RESEARCH ARTICLE

Spatio-temporal characteristics and control strategies in the early period of COVID-19 spread: a case study of the mainland China

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Abstract

COVID-19 has caused huge impacts on human health and the economic operation of the world. Analyzing and summarizing the early propagation law can help reduce the losses caused by public health emergencies in the future. Early data on the spread of COVID-19 in 30 provinces (autonomous regions and municipalities) of mainland China except for Hubei, Hong Kong, Macao, and Taiwan were selected in this study. Spatio-temporal analysis, inflection point analysis, and correlation analysis are used to explore the spatio-temporal characteristics in the early COVID-19 spread. The results suggested that (1) the total confirmed cases have risen in an "S"-shaped curve over time, and the daily new cases have first increased and finally decreased; (2) the spatial distributions of both total and daily new cases show a trend of more in the east and less in the west, with a "multi-center agglomeration distribution" around Hubei Province and some major cities; (3) the spatial agglomeration of total confirmed cases has been increasing over time, while that of the daily new cases shows much more obvious in the mid-stage; and (4) timely release of the first-level public health emergency response can accelerate the emergence of the epidemic inflection point. The above analysis results have a specific reference value for the government's policy-making and measures to face public health emergencies.

Keywords COVID-19 · Spatio-temporal analysis · Inflection point · Policy-making · China

Introduction

COVID-19 is the most severe public health crisis that humanity has faced since the beginning of the twenty-first century (Chakraborty and Maity 2020; Guo et al. 2020). At present, researchers are still in the process of tracing the source of the virus, and discoveries are constantly being made (Han et al.

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2020). Since the full outbreak of the epidemic, it has caused a tremendous and lasting impact on the economy, society, human health, and development of all countries in the world (Rudrapal et al. 2020; Sanchez-Duque et al. 2020; Qiu et al. 2020; Verikios 2020; Khurshid and Khan 2021). Many studies have shown that COVID-19 is highly infectious, widespread, and prone to mutation (Chen et al. 2020). These characteristics have also made COVID-19 prevention and control in many countries more complicated, and the pressure is also rising (Huang et al. 2020a; Rahimi and Abadi 2020). Although the vaccine has been developed and used in some groups, there are still no specific drugs to treat COVID-19 (Huang et al. 2020b; Zhu et al. 2020). Nevertheless, the government and the public could reduce the negative impact of COVID-19 by taking the necessary measures (Paraskevis et al. 2020; Ficetola and Rubolini 2021; Wu et al. 2021).

In December 2019, some people were found to be infected with COVID-19 in Wuhan, China (Salata et al. 2019). Due to the low number of confirmed cases at that time, some infected people did not show obvious symptoms during the incubation period, and population mobility was relatively low at that time, the epidemic was spread on a relative small-scale

(Chen and Cao 2020; Backer et al. 2020). However, Wuhan has a large floating population and an excellent transportation capacity. The scale of population movement in Wuhan and even across China was increased significantly in a short period with the arrival of the Chinese New Year (Liu et al. 2020b). Various means of transportation are essential carriers of population movement and also provide a necessary way for the spread of the virus (Coelho et al. 2020; Zhong et al. 2020). Besides, regional cluster infections are much more likely to occur due to the lack of public awareness of protection in the early stage of the epidemic (Li et al. 2020b). The combination of multiple factors eventually led to the concentrated outbreak and spread of the epidemic in many parts of China.

China has made tremendous efforts and costs to prevent and control COVID-19 (Bangura et al. 2020). Wuhan, the most severely affected city, was on lockdown to contain the outbreak. Simultaneously, other regions in China have successively initiated response strategies, implementing various measures to protect people's lives, health, and safety (Peng et al. 2020; Gostin and Wiley 2020). Although these measures have caused a short-term stagnation in China's economy, they have also laid the foundation for a quick turnaround of the epidemic prevention and control situation (Xu et al. 2020a; Gupta et al. 2020). Since mid-February 2020, the number of daily new cases in most mainland China areas has begun to decline, and the epidemic's prevention and control have achieved initial results. After April 2020, COVID-19 in mainland China has generally stabilized, and the epidemic prevention and control has entered a regular stage (Jiang 2020; Lai et al. 2020). Facts have proved that the prevention and control measures adopted by the Chinese government have contained the spread of COVID-19 to the maximum extent and have taken the lead in realizing economic recovery (Feng et al. 2020; Younis et al. 2020; Liu et al. 2021). China's experience can provide some reference for other countries in the world.

Although the COVID-19 is a newly discovered infectious disease, it can be controlled once the government and the public are aware of prevention and control (Alanezi et al. 2020; Burki 2020). Taking mainland China as an example, since the first round of the epidemic disappeared, no large-scale outbreak has been caused except for scattered cases in some regions. Therefore, some COVID-19 studies focused on the early period of the epidemic (Shang et al. 2020; Tang et al. 2020; Zhang et al. 2020b). On the one hand, this period can fully reflect the epidemic's process from outbreak to containment (Xiong et al. 2020; Chen et al. 2021). On the other hand, this period exists in almost all new infectious diseases (Zhang et al. 2020a). Once a contagious disease breaks out in a region, it is vital to take the necessary measures to prevent and control it (Li et al. 2020c; Liu et al. 2020c). The researches on the early period epidemic spread can provide some references.

Since the outbreak of COVID-19 in China, two phenomena are worthy of attention. First, with the help of increasingly advanced and convenient media platforms, spatial visualization of geographic data has played an essential role in public propaganda (Franch-Pardo et al. 2020; Yalcin 2020; Han et al. 2021; Luo et al. 2021). During the epidemic, the public can make self-judgment based on the spatio-temporal law of the epidemic development through the map. It has awakened people's awareness of taking the initiative to prevent the spread of the epidemic and thus played a positive role in overcoming the epidemic. Second, to control the epidemic disease, all provincial-level administrative regions in mainland China have successively implemented the first-level public health emergency response (Cheng et al. 2020; Wang et al. 2020b; Liu et al. 2021). Such large-scale and high-standard emergency measures are relatively rare in mainland China. Therefore, whether the different starting times affected epidemic control has attracted much attention. Some previous researches have focused on the above two aspects. The core content of the macroscopic spreading mechanism research on COVID-19 is to analyze and discuss the temporal trends and spatial distribution characteristics of the epidemic in different regions. For temporal trends, the changes of some widely concerned indicators have been analyzed, and some important periods have been divided, since the outbreak of the disease (Cheng et al. 2020; Wang et al. 2020a; Xu et al. 2020b; Zhao et al. 2020; Chen et al. 2021). Some studies also used mathematical modeling to predict the future development of the epidemic (Leung et al. 2020; Liu et al. 2020a; Sun et al. 2020). With respect to spatial characteristics, COVID-19 data were put on the map to visually show the spread and distribution characteristics of the epidemic at the regional level (Mo et al. 2020; Xie et al. 2020; Wang et al. 2020a). With the help of exploratory spatial analysis methods, e.g., Moran's I and Getis-Ord General G, the spatial agglomeration effect of the epidemic was described, as well as the distribution of agglomeration regions and hot spots (Li et al. 2020a; Li et al. 2021). The research about government control was generally based on mainland China because all government levels there have implemented interventional measures, such as locking down cities, curbing population flow, and controlling traffic (Liu et al. 2020d; Shen 2020; Wei et al. 2021). Moreover, the implementation of such interventional measures owned a precise start time, which was also conducive to the accuracy of the evaluation (Liu et al. 2021). Some articles analyzed and summarized the differences in epidemics' development before and after government control or the possible situation under different control intensities (Ye and Hu 2020; Chen et al. 2021). In particular, as the core area, Wuhan's lockdown had impacted other regions on the epidemic spread, which became the key to these studies (Lau et al. 2020; Shi et al. 2021). Besides, some studies simulated the impact of Wuhan's lockdown starting time on the epidemic trend, verifying timely government intervention's effectiveness

from a new perspective (Liu et al. 2020b; Sun et al. 2020). These researches provide a factual basis for precise prevention and control.

While studying the macroscopic spreading mechanism of COVID-19 and analyzing government control's role in it can help to better deal with similar health emergencies in the future, there are some shortcomings in the past researches. Firstly, some researchers focused on the total confirmed cases but ignored the daily new cases, when describing and analyzing the epidemic's spatial agglomeration (Li et al. 2020a; Liu et al. 2020d; Xie et al. 2020; Xu et al. 2020b). In fact, studying the spatial agglomeration effect of daily new cases and their temporal trends are more conducive to show the epidemic's whole process, i.e., from sporadic emergence to agglomeration and finally disappearance, which can benefit the public's understanding of the epidemic. Secondly, while using various methods to simulate the epidemic curve and calculate the inflection point was an important part of COVID-19 research, previous researches mainly did it from the perspective of the entire country or a specific region, lacking horizontal and spatial comparison (Liu et al. 2020a; Shang et al. 2020; Ye et al., 2020).

Based on previous scholars' researches, this paper was organized as follows: firstly, describing the characteristics of the total confirmed cases and daily new cases, focusing on analyzing their spatial agglomeration effects and temporal trends; secondly, fitting the curve of confirmed cases and calculating the inflection point of COVID-19 for each province; and thirdly, comprehensively considering the start date of the epidemic, the activation date of the first-level public health emergency response, and the inflection point, to evaluate the response timeliness's impact on epidemic control at the provincial level.

Research methods and data sources

Research methods

Descriptive spatio-temporal analysis

The outbreak and spread of infectious diseases have the characteristics of time and space (Brooks et al. 2008). Traditional time series analysis or spatial cross-sectional analysis is not sufficient to describe the development of the epidemic comprehensively and dynamically. Based on the time series analysis, this article combines the data visualization function of the ArcGIS platform to display the spatial distribution of COVID-19 at different time nodes in the form of a map so as to better analyze and evaluate the characteristics and trends of the epidemic at both the time and space levels. It will be carried out according to the following two indicators: (1) Total confirmed cases. Six times nodes are selected to analyze the spatial evolution of the total confirmed cases and focus on evaluating the causes and influencing factors of high-value zones. (2)

Daily new cases. According to the time nodes selected by the total confirmed cases, the spatial distribution of the number of daily new cases at two adjacent time nodes is evaluated separately, and the characteristics of the evolution of the daily new cases over time are analyzed from a macro perspective.

Exploratory spatial data analysis

Infectious diseases generally have distribution characteristics of spatial autocorrelation (Adham et al. 2020; Masinaei et al. 2020; Ding et al. 2021). Spatial autocorrelation embodies the distribution law of the agglomeration or dispersion of infectious diseases on the spatial level, which is of great significance to the stage analysis and situation prediction of diseases (Zhang et al. 2019; Mao et al. 2020).

Moran's I is a commonly used indicator to measure spatial autocorrelation effects and has been widely used in many fields including epidemiology (Ren et al. 2020; Thompson et al. 2018). For an indicator x, its Moran's I is calculated as follows:

$$I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \times \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2} \quad (1)$$

where I is the value of Moran's I; x_i and x_j are the observed values of regions i and j; $\overline{x}$ is the average of the observed values of all regions; n is the number of regions; w_{ij} is the judgment of whether the regions i and j are spatially adjacent, if $w_{ij} = 1$, the region i and j are adjacent, if $w_{ij} = 0$, the region i and j are not adjacent; and all w_{ij} constitute an n×n matrix W, which is called spatial weight matrix.

The value range of Moran's I is [−1, 1]. The closer I is to 1, the stronger the spatial positive autocorrelation of the indicator, which shows the spatial agglomeration effect; the closer I is to −1, the stronger the spatial negative autocorrelation of the indicator, which is manifested as the spatial dispersion effect; if I is close to 0, it means that there is no spatial autocorrelation, and the indicator shows spatial random distribution.

Inflection point analysis of total confirmed cases

After the outbreak and spread of infectious diseases, there is a certain functional relationship between the number of total confirmed cases and time in a specific space (Wu and Lin 2009). At the beginning of the epidemic, there are few total confirmed cases, but the number of daily new cases increases with time; when the epidemic develops to a certain stage, the number of daily new cases begins to decrease gradually with time, but the number of total confirmed cases continues to rise; after a while, the number of total confirmed cases tends to be stable, and there are almost no daily new cases. The function image is similar to an "S"-shaped curve (Wang et al. 2008). Within a certain interval,

the unary cubic function can describe the curve more accurately (Pothen and Welsch 2019; Narison and Maltezos 2021). Therefore, this study selects the unary cubic function to fit the growth curve of total confirmed cases in various regions. The specific form of the function is:

$$y = at^3 + bt^2 + ct + d \ (a \neq 0 \text{ and } t > 0) \tag{2}$$

where y is the number of total confirmed cases of COVID-19; t is the time; and a, b, c, and d are the parameters.

When the second derivative of the dependent variable to the independent variable is 0 ($\frac{\partial^2 y}{\partial t^2} = 0$), the value of the corresponding independent variable is called the inflection point of the function. The emergence of the inflection point means that the number of daily new cases has gradually declined, which is of great significance to the development and prediction of the epidemic (Gu et al. 2020). Record t_0 as the time corresponding to the inflection point of the total confirmed cases, then t_0 can be expressed as:

$$t_0 = -\frac{b}{3a} \ (a \neq 0 \text{ and } t > 0) \tag{3}$$

Correlation analysis

Correlation analysis is a statistical method for studying the relationship between two or more random variables (Zhao et al. 2019). The correlation between two variables can be judged by the correlation coefficient r, and the value range of r is $[-1, 1]$. The greater the absolute value of r, the stronger the correlation between the two variables; when r is positive, it means that the two variables are positively correlated; when r is negative, it means that the two variables are negatively correlated; when r is equal to 0, it means that the two variables are independent of each other and there is no correlation.

Pearson correlation coefficient is a widely used index to measure the degree of correlation between variables (Shahzad et al. 2020; Coccia 2021). The formula is as follows:

$$r = \frac{\sum_{i=1}^{n} \left(p_i - \overline{p} \right) \left(q_i - \overline{q} \right)}{\sqrt{\sum_{i=1}^{n} \left(p_i - \overline{p} \right)^2} \sqrt{\sum_{i=1}^{n} \left(q_i - \overline{q} \right)^2}} \tag{4}$$

where p_i and q_i are the values of the two indicators in region i, $\overline{p}$ and $\overline{q}$ are the average values of the indicators, and n is the number of regions.

In this study, the Pearson correlation coefficient is used to analyze the correlation between the time interval from the first confirmed case to the activation of first-level public health emergency response and the time interval from the first confirmed case to the inflection point of the total confirmed cases in different regions.

For the selection of statistical units, in terms of descriptive spatio-temporal analysis and exploratory spatial data analysis, prefecture-level administrative regions (including some county-level administrative units directly managed by the province) are used as samples; for inflection point analysis and correlation analysis, the samples are the provincial administrative regions.

Data source

The data on the total confirmed cases, daily new cases, and the time of activating first-level public health emergency responses in this study are derived from relevant information published by the official website of the National Health Commission and Health Commission of provincial administrative regions (http://www.nhc.gov.cn/).

Considering the purpose of this study, the time of initial transmission, the delay time of treatment, and the particularity of the management system, the study ignores the samples from Hubei, Taiwan, Hong Kong, and Macao. To unify the time series analysis, January 19, 2020, and February 16, 2020, are set as the starting and ending time of this study.

Results

Spatio-temporal characteristics and spatial autocorrelation analysis of COVID-19 distribution

Spatio-temporal characteristics of total and daily new cases

At the time level, the number of total confirmed cases shows an "S"-shaped curve characteristic that gradually increases and tends to stabilize, and the number of daily new cases shows a pattern of "first increasing and finally decreasing." These two indicators are consistent in the mathematical sense, as shown in Fig. 1. From the perspective of spatial distribution (Figs. 2 and 3), the number of total confirmed cases is more in the east while less in the west, showing the characteristics of "multi-center agglomeration distribution," which is concentrated in Hubei Province and some major cities and their surrounding areas. This feature gradually becomes obvious over time. The spatial distribution characteristics of daily new cases are similar to total confirmed cases. The difference is that this characteristic is the most prominent in the middle stage of the epidemic while relatively less obvious in other periods. To better explore the distribution pattern of the epidemic and analyze the causes, this article divides the development of the epidemic during the study period into three stages.

Stage 1 (before January 26, 2020). Judging from the total confirmed cases, before January 21, 2020, most regions of China had no epidemics except for Hubei Province, while only some municipalities, provincial capitals, and coastal
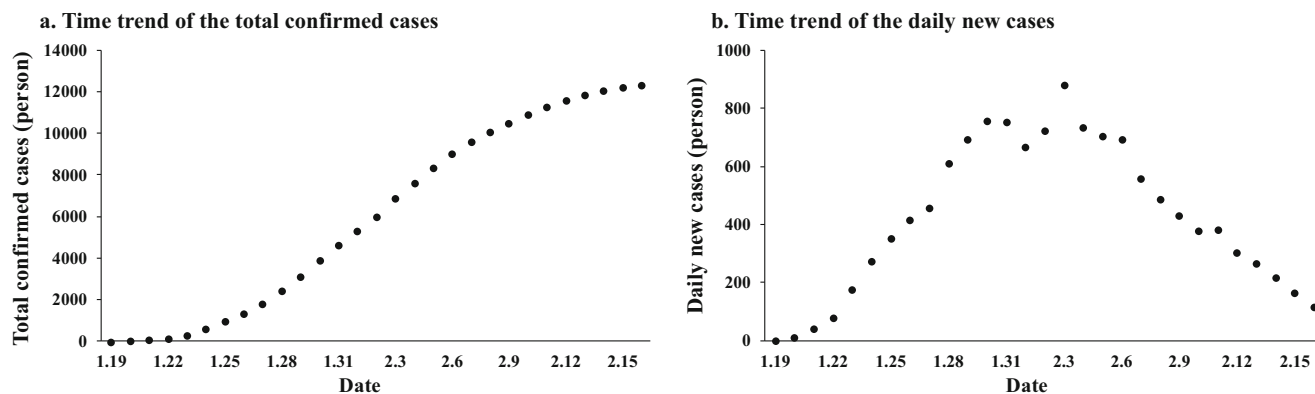
Fig. 1 Temporal variation trend of (**a**) the total confirmed cases and (**b**) the daily new cases

cities had confirmed cases with less than 10 people. By January 26, 2020, most cities in the eastern region have begun to report confirmed cases. At this stage, it can be found that the spatial characteristics of confirmed cases have begun to appear signs of weak agglomeration distribution, but not obvious. The number of daily new cases has started from a relatively low initial level and gradually developed to a medium scale. The regions with faster growth of confirmed cases are mainly around Hubei Province and some major cities in the center or east, which are jointly determined by factors such as spatial distance and economic strength.

Stage 2 (from January 26, 2020, to February 6, 2020). The spatial distribution of total confirmed cases on February 1, 2020, and February 6, 2020, indicates that the epidemic has entered a state of full-scale spread in this stage. The number of total confirmed cases in some major cities has exceeded 200; the situation in the central and eastern regions is relatively severe. The spatial characteristics of this stage have shown an obvious state of agglomeration distribution. The confirmed cases and agglomeration of the surrounding regions of Hubei Province are enhanced. Beijing-Tianjin-Hebei Urban Agglomerations, Yangtze River Delta Urban Agglomerations, Pearl River Delta Urban Agglomerations, and Chengdu-Chongqing City Group have become the most severely affected areas except Hubei Province and its surrounding regions. Besides, in Heilongjiang Province of northeastern China, an agglomeration distribution region has also been formed with its provincial capital Harbin as the center. Meanwhile, the number of daily new cases increased rapidly and then remained fluctuating for a period. It reached the peak of the entire study stage on February 3 (Chen et al. 2021). A large number of daily new cases appeared in cities near Hubei Province and some developed urban agglomerations and spread outwards with these regions as the center, indicating that the growth of daily new cases showed a concentrated distribution. This stage is also the most critical period for epidemic prevention and control.

Stage 3 (from February 6, 2020, to February 16, 2020). At this stage, the number of daily new cases has begun to gradually decline. Especially after February 11, the number of daily new cases in most cities has fallen below 10 people. Although the daily new cases in some regions with more severe epidemics still have a certain scale (because of the large base of confirmed cases and the relatively large number of infections), the longitudinal comparison shows that the decline is also obvious. And the growing scale of concentrated concatenation has gradually weakened. This pattern is also reflected in the spatial distribution of total confirmed cases. According to the distribution of total confirmed cases on February 11 and 16, it can be found that compared with before, the change in the spatial distribution of the epidemic has been relatively insignificant, and the spatial pattern has shown a gradually stable distribution, indicating that the prevention and control measures have achieved certain results.

Time series characteristics of spatial agglomeration of total and daily new cases

The descriptive analysis method mentioned above can roughly judge that the total and daily new cases may have spatial agglomeration characteristics. The Moran's I can accurately measure the strength of spatial agglomeration. Through spatial autocorrelation modeling, the Moran's I of total and daily new cases and their trends over time are obtained, as shown in Fig. 4. It can be seen from the Moran's I of the total confirmed cases that in the initial period of time, the value of the Moran's I rises with time, and its significance level gradually reaches and exceeds the critical value. It shows that the spatial distribution characteristics of the epidemic were random at the beginning. With time, the randomness gradually decreased, and the agglomeration effect began to strengthen. Therefore, the law of epidemic development shows the characteristics from dispersion to concentration. Then the value of Moran's I further increased and turned into a long-term stable state after reaching a certain level. During this process, the significance level of Moran's I is always very high, and the characteristics of "high-high" agglomeration (the regions with more total confirmed cases, which also have more total confirmed cases in the surrounding regions) and "low-low"
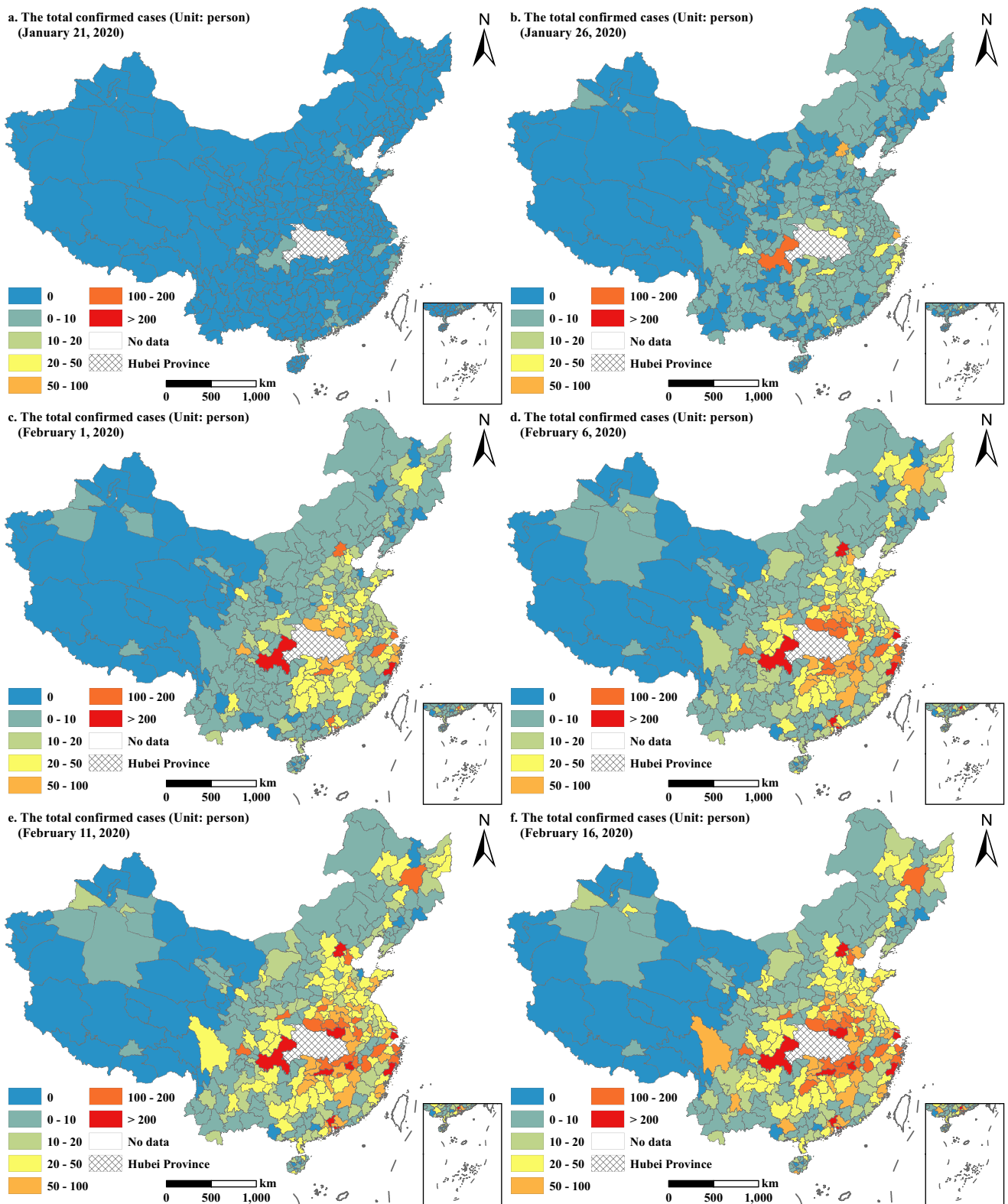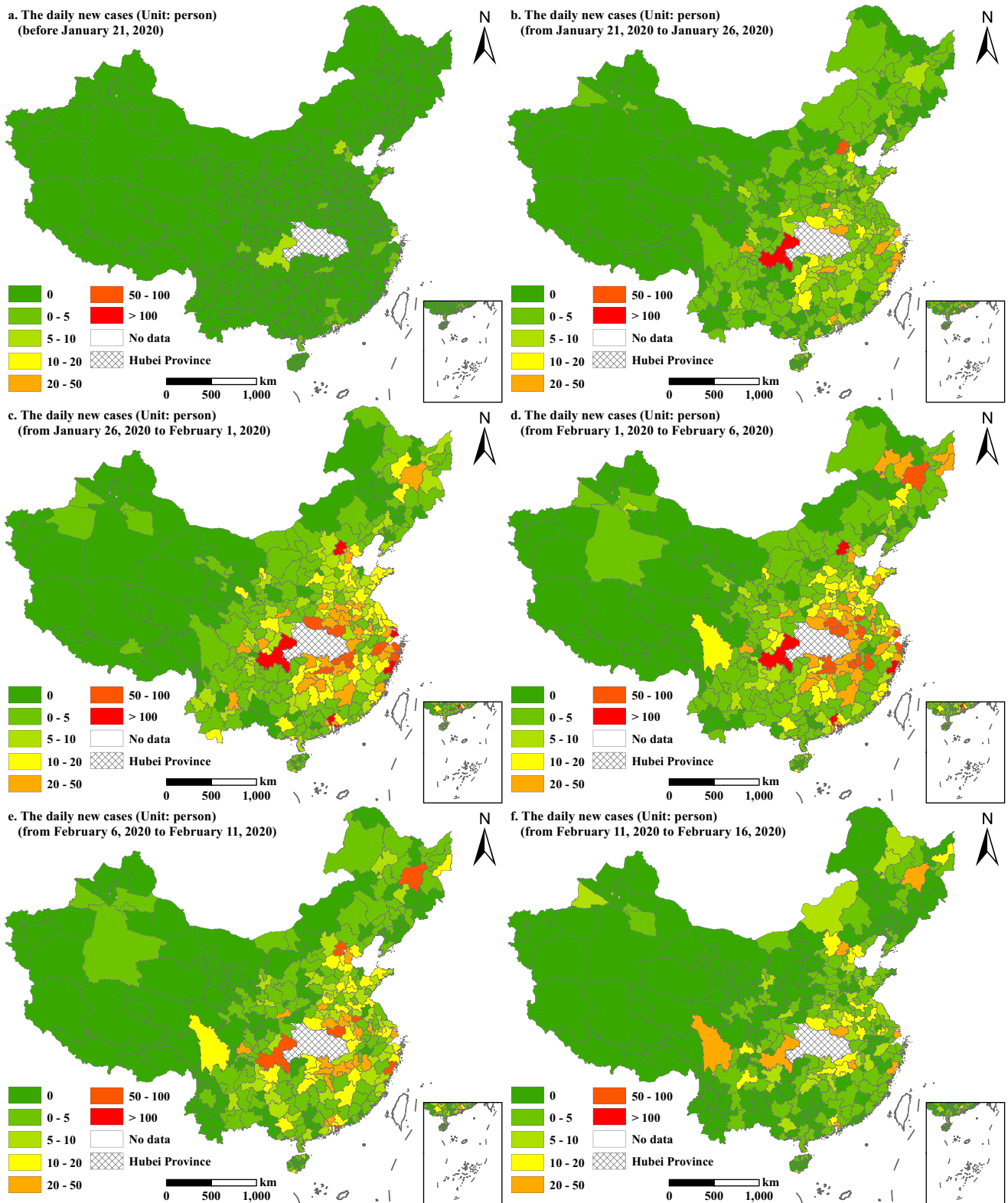
Fig. 2 Spatio-temporal distribution of the total confirmed cases: (**a**) January 21, 2020; (**b**) January 26, 2020; (**c**) February 1, 2020; (**d**) February 6, 2020; (**e**) February 11, 2020 and (**f**) February 16, 2020

agglomeration (the regions with less total confirmed cases, which also have less total confirmed cases in the surrounding regions) are quite obvious. These phenomena show that the

development of the epidemic follows the spatial law, and it is easy to form large-scale agglomerative contiguous areas with key areas as the center.

Fig. 3 Spatio-temporal distribution of the daily new cases: (**a**) before January 21, 2020; (**b**) from January 21, 2020 to January 26, 2020; (**c**) from January 26, 2020 to February 1, 2020; (**d**) from February 1, 2020 to February 6, 2020; (**e**) from February 6, 2020 to February 11, 2020 and (**f**) from February 11, 2020 to February 16, 2020
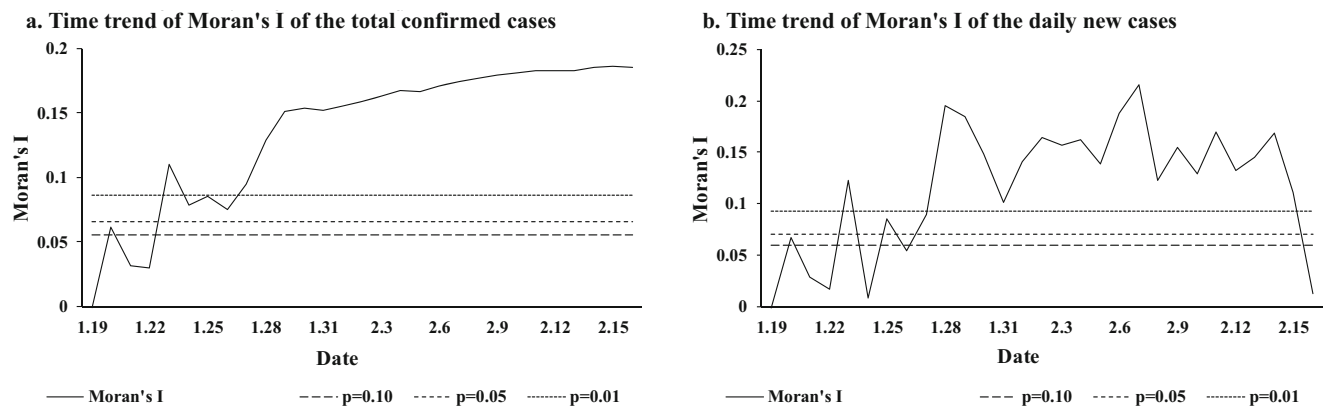
Fig. 4 Temporal variation trend of Moran's I of (**a**) the total confirmed cases and (**b**) the daily new cases

The Moran's I of daily new cases has a fluctuation characteristic of "first increasing, then fluctuating and stable, and finally decreasing" with time series. It suggests that at the beginning of the epidemic, the spatial distribution of daily new cases is in a random state, and it is difficult to judge the specific law subjectively, which is consistent with the above results. In the next phase, the Moran's I is relatively high and very significant. Although the Moran's I had fluctuations, it does not affect the obvious spatial agglomeration effect. It shows that after a period of transmission, the outbreak was particularly prone to concentrate in several adjacent areas. When the epidemic has reached a relatively stable stage and there is no significant increase of daily new cases in most regions, the Moran's I would continue to decline until it reached an insignificant level. The spatial distribution during this period is similar to that of the initial stage, and the daily new cases are also randomly distributed, indicating that the effects of management and control began to appear.

Analysis of the inflection point and its influencing factors of total confirmed cases

The total confirmed cases curve fitted by the unary cubic function has achieved good results in the study interval. Among the 30 samples involved in the calculation, the goodness of fit of 26 samples was over 0.99, and the goodness of fit of 29 samples was over 0.97, which indicates that the results calculated by this method are highly reliable within the research interval. Table 1 provides the time when the total confirmed cases of each provincial administrative region participating in the study reached the inflection point. It can be found that there are significant differences in the time to reach the inflection point in each region. The first regions to reach the inflection point were Qinghai and Yunnan (January 31, 2020), Xinjiang was the latest area to reach the inflection point (February 10, 2020), and most other regions concentrated on reaching the inflection point from February 1, 2020, to

February 3, 2020.

After the outbreak, all provincial administrative regions of China have successively activated first-level public health emergency responses. This behavior marks that the most stringent prevention and control measures have been taken within the administrative region to deal with the spread of the epidemic. Therefore, this study hypothesized that if the first-level public health emergency response can be activated as soon as possible, it will be conducive to the early arrival for the inflection point of the total confirmed cases. To prove this view, this study analyzed the relationship between the time interval from the first confirmed case to the activation of first-level public health emergency response and the time interval from the first confirmed case to the inflection point of the total confirmed cases in each region. As can be seen from Fig. 5, the first-level public health emergency response will be activated within 2~3 days after the first confirmed case was discovered for most regions of China. The time interval is 4 days in Guangdong and Shanghai, because the first confirmed case was discovered earlier in these places, and the epidemic had not spread on a large scale at that time, leading to a lag in the judgment of the epidemic, so the time interval is longer. Several regions in the west activated first-level public health emergency responses relatively rapid, because when the first confirmed case was discovered in these regions, the epidemic had spread widely in other regions, and local governments had already taken adequate measures to deal with it. The time to reach the inflection point is generally concentrated 1~2 weeks after the first case was confirmed. The results of the correlation analysis show that the correlation coefficient between the time interval from the first confirmed case to the activation of first-level public health emergency response, and the time interval from the first confirmed case to the inflection point of the total confirmed cases is 0.642 ($p<0.001$), which showed that there was a highly significant positive linear correlation between the two indicators. Therefore, there are sufficient reasons to believe that if response measures are taken as soon as possible after confirmed cases are found, it will be conducive to the

Table 1 The time for each provincial administrative region to reach the inflection point of the total confirmed cases

| The time to reach the inflection point	Provincial administrative region
January 31, 2020	Yunnan, Qinghai
February 1, 2020	Liaoning, Shanghai, Zhejiang, Fujian, Chongqing
February 2, 2020	Beijing, Shanxi, Hunan, Guangdong, Guangxi, Sichuan, Tibet, Shaanxi, Gansu
February 3, 2020	Inner Mongolia, Anhui, Jiangxi, Shandong, Henan, Hainan
February 4, 2020	Jilin, Jiangsu
February 5, 2020	Tianjin, Ningxia
February 6, 2020	Hebei, Heilongjiang, Guizhou
February 10, 2020	Xinjiang

early arrival for the inflection point of the total confirmed cases.

Discussion and suggestions

The spreading ways of COVID-19

Through the analysis of the research results, it can be considered that there are roughly three ways for the spread of COVID-19, and these three ways have a certain chronological order. Except for Hubei Province, the regions where the first confirmed cases were reported before the Chinese New Year were all from some developed cities. This shows that the initial way for the spread of COVID-19 is mainly the flow of business personnel, because these flows are mostly concentrated in developed cities, there are no obvious seasonal and holiday characteristics, and the spatial dispersion is relatively strong. However, the number of such people is limited, which

may not cause a large-scale spread of the virus in a short time. The next way for the spread of the epidemic is the migration of the floating population. It is well known that the outbreak of COVID-19 in China coincides with the Chinese New Year. In the process, a large number of people moved from large cities to medium-sized or small cities. As a result, confirmed cases have also appeared in these cities. This phenomenon can be clearly discovered from the spatial distribution of total confirmed cases after January 26, 2020. At that time, most cities in the east have confirmed cases, and it is even more obvious around Hubei Province. The third way for the spread of COVID-19 is the transmission within regions, which basically occurs after the floating populations return to their hometowns. During the Chinese New Year, due to traditional customs, the flow of people within regions is relatively frequent, and people are prone to gathering. These behaviors provide favorable conditions for the further spread of the epidemic. Through the analysis of the three ways and the main periods of their impact, it can be considered that the migration of the
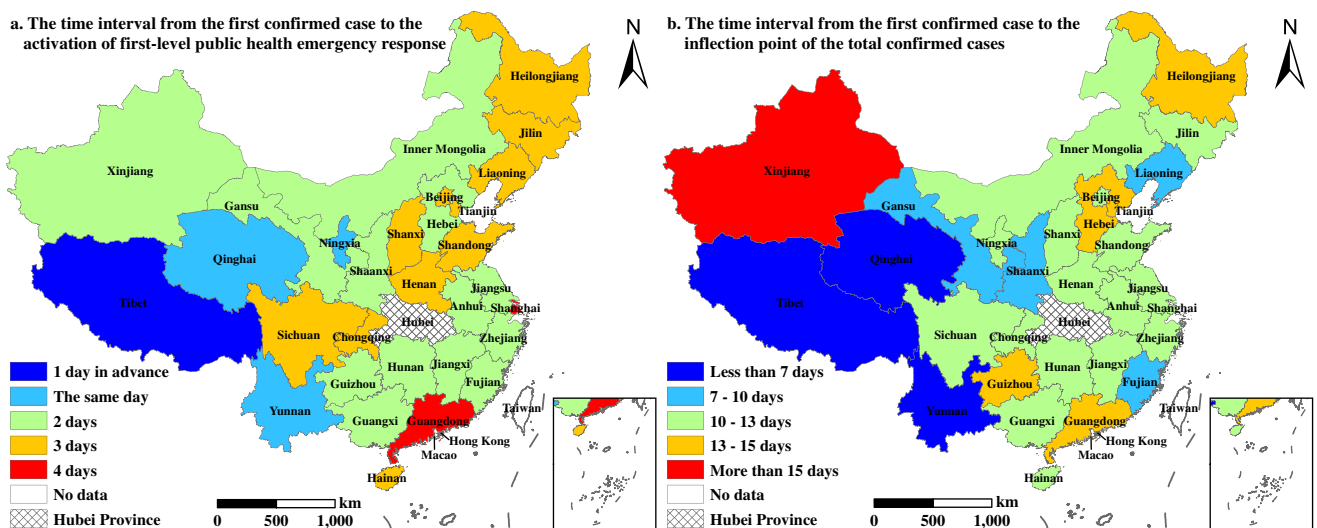
Fig. 5 (**a**) The time interval from the first confirmed case to the activation of first-level public health emergency response and (**b**) the time interval from the first confirmed case to the inflection point of the total confirmed cases in each provincial administrative region.

floating population has played a vital role in the overall spread of COVID-19. This is because the number of the floating population is large, the activity area is quite wide, and the possibility of contact with other people is high (Jiang and Luo 2020). After the infected floating population arrives at the destination, if control measures are not taken in time, it is easy to cause new transmission. Therefore, reasonable investigation of the floating population and effective control of the infected people will have a very positive effect on the further spread of the epidemic and could even cut off the transmission route (Liu et al. 2020b).

Spatial distribution characteristics of COVID-19

Compared with previous infectious diseases, COVID-19 affects wider regions and has more confirmed cases. There may be three reasons to explain this phenomenon. First of all, COVID-19 is relatively highly contagious and can easily cause infection in the populations (Ashour et al. 2020). Second, the epidemic coincides with the Chinese New Year; the scale of population movement is almost the highest peak of a year, which is very easy to cause the number of infected people to increase rapidly (Wang and Teunis 2020). Besides, the well-developed transportation network is also likely to cause a large-scale spread of the epidemic, because China's transportation industry has made great progress over the past 10 years, especially the popularization of high-speed railways has greatly shortened the cost of time (Ding et al. 2004). Therefore, it can be found that in this epidemic, the regions with more total confirmed cases are not only concentrated in the vicinity of Hubei Province; some municipalities, provincial capitals, developed cities, and their surrounding areas have also appeared in various scales of agglomeration distribution regions. This is because most of these cities are regional cores or transportation hubs, with a larger population and flow of people, so the epidemic is more likely to spread in these areas. Analyzing the time trend of the Moran's I of total confirmed cases further proves the existence of spatial agglomeration effects. It can be considered that during the study period, COVID-19 showed a spatial pattern of "multi-center agglomeration distribution" in China.

It is worth paying attention to the time trend of the Moran's I of daily new cases. At the beginning and the end of the study period, that is, at the early stage of the outbreak and the epidemic reached a stable state, the spatial distribution of daily new cases was mostly random, with no obvious signs of spatial autocorrelation. However, in the middle of the study period, the daily new cases showed significant spatial agglomeration. It shows that at this stage, a concentrated and contiguous outbreak of epidemics is extremely prone to occur. This phenomenon reminds managers that after the outbreak of infectious diseases, it is recommended to manage and control regions of different scales as units and cut off the connection between regions if necessary, which can strictly limit the epidemic to a certain space and prevent large-scale spread (Hsiang et al. 2020; Xia et al. 2020; Yin et al. 2021).

The important role of government response in epidemic prevention and control

For newly emerging infectious diseases, the government generally understands more timely and comprehensively than the public. So the government will take corresponding measures according to the characteristics of infectious diseases. Since the outbreak of the COVID-19, various provincial administrative regions of China have successively activated the first-level public health emergency responses and adopted the most stringent measures to face it (Younis et al. 2020; Liu et al. 2021). The result proves that the speed of the government's response largely affects the development of the epidemic situation, even determines whether the inflection point of the total confirmed cases can come as soon as possible (Fang et al. 2020). Hence, activating the response in time can minimize losses caused by the epidemic and better protect the safety of people's lives and health (Tian et al. 2020; Wu et al. 2021). From a short-term perspective, there is still a possibility of the outbreak of COVID-19. Looking to the future, people will face more unknown infectious diseases. For many regions, especially underdeveloped regions, implementing control measures in time is still an effective way to control the spread of the epidemic.

Conclusion

This article analyzed the spatio-temporal transmission characteristics of COVID-19 at the early outbreak stage in mainland China and proposed corresponding prevention and control strategies. Compared with previous studies, this study quantified the spatial agglomeration of cases and their temporal trends, pointed out the key stages of epidemic prevention and control, and more clearly demonstrated the whole process of the epidemic from sporadic emergence to agglomeration and finally stability. Besides, the date when the inflection point appeared in each province was determined and compared according to the actual situation. Research findings are as follows.

(1) The total confirmed cases rose in an "S"-shaped curve over time, and the daily new cases increased first and decreased finally.
(2) The spatial distributions of both total and daily new cases showed more in the east and less in the west, with a

"multi-center agglomeration distribution" around Hubei Province and some major cities.

(3)   The spatial agglomeration of total confirmed cases was increasing always, while the spatial agglomeration of daily new cases was most obvious in the mid-stage.

(4)   The timeliness of the first-level public health emergency response could bring an early emergence of the epidemic inflection point.

Data availability The data on the total confirmed cases, daily new cases, and the time of activating first-level public health emergency responses in this study are derived from relevant information published by the official website of the National Health Commission and Health Commission of provincial administrative regions.

Declarations

Ethics approval   Not applicable.

Consent to participate   Not applicable.

Consent for publication   Not applicable.

Competing interests   The authors declare no competing interests.

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