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An Analysis of Spatiotemporal Pattern for COIVD-19 in China based on Space-Time Cube

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Abstract

This study seeks to examine and analyze the spatial and temporal patterns of COVID-19 outbreaks and identify the spatiotemporal distribution characteristics and changing trends of cases. Hence, local outlier analysis and emerging spatiotemporal hot spot analysis were performed to analyze the spatiotemporal clustering pattern and cold\hot spot trends of COVID-19 cases based on space-time cube during the period from January 23, 2020 to February 24, 2020. The main findings are as follows. 1) The outbreak had spread rapidly throughout the country within a short time and the current totality incidence rate has decreased. 2) The spatiotemporal distribution of cases was uneven. In terms of the

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spatiotemporal clustering pattern, Wuhan and Shiyan city were the center as both cities had high–high clustering pattern with a surrounding unstable multiple type pattern in partial areas of Henan, Anhui, Jiangxi, and Hunan provinces, and Chongqing city. Those regions are continuously in the hot spot on the spatiotemporal tendency. 3) The spatiotemporal analysis technology based on the space-time cube can analyze comprehensively the spatiotemporal pattern of epidemiological data and produce a visual output of the consequences, which can reflect intuitively the distribution and trend of data in space–time. Therefore, the Chinese government should strengthen the prevention and control efforts in a targeted manner to cope with a highly changeable situation.

Keyword: COVID-19, space-time cube, local outlier analysis, emerging spatiotemporal hot spots analysis

Introduction

Throughout the development of human society, infectious diseases have been a public health problem that cannot be overlooked. These diseases have posed serious threats to human health and socio–economic development. On December 8, 2019, the Wuhan Municipal Health and Health Committee reported a cluster of unexplained pneumonia (later officially named 2019 novel coronavirus disease, COVID-19, by the World Health Organization[1]). Cases spread rapidly from Wuhan to other cities in China. As of February 24, 2020, a total of 77,658 confirmed cases and 2663 deaths have been reported in 34 provinces and municipalities. The number continues to increase, and the peak has yet to be reached. Most cases originated from Hubei province. More than 2000 confirmed cases have been reported in more than 20 countries, such as South Korea, Italy, and Japan. The number of infected people is 17 times that of the severe acute respiratory syndrome coronavirus (SARS-Cov) outbreak in Guangdong, China in 2003[2] and 50 times that of the Middle East respiratory syndrome coronavirus (MERS-Cov) outbreak in the Middle East in 2018[3], which also became global public health events[4].

Studies found that COVID-19 is caused by the novel coronavirus, SARS-CoV-2. It is a novel betacoronavirus belonging to the lineage B (subgenus: sarbecovirus) that also contains SARS-Cov[5]. Genetic analysis indicated that SARS-CoV-2 is genetically highly similar to SARS-Cov and the coronaviruses isolated from bats, but the symptoms are significantly distinct[6]. SARS-CoV-2 spread mainly through respiratory droplets and contact transmission similar to the common flu, but potential transmission through feces–oral is possible according to some studies. Hence, maintaining vigilance is important, although this result was suspectable[5]. Despite efforts in clinical research and epidemiological investigation, we still have no answers to the following questions: 1) What is the range of the full spectrum of disease severity? 2) Who are infectious? Can we identify them? 3) How does the vital interest role of asymptomatic infected individuals play in the transmission? 4) How can we identify potential high-risk groups or areas for prevention and control so that we can focus on optimization resources?[7] Previous experience with SARS, MERS, and other outbreaks has indicated that focusing only on treating the sick is insufficient. We face an urgent need to expand public health activities to elucidate the epidemiology of the novel virus and characterize its potential impact as the epidemic evolves. A previous study[8,9] analyzed the epic- characteristics of population distribution and transmission dynamics of COVID-19. Another study performed geo-temporal analysis of viral spread at several periods, while discussed comprehensively the case characteristics, mortality, population distribution, and spatiotemporal characteristics based on a large sample of more than 40,000 cases[10].

A large number of epidemiological studies have been launched, but most of them focus on disease characteristics, population distribution, and indicators. Several studies involving spatial and temporal distribution analysis only discussed the temporal and spatial information of cases separately. Those studies destroyed the continuity and ignored the possible interaction of spatiotemporal data and thus cannot reflect the temporal and spatial evolution of the epidemic accurately. Therefore, using the spatiotemporal information of the cases comprehensively is imperative to further exploring the potential spatiotemporal distribution characteristics and variation rules.

The space-time cube (STC) model proposed by Hagerstrand[11] has been used extensively in traffic safety, public health, and other areas[12,13]. It can be aggregated while preserving the continuity of spatiotemporal data[14] and thus, the model can be useful in conducting a spatiotemporal analysis of disease[15]. The present study will identify the space–time clustering pattern, determine the cold and hot spot trends, and show the results of the visual output for COVID-19 outbreak through the spatiotemporal analysis technique based on STC to enable observation of the identification of high and low risk areas intuitively and provide information that can be used as basis for the next step in prevention and control strategy formulation.

2. Materials and methods

2.1 Data Sources

All data in the present study were gathered from the Internet. The COVID-19 data, including confirmed cases, suspected cases, and deaths from January 23, 2020 to February 24, 2020, were obtained from the Chinese Center for Disease Control and Prevention website[16]. Permanent resident population data of cities were collected from the China Statistical Yearbook for Cities[17]. Geographic coordinates and vector maps for each city were collected from Google Maps and National Administration of Surveying, Mapping, and Geoinformation website, respectively[18]. We collected the above data on the following cities and municipalities (e.g., Beijing, Tianjin, Shanghai, and Chongqi) in China, except for Hong Kong, Macau, and Taiwan because of the inadequate data from those districts. This study has been endorsed by the ethics committee of Guilin Medical University.

2.2 Analysis methods

In the analysis process, MS Excel 2019 (Microsoft) was used to collate the original data and calculate the daily incidence (per 100,000) of each city. The collated data were then converted into geographic information system (GIS) data. ArcGIS Desktop software (version 10.7, Environmental Systems Research Institute, Inc) provided analysis tools for kernel density analysis, STC construction, local outlier analysis, and emerging spatial and temporal hot spot analysis, and provided the visualization of the results.

2.2.1 Construction of space-time cube (STC)

The spatiotemporal information on epidemiological data is aggregated into spatiotemporal bin and generates a special data structure named NetCDF in STC, where x and y dimensions represent space and t dimension represents time. Each bin has a fixed location in space (x, y) and time (t). Columns covering the same (x, y) region share the same location ID, and these columns can be combined to represent a bin time series. The count value of each bin reflects the number of events or records that occur at a relevant location during the relevant time step interval. In this way, at any given moment, the corresponding section can be achieved in the three-dimensional STC, that is, the plane geometry state of the real world (Figure 1).

2.2.2 Analysis of local outliers

Local outlier analysis can be used to analyze data clustering and outlier, which refers to the implementation of local Anselin Locan Moran's I statistics in space and time dimensions. It can recognize spatiotemporal statistically significant locations between research areas and its neighborhood by using neighborhood distance and time step neighborhood parameter to estimate Anselin Locan Moran's I statistics for each bin and output the six kinds of patterns as follows: only high–high cluster, only high–low outlier, only low–high outlier, only low–low cluster, multiple types, and never significant[19].

2.2.3 Analysis of emerging spatial and temporal hots pots

Emerging spatiotemporal hot spot analysis can identify trends of epidemiologic data based on STC. Getis–Ord Gi* statistics[20], including Z-score, p-value, and classification of each bin are calculated on the premise of setting neighborhood distance and time step parameter values and inputted into the STC. Then, the Mann–Kendall trend test is utilized to assess the tendency of the hot and cold spots[21]. Finally, according to the Z score and p-values of those location with data and of each bin, research areas will be classified into the spatiotemporal pattern as follows: new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, historical hot/cold spot, and no pattern detected.

3 Results and Analysis

3.1 Prevalence of COVID-19

We used line graph and thematic disease maps to analyze primarily the trend and distribution of COVID-19 and show the overall situation of the outbreak. Figure 2.a shows the changes of the national epidemic from January 20, 2020 to February 24, 2020. The overall trend of confirmed cases and deaths rose rapidly and then slowed down. On February 12, 2020, the cumulative number of confirmed cases increased suddenly to 59,804, with 15,151 new cases on this day. The increase was attributed to the update of diagnostic criteria for COVID-19. Since February 13, 2020, the growth of the cumulative number of confirmed cases slowed down gradually, but the cumulative number of deaths has been increasing at a relatively steady rate. The bar chart shows the change in newly confirmed cases that indicate mainly a trend of increase and then decrease, which peaked on February 12, 2020 then declined rapidly and remained at a low level.

We analyzed the change in the epidemic situation in Hubei province during the same period. As the hardest hit area of the epidemic, Hubei province has the highest proportion of all kinds of cases in China. As of February 24, 2020, Hubei had 64,786 confirmed cases and 2,563 deaths, accounting for 83.4% and 96.2% of the total number of cases in China, respectively. Wuhan, which is the capital city of Hubei province, has reported a total of 47,071 confirmed cases and 203 deaths, accounting for 72.7% and 79.7% of the total cases in Hubei province, respectively. Figure 2.b shows that the variation trend of the number of confirmed cases in Hubei and Wuhan is the same as that in the whole country. Similarly, the number of deaths in Hubei and Wuhan has been rising steadily, with most deaths having occurred in Wuhan.

We drew thematic maps (Figure 3) of the nation and Hubei province on January 23, February 11, and February 24, and introduced the distribution of confirmed cases based on the data of the accumulated confirmed cases. On January 23, all provinces reported confirmed cases except Tibet, Gansu, and Xinjiang, and those cases were distributed mainly in Hubei, Guangdong, Hunan, Chongqing, Zhejiang, and Beijing (Figure 3.a). Over time, the outbreak spread rapidly, and the situation in Hubei and its surrounding provinces became worse, with Hubei being the worst (Figures 3.b and 3.c). On January 23, eight cities in Hubei, including Wuhan, Xiaogan, Huanggang, and Xiantao, reported confirmed cases only (Figure 3.d), but an increasing number of cities in Hubei had reported confirmed cases and the situation was becoming increasingly worse (Figures 3.e and 3.f) as time went on.

We explored the central tendency of the disease preliminarily by using kernel density analysis. Figure 4 shows the results of cumulative confirmed cases of COVID-19 during three periods. On January 24 (Figure 4a), the shadow was distributed mainly in the south and northern region of China, whereas no shadow was observed in the northwest and Qinghai–Tibet region temporarily. Hubei had the highest density shadow, followed by Zhejiang, Beijing, and Guangdong. On February 11 (Figure 4b), the area of shadow expanded, with the high-density shadow concentrated mainly in Hubei and its surrounding provinces, which had scattered high-density shadows. On February 24 (Figure 4c), the case concentration trend became more obvious. The density shadow was concentrated mainly in Hubei, and the emission density shadow had disappeared.

3.2 STC of COVID-19.

A total of 868 spatial locations comprising 135 km ×135 km square were generated in the SCT of COVID-19, and the time step interval of the model was one day. Thus, a total of 28,644 time–space bins were generated and the values in each bin recorded the corresponding morbidity. After the model was established, the nonparametric Mann-Kendall statistical method was used to analyze and evaluate the overall trend of morbidity. The output results were $Z = -1.9678$ and p= 0.0491 (<0.05), which was statistically significant. This result indicated a downward trend in the overall incidence rate of COVID-19. The incidence rate of COVID-19 in 3D STC was divided by the method of natural breakpoint: 0–0.239, 0.240–0.943, 0.944–2.375, 2.376–5.100, 5.101–10.515, and 10.516–41.836 (per 100,000; Figure 5).

3.3 Result of local outlier analysis

We conducted local outlier analysis of 218 locations based on the STC of COVID-19 and the analysis results are presented in Table 1. The spatiotemporal clustering pattern of COVID-19 was dominated mainly by a single clustering pattern, with 2 only high–high (0.92%) and 167 only low–low clustering locations (76.61%). The locations of the two clustering patterns were 169 in total, accounting for 77.53% of the absolute locations. A total of 29 (13.3%) multiple types and 6 locations containing only high–low and only low–high outliers were present, accounting for 2.75% of the total locations. The above analysis results suggested that the outbreak presented a strong clustering pattern during the period of study, and the only low–low clustering was the mainly spatial and temporal clustering pattern.

Visualization results of local outlier analysis are shown in Figure 6. Most single clustering patterns and multiple types are distributed in the southern and northern regions of China, but the distribution is uneven. The only high–high clustering pattern distributes in Wuhan and Shiyan, Hubei province. Multiple type patterns are present in the surrounding provinces, including Henan, Anhui, Jiangxi, Hunan, and Chongqing, indicating that at least one spatial clustering pattern is present previously in these areas and still contain the possibility of developing into single clustering patterns. Wuhan is still the center of the epidemic and affects the situation of those surrounding areas. All other regions except the above-mentioned areas are dominated by a significant only low–low clustering pattern, indicating that the epidemic situation remains at a relatively low level in general.

3.4 Result of emerging spatiotemporal hot spots

The analysis results are shown in Table 2. In the 218 locations, 47 locations show spatiotemporal trend of cold\hot spots, including 38 consecutive hot and 19 cold spots (i.e., 5 new and 14 consecutive cold spots). Most areas do not show significant spatial and temporal trends as shown in Figure 7, and most of the cold and hot spots are concentrated in the south and north region of China. The consecutive hot spots are concentrated mainly in Hubei and its surrounding provinces, including Henan, Anhui, Jiangxi, and Hunan. This result indicates the incidence rate in this area has been at a high level. The consecutive cold spots distributed in Shanxi, Hebei, Shandong, Guizhou, and Guangxi suggest that the incidence rate in these areas has been low. New cold spots have appeared in Ningxia, Shanxi, Hebei, and Shandong provinces, manifesting that the epidemic situation in these places has been controlled effectively and that the incidence rate has changed from high to low. No significant intensifying or new hot spots were found in this study, indicating that the epidemic situation in China is basically stable and developing in a better direction.

4 Discussion

In this study, we analyze and excavate the spatiotemporal pattern of COVID-19 outbreak and determine the high and low risk areas of the epidemic by identifying the spatiotemporal clustering pattern and cold or hot spot trends of cases based on STC and spatiotemporal analysis technology. The main findings are as follows. 1) The outbreak spread rapidly throughout the country within a short time and the totality incidence rate has decreased. 2) The spatiotemporal distribution of cases is uneven. On the spatiotemporal clustering pattern, Wuhan and Shiyan cities are at the center of the spatiotemporal clustering pattern, with high–high clustering pattern surrounding unstable multiple type patten in partial areas of Henan, Anhui, Jiangxi, and Hunan provinces, and Chongqing city. Those regions are in a consecutive hot spot on the spatiotemporal trend. 3) The spatiotemporal analysis technology based on the STC can analyze comprehensively the spatiotemporal pattern of epidemiological data and produce a visual output of the consequences, which can reflect intuitively the distribution and trend of data in space–time.

The outbreak is a serious public health emergency in the history of the People's Republic of China, resulting in human deaths and economic losses. COVID-19 is more infectious compared with SARS, with an average incubation period of 5 days (range of 0–24 days)[22] and a basic reproduction index of 2–2.5[23]. Droplet and contact transmission are the main transmission methods, but the live virus isolated from the feces of the sick indicates a potential "fecal-oral" transmission method is possible [24]. Convenience of spread of the virus contributes to the various transmission approaches. SARS-CoV-2 asymptomatic cases, which were few in SARS, are common and can infect others. If they are unidentified, they will be at great risk of infecting others. As the capital of Hubei province, a large number of floating populations are attracted to Wuhan from other cities surrounding Hubei. After the outbreak, more than 5 million people emigrated from Wuhan before the city lockdown[24]. Therefore, those asymptomatic or symptomatic cases bring potential risk of infection all over the country. Those cases, according to other reports from different cities, with exposure due to travel or coming into contact with the individuals who came from Wuhan or Hubei also confirmed this view. With the passage of time, asymptomatic or second-generation cases began to be sick sequentially after the first or second incubation period. Most cases are concentrated in Wuhan because it is the place of origin. With efforts currently under way in China, the outbreak has been controlled effectively, and the number of cases is decreasing gradually in most areas besides Hubei. However, Hubei still faces multiple pressures including tension of medical and preventive personnel and material, enormous base number of cases (i.e., confirmed and suspected), and high-risk outbreak rebound. Therefore, the space–time pattern in the region remains a hot spot trend. Previous experience has suggested that the closer an outbreak occurs, the greater the risk of infection, which can explain in part the influence of Wuhan on its surrounding areas. Under the current situation of absence of effective drugs and vaccines against SARS-CoV-2, nonpharmaceutical interventions remain central for prevention[26]. The continued enhancement of the prevention and control efforts by the Chinese government in the above-mentioned areas is significant to cope with the possible changes in the epidemic situation.

In the present study, the epidemic trend and distribution of the outbreak were analyzed briefly by using line graph and thematic maps, and the case density and clustering were verified simply by using kernel density analysis at different periods. The above methods were all based on time (one-dimensional) or space (two-dimensional) information. A simultaneous and comprehensive analysis of the time–space information was difficult. The line graph can show directly the general trend of change, but reflecting the spatial information is difficult. The thematic maps and kernel density analysis can display distribution information, but certain deficiencies are present in dealing with the time dimension. STC can aggregate the spatial–temporal information in the same data set, which provides a new method for the spatial–temporal analysis of the epidemic, meets the requirements of preservation time and spatial continuity, and visualizes the analysis results[27]. Therefore, we can observe the spatial–temporal clustering pattern and change trend of the outbreak more intuitively. The WHO considers timely mathematical models to play an important role in epidemic assessment, making health decisions, and evaluating the intervention effect[23]. Thus, the results of this study may provide basic information on epidemic space–time for decision makers.

Further research is needed in the following aspects for this study as follows. First, does the reported case represent actual certainty? Therefore, the accuracy of spatiotemporal analysis results based on reported cases may be suspected. Second, the spatial information of the case is accurate only to the city level, which will be considered large in this study and may have caused many spatial information to be ignored, which affected the accuracy of spatial analysis. Third, other factors that may have affected the outbreak were not considered, such as movement of personnel, population density, and demographic characteristics of each region. Therefore, we will supplement and improve the relevant data to compensate for the above defects.

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Authors' Contributions

Conception and design: Chunbao Mo and Chunhua Bei; Acquisition of data: Chunbao Mo, Dechan Tan and Tingyu Mai; Analysis and interpretation of data: Chunbao Mo, Chunhua Bei, Jian Qin and Weiyi Pang; Writing, review, and/or revision of the manuscript: Chunbao Mo, Chunhua Bei, Jian Qin and Zhiyong Zhang; Administrative, technical, or material support: Chunhua Bei, Jian Qin and Weiyi Pang; Study supervision: Zhiyong Zhang. All authors approved the final manuscript.

Conflict of interests

The authors declare that there is no conflict of interests.

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Figures

Figure 1. Structure of space-time cube(http://pro.arcgis.com)

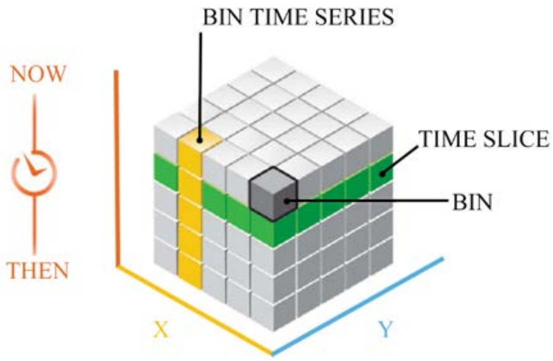

Figure 2 The trend of COVID-19. (a) China; (b) Hubei province and Wuhan city.

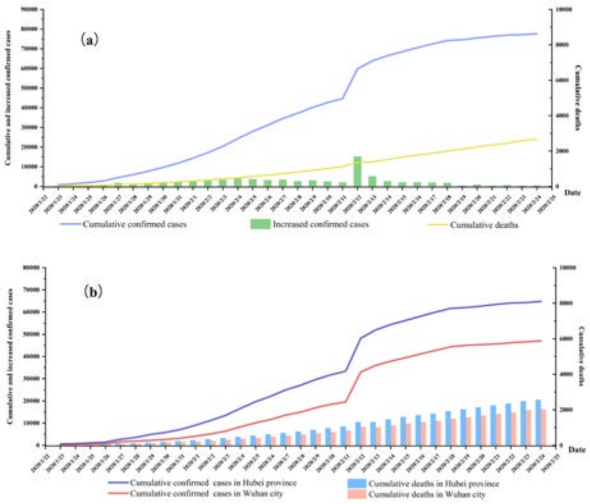

Figure 3 COVID-19 Cases distribution in China and Hubei province. a, b, c: Nationwide case distribution on January 23, February 11, and February 24, respectively. d, e, f: Hubei province case distribution on January 23, February 11, and February 24, respectively.

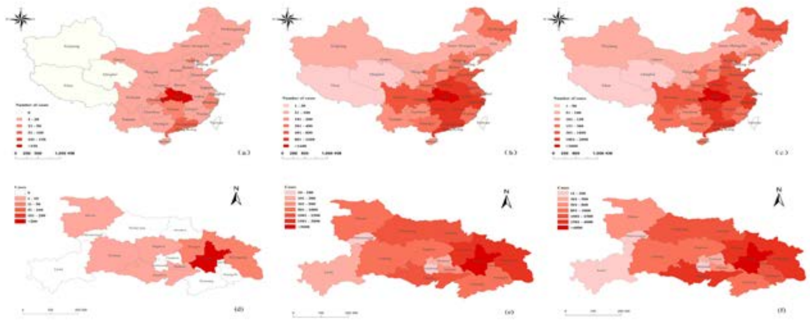

Figure 4 Concentrated regions of COVID-19 cases using kernel density analysis. a, b, c: The kernel density analysis result on January 23, February 11, and February 24, respectively. d: Geographical boundaries.

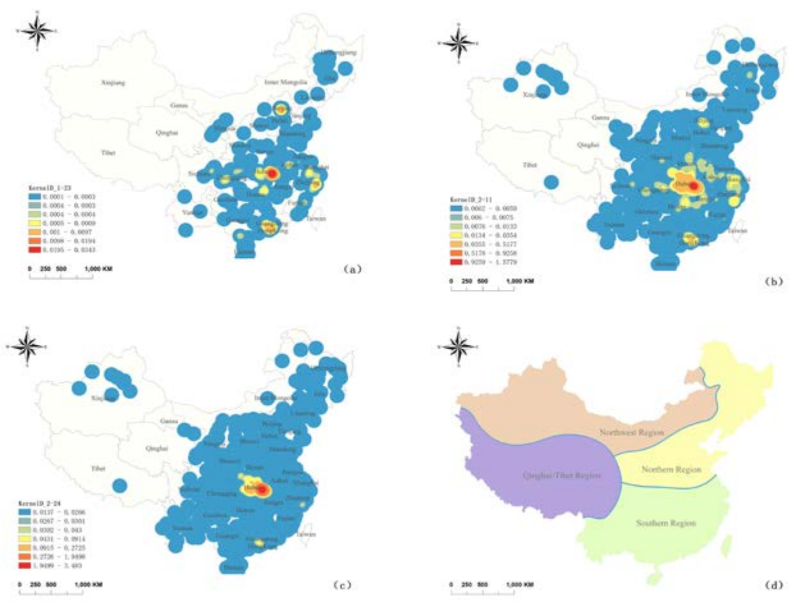

Figure 5 Generated space-time cub of COVID-19.

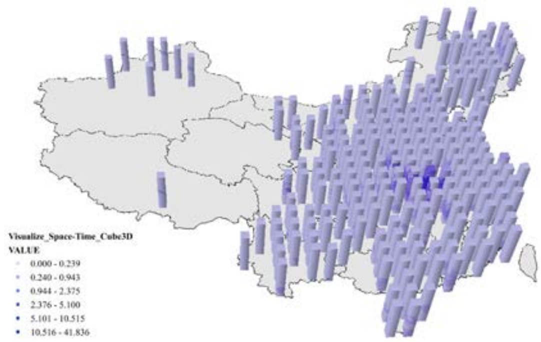

Figure 6 Visual results of local outlier analysis for COVID-19.

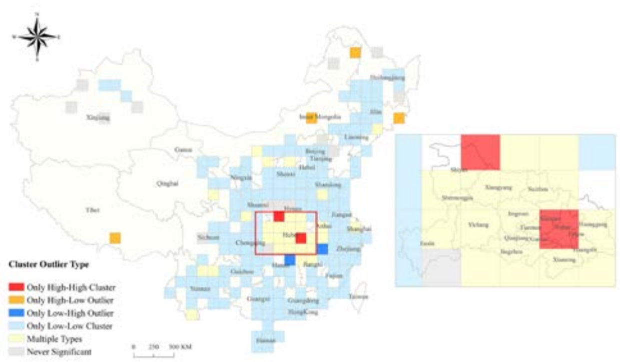

Figure 7 Visual results of emerging spatiotemporal hot spots analysis for COVID-19.

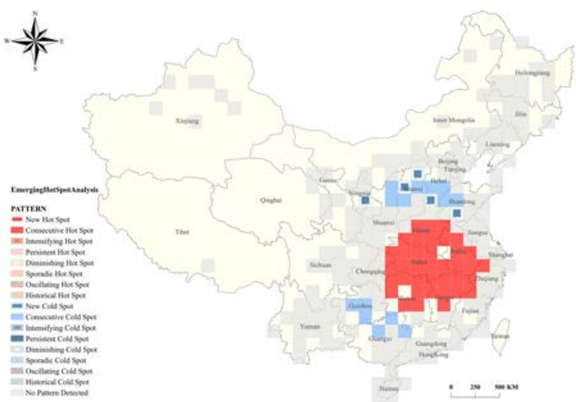

Table 1 The result of outliers

Patterns	NL	NL%
only high–high cluster	2	0.92
only high–low outlier	4	1.83
only low–high outlier	2	0.92
only low–low cluster	167	76.61
Never significant	14	6.42
multiple types	29	13.3
sum	218	100%

NL: The number of location.

Table 2 The result of emerging spatiotemporal hot spots analysis.

Patterns	Hot spot	Cold spot
New	0	5
Consecutive	38	14
Intensifying	0	0
Persistent,	0	0

Diminishing	0	0
Sporadic	0	0
Oscillating	0	0
Historical	0	0
Sum	38	19