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

Qingan Wang [a,b,1], Yu Zhao [a,b,1], Yajuan Zhang [a,b], Jiangwei Qiu [a,b], Juan Li [a,b], Ni Yan [a,b], Nan Li [a,b], Jiaxing Zhang [a,b], Di Tian [a,b], Xiaolan Sha [a,b], Jinyun Jing [a,b], Chan Yang [a,b], Kairong Wang [a,b], Rongbin Xu [c], Yuhong Zhang [a,b], Huifang Yang [a,b], Shi Zhao [d,e,*], Yi Zhao [a,b,**]

[a] School of Public Health and Management, Ningxia Medical University, Yinchuan, 750001, Ningxia, China
[b] The Key Laboratory of Environmental Factors and Chronic Disease Control of Ningxia, Yinchuan, 750001, Ningxia, China
[c] Department of Epidemiology and Preventive Medicine, School of Public Health and Preventive Medicine, Monash University, Melbourne, VIC, 3004, Australia
[d] JC School of Public Health and Primary Care, Chinese University of Hong Kong, Hong Kong SAR, China
[e] CUHK Shenzhen Research Institute, Shenzhen, 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 12,745 COVID-19 cases collected in the study areas. We report the associated effect of temperature on R_t is likely to be negative but not of statistical significance, which holds for most Chinese regions.
Conclusions: We found little statistical evidence for that the higher temperature may reduce the transmissibility of COVID-19. Since intensive control measures against the COVID-19 epidemics were implemented in China, we acknowledge this may impact the underlying effect size estimation, and thus cautiousness should be taken when interpreting our findings.

1. Introduction

Meteorological factors, e.g., ambient temperature, may be of importance in affecting the spread of infectious diseases. Dengue fever and malaria increase in morbidity as temperature rise around the world could be typical examples (Watts et al., 2019). The seasonal outbreaks of influenza in cold months also exemplify partly relationship between meteorological factors and infectious diseases (Lowen; et al., 2007). In the end of 2019, a new coronavirus caused by SARS-CoV-2 (or formerly, 2019-nCoV), can make humans suffer from atypical pneumonia, as one of the serious types of coronavirus disease 2019 (COVID-19) (Chen et al., 2020a; Lu et al., 2020). Compared to the severe acute respiratory syndrome (SARS) during 2002–03 (Drosten et al., 2003), COVID-19 shares genetic similarities with SARS but has stronger infectiousness and has been bringing about unprecedented damage globally. Motivated by the researchers found there was an inverse relationship between temperature and SARS (Cai et al., 2007), 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 (Wang et al., 2020) found there was a non-linear relationship between temperature and cumulative number of cases, 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 (Xie and Zhu, 2020). In addition, previous work investigated the association between the basic reproductive number and the weather conditions, however, they did not detect any evident association (Yao et al., 2020). Ran et al. (2020) explored the association between temperature and COVID-19 transmissibility with an ecological study design, and they found that the overall nonlinear association between basic reproductive number and temperature was of statistical significance. As such, how ambient temperature may influence the transmissibility of COVID-19 remains unclear.

Many studies on this issue considered the city of Wuhan (or Hubei province) as the target region, this may involve some bias in analysis. One of the main reasons is that there were numerous confirmed cases in Wuhan (or Hubei) compared to other Chinese regions, and such difference may affect the inference of role of temperature in COVID-19 transmission. In addition, the settings of medical resources and control interventions in Hubei and the other regions in China appear different, which may also affect the inference of association between air temperature and COVID-19 morbidity.

In this study, we aim to explore the association of temperatures with risks of transmissibility 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. The generalized additive model was used to assess the relationship between mean temperature and reproductive number, R_t. Furthermore, we perform the sensitivity analysis to test the robustness of the results. We further discussion the public health relevance of our estimates.

2. Materials and methods

2.1. Study regions

According to Chinese Geographical Division, China is divided into seven regions (Fig. 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, Shannxi 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
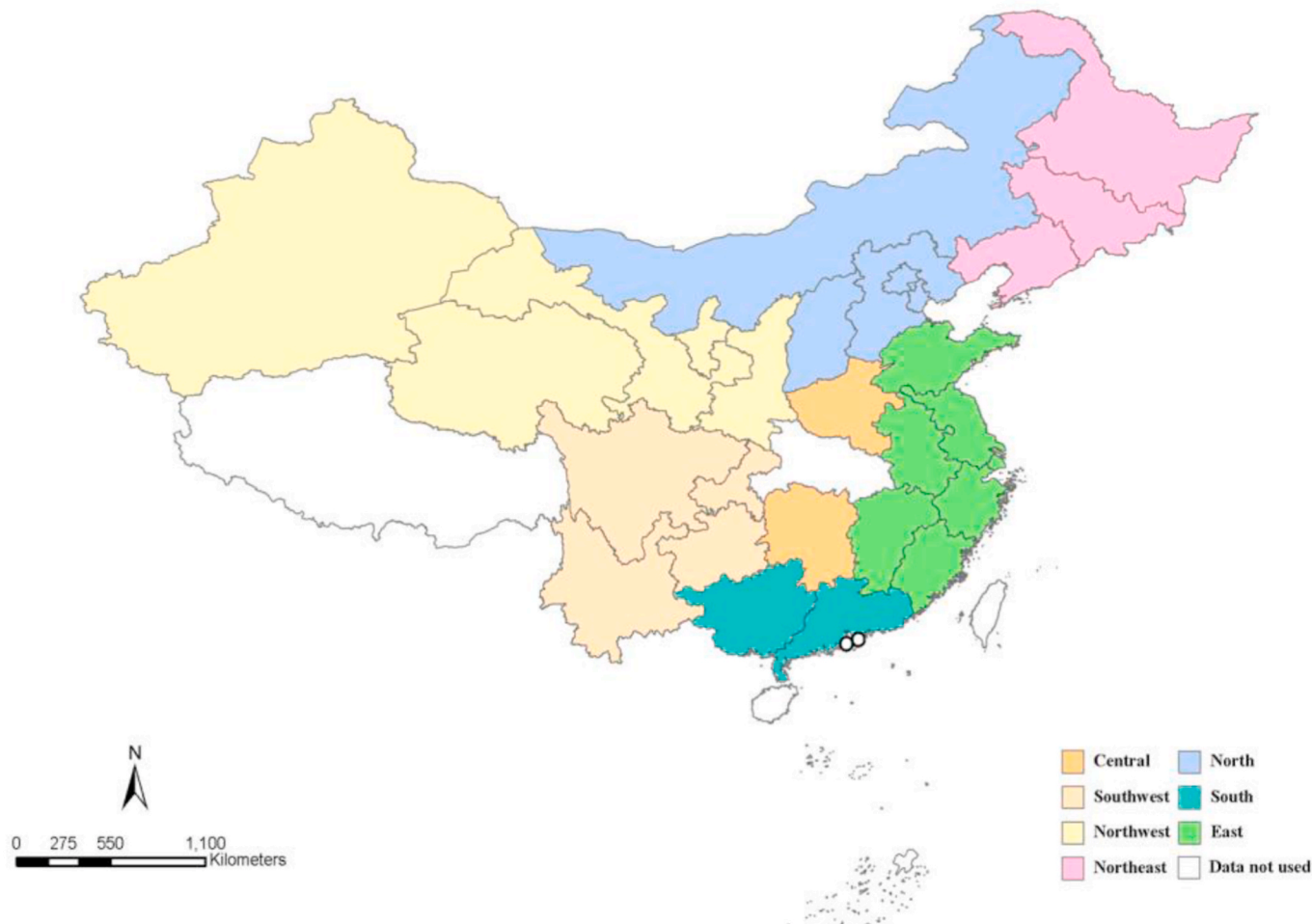

Fig. 1. Map of Chinese regions included or excluded in this study. Different colors represent different regions. White colors indicate that the data in these areas were not used. Tibet is classified in Southwest China. Hubei is classified in Central China. Hainan, Hong Kong and Macao are classified in South China. Taiwan is classified in East China.

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 from analysis, and they include Hong Kong, Hainan, and Taiwan for unavailable meteorological data, and Tibet for lack of COVID-19 case.

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 nearly 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 (Ma et al., 2020; Oliveiros, 2020).

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 (Cori, 2013; Fine, 2003). The statistical framework for estimating the instantaneous reproductive number R_t at the t-th day has following formula (Ferretti et al., 2020; Thompson et al., 2019):

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

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 denotes 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 estimate R_t was approximated by a Gamma distribution with mean 5.5 days and standard deviation (SD) 3.3 days (Zhao, 2020).

2.4. Statistical analysis

Statistical analyses mainly consisting of the following two steps: (i) as (Zhao, 2020) 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:

$$\log(R_t) = \alpha + \beta \times \text{Temp}_t + S(\text{Humidity}_t,\ df = 3) + S(\text{Pressure}_t,\ df$$
$$= 3) + S(\text{Wind}_t,\ df = 3) + \gamma \times \text{DOW} + \delta \times \log(R_{t-1}), \quad (1)$$

where α is the interception, Temp_t is the mean temperature on the t-th day. The Humidity_t, Pressure_t and Wind_t are relative humidity, air pressure and wind speed on the t-th day, respectively. The function S

denotes the natural cubic spline function with degrees of freedom (df) fixed at 3. The DOW is the day of week, a categorical variable with coefficient γ. Considering the autocorrelation of time series data, we added the term $\delta \times \log(R_{t-1})$ to adjust for 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.

2.5. Sensitivity analysis

To test the robustness of the results, we performed the sensitivity analyses as follows: (i) We used daily maximum and minimum temperatures as the interested indicators to explore the temperature-disease relationships, respectively. (ii) The model is also applied for the whole studied areas by using mean, maximum and minimum temperature, respectively. (iii) We extended the endpoint of study period from February 29, 2020 to April 30, 2020. (iv) Additionally, considering the Baidu Index (BDI) may be an effective proxy to measure public awareness, which may affect public behavior (Zhao et al., 2020), we used BDI as a covariate in model (1) to adjust the potential effect of human behavior (public awareness). The more details with respect to BDI were given in the supplementary materials.

Data analyses were conducted in **R** statistical software (version 4.0.2).

3. Results

During the study period, there were 12,745 COVID-19 cases collected in total, among which the most cases existed in East China (5150), and were roughly 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 °C (16.0 and 10.4, respectively). The coldest region was Northeast China (−8.4). For other regions, the temperatures from high to low followed by East (8.4), Central (7.5), North (−0.7) and Northwest (−1.3). 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.

There were some estimated results of the reproductive number of COVID-19 of China recently. For example, Ran et al. (2020) estimated the reproductive number for the 154 cities (15 inside Hubei and 139 outside Hubei) from December 2019 to February 2020 have a mean ± standard deviation of 1.4 ± 0.3. Yao et al. (2020) also given an estimation of the reproductive number in 62 Chinese cities was 1.4 ± 0.3. Thus, our estimated reproductive number of COVID-19 was largely consistent with these reported works.

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 intervals 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.

Fig. 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 (The corresponding values of RR and their 95% CI, see Table S5).

For sensitivity analysis, the results were similar in term of the effect size of statistical significance, when we replaced mean temperature with

Table 1
Summary of meteorological variables, released COVID-19 cases in different regions of 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 China	Anhui	990	6.5 (3.4)	78.2 (12.4)	2.4 (0.9)	1007.6 (4.5)
	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 China	Beijing	413	0.8 (2.9)	55.3 (17.8)	1.4 (0.9)	1022.9 (5.5)
	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 China	Henan	1272	5.4 (3.3)	66.9 (16.5)	2.0 (0.6)	1007.2 (5.3)
	Hunan	1018	9.5 (3.9)	81.7 (12.4)	1.4 (0.8)	1003.5 (4.9)
	Regional cases	2290				
South China	Guangdong	1349	16.6 (3.6)	75.4 (12.2)	1.7 (0.6)	1014.5 (3.6)
	Guangxi	249	15.4 (4.3)	75.4 (14.2)	1.9 (0.6)	1006.2 (4.1)
	Total case	1598				
Northeast China	Heilongjiang	480	−13.0 (4.5)	63.2 (6.3)	1.9 (0.6)	999.9 (5.1)
	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 China	Gansu	91	−0.7 (3.6)	42.3 (11.1)	1.6 (0.5)	855.6 (3.8)
	Ningxia	73	−0.3 (3.9)	42.2 (12.4)	1.6 (0.9)	876.8 (4.4)
	Qinghai	18	−1.5 (3.6)	36.8 (12.0)	1.9 (0.7)	789.8 (3.5)
	Shannxi	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 China	Chongqing	576	10.7 (2.0)	80.0 (10.3)	0.7 (0.6)	991.4 (5.2)
	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		12,745				

Table 2
Summary of estimated instantaneous reproductive number (R_t) in different regions, China from January 2020 to February 2020.

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

maximum and minimum temperature, respectively (see Table S2; Table S3; Figure S1; Figure S2). When all regions were analyzed as a whole, the results also suggested that the association between temperature and COVID-19 is insignificant (Table S4). Hence, we consider our estimates with higher confidence, and unlikely to be altered by different meteorological indicators or varying the study period.

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 (Ma et al., 2020;

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 of China.

Chinese Region	RR (95% CI)			
	Lag 0	Lag 1	Lag 2	Lag 3
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)

Oliveiros et al., 2020; Wang et al., 2020; Xie and Zhu, 2020). The study conducted by Islam (Islam et al. (2020) also suggested that higher daily maximum temperature decreased the incidence rate ratio of COVID-19 at the current day.

The results should be interpreted with cautions. First, the contribution of temperature in explaining the variation in COVID-19's transmissibility appears low (Oliveiros et al., 2020; Prata et al., 2020; Wang et al., 2020), which means that if there exists real relationship, temperature may only explain a minor part of the transmissibility. Other
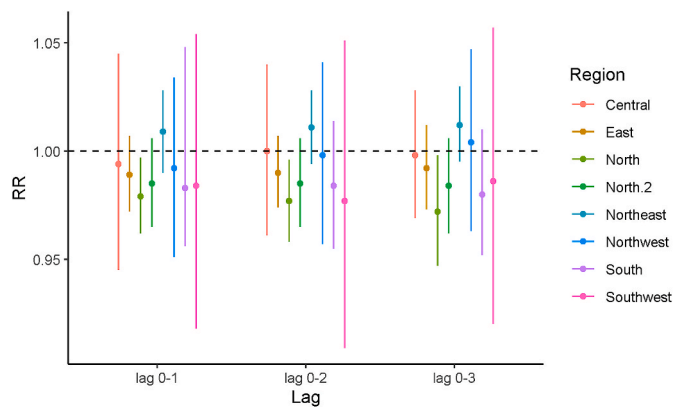
Fig. 2. Relative risks (point) and 95% confidence intervals (bar) for COVID-19 associated with different moving average, per one unit (in °C) increase in temperature. The label 'North.2' indicates North China without Inner Mongolia.

factors, such as geographical characteristics (Sajadi et al., 2020), individual behavior (Anderson et al., 2020), population mobility (Sam Engle et al., 2020; Sirkeci and Yucesahin, 2020), control measures (Nussbaumer-Streit et al., 2020), may largely influence the epidemic of infectious diseases. The association between temperature and COVID-19 is insignificant based on our model (1), a nonlinear association may exist (Ran et al., 2020). Second, the most important and cannot be ignored issue is related to the particularity of infectious diseases. That is, the number of incidences for infectious diseases is determined by transmissibility (Wallinga and Lipsitch, 2007). Unlike non-communicable diseases (NCD), using case number as response modeling the relationship between infectious disease and environmental factors may produce non-causal associations (Zhao, 2020). 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 (Tian et al., 2020), 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 (Zhao et al., 2020). Thus, from January to February, the rising temperature in China may lead to a non-causal association to the morbidity related to COVID-19. 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 (Qasim Bukhari and Jameel, 2020), such as India and Brazil (Kumar, 2020; Prata et al., 2020), the epidemic situation is not more optimistic than China. Third, we should point out that our analysis found insignificant association between the ambient temperature and the transmission of COVID-19, but the RR estimation results (see Table 3) suggested that there likely exists a negative correlation between temperature and the transmission of COVID-19. By using global data, Chen et al. (2020b) lately examined the relationship between temperature and the spread of COVID-19, and found that there is a robust and significant negative association between COVID-19 transmissibility and ambient temperature at the country level. Ran et al. (2020) observed that the ambient temperature was found to have a nonlinear negative association with COVID-19 transmissibility based on the discontinuity regression method. Inconsistent results may be due to the different model frameworks, thus, more multi-data evidences might be needed to further test the association between ambient temperature and COVID-19 transmissibility.

According to the study by (Zhao, 2020), 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. (2020), they found temperature and ultraviolet radiation have no significant effects on COVID-19 transmission. Similar results were also

found in Canada and Spain (Briz-Redon and Serrano-Aroca, 2020; To et al., 2020). A study in Iran (Ahmadi et al., 2020) 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 has some advantages. First, the association between ambient temperature and transmissibility of COVID-19 in different regions across China was studied. A total of 28 Chinese provincial regions were included in this study, which may be benefit to obtain a reliable conclusion. Second, for aggregated data, the instantaneous reproductive number was used to avoid the noncausal association between environmental factor and COVID-19. This result was different with that obtained by using the infected cases data. Third, compared to the SARS, the association between temperature and COVID-19 is insignificant across China, which is of important reference value for specific public health strategy.

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. Third, with increase of the intervention prevention and control strategy of China, the effect size estimated in this study might be in small scale, and thus the true association between temperature and COVID-19 may be affected through the under controlled infected cases of COVID-19. Last, due to lack of information, our estimation of R_t neglected 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. Conclusions

We found little statistical evidence for that the higher temperature may reduce the transmissibility of COVID-19. Since intensive control measures against the COVID-19 epidemics were implemented in China, we acknowledge this may impact the underlying effect size estimation, and thus cautiousness should be taken when interpreting our findings.

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.

Acknowledgement

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2020.110576.

Data availability

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

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