of these studies mainly focus on statistical analysis at an aggregated level and their results are mostly statistical values without sufficient spatial-related visual representations. Comprehensive analysis at multi-scales and intuitive visualizations are still needed.

The outbreak and spread of the COVID-19 pandemic reflect the vulnerability of the urban system and pose challenges for urban disaster resistance (Shamsuddin, 2020). However, in urban research field, there is still little research on the impact of COVID-19 on human mobility (Ghosh et al., 2020; Liu, 2020), especially based on bike-sharing data. More works with this regard are needed to help people understand the impact of the pandemic on the urban system and assist in the prevention and management of public health events in future cities.

3. Study area and data

The analysis in this research utilizes bike-sharing datasets from New York City, which is the most populous city in the United States, and has been seriously affected by the COVID-19 pandemic. There are five administrative regions in New York, including Manhattan, Brooklyn, Queens, Bronx, and Staten Island. Since Bronx and State Island has not bicycle stations, we selected the three administrative regions of Manhattan, Brooklyn and Queens with bicycle stations as the study area. Fig. 1 shows the study area and the distribution of the bicycle stations.

The data is collected from the official website of Citi Bike,[1] the largest public bike system in the United States (Tedeschi, 2016). Citi Bike was launched in May 2013 and is a kind of dock-based bike-sharing system. On its website, Citi Bike provides free available trip data from July 2013 in the format of CSV files with each file containing the amount of data items for one month.

To provide the context knowledge, we visualized the timeline of the pandemic in New York City in the first half of 2020 in Fig. 2, it shows that the impact of the pandemic at the initial stage is very serious with the number of infections reaching the peak in March and April. Some important policies related to pandemic protection were announced during this period. To make a comparative analysis of the pandemic influence, we select the bike-sharing data of New York City from January to April in 2020, which conclude the initial stage of the pandemic, and the same months in 2019. There are in total of 9,143,730

records in this dataset. The original data contains data of Jersey City which does not belong to the study area of this research. Thus, we removed this part of the data. The data are typical OD data that records the origin and the destination of every single riding. Table 1 shows the attributes and example values of the data.

4. Framework of research methods

Our framework consists of three general steps as shown in Fig. 3. First, the bike-sharing network is constructed with nodes representing bike-sharing stations and edges riding trips. Second, based on the constructed network, spatiotemporal data analysis is carried out at the macro-, meso- and micro-scale of the whole system, the network communities and the bicycle stations respectively. At the macro-scale, we focus on the overall statistical analysis of the data, and the observation of the general trend of the data by means of kernel density visualization. At the meso-scale, we detect network communities, analyze the spatial and temporal distributions of the detected communities, and carry out the spatial visual analysis of community network indicators. At the micro-scale, we focus on the unit of the station, and analyze the differences of relevant network indicators in different periods. Finally, the multi-scale spatiotemporal network analysis and the comparison of differences between the pandemic and the normal periods allow us to investigate the impact of the pandemic on the bike-sharing system and on urban human mobility. For the network construction and analysis in this study, we mainly use two libraries: Python-Igraph package (Csardi & Nepusz, 2006) and Python-NetworkX package (Hagberg et al., 2008).

4.1. Network construction

To construct the network, we first extract the bicycle stations from the raw data as the nodes of the network. Then we extract the trip connection relationships between each pair of origin and destination stations. We further aggregate them based on the pair of origins and the destinations to obtain the edges of the network. The direction of an edge is the riding direction between stations. The weight of an edge is reflected by the bike flow between the OD pair. Finally, we obtain a weighted directed network constructed from riding data. An example of the constructed bike-sharing network is shown in Fig. 4 where red dots represent bicycle stations, gray lines represent directed edges between the stations, and the widths of these edges represent bike flows. In this network, there are more bike flows from Station A to Station B than vice versa. A large number of flows is from Station C to Station B, while only a few from Station A to Station C.

4.2. Macro-scale analysis

At the macro scale, we first analyze the statistical indicators of the riding data. Then we analyze the network statistical indicators related to the network topology and network flow. Finally, we apply line charts, bar charts and kernel density estimation for the visualization and analysis of the statistics and the spatial distributions.

4.2.1. Statistical indicator analysis of riding data

Trip volume derived from riding data is an intuitive indicator of urban human mobility. A large trip volume reflects high urban human mobility of to a certain extent. The trip volume usually has time-varying characteristics. For instance, riding flows are significantly affected by varying temperatures, and by human activity patterns such as daily commuting patterns.

Riding duration is another indicator that can be used to reflect different riding purposes. For instance, short-duration riding is often used to connect the last/first mile with subway stations and other transport hubs, while long-duration riding is often used for leisure purposes. Due to different purposes of riding, the riding behaviors will follow distinct spatial and temporal distribution patterns (Xu et al.,
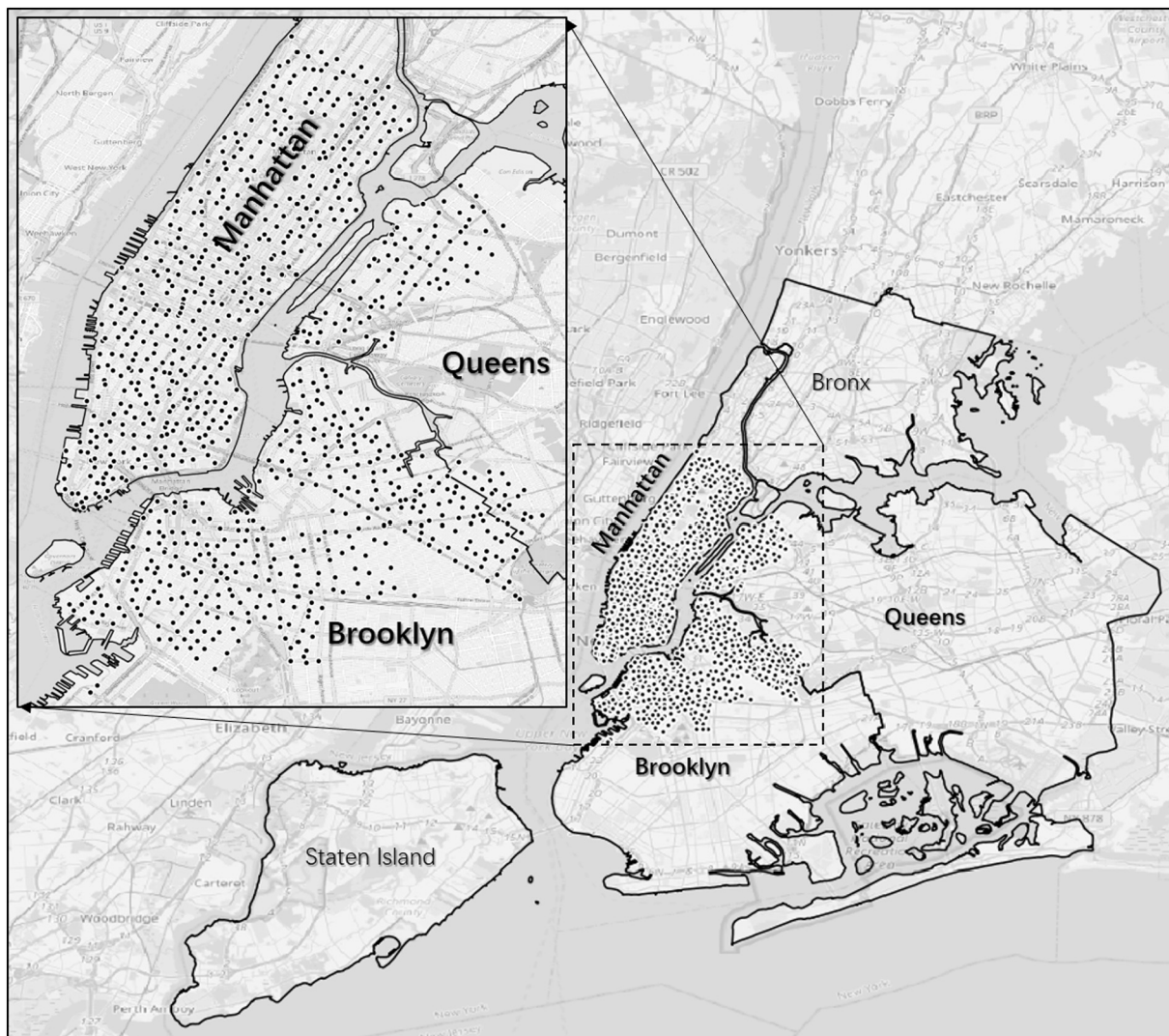

Fig. 1. Study area of New York City in this study (Black dots represent bicycle stations).
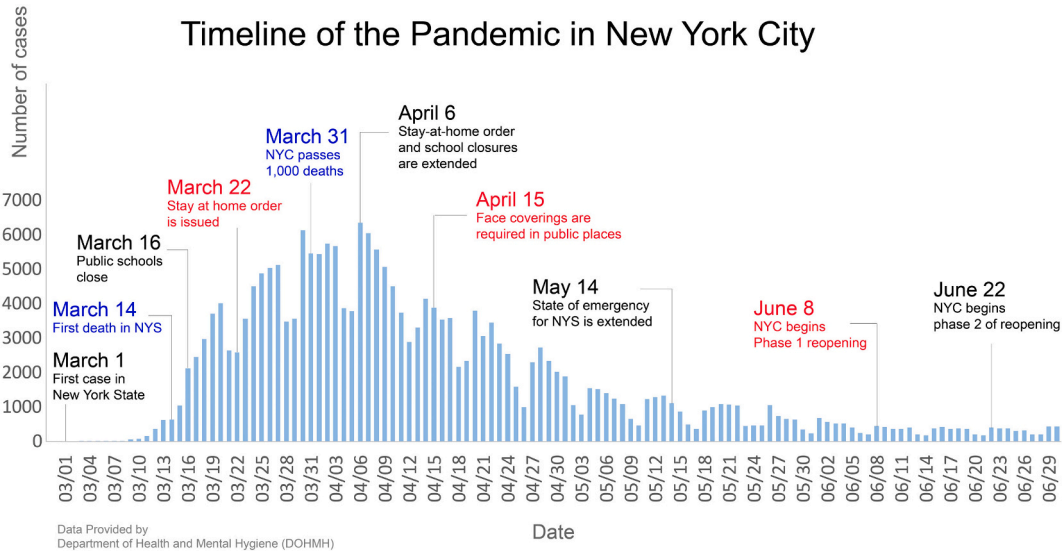

Fig. 2. Timeline of the Pandemic in New York City (blue text: crucial dates for deaths; red text: dates that government announcing crucial pandemic policies; black text: other crucial dates). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1

Trip data attributes and example values of Citi Bike.

Attributes	Example values
Trip Duration	320 (seconds)
Start/Stop Time and Date	2019/1/1 0:01:47
Start/Stop Station Name	Central Park West & W 76 St
Start/Stop Station ID	3160
Start/Stop Station Latitude	40.77896784
Start/Stop Station Longitude	−73.97374737
Bike ID	15,839
User Type	Subscriber/Customer
Gender	1(male)/2(female)
Year of Birth	1971

2019). For instance, bike ridings for commuting purpose often connect accommodation or organizations with transportation hubs in the morning and evening rush hours, while leisure ridings are mostly distributed in scenic spots. In addition, different riding durations lead to different losses to bikes, which will also affect the maintenance cost and riding pricing of the bike-sharing company. In terms of bike usage, indicators such as average use times and average use duration can not only

be used to analyze users' riding behavior, but also provide assistance for bike companies' daily operations such as renewal and maintenance strategies.

4.2.2. Statistical indicator analysis of bike-sharing network

The network statistical indicators in this study mainly cover two aspects: network topology and network flow. The former contributes to the analysis of the structure and the exploration of the connectivity and connection characteristics between bicycle stations. The latter focuses on the understanding of the characteristics and distribution of the flows on the network. Besides, we use some computational indicators to explore the distribution of the above indicators. Below we introduce each indicator in detail.

4.2.2.1. Network topology indicators. We use three indictors, i.e., degree, connectivity, and aggregation coefficient, to reflect the topology characteristics of the whole network. In a network, the degree K of a node is the number of edges directly connected to the node. For the bike-sharing network, it is the number of ride connections at a station. In a directed network, depending on the direction of the edge, it can be
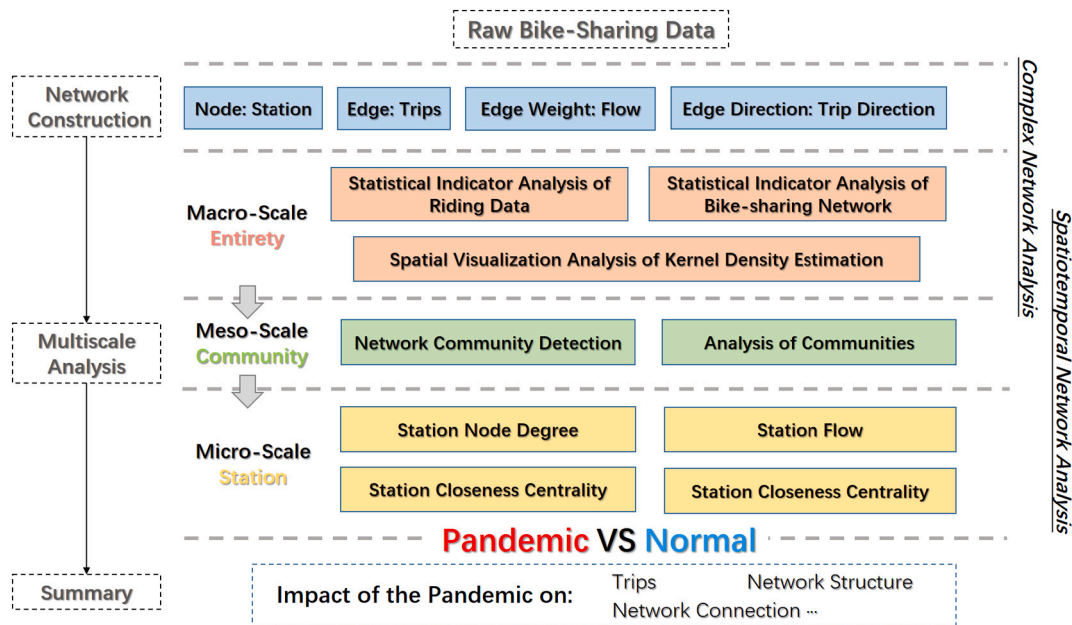

Fig. 3. The framework showing the workflow of our multi-scale analytical approach.
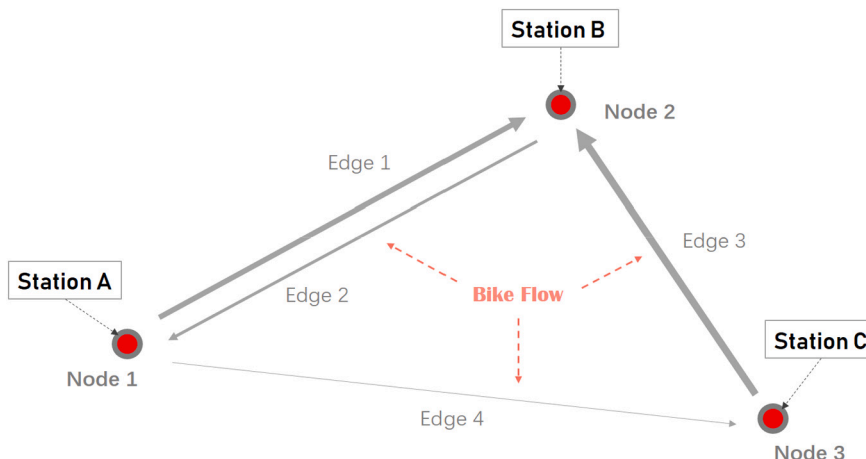

Fig. 4. Illustration of the constructed bike-sharing network.

divided into out-degree and in-degree. A high degree of a node means a bicycle station has extensive riding connections with other stations.

The connectivity of the whole network δ is quantitatively calculated by Eq. (1), in which N is the number of nodes and L is the number of edges. A large δ indicates that the riding connections between stations in the bike-sharing network is relatively denser and thus the overall connectivity of the network is better.

$$\delta = \frac{2 \times L}{N^2} \tag{1}$$

For the description of connection characteristics or the connection trend of nodes in the network, this study chose the global aggregation coefficient which describes the aggregation degree of bicycle stations caused by riding connections. This indicator helps investigate the change of aggregation degree in the bike-sharing network during the pandemic and thus understand the impact of the pandemic on network topology. The global aggregation coefficient C is defined in Eq. (2) and is based on the triplets of nodes. In the network, three nodes, which are connected by three edges, are called closed triplet (a, b, c in Fig. 5), and G_C is the number of closed triplets in the network. The connected three nodes with two edges are called open triplet (c, d, e in Fig. 5), and G_o is the number of open triplets in the network. The reason for the coefficient 3 in the equation is to ensure that the global aggregation coefficient of a complete graph is 1. The larger the C, the higher the aggregation within the bike-sharing network, which means that the connection between bicycle stations is denser.

$$C = \frac{3 \times G_c}{3 \times G_c + G_o} \tag{2}$$

4.2.2.2. Network flow indicators. We use edge flow and node flow as two indicators for the analysis of the network flow. The edge flow W in Eq. (3) represents the riding flow in a specific direction between the two bicycle stations. r_i represents one trip in this direction and m is the total number of such trips. The node flow F is calculated using Eq. (4) as the sum of flow on all edges directly connected to the node. W_i represents flow on $edge_i$, including in-flow and out-flow for the directed network. In the bike-sharing network, it represents the total riding flow entering and leaving the bicycle station. These two indicators provide intuitive reference for the study of mobility in bike-sharing network. By comparing the temporal changes of these indicator values before and after the pandemic, we can have a better understanding of the impact of pandemic on network mobility.
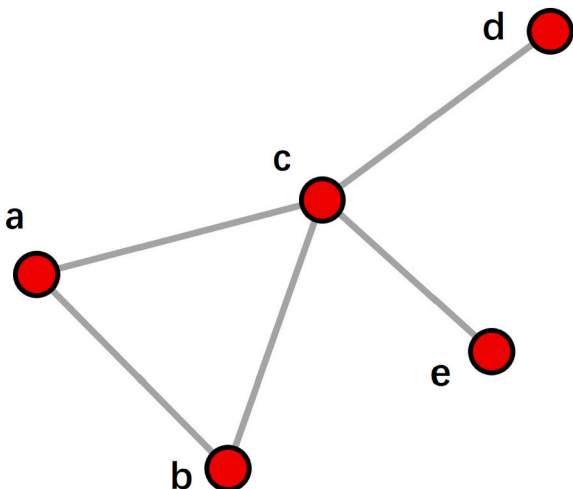
$$W = \sum_{i=1}^{m} r_i \tag{3}$$

Fig. 5. Illustration of triplets of nodes.

$$F = \sum_{i=1}^{n} W_i \tag{4}$$

4.2.2.3. Indicator distributions. For any indicator x of the network like degree, node flow and edge flow, its value distribution can be generally examined by calculating the average value <x> as shown in Eq. (5). In this equation, n represents the number of nodes. When calculating the node average flow <F>, d is the number of days in the current month. When calculating the node average degree <K>, d is set to 1. For the calculation of edge average flow <W>, n represents the number of edges and d is the number of days in the current month.

To further investigate the discrete characteristics of network indicator distribution, we introduce the standardized measure coefficient of variation CV(x) in Eq. (6), where [x] is the standard deviation and <x> is the average value. In particular, the coefficient of variation is not affected by measurement scale and dimension.

$$< x >= \frac{\sum_{i=1}^{n} x_i}{n \times d} \tag{5}$$

$$CV(x) = \frac{[x]}{< x >} \tag{6}$$

4.2.3. Spatial visualization analysis of kernel density estimation

Bicycle stations can be regarded as discrete points in space. Density visualization can present the spatial distribution of these points in an intuitive way and help an immediate perception and understanding of the macro characteristics. Compared to the commonly used point density calculation methods, e.g., quadrat method and Voronoi diagram method, that ignores the heterogeneity of spatial distribution or the continuity of spatial phenomena, kernel density estimation method (Parzen, 1962) has the attenuation effect that takes both spatial heterogeneity and continuity into account. As a field representation of spatial phenomena, kernel density estimation visualization based on spatial smoothing and spatial interpolation technologies can be applied in our study to explore the bike flow intensity and its temporal change from a macro spatial perspective.

The kernel density estimation f(x) is calculated using Eq. (7), where h is the bandwidth, n is the number of discrete points in the bandwidth range, and K(x) is the kernel function. Previous studies have shown that the selection of kernel function barely affects the results while it is necessary to pay attention to the selection of bandwidth (Wu et al., 2018). The selection of h is related to the scale of analysis. Generally, larger values of h correspond to the analysis at the macro scale that reflects the trend distribution, whereas smaller values of h are helpful to find local characteristics. In addition, the selection of h is generally positively related to the dispersion degree of points. Therefore, in practice it is necessary to adjust h according to the analysis needs and actual effects to achieve optimal results.

$$f(x) = \frac{1}{h^2} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \tag{7}$$

4.3. Meso-scale analysis

At the meso-scale, we focus on the analysis of network communities. We first detect the communities using the Infomap algorithm (Rosvall & Bergstrom, 2008), and then use multiple small maps to visualize the dynamic patterns of the detected communities.

4.3.1. Community detection

Nodes closely connected in the network can form a node subset, or network community (Leskovec et al., 2008). Community detection aims to divide these nodes into local communities such that nodes in the same community have stronger connections than nodes in different

communities. In this study, the node set in one community corresponds to the bicycle station set with more frequent riding connections in the bike-sharing network. The community detection relies not on the proximity of spatial locations but the high strength connections between the nodes. Based on the detected communities, we can analyze their spatial distributions in combination with spatial visual analysis. Dynamic changes of community structure can be further observed by integrating temporal information. In the context of COVID-19, this is especially important for providing a reference for exploring the impact of the pandemic on the bike-sharing network structure. In addition, as the intermediate scale between the bike-sharing system and station, the network community analysis provides a meso-scale perspective for understanding the characteristics of the sub-networks.

Community detection is a basic research problem of complex networks. For the weighted directed networks in this study, Infomap algorithm is one of the few algorithms suitable for community detection of small and medium-sized networks (Rosvall & Bergstrom, 2008). The comparative analysis of many studies shows that Infomap performs well for the above-mentioned tasks (Lancichinetti & Fortunato, 2009; Yang et al., 2016). Therefore, this study selects Infomap algorithm for the community detection.

The basic idea of Infomap algorithm is as follows. Based on Shannon's information theory (Shannon, 1948), Infomap uses random walks on the network to obtain a probability path as the proxy of information flow in the real system. An appropriate encoding scheme is selected to encode the random walk path. The essential goal is to find the optimal community division scheme by minimizing the coding length here.

For the quantitative description of above random walk path codes, suppose that there is a community division scheme M, which divides nodes into m communities, then the average coding length per step describing a random walk can be measured by Eq. (8). It consists of two parts: the coding length H(Q) of the movement between communities, and the coding length H(P^i) of the movement within communities. Each part is weighted according to the frequency of occurrence, p_{out} is the probability of random walk switching community, p_{in}^i is the probability of moving within community i.

$$L(M) = p_{out}H(Q) + \sum_{i=1}^{m} p_{in}^i H(P^i) \qquad (8)$$

The implementation of Infomap algorithm is mainly divided into the following steps:

1. Each node in the network is regarded as an independent community to obtain the initial community division scheme M1. At this stage, the number of communities is equal to the number of nodes in the network.
2. Randomly sample a node sequence from the network, and take the following actions for each node in the sequence in order:
   2.1. Try to assign the node to the communities where its neighbor nodes are located, and calculate the change of L(M) in each assignment.
   2.2. If L(M) decreases during the above process, change the ownership of the node to the community where L(M) decreases the most after the node is assigned. Otherwise, the community ownership of the node remains unchanged.
3. Repeat step 2 (in a different random order each time) until L(M) does not decrease. The community division scheme Mn at this time is the final output.

The above process can combine with optimization algorithms such as simulated annealing to improve optimization efficiency. Based on the final output from the above algorithm, we can determine the community ownership of each bicycle station in the bike-sharing network. The Infomap algorithm in this study is implemented by Python-Igraph package (Csardi & Nepusz, 2006).

4.3.2. Spatiotemporal visual analysis of communities

Both the locations of stations and the flow intensity between stations will affect the community detection results. It is necessary to carry out spatiotemporal analysis of the community results, for example, whether the pandemic will affect the trip volume, trip location, etc., and whether these will further affect the network structure, such as community detection results.

Each community can be regarded as a new network constructed by the nodes within the community and the edges between these nodes. As shown in Fig. 6, the community is at the middle scale of the entire network and bicycle stations. Current network statistical analysis in general only focuses on the entire network, and various indicators are described using numerical values, e.g., listed in a table. In this study, we combine the statistical analysis with spatial visualization to visually display various network statistical indicators of the community networks. Different from the previous studies that only focused on the analysis of community division results, this study takes each community as an analysis unit to further carry out a visual comparative analysis between them, observe the temporal character of various indicators, and analyze the network structure more deeply.

4.4. Micro-scale analysis

The analysis unit at the micro-scale is station, which is the basic unit of bike-sharing data statistics. As the smallest component of the network, the analysis of station mainly focuses on network topology and network flow in Section 4.2.2. For the network topology, we will investigate the connection relationship between directly connected nodes and indirectly connected nodes in the network respectively. For the network flow, we will investigate the flow of each station.

For the directly connected nodes, node degree is intuitive to reflect the connection relationship between the target node and its directly linked nodes. We first calculate the degree of each node. To investigate the aggregation between the node and its connected nodes, we calculate the local aggregation coefficient. For any node i in the network, its local aggregation coefficient LC_i can be calculated by Eq. (9) (Fagiolo, 2007). In Eq. (9), k_i is the node degree and the calculation of $k_i^{\leftrightarrow}$ is shown in Eq. (10), if and only if there is an edge connection between node i and node j, $a_{ij} = 1$, otherwise $a_{ij} = 0$. In the bike-sharing network in this study, a high LC value indicates that there is good aggregation between the target station and the stations directly connected to it.

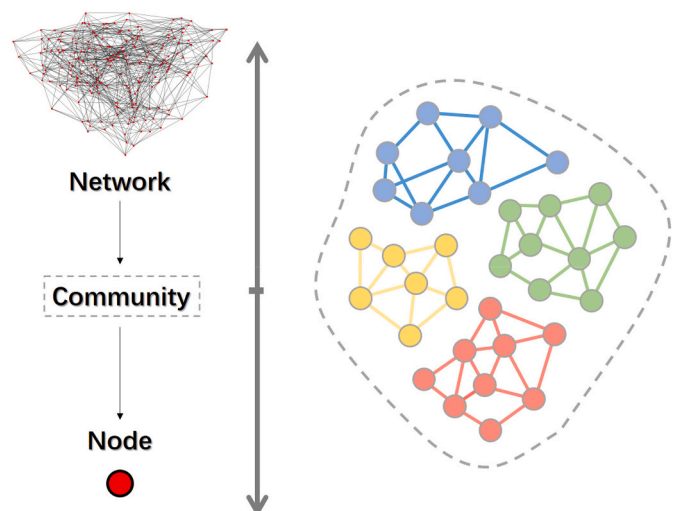$$LC_i = \frac{\sum_h \sum_j (a_{ij} + a_{ji})(a_{jh} + a_{hj})(a_{hi} + a_{ih})}{2[k_i(k_i - 1) - 2k_i^{\leftrightarrow}]} \qquad (9)$$

Fig. 6. The three-tier structure of network, community and node.

$$k_i^{\leftrightarrow} = \sum_{i \neq j} a_{ij} a_{ji} \qquad (10)$$

For the indirectly connected nodes, closeness centrality CC can be used to reflect the degree of network proximity between them. If the path from one node to every other node on the network is very short, the node has good connectivity to other nodes and has the characteristics of a hub. The CC_i of node i is calculated based on the average shortest path on the network from this node to all other nodes. The calculation of CC is shown in Eq. (11), where N is the number of nodes in the network, and d (i,j) is the shortest path between nodes i and j. The larger the CC_i, the higher the closeness centrality of the node, and the better the connection the node is with other nodes. In this study, a large CC_i means the bicycle station has good riding contact with other bicycle stations and the connection from this bicycle station to other bicycle stations is very smooth and does not need too many turns.

$$CC_i = \frac{N-1}{\sum_{i \neq j} d(i,j)} \qquad (11)$$

In order to facilitate the discovery of the temporal changes of the status of stations in pandemic and normal periods, this study makes a spatiotemporal visual analysis of the differences between the indicator values in these two periods. First, same stations in the normal period and the pandemic period need to be extracted, because new bicycle stations have no historical information and thus should be excluded. Next, the differences between the indicator values in the pandemic period and the normal period of these bicycle stations are calculated. Finally, the spatial patterns of the value differences at different periods of the day are visualized for the spatiotemporal visual analysis.

We summarize of the complex network indicators of bike-sharing network analysis introduced in this study in Table 2.

5. Experiment and analysis

In this section, we describe the experiment and the analysis results following the steps and methods in our framework. The networks are constructed separately based on the riding data from January to April in 2019 and 2020. Complex network analysis and spatiotemporal visual analysis methods are combined to provide the multi-scale analysis of bike-sharing network.

5.1. Macro-scale: bike-sharing system

In this section, we calculate relevant statistical indicators at the macro scale and use a variety of diagrams and maps to visualize the spatial and temporal distributions of the bike-sharing data.

5.1.1. Statistical analysis of trip data

In this section, we first analyze the general distribution of trips from the bike-sharing data. We calculate the monthly statistics of four

Table 2
Complex network indicators and their description.

Type	Indicator	Description
Network topology	K	The number of edges directly connected to the node.
	δ	The connectivity of the whole network.
	C	The aggregation degree of nodes connections in the network.
	LC	Local aggregation coefficient.
	CC	Closeness centrality.
Network flow	F	The sum of flow on all edges directly connected to the node.
	W	The flow on the edge.
Indicator distribution calculation	<x>	The average value of the indicator x.
	CV(x)	The coefficient of variation of the indicator x.

indicators from January to April 2019 and 2020. They are the total number of trips, the average trip duration, the average daily service times of each bike, and the average daily service duration of each bike. We visualize their monthly distributions using line charts in Fig. 7.

The trip volume (Fig. 7 (a)) in January and February in both 2019 and 2020 showed a slight downward trend, but in 2020 it is higher than in 2019. However, different from the large increasing trend from March to April in 2019, the trip volume in these two months in 2020 shows a large downward trend. The average trip duration (Fig. 7 (b)) in January and February of 2019 and 2020 has a similar pattern. However, it increased more violently in March and April 2020 compared to the corresponding period of 2019 (Fig. 7 (b)). Both the average daily service times and duration of each bike, as shown in Fig. 7 (c) and (d), had an overall increasing trend in 2019, but this trend disappeared in 2020, mainly due to abnormal performance in March and April 2020. For instance, the daily average service times sharply decreased in March and April 2020. In addition, unlike the sharp increase in the average service duration since March and April 2019, the duration of the corresponding period in 2020 remained stable with around 40 min. To sum up, in March and April 2020 when there is a pandemic, there are many anomalies compared with the normal period, many key indicators of both the user riding and bike use reveal that the mobility of the bike system has been greatly affected during the pandemic. From January to April in a normal year, with the weather getting warmer, the trip volume of bike-sharing will increase. This will also lead to the increase of other relevant indicators and improve the system mobility. However, the unusual changes of the above indicators during the corresponding period indicates that the arrival of the pandemic has a great impact on shared bicycle riding. The mobility of the system, which should have been increasing due to seasonal changes as normal period, was weakened due to the pandemic.

We further investigate the daily riding volume distribution in each month and visualize them in Fig. 8. The red and green lines represent the daily trip volume distributions in 2020 and 2019 respectively. These lines also roughly reflect the above-mentioned riding volume change patterns. In most days of January and February in 2020, the trip volume exceeded that of the same period in 2019. However, the situation changed in mid-March 2020 with a dramatic decrease of the riding volume. The riding volume after mid-March is much lower than that in the same period in 2019. We marked some critical time points of the pandemic using vertical dashed lines in Fig. 8. For instance, on March 13, 2020 (dashed line a in Fig. 8) the White House declared a state of emergency. A day later (March 14), there was the first case of patient death in New York. It can be seen in Fig. 8 that after March 14 the riding volume dropped dramatically and remained at the low volume until April. On April 19th (dashed line b in Fig. 8), the public authorities of New York announced that various indicators, including the number of new deaths per day, showed that the pandemic in New York state began to fall. On April 25 (dashed line c in Fig. 8), the public authorities of New York stated again that the number of new hospitalizations and deaths in the state continued to decline, indicating that the pandemic had turned better. On these two days the riding volumes increased dramatically reaching local peaks, which reflects to some extent that the above-mentioned public reports may affect people's travel decisions. In addition, these two days are weekends and the weather was fine[2] which may also stimulate more bicycle travels. There were more ridings in the above two days, making the corresponding curve nodes in the peak positions.

Generally, the riding duration should increase when the weather becomes warm. However, as shown in Fig. 7 (b), compared with the slow increase in riding duration in 2019, the increase in March and April 2020 is very obvious. We further investigate the proportions of different trip durations in March and April in 2020 and the corresponding period

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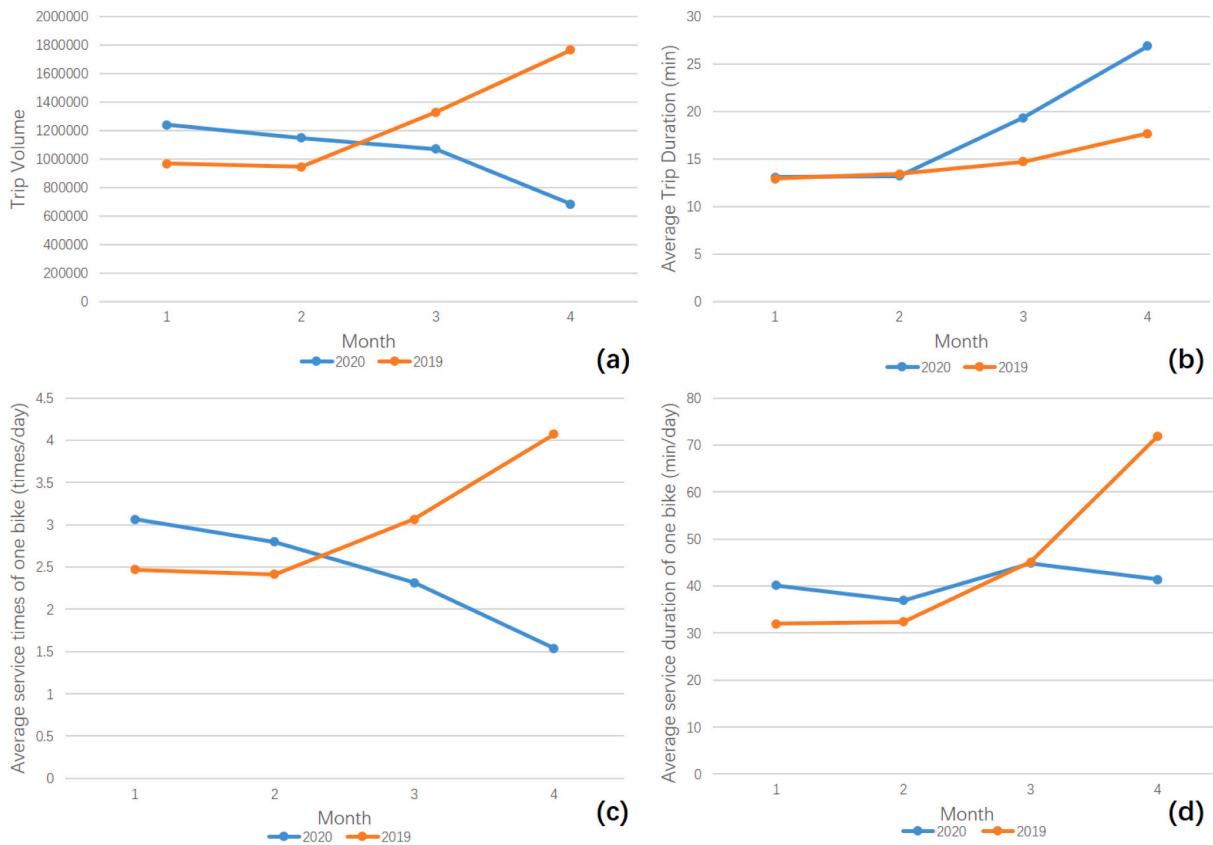[2] According to the information from https://weather.com/

Fig. 7. Line charts of (a) the trip volume; (b) the average trip duration; (c) the average daily service times of each bike; (d) the average daily service duration of each bike.
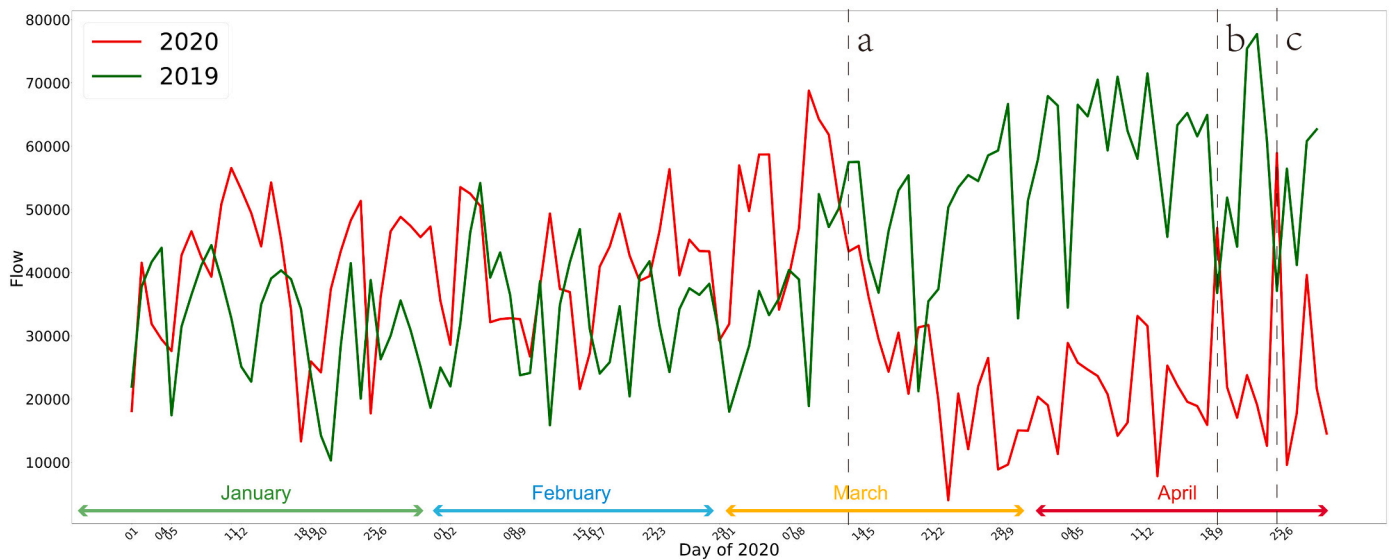

Fig. 8. Line charts of daily trips (The labels of x-axis show the holidays in 2020).

in 2019 in Table 3. During March and April 2020, the proportion of short-term ridings decreased significantly, while the proportion of long-duration ridings (e.g., over 20 min) increased significantly. These facts show that during the pandemic period, people reduced the number of rides, but they rode longer. This may because of the following reasons: (1) due to the low safety factor of tight space in subway or bus, bike riding undertook some main commuting tasks during the pandemic period; (2) riding has become an alternative way of sports and leisure

during the closure of entertainment facilities. In addition, the time distribution of riding behavior also changed significantly. In terms of the start time of riding, as shown in Fig. 9, the morning peak during the pandemic period (in March and April) has been weakened and delayed. This may be related to the start of the home-office or the shifting of the commuting time to avoid social contact clustering.

Table 3
The proportions of different trip durations (td, unit: minutes).

	td ≤ 10	10 < td ≤ 20	20 < td ≤ 30	30 < td ≤ 40	40 < td
2019.3	55.4%	27.6%	10.3%	4.1%	2.6%
2019.4	49.6%	29.1%	12.7%	5.1%	3.4%
2020.3	44.5%	29.1%	14.5%	6.9%	5%
2020.4	32.4%	26.6%	19.4%	11.2%	10.4%

5.1.2. Statistical analysis of complex network indicators

In this section, we calculate the statistics of the complex network indicators based on the equations introduced in Section 4. In order to take into account the impact of seasonal change factors, we calculate and analyze the indicators respectively from January to April of the two years. The computing results are shown in Table 4. Compared with 2019, there are more network nodes (N) in the corresponding period in 2020, which indicates that with the promotion of the bike-sharing system and the improvement of people's acceptance of bike-sharing, more and more bicycle stations have been added in the city.

In terms of network topology, the comparison of the same periods between 2019 and 2020 shows that in January, February and March 2020, new riding connections (i.e., the number of network edges L) emerged between stations. With the development of the pandemic, the number of edges in April 2020 decreased significantly compared with April 2019. The pandemic has a stronger negative effect than the expected normal growth of the bicycle usage. In terms of the monthly trend, compared to the increasing patterns from January to April in 2019, the number of network edges (L) decreased from March to April in 2020. To sum up, whether compared with the same period of the other year or other times in the same year, the pandemic has reduced the riding connections in the bike-sharing network.

The change of the number of network edges affects the average degree of nodes <K>. <K>, which increased with the increase of network edges in normal period, decreased significantly in April 2020. It shows that the pandemic reduces the external contact of bicycle stations on the whole, making it significantly lower than that in the same period in 2019. Similarly, the network connectivity (δ) of bike-sharing networks in 2020 does not show a rising trend as in normal times, but show an obvious decline in April, lower than the level in the same period in 2019. Finally, the analysis of the global aggregation coefficient C suggests it decreases with the development of the pandemic in 2020. The decrease of network edges caused by the pandemic reduces the density of connections between bicycle stations and the number of closed triplets, which weakens the cluster connection between bicycle stations.

In terms of network flow, both the node average flow <F> and the edge average flow <W> of March and April in 2020 are far lower than that in the same period in 2019. However, in normal periods, such as January and February in 2020, both flow indicators are higher than that in the same period in 2019. That is, with the development of the bike-sharing system and the improvement of people's acceptance of it, the riding flow should increase year by year. During the pandemic period, due to people's concern about infection and the impact of relevant lockdown policies, the riding flow in the city decreased significantly. In terms of flow distribution, the coefficient of variation of station flow CV (F) in January and February in 2020 are higher than that in the same period in 2019, and become lower in March and April than the same period in 2019. It means that compared with the normal period, the station flow distribution during the pandemic becomes more homogeneous. The high coefficient of variation of edge flow CV(W) in each period indicates the strong heterogeneity of edge flow distribution in the bike-sharing network. The heterogeneity of edge flow in 2020 has experienced an obvious pattern of first decline and then rise, and the
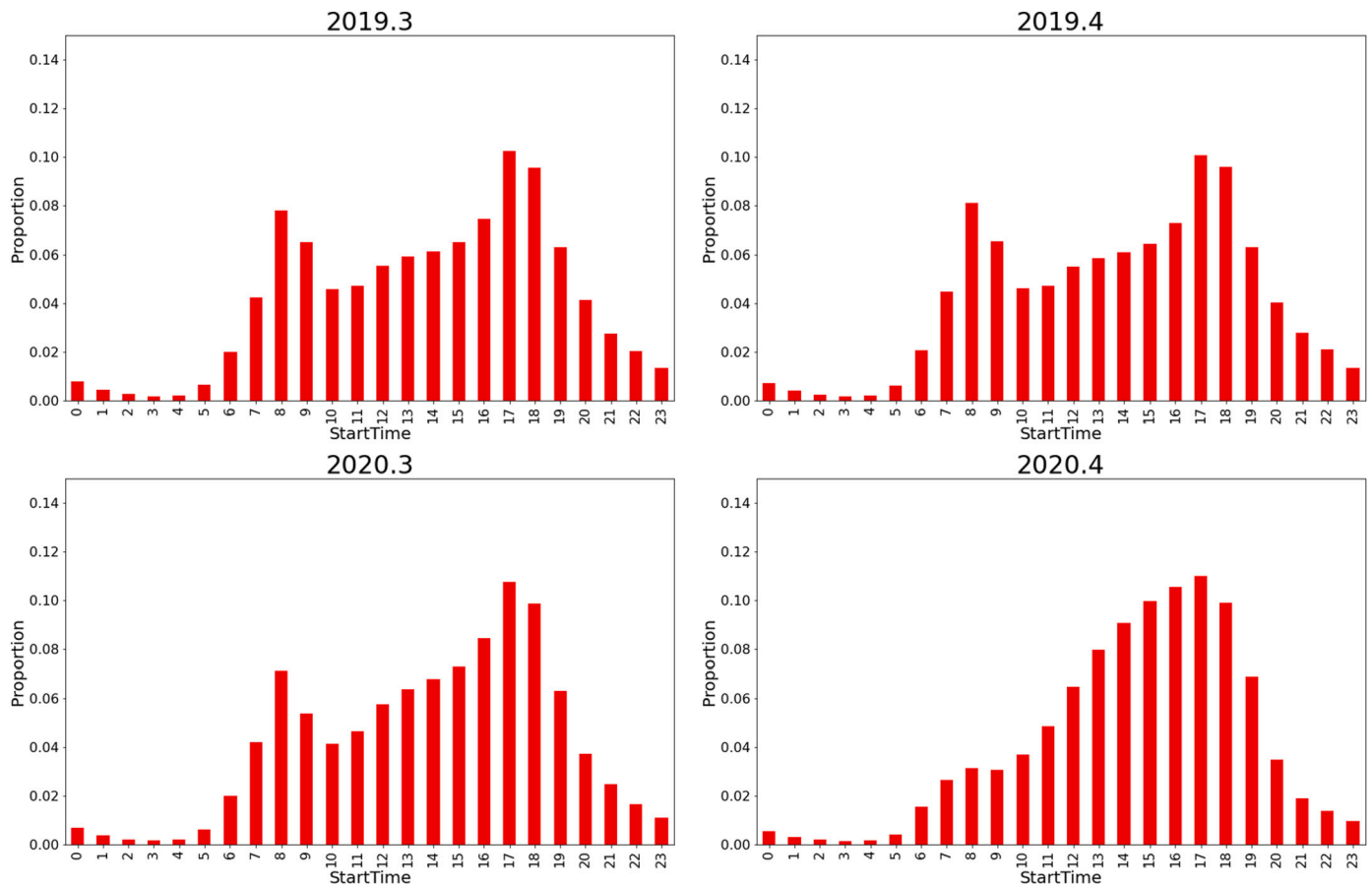

Fig. 9. Histogram of riding start time proportion.

Table 4
The macro-scale network indicators.

Indicator	Description		January	February	March	April
N	The number of nodes	2019	825	796	805	787
		2020	895	891	890	888
L	The number of edges	2019	128,070	132,020	165,126	187,514
		2020	153,712	151,784	184,933	157,357
<K>	Node average degree	2019	310.47	331.71	410.25	476.53
		2020	343.49	340.7	415.58	354.41
δ	Network connectivity	2019	0.38	0.42	0.51	0.61
		2020	0.38	0.38	0.47	0.4
C	Global aggregation	2019	0.55	0.55	0.57	0.59
		2020	0.56	0.55	0.55	0.49
<F>(/day)	Node average flow	2019	75.6428	84.6861	106.4282	149.605
		2020	89.4282	88.7669	77.4515	51.2579
CV(F)	Coefficient of variation of node flow	2019	1.02	0.98	0.95	0.92
		2020	1.05	1.04	0.93	0.87
<W>(/day)	Edge average flow	2019	0.2436	0.2553	0.2594	0.3139
		2020	0.2603	0.2605	0.1863	0.1446
CV(W)	Coefficient of variation of edge flow	2019	1.95	1.92	2.01	2.07
		2020	1.99	1.96	1.83	2.08

valley is in March when the pandemic broke out. At the beginning of the pandemic, the edge flow on the network is reduced and its distribution is more uniform. However, this trend did not continue with the continuous decrease of edge flow.

5.1.3. Spatiotemporal distribution analysis of station flow

To investigate the spatiotemporal patterns of station flows, we divide each day into five time slots: 0:00–6:00, 6:00–10:00, 10:00–16:00, 16:00–20:00 and 20:00–24:00 (Faghih-Imani & Eluru, 2015). For each time slots in March and April in 2020 and 2019, we interpolate the station flows using the kernel density estimation method.

As shown in Fig. 10, the temporal distribution of the station flows has an obvious daily pattern, which increased first, reached the peak at 10–16 and 16–20, and then decreased. In terms of the spatial distribution, the stations of large flow are mainly distributed in south Manhattan. The monthly spatiotemporal distribution follows similar patterns. However, different from the gradual increase of overall flow intensity from March to April in 2019, the overall flow intensity of these two months in 2020 is gradually weakened. In addition, the flow intensity in each time slot in a day is decreased in the pandemic period compared to the normal months. As shown in Fig. 10, with the development of the pandemic, the overall flow intensity is the weakest in April in 2020. In March and April in 2019, we can find several hotspots representing the station groups with high flow. However, during the pandemic period, such as April in 2020, there are no significant hotspot areas. The kernel density estimation can intuitively reflect the attenuation of riding in the city during the pandemic period.

5.2. Meso-scale analysis of network communities

This section introduces the detection of the network communities, and the calculation and visualization results of the statistical indicators of the detected communities.

5.2.1. Network community detection

We detect the network communities from the four-month data of March and April in 2019 and 2020 using the algorithms introduced in Section 4.3. The detected communities are shown in Fig. 11 and represented in different colors. We can see that in March and April 2019 there are five communities detected respectively, and these communities have similar structures in terms of the division form and the geographic coverage. In the corresponding period in 2020, the number of bicycle stations is increased and their coverage area become larger. Both blue community and yellow community extend eastward. Especially, the blue community extends to the south and absorbs a small part of yellow community. From March to April in 2020, the community structure

began to change, two big communities (in red and green) in Manhattan of Fig. 11 (c) merged into one larger community (in green) in Fig. 11 (d). The development of the pandemic promoted the integration of communities, which resulted in the decrease of the number of communities and the expansion of their geographic coverage.

Recall that in Table 3 there are more short-duration ridings in normal months. The short-duration riding will limit the range of riding activities, making the area connected by riding more local, thus forming a larger number of communities with a smaller range. In the pandemic months, bike-sharing is no longer limited to the short-distance connection, and the mid- or long-distance tasks undertaken by public transportation systems in the past may be partially replaced by shared bicycles. With the increase of the proportion of long-duration riding, the area of riding connection becomes larger and the community coverage expands.

5.2.2. Spatiotemporal statistical analysis of network community

In previous research work, the network indicators were oriented to the whole network. Our approach extends the work to allow a detailed exploration at community scale. We achieve this by first calculating the network connectivity δ, the global aggregation indicator C, the coefficient of variation of station flow CV(F) and the coefficient of variation of edge flow CV(W) of these community networks. The results are shown in Table 5 and visualized in Fig. 12. When calculating a community, F and W are the station flow and edge flow in the community network respectively. Substituting F and W into Eq. (6), we can obtain CV(F) describing the station flow distribution of this community network and CV(W) describing the edge flow distribution of this community network. Fig. 12 visualizes these statistical indicators of the community network.

In terms of network topology, the network connectivity δ of most communities increased in the normal period and decreased in the pandemic period which is consistent with the change of the overall network indicator. The Long Island region where community 1 is located has low network connectivity in normal times. With the development of the pandemic, it became the community with the best network connectivity in April in 2020. This region is isolated by natural rivers and less connected with other regions, so the network structure is relatively stable and its connectivity is relatively less affected by the pandemic. For global aggregation indicator C, we can see from Table 5 and Fig. 12 that the communities near north of Brooklyn and south of Manhattan in the normal months exhibit higher clustering character. In the pandemic months, the global aggregation of the south of Manhattan in March and Long Island in April is higher. This means that during the pandemic period, the bike-sharing community network in Long Island not only maintained high connectivity, but also kept high aggregation characteristics among bicycle stations.
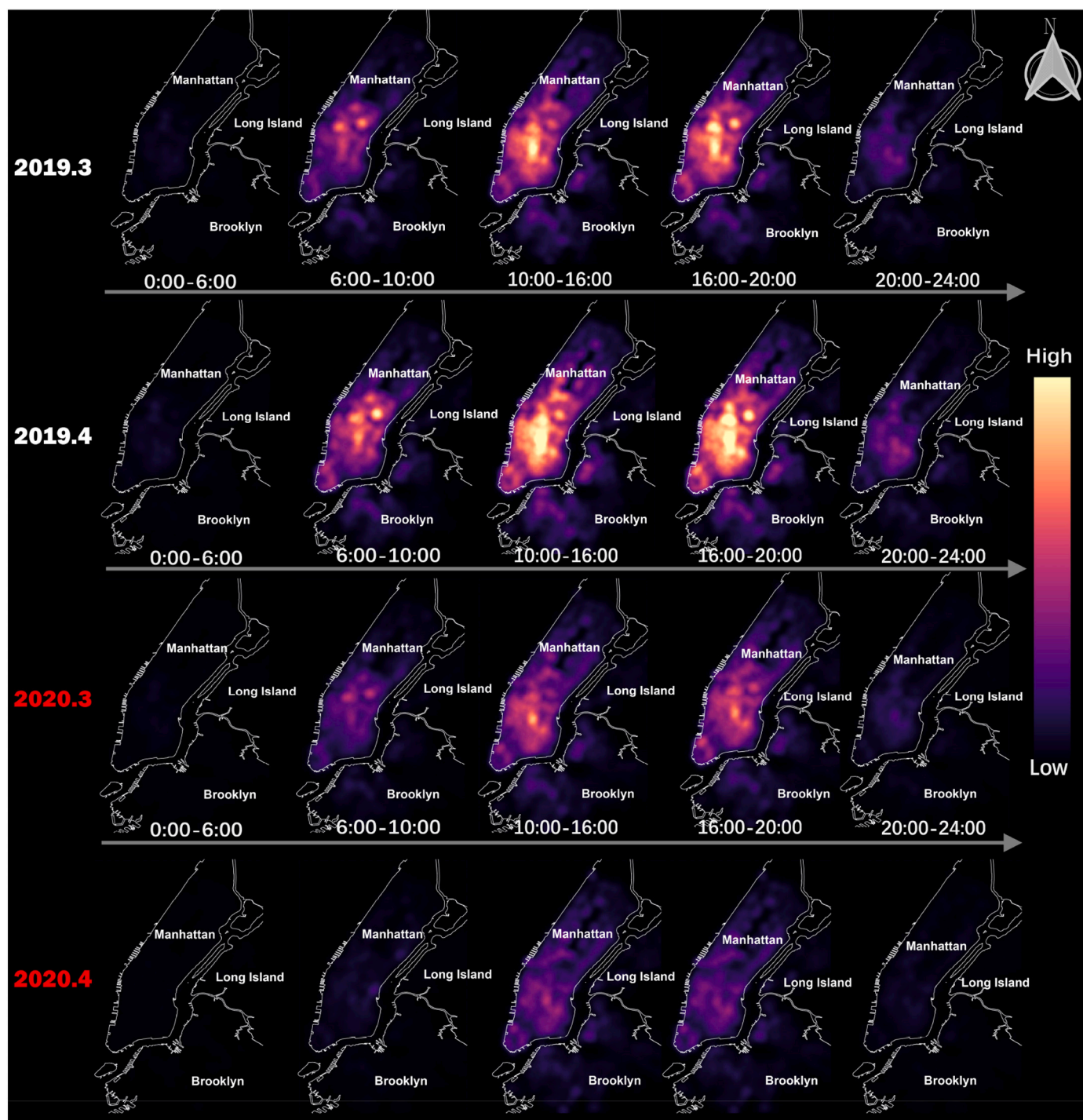
Fig. 10. Spatiotemporal comparison of kernel density interpolation results.

In terms of network flow, some regions tend to show phenomena different from the overall trend. For instance, different from the overall downward trend of CV(F) in the two months of 2020 shown in Table 4, the CV(F) of Long Island region where community 1 is located and northwest Brooklyn region where community 3 is located increased during this period. That is, with the development of the pandemic, the flow distribution of bicycle stations in these two regions is more uneven. For CV(W) of the communities, it can be seen from the data in March 2020 that the arrival of the pandemic has reduced the CV(W) of most communities, that is, the heterogeneity of edge flow distribution is weaker. This is consistent with the overall trend of the whole network in

Table 4. However, as the development of pandemic, the heterogeneity of edge flow distribution within communities is still declining in April 2020 which is different from the overall trend of the whole network. This may be caused by the network analysis of communities mainly focusing on internal flow rather than riding flow between communities. Although the impact of the pandemic on the edge flow heterogeneity of the whole network recovers rapidly, this impact continues within the community.

On the basis of the overall trend of the network system, the network analysis at the community scale allows a deeper observation of the internal characteristics of the communities, and obtain the local
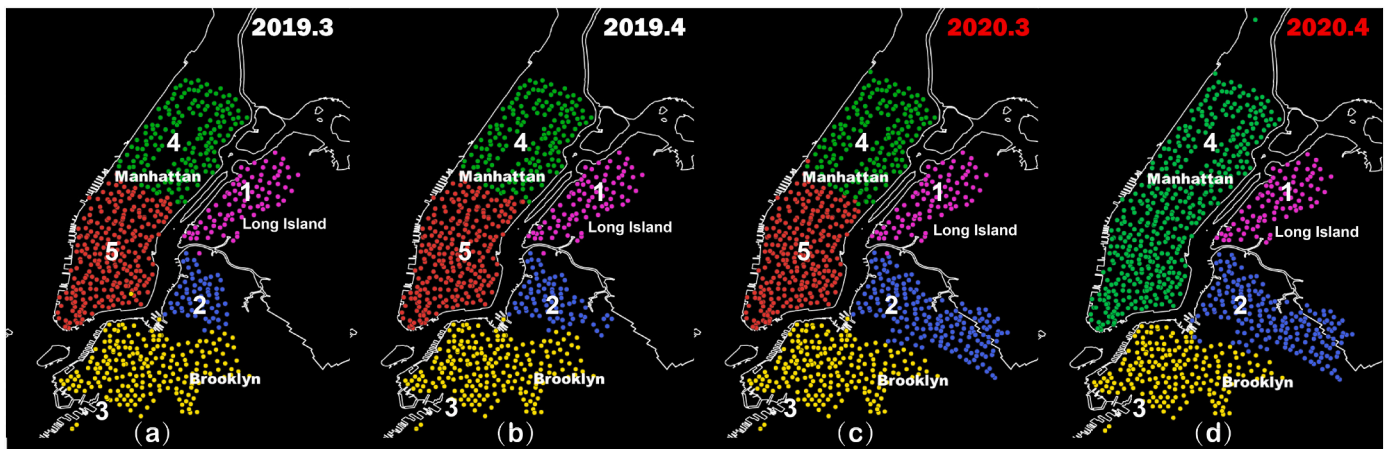
Fig. 11. The detected communities.

Table 5
Network indicator statistics of communities.

	2019.3					2019.4					2020.3					2020.4			
Community	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4
δ	1.21	1.76	1.08	1.36	1.66	1.37	1.47	1.22	1.47	1.73	1.29	0.72	1.1	1.35	1.65	1.24	0.68	0.92	0.97
C	0.79	0.96	0.76	0.84	0.93	0.85	0.9	0.8	0.87	0.95	0.82	0.62	0.76	0.83	0.93	0.81	0.59	0.68	0.72
CV(F)	0.69	0.64	0.65	0.64	0.5	0.68	0.83	0.65	0.71	0.5	0.56	1.12	0.61	0.62	0.47	0.62	0.97	0.66	0.59
CV(W)	2.23	1.66	1.94	1.79	1.56	2.14	1.79	1.92	1.95	1.52	1.46	1.82	1.53	1.58	1.4	1.14	1.39	1.42	1.48

characteristics hidden by global indicators.

5.3. Micro-scale analysis of bicycle stations

At the micro-scale, we first calculate the network topology related indicators. In terms of direct connection indicators, the spatiotemporal distribution of the node degree difference in the corresponding periods of 2020 and 2019 is shown in Fig. 13. In March, the differences of station degree between the two years are not very large reflected by the light color in Fig. 13, especially in the time slot of 6–20. The stations with increased degree and decreased degree are relatively uniform in the overall spatial distribution, showing a mixed state. This means that the number of riding connections at the stations changed little at this time. In the time slots of 0–6 and 20–24 in March, the overall light blue color indicates that there are more stations with reduced degree, and stations with reduced number of riding connections occupy a large area. This means that the impact of the pandemic on the number of riding connections at the stations is light in the early stage, mainly concentrated in the early morning and the late night of the day. In April, the number of stations with reduced degrees increased significantly, and the degree reduction range also increased. The large areas with dark blue indicates that the stations in these areas lost a large number of riding connections. In terms of temporal and spatial distribution, this type of areas began to appear in the south of Manhattan Island during 0–6 and reach the peak in intensity and distribution range in 6–10. These areas mainly distribute in the south of Manhattan Island, on both sides of Central Park and along the riverbank of Brooklyn. In general, with the development of the pandemic, the impact on the number of riding connections at stations presents the characteristics for the whole day, and the areas with serious impact are widely distributed in space.

Another direct connection indicator we calculated is the difference of local aggregation coefficient LC in each daily time slot between 2020 and 2019. As shown in Fig. 14, compared with the same period in 2019, the local aggregation coefficient of most bicycle stations is declined in the two months of 2020, and the decline gets more serious in April 2020. The arrival of the pandemic generally weakens the riding connection

between stations and their surrounding stations and destroys the aggregation between them. Although many stations with increased local aggregation can be found in multiple time slots in March 2020 in areas such as northern Manhattan, Long Island and northwest area of Brooklyn, this phenomenon was greatly weakened in April 2020. The stations with increased local aggregation only appear in the above-mentioned areas in individual time slots, and the spatial distribution range shrank significantly. In April 2020, stations with weakened local aggregation show the characteristics of a wide distribution range and a large weakening range. The stations with the most obvious weakened local aggregation are mostly concentrated in the south of Manhattan and Brooklyn during the time slots of 6–10 and 20–24.

In order to further investigate the connection between stations, the indirect connection indicator is selected for analysis. The difference of closeness centrality CC of each time slot between 2020 and 2019 is calculated. The result is visualized in Fig. 15. It can be seen that in March 2020, the stations with reduced closeness centrality occupy the majority, only some areas, such as Brooklyn, Long Island and northern Manhattan, have some stations with increased closeness centrality in the time slot 6–20. Unlike most stations in the bike-sharing system, the average shortest path between these stations and other stations is reduced. By April 2020, the stations with increased closeness centrality shrank in time and space, and the closeness centrality of stations in each time slot was declined as a whole. The arrival of the pandemic weakened the indirect connectivity between stations. Although the indirect connectivity of some stations increased, this phenomenon did not continue. With the aggravation of the pandemic, the indirect connectivity of stations was further weakened.

Finally, the indicator related to network flow is calculated. The spatial distributions of the differences between the station flows in March and April 2020 and the same period in 2019 are visualized in Fig. 16. The main trend is that the station flows decreased in the two months of 2020. Some stations with increased flow in March are densely distributed near the Central Park in northern Manhattan and Long Island, and also scattered along the coast of Manhattan Island. The increased flow in this part may belong to leisure riding. For instance,
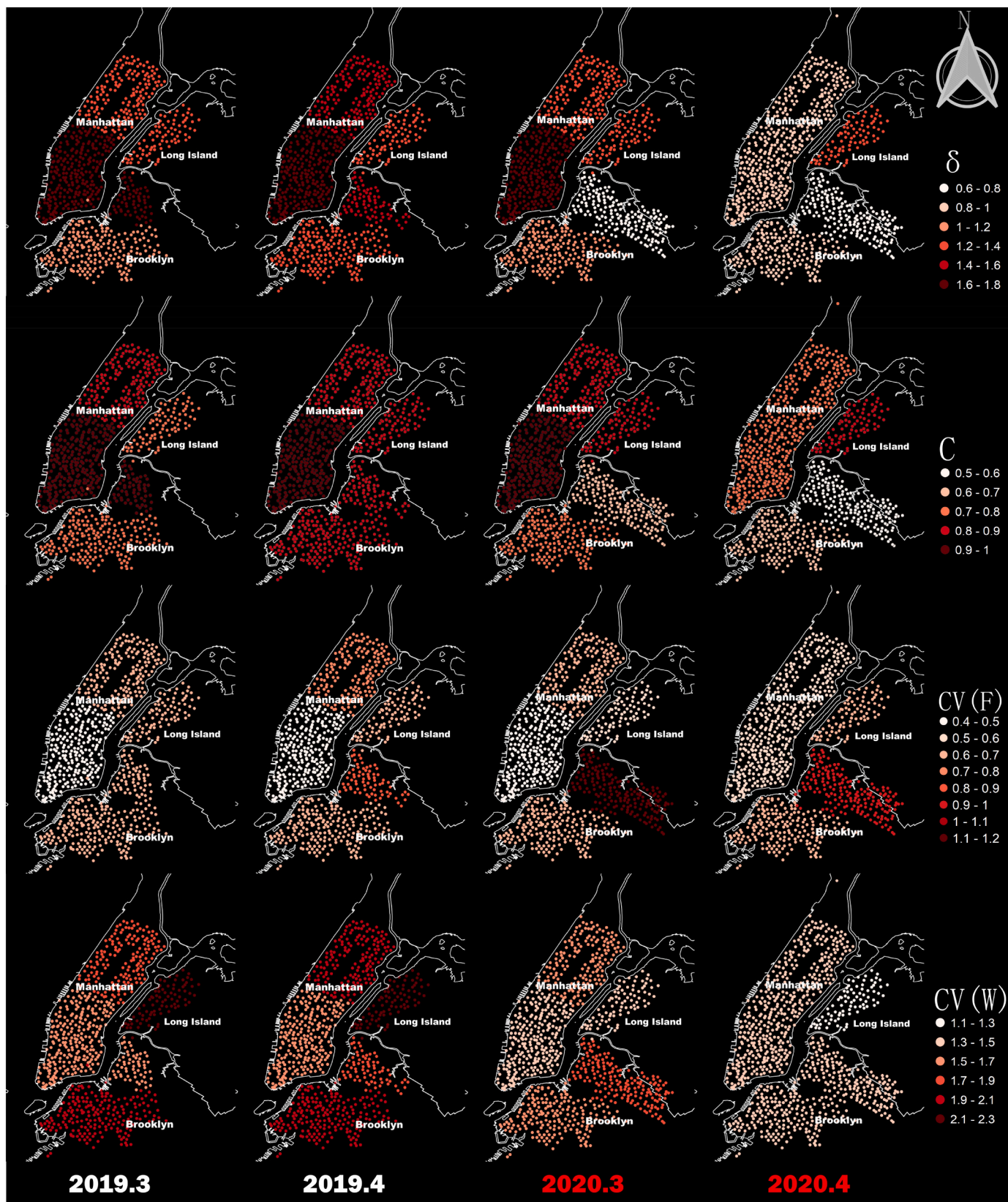
Fig. 12. Visualization of community network statistical indicators of the network connectivity δ, the global aggregation coefficient (C), the coefficient of variation of node flow (CV(F)) and edge flow (CV(W)).
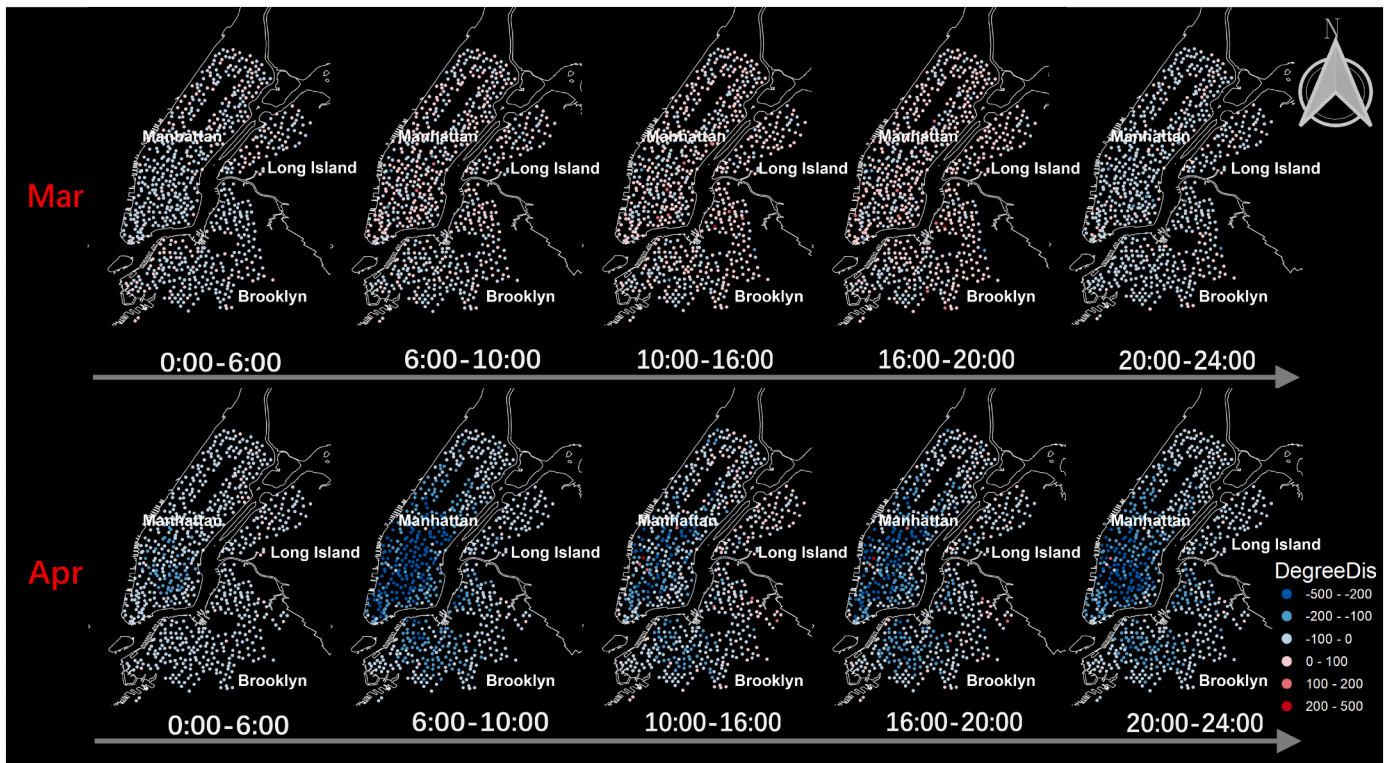
Fig. 13. The dynamic changes of degree difference of stations in March and April between 2020 and 2019.
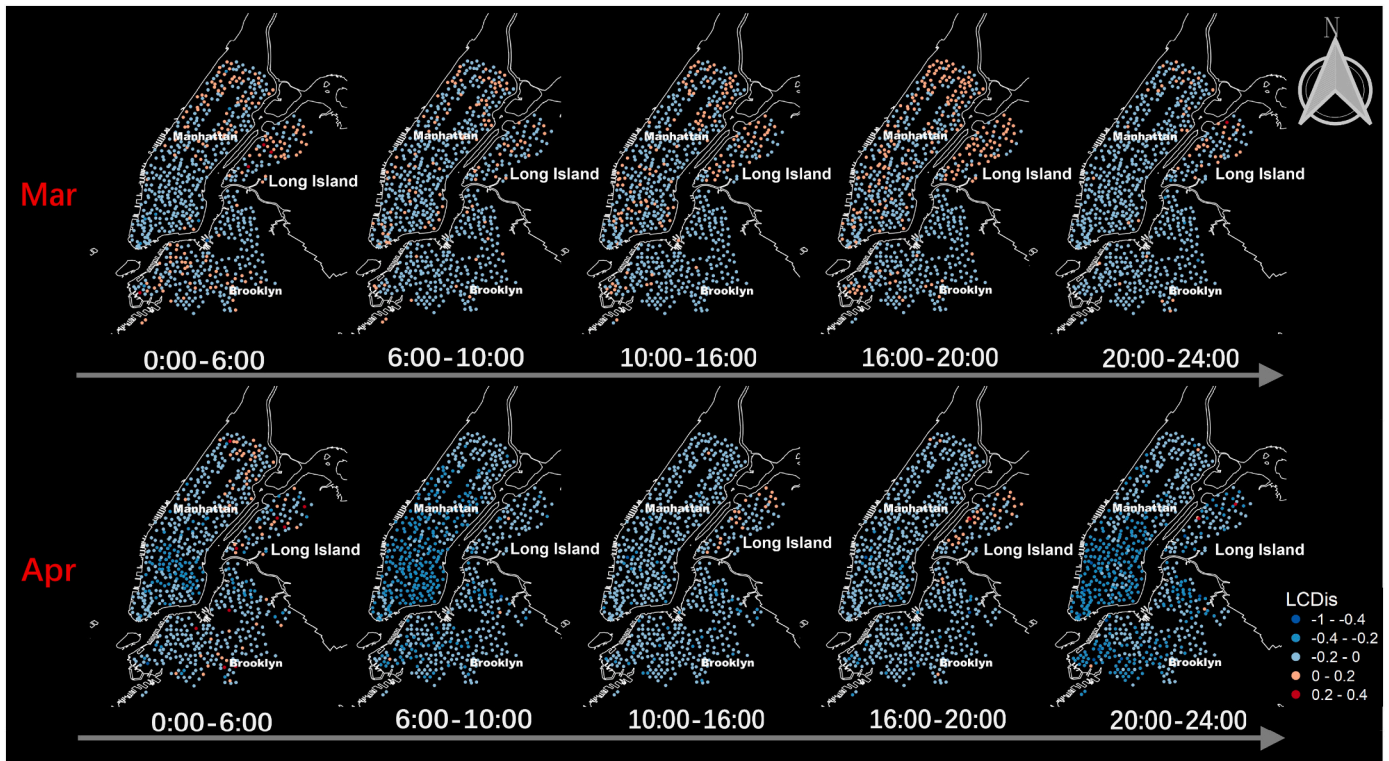

Fig. 14. The dynamic changes of local aggregation coefficient difference of stations in March and April between 2020 and 2019.

stations such as Pier 40-Hudson River Park and West St & Chambers St, which have greatly increased flow in the period of 16–20 as shown in the red ellipse in Fig. 16, are located near a series of river parks such as Hudson River Park, Teardrop Park, and Rockefeller Park. During the

pandemic period, the lockdown policy closed many public entertainment places. Since riding activities happen in an open environment and people can maintain a certain safe distance, it is a good choice for leisure purpose. The flow increase of stations in Long Island area remains in
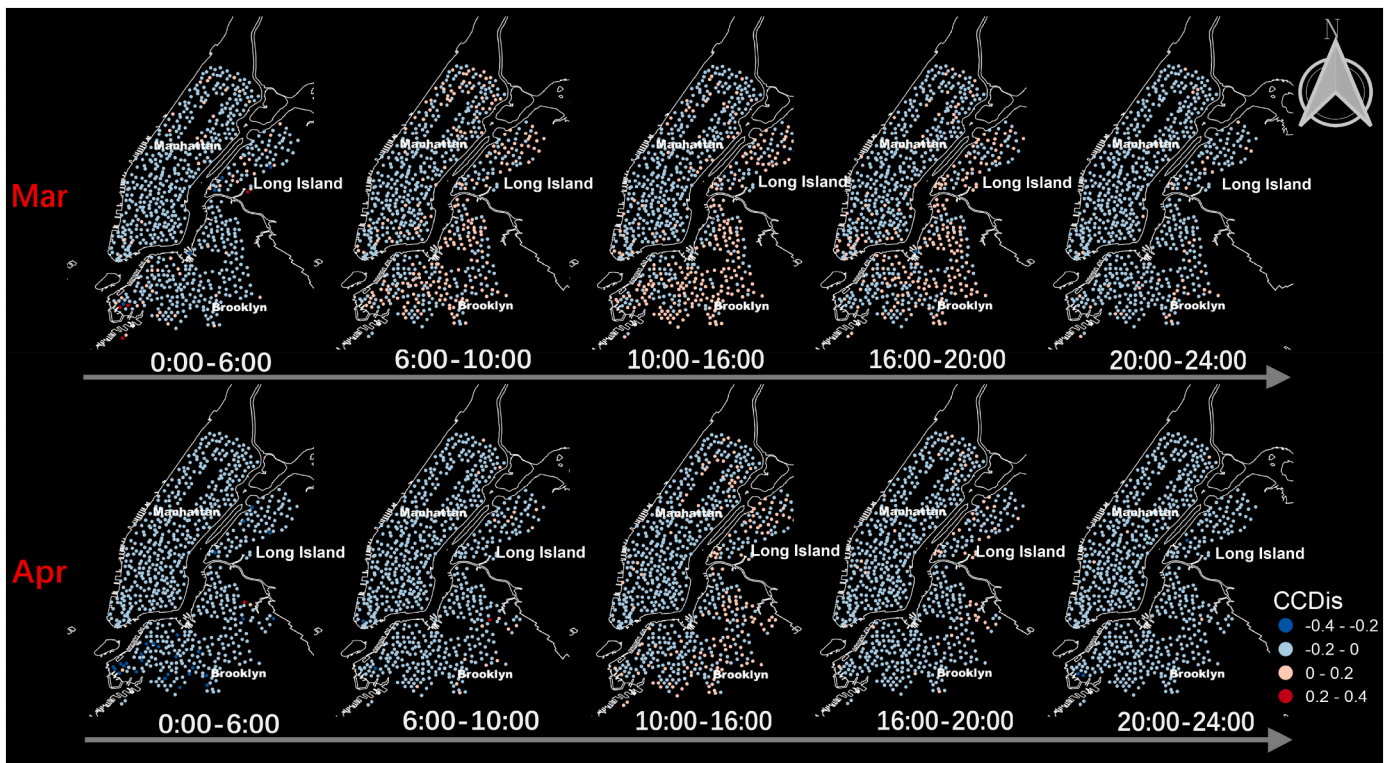
Fig. 15. The dynamic changes of closeness centrality difference of stations in March and April between 2020 and 2019.
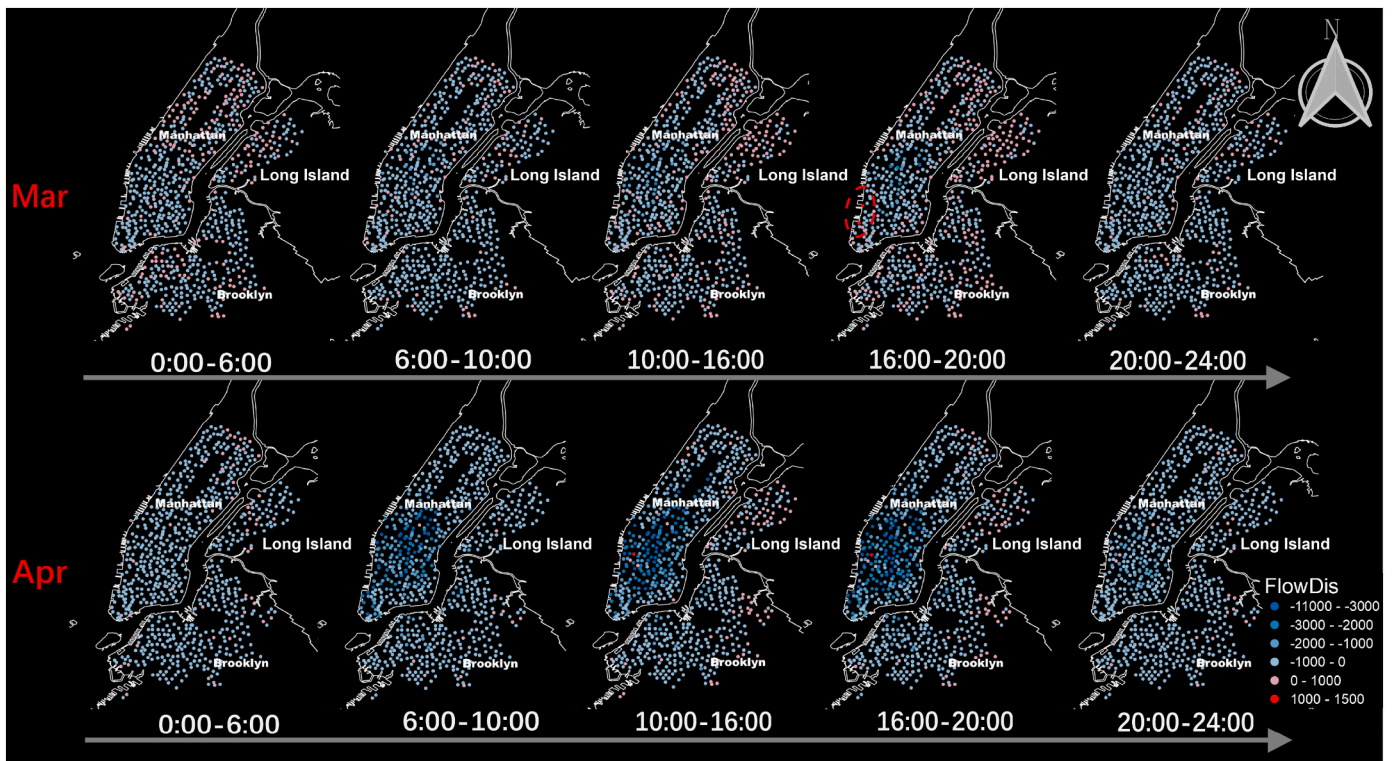

Fig. 16. The dynamic changes of flow difference of stations in March and April between 2020 and 2019.

April. At this time, the flow of stations in most of the study areas was reduced, especially in the southern Manhattan during the time slot of 6–20. This area in dark blue indicate that the flow decline of stations was very serious compared with the same period in 2019. The development

of the pandemic has prompted the introduction of the urban lockdown policy. Home office reduced the use of bike-sharing for commuting to work, thus greatly reducing the number of flow. As a very crowded and prosperous area of Manhattan, the station flow of this area was also

affected by the above factors.

6. Discussion

In this section, we summarize the main analysis results and discuss the influence of the pandemic on urban human mobility. These research results could be helpful for different stakeholders in their decision-making process. Meanwhile, we also discuss the policy recommendations, the limitations of this study and possible future research work.

6.1. Analysis results and their significance

This research has the following main analysis results. Firstly, the amount of bike-sharing riding in the city decreased significantly during the pandemic period. From the visualization results of kernel density estimation, we can see that previous mobility hot spots are weakened or disappeared in the pandemic period. The pandemic also led to the delay and weakness of the morning peak of bike-sharing trips. However, the average riding duration increased significantly, with the proportion of short-duration riding largely decreased and long-duration riding increased. Secondly, from the point of view of bike-sharing companies, the reduced riding volume led to the decline of average service times and average service duration of bicycles. Thirdly, with the development of the pandemic, the riding connections in the bicycle network are reduced. In terms of network topology, whether at the scales of station or the whole network, the connectivity is reduced. For connection characteristics, both the global aggregation of bike-sharing network and the local aggregation between bicycle stations decreased. In terms of network flow, both station flow and edge flow decreased significantly, and the heterogeneity of flow distribution was also affected. Fourthly, with the development of the pandemic, the number of network communities decreased and the area of community coverage increased. Some network communities exhibit different spatiotemporal characters from the whole network in terms of the network indicators. Finally, with the development of the pandemic, the indicators of stations are constantly affected. The impact is mild in March and aggravated in April. In March, there were still some areas that is contrary to the overall trend. In April, this type of areas is greatly reduced in both temporal and spatial distribution. In terms of indicator performance, the regions contrary to the overall trend are represented by Long Island, which is relatively independent in geographical location, while the most affected regions are concentrated in the former prosperous southern Manhattan.

Overall, the pandemic has a strong negative impact on the stability of the bike-sharing system. It has led to a reduced number of urban riding trips and changed people's riding habits to some extent. Besides, it has changed the connection structure and connection character of the bike-sharing network. All of these changes will further affect the structure of the network community and the characteristic of stations.

These research results can also support the decision-making for bike users, bike companies and government agencies. Firstly, in terms of bike users, on the one hand, the temporal pattern of the riding behavior and the spatial distribution of riding flow can provide useful reference for travel. Users can formulate appropriate travel plans in combination with their location and target region, so as to avoid travel peaks and high-flow areas. This can help reduce aggregation and thus reduce the risk of infection. On the other hand, the decrease of riding volume undoubtedly indicates travel risk, but from the generally increased riding duration, it proves the feasibility of long-distance riding for commuting and leisure purposes which may bring beneficial inspiration to citizens. Compared with the closed space of public transportation, the riding space is more open and is thus easy for bike riders to maintain a safe distance. Under the premise of adequate personal protection, it serves as an alternative way for commuting and leisure purposes. Secondly, from the perspective of bike-sharing companies, they should pay attention to the loss caused by the decrease of trip volumes during the pandemic and come up with corresponding schemes to reduce economic losses.

However, the pandemic may bring new tasks and potentials for bike-sharing, which will also provide a reference for the company's future business strategy. Besides, our work suggests that the companies should pay attention to the hot spot areas of bike flow to dispatch the bikes timely and to disinfect bike, especially the frequently used bikes, to ensure the safe use of bikes during the pandemic. Finally, for the government, the urban public transport system was severely impacted during the pandemic, and many lines may have to be temporally closed to ensure safety. To some extent, bike-sharing provides an alternative possibility to promote urban traffic during the pandemic. In this special period of reducing travel clustering, promoting healthy travels, and making pandemic recovery plans, the government should assess the advantages and risks of bike-sharing riding during the pandemic through rigorous and neutral investigations, and make appropriate decisions.

6.2. Policy recommendations

In terms of local practice, this study provides empirical evidence for more long-duration bicycle riding during the pandemic, which indicates shared bicycles may undertake more tasks for leisure and commuting. It is recommended to add temporary bicycle stations in leisure areas distributed in the city. In particular, it is necessary to pay attention to avoid riding aggregation when setting up stations. This would be beneficial to increasing the accessibility and convenience of citizens' bike-sharing use and enrich their leisure activities during the pandemic.

Since shared bicycles is a relatively safe way of travel during the pandemic, temporary bicycle lanes could be appropriately added. Although there were a lot of home office work, people such as doctors and nurses still need to go to the workplace during the pandemic and there is a large demand for medical treatment. This measure can promote the convenience of citizens' riding travel during the pandemic. In particular, the location of temporary lanes should be more inclined to hospitals and other places that are critical to resist the pandemic and protect people's life and health.

Further recommendations are on guaranteeing safety for riding. For instance, publishing real-time bike-sharing flow distribution will be helpful for citizens' travel decision-making, and the kernel density visualization in this study serves as a good reference and a starting point. In addition, disinfection should be strengthened at flow-intensive stations considering the spatiotemporal distribution patterns of riding flow found in this study.

The implementation of relevant policies requires financial support. In particular, the subsidy policies for bike-sharing companies need to be formulated as the stable operation of these companies is conducive to urban traffic during the pandemic.

In terms of international practice, for other cities with bike-sharing, out findings could not be overgeneralized but can provide some references in combination with their specific circumstances. For cities where bike-sharing is not yet popular, we recommend them to increase investment in bike-sharing as a green and safe transportation mode. In addition, bike-sharing not only meets the needs of daily commuting connection and leisure, but also a substitute for public transport during the pandemic. This is beneficial for maintaining the normal operation of the city in critical time.

6.3. Limitations of the study

Our analysis confirmed that bike-sharing data can be used to explore and reveal the impact of the pandemic on urban human mobility. However, the use of bike-sharing data does have some limitations in understanding urban human mobility. The spatial coverage of bike-sharing system in cities is limited and bike-sharing data does not represent all mobility activities. On the one hand, it only records the bicycle usage of bike-sharing companies, but other private bicycle trips cannot be counted. On the other hand, the bike-sharing system is only an

integral part of the transportation system, other travel modes, such as buses, subways and taxis, should be also included for a comprehensive understanding of urban mobility.

6.4. Future work

The research methods proposed in this study has great potential to be applied to other cities worldwide and for the understanding of the impact of the pandemic on urban mobility if there is bike-sharing data available. As a global outbreak, COVID-19 has a huge impact scope. Therefore, we see a wide scope of applications. In fact, these methods can be applied to typical OD data including bike-sharing data from other cities or other companies and other types of OD data suitable for studying the human mobility.

In terms of research results, some results of this study may be universal, which could provide reference for different cities to understand the impact of the COVID-19 on bike-sharing. However, due to diverse influencing factors of urban human mobility such as the severity levels of the pandemic and local government policies in different cities, the research results of other cities will show personalized characteristics. Dedicated research needs to be conducted for the exploration of urban mobility patterns in specific cities by applying our methods to their data, which also constitutes the motivation for the extension of our methods to other places.

As the COVID-19 pandemic is still on-going, future research will collect latest data from New York and continue to track the impact of the COVID-19 on New York bike-sharing. Meanwhile, we will collect more data from other cities around the world to carry out comparative analysis of the pandemic impact on the use of bike-sharing from an international perspective.

For other aspects, more types of human mobility data and big crowdsourced data like taxi data, flight data, mobile phone data and geotagged social media data will be collected for in-depth and comprehensive study on urban human mobility during pandemic. In addition, other data sources, such as accurate pandemic data, land use data, urban POI (Point of Interest) data and demographic data, should be involved for correlation analysis and a more comprehensive understanding of the impact of the COVID-19 pandemic.

7. Conclusion

The outbreak of COVID-19 has a huge impact on our societies and greatly reduced the social and economic activities of many cities. In this study, we have used geospatial network methodology to study the bike-sharing system of New York which confirms the feasibility of studying urban human mobility during the pandemic using bike-sharing data. In the design of research methods, we combine spatial and temporal factors, abstract network indicators and concrete spatial visualization methods to obtain more comprehensive analysis results. Aiming at solving the problems existing in the current research and providing a new perspective for understanding the pandemic impact, a multi-scale geospatial complex network analysis framework is proposed for the exploration of shared bicycle riding. The spatiotemporal variations of the topology and flow of bike-sharing network is explored comprehensively. Many interesting results have been found regarding the changes of the connectivity and aggregation etc., of bike-sharing networks during pandemic. In addition, we combine spatial visualization and complex network analysis to present the spatiotemporal distribution of abstract indicators in an intuitive way.

To answer the questions raised at the beginning of this paper, our analysis showed that the pandemic had a considerable impact on the urban human mobility represented by the shared bicycle riding. Specifically, we discussed that the spatiotemporal patterns of shared bicycle riding changed significantly during the pandemic, reflected in aspects such as riding temporal distribution and the spatial flow distribution. Furthermore, the multi-scale analysis showed that the pandemic has

comprehensively affected the riding network, changed the network community structure, and had a negative impact on the network topology and network flow at different scales. Our research results can serve as a reference for other researchers worldwide conducting similar work and for a world effort to combat the pandemic.

CRediT authorship contribution statement

Rui Xin: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Tinghua Ai:** Conceptualization, Supervision. **Linfang Ding:** Methodology, Writing – review & editing. **Ruoxin Zhu:** Methodology, Formal analysis. **Liqiu Meng:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare no conflict of interest.

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