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Impacts of geographic factors and population density on the COVID-19 spreading under the lockdown policies of China

Zhibin Sun, Hui Zhang, Yifei Yang, Hua Wan, Yixiang Wang

HIGHLIGHTS
- The first wave of COVID-19 outbreak in China lasted around 20 days.
- Negative correlations between cumulative COVID-19 infected number and latitude/altitude.
- Population density cannot affect COVID-19 spreading under strict lockdown policies.
- Lockdown policies of China effectively restrict COVID-19 spreading speed.

ABSTRACT
The outbreak of COVID-19 pandemic has a high spreading rate and a high fatality rate. To control the rapid spreading of COVID-19 virus, Chinese government ordered lockdown policies since late January 2020. The aims of this study are to quantify the relationship between geographic information (i.e., latitude, longitude and altitude) and cumulative infected population, and to unveil the importance of the population density in the spreading speed during the lockdown. COVID-19 data during the period from December 8, 2019 to April 8, 2020 were collected before and after lockdown. After discovering two important geographic factors (i.e., latitude and altitude) by estimating the correlation coefficients between each of them and cumulative infected population and COVID-19 spreading speed were constructed based on these two factors. Overall, our findings from the models showed a negative correlation between the provincial daily cumulative COVID-19 infected number and latitude/altitude. In addition, population density is not an important factor in COVID-19 spreading under strict lockdown policies. Our study suggests that lockdown policies of China can effectively restrict COVID-19 spreading speed.

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1. Introduction

In December 2019, a series of pneumonia cases of unknown causes (later named COVID-19) occurred in Wuhan, Hubei, China (Lu et al., 2020; Zhu et al., 2020). The outbreak of COVID-19 disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was declared as a pandemic on March 11, 2020 (WHO, 2020). This epidemic resulting in progressive respiratory failure and death has a high spreading rate and a high fatality rate (Wang et al., 2020a). To June 18, 2020, more than eight million cases of COVID-19 have been reported in 216 countries and regions, resulting in more than 444,813 deaths (https://www.who.int/emergencies/diseases/novel-coronavirus-2019). The rapid spreading of COVID-19 has serious impacts on global public health, and this virus in different cities has presented different spreading speeds (Liu et al., 2020b). However, the reasons resulting in the difference in spreading speed worldwide are still not clear.

There are some studies to analyze the relationship between COVID-19 and geographic indicators. Current studies reported that COVID-19 activities decreased with increasing temperature (Ma et al., 2020; Wang et al., 2020b). For an example, Ma et al. (2020) suggested that there is a negative relationship between COVID-19 mortality and temperature, and lower temperature is conducive to the virus' transmission. However, Bashir et al. (2020) revealed that there is no scientific evidence that warm weather would suppress COVID-19 epidemic based on the data from New York, USA. On the other hand, although each geographic location has its typical climate, the geographic parameters are invariant compared with climate parameters. Thus, it is more reliable to study the relations between COVID-19 and geographic parameters. However, no detailed study has been reported from this point of view. Furthermore, population density is also important to affect COVID-19 spreading (Byass, 2020), and it has been revealed that human-to-human transmission (measured with population density) is one of the COVID-19 transmission mechanisms in Italy (Coccia, 2020).

To better understand this new epidemic from the perspectives of geographic and population density, we selected China as the study region because of three reasons. First, China was the first seriously impacted country by COVID-19, and its lockdown policies were applied into all provinces with the same way, unlike other countries with more or less different lockdown policies. Those lockdown policies to prevent the further spreading of the COVID-19 epidemic in China included reducing human interaction, strictly restricting industrial activities, restricting private and public transportation, prohibiting private and public gatherings. Second, the geographic region of China is wide. For examples, the longitude of its provincial capitals is from 85.61°E to 128.05°E, the latitude covers from 19.18°N to 47.36°N, and the altitude is from 2 to 3652 m. Third, the number of Chinese populations is the largest in the world with the population over 1.4 billion and the population density of different province varies a lot (i.e., from 3 to 3850 count/km²).

In order to control/mitigate the spreading of COVID-19, many countries have implemented their lockdown policies under different strict levels. However, it is still not well understood for the significances and effects of lockdown policies on COVID-19 daily infected population, as well as its correlations with geographic factors and population density. The nationwide lockdown of COVID-19 pandemic of China provides a unique opportunity to study in this direction. Specifically, the following hypotheses are tested in this study. (1) COVID-19 spreading speed is related with geographic location, and (2) COVID-19 spreading speed is positively correlated with population density. In order to prove or disprove the hypotheses, this study focuses on (i) comparing the provincial daily cumulative infected population and spreading speed in China during lockdown periods, (ii) quantifying the relationship between geographic information (i.e., latitude, longitude and altitude) and daily cumulative infected population, and (iii) unveiling the importance of the population density in the spreading speed during lockdown periods. This study will help researchers and health policy-makers understand the implications of geographic location and population density to COVID-19 spreading under strict lockdown policies.

2. Methodology

2.1. Study area and data

China mainland is selected as the study region. There are 31 provinces, autonomous regions and municipalities across entire China mainland. Among these 31 regions, one province and one autonomous region, Hubei and Xizang, are excluded from our analyses, because their data quality is not suitable in this study. Hubei, as the first outbreak location of COVID-19 in China, started its lockdown policy as the first one in the country, but the policy starting day was significantly later than all other provinces in terms of the first day with cumulative number of infected cases ≥1 (count per million). Thus, Hubei's data is not comparable to those of all other provinces that have enforced the policy at the very early stage. Xizang, however, had only one infected case, which is not qualified for statistical analysis. The geographic map and provincial population density map of total qualified 29 analyzed provincial regions in this study are shown in Fig. 1.

Daily infected number of COVID-19 data for the period from December 8, 2019 to April 8, 2020 was collected from a website (http://www.sy72.com/covid19/), which collected data from the official websites of local Health Commission of China and local government websites.
without any data processing. The geographic information (i.e., latitude, longitude and altitude) of each provincial capital is used to represent its province/region/municipality, and its population is the number of its permanent residents reported from its provincial statistical bulletin in April 2020. Lockdown information of local government were collected city by city from news media and governmental announcements.

After provincial cumulative infected case numbers are divided by provincial population, the cumulative numbers of infected cases (CNIC) (unit: count per million) used in this study are shown in Fig. A1 (in Appendix) from January 19 to April 8, 2020.

2.2. Analyzing methods

• Time-shifting provincial data

Because the starting date of the first reported infected case in different provincial region varies and this date could have error due to possible late confirmation, each time series of provincial CNIC needs to be relocated or rescaled so that the time series of all provinces can be compared or analyzed on the same page. Thus, we chose the first day with CNIC ≥ 1 (count per million) as the zero day uniformly for each time series (Fig. 2(a)). That means each time series is shifted in time to share the same initial condition/state.

• Identify correlations with geographic factors and population density

As there are three pieces of geographic information are available (i.e., latitude, longitude and altitude), it is necessary to first assess the correlations between each geographic variable and CNIC, as well as the one between population density and CNIC. It can not only identify the significantly related factors to CNIC, but also provide firsthand knowledge for further studying their nonlinear relationships. Besides CNIC, the infective spreading speed (ISS) (unit: count per million*day), which is defined as the 4-day-window slope of each time series of CNIC, is used to identify its linear correlations with these three variables and population density. In particular, ISS of day $d = (\text{CNIC of day } (d + 2) - \text{CNIC of day } (d - 2)) / 4$. The abovementioned correlation analysis consists of Pearson correlation coefficient (CC) and its corresponding $P$ value for testing null hypothesis between two variables (e.g., CNIC vs latitude).

After identifying significantly correlated factors (i.e., geographic variables or population density), linear regressions can be carried out to describe the relationship (i) between the CNIC and the factors and (ii) between the ISS and the factors. By analyzing final regression models, quantified linear relationship of each variable can be achieved, which will reveal which factor is important in determining the CNIC (or the ISS) across China mainland.

• Linear regressions between COVID-19 spreading speed and influencing factors

Later results in Section 3 will show that CNIC and ISS have significant linear relationships with both latitude and altitude, not with either longitude or population density. In addition, the linear relationship between latitude and altitude is insignificant (CC = 0.1021, $P$ value = .5982), thus only latitude (L) and altitude (A) are used in constructing the linear models of CNIC and ISS. Two corresponding models are described as:

\[ \text{CNIC} = a_{\text{CNIC}} L + b_{\text{CNIC}} A + c_{\text{CNIC}} \]  
\[ \text{ISS} = a_{\text{ISS}} L + b_{\text{ISS}} A + c_{\text{ISS}} \]

where $a$ and $b$ are the coefficients of latitude and altitude, respectively, and $c$ is the intersection. To compare the importance of latitude and altitude variables in the models, standardized coefficients ($a_{SC}$ and $b_{SC}$) of both variables are also calculated via:

\[ a_{SC}^{CNIC} = \frac{a_{\text{CNIC}} \cdot \text{std}(L)}{\text{std(CNIC)}} \text{ and } b_{SC}^{CNIC} = \frac{b_{\text{CNIC}} \cdot \text{std}(A)}{\text{std(CNIC)}} \]

\[ a_{SC}^{ISS} = \frac{a_{\text{ISS}} \cdot \text{std}(L)}{\text{std(ISS)}} \text{ and } b_{SC}^{ISS} = \frac{b_{\text{ISS}} \cdot \text{std}(A)}{\text{std(ISS)}} \]

where $\text{std}(x)$ stands for the standard deviation of $x$.

Regression models and their related statistics can provide quantitative descriptions of the relationships between geographic factors and CNIC (or ISS), as well as how much information of CNIC and ISS in the models can be represented by those factors.

All analyses and plotted figures were performed using Matlab 2019b. Results were considered statistically significant if $P$ values are less than 0.05.

3. Results

• The length of the first wave of COVID-19

In general, Fig. 2(a) illustrates the CNIC has a rapid increase from day 0 to 20, and then becomes steady over the period of day 21 to 50 except...
for a couple of provinces that shows a clear case increasing with less magnitude than the first 20 days. This indicates the first wave of COVID-19 outbreak under Chinese lockdown policies lasted about 20 days with the greatest magnitude, which can also be shown more clearly from ISS (Fig. 2(b)).

- **Geographic correlations with COVID-19**

The linear relationships between geographic variables and time-shifted CNIC (Fig. 2(a)) / ISS (Fig. 2(b)) are estimated and shown in Fig. 3(a)-(c). It indicates that longitude has no significant linear relationship with either the CNIC or the ISS (Fig. 3(b)). However, as to latitude (Fig. 3(a)), significant negative linear relationship is observed all time for the CNIC (CC is around $-0.4$), and the first 21 days for the ISS (CC is around $-0.5$), which is about the first wave during lockdown period (Fig. 2(b)). As to altitude (Fig. 3(c)), it is similar to the results of latitude. Relatively significant (i.e., $P < 0.1$) negative linear relationship is observed all time for the CNIC (CC is around $-0.4$), and the first 3 to 23 days for the ISS (CC is around $-0.4$), which is also about the first wave during lockdown period.

- **Population density correlation with COVID-19**

The linear relationship between population density and the CNIC (or the ISS) is estimated and shown in Fig. 3(d). There exists insignificant positive correlation with CNIC all the time, while at only the 21st day a significant positive correlation with ISS (CC = 0.35) is observed during the first wave. Thus, it can conclude that no significant correlation between population and COVID-19 spreading during the first wave.

- **Effects of geographic factors on COVID-19**

Model (1) and (2) defined in Section 2.2 are used for regressions of CNIC and ISS, because only latitude and altitude have significant correlations with them. Estimation results for Model (1) are shown in Fig. 4. They indicate that from the 6th day both latitude and altitude play equivalently significant roles with standardized coefficient around $-0.4$ in the model, and the CNIC's interception firstly steadily increases until the 20th day and then remains steady to the end. On the other hand, the estimation results of Model (2) in Fig. 5 show that, from the 2nd to 20th day, both latitude and altitude also play equivalently significant roles with standardized coefficient around $-0.4$ in the model, and the ISS's interception firstly has a fluctuate increase and then slows down to approach to zero from the 23rd day, indicating the end of the first wave. Both models imply that both latitude and altitude are equally important in COVID-19 spreading during the first wave.

In addition, four other statistics of Model (1) and (2) are shown in Fig. 6. P-values of Model (1) show that its regression results are significant from the 3rd day to the end, while those of Model (2) show that its regression results are significant from the 9th day to the 20th day, confirming both regressions work well during the first wave.

4. Discussions

On July 21st, 2020, WHO has reported 14,562,550 COVID-19 cases in 216 countries, areas or territories with a very fast spreading speed (https://www.who.int/emergencies/diseases/novel-coronavirus-2019), although almost all countries have adopted different levels of
Fig. 4. The daily linear regression results for Model (1) of CNIC. (a) Standardized coefficients of estimated daily $a_{CNIC}$ and $b_{CNIC}$, as well as their corresponding $P$-values (only showing $P$-values $<0.1$). (b) Estimated daily $c_{CNIC}$ and its corresponding $P$ values. CNIC: cumulative numbers of infected cases.

Fig. 5. The daily linear regression results for Model (2) of ISS. (a) Standardized coefficients of estimated daily $a_{ISS}$ and $b_{ISS}$, as well as their corresponding $P$-values (only showing $P$-values $<0.1$). (b) Estimated daily $c_{ISS}$ and its corresponding $P$ values. ISS: infective spreading speed.

Fig. 6. (a) Four statistics of daily linear regression model (Eq.(1)) of CNIC. (b) Four statistics of daily linear regression model (Eq.(2)) of ISS. CNIC: cumulative numbers of infected cases. ISS: infective spreading speed. $R^2$: coefficient of determination. Adjusted $R^2$: adjusted coefficient of determination. F-statistic: test statistic for the F-test on the regression model. $P$-value: $P$-value for the F-test on the model.
lockdown policies. Previous studies found that several factors can influence COVID-19’s spreading, including meteorological variables, population density and mobility, and medical care (Wang et al., 2020b; Tosepu, 2020; Barcelo, 2020; Ma et al., 2020; Byass, 2020; Coccia, 2020). This is the first study to quantify the impacts of geographic factors and population density on the daily COVID-19 spreading under the strict lockdown policies of China. It may help to consider whether lockdown is an effective measure for altering/limiting the relationship between COVID-19 spreading and geographic location, and that between COVID-19 spreading and population density.

In this study, we found that COVID-19 spreading (measured with CNIC and ISS) are negatively correlated with latitude and altitude with equivalent temperature, but not correlated with longitude. Thus, these results support our first hypothesis with latitude and altitude. Although some studies found that areas with significant community transmission of COVID-19 had distribution roughly along the 30°–50°N corridor at the scale of country (Sajadi et al., 2020; Bisoyi, 2020), they had not identified the negative correlation between infected population and latitude like this study, and our study region ranges from about 20°N to 50°N at the scale of province with strict lockdown policies of China. Sarmadi et al. (2020) revealed that the number of COVID-19 cases is higher in high-income countries located in higher latitudes. It seems to be different from our finding of negative correlation with latitude, but our finding is the analysis at the provincial scale with uniformly strict lockdown policies. Therefore, our finding reflects fine-scale patterns at provincial level, which can clearly describe the geographic factors to COVID-19 spreading within one period (i.e., the first wave) in a big country with strict lockdown policies, while the results from Sarmadi et al. (2020) show coarse-scale patterns at country level with or without lockdown.

In general, higher altitude means lower temperature, which implies that in this study CNIC and ISS could significantly positively correlate with temperature during the first wave. Most studies reported that temperature showed negative associations with COVID-19 (Liu et al., 2020a; Qi et al., 2020; Sarmadi et al., 2020; Shi et al., 2020; Sobral et al., 2020; Wu et al., 2020). However, Zhu and Xie (2020) found that there was no evidence supporting that COVID-19 case counts of COVID-19 decline with warmer weather. After examining the asymmetrical effect of temperature on COVID-19 from January 22nd to March 31st, 2020 in the ten most affected provinces in China, Shahzad et al. (2020) showed that the relationship between temperature and COVID-19 is mostly positive for three provinces, while mostly negative for two provinces and mixed trends for the remaining five provinces. The above studies from others imply that temperature played a complicated role in the spreading of COVID-19 in China during the periods which are longer than the first wave of outbreak (i.e., around January 23rd to February 16th, 2020) for different provincial regions (see Figs. A1 and 2), while our studies imply the spreading during the first wave could significantly positively correlate with temperature.

In our current studies, we also found that there was no significant relationship between COVID-19 spreading and population density, which rejects our second hypothesis that population density is positively correlated with COVID-19 spreading. Our findings seem inconsistent with the studies of Pequeno et al. (2020) and Coccia (2020). The former reported that the number of confirmed cases was mainly positively related to population density in Brazil (Pequeno et al., 2020). The latter revealed that population density is one of the COVID-19 transmission mechanisms in Italy (Coccia, 2020). Both studies did not report the same relationship as our study, which may be due to the different strict levels of lockdown policies. Lockdown policies in different regions of the world are different. The unprecedented lockdown policies in China included the prohibition of unnecessary commercial activities in people’s daily lives, preventing any types of people gathering by urging people to stay at home, and restrictions on private (vehicle) and public transportation. It made Chinese ones the strictest in the world. Similar to our results, a study by Byass (2020) also demonstrated that there exists somewhat counterintuitive relationship between population density and COVID-19 incidence in China. Our results reflect that the lockdown policies of China could effectively reduce the human-to-human infective possibility even in the regions with high population density.

On the other hand, based on the COVID-19 survey data of 32 countries and regions (e.g., USA, Italy, France) from John Hopkins University (https://github.com/CSSEGISandData/COVID-19) accessed by Knafo (2020) on May 9th, 2020, the cumulated infected case numbers of those countries/regions show that the first wave of a majority of countries/regions lasted over 40 days (Knafo, 2020). For example, Iran started its lockdown on March 14th and ended on April 20th, 2020, but its first wave was still continuing to date (i.e., June 18th, 2020). The countries with first wave less than 40 days include South Korea and Philippines, both of which had strict lockdown policies. It can be concluded that the lockdown policies of China are effective to achieve a much shorter period (i.e., around 20 days) of the average first wave of countries.

Our results indicated that under strict lockdown policies, COVID-19 spreading may be affected by latitude and altitude factors, while population density factor can be limited. These findings suggest that Chinese strict lockdown strategies are highly effective on controlling the diffusion and deterioration of the novel coronavirus-infected pneumonia. These strategies can provide experience and guidelines for other countries to better control the COVID-19 epidemic.

The major advantage in our methodology is not to use linear regressions to model COVID-19 spreading but the way to determine the important factors among possible ones for a model. After the significant correlations with COVID-19 spreading were confirmed from both latitude and altitude instead of either longitude or population density, as well as the insignificant correlation between latitude and altitude, it can conclude that latitude and altitude are two important factors in the regressions, leading to successful regressions. Although both regression models can well utilize the significant correlation information between COVID-19 spreading and geographic factors, they still can be improved in future studies. In Fig. 6, the $R^2$ values of both models during the first wave are less than 0.5, even though their corresponding $P$ values are significant. It implies that although geographic factors are important to CNIC and ISS, there are still other important missing factors other than geographic parameters to affect CNIC and ISS. Further studies are needed to discover those factors and to quantify their relationship with CNIC and ISS by comparing their impacts together with geographic factors. Besides, nonlinear regressions could be considered to improve the regression accuracy by introducing nonlinear factors, such as $L^2$, $A^3$ and $L^A$, which needs other mathematical/statistical methods to confirm those factors.

To conclude, the results of this study may help to evaluate how strict lockdown policies like the ones of China could alter the relationships between COVID-19 spreading and geographic location / population density. The regression models in this study can serve as the base models to study COVID-19 spreading in a large region by adding more complicated factors/relationships under different environmental/political conditions.

CRediT authorship contribution statement

Zhibin Sun: Methodology, Writing - review & editing. Hui Zhang: Data curation, Validation. Yifei Yang: Investigation. Hua Wan: Investigation. Yixiang Wang: Conceptualization, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Appendix A

Fig. A1 The provincial CNIC (unit: count per million) from January 19 to April 8, 2020. Each colored curve represents the CNIC time series of one province/region/municipality, and its color is only for better visual effect. CNIC: cumulative numbers of infected cases.

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