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A Study of COVID-19 in the Wuhan, Beijing, Urumqi and Dalian Cities based on the Regional Disease Vulnerability Index

Zekun Gao,1 Yutong Jiang,1 Junyu He,1 Jiaping Wu,1 Jian Xu,3 and George Christakos1,*

1 Ocean college, Zhejiang University, Zhoushan, 316021, China
2 Ocean Academy, Zhejiang University, Zhoushan, 316021, China
3 Department of Geography, San Diego State University, California, 92182, USA; gchrista@sdsu.edu
* Corresponding author: gchrista@sdsu.edu

Abstract:

Background
Since the COVID-19 outbreak, four cities -- Wuhan, Beijing, Urumqi and Dalian -- have experienced the process from outbreak to stabilization. Geographic location, population density, population mobility and epidemic prevention measures show relatively large differences among the four regions of interest, providing the possibility to use these regional conventional attributes and pathological infectious disease attributes to assess the risk of an infectious disease outbreak in an area.

Methods
According to the China Statistical Yearbook and China Center for Disease Control records, regional, pathological, medical and response attributes were selected as regional vulnerability factors of infectious diseases. Then the Analytic Hierarchy Process
(AHP) method was used to build a regional vulnerability index model for the infectious disease.

**Results**

The influence of the COVID-19 outbreak at a certain place was assessed computationally in terms of the number of days of epidemic duration and cumulative number of infections, and then fitted to the city data. The resulting correlation coefficient was 0.999952. The range of the regional vulnerability index for COVID-19 virus was from 0.0513 to 0.9379. The vulnerability indexes of Wuhan, Urumqi, Beijing and Dalian were 0.8733, 0.1951, 0.1566 and 0.1119, respectively.

**Conclusions**

The lack of understanding of the virus became the biggest breakthrough point for the rapid spread of the virus in Wuhan. Due to inadequate prevention and control measures, the city of Urumqi was unable to trace the source of infection and close contacts, resulting in a relatively large impact. Beijing has both high population density and migration rate, which imply that the disease outbreak in this city had a great impact. Dalian has perfect prevention and good regional attributes. In addition, the regional vulnerability index model was used to analyze other Chinese cities. Accordingly, the regional vulnerability index and the prevention and control suggestions for them were discussed.

*Key words: COVID-19; AHP; Regional Disease Vulnerability Index; Correlation Coefficient*
1. Introduction

As is well known, the COVID-19 epidemic first broke out in Wuhan, China, on December 12, 2019. Due to the highly infectious nature of COVID-19 and its occurrence during the time of the traditional Chinese festival during which the country experiences a huge passenger volume, the new crown pneumonia swept all Chinese provinces in less than a month, and then spread worldwide\(^1\). There is no doubt that the COVID-19 poses a huge threat to human health all over the world, and it has also caused serious damage to the world economic situation\(^2\).

Epidemic prediction models play a very important role in the prevention and control of infectious diseases. The most commonly used model is the susceptible-infected (SI) model and other variations derived from it\(^3,4\). Among them, the susceptible-exposed-infected-removed (SEIR) model currently performs best in the case of COVID-19\(^5\). The approach of inferring long-term trends from short-term results is mathematically simple and effective under certain conditions. However, since it needs to use short-term data that are available after the outbreak, it can neither provide early warnings of a disease that has not yet occurred, nor analyze specifically the weak links in disease prevention and control to offer targeted prevention suggestions. Therefore, this work uses regional conventional attributes together with pathological infectious disease attributes to assess the risk of an infectious disease outbreak in a region. Following risk assessment, the goal of the work is threefold: (a) to analyze the region’s vulnerability factors related to the disease in order to prevent its spread in advance, (b) to identify the potential weaknesses of epidemic prevention, and (c) to make comprehensive
recommendations that can help optimize infectious disease prevention and control.

The cities of Wuhan, Beijing, Dalian and Urumqi went through the process leading from outbreak to stabilization (i.e., when no new cases were reported in the city during the 14-day incubation period). In addition to the pathological properties of the disease itself, previous research has shown that factors such as geographic location, population density, population mobility and epidemic prevention measures can, indeed, impact the development of the epidemic. In fact, these factors exhibit relatively large differences in the four regions of interest.

In section 2 the study regions and data sources are described, followed by an outline of the proposed study methodology. In section 3, the study conclusions are discussed. Section 4 outlines the pros and cons of the proposed vulnerability model, and offers suggestions for the prevention and control of COVID-19 based on the vulnerability modeling results obtained. Lastly, section 5 provides a brief study summary.

2. Methods

2.1 Study regions and data sources

The four research regions considered in this work are Beijing, Wuhan, Urumqi and Dalian.

The epidemic data are all from the bulletin of the Chinese health commission and the health commissions of all provinces in China. The basic regional information data, on the other hand, are all obtained from the statistical yearbook published by the National Bureau of Statistics and the provincial administrative regions of China.
2.2 Study Method

The study method followed in the present COVID-19 work consisted of four main parts:

(a) All variables considered in the modeling of the regional vulnerability to the infectious disease were rigorously defined.

(b) Factor analysis was used to analyze the level of regional higher education.

(c) The AHP method was used to construct the importance matrix of the regional disease vulnerability factors and the associated influencing variables.

(d) The regional disease vulnerability index was computed based on the influencing factors of the regional vulnerability and their variables considered in step b above.

(e) A regression analysis of the vulnerability models was used for model optimization purposes.
2.3 Variables of the regional disease vulnerability model

The variables considered in the present study were divided into four groups: regional attribute variables, pathological attribute variables, medical attribute variables and response attribute variables. In addition, outbreak attribute variables for the infectious disease were also included. The detailed definitions of these variables are shown in Table 1.

| Attribute | Symbol | Designation                          | Unit                               | Definition                                                                 |
|-----------|--------|--------------------------------------|------------------------------------|---------------------------------------------------------------------------|
| GDP       | GDP    | Gross domestic product               | Hundred million                    | Annual GDP of the region                                                  |
| PD        | PD     | Population density                  | People per square kilometer        | Population density of the area at the end of the year                     |
| PRP       | PRP    | Permanent resident population        | Thousands of people                | Number of permanent residents at the end of the year                      |
| City      | RP     | Registered population                | Thousands of people                | Number of registered population at the end of the year                    |
|           | RPK    | Passengers-kilometers               | Million passengers-kilometer       | Total passenger turnover at the end of the year                           |
|           | SCH    | Number of universities above junior college | /                                 | Number of the universities above junior college in the region at the end of the year |
| STU | Number of students with a college degree or above | Number of the students with a college degree or above in the region at the end of the year |
|-----|--------------------------------------------------|----------------------------------------------------------------------------------------|
| EIH | Enrollment of institutions of higher learning    | Number of regional colleges and universities at the end of the year                    |
| R0  | Number of basic infections                       | Average number of people transmitted by a person infected in the absence of intervention |
| IP  | Incubation period (Day)                          | The longest period during which a pathogenic irritant invades or acts on the organism until the organism reacts or begins to exhibit symptoms |
| MI  | Number of medical institutions                    | Number of institutions in a region with license to provide medical services, public health services or to engage in medical research an on-the-job training for the community at the end of a certain year |
| BED | Number of medical beds                           | Number of medical beds                                                                  |
2.4 Construction of the AHP matrix and calculation of the vulnerability factor weight

### 2.4.1 AHP modeling

| Symbol | Description                                                                 | Units       |
|--------|-----------------------------------------------------------------------------|-------------|
| MS     | Number of medical employees /                                               |             |
| MEA    | Level of measures                                                          | [0,1]       |
| UND    | Knowledge                                                                  | [0,1]       |
| DAY    | Outbreak duration                                                          | Day        |
| NUMBER | Cumulative number of infected persons /                                    |             |

- **MS (Number of medical employees)**: Number of medical employees working in hospitals, primary medical and health institutions, professional public health institutions and other medical and health institutions in a certain region at the end of a certain year.
- **MEA (Level of measures)**: Level of protective measures against infectious diseases.
- **UND (Knowledge)**: Knowledge of infectious diseases.
- **DAY (Outbreak duration)**: Number of days from an outbreak of an infectious disease to a steady state.
- **NUMBER (Cumulative number of infected persons)**: The cumulative number of infections caused by the outbreak of infectious diseases.
The Analytic Hierarchy Process (AHP) method\textsuperscript{32} is a multi-objective decision scheme that is widely used in many fields and can be organically combined with many other methods.

In the present work, the hierarchical model is constructed according to the AHP method in terms of the attributes described above.

The dynamic population (MP) is computed as the difference

\[
MP = PRP - RP
\]

where the PRP and RP are the CITY variables defined in Table 1.

Population quality (PQ) was calculated by SCH, STU and EIH. These three figures have been proven to represent more than 90% of educational development in a region\textsuperscript{34}. The score model of three common factors can be obtained by using factor rotation method by SPSS statistics\textsuperscript{35}. The specific formula is shown in Equation (2) as follows,

\[
\begin{align*}
SCH &= 0.258 \times F1 - 0.017 \times F2 - 0.105 \times F3 \\
EIH &= 0.247 \times F1 - 0.04 \times F2 + 0.021 \times F3 \\
STU &= 0.253 \times F1 - 0.031 \times F2 - 0.007 \times F3 \\
PQ &= F4 = (0.5671 \times F1 + 0.3213 \times F2 + 0.0811 \times F3) / 0.9695
\end{align*}
\]

(F1: the scale of higher education ; F2 : the financial support of higher education ; F3 : the structure factor of higher education)

The R0 value in the same region will change as the epidemic develops and the local prevention and control measures are implemented, accordingly\textsuperscript{35-38}. Hence, the present work refers mainly to the data provided by WHO when a relevant decision needs to be made. Based on previous studies, the temporary R0 value was set to 2.5.
Regarding the regional medical capacity factor, and taking the current situation in China as a reference, the medical capacity of most regions is sufficiently strong in the case of no emergency. Therefore, the medical attribute parameter is associated with the UND value in this model. The medical attribute parameter is considered only when the UND value is less than 1. When the UND value is equal to 1, that is, when the infectious disease is fully understood, the influence of the medical attribute parameter will not be considered.

2.4.2 Judgment matrix of the importance degree.

According to the regional disease vulnerability index model proposed above, the comparative matrix of importance of various elements can be constructed by combining literature research, expert opinion and comprehensive analysis. The assignment method adopts the standard Saaty nine-level scaling method.33

After a comprehensive consideration of all relevant factors, the regional vulnerability index matrix of infectious diseases is shown in Table 2.

Table 2: Judgment matrix of vulnerability factors.

|       | CITY | R0  | IP  | MEA | MED | UND |
|-------|------|-----|-----|-----|-----|-----|
| CITY  | 1    | 3   | 3   | 1/7 | 5   | 1/7 |
| R0    | 1/3  | 1   | 1   | 1/8 | 4   | 1/8 |
| IP    | 1/3  | 1   | 1   | 1/8 | 4   | 1/8 |
| MEA   | 7    | 8   | 8   | 1   | 9   | 1   |
2.4.3 Attribute element weights

After calculating the eigenvectors of the judgment matrix for each importance degree, the weight values of each element in the calculation of the risk coefficient can be obtained as shown in Table 3.

**Table 3: Weight of each Factor**

| Target Layer | the Weight of the Factor Layer to the Target Layer | the Indicator Layer | the Weight of the Indicator Layer to the Target Layer | Rank |
|--------------|---------------------------------------------------|---------------------|------------------------------------------------------|------|
| GDP          | x11=0.00629964                                    |                     |                                                      | 8    |
| PD           | x12=0.0498636                                     |                     |                                                      | 3    |
| CITY x1=0.1026 |                                                 |                     |                                                      | 4    |
| MP           | x13=0.0235467                                     |                     |                                                      | 5    |
| RPK          | x14=0.01731888                                    |                     |                                                      | 2    |
| PQ           | x15=0.00558144                                    |                     |                                                      | 2    |
| MEA x4=0.379 |                                                   |                     |                                                      | 1    |
2.4.4 Vulnerability index and model optimization.

Since the ranges of the attribute values are different, the corresponding functions are used to normalize each attribute value and then sum them up, so that the calculated city attribute value (YCITY) is given by

\[
YCITY = (X_{11} \times GDP + X_{12} \times PD + X_{13} \times MP + X_{14} \times PRK + X_{15} \times \frac{2}{P_i} \tan^{-1}(PQ))
\]  

where the weights are given in Table 3.

The medical attribute factor value (YMED) is obtained by multiplying the medical attribute parameter values in Table 1 by the weights of the medical attribute parameter values in Table 3, i.e.,

\[
YMED = x61 \times MO + x62 \times BED + x63 \times MS
\]  

After all the vulnerability attribute factors were determined, the overall regional vulnerability index was obtained.

\[
Y = X1 \times \frac{2}{P_i} \times \tan^{-1}(YCITY) + X2 \times \left(\frac{2}{P_i} \times \tan^{-1}(R0) +
\right.
\]
\[
X3 \times \left(\frac{2}{P_i} \times \tan^{-1}(IP) + X4 \times MEA +
\right.
\]
\[
X5 \times \left(\frac{2}{P_i} \times \tan^{-1}(YMED) + X6 \times UND
\right)
\]
For illustration, in the case of an UND value equal to 1, the vulnerability index value is calculated by

\[ Y = X_1 \left( \frac{2}{P_i} \right) \tan^{-1}(YCITY) + X_2 \left( \frac{2}{P_i} \right) \tan^{-1}(R0) + X_3 \left( \frac{2}{P_i} \right) \tan^{-1}(IP) + X_4 \times MEA + X_6 \times UND \]  

which is a special case of Eq (5).

3. Results

3.1 Model accuracy verification using epidemic data fitting

The number of confirmed cases and the duration of the epidemic were taken as independent variables, and the vulnerability indexes of the four cities (calculated according to the above formula) were taken as dependent variables for regression analysis purposes.

See Table 4 for details.

| Table 4: Details about the Vulnerable Index of the four cities. |
|---------------------------------------------------------------|
|                  | Beijing | Wuhan | Dalian | Urumqi |
| Vulnerable Index  | 0.1566  | 0.8733 | 0.1119 | 0.1951 |
| DAY              | 25      | 182    | 15     | 31     |
| NUMBER           | 335     | 81260  | 93     | 826    |

Regression Analysis

|                        | Multiple R | R Square | Adjusted R Square | Standard Error |
|------------------------|-------------|----------|-------------------|----------------|
| df                     | 2           | 55       | MS                | F              |
| X1 \left( \frac{2}{pi} \right) \times [1/\tan(YCITY)] | 0.0718     | 0.0539   | 0.0271            | 0.0193         |
| X2 \left( \frac{2}{pi} \right) \times [1/\tan(R0)]    | 0.0429     | 0.0429   | 0.0429            | 0.0429         |
According to the regression analysis (Table 4), there is a correlation between the calculated vulnerability index and the number and duration of the epidemic, so the vulnerability index can be used to distinguish the epidemic situation.

### 3.2 Vulnerability index scope and criteria

Taking into account the different virus attributes, the regional disease vulnerability model can be used to compute the value range of the disease vulnerability index. For example, for the COVID-19 virus the vulnerability index range is between 0.0513 and 0.9379.

The basic threshold range of the index can be divided into four levels: safe, which the range is from 0.0513 to 0.2729; mildly risk, when the range is from 0.2729 to 0.4946; severely risk, when the range is from 0.4946 to 0.7162; extremely risk, when the range is from 0.7162 to 0.9379.

### 3.3 Application of the vulnerability model in the four cities
Based on the above analysis, the vulnerability index of Beijing, Wuhan, Dalian and Urumqi as well as the scores of the various dependent vulnerability factors were calculated as shown in Table 4.

Being the outbreak source, Wuhan has suffered the greatest impact. A main reason why Wuhan suffered such a big impact is that before the COVID-19 outbreak at Wuhan, China and the entire World had no understanding of the virus, so no optimal measures could be taken at the time of the outbreak in terms of treatment or prevention. Also, it was because of the significant lack of response attribute factors that the vulnerable index of Wuhan at that time differed greatly from that of other cities (i.e., it was one order of magnitude higher than in other cities). In other words, if unprepared, the impact of the outbreak would be huge in any city, and surely at a much larger degree than in cities where an early warning happens to be available.

The second biggest impact occurred in Urumqi. The first case of COVID-19 occurred in Urumqi on July 16. After the epidemic outbreak, Urumqi adopted the strategy of closing down the city and restricting the movement of population in time, but source control was not carried out timely. It was not until July 23 that the outbreak source was grasped, but the best opportunity for optimal prevention and control tracking was missed. Therefore, the response attribute factor index was high, leading to a noticeable gap between Urumqi's vulnerability index and those of Beijing and Dalian.

A diagram comparing the regional properties of the four cities is shown in Table 4.

The impact of the epidemic in Beijing is higher than that in Dalian, which is reflected in
the comparison of the regional attributes. In Table 3, the population density, floating population and passenger turnover rank 3, 4 and 5 among the regional attribute factors, respectively. Beijing is at a significantly higher risk than Dalian in terms of these three indicators. Therefore, the Beijing risk coefficient is higher than that of Dalian assuming the same pathological and response attributes. This result was also confirmed during the development of the epidemic. Both the duration of the epidemic and the total number of infected people were lower in Dalian than in Beijing.

Overall, the analysis of the vulnerability index of COVID-19 outbreaks in the four cities -- Beijing, Wuhan, Dalian and Urumqi -- using the above model is basically accurate. In addition, the distribution of all influencing factors is reasonable, and the results are basically in line with expectations. To some extent, this indicates that the regional vulnerability model of infectious diseases proposed in this paper has a certain universality, which is of great significance for the promotion and application of the model.

3.4 Application of the vulnerability model in provincial-level administrative regions and prefecture-level cities in Zhejiang Province

According to the above formula, the vulnerability index to the COVID-19 virus is shown in Figure 2 assuming the same knowledge level and measures in each province.
The biggest characteristic of infectious diseases is that the more densely populated the region is, the more frequently people move and have contacts with each other, the higher the risk factor is. According to the previous analysis, among the regional attribute indicators, the importance of population density, the floating population and the passenger turnover are at the top. The top five and even seven provincial-level regions (Shanghai, Guangdong, Beijing, Henan, Tianjin, Jiangsu and Zhejiang) share the same socioeconomic characteristics. They are all developed municipalities directly under the central government, populous provinces, or coastal economically developed cities with a large number of migrant workers, trade contacts and even tourists, with the common characteristics of high population density. Accordingly, they have a higher floating population and tourist turnover. This view is also supported by the conditions at the five provinces at the bottom of the list. These provinces are characterized by a relatively low population density and a relatively small number of
migrants, thus reducing the risk of an infectious disease outbreak. The above findings assume that the same measures are taken. These regions are also prone to poor prevention arrangements due to their low vulnerability index.

According to the above formula, the risk factors for the COVID-19 outbreak in all prefecture-level cities in Zhejiang province are shown in Figure 3, with the same level of understanding and measures.

![Figure 3: the Predictive Vulnerable Index of each City in Zhejiang](image)

The top five Zhejiang prefecture-level cities in terms of the vulnerability index are Hangzhou, Ningbo, Wenzhou, Jiaxing and Taizhou. Among them, Ningbo city and Hangzhou city are the two highest developed cities in the Zhejiang Province, with high population
density and floating population. Wenzhou ranked third with higher passenger turnover than Hangzhou and Ningbo. Jiaxing, in fourth place, has the highest population density of any prefecture-level city in Zhejiang province. Finally, Taizhou is a prefecture-level city with relatively average indicators. From the comparison of these cities, it was found that developed cities generally have a higher number of floating population and passenger turnover, which will relatively increase the epidemic outbreak risk. Compared to other cities, transportation hub cities with special attributes or cities with developed trade will have prominent passenger turnover. Cities with a small regional area are more likely to have high population density, which is a factor leading to an increase of the regional vulnerability index.

4. Discussion

4.1 Advantages of the vulnerability model

The most important advantage of the regional disease vulnerability model is flexibility. This flexibility is concretely demonstrated in three respects, as follows.

The model can be easily adjusted to the scope of the study region. It is only necessary to specify the appropriate average variable to be combined with the regional data at the same level, and the vulnerability index assessment of the corresponding regional scope is obtained without the user modifying the model variables and fixed parameters.

Regional vulnerability index modeling does not involve the transmission factors of the epidemic itself. The model can assess the regional characteristics and preventive measures before an outbreak.
The model can use the control variable method to study the impact of the same virus outbreak in different regions, or the impact of different virus outbreaks in the same region, so as to comprehensively identify the weak links and problems that need attention concerning the epidemic prevention and control of each region. For example, depending on the known pathological properties of a virus and the regional properties of each region, the level of prevention measures can be adjusted to verify the extent to which the virus is circulating in that region when different prevention measures are taken. It is even possible to simulate the virus pathology during periods when there is no threat, and to test the impact of a sudden emergence of an infectious disease in an area.

4.2 COVID-19 prevention and control recommendations

In order to prevent COVID-19, detailed prevention and control measures should be formulated early. Among the factors affecting the regional disease vulnerability index, the response attribute factors are the most important. The three major measures for disease prevention and treatment (namely, controlling the source of infection, cutting off the route of transmission, and protecting vulnerable groups) can be artificially intervened. A very important part of prevention and control is to find the infection source in a timely manner, make a network of relationships immediately, isolate the close contacts, and prevent the emergence of super spreaders\textsuperscript{15-24}. In addition, wearing masks, banning crowd behavior and calling on people to isolate themselves at home are also important measures to prevent the spread of infectious diseases, which should be taken actively at the early stage of their spread\textsuperscript{18-21}. Depending on the extent of the epidemic, it is critical to have the flexibility of taking different levels of action. In addition, a very strong medical foundation is needed to
support scientific research on the new virus, the study of its pathological properties, the proposal of a simple and rapid diagnosis scheme, and the development of an effective vaccine. In sum, strengthening the medical and health care systems, as well as establishing a sound medical system, is a matter of life and death for any country.

Medical attribute factors are also very important. For example, in Wuhan, the worst hit city during the early stages of the COVID-19 outbreak, the lack of early medical personnel and facilities has been a major obstacle to effective disease prevention and control.

As for regional attribute factors, more attention should be paid to the characteristics of the region itself. For most developed cities, large population density, large number of migrants and high passenger turnover are quite normal phenomena. Naturally, a city should establish the best infectious disease prevention system for the case. Once an infectious disease risk is detected, a timely warning should be issued, so as greater losses are avoided. For some port and transportation hub cities, it carries a very large passenger volume. In this case, it is necessary to strengthen human surveillance in transport facilities such as railway stations and airports, to maintain sanitation in public areas and to minimize the possibility of foreign virus spread\textsuperscript{14-17}. Although the population density is lower in some sparsely populated cities, such cities also have weaker medical conditions and regulatory measures. In this kind of a city, people need to be increasingly conscious. Once there is any situation that requires people to report their concerns in a timely manner, the relevant departments should actively take relevant measures to prevent infectious disease spread.

5. Conclusions
Combined with knowledge obtained in relevant studies on infectious diseases available in the literature, the present study identified four types of vulnerability factors: regional, pathological, medical and response attribute factors. The AHP model can be used to analyze quantitatively the importance of various vulnerability factors. On this basis, a complete regional vulnerability model of infectious diseases could be developed. The model exhibited a good fit to in Beijing, Wuhan, Urumqi and Dalian data, and can be applied to study regional disease vulnerability factors in various regions.

However, as discussed above, the current vulnerability model still leaves plenty of room for improvement. For example, by extending the model in a space-time context, the combined spatio-temporal evolution of an epidemic could be predicted, which can make the results more specific and intuitive. For example, a region's vulnerability index can be combined with modern spatiotemporal geostatistics methods to make more informative predictions and judgments about the epidemic spread in that region\textsuperscript{39-40}.

Conflict of Interest:

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The work have no competing interests.

This study uses only public data and therefore the ethical approval was not required.
References

[1] Jia J, Lu X, Yuan Y et al. Population Flow Drives Spatio-temporal Distribution of COVID-19 in China. Nature 2020; 582(7812):1-11.

[2] Wale-Awe O I. The COVID-19 Pandemic Lockdown: Curtailing the Negative Economic Impacts. BizEcons Quarterly 2020; 8: 3-14

[3] Anderson R M, May R M. Population biology of infectious diseases: Part I. Nature 1979; 280(5721):361-367.

[4] May R M, Anderson R M. Population biology of infectious diseases: Part II. Nature 1979; 280:455-461

[5] He J, Chen G, Jiang Y et al. Comparative Infection Modeling and Control of COVID-19 Transmission Patterns in China, South Korea, Italy and Iran. Sci Total Environ 2020;747:141447-

[6] Xiong Y, Wang Y, Chen F et al. Spatial Statistics and Influencing Factors of the COVID-19 Epidemic at Both Prefecture and County Levels in Hubei Province, China. Int J Environ Res Public Health 2020;17(11):3903.

[7] Zhang C, Schwartz G. Spatial Disparities in Coronavirus Incidence and Mortality in the United States: An Ecological Analysis as of May 2020. J Rural Health 2020; 36(3).

[8] Desjardins M, Hohl A, Delmelle E. Rapid surveillance of COVID-19 in the United States using a prospective space-time scan statistic: Detecting and evaluating emerging clusters. Applied Geography 2020; 118.
[9] Liu K, Ai S, Song S et al. Population Movement, City Closure in Wuhan, and Geographical Expansion of the COVID-19 Infection in China in January 2020. Clin Infect Dis 2020;71(16):2045-2051.

[10] Zhang Y, Zhang A, Wang J. Exploring the roles of high-speed train, air and coach services in the spread of COVID-19 in China. Transp Policy (Oxf) 2020; 94:34-42.

[11] Wu H, Huang J, Zhang C et al. Facemask shortage and the novel coronavirus disease (COVID-19) outbreak: Reflections on public health measures. EClinicalMedicine 2020; 21:100329.

[12] Wells C, Fitzpatrick M, Sah P et al. Projecting the demand for ventilators at the peak of the COVID-19 outbreak in the USA. Lancet Infect Dis 2020;20(10):1123-1125.

[13] Moghadas S, Shoukat A, Fitzpatrick M et al. Projecting hospital utilization during the COVID-19 outbreaks in the United States. Proc Natl Acad Sci U S A 2020; 117(16):9122-9126.

[14] Tian H, Liu Y, Li Y et al. An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. Science 2020;368:638-642.

[15] Chinazzi M, Davis J, Ajelli M et al. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. Science 2020; 368(6489):395-400.

[16] Lai S, Ruktanonchai N, Zhou L et al. Effect of non-pharmaceutical interventions to contain COVID-19 in China. Nature 2020;585(7825):410-413.

[17] Linka K, Peirlinck M, Costabal F et al. Outbreak dynamics of COVID-19 in Europe and the effect of travel restrictions. Comput Methods Biomech Biomed Engin 2020;23(11):710-717.

[18] C R, MacIntyre et al. The First Randomized, Controlled Clinical Trial of Mask Use in Households to Prevent Respiratory Virus Transmission. Int J Infect Dis 2008;12:328
[19] Koo J, Cook A, Park M et al. Interventions to mitigate early spread of SARS-CoV-2 in Singapore: a modelling study. Lancet Infect Dis 2020; 20(6):678-688

[20] Fowler J, Hill S, Levin R Z et al. The Effect of Stay-at-Home Orders on COVID-19 Infections in the United States. Social ence Electronic Publishing.

[21] Zhang J, Litvinova M, Liang Y et al. Changes in contact patterns shape the dynamics of the COVID-19 outbreak in China. Science 2020; 368(6498):1481-1486.

[22] Lai S, Ruktanonchai N, Zhou L et al. Effect of non-pharmaceutical interventions to contain COVID-19 in China. Nature 2020;585(7825):410-413.

[23] Hellewell J, Abbott S, Gimma A et al. Feasibility of controlling COVID-19 outbreaks by isolation of cases and contacts. Lancet Glob Health 2020; 8(4):488-496.

[24] Ferretti L, Wymant C, Kendall M et al. Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. Science 2020, 368(6491)

[25] Li Q, Guan X, Wu P et al. Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus–Infected Pneumonia. N Engl J Med 2020;382(13)

[26] Huang C, Wang Y, Li X et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet 2020;395(10223).

[27] Riou J, Althaus C. Pattern of early human-to-human transmission of Wuhan 2019 novel coronavirus (2019-nCoV), December 2019 to January 2020. Euro Surveill 2020;25(4)

[28] Zhao S, Lin Qi, Ran J et al. Preliminary estimation of the basic reproduction number of novel coronavirus (2019-nCoV in China, from 2019 to 2020: A data-driven analysis in the early phase of the
outbreak. Int J Infect Dis 2020; 94:72-73.

[29] Ying S, Li F, Li Z. Spread and control of COVID-19 in China and their associations with population movement, public health emergency measures, and medical resources.

[30] Peng Z, Song W, Ding Z et al. Linking key intervention timings to rapid declining effective reproduction number to quantify lessons against COVID-19. Front Med 2020;14(5):623-629.

[31] Tian H, Liu Y, Li Y et al. An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. Science 2020;368(6491):638-642

[32] Saaty T L. Analytic hierarchy process. 2001.

[33] Yu H. An Empirical Study on the Regional Differences in the Level of Higher Education Development Based on SPSS Factor Analysis. Jiangsu Higher Education 2019;06:78-82

[34] Nie, Norman H. SPSS Statistical Package for the Social Sciences. Encyclopedia of Information Systems 2003;13(1):187-196.

[35] Yadav S, Yadav P, Kishore M et al. Basic Reproduction Rate and Case Fatality Rate of COVID-19: Application of Meta-analysis. Demography India 2020; 49(Special Issue):76-97.

[36] Zhao Y, Wang R, Li J et al. Analysis of the Transmissibility Change of 2019-Novel Coronavirus Pneumonia and Its Potential Factors in China from 2019 to 2020. Biomed Res Int 2020; 2020:1-7.

[37] Stedman M, Davies M, Lunt M et al. A phased approach to unlocking during the COVID pandemic – Lessons from trend analysis. Int J Clin Pract 2020;74(8)

[38] Peng Z, Song W, Ding Z et al. Linking key intervention timings to rapid declining effective reproduction number to quantify lessons against COVID-19. Front Med 2020;14(5):623-629
[39] Christakos G. A Bayesian/maximum-entropy view to the spatial estimation problem. Math Geosci 1990; 22:763–777

[40] Christakos G (2000) Modern spatiotemporal geostatistics. Oxford University Press, New York
Appendix

**Table 1:** Judgment matrix of the CITY attribute factors

|       | GDP | PD   | MP   | RPK  | PQ  |
|-------|-----|------|------|------|-----|
| GDP   | 1   | 1/5  | 1/4  | 1/4  | 1   |
| PD    | 5   | 1    | 4    | 3    | 8   |
| MP    | 4   | 1/4  | 1    | 2    | 5   |
| RPK   | 4   | 1/3  | 1/2  | 1    | 3   |
| PQ    | 1   | 1/8  | 1/5  | 1/3  | 1   |

**Table 2:** Judgment Matrix of Medical Attribute Factors

|       | MI  | BED | MS  |
|-------|-----|-----|-----|
| MI    | 1   | 4   | 1/6 |
| BED   | 1/4 | 1   | 1/3 |
| MS    | 6   | 3   | 1   |

**Table 3:** Regression analysis results.

Regression Analysis

Multiple R 0.999952
### Table 4: Predictive vulnerability index of each provincial administrative region in China.

| Area   | Vulnerable Index |
|--------|------------------|
| Anhui  | 0.1441           |
| Beijing| 0.1558           |
| Chongqing | 0.1273         |
| Fujian | 0.1225           |
| Gansu  | 0.1036           |
| Guangdong | 0.1627        |
| Guangxi | 0.1329          |
| Guizhou| 0.1356           |
| Hainan | 0.1079           |
| Hebei  | 0.133            |
| Province       | Value   |
|---------------|---------|
| Heilongjiang  | 0.104   |
| Henan         | 0.1557  |
| Hubei         | 0.1287  |
| Hunan         | 0.135   |
| Inner Mongolia| 0.0937  |
| Jiangsu       | 0.1472  |
| Jiangxi       | 0.1295  |
| Jilin         | 0.1025  |
| Liaoning      | 0.1243  |
| Ningxia       | 0.0924  |
| Qinghai       | 0.0861  |
| Shandong      | 0.1412  |
| Shanghai      | 0.1736  |
| Shanxi        | 0.118   |
| Shaanxi       | 0.1109  |
| Sichuan       | 0.1334  |
| Tianjin       | 0.1523  |
| City    | Vulnerable Index |
|---------|------------------|
| Xinjiang| 0.1044           |
| Xizang  | 0.0846           |
| Yunnan  | 0.1026           |
| Zhejiang| 0.1467           |

Table 5: Predictive vulnerability index of each city in Zhejiang Province.

| City     | Vulnerable Index |
|----------|------------------|
| Hangzhou | 0.1496           |
| Ningbo   | 0.1493           |
| Wenzhou  | 0.146            |
| Shaoxing | 0.1299           |
| Huzhou   | 0.1183           |
| Jiaxing  | 0.1411           |
| Jinhua   | 0.1309           |
| Quzhou   | 0.1072           |
| Taizhou  | 0.1314           |
| Lishui   | 0.1076           |
| Zhoushan | 0.1286           |
Figure 1: Knowledge levels of an infectious disease.

Figure 2: Kinds of infectious disease measures.