Could the ambient higher temperature decrease the transmissibility of COVID-19 in China?

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Abstract.

Background: Existing literatures demonstrated that meteorological factors could be of importance in affecting the spread patterns of the respiratory infectious diseases. However, how ambient temperature may influence the transmissibility of COVID-19 remains unclear.

Objectives: We explore the association between ambient temperature and transmissibility of COVID-19 in different regions across China.

Methods: The surveillance data on COVID-19 and meteorological factors were collected from 28 provincial level regions in China, and estimated the instantaneous reproductive number ($R_t$). The generalized additive model was used to assess the relationship between mean temperature and $R_t$.

Results: There were 12745 COVID-19 cases collected in the study areas. We report the effect of temperature on $R_t$ is not of statistical significance, which holds for most of included regions except for those in North China.

Conclusions: We found little statistical evidence for that the higher temperature may reduce the transmissibility of COVID-19.

Keywords: COVID-19; Ambient temperature; Transmissibility; Association

1. Introduction

Meteorological factors, e.g., ambient temperature, play a significant role in the spread of many infectious diseases. Dengue fever and malaria increase in morbidity as temperature rise around the world could be typical examples [1]. The seasonal outbreaks of influenza in cold months also exemplify partly relationship between meteorological factors and infectious diseases [2]. In the end of 2019, a new coronavirus by the name of SARS-CoV-2 (or formerly 2019-nCoV), can make humans suffer from atypical pneumonia, one serious type of coronavirus disease 2019 (COVID-19) [3,4]. Compared to the SARS coronavirus (SARS-CoV), a notorious coronavirus caused severe acute respiratory syndrome (SARS) during 2002-03 [5], COVID-19 shares genetic similarities with SARS but has stronger infectiousness and has been bringing about unprecedented damage globally so far. Motivated by the researchers found there was an inverse relationship between temperature and SARS [6], it is tempting to assume that such association could apply to COVID-19 as well, which may provide the region-specific prevention measures.

Earlier research on this issue in China including over 400 cities found there was a non-linear relationship between temperature and cumulative number of cases [7], they found that as the temperature rise, the transmissibility rise first and then fall. Another study also found a non-
linear relationship between temperature and daily cases of COVID-19, but they suggested that the infected cases would continue to increase in spite of rising temperature, which implies that the rising temperature may only reduce the growth rate of disease [8]. In addition, Yao et al investigated the association between the basic reproduction number and the weather conditions, however, they did not find any evident result between temperature and transmissibility of COVID-19 [9].

Studies in China on this issue mostly considered the city of Wuhan (or Hubei province), this may cause some bias in analysis since there are numerous confirmed cases in Wuhan (or Hubei) compared to other regions in China, such difference of confirmed case scale between Hubei province and other regions in China may misestimated the effect of temperature on COVID-19 morbidity. In addition, the medical resources and control interventions between Hubei and the other regions in China exist different, which may also affect the analysis result of association between air temperature and COVID-19 morbidity. For dealing with this problem and identifying the reasonable evidence among different study results, in this study, we aim to explore the association of temperatures with risks of morbidity on COVID-19 outside Hubei in China. In view of the influence on different demographic and geographic characteristics, China was divided into seven regions according to Chinese Geographical Division.

2. Materials and methods

2.1 Study regions

According to Chinese Geographical Division, China is divided into seven regions (Figure 1), there are East China (Anhui, Fujian, Jiangsu, Jiangxi, Shandong, Shanghai, Taiwan and Zhejiang), North China (Beijing, Hebei, Inner Mongolia, Shanxi, and Tianjin), Central China (Henan, Hubei and Hunan), South China (Guangdong, Guangxi, Hainan, Hong Kong and Macao), Northeast China (Heilongjiang, Jilin and Liaoning), Northwest China (Gansu, Ningxia, Qinghai, Shanxi and Xinjiang), and Southwest China (Chongqing, Guizhou, Sichuan, Tibet and Yunnan). We selected a total of 28 Chinese provincial regions as study place in this work. Since Wuhan (in Hubei province, China) was the epicenter of COVID-19 in China, where relatively intensive control measures were implemented, we avoid including COVID-19 data in Hubei province. Moreover, there were enormously larger number of cases in Wuhan than other cities, so it may be inappropriate for comparison among these regions. Besides, we excluded these cities in analysis stage: Hong Kong, Hainan, Taiwan (for meteorological data being not available), and Tibet (for only one case in the study period).
2.2 Data collection

The surveillance data of COVID-19 number of cases were collected from the reports released on the official websites of the Health Commissions. We collected case data from January 20 to February 29, 2020, for two reasons: (i) in almost all regions outside Hubei, the first case was reported in January 20, 2020, and ended up in February 29, 2020 (Table S1), and (ii) to compare with the results from other similar studies that also choose this period of time [10][11].

Meteorological data were collected from Houzhi Weather (see http://hz.zc12369.com) during the same time period for each city, including mean temperature (in °C), relative humidity (in %), air pressure (in hpa), and wind speed (in m per s, or m/s).

2.3 Transmissibility of COVID-19

We quantify the transmissibility of COVID-19 by using the number of incidences time series and serial interval (SI) that is defined as the time between the onset of symptoms in a primary case and the onset of symptoms of secondary cases [12]. Cori et al proposed a statistical framework for estimating the instantaneous reproductive number $R_t$ at the $t$-th day has following formula [13][14].

$$R_t = \frac{I_t}{\sum_{k=0}^{n} \omega(k) I_{t-k}},$$

where $I_t$ is the confirmed case of COVID-19 at the $t$-th day, $\sum_{k=0}^{n} \omega(k) I_{t-k}$ is the weighted sum of infection incidence up to the time step $t - 1$, and $\omega(k)$ is the weighted function determined by the distribution of SI of COVID-19, and $n$ is the upper bound of the SI distribution (in days).

The estimation of $R_t$ is conducted with a Poisson-distributed likelihood profile for the number of incidences. To set up the model, the distribution of SI used to estimated $R_t$ was approximated by a Gamma distribution with mean 5.5 days and standard deviation (SD) 3.3 days [15].

2.4 Statistical analysis

Statistical analyses mainly consisting of the following two steps: (i) just as Zhao [16] pointed out that there may exist flawed analytical procedures by directly using the case number as response to modeling the temperature-morbidity relationship for infectious diseases, thus, we estimated instantaneous reproductive number ($R_t$) as the proxy of the transmissibility of COVID-19. (ii) A generalized additive model (GAM) was built with $log(R_t)$ as a function of mean temperature (linear) and other meteorological variables (natural cubic spline) at city-specific level, then combining the city-level results to the region-level with meta-analysis, we calculated the relative risk (RR) of
each region with different lag days. The model is described as follows:

$$\log(R_t) = \alpha + \beta \times \text{Temp}_t + S(\text{Humidity}_t, df = 3) + S(\text{Pressure}_t, df = 3)$$

$$+ S(\text{Wind}_t, df = 3) + \gamma \text{DOW} + \delta \times \log(R_{t-1}),$$

where we assume that $R_t$ is subjected to Poisson distribution, $\alpha$ is the interception, $\text{Temp}_t$ is the mean temperature at $t$ day. The $\text{Humidity}_t$, $\text{Pressure}_t$ and $\text{Wind}_t$ are relative humidity, air pressure and wind speed at $t$ day, respectively, and $S$ denotes the natural cubic spline function with degrees of freedom (df) of 3. The $\text{DOW}$ is the day of week, a categorical variable with coefficient $\gamma$. Since the autocorrelation of time series data, so we added the term $\delta \times \log(R_{t-1})$ to correct the autocorrelation.

The relative risk (RR) and its 95% confidence interval (95% CI) were employed to measure the association between temperature and the COVID-19 transmissibility ($R_t$) by using the generalized additive model. We respectively calculated the effects of the current day, lag for 1 day, lag for 2 days, lag for 3 days and their moving averages by using generalized additive model. Data analyses were conducted in R statistical software (version 4.0.2).

3. Results

During the study period, there were 12745 total collected COVID-19 cases, of which the most cases in East China (5150), almost 10 times of the cases in Northwest China that had the least number of cases (503). The two warmest regions were South China and Southwest China, which the average daily mean temperatures exceeded 10 degrees Celsius (16.1 and 10.2, respectively). The coldest region was Northeast China (-8.1). For other regions, the temperatures from high to low followed by East (8.5), Central (7.8), North (-0.2) and Northwest (-1.1). Details of statistics of confirmed cases of COVID-19 and other meteorological variables shows in Table 1.

As table 2 shows, the estimated reproductive number ranges from 1.1 to 1.5 across Chinese regions, and the virus was more infectious in East China, while in the North China was weaker.

Table 3 shows the delayed effects of mean temperature on the transmissibility of COVID-19. Almost all the estimated RR in different regions (except North China) with different lag days were nearly 1, and their estimated confidence interval crossed 1. While in North China, the weak effect was found at lag 1 day (RR: 0.981, 95% CI: 0.964-0.999) and lag 2 day (RR: 0.982, 95% CI: 0.965-0.999). These results indicated that the association between the mean temperature and transmissibility of COVID-19 is not statistically clear.

Figure 2 shows the temperature moving average effect. Similar as in Table 2, the significant result only found in North China. However, the correlation of temperature and COVID-19 becomes insignificant when we excluded Inner Mongolia.
4. Discussion

COVID-19 has been widely spread in China and overseas and caused severe health burden around the world, and the peak of the outbreak in most cities in China was in February. This study explored the association between ambient temperature and COVID-19 transmissibility in different regions in China. However, there was no apparent effect between temperature and transmissibility of COVID-19 in our study.

Previous studies on this topic in China suggested a slightly nonlinear or linear relationship between temperature and cases [7,8,10,11]. The study conducted by Islam et al. [17] also suggested that higher daily maximum temperature decreased the incidence rate ratio of COVID-19 at the current day.

However, there are some issues must be pointed out. First, the temperature of the model contributed to the variation in some studies were lower [7,11,18], which means that if there exists truly relationship, temperature may only explain minor of the association, while other factors such as geographical characteristics, individual behavior, population mobility, isolation measure also influenced the epidemic of infectious diseases [19–23]. The second issue which is the most important and cannot ignored is related to the particularity of infectious diseases. That is, the number of incidences for infectious diseases is determined by transmissibility [24], unlike non-infectious diseases, using case number as response modeling the relationship between infectious disease and environmental factors may produce false associations [16]. In China, quarantine measures are the most stringent in the world, as well as earliest, the whole city of Wuhan was lockdown on January 23 [25], followed by Hubei and the other provinces. During policy implementation period, most people stay at home during the outbreak and maintain social distance outside, which could effectively reduce the spread of COVID-19 [26]. Thus, the rising temperature from January to February accordingly in China may form a false conclusion of the temperature-morbidity relationship. Besides, a counterexample that raises suspicion is that there are some countries more warmer and the prevention measures more looser than China during the same period [27], such as India and Brazil [18,28], the epidemic situation is not more optimistic than China.

According to the study by [16], the instantaneous reproductive number $R_t$ could be more representative for the transmissibility of COVID-19. In our study, we used $R_t$ in place of daily confirmed cases, and did not find the significant association between temperature and COVID-19. This result is in agreement with the study conducted by Yao et al. [9], they found temperature and ultraviolet radiation have no significant effects on COVID-19 transmission. Similar results were also found in Canada and Spain [29,30]. A study in Iran [31] suggested the population density and intra-provincial movement were the most important factors affecting the COVID-19 outbreak.
rate, and high solar radiation was a protective factor, but the temperature is unlikely.

A special case is that in North China, we found slightly significant negative association between
temperature and $R_t$. However, when we re-estimated the relationship without Inner Mongolia, the
weak correlation was disappeared, which indicate this association appears not sufficiently stable.
The reason why Inner Mongolia was an exception in our analysis is not clear as the weather-diseases
relationship is more complicated and easily affected by the other non-meteorological factors, thus,
this phenomenon may need further research. We still prefer to believe that the effect of temperature
on COVID-19 is weak in that the exception of one city may not be convinced.

Our study also has some limitations. First, there was a time-series ecological study, it is difficult
to check the causal relationship between temperature and transmissibility of COVID-19. Second,
it is difficult to obtain the meteorological data at the individual level. Third, there are some other
important factors such as air pollution, medical resources, governmental interventions may also
affect the transmissibility of COVID-19. Last, due to lack of information, our estimation of $R_t$
eglected the difference between local and imported cases. We remark the analytical framework
adopted in this study can be extended to address this limitation with cases’ import or local status
available. These issues should be addressed in future.

5. Conclusion

We found little statistical evidence for that the higher temperature may reduce the transmis-
sibility of COVID-19.

Ethical Approval and Consent to participate

Not applicable.

Consent for publication

All authors read and approved this study for publication.

Availability of supporting data

The data used to support the findings of this study is available from the corresponding author
upon request or from the website.

Competing interests

The authors declare that they have no conflict of interest.
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Authors’ contributions

Qingan Wang, Shi Zhao, Yu Zhao, Yajuan Zhang conceived and proposed this work. Jiangwei Qiu, Juan Li, Ni Yan, Nan Li, Jiaxing Zhang, Di Tian, Xiaolan Sha, Jinyun Jing, Chan Yang, Kairong Wang collected the data. Huifang Yang, Yuhong Zhang, Rongbin Xu and Yi Zhao improved the paper.

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Figure 1: Map of Chinese regions included or excluded in this study. Different colors represent different regions. White colors indicate that the data in these areas were not used. Tibet is classified in Southwest China. Hubei is classified in Central China. Hainan, Hong Kong and Macao are classified in South China. Taiwan is classified in East China.
| Region    | City          | Cum. of cases | Average temperature (°C) | Relative humidity (%) | Wind speed (m/s) | Air pressure (hpa) |
|-----------|---------------|---------------|--------------------------|-----------------------|-----------------|-------------------|
|           |               |               | Mean(SD)                 | Mean(SD)              | Mean(SD)        | Mean(SD)          |
| East      | Anhui         | 990           | 6.5 (3.4)                | 78.2 (12.4)           | 2.4 (0.9)       | 1007.6 (4.5)      |
| China     | Fujian        | 296           | 14.1 (3.5)               | 72.6 (12.6)           | 1.5 (0.4)       | 1007.2 (3.9)      |
|           | Jiangsu       | 631           | 6.8 (3.0)                | 74.4 (12.8)           | 2.0 (0.8)       | 1024.1 (4.8)      |
|           | Jiangxi       | 935           | 10.5 (4.0)               | 78.6 (11.6)           | 1.4 (0.5)       | 1011.9 (4.6)      |
|           | Shandong      | 756           | 3.4 (3.5)                | 65.4 (12.1)           | 2.3 (0.7)       | 1006.8 (5.0)      |
|           | Shanghai      | 337           | 8.1 (3.3)                | 76.6 (13.7)           | 2.0 (0.9)       | 1025.4 (4.7)      |
|           | Zhejiang      | 1205          | 9.7 (3.3)                | 76.5 (12.8)           | 1.7 (0.7)       | 1021.3 (4.6)      |
| Regional cases |           | 5150          |                          |                       |                 |                   |
| North     | Beijing       | 413           | 0.8 (2.9)                | 55.3 (17.8)           | 1.4 (0.9)       | 1022.9 (5.5)      |
| China     | Hebei         | 318           | 1.1 (3.0)                | 60.9 (13.0)           | 1.6 (0.6)       | 1007.3 (5.5)      |
|           | Inner Mongolia| 75            | -7.4 (4.6)               | 55.1 (7.5)            | 2.1 (0.6)       | 916.4 (4.5)       |
|           | Shanxi        | 133           | 0.3 (2.9)                | 54.1 (15.0)           | 1.6 (0.8)       | 926.9 (4.6)       |
|           | Tianjin       | 136           | 1.5 (3.0)                | 64.7 (16.0)           | 1.8 (1.1)       | 1026.6 (5.8)      |
| Regional cases |           | 1075          |                          |                       |                 |                   |
| Central   | Henan         | 1272          | 5.4 (3.3)                | 66.9 (16.5)           | 2.0 (0.6)       | 1007.2 (5.3)      |
| China     | Huan          | 1018          | 9.5 (3.9)                | 81.7 (12.4)           | 1.4 (0.8)       | 1003.5 (4.9)      |
| Regional cases |           | 2290          |                          |                       |                 |                   |
| South     | Guangdong     | 1349          | 16.6 (3.6)               | 75.4 (12.2)           | 1.7 (0.6)       | 1014.5 (3.6)      |
| China     | Guangxi       | 249           | 15.4 (4.3)               | 75.4 (14.2)           | 1.9 (0.6)       | 1006.2 (4.1)      |
| Regional cases |           | 1598          |                          |                       |                 |                   |
| Northeast | Heilongjiang  | 480           | -13.0 (4.5)              | 63.2 (6.3)            | 1.9 (0.6)       | 999.9 (5.1)       |
| China     | Jilin         | 93            | -9.0 (5.8)               | 65.7 (7.6)            | 1.7 (0.7)       | 997.1 (5.2)       |
|           | Liaoning      | 122           | -3.3 (4.7)               | 58.8 (11.7)           | 2.3 (1.0)       | 1016.7 (5.2)      |
| Regional cases |           | 695           |                          |                       |                 |                   |
| Northwest | Gansu         | 91            | -0.7 (3.6)               | 42.3 (11.1)           | 1.6 (0.5)       | 855.6 (3.8)       |
| China     | Ningxia       | 73            | -0.3 (3.9)               | 42.2 (12.4)           | 1.6 (0.9)       | 876.8 (4.4)       |
|           | Shaanxi       | 245           | 3.2 (3.2)                | 52.3 (15.6)           | 1.8 (0.7)       | 944.9 (5.4)       |
|           | Xinjiang      | 76            | -7.1 (5.5)               | 68.2 (6.7)            | 1.0 (0.3)       | 964.2 (4.9)       |
| Regional cases |           | 503           |                          |                       |                 |                   |
| Southwest | Chongqing     | 576           | 10.7 (2.0)               | 80.0 (10.3)           | 0.7 (0.6)       | 991.4 (5.2)       |
| China     | Guizhou       | 146           | 9.2 (3.7)                | 78.5 (6.5)            | 1.2 (0.4)       | 891.2 (3.7)       |
|           | Sichuan       | 538           | 10.3 (2.3)               | 73.5 (9.2)            | 1.0 (0.4)       | 965.1 (4.7)       |
|           | Yunnan        | 174           | 10.5 (2.5)               | 61.8 (6.6)            | 1.5 (0.2)       | 821.3 (2.5)       |
| Regional cases |           | 1434          |                          |                       |                 |                   |
| Total Cases |             | 12745         |                          |                       |                 |                   |
Table 2. Summary of estimated instantaneous reproductive number ($R_t$) in different regions, China.

| Chinese Region | Mean(SD) | 25% percentile | Median | 75% percentile |
|----------------|----------|----------------|--------|----------------|
| East           | 1.5 (1.7)| 0.5            | 0.7    | 1.7            |
| North          | 1.3 (1.3)| 0.4            | 0.8    | 1.6            |
| Central        | 1.3 (1.7)| 0.2            | 0.6    | 1.6            |
| South          | 1.2 (1.3)| 0.3            | 0.6    | 1.8            |
| Northeast      | 1.2 (1.1)| 0.4            | 0.7    | 2.2            |
| Northwest      | 1.1 (1.2)| 0.3            | 0.7    | 1.4            |
| Southwest      | 1.2 (1.3)| 0.4            | 0.7    | 1.4            |

Table 3. Summary of the relative risks (RR) and 95% confidence intervals (CI) for COVID-19 associated with one unit increase in mean temperatures at different lag days in different regions, China.

| Chinese Region | RR (95% CI) |
|----------------|-------------|
|                | lag0 | lag1 | lag2 | lag3 |
| East           | 0.988 (0.970, 1.006) | 0.996 (0.983, 1.009) | 0.996 (0.981, 1.011) | 0.994 (0.964, 1.026) |
| North          | 0.981 (0.964, 0.999) | 0.982 (0.965, 0.999) | 0.987 (0.972, 1.002) | 0.989 (0.973, 1.004) |
| Central        | 0.995 (0.947, 1.046) | 0.999 (0.968, 1.030) | 1.001 (0.998, 1.014) | 0.997 (0.985, 1.010) |
| South          | 0.984 (0.956, 1.012) | 0.990 (0.970, 1.011) | 0.997 (0.981, 1.013) | 0.993 (0.974, 1.011) |
| Northeast      | 1.002 (0.980, 1.023) | 1.000 (0.996, 1.002) | 1.009 (0.997, 1.022) | 0.991 (0.953, 1.030) |
| Northwest      | 0.988 (0.949, 1.029) | 0.998 (0.969, 1.027) | 1.007 (0.986, 1.028) | 1.005 (0.988, 1.022) |
| Southwest      | 0.988 (0.932, 1.047) | 0.988 (0.933, 1.047) | 0.933 (0.963, 1.023) | 1.005 (0.973, 1.038) |
Figure 2: Relative risks (point) and 95% confidence intervals (bar) for COVID-19 associated with different moving average, per one unit (in °C) increase in temperature. (North. 2: North China without Mongolia.)