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Virus Spatiotemporal Diffusion Distribution and Control Based on Micro-Simulation Travel Model

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Abstract: With the development of social economy, people's communication activities are increasingly frequent. Coronavirus Disease (COVID-19) and other respiratory infectious diseases are closely related to people's daily activities and travel behavior. It is necessary to study the spatiotemporal distribution of respiratory diseases in urban planning and management. Based on the travel survey data of a provincial capital city in Southwest China, this paper develops a micro travel model to simulate the dynamic transmission of viruses in both urban central area and metropolitan area. Due to the narrow space of public transit, the dense population and the high probability of passenger infection, the paper simulates the effect of restraining the transit transmission and taking precautions. The results show that these measures can effectively reduce the infection speed and spread range of the virus in the population, which leaves a longer window period for early virus control. The method discussed in the paper can help urban management departments to make accurate decisions in the early stage of the epidemic, which can also provide reference for future urban and rural planning on how to deal with public health emergency. **DOI:** 10.13813/j.cn11-5141/u.2020.0027-en

Keywords: transportation model; micro-simulation; travel behavior; MATSim; virus transmission

0 Introduction

In early 2020, the rapid spread of Coronavirus Disease (COVID-19) in a short period aroused great concern throughout China, causing significant obstacles and threats to the normal production and living order of the people. Mr. Zhong Nanshan stated that if effective measures could be taken early, the spread of the virus would be greatly avoided. Scholars have begun to study the transmission mechanism and dynamic characteristics of various diseases by establishing transmission models. As early as 1927, Kermark and Mekendrick proposed the Susceptible–Infected–Recovered (SIR) model while studying the Black Death, which was widespread in London, and they further established the Susceptible–Infected–Susceptible (SIS) model in 1932. Through the study of the virus propagation model, the threshold theory for infectious disease dynamics was proposed [1–2]. In the past 20 years, research on the dynamics of disease propagation based on complex network models has begun to flourish. The nodes and edges in the complex network theory are assumed to be individuals and their crossing paths, respectively. Based on the complex network theory, the disease transmission rate related to connectivity is proposed to establish a disease propagation model [3]. The complex network model is based on the mean field theory, and the SIR model is used to group the individuals with the same connectivity to calculate the results of disease transmission. Because the model averages the spatial interaction between individuals, namely that the chances of contact between individuals are equal, the calculation result is far from reality. The Agent model based on complex networks is used to overcome the deficiencies of the population mean. Through the settings of different attributes and individual values of behavior, the disease propagation process is simulated [4–5]. At present, the limitation of the Agent model lies in the lack of research on the contact behavior of individuals in the real-time space-time distribution. Most studies depend on spatial environment and behavior data under certain assumptions [6].

According to the COVID-19 infection data released by the National Health Commission of China, healthy individuals are mainly infected in close contact with pathogens or infected individuals. Whether an individual is infected is closely related to their activities in a certain time and space. In order to study the spread of the virus in the population under conditions closer to the real environment, this paper uses a micro-simulation model based on activity-travel data, traffic travel data and traffic network of the case city to carry out dynamic simulation of normal activity-travel behavior

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across the city. On this basis, it sets a specific infection source to observe the spatial distribution of and countermeasures against virus transmission in the crowd. In the past, the research on urban transportation generally focuses on transportation infrastructure, traffic congestion and other transportation fields, and the application research in the field of public health was insufficient. The reason can be found in two aspects: On the one hand, most of the mainstream traffic models belong to the category of the "four-stage method." Macroscopic statistical data modeling is used to focus on the "quantity" of traffic trips [7], lacking the description of the spatiotemporal characteristics of activity-travel behavior. On the other hand, activity-based traffic models and microscopic traffic simulation technologies are mostly in the experimental research stage in China [8–9]. According to the experience of international research, the current MATSim micro-simulation platform can dynamically simulate the travel behavior in the real environment, support operations of big data, and output discrete-time travel data [10–11]. Because the output data of the model has the real time and space attributes of residents' travel activities, this paper uses the simulation program after the secondary development in VB language and employs the propagation characteristics of COVID-19 to simulate the spread of viruses in the real environment. Thus, its spatial propagation characteristics and control measures are studied.

1 Analysis of propagation characteristics of COVID-19

According to the epidemic data released by Health Commission of Hubei Province, as of February 25, 2020, 47,441 COVID-19 cases had been confirmed in Wuhan, Hubei Province, China, and the number of viral infections had increased by 1,148 times within just 40 days. According to the growth pattern of statistical data, it can be determined that the cumulative number of confirmed cases generally shows an S-shaped change: The prevalence of virus in the early stage is extremely rapid, and the cumulative number of confirmed cases rises quickly. By the end March, 2020, the trend shows signs of flattening (Figure 1).

According to the calculation and analysis of the data released by the National Health Commission of the People's Republic of China on February 26, 2020, as of February 25, 2020, there had been 2,085 cases of deaths in Wuhan City, and the mortality rate for COVID-19 was about 4.39%. In China's statistical analysis, the mortality rate for COVID-19 is 3.48%, and the mortality rate except Hubei Province is about 0.78%. To control the spread of the virus, Wuhan City announced on January 23, 2020 that the city's buses, subways, ferries, and long-distance passenger vehicles would be suspended, and the railway and airport departure routes would be closed. Hubei Province launched the Level I response to the major public health emergency on February 11. Residential communities in Wuhan began to implement closed management, minimizing the flow of personnel, and at the same time, large-scale medical resources were allocated to Wuhan. The implementation of these measures achieved significant results, and the number of COVID-19 cases in Wuhan has dropped significantly since February 18.

It can be seen from the above observations that the outbreak was largely due to the extremely rapid spread of COVID-19, especially within the first 10 days before the virus becomes apparent. If the temporal and spatial spread of the virus can be quickly predicted at this time based on the existing confirmed cases, the spatiotemporal characteristics will play an active role in the government's rapid response and containing the spread of the virus.

2 Propagation model

In view of the current medical research, COVID-19 is mainly transmitted through close contact amongst people. Thus the isolation measures have a significant effect on suppressing propagation [12–13].

This paper focuses on the early transmission characteristics of the epidemic and then compares the effects of different interventions. To construct a sound environment for research, we select the survey data of residents in a city in south China (hereinafter referred to as City W) to construct the background of the spatiotemporal connection between social and economic activities, such as residents' commuting and other activities of daily life. The MATSim micro-simulation platform is used to determine whether each simulated individual is in close contact from the time and space dimensions, and the infection process is further simulated by the probability of infection. MATSim is an activity-based, extensible, multi-agent (Agent), and open-source simulation platform [14], which can simulate the spatiotemporal behavior of individuals traveling in the road network in a day or a few days and output the data in the format of Extensible Markup Language (XML). The data have good versatility and expansibility, which are conducive to later analysis of results and secondary development. In the MATSim simulation model, each traveler is an agent. Each agent has its distinct activity-travel plan which includes the individual's activity location, travel time, travel path, travel method, and so on. Moreover, the utility value of the travel plan is calculated according to individual activities through utility functions. When the external travel environment changes, the utility value of the individual activity-travel plan also changes, and the individual behavior will alter accordingly. The platform follows the principle of co-evolution through continuous optimization of individual activity-travel plans in the iterative calculation process to achieve the goal of maximizing individual utility value and micro-simulation of the impact of external environment changes on individual behavior. Its operation is illustrated in Figure 2.

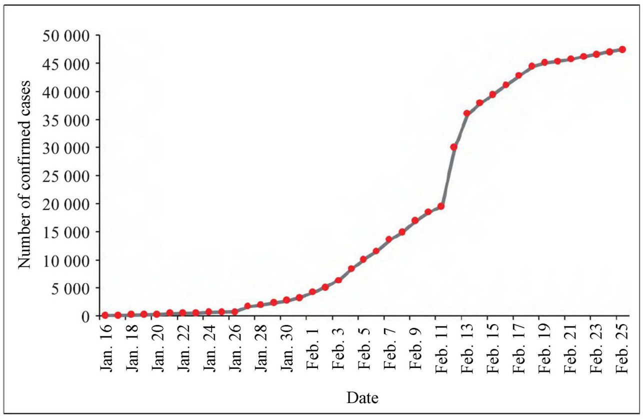

Figure 1 Trend of confirmed cases with COVID-19 in Wuhan

Source: official website of Health Commission of Hubei Province (http://wjw.hubei.gov.cn/).

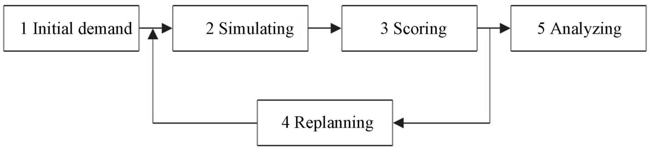

Figure 2 Flow chart of micro-simulation by MATSim

Source: Reference [14].

The close contact in the model is mainly set up in the two following categories: 1) spatial contact, namely that individuals are close in space and overlap in time; 2) public transportation contact, namely that different individuals are in the same public transport means at the same time and close contact occurs within the vehicle. The study only simulates the early transmission process of the virus, which does not involve changes in the virus transmission process after medical measures are taken for infection cases.

The traffic simulation model uses the all-day travel data of a total of 80,574 individuals, which are obtained from the citywide survey of City W. Based on the simulated travel data, the simulation program written in VB language is adopted to conduct a secondary simulation of virus propagation. As shown in Figure 3, according to the setting of close contact, an association model is established for individuals in close contact with each other in the space, and 1% of the samples are randomly selected for visualization. It can be observed that the residents in the city have close spatial contact, especially those in the downtown area.

First, an individual working in a large wholesale market of fresh produce in City W is designated as No. 0 infection case. This individual serves as the starting point for the spread of an unknown virus. In space, when the movement distance between No. 0 case and other individuals is less than the threshold D_c for close contact, it is further determined whether there is a time overlap between individuals with the contact distance less than D_c. If the overlap exists, a possible infection case can be determined. A certain infection probability P_c is set to extract the infection case from the contacts.

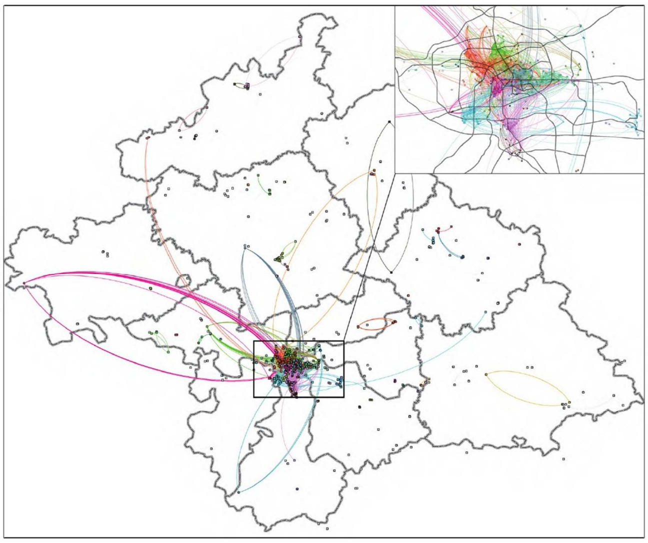

Figure 3 Close contact network for residents' activity-travel

In public transportation (mainly buses), whether No. 0 case and other individuals take the same bus is first determined, followed by whether there is time overlap between loading and unloading. If there is an overlap, there is a possibility of infection, and probability P_c is referred to randomly determine the infection cases from individuals on the same bus and at the same time. All infection cases are taken as the source of infection on the next day. Then it is determined whether there is a close contact between them with other individuals and the probability of other individuals being infected during the contact process in the above manner. The program iteratively calculates results for 30 times to simulate the virus transmission characteristics within 30 days.

The determination of the main parameters in the model proceeds as follows:

1) Close contact threshold (D_c): According to relevant medical investigations, the short distance is mainly in the range of 1–2 m [15]. Considering that the traffic travel data are sampling data, the model is set with $D_c = 10$ m (1);

2) Probability of infection (P_c): Since the current COVID-19 epidemic is still spreading, the estimation of the number of basic infections (R_0) is constantly changing. On January 23, 2020, the statement issued by the World Health Organization confirmed that "human-to-human" transmission of COVID-19 is happening, and the preliminary estimate of R_0 is 1.5–2.5. As of January 24, 2020, a study published on the medRxiv platform for preprints of medical research papers estimated the epidemiological parameters of the virus. The study established a propagation model based on the incidence information for January 1–21, 2020. It is calculated that the basic infection number (R_0) of COVID-19 is significantly greater than 1, at 3.8 (95% confidence interval: 3.6–4.0). This means that an infection case can cause an average of 3.8 others to be infected.

In view of the uncertainty of R_0, this paper assumes that R_0 is 3 for the research. In other words, assuming that under normal circumstances, an individual will have 15 close contacts on average in one day. Considering the average incubation period of COVID-19 as seven days, the individual will have 105 close contacts within seven days. If three of them are infected, the interpersonal probability of infection P_c of the virus can be taken as 3%.

3 Analysis of simulation results

The model randomly determines that the first virus-infection case appears in a wholesale market of fresh produce in the northern part of the city. The first infection case will contact other people at places of activities or during travel by public transit without knowing it. It means that the virus can be transmitted to the second case through close contact, and then the second case can infect other people, and so on. By observing the simulation process, we can know that from the day with the first case to the 30th day, the number of infected people undergoes a rapid increase and gradually eases. In the case of no control measures, the number of infection cases on the 30th day is 30,567, accounting for 38% of the total simulated population. It can be seen from Figure 4 that the growth rate of infection cases in the first 10 days is relatively small, but it rises sharply on Days 11–20; the growth rate of viral infections gradually slows down on Days 21–30, and the growth curve shows the characteristics of S-shaped changes.

It can be seen from Figure 5 that the spatial evolution of infection cases in the downtown area of City W shows an overall spread from inside to outside. The infection cases begin to spread to all directions of the city on the 10th day and form the first peak area of infection around the first case. Then the second peak area of infection appears in the downtown area of the city on the 15th day. After that, the peak area of infection cases begins to spread in various areas of the city, and the number of infection cases begins to soar. It can be seen from the simulation that the infection case has obvious characteristics of dispersion and aggregation in space, and the spread of the virus in space is characterized by saltation.

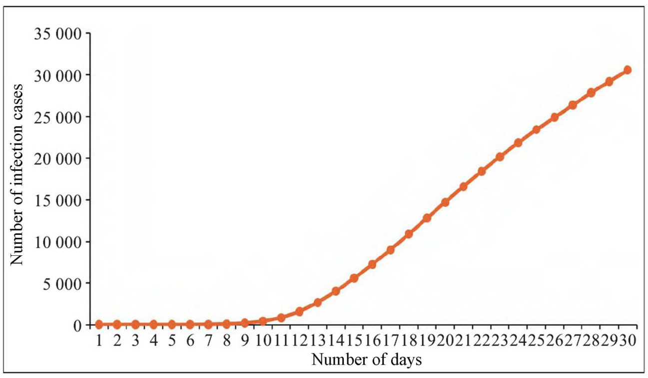

Figure 4 Changes in the number of virus infections in simulated City W

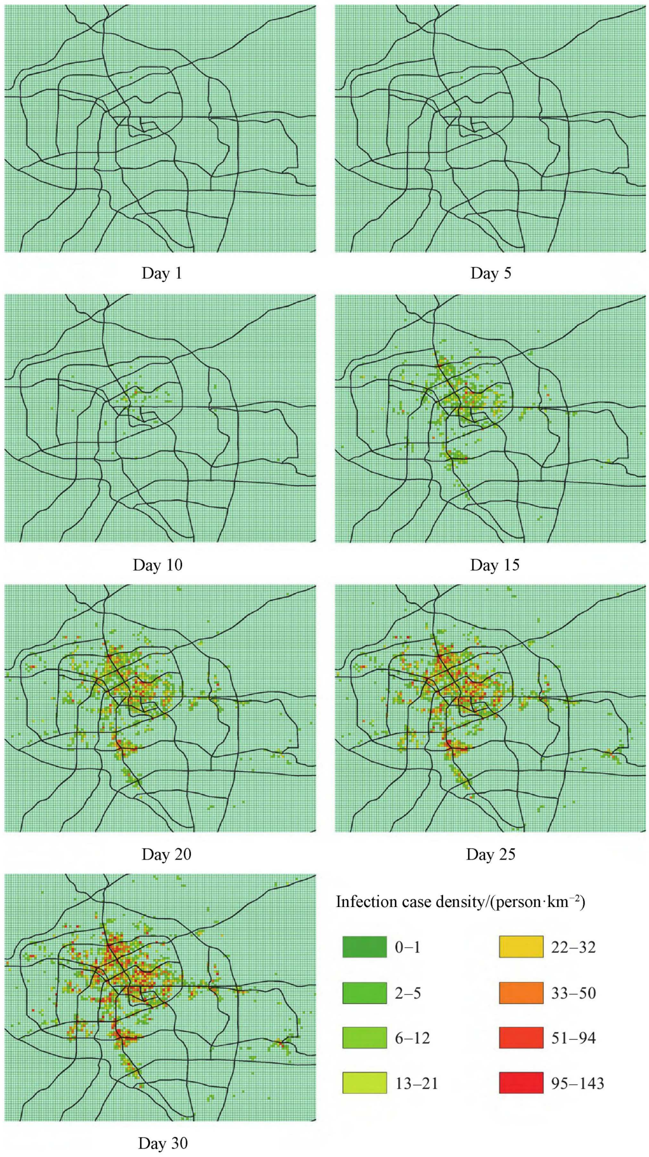

Figure 5 Spatial density change of infection cases in the simulated downtown area of City W

Figure 6 shows the spatial distribution of infection cases in City W. The spread of infection cases in the city space starts from the 11th day, and an infection case first appears in the northern area of the city; the infection cases spread to the whole city on the 20th day, and the spatial distribution of infection cases presents a patchy shape; the spatial distribution of infection cases presents homogeneous spread by the 30th day, and the spatial transmission process also shows significant saltation.

The simulation results show that the virus propagations rapidly in space, and the shape of the spatial spread is first patchy and then homogeneous, exhibiting saltation. From the perspective of the time characteristics of transmission, the optimal control window period of the virus in the community space is Days 1–7 after the virus appears. The optimal control window period of the virus in the municipal area is Days

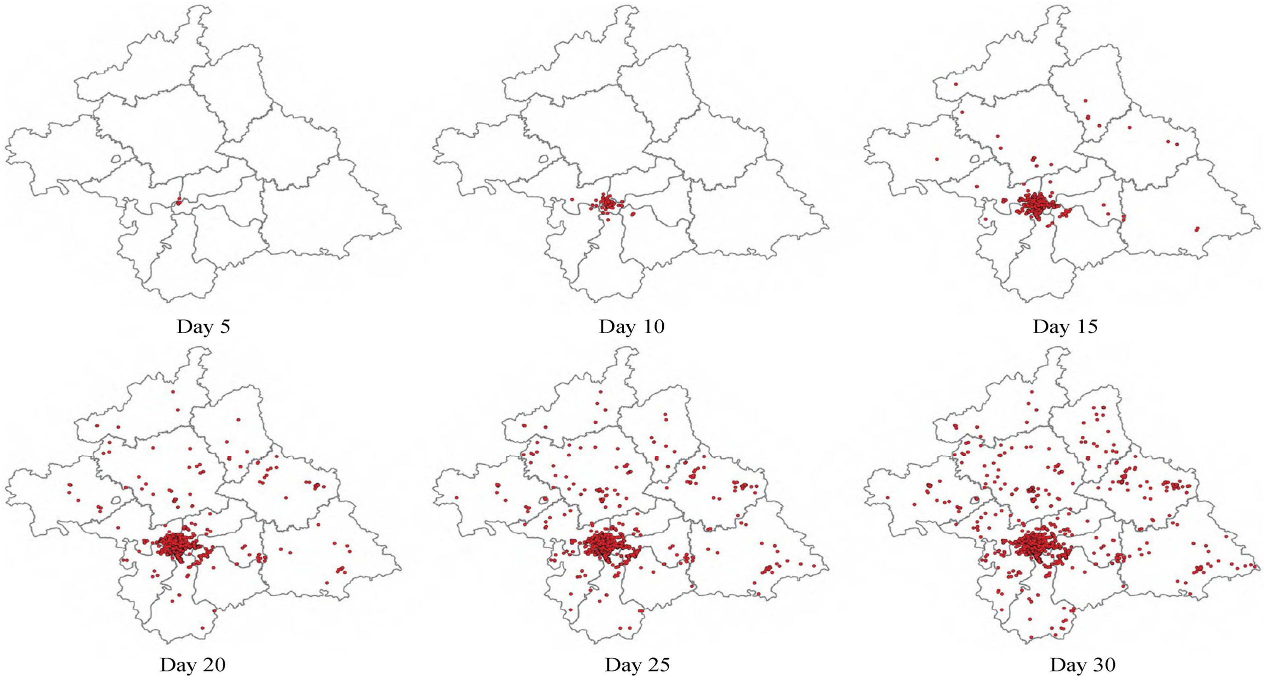

Figure 6 Spatial distribution of infection cases in City W

7–10; 15 days later, the virus will spread to every area of the city and further expand on a large scale. It can be observed that the planning of anti-epidemic facilities at the community level has important practical significance [16–17].

Wuhan City, which has suffered the most severe outbreak of COVID-19 in China, can be taken as an example. Here, the early control strategy of the virus was hesitant, and the virus quickly spread from person to person. To control the spread of COVID-19 among people, the government shut down all public transportation in Wuhan, followed by the closure of the city, which played a decisive role in the control of the epidemic. Because the early spread of unknown viruses is concealed and the degree of harm is difficult to judge, it is hard to make extreme decisions like "stopping bus services and shutting down the city" in the initial outbreak, so early prevention and control decisions are particularly important. For example, reasonable precautions should be taken in densely-populated public transport means and gathering places for personnel activities to reduce the probability of virus transmission.

In this paper, by changing the virus transmission parameters, we simulate the changes in virus transmission characteristics after the anti-epidemic measures in public transit (such as vehicle disinfection and reducing passenger density) and universal precautions (e.g., wearing masks) are taken. This paper aims at the problems in the early stage of the epidemic. Since people's life rhythms have not been significantly adjusted, the activity-travel plans of all individuals in the model are unchanged. However, the congestion of public transportation has begun to be controlled. Here, the real passenger load of public transportation is reduced to 50% of normal, and the distance between passengers inside the vehicle is increased. At the same time, a lower passenger load will inevitably lead to an increase in waiting time. Here, it is assumed that the probability of infection of individuals traveling by public transit is 2.5%. In addition, when the entire population takes certain precautions, the probability of infection of individuals in close contact will also decrease to 2%.

Through simulation, in the case of anti-epidemic measures in public transport, the number of infection cases on the 30th day is 26,189, accounting for 33% of the total simulated population, which is 14% lower than before. After universal precautions, there are 9,853 infection cases after 30 days, accounting for 12% of the total simulated population, which is 68% lower than before. It can be seen from Table 1 that the two measures outlined above have the most significant effects on the 8th–25th days. Therefore, the earlier precautions against the virus can yield a better result. The simulation results also show that under the circumstances of limiting the number of passengers in public transportation and avoiding congestion, the share of public transit will drop by 33.2%; the average waiting time of passengers will increase by 11 min; the share of cars will rise by 9.5%.

Table 1 Number and change rate of simulated infection cases

Number of days	Infection cases during normal activities	Infection cases after anti-epidemic measures in public transit	Rate of change/%	Infection cases after universal precautions	Rate of change/%
10	410	311	−24.15	108	−73.66
20	14 718	10 423	−29.18	2 422	−83.54
30	30 567	26 189	−14.32	9 853	−67.77

It should be noted that once the virus starts to spread, if the infection cases cannot be traced for isolation and treatment, even if strict precautions are taken, there will still be a risk of continued infection. In the case of anti-epidemic measures in public transit and universal precautions, the curve of virus propagation still shows slow growth (see Figure 7). This demonstrates that if people continue to travel in space and contact with each other, the interpersonal transmission of the virus cannot be completely stopped, and universal precautions are relatively more important (see Table 1).

By comparing the spatial distribution of virus transmission in the downtown area before and after taking measures, we can find that the speed and intensity of virus propagation are significantly weakened after anti-epidemic measures in public transit and universal precautions are applied, especially after effective universal precautions. This has a significant effect on suppressing the spatial spread of the virus (Figure 8).

After anti-epidemic measures in public transit and universal precautions are implemented, the rate of spread of the virus in the metropolitan area slows significantly (see Figure 9). Through observation, it can be found that although the universal precautions have a significant effect on the virus as a whole, an infection case occurs in a county in the northernmost part of the city on the 10th day. It can be observed that the spread of the virus between people has spatiotemporal saltation. The spatial distribution of the propagation process must be determined through micro-simulation.

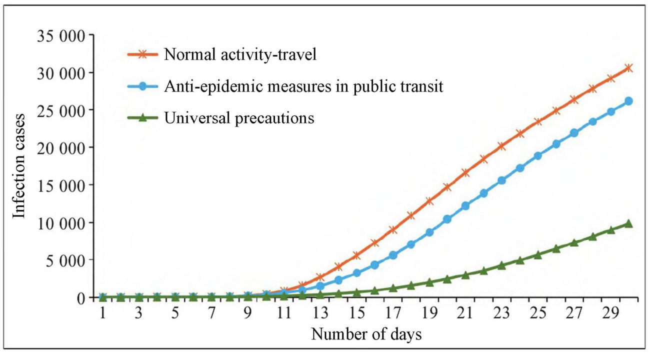

Figure 7 Infection cases under different policies and measures

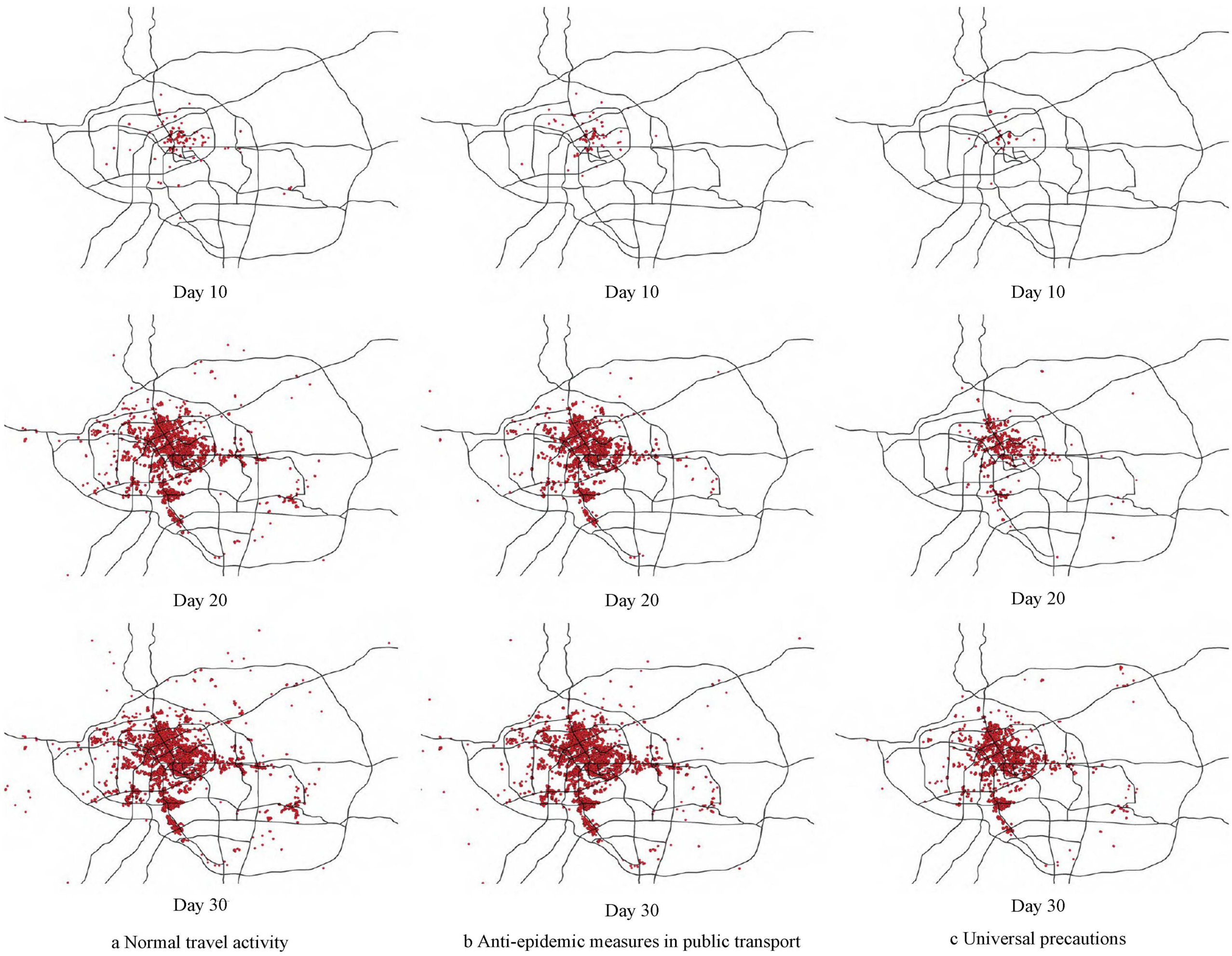

Figure 8 Spatial distribution of infection cases in the downtown area under different measures

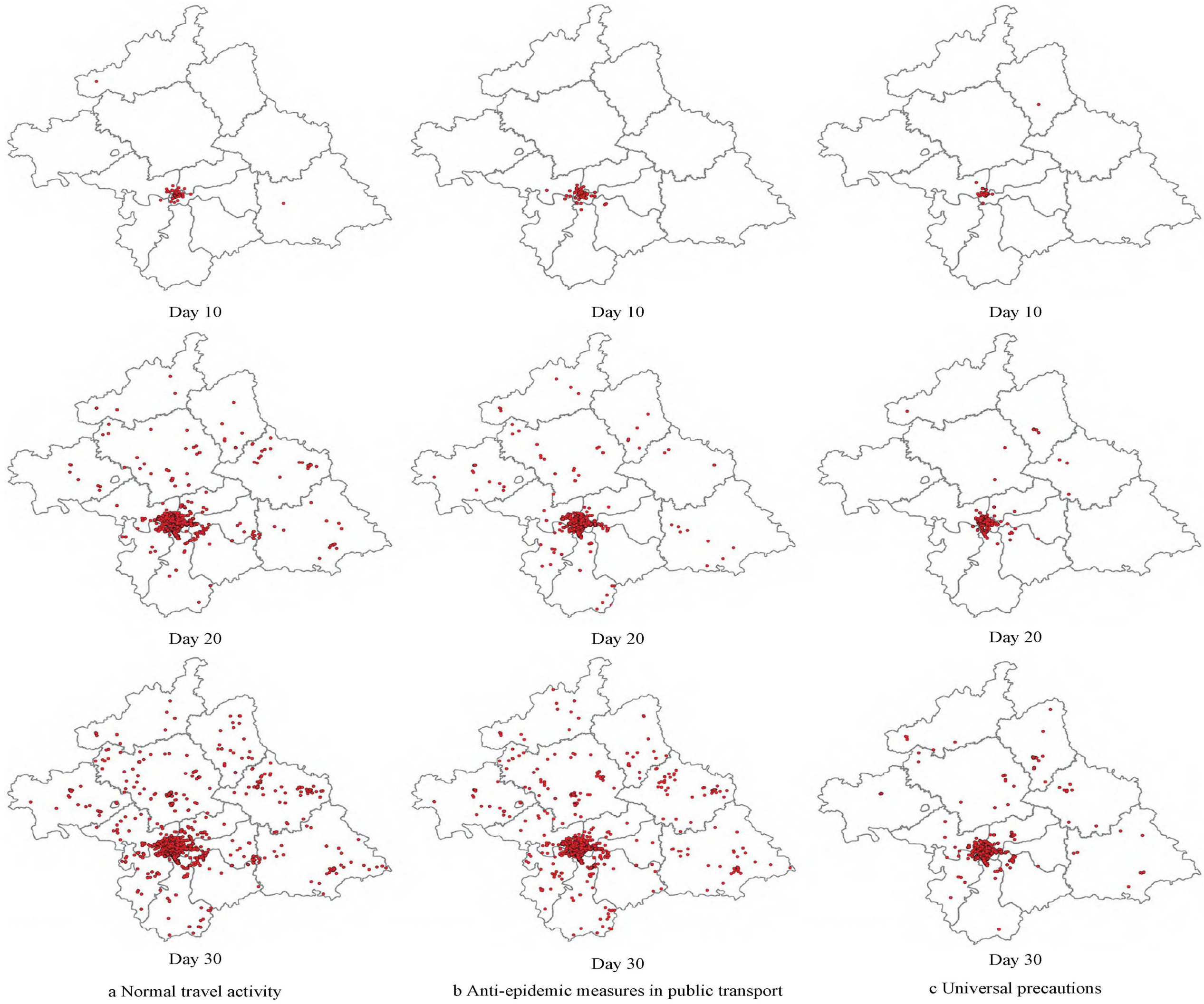

Figure 9 Spatial distribution of virus transmission in metropolitan area under different measures

4 Conclusion

The activity-based micro-simulation travel model facilitates to grasp the laws of virus distribution in space and time. Traditional models that study the spread of viruses, such as SIR models, complex network models, and Agent-based models, all focus on the scale of virus propagation and its evolution over time. Although those models and research methods are constantly improving, they still cannot represent the real spatial distribution of people in real life. The spread of COVID-19 is related to real close contact behavior, and the traditional models of virus propagation have difficulties in mastering the spatiotemporal characteristics of virus transmission. MATSim can be used to build an activity-based micro-simulation model to simulate residents' real activity-travel behavior in a large geographic space and store the data in the format of XML, which is highly conducive to the cross-platform secondary use of data. For cities that have organized surveys of resident travel, if they can properly process the acquired data and construct an activity-based model of traffic travel behavior, the results can be used not only in urban transport but also in combination with epidemiological surveys for secondary development and application. They can also serve for other areas, such as prevention and control of urban epidemics.

Urban and rural planning should focus on the layout of community-level spaces and facilities for epidemic prevention. From the simulation results, it can be observed that there is a window period of prevention and control for the virus propagation in space. Timely detection and early warning can avoid the rapid virus propagation at the community level and prevent the situation from becoming worse, which has a positive significance for the response to public health emergencies. It is appropriate to reserve space for epidemic prevention and isolation in medical and health facilities at the community level in the planning.

The spread of the virus among the population is characterized by randomness and saltation. On the one hand, the individual in the crowd is very different, and the probability of infection is varied; on the other hand, people's behavior is changing, and the contact between them is random. For the prediction of virus propagation in space, the requirement for timeliness of travel data is extremely high. Even if the latest data are used to build a model, the individual prediction of virus propagation in space is still probabilistic prediction. The more important significance of the model lies in the study of the macroscopic characteristics of virus propagation.

Based on the MATSim framework, an activity-based micro-simulation travel model is constructed, which can perform dynamic simulation of individual activity-travel behaviors in various traffic modes for several days, combined with the acquisition of big data on travel. It can be widely used in the future to prevent disease transmission and other public health emergencies, which provides a basis for accurate decision-making in public health crises.

This paper mainly discusses the dynamic spatiotemporal distribution of virus propagation. For more accurate prediction, we have to check the data in the in-depth study of epidemiological investigation. According to the results of this research, even in the case of limited urban data, this method is still conducive to analyzing the effect of intervention in the early stage of the outbreak, so as to prevent serious deterioration.

The data and the probability of infection can be adjusted accordingly based on our in-depth knowledge of virus transmission characteristics.

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