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Interpretation of Discrepancies between Cities in the Transmission of COVID-19: Evidence from China in the First Weeks of the Pandemic

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ABSTRACT

Objectives: This study aims to examine and explain the differences at city level in cumulative COVID-19 cases and time from first to last infection during the first 6 weeks of the epidemic in China.
Methods: A quantitative study is conducted in China based on the multisource spatial data of 315 Chinese cities. Firstly, the spatial discrepancy of COVID-19 transmission was examined based on spatial autocorrelation analysis and hot pot analysis. Next, a comprehensive indicator framework was established by including a wide range of factors such as human mobility, geographical features, public health measures, and residents' awareness. Finally, multivariate regression models using these variables were constructed to identify the determinants of COVID-19 transmission.
Results: Significant spatial discrepancy of transmission was proved, and 10 determinants were identified.
Conclusions: The transmission consequence (measured by the number of cumulative cases) was mostly correlated with the migration scale from Wuhan, followed by socioeconomic factors. Transmission duration (measured as the time from the first to last case within the city) was mostly determined by total migration scale and lockdown speed, which suggests that timely implementation of public health measures facilitated fast control of transmission. Residents' attention to COVID-19 was proved to be not only helpful for reducing confirmed cases, but also in favor of rapid transmission control. Altitude produced slight but significant effect on transmission duration. These conclusions are expected to provide decision support for the local governments of China and other jurisdictions.

1. Introduction

Since its outbreak in December 2019, COVID-19 has caused a serious impact on the world. As of January 1, 2022, the global cumulative number of confirmed cases has exceeded 300 million, and the number of deaths has reached 5,521,161. The terrible situation has also slowed down global economic growth. Unfortunately, the new coronavirus continues spreading and is expected to lead to more serious consequences (Shahzad et al., 2020; Lee, 2020).

Transmission of COVID-19 is affected by both natural and socioeconomic factors (Wang et al., 2021). From the perspective of natural factors, scholars have studied the relationship between COVID-19 transmission and environmental and geographical factors (eg, temperature, humidity, and air quality) (Bashir et al., 2020; Ma et al., 2020; Zeng et al., 2020). Others focused on the spatial dynamics of the coronavirus and further explained its potential spreading routes(Adekunle et al., 2020). From the socioeconomic perspective, scholars considered the positive effects of a serious control measure (eg, social distancing, city lockdown, risk screening) on the transmission (Gostic et al., 2020; Ayyoubzadeh et al., 2020; Sirkeci and Yucesahin, 2020). Other studies predicted future transmission completely based on historical data (eg, daily increases and daily deaths) (Li et al., 2020).

Although previous studies have proposed and verified a number of determinants of COVID-19 transmission, there are some key problems, which need consideration. First, previous studies mostly focus on the transmission of COVID-19 in specific regions and only a few consider the differences in transmission among different regions (termed as spatial discrepancy in this paper), which causes poor generality of proposed conclusions. For example, Ma et al (2020) proved that COVID-19 transmission was negatively correlated with temperature based on data from Wuhan, but Shi et al (2020) found that the effect of temperature on the

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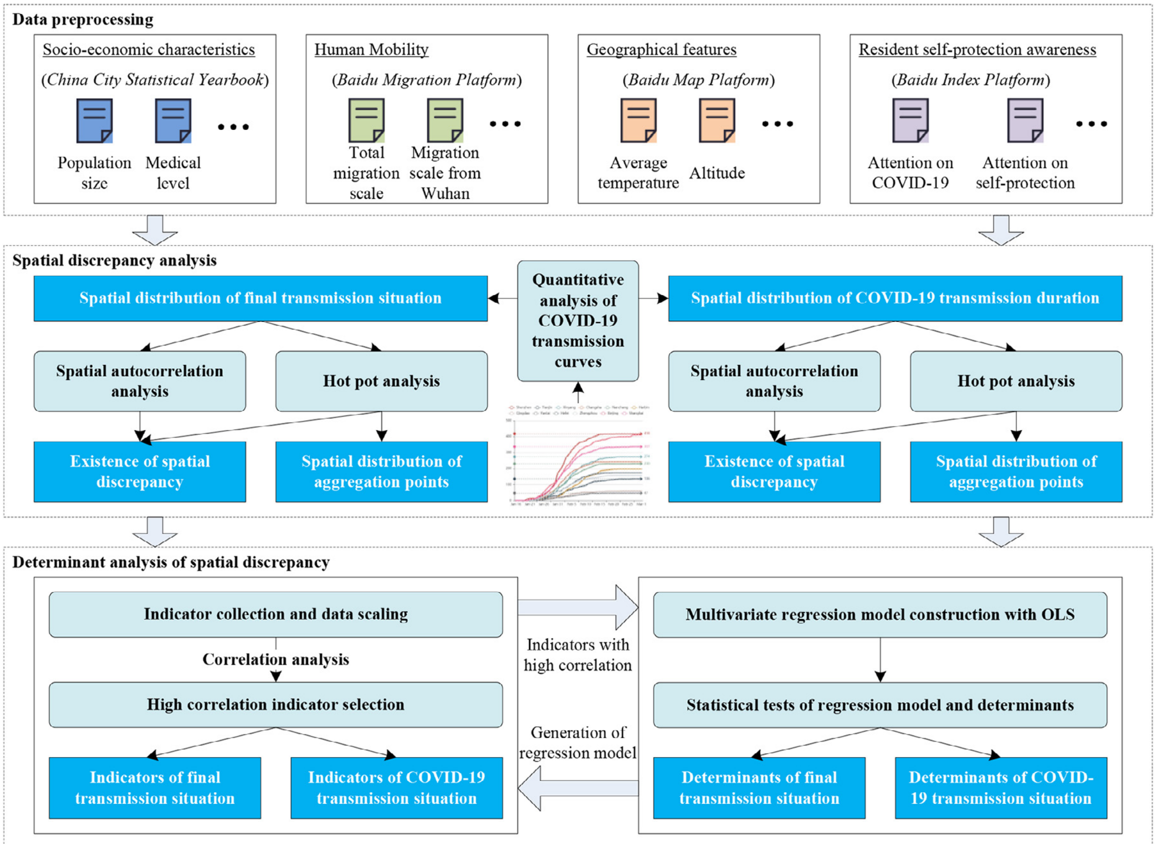

Fig. 1. The flow chart of spatial discrepancy analysis of COVID-19 transmission in China.

transmission was most significant when the temperature was between 8–10°C based on data from different provinces in China. Second, previous studies often measure COVID-19 transmission according to transmission consequence (eg, confirmed cases and deaths) (Rubino et al., 2020), lacking the analysis of transmission duration. Some epidemic dynamics models (Zhang et al., 2020; Tomar and Gupta, 2020) consider this by analyzing real-time transmission. However, most socioeconomic features (eg, population) are static but spatially different, which limits the effects of these models. Third, previous studies basically analyze COVID-19 transmission at a national or regional level (Tomar and Gupta, 2020; National Health Committee of the People's Republic of China, 2020) and only a few conducts city-wide analysis.

Considering the potential spatial discrepancy of COVID-19 transmission, this study analyzed the determinants of COVID-19 transmission based on the multisource spatial data of 315 Chinese cities to reach conclusions with higher generalizability. The flow chart of spatial discrepancy analysis of COVID-19 transmission is shown in Fig. 1.

2. Methods

2.1. Data sources

A total of 315 cities were analyzed in this study, including 30 provincial cities, 267 prefecture-level cities and 18 county-level cities. Hubei province was excluded as it was the epidemic center and its lockdown polices are different from other provinces. According to the China city statistical yearbook (National Health Committee of the People's Republic of China, 2020), by 2018, Chinese mainland had 31 provincial cities and 280 prefecture-level cities. The sample generally covered the cities in mainland China, and, therefore, can be used to analyze coronavirus transmission across different cities. Some cities were excluded mainly owing to the incompleteness of relevant data. The spatial distribution of the selected cities is shown in Fig. 2.

A total of 6 types of spatial data were included in this study with the time period from January 20, 2020 to March 1, 2020.

(1) Socioeconomic characteristics. Common socioeconomic characteristics such as population size, industrial development level, and medical level were derived from China city statistical yearbook (National Bureau of Statistics of China, 2020).
(2) Geographical features. Distance to Wuhan, average temperature, and average altitude were used to analyze the effects of geographical factors on coronavirus transmission. Among them, distance to Wuhan was obtained with the application programming interface (API) provided by Baidu Map platform. Average temperature and altitude were generated with Baidu Search platform.
(3) Human mobility data. Human mobility data included total migration scale, migration scale from Wuhan, and travel intensity within the city, which were all derived from Baidu Migration platform (Baidu, 2020). Specifically, these travel and migration data were generated by analyzing the mobile phone location data after authorization.
(4) Public health measures. The lockdown speed (measured by the number of days before the lockdown) and the lockdown strength (measured by the level of city emergency response) were considered in this paper. These data were obtained from the official websites of the sample cities. It should be noted that the emergency response in China was divided into 3 levels, and public health measures in the same level were similar. To

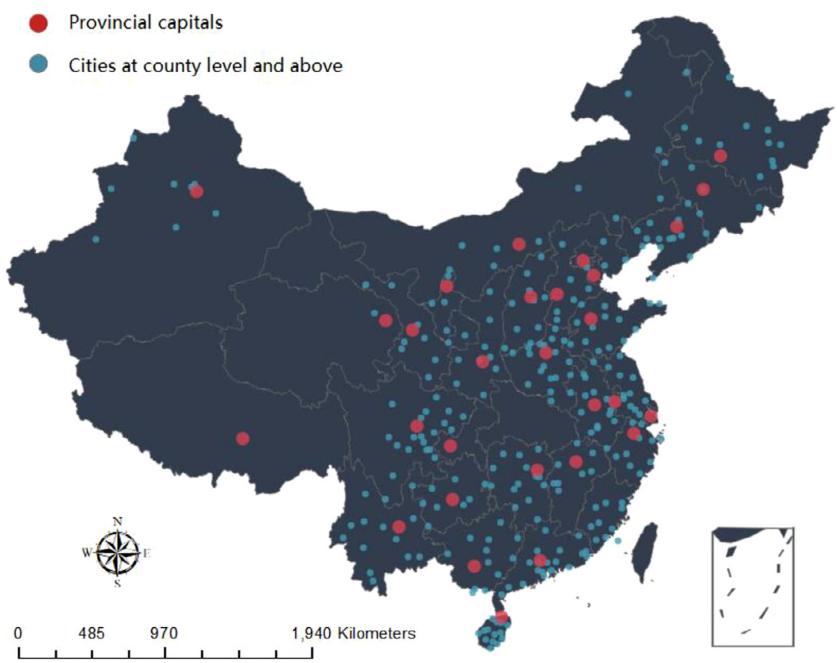

Fig. 2. Spatial distribution of the selected cities in this study.

simplify the analysis, lockdown strength was adopted to replace the various public health measures.

(5) Data about self-protection awareness. Residents' self-protection awareness was assessed according to the web search volume of COVID-19-related keywords. Search data were obtained through Baidu Index platform (Baidu, 2020).

(6) COVID-19 transmission data, including the number of cumulative cases and transmission duration (measured by the time from the first to last case within the city). These 2 data items were calculated according to the number of daily confirmed cases, which was obtained from the website of the National Health Committee of China. This paper selected the time interval from January 20, 2020 to March 1, 2020 for data analysis of coronavirus transmission. This is because the first confirmed case in mainland China (except Hubei province) was reported on January 20, 2020 and the cumulative cases in mainland China have generally not increased after March 1, 2020.

2.2. Spatial discrepancy analysis of COVID-19 transmission in China

2.2.1. Quantitative analysis of COVID-19 transmission curves

To understand the existence of the spatial discrepancy of COVID-19 transmission, the quantitative features for describing COVID-19 transmission curves of different cities were needed. The transmission curves of the typical cities (that cover the earliest start and latest finish) are shown in Fig. 3 and the start and end dates for each city were listed in Table 1. As shown in Fig. 3, the discrepancies of coronavirus transmission were mainly reflected in 2 aspects (ie, transmission consequence and transmission duration).

(1) Transmission consequence. The quantitative indicators of transmission consequence include number of cumulative cases, deaths, cured cases, and so on. Among these indicators, the number of cumulative cases is the one that can directly reflect COVID-19 transmission and is most commonly used (Chintalapudi et al., 2020; Ahmar and del Val, 2020). This paper measures transmission consequence according to the number of cumulative cases.

(2) Transmission duration. Transmission duration in this paper starts when the first confirmed case is reported and ends when cumulative cases have not increased. Shorter time of transmission illustrates that these cities can achieve epidemic control quickly and avoid further transmission and more serious consequence (Zhang et al., 2020; Tomar and Gupta, 2020; Guliyev, 2020).

2.2.2. Spatial discrepancy analysis

To analyze spatial discrepancy, the spatial pattern of COVID-19 transmission needs to be generated. In spatial statistical analysis, spatial pattern refers to the spatial distribution of aggregation points (where cities were grouped according to specific indicators, that is the number cumulative cases and transmission duration in this paper) and the overall aggregation degree. In this paper, the spatial pattern of transmission was generated using the spatial statistical function in ArcGIS software. Specifically, the overall aggregation degree was measured with spatial autocorrelation function (which is also called Global Moran's function) and the distribution of aggregation points were generated using the hot pot analysis function.

2.3. Indicators for interpreting spatial discrepancy

To figure out the spatial discrepancy determinants of COVID-19 transmission, based on previous research on the socioeconomic factors of epidemic transmission (Simonsen et al., 2008; Gasparni et al., 2012; Stojkoski et al., 2020), this paper established a relatively comprehensive indicator framework accounting for other aspects of indicators (ie, geographical features) (Kang et al., 2020; Zheng et al., 2020; Hu et al., 2012), human mobility (Chen et al., 2020; Kong et al., 2020; Feng et al., 2020), public health measures, and residents' self-protection awareness. The framework involves 16 quantitative indicators that are shown in Table 2.

2.4. Regression analysis for interpreting spatial discrepancy

The multivariate regression models between selected indicators and COVID-19 transmission (including transmission consequence

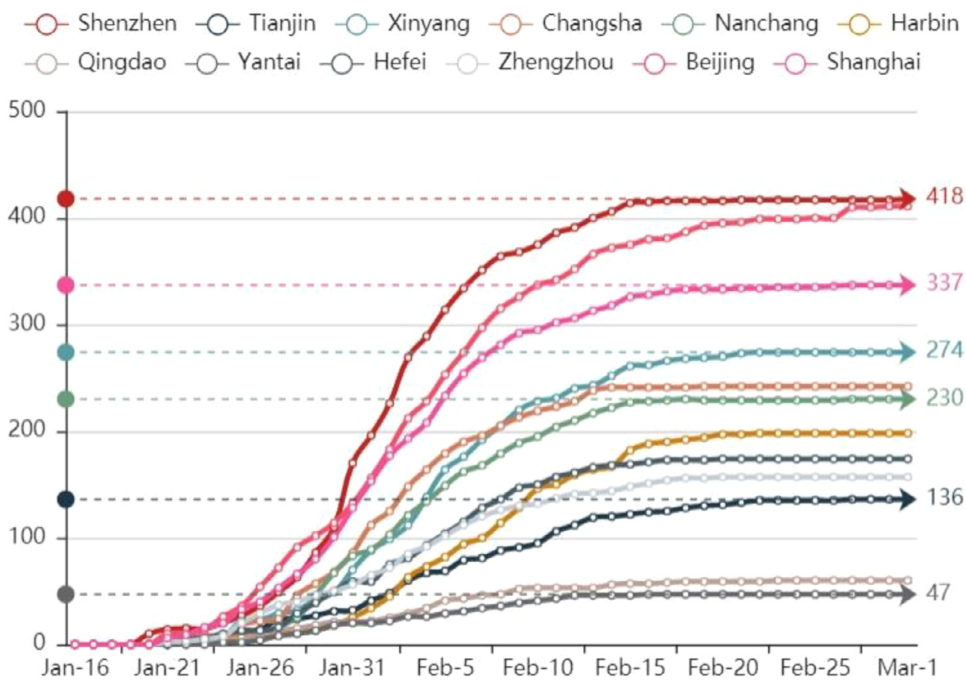

Fig. 3. Comparison of the COVID-19 development curves of different cities. Vertical axis represents the number of cumulative cases.

Table 1
The key figures of transmission for typical cities (listed in Fig. 3).

City name	Cumulative cases (Mar-1)	Start date	End date	Duration (days)
Shenzhen	418	Jan-20	Mar-1	42
Tianjin	136	Jan-21	Feb-27	39
Xinyang	274	Jan-23	Feb-22	34
Changsha	242	Jan-21	Feb-19	31
Nanchang	230	Jan-22	Feb-27	39
Harbin	198	Jan-22	Feb-22	34
Qingdao	60	Jan-21	Feb-22	34
Yantai	47	Jan-24	Feb-16	28
Hefei	174	Jan-22	Feb-20	32
Zhengzhou	157	Jan-21	Feb-20	32
Beijing	413	Jan-21	Mar-1	42
Shanghai	337	Jan-21	Feb-27	39

and transmission duration) were constructed with ordinary least squares (OLS) to provide evidence for interpreting the spatial discrepancy. Coefficient of determination (R^2), p-value of analysis of variance (ANOVA), and variance inflation factor (VIF) were used to evaluate the effect of the regression models (Vu et al., 2015). VIF was used to explain the multicollinearity between explanative variables (Chen et al., 2022). When VIF exceeds 10, there is strong correlation between explanative variables, and the multicollinearity needs to be reduced.

3. Results

3.1. Spatial discrepancy of COVID-19 transmission

3.1.1. Spatial discrepancy of transmission consequence

The spatial distribution of the final cumulative cases is shown in Fig. 4 (A). Spatial statistical results show that there was significant spatial aggregation of final cumulative cases with z-score = 3.935. In addition, Moran index was 0.121, which denotes a positive spatial aggregation. The spatial distribution of the aggregation points is shown in Fig. 4 (B). The results of hot pot analysis showed that there was a total of 8 HH-type aggregation points. The cities within same aggregation points had similar and high cumulative cases. Besides, these aggregation points were diversely distributed around Hubei province, which illustrates that spatial discrepancy still existed.

3.1.2. Spatial discrepancy of COVID-19 transmission duration

The spatial distribution of COVID-19 transmission duration is shown in Fig. 5 (A). Spatial statistical results showed that there was significant spatial aggregation of transmission duration with z-score = 6.170. In addition, Moran index was 0.203, which denotes a positive spatial aggregation. The spatial distribution of the aggregation points is shown in Fig. 5 (B). Compared with final transmission duration, there were much fewer aggregation points of transmission duration (with only 2 major HH-type points). However, the average transmission duration of Shanghai point was 29 days and that of Guangzhou was 40 days. This result illustrated that the transmission duration of the 2 aggregation points was completely different. In addition, there was no aggregation point in other parts of mainland China. Therefore, there was still a significant spatial discrepancy of transmission duration.

3.2. Multivariate regression analysis results

3.2.1. Key indicator selection

The Pearson correlation coefficients of each indicator and COVID-19 transmission was calculated and the p-value was gen-

Table 2
The indicators used in this study and corresponding explanations.

Indicator type	Indicator	Statistical item	Index
Common socioeconomic characteristics	Population size	Registered population at year end	X_1
	Population density	Population density	X_2
	Aging population	Registered aging population at year end	X_3
	Per capita GRP	Per capita GRP	X_4
	Consumption volume	The retail sales of consumer goods divided by population size	X_5
	Industrial development level	Number of industrial enterprises	X_6
	Education level	The number of students enrollment divided by population size	X_7
	Medical level	The number of hospitals divided by population size	X_8
Geographical factors	Distance to Wuhan	Distance from the city to Wuhan	X_9
	Altitude	Average altitude	X_{10}
	Average temperature	Average temperature during COVID-19	X_{11}
Human movement	Total migration scale	The average ratio of migrated population to the total population (in 20 days before COVID-19 outbreak)	X_{12}
	Migration scale from Wuhan	The average ratio of migrated population from Wuhan to the total population (in 20 days before COVID-19 outbreak)	X_{13}
	Travel intensity within city	The average ratio of traveled population to the total population (in 20 days before COVID-19 outbreak)	X_{14}
Public health measures	Lockdown speed	The number of days before the lockdown	X_{15}
	Lockdown strength	The level of COVID-19 emergency response	X_{16}
Resident self-protection awareness	Attention on COVID-19	Average Baidu Index of 'COVID-19' and related keywords	X_{17}
	Attention on self-protection	Average Baidu Index of 'Prevention', 'Measures' and other related keywords	X_{18}
COVID-19 development	Final COVID-19 situation	Number of final confirmed cases	Y_1
	Transmission duration	Days to reach final COVID-19 situation	Y_2

GRP, gross regional product.

Table 3
Correlation analysis results. Y_1 represents transmission consequence, Y_2 represents transmission duration.

Indicator	Y_1	Y_2	Indicator	Y_1	Y_2
X_1 (Population size)	0.678**	0.386**	X_{10} (Altitude)	-0.195	-0.325**
X_2 (Population density)	0.111	0.120	X_{11} (Average temperature)	-0.196	-0.211
X_3 (Aging population)	0.125	0.115	X_{12} (Total migration scale)	0.713**	0.574**
X_4 (Per capita GRP)	0.203	0.209	X_{13} (Migration scale from Wuhan)	0.806**	0.424**
X_5 (Consumption volume)	0.719**	0.534**	X_{14} (Travel intensity within city)	-0.173	0.423**
X_6 (Industrial development level)	0.596**	0.529**	X_{15} (Lockdown speed)	0.261	0.482**
X_7 (Education level)	0.629**	0.424**	X_{16} (Lockdown strength)	-0.084	-0.136
X_8 (Medical level)	0.459**	0.205	X_{17} (Attention on COVID-19)	-0.595**	-0.377**
X_9 (Distance to Wuhan)	-0.240**	-0.250**	X_{18} (Attention on self-protection)	-0.527**	-0.328**

*$p < 0.1$, **$p < 0.05$
GRP, gross regional product.

erated with the correlation analysis in SPSS software. The results were shown in Table 3. Finally, 10 indicators were selected for interpreting the spatial discrepancy of transmission consequence. At the same time, 12 indicators were selected for interpreting the spatial discrepancy of transmission duration.

3.2.2. Determinants of transmission consequence

Stepwise regression was used to establish the regression model (as noted in Table 4). Model 6 was finally selected for interpreting the transmission consequence of COVID-19. The results showed that the migration scale from Wuhan had the greatest effect on transmission consequence, which illustrated that the timely lockdown of the epidemic center was effective in reducing final cumulative cases. The effects of socioeconomic factors ranked the second, which are all relevant to the aggregation degree of population (Yezli and Khan, 2020). Residents' understanding on COVID-19 proved to produce certain influence on transmission situation. In addition, this result explained that the search index can reflect residents' awareness to a certain degree. The effects of geographical factors were not significant, which did not mean that the factors had no effect, but that there may be a more complex relationship.

3.2.3. Determinants of COVID-19 transmission duration

Stepwise regression was used to establish the regression model (as noted in Table 4). Model 7 was finally selected for interpreting COVID-19 transmission duration. It can be seen in the results that, apart from typical human movement and socioeconomic factors, timely implementation of lockdown measures (eg, travel control, social distancing, and crowd place management) played an important role in shortening the transmission duration. These effects were not strong, partly because all the provinces and cities in China have initiated the highest lockdown level only within 6 days

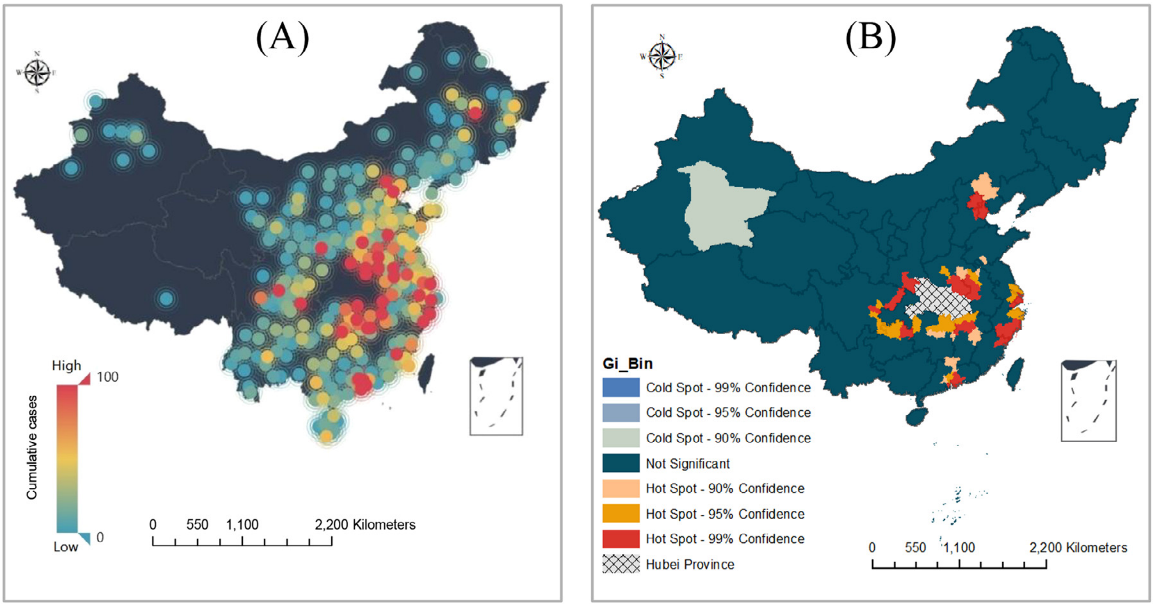

Fig. 4. Spatial autocorrelation results of transmission consequence. Transmission consequence was measured by the number of cumulative cases. (A) is the spatial distribution of final cumulative cases. (B) is the spatial distribution of aggregation points.

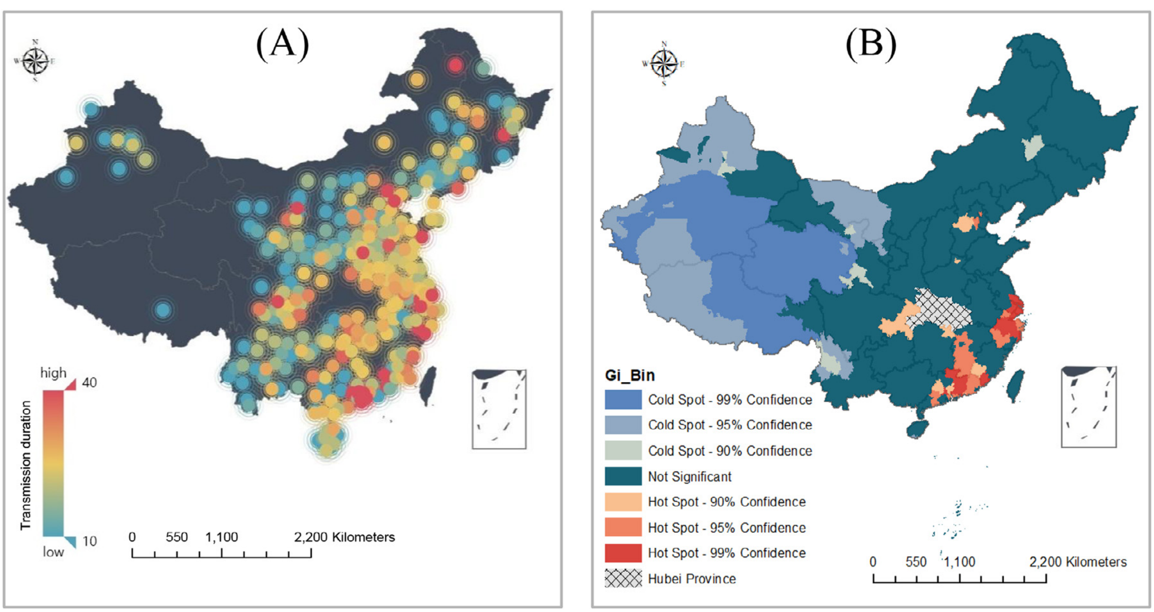

Fig. 5. Spatial autocorrelation results of COVID-19 transmission duration. COVID-19 transmission duration was measured by the days from the first to last case within the city. (A) is the spatial distribution of COVID-19 transmission duration. (B) is the spatial distribution of aggregation points generated by hot pot analysis.

Table 4
Multivariate regression model of transmission consequence.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
X_{13} (migration scale from Wuhan)	0.806***	0.590***	0.595***	0.579***	0.582***	0.569***
X_5 (consumption volume)		0.320***	0.509***	0.407***	0.210**	0.205**
X_{16} (attention on COVID-19)			-0.218***	-0.231***	-0.202**	-0.192**
X_1 (population size)				0.149**	0.169***	0.157***
X_6 (industrial development level)					0.129**	0.128**
X_7 (education level)						0.104**
R^2	0.574[a]	0.599[b]	0.659[c]	0.711[d]	0.782[e]	0.801[f]
ANOVA p-value	0.000	0.000	0.000	0.000	0.000	0.000

*p-value < 0.1, **p-value < 0.05, ***p-value < 0.01
ANOVA, analysis of variance.

Table 5
Multivariate regression model of COVID-19 transmission duration.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
X_{12} (total migration scale)	0.574***	0.347***	0.288***	0.279***	0.272***	0.265***	0.251***
X_{15} (lockdown initiation time)		0.286***	0.243***	0.236***	0.229***	0.212***	0.208***
X_6 (industrial development level)			0.162***	0.158***	0.147**	0.133**	0.124**
X_5 (consumption volume)				0.123**	0.118**	0.116**	0.112*
X_{16} (attention on COVID-19)					-0.102**	-0.105**	-0.101**
X_{14} (travel intensity within city)						0.092*	0.087*
X_{10} (altitude)							-0.081*
R^2	0.521[a]	0.663[b]	0.679[c]	0.701[d]	0.718[e]	0.722[f]	0.739[g]
ANOVA p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*p-value $<$ 0.1, **p-value $<$ 0.05, ***p-value $<$ 0.01
ANOVA, analysis of variance.

after the outbreak. Moreover, residents' high attention on COVID-19 was found to facilitate rapid coronavirus control. This is partly due to the positive effects of infection risk communication and daily public health education. In addition, altitude was proven to have a certain effect on transmission duration, which can be explained from a number of aspects such as travel demand and temperature. For example, the Chinese cities with high altitudes are generally underdeveloped and have low temperature, and, therefore, the low travel demand in those cities may be in favor of effective transmission control.

4. Discussion

4.1. Implications

First, this paper analyzed the spatial discrepancy of COVID-19 transmission based on data from 315 Chinese cities and then proposed the determinants of coronavirus with relatively high generalizability. The generalizability of COVID-19 determinants has gained more and more attention. Recently, Fronza et al (2020) studied the dynamics of COVID-19 infection on the basis of spatial data from Italy, Spain, Germany, and France and concluded that atmospheric air pollutants can serve as surrogate markers to complement COVID-19 outbreaks. Compared with the conclusions obtained from specific regions, such conclusions have high generalizability and are more helpful in making decisions. Second, this study proposed a comprehensive indicator framework for interpreting COVID-19 transmission. Third, this study comprehensively measured COVID-19 transmission on 2 dimensions (ie, transmission consequence and transmission duration).

4.2. Limitations

First, this paper lacks detailed analysis of different public health measures. In this paper, the public health measures were roughly analyses according to the strength and speed of city lockdown, although the lockdown in Chinese cities covers similar measures such as social distancing and travel control. The detailed analysis was limited to data availability of emergency responses. Future studies should focus on the effects of different measures. Secondly, this study only analyzed the linear relationships between coronavirus transmission and the indicators, lacking the nonlinear analysis of the relationships. In the follow-up studies, the nonlinear relationships will be further explored. Third, the mention on social media of individual words such as "covid" or "prevention" may not necessarily mean that the writer of the message feels that protection is necessary. This problem could be addressed by using meaningful phrases which indicate concern.

5. Conclusion

Both the transmission consequence and transmission duration of COVID-19 were mostly affected by human mobility factors (ie, the migration scale from Wuhan, total migration scale and travel intensity within city), showing that the timely reduction of migration and travel within cities was effective for controlling COVID-19 transmission. For transmission control, the speed of city lockdown could significantly reduce the transmission duration. Moreover, the residents' attention on COVID-19 was proven to be not only helpful in reducing transmission consequence, but also effective in achieving rapid transmission control. In addition, high-altitude cities may have shorter transmission duration partly because of the lower travel demand, which deserves further studies.

Conflict of Interest

None.

Acknowledgements

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Ethical Approval statement

Not applicable.

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