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Research Article

Evaluating the Real-Time Impact of COVID-19 on Cities: China as a Case Study

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Since the beginning of 2020, the COVID-19 epidemic has dramatically influenced the human socioeconomic system. If we conceive of the city as a complex organism with a metabolism, then the daily flows of people, materials, and information into and out of a city can be regarded as its metabolism. To evaluate the real-time impact of COVID-19 on a city's economy and society, we construct a health index of cities (HIC) using human mobility big data from Baidu and analyze the temporal and spatial changes of the HIC in China. The results show that both internal and intercity population movements have been significantly affected by the COVID-19 epidemic, and the decline in both was more than 50% at some points. The intercity movement is more affected than the intracity movement, and the impact is more sustained. Compared with the same period before the outbreak, the HIC in China decreased by 28.6% from January 20 to April 21, 2020. The deterioration rate of the HIC was faster than the growth rate of COVID-19 cases, but the improvement in the HIC was much slower than the decline in COVID-19 cases. Although the HIC is highly correlated with COVID-19 in both the spatial and temporal dimensions, the effect of the epidemic on the HIC varied across regions. The HIC fell more significantly in provincial capitals, such as Beijing, Shanghai, Guangzhou, and Zhengzhou, and in urban agglomerations, and these cities' HICs were lower with a longer-lasting reduction. This study can serve as a frame of reference for studying the real-time impact of the epidemic, helping cities' policymakers to quickly assess its socioeconomic impact. By extension, this index can be applied to other countries and other public health emergencies.

1. Introduction

Through July 31, 2020, there have been more than 17 million confirmed cases of COVID-19 in the world, including 668,910 deaths, reported to the WHO. The COVID-19 pandemic is also a global threat with great economic and social challenges. The global economy is predicted to shrink by 5.2% this year, representing the deepest recession since World War II [1], and Director-General Tedros of the WHO has stated that the impact of the coronavirus will be felt for decades to come [2]. COVID-19 is exposing the fragility of the goals adopted by the United Nations, and a global depression looms [3]. As the center of human production and life, approximately 55% of the world's population—4.2 billion inhabitants—live in cities. Urban systems are ground zero of the COVID-19 pandemic, with 90% of reported cases [4]. During the pandemic, the manufacturing, transportation, tourism, catering, education, entertainment, sports, and other industries in cities have been suffering an enormous blow [5]. COVID-19 has not only made people sick but has also made the city "sick," leading to a series of problems, such as sharply rising unemployment, lower wages, rising urban poverty, and declining quality of life [6–8], which has a great impact on urban resilience and sustainability [9, 10]. The outbreak in China occurred earlier than in other parts of the world and was most severe from February to April. An unprecedented effort was adopted in China to stop the spread of COVID-19, including travel restrictions, social distancing, and closing nonessential facilities and services in cities [11, 12]. At present, although the pandemic has been well suppressed, it has also had a strong effect on the urban economy and people's lives.
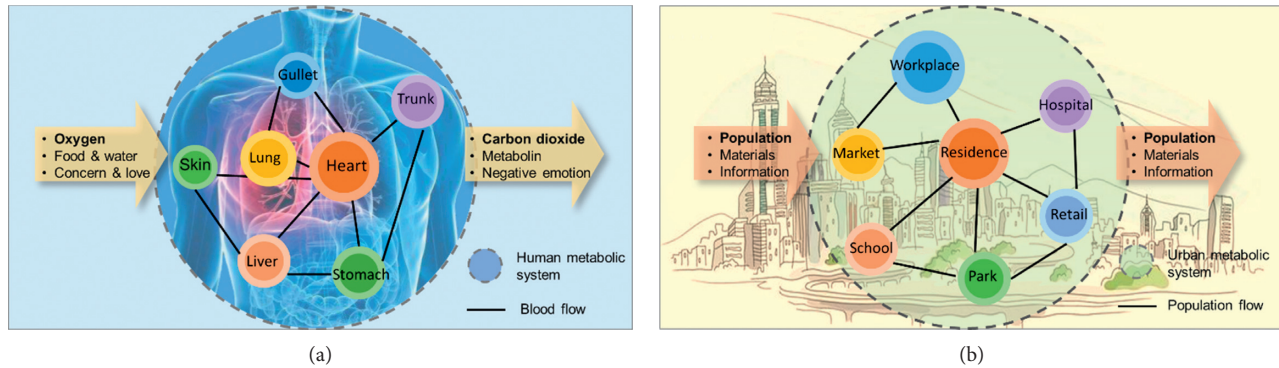
(a)

(b)

FIGURE 1: Schematic diagram of the human metabolic system and urban metabolic system. (a) Human metabolic system. (b) Urban metabolic system.

Many studies have been conducted on the complex socioeconomic impact of the COVID-19 pandemic [5, 13, 14]. For instance, using input-output analysis, the impact of epidemic mitigation and suppression measures on the workforce was modeled in the US [15]. An integrative literature review was carried out to assess the consequences of the global pandemic economic crisis on poor communities on four different continents [16]. By the end of 2020, the economic impact from aviation losses due to the pandemic could reduce the world GDP by 1.41–1.67%, and job losses may reach 25–30 million [17]. The tourism and hotel industries have also been hit hard by the pandemic [18, 19]. There have also been a number of simulation analyses of the long-term effects on the future socioeconomic development [20, 21], including the Global Economic Prospects from the World Bank. Moreover, based on social big data, psychological health in the COVID-19 context was examined. The impacts, both positive and negative, of COVID-19 on the environment were also analyzed [22, 23], such as enhanced air and water quality in urban areas [24, 25]. However, these studies are limited by the lack of temporal granularity and are not timely. For instance, the gross domestic product (GDP) is usually reported quarterly in national economic reports. Additionally, these reports are limited to a particular industry or region [26] and lack an analysis of the overall impact at the city scale.

Thus, to evaluate the holistic socioeconomic impact of COVID-19 on cities in real time and analyze temporal and spatial variations in that impact, we construct a health index of cities (HIC) to measure the real-time impact of COVID-19 on cities' socioeconomic development. Based on the idea of urban metabolism, the following section constructs a HIC with Baidu's big data on population movement within and between cities. Section 3 takes China as a case to analyze the changes of the epidemic, the spatial-temporal changes of the HIC, and the relationship between them. In Section 4, the reliability and generalization of the HIC are discussed. The final section of this paper is the conclusion.

2. Methodology and Data

2.1. Health Index of Cities (HIC)

2.1.1 Theoretical Background: Urban Metabolic System Based on Human Mobility. A city is a complex system with people at its core, including residences, industrial districts, business zones, roads, parks, schools, hospitals, and other places, which are connected to each other and full of vitality through the movement of people [27–29]. Figure 1(a) shows the basic metabolism of the human body. Oxygen and nutrients are transmitted to various organs in the human body through the blood. When a virus infects the lungs, oxygen has difficulty entering the body, resulting in poor health. Similarly, if we conceive of the city as a complex organism with metabolism, the daily flows of people, materials, and information into and out of a city can be regarded as that metabolism, as shown in Figure 1(b) [30, 31]. Previous studies on urban metabolism have paid more attention to the role of material flow and energy flow arising from urban socioeconomic activities and regional biogeochemical processes [32, 33], and the research scale is always limited within the city [34]. However, this paper argues that cities thrive on people, who are the soul and vital stream of urban development. Moreover, much of the flow of matter, energy, and information attaches to the flow of the population, and the free movement of the population is particularly important for the health and vitality of urban systems. As such, more attention has recently been paid to the role of human beings and the related industrialization and urbanization in the study of urban metabolism [35]. On the other hand, human mobility is closely associated with socioeconomic indicators [36]. For instance, a study in Italy investigated how lockdown strategies affect the economic conditions of individuals and local governments using human mobility data provided by Facebook [37]. Therefore, different from previous literature, this study focuses on the urban metabolic system based on human mobility within and between cities from a macroperspective.

The main symptoms of COVID-19 are difficulty breathing and impaired lung function, which lead to a

decline in physical function and even death. Similarly, blocked human mobility will make breathing difficult and undernutrition for cities, leading to sharp decreases in business, industry, and cultural exchanges and a reduction in cities' vitality. This blockage, without any doubt, will cripple the normal socioeconomic functioning and the overall health and resilience of the urban system.

2.1.2 HIC Construction. Based on the above analysis, we used two types of human mobility data from Baidu (viz., Baidu mobile data) to construct the HIC. Baidu is one of the largest map service providers in China, and its migration big data have been widely used in research and policies [38, 39] and also represented a critical arsenal of tools for supporting public health actions across all phases of the COVID-19 epidemic [40]. The first is the individuals' daily travel intensity within the city, which refers to the ratio of the daily travel population to the permanent population. The second is the flow of people between cities, including the daily inflow and outflow of people from the city. These two types of data are both from location-based services and Baidu applications that facilitate the self-guided collection of mobility data. Accordingly, two human mobility indexes are constructed: the mobility-within-city index (MWCI) and the mobility-between-cities index (MBCI).

Considering that long-term daily human mobility usually displays temporal and spatial regularity [41], to better reflect the changes in population movement affected by the epidemic, an appropriate baseline value from before the outbreak should be selected. The baseline reference date for mobility within the city is chosen from January 6 to 12, 2020, the last full week before the outbreak began. The data for the same period in the 2019 lunar calendar are used as a reference to reflect the impact of the epidemic on human mobility between cities. Thus, the two mobility indexes—MWCI and MBCI—are calculated as (actual value − reference value)/reference value. The MWCI represents the change in individuals' daily travel intensity over the study period compared to the control week. The MBCI represents the change in human mobility between cities compared with the same period last year.

The flowing population into and out of each city daily is like the breath of the city, and human mobility within a city is like oxygen and nutrient circulating through all parts of the city. It is hard to say whether breathing is more important or blood circulation is more important. Human mobility within and between cities should be taken into account systematically. In this study, after consulting relevant experts, we assume that both are of equal importance, and the health index of cities (HIC) based on human mobility is defined as follows:

$$HIC = \left(\frac{MWCI + MBCI}{2} \right). \tag{1}$$

The HIC reflects the overall health and vitality of a city. This paper uses the HIC to evaluate the near-real-time impact of the epidemic on cities. Obviously, the HIC in this

research is negative; the smaller the value, the harder it is for a city to breathe and metabolize and the greater the impact of the epidemic on the city's health.

The time span of the Baidu mobile data collected for this paper is January 20 to April 21 (January 20 marks the announcement of COVID-19 human-to-human transmission in China). Confirmed COVID-19 cases come from the National Health Commission of China. It is important to note that the health index constructed in this study reflects the macrostatus of the urban organism; it does not focus on people's disease and health status [42]. The latter falls under the narrow scope of urban health research, which studies noise and air pollution risk and the various diseases they bring to humans [43].

2.2. Bivariate Spatial Autocorrelation Analysis. Bivariate spatial autocorrelation is also known as bivariate Lisa clustering. It is highly applicable and has strong validity in describing the spatial correlation and dependency characteristics between two geographical elements. Human mobility is closely related to COVID-19, so bivariate spatial autocorrelation can be used to quantitatively characterize the spatial correlation between the two. In the results, the H-H (high-high) and L-L (low-low) concentrations are positively correlated in space, indicating that the city has a serious epidemic situation but a high degree of urban health and that the city has a low degree of urban health but not a serious epidemic situation, respectively. The H-L (high-low) and L-H (low-high) concentrations are negatively correlated in space, indicating that the urban epidemic situation is serious and the urban health degree is low and that the epidemic situation is not serious and the urban health degree is high, respectively. The formula is as follows [44]:

$$I_{lm}^{j} = z_m^j \cdot \sum_{i=1}^{n} W_{ij} \cdot z_l^i, \tag{2}$$

where I_{lm}^{j} is the bivariate local Moran's I of city j; $z_m^j = (X_m^j - \overline{X}_m)/\sigma_m$; $z_l^i = (X_l^i - \overline{X}_l)/\sigma_l$; X_m^j is the cumulative number of confirmed cases in city j; X_l^i is the health index of city i; and σ_m and σ_l are the variances of the cumulative number of confirmed cases and the HIC, respectively. $\overline{X}_m$ and $\overline{X}_l$ are the mean values of the cumulative number of confirmed cases and the HIC, respectively. W_{ij} is the inverse distance weighted (IDW) matrix, and the calculation formula is as follows:

$$W_{ij} = \begin{cases} \dfrac{1}{S_{ij}}, & i \neq j, \\ \\ 0, & i = j, \end{cases} \tag{3}$$

where W_{ij} represents the spatial weight between cities i and j and S_{ij} is the Euclidean distance calculated by using the geometric center coordinates of cities i and j.

3. Results

3.1. Evolution of Human Mobility and HIC on a National Scale. Figure 2 shows the daily variation in average human mobility within and between cities during the epidemic of COVID-19 in China. Both internal and intercity population movements were significantly affected by the epidemic and fluctuated on a weekly basis. Between the two, mobility within cities has a stronger correlation with the epidemic. Since January 23, when Wuhan was locked down, mobility within cities across the country has fallen rapidly, and the MWCI was −58% by February 8, a 58% reduction in human activity compared to before the outbreak. The number of COVID-19 cases in China peaked on February 17 and then moderated gradually. At the same time, the MWCI has been gradually rising and has stabilized between −3 and −9 percent since March 23.

MBCI, by contrast, is more deeply and persistently affected by the epidemic. MBCI reached a peak of −57% on February 2 (the last day of the Spring Festival holiday in 2020) and then rose slightly. However, even into April, when the outbreak was under control, MBCI was still between −35% and −25%; that is, intercity migration is still down by one-quarter to one-third compared with the same period in 2019. Intercity human mobility declined again around March 28, mainly due to the Qingming Festival holiday.

Figure 3 shows the evolution of the average HIC and COVID-19 cases across all cities in China. Overall, the HIC has a high correlation with the COVID-19 epidemic trends. Notably, the deterioration rate of the HIC was faster than the growth rate of COVID-19 cases, and the peak in the HIC was 15 days earlier than the peak in cases. However, the improvement in the HIC was much slower than the decline in COVID-19 cases. In other words, the cities' "disease" was getting worse quickly but getting better slowly compared to pneumonia in humans. In this sense, cities seem to be less virus-resistant than humans. Compared with the same period before the outbreak, the HIC of China decreased by 28.6% from January 20 to April 21, 2020. Although the COVID-19 outbreak has been contained since April, the overall health index is still nearly 18% lower than that of the normal period.

3.2. Spatial and Temporal Characteristics of HIC during the COVID-19 Outbreak. To better assess the impact of COVID-19 on urban health and reveal regional differences, we visualize the decrease in the HIC in China using maps. Figure 4 includes four key dates: on January 23, China locked down Wuhan, the capital of central China's Hubei Province and the epicenter of the COVID-19 outbreak. In the wake of the Wuhan lockdown, many other cities were also subjected to travel restrictions. The Spring Festival holiday ended on February 3, when the virus was spreading rapidly in China. On March 2, the existing confirmed COVID-19 cases were half of their peak. Wuhan reopened on April 8, when the epidemic across the country was under control.

On January 23, the lowest values (<−0.6) of the HIC were mainly located in provincial capitals and cities in the Yangtze River Delta and the Pearl River Delta. However, Hubei Province, the epicenter of the epidemic, did not show a significant drop in the HIC except in Wuhan, which may be related to lags in the response levels. The first-level response to major public health emergencies was activated in all regions of the country on February 3, and the HIC dropped below −0.5 in most cities in Central and East China, with only some cities on the Qinghai-Tibet Plateau not affected. On March 2, with the number of confirmed cases halved, the HIC also demonstrated a large recovery. In addition to the provincial capitals, the cities that are still affected by the epidemic are mainly distributed in Hubei Province and the surrounding areas and in some urban agglomerations, such as Beijing-Tianjin-Hebei, the Yangtze River Delta, Ha-Chang, and the Tianshan North Slope. By April 8, western China, except for Urumqi and Lhasa, had returned to normal. The HIC in Beijing, Wuhan, and Shanghai was still under −0.5, and Hubei, Henan, Jiangsu, Shandong, Tianjin, and other provinces were between −0.35 and −0.2.

Since the epidemic had a more significant impact on provincial capitals and municipalities, we isolated these cities and used a heatmap for observation. As shown in Figure 5, most cities were hit hard by the epidemic between January 23 and March 8. Wuhan was the worst affected among the provincial capitals, while Lhasa was the least affected. Overall, the value of the HIC was lower, and this low value lasted longer in megacities such as Beijing, Guangzhou, Shanghai, Zhengzhou, and Xi'an. Western cities were less affected, and the duration of the low HIC value was shorter than in the east.

3.3. Spatial Correlation between the HIC and Confirmed COVID-19 Cases. The above analysis shows that the HIC is highly correlated with temporal COVID-19 trends (Figure 3). Therefore, is there a similar high correlation in the spatial dimension? In China, the epicenter of the COVID-19 outbreak is Hubei Province, and areas badly affected by the outbreak are mainly distributed across provincial capitals. Figures 6(a) and 6(b) show the spatial distribution of the HIC and COVID-19 cases from January 20 to April 21, 2020. The figure reveals a strong correlation in the spatial distribution between the two; however, the effect of the epidemic on the HIC varies from region to region. To analyze the correlation quantitatively, we made a scatter plot and bivariate Lisa cluster map.

As shown in Figure 6(c), there is a significant linear relationship between the HIC and log COVID-19 cases ($R^2 = 0.4965$, P value = 0.001). Lisa clustering in Figure 6(d) shows more locally related features. The "L-H" type cities, where the HIC is low and the number of cases is high, are mainly distributed in Hubei and surrounding cities, Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta. The "H-L" type cities, where the HIC is high
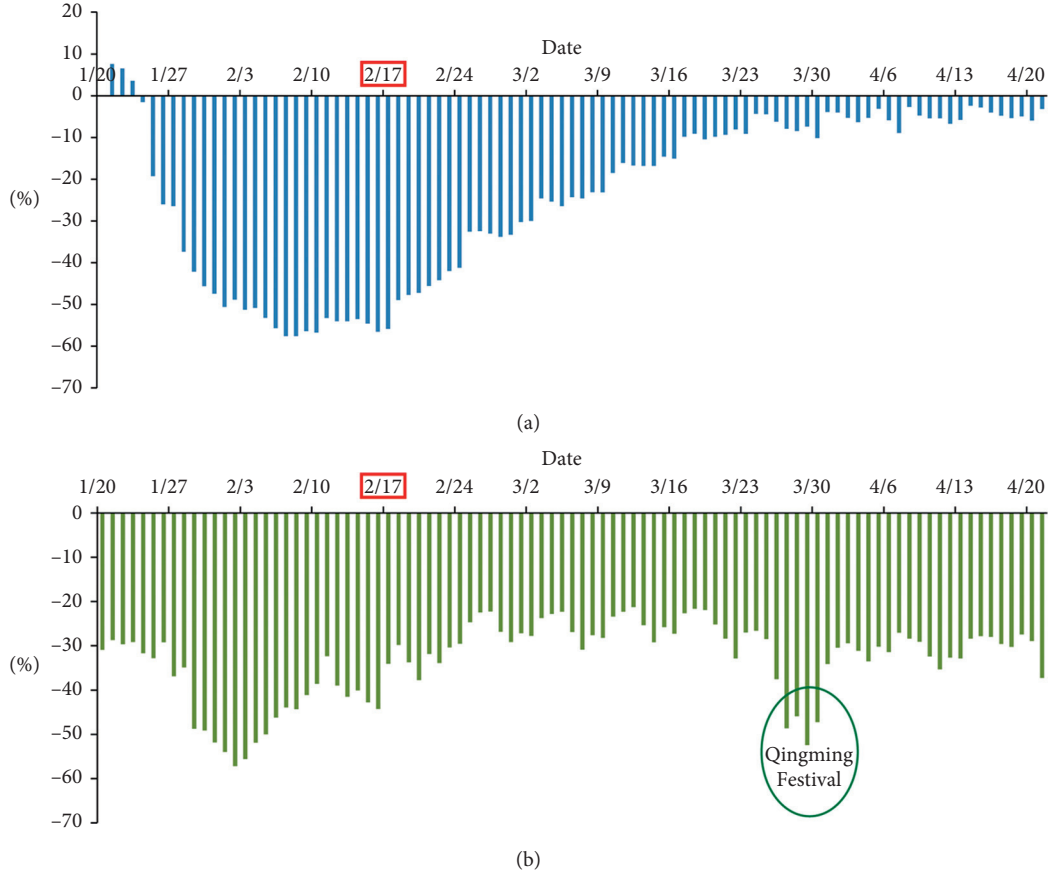
(a)

(b)

FIGURE 2: Daily variation in the average mobility-within-city index and mobility-between-cities index during the epidemic of COVID-19 in China, January 20 to April 21, 2020. (a) Mobility-within-city index (MWCI). (b) Mobility-between-cities index (MBCI).
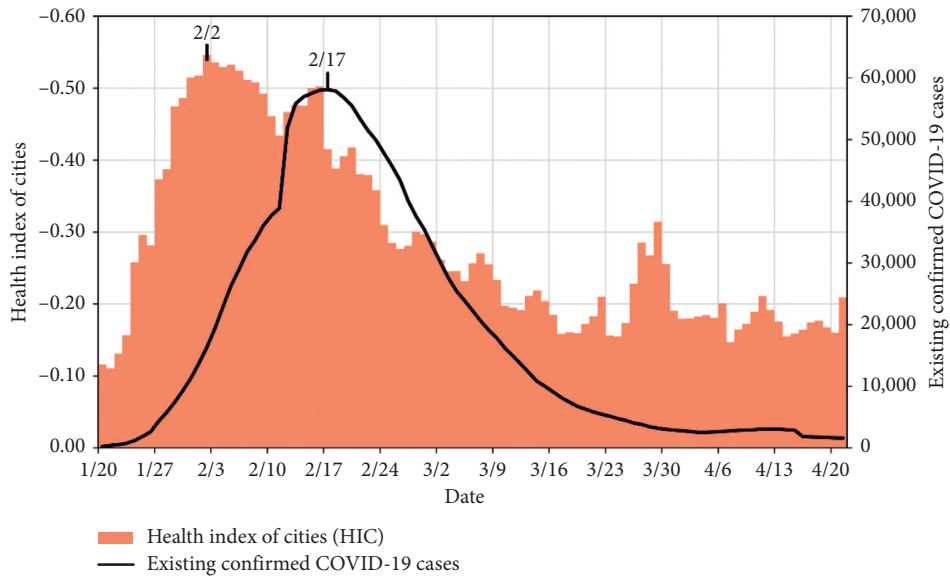

FIGURE 3: Daily variation in the health index of cities and existing confirmed COVID-19 cases in China. The HIC here is the average of all.

and the number of cases is low, are mainly distributed in western cities with low epidemic transmission. There are fewer "H–H" or "L-L" type cities than "H-L" or "L-H" type cities. The former has good resilience, including Qianjiang, Suizhou, and Anqing. The latter are relatively vulnerable, including Xining, Ordos, and Anshan.
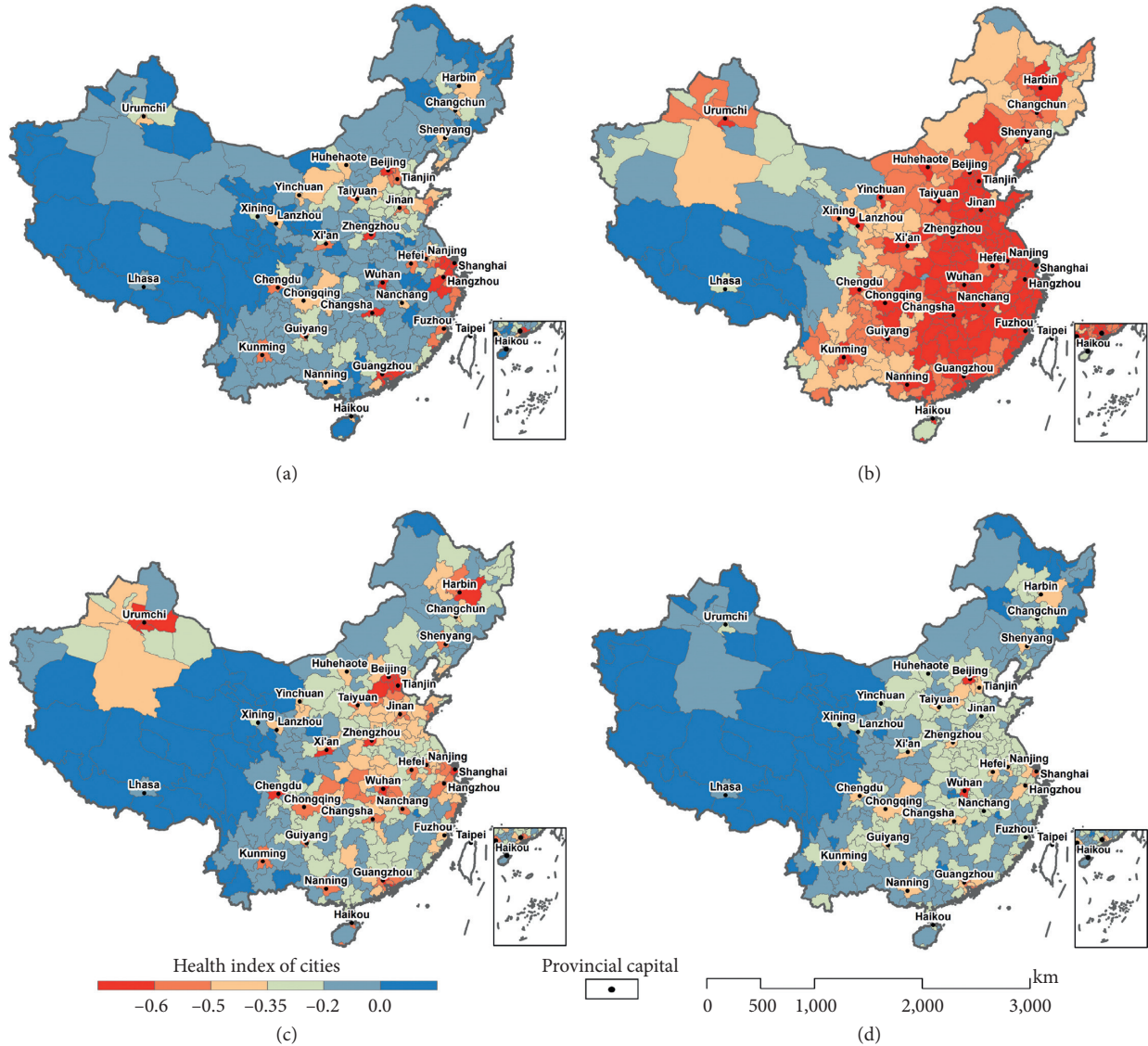
(a)

(b)

Health index of cities

−0.6   −0.5   −0.35   −0.2   0.0

(c)

Provincial capital

•

0   500 1,000   2,000   3,000   km

(d)

Figure 4: Spatial and temporal characteristics of the HIC. (a) January 23rd, (b) February 3rd, (c) March 2nd, and (d) April 8th.

4. Discussion

4.1. Comparison and Validation of the Results. Previous relevant studies have been carried out using event reviews, questionnaire surveys, and statistical data, which mainly analyze the impact of the epidemic on the urban economy. For instance, according to an investigation by a China Economist, the epidemic has had a significant short-term impact on China's economy but a limited long-term impact. The service industry has suffered heavy losses, while small and microprivate enterprises and self-employed people are the most affected [45]. Some studies use monthly statistics to analyze the impact of the epidemic on China's economy from the perspectives of production, demand, income, and price [46].

Furthermore, we compare the results of this paper with traditional statistical data on China's economic and social development (Figure 7). In fact, the COVID-19 outbreak in China mainly occurred from January to April.

Figure 7 shows the year-on-year change in the relevant socioeconomic indexes during this period. Passenger transport has been most affected by the epidemic, with all three types of passenger traffic reduced by more than half. In addition, the total profits of industrial enterprises decreased by 27.4%, state budget revenue decreased by 14.5%, the retail value of goods decreased by 14.7%, and commercial housing sales decreased by 18.6 percent. The average HIC for Chinese cities from January to April was −28.6, representing a 28.6% reduction in urban health and vitality. China's GDP fell 6.8% in the first quarter and grew 3.2% in the second, year-on-year. Overall, the decrease rate of HIC is lower than that of passenger volume, but higher than that of other macroeconomic indicators, and closest to that of the total profits of industrial enterprises.

On the whole, based on the leading role of people in urban and regional development, the HIC reflects cities' overall development. Additionally, the HIC is a real-time index and is
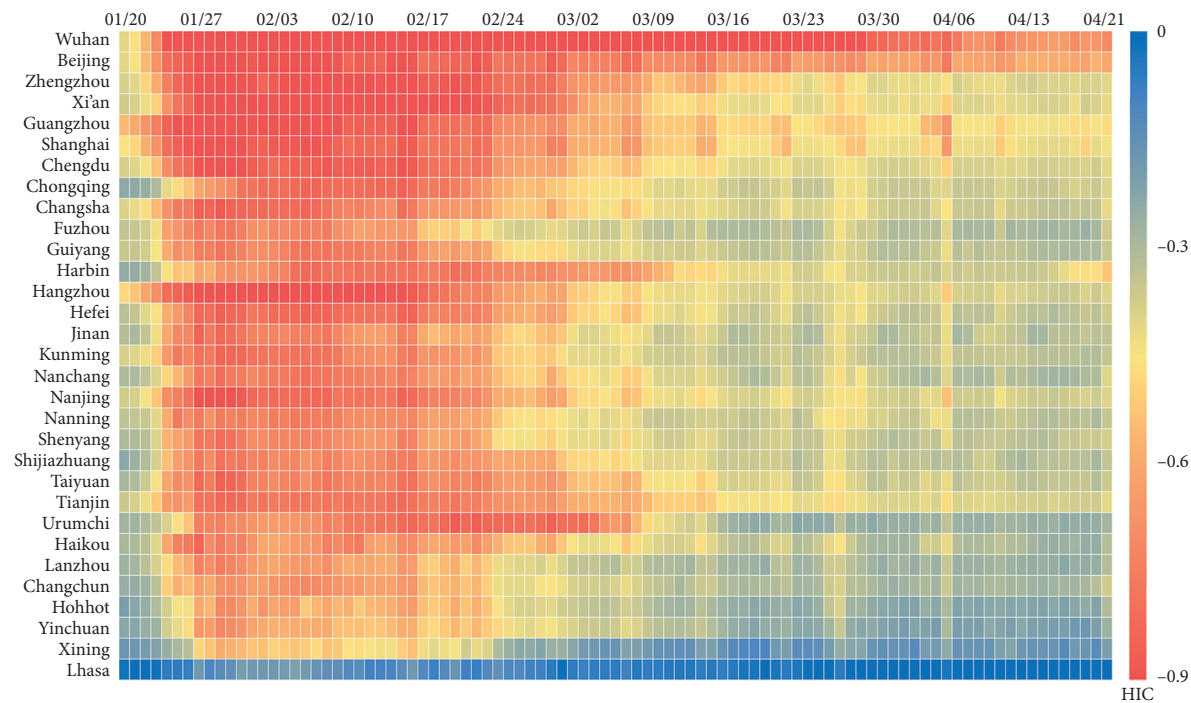
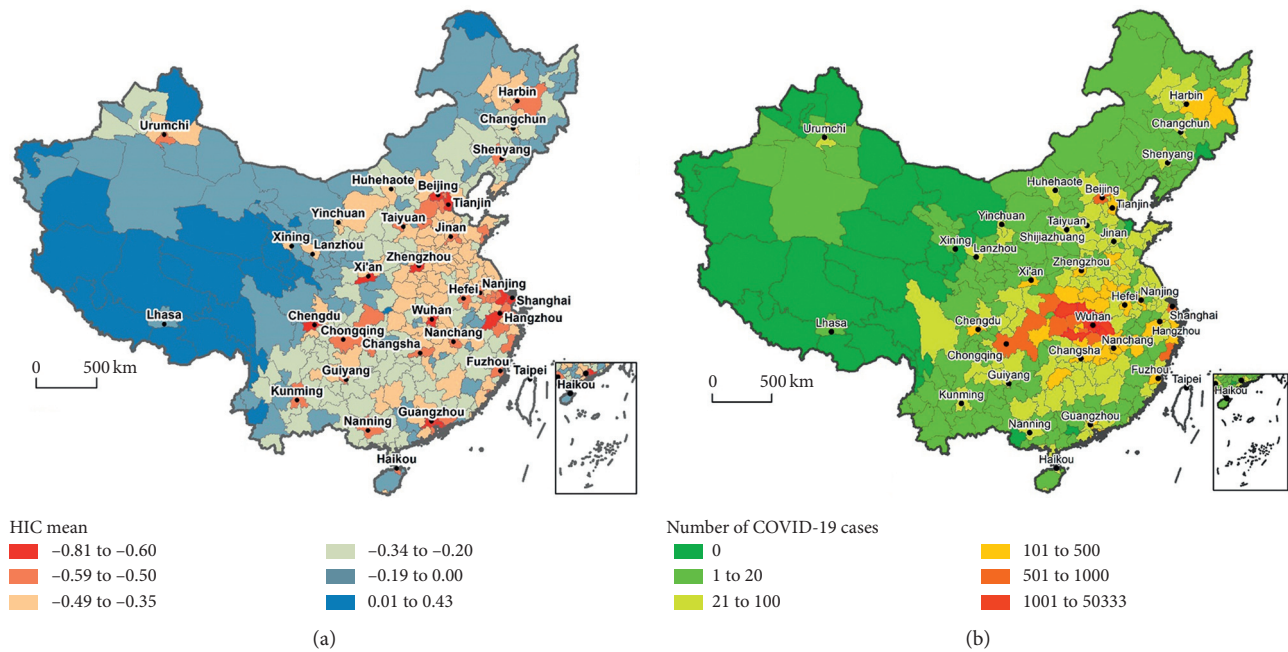Figure 5: Heatmap of the daily HIC in key cities in China.

HIC mean
- −0.81 to −0.60
- −0.59 to −0.50
- −0.49 to −0.35
- −0.34 to −0.20
- −0.19 to 0.00
- 0.01 to 0.43

(a)

Number of COVID-19 cases
- 0
- 1 to 20
- 21 to 100
- 101 to 500
- 501 to 1000
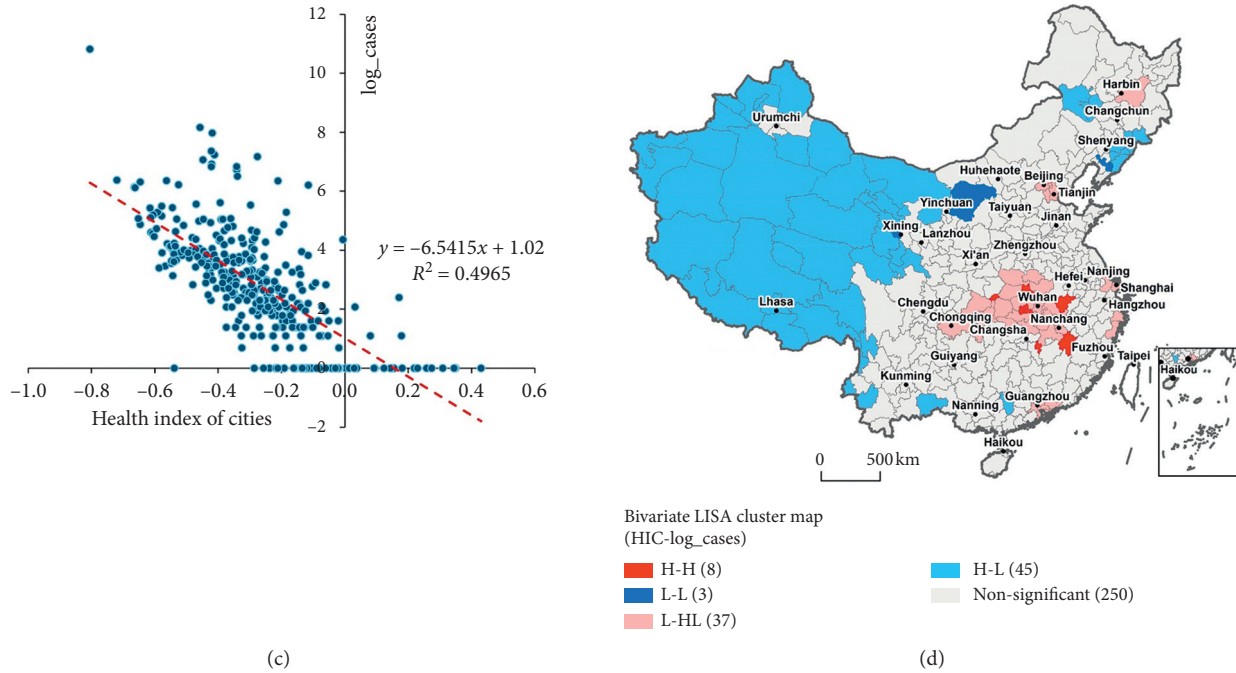- 1001 to 50333

(b)

Figure 6: Continued.

(c)

(d)

FIGURE 6: Spatial correlation between the HIC and the confirmed COVID-19 cases. (a) Mean HIC from January 20 to April 21, 2020. (b) Cumulative COVID-19 cases from January 20 to April 21, 2020. (c) Scatter plot between the HIC and log COVID-19 cases. (d) Bivariate Lisa cluster map of confirmed COVID-19 cases and the HIC.
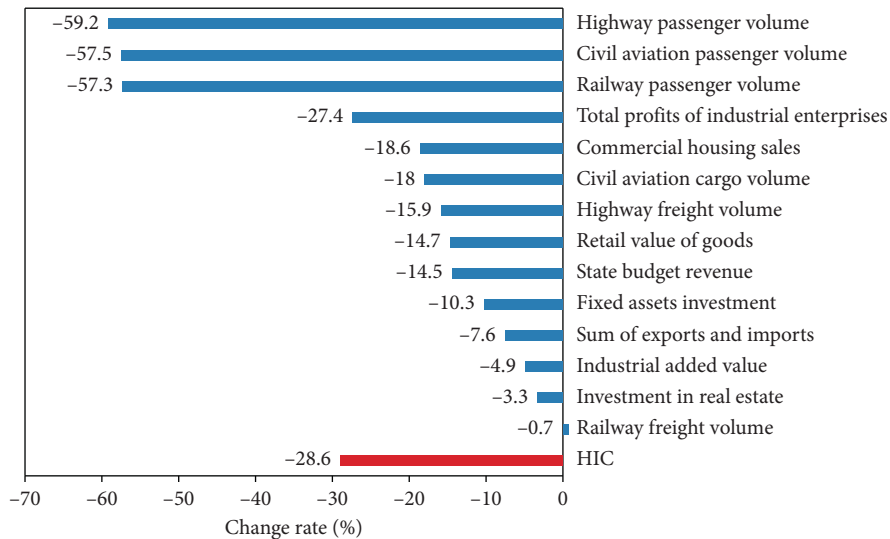
FIGURE 7: HIC and the year-on-year growth of socioeconomic indicators from January to April 2020.

much timelier than government statistics. With a simple calculation method and easily acquired data, this index can be well applied in future research on the COVID-19 epidemic.

4.2. Generalization of the HIC Index. The popularity of mobile Internet usage makes it easy to obtain big data on human mobility based on current locations. This paper takes China as a case study, using the most popular Baidu data in China. Similarly, the HIC of other countries can be calculated using data provided by local location-based services companies, for instance, the community mobility data released by Google (https://www.google.com/covid19/mobility/). The research scale of this paper focuses on cities, and other scales, such as communities or countries, need to be further studied in the future. Community health and national health measures based on human mobility can also have reference value. In addition, the HIC constructed in this research can be used not only during the COVID-19 epidemic but also during other major public health events.

4.3. Research Limitations and Prospects. This study has several limitations. First, the HIC developed in this paper is based only on human mobility, which has some limitations. In the future, by integrating big data on logistics, business, and government and by adding real-time data on material, energy, and information flows, the HIC could be improved. Second, the original data used to calculate the HIC accounted for personal privacy and did not distinguish different age, gender, and income groups, and, therefore, the index could not accurately reflect the impact of the epidemic on different groups [47] nor the other consequences of epidemics, such as the mental health impacts associated with social isolation and the disproportionate effects on different socioeconomic groups [15].

Throughout history, the epidemic and pandemic crises (e.g., Asiatic Cholera (1826-37) and Spanish Flu (1918-19)) have frequently affected cities. COVID-19 is an unexpected ordeal for both humans and cities. It is believed that after the ordeal of this pandemic, like many other major infectious diseases in history, the city will develop a new "antibody" and be more tenacious and healthier. In the postpandemic era, how mobile big data can help cities recover and predict new risks is an important research direction for the future. Besides, population density, urban form and size, and urbanization pattern influence the spread of the epidemic [48, 49]. In this study, there seems to be some kind of correlation between HIC and city size from Figures 4 and 6. This correlation also deserves further study.

The lockdown as a nonpharmaceutical intervention has played a significant role in interrupting the spread of COVID-19 in China [50]. However, the downside of this stringent quarantine measure is also evident. Impeding normal urban socioeconomic activities has led to a 6.8% decline in China's GDP in the first quarter of 2020, the largest drop in the past four decades. The bulk of COVID-19 sufferers in China recovered by June 28. However, it is estimated that pandemic prevention measures will continue beyond this time until a vaccine is available. More effort and wisdom are still needed to isolate the virus and maintain the normal health of cities simultaneously, especially in urban agglomerations. Because to be or not to be is decided by the ability of both the lungs and cities to breathe. And now is our chance to recover better, by building a more resilient, inclusive, sustainable, and healthy urban system [4].

5. Conclusions

In this paper, the city was seen as a complex organism with a metabolism. The HIC was constructed based on the analogy and population migration big data to evaluate the overall health status of cities affected by the COVID-19 epidemic, and some interesting results were obtained. Both internal and intercity population movements have been significantly affected by the COVID-19 epidemic, and the decline in both was more than 50% at some points. The intercity movement is more affected than the intracity movement, and the impact is more sustained. Compared with the same period before the outbreak, the HIC in China decreased by 28.6% from

January 20 to April 21, 2020. The deterioration rate of the HIC was faster than the growth rate of COVID-19 cases, but the improvement in the HIC was much slower than the decline in COVID-19 cases. Although the HIC is highly correlated with COVID-19 in both the spatial and temporal dimensions, the effect of the epidemic on the HIC varied across regions. The HIC fell more significantly in provincial capitals, such as Beijing, Shanghai, Guangzhou, and Zhengzhou, and in urban agglomerations, and these cities' HICs were lower with a longer-lasting reduction. Only cities on the Qinghai-Tibet Plateau were not much affected.

As a complex dynamic system, the overall impact of the COVID-19 pandemic is difficult to evaluate until it ends or at least until its peak is reached. However, our study can serve as a frame of reference for studying the real-time impact of the pandemic, helping cities' policymakers to quickly assess its socioeconomic impact so that we can make a more accurate assessment of its long-term impact in the future. By extension, this index can be applied to other countries and other public health emergencies.

Data Availability

The human mobility data used in this paper could be downloaded from https://doi.org/10.7910/DVN/FAEZIO, and the original data source is from Baidu company. Confirmed COVID-19 cases come from the National Health Commission of China (http://www.nhc.gov.cn/xcs/yqtb/list_gzbd.shtml).

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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