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Region-specific air pollutants and meteorological parameters influence COVID-19: A study from mainland China

Shaowei Lin [a,1], Donghong Wei [a,b,1], Yi Sun [a,1], Kun Chen [a], Le Yang [a], Bang Liu [a], Qing Huang [a,c], Monica Maria Bastos Paoliello [d,e], Huangyuan Li [f,*], Siying Wu [a,**]

[a] Department of Epidemiology and Health Statistics, School of Public Health, Fujian Medical University, Fuzhou, 350122, China
[b] Department of Preventive Medicine, School of Inspection and Prevention, Quanzhou Medical College, Quanzhou, 362011, China
[c] The Second Affiliated Hospital of Fujian Medical University, Quanzhou, 362000, China
[d] Department of Molecular Pharmacology, Albert Einstein College of Medicine, Bronx, NY, 10461, USA
[e] Graduate Program in Public Health, Center of Health Sciences, State University of Londrina, PR, 86038-350, Brazil
[f] Department of Preventive Medicine, School of Public Health, Fujian Medical University, Fuzhou, 350122, China

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ABSTRACT

Coronavirus disease 2019 (COVID-19) was first detected in December 2019 in Wuhan, China, with 11,669,259 positive cases and 539,906 deaths globally as of July 8, 2020. The objective of the present study was to determine whether meteorological parameters and air quality affect the transmission of COVID-19, analogous to SARS. We captured data from 29 provinces, including numbers of COVID-19 cases, meteorological parameters, air quality and population flow data, between Jan 21, 2020 and Apr 3, 2020. To evaluate the transmissibility of COVID-19, the basic reproductive ratio (R_0) was calculated with the maximum likelihood "removal" method, which is based on chain-binomial model, and the association between COVID-19 and air pollutants or meteorological parameters was estimated by correlation analyses. The mean estimated value of R_0 was 1.79 ± 0.31 in 29 provinces, ranging from 1.08 to 2.45. The correlation between R_0 and the mean relative humidity was positive, with coefficient of 0.370. In provinces with high flow, indicators such as carbon monoxide (CO) and 24-h average concentration of carbon monoxide (CO_24 h) were positively correlated with R_0, while nitrogen dioxide (NO_2), 24-h average concentration of nitrogen dioxide (NO_2_24 h) and daily maximum temperature were inversely correlated to R_0, with coefficients of 0.644, 0.661, −0.636, −0.657, −0.645, respectively. In provinces with medium flow, only the weather factors were correlated with R_0, including mean/maximum/minimum air pressure and mean wind speed, with coefficients of −0.697, −0.697, −0.697 and −0.841, respectively. There was no correlation with R_0 and meteorological parameters or air pollutants in provinces with low flow. Our findings suggest that higher ambient CO concentration is a risk factor for increased transmissibility of the novel coronavirus, while higher temperature and air pressure, and efficient ventilation reduce its transmissibility. The effect of meteorological parameters and air pollutants varies in different regions, and requires that these issues be considered in future modeling disease transmissibility.

1. Introduction

Coronavirus disease 2019 (COVID-19) was first detected in early December 2019 in Wuhan, China. The World Health Organization declared COVID-19 as a pandemic on March 11, 2020 (WHO, 2020b). As of July 8, 2020, 11,669,259 positive cases have been confirmed and 539, 906 deaths reported globally (WHO, 2020c).

Although several studies have addressed various epidemic trends of

* Corresponding author. Department of Preventive Medicine, School of Public Health, Fujian Medical University, Minhou County, Fuzhou, 350122, China.
** Corresponding author. Department of Epidemiology and Health Statistics, School of Public Health, Fujian Medical University, Minhou County, Fuzhou, 350122, China.

E-mail addresses: 9410526@qq.com (S. Lin), bengqie@163.com (D. Wei), fmusxy@163.com (Y. Sun), 369573549@qq.com (K. Chen), yangle@fjmu.edu.cn (L. Yang), 382549920@qq.com (B. Liu), 516890546@qq.com (Q. Huang), monibas2@gmail.com (M.M.B. Paoliello), fmulhy@163.com (H. Li), fmuwsy@163.com (S. Wu).

[1] These authors contributed equally to this work.

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COVID-19, its clinical characteristics, diagnostic tests, and therapeutic modalities, there is dearth of information on transmission dynamics of this novel virus. A previous study has estimated the outbreak size in Wuhan and the transmissibility of COVID-19 from confirmed cases in Wuhan to other cities in China (Wu et al., 2020). However, few studies have systematically assessed the correlation between the virus and meteorological conditions and air quality.

Exposure to climate changes and air pollution have been shown to be associated with the spread and prevalence of infectious diseases, hand-foot-mouth disease (HFMD) (Yu et al., 2019) and mumps (Hao et al., 2019), to name a few. Yet, whether these factors contribute to the transmissibility of the novel coronavirus has yet to be determined. Here, we addressed the impact of meteorological factors and air quality in several regions of Mainland China on COVID-19 transmissibility. We collected meteorological parameters and air quality indices between Jan 21, 2020 and Apr 3, 2020 in a number of Chinese provinces. The study objective was to analyze the relationship between these factors and the basic reproductive ratio (R_0) of COVID-19.

2. Methods

2.1. Source of data

The time interval required to calculate R_0 is from the first positive case confirmed until the number of cases returned to zero. Therefore, the numbers of confirmed positive cases, suspected cases, recovered cases and deaths due to COVID-19 were collected from January 21, 2020, to April 3, 2020, showing province-specific variations (Table A.1). The above data were extracted from websites of the National Health Commission of China (https://github.com/canghailan/Wuhan-2019-nCoV) , and sorted out by province. Concomitantly, we collected meteorological data and air quality data for the same provinces.

Daily meteorological data included mean/maximum/minimum air pressure (kPa), mean/maximum/minimum temperature (°C), mean/minimum relative humidity (%), cumulative precipitation (mm), mean/maximum/extreme wind velocity (m/s), duration of sunshine (h), mean/maximum/minimum surface temperature (°C). The data above were extracted from daily datasets of climate from Chinese surface stations, downloaded from the National Meteorological Information Center (Version 3.0) (http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_CES_V3.0.html).

Daily air quality data were listed in Table A.2. Provincial air quality data were obtained from the China National Urban Air Quality Real-time DAY e Publishing Platform, which belongs to China National Environmental Monitoring Center. Air quality data for Beijing were provided by the Beijing Environmental Protection Monitoring Center (http://beijingair.sinaapp.com/).

In addition, we collected information about Wuhan's population flow, including the provinces where Wuhan's population exported to and the corresponding proportions. The information was provided by the Baidu Migration (https://qianxi.baidu.com/2020/), and was collected between January 10, 2020 and January 24, 2020. It was a time period corresponding to festivities associated with the Chinese Spring Festival travel rush, and was also inclusive of a COVID-19 incubation period prior to the Government's imposed Wuhan's lockdown.

2.2. Statistical analysis

To evaluate the transmissibility of COVID-19, we used the basic reproductive ratio, R_0, which was calculated by the model developed by Ferrari et al. (2005), who proposed a maximum likelihood "removal" method for estimating R_0 for the simple epidemic based on the so-called "chain-binomial" model of infectious disease dynamics. The chain-binomial model is a discrete-time, stochastic alternative to the continuous-time, deterministic SIR model. The 95% confidence interval (*CI*) of R_0 was also estimated in this study. All analyses were completed by R soft version 3.6.2 (R Foundation for Statistical Computing). The correlations of R_0 and meteorological data, air quality data were described by Pearson Correlation Coefficient (r), or Spearman Correlation Coefficient (r_s, if the data were not normally distributed), and the trend of R_0 with meteorological factors and air quality factors was plotted. All statistical analyses were performed using IBM SPSS Statistics version 23.0, and the figures were drawn with Microsoft Excel 2019. P values were 2-tailed with statistical significance set at $P < 0.05$.

3. Results

We used data from 29 provinces in mainland China. The Tibet Autonomous Region and Qing Hai Province were not included in the analyses as no COVID-19 positive cases were reported during the data collection period.

3.1. Estimation of R_0 for COVID-19

As depicted in Fig. 1, the mean R_0 in the 29 provinces was 1.79 ± 0.31, ranging from 1.08 to 2.45. The 3 provinces with the highest R_0 were Jilin, Henan, and Guizhou, with mean R_0 of 2.45, 2.26, and 2.23, respectively.

3.2. Correlations of daily meteorological, air quality data with R_0 for COVID-19

There was a positive correlation between R_0 and the mean relative humidity, with a correlation coefficient of 0.370. No other meteorological parameters (Table 1) or air quality indices (Table 2) had a significant correlation with R_0.

3.3. Factors associated with R_0 for COVID-19 in different regions

Based on the population export from Wuhan, we divided the 29 provinces into three subgroups, high, medium and low flow (Table A3), based on the percentile of the flow ratio; similar grouping methods have been previously reported (Yang et al., 2020). Air pollutants and meteorological parameters related to R_0 varied in the medium and high flow subgroups. In the high flow, indicators such as CO and CO_24 h were positively correlated with R_0, while NO_2, NO_2 24 h and daily maximum temperature were inversely related to R_0, with coefficients of 0.644, 0.661, −0.636, −0.657, and −0.645, respectively. With respect to the medium flow, only weather factors were associated with R_0, including mean/maximum/minimum air pressure and mean wind speed, with coefficients of −0.697, −0.697, −0.697, and −0.841, respectively. There was no association between R_0 and meteorological or air quality factors in the low flow subgroup (Table 3 and Table 4). The trend for R_0 and meteorological parameters or air pollutants noted above is also shown in Fig. 2A–E and Fig. 3A–D.

4. Discussion

The COVID-19 pandemic continues to pose an urgent and enormous challenge worldwide. In this study, meteorological factors, such as relative humidity, air pressure, temperature, and air pollutants such as CO and NO_2 were evaluated to determine their regional impact on the transmission of COVID-19.

R_0 is an important epidemiological value, which predicts the spreading potential of an infectious disease from a positive individual to an expected number of secondary cases. It quantifies the contagiousness or transmissibility of infectious agents. However, it has yet to be defined globally. Herein, the values of R_0 were similar to those reported on January 23, 2020 by the WHO (WHO, 2020a) and Yao et al. (2020), ranging between 1.4 and 2.5, and 0.6 to 2.5, respectively. Our values are lower than those obtained by Wu et al. (2020) and Zhao et al. (2020), who reported R_0 values of 2.68 (2.47, 2.86) and 3.58 (2.89, 4.39),

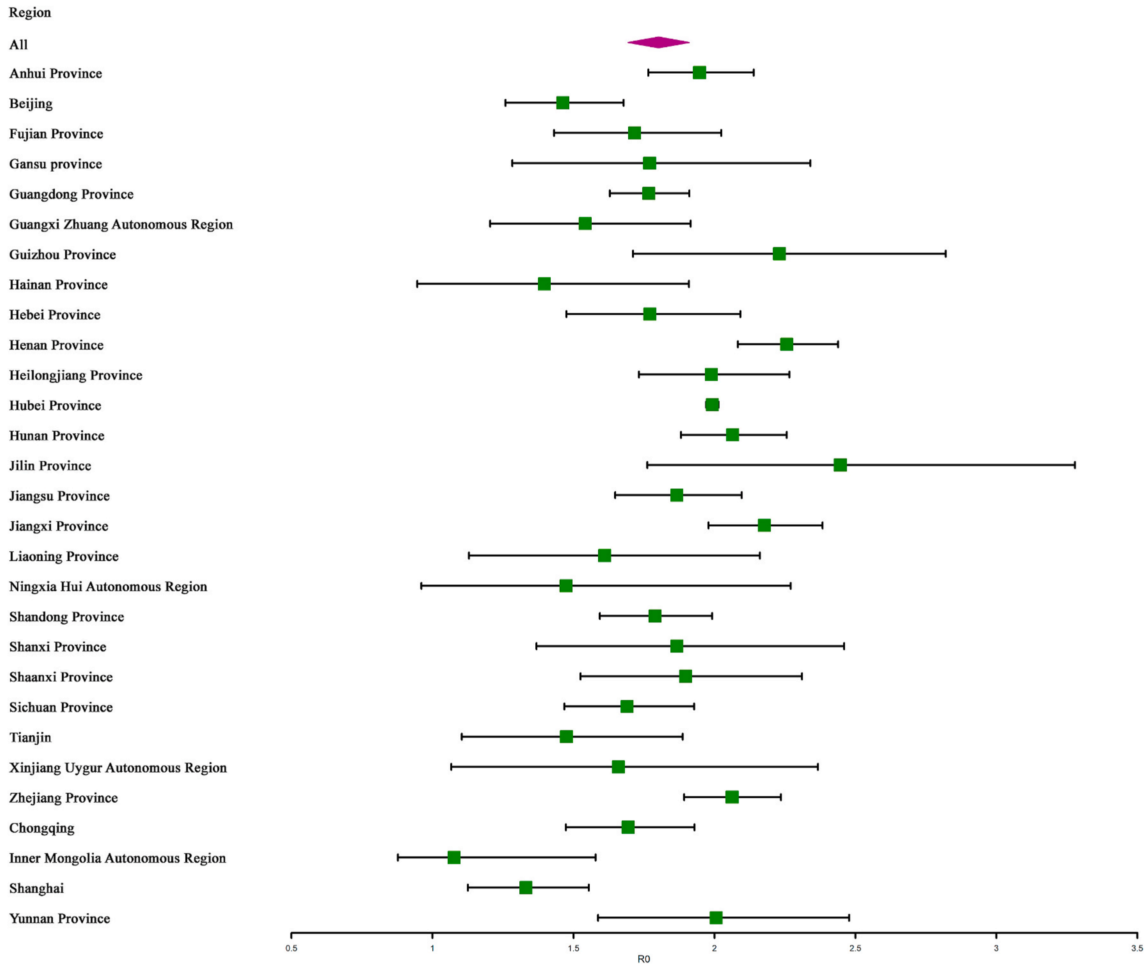

Fig. 1. The values of R_0 in 29 provinces, China.

Table 1
Correlation analysis between R_0 and daily meteorological data ($n = 29$).

Index	Coefficient	*P*
Mean air pressure of the station	-0.122	0.528
Maximum air pressure of the station	-0.129	0.505
Minimum air pressure of the station	-0.129	0.576
Mean temperature	-0.017[a]	0.928
Maximum temperature	−0.061[a]	0.753
Minimum temperature	0.019[a]	0.921
Mean relative humidity	**0.370**	**0.048**
Minimum relative humidity	0.229	0.232
Cumulative precipitation	0.221	0.249
Mean wind velocity	−0.337[a]	0.074
Maximum wind speed	−0.336[a]	0.075
Extreme wind speed	−0.272[a]	0.153
Duration of sunshine	−0.196[a]	0.307
Mean surface temperature	−0.024[a]	0.900
Maximum surface temperature	−0.220[a]	0.252
Minimum surface temperature	0.104[a]	0.590
Pressure difference	−0.123[a]	0.524
Temperature difference	−0.185[a]	0.336
Surface temperature difference	−0.370[a]	0.048

The correlations were quantified by Pearson correlation coefficient (designated with "a") or with Spearman correlation coefficient (no letter designation).

Table 2
Correlation analysis between R_0 and daily air quality data ($n = 29$).

Index	Coefficient	*P*
AQI	0.006[a]	0.974
CO	0.145	0.452
CO_24 h	0.141	0.464
NO_2	−0.320[a]	0.090
NO_2_24 h	−0.318[a]	0.092
O_3	−0.171[a]	0.375
O_3_24 h	−0.166	0.389
O_3_8 h	−0.166[a]	0.389
O_3_8 h_24 h	−0.164[a]	0.390
PM_{10}	−0.013[a]	0.948
PM_{10}_24 h	−0.002[a]	0.990
$PM_{2.5}$	0.064[a]	0.741
$PM_{2.5}$_24 h	0.070[a]	0.719
SO_2	-0.064	0.741
SO_2_24 h	-0.063	0.745

The correlations were quantified by Pearson correlation coefficient (designated with "a") or with Spearman correlation coefficient (no letter designation).

respectively. Considering the longer observation time in our study (Jan 21, 2020 to Apr 3, 2020) *vs*. the others, the transmissibility may be subject to modification dependent upon the study duration (Steven Riley et al., 2003).

It is noteworthy, the R_0 in Hubei, where the province Wuhan is located, was 1.99, which is not in the top 3 highest values reported in China. R_0 is a threshold parameter representing the expected number of secondary cases generated, and generally, the larger the R_0, the more difficult it becomes to curtail the outbreak. However, R_0 is also modified by the contact rate (Steven Riley et al., 2003), which may explain why the Hubei R_0 was not within the highest range. Faced with the epidemic, the Chinese Authorities have implemented response measures nationwide, and more stringent public health interventions in Hubei province,

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Table 3
Correlation analysis between R_0 and meteorological factors in the low, medium and high flow subgroups.

Meteorological factors	Low flow ($n = 9$)		Medium flow ($n = 10$)		High flow ($n = 10$)	
	Coefficient	*P*	Coefficient	*P*	Coefficient	*P*
Mean air pressure of the station	0.165[a]	0.672	**−0.697**	**0.025**	0.273	0.446
Maximum air pressure of the station	0.166[a]	0.670	**−0.697**	**0.025**	0.273	0.446
Minimum air pressure of the station	0.163[a]	0.676	**−0.697**	**0.025**	0.273	0.446
Mean temperature	−0.400	0.286	−0.118[a]	0.746	−0.321	0.365
Maximum temperature	−0.370[a]	0.327	−0.100[a]	0.784	**−0.636**	**0.048**
Minimum temperature	−0.400	0.286	−0.079[a]	0.829	−0.269[a]	0.453
Mean relative humidity	0.097[a]	0.803	0.169[a]	0.641	0.442	0.200
Minimum relative humidity	0.007[a]	0.985	0.200	0.580	0.202[a]	0.576
Cumulative precipitation	0.003[a]	0.994	−0.122[a]	0.736	0.309	0.385
Mean wind velocity	−0.217	0.576	**−0.841[a]**	**0.002**	−0.173[a]	0.633
Maximum wind speed	−0.078[a]	0.842	−0.502[a]	0.139	−0.322[a]	0.364
Extreme wind speed	−0.183	0.637	−0.264[a]	0.461	−0.294[a]	0.410
Duration of sunshine	0.346[a]	0.361	−0.098[a]	0.787	−0.184[a]	0.611
Mean surface temperature	−0.267	0.488	−0.074[a]	0.839	−0.527	0.117
Maximum surface temperature	−0.503[a]	0.167	−0.036[a]	0.922	−0.624	0.054
Minimum surface temperature	0.150	0.700	−0.025[a]	0.945	−0.237[a]	0.510
Pressure difference	0.280[a]	0.465	−0.429[a]	0.216	−0.505[a]	0.137
Temperature difference	0.012[a]	0.976	0.008[a]	0.983	−0.125[a]	0.732
Surface temperature difference	−0.544[a]	0.130	−0.015[a]	0.967	−0.224	0.533

The correlations were quantified by Pearson's correlation coefficient (designated with "a") or with Spearman correlation coefficient (no letter designation).

Table 4
Correlation analysis between R_0 and air quality factors in low, medium and high flow.

Air quality factors	Low flow ($n = 9$) Coefficient	*P*	Medium flow ($n = 10$) Coefficient	*P*	High flow ($n = 10$) Coefficient	*P*
AQI	0.019[a]	0.961	−0.149[a]	0.681	0.401[a]	0.251
CO	0.038[a]	0.923	0.095[a]	0.794	0.644[a]	0.044
CO_24 h	0.036[a]	0.927	0.100[a]	0.784	0.661[a]	0.038
NO_2	−0.043[a]	0.913	−0.512[a]	0.131	−0.657[a]	0.039
NO_2_24 h	−0.047[a]	0.905	−0.509[a]	0.133	−0.645[a]	0.044
O_3	0.114[a]	0.770	−0.143[a]	0.693	0.042[a]	0.909
O_3_24 h	0.004[a]	0.991	−0.135[a]	0.711	−0.213[a]	0.555
O_3_8 h	0.128[a]	0.743	−0.146[a]	0.686	0.048[a]	0.896
O_3_8 h_24 h	0.176[a]	0.650	−0.157[a]	0.665	0.014[a]	0.970
PM_{10}	0.005[a]	0.990	−0.067	0.855	0.230[a]	0.522
PM_{10}_24 h	0.012[a]	0.976	−0.067	0.855	0.241[a]	0.502
$PM_{2.5}$	0.053[a]	0.893	−0.152[a]	0.675	0.459[a]	0.182
$PM_{2.5}$_24 h	0.052[a]	0.894	−0.141[a]	0.697	0.469[a]	0.171
SO_2	0.069[a]	0.861	0.370	0.293	−0.118[a]	0.744
SO_2_24 h	0.066[a]	0.867	0.370	0.293	−0.099[a]	0.786

The correlations were quantified by Pearson correlation coefficient (designated with "a") or with Spearman correlation coefficient (no letter designation).

especially in Wuhan. We analyzed the difference in the R_0 in the Hubei province pre- and post-lockdown, with corresponding R_0 of 3.20 vs. 1.85, respectively, corroborating this speculation. Moreover, in considering whether different interventions in Hubei *vs*. other provinces affect the correlation of R_0 values and meteorological or air quality factors, we compared the results with or without inclusion of Hubei province. The significant variables and the direction of their correlation coefficients were consistent in both cases.

In addition to the magnitude of the transmissibility, concern has been raised regarding the propensity of meteorological conditions to impact the transmissibility of COVID-19. Our findings establish that lower relative humidity, higher temperature, higher air pressure and higher wind speed decrease the spread of COVID-19.

Based on findings in previous studies, many infectious diseases have seasonal prevalence (Morawska et al., 2020), especially respiratory viral infections (Moriyama et al., 2020). For example, in 2003, when the weather turned warmer SARS infections decreased (Yuan et al., 2006). Our results showed a similar trend in provinces belonging to high flow, where an inverse association between R_0 and daily maximum temperature was found. In general, viruses are sensitive to high temperatures, making it more difficult for them to survive, consistent with our observations. In addition, colder weather favors human indoor activities, increasing the risk of infection (Bunker et al., 2016). Analogous conclusions to ours on the relationship between virus persistence in the environment and ambient temperature have been noted in several studies (Ma et al., 2020; Mohammad M. Sajadi et al., 2020). The incidence rate of positive case of COVID-19 ranged from 0 to 60% with daily maximal temperature between 12.2 °C and 22.8 °C; for an average increase of 1 °C in maximum temperature, the incidence rate decreased by −7.5% on the same day (Aurelio et al., 2020). However, other studies have noted contradictory findings, pointing to positive correlations between diurnal temperature range and COVID-19 daily deaths (Ma et al., 2020). Consistent with our findings, an earlier study (Liu et al., 2020) addressing the impact of meteorological factors on covid-19 transmission, after controlling for population migration in provincial capital cities in China, showed that low temperature, mild diurnal temperature range and low humidity favored COVID-19 transmission. In contrast, in a study performed in 122 Chinese cities, there was no evidence to support that COVID-19 case numbers decline with warmer weather (Xie and Zhu., 2020).

Humidity is another environmental factor that contributes to the seasonal nature of respiratory viral infections, including COVID-19 (Ma et al., 2020). In our analysis, mean relative humidity was correlated to R_0, but this relationship was not maintained after controlling for regional variables.

Average wind velocity and air pressure are also relevant weather parameters to the spread of COVID-19. Higher wind velocity is reflected in shorter suspension time of droplets in outdoor air, and better ventilation in indoor environments (Morawska et al., 2020), reducing the likelihood of infection. Air pressure is also a factor affecting COVID-19 transmissibility. For example, daily average air pressure has been shown to be inversely associated with secondary attack rate of SARS, *OR* = 0.53 (95% *CI*: 0.42 to 0.66) (Cai et al., 2007). The study inferred high air pressure may shorten the suspension time of droplets in air, analogous to wind velocity, reducing the transmissibility of SARS. But a contradictory study showed that increased maximum/minimum/mean atmospheric pressure may aggravate the epidemics of dengue (Zhu, 2019).

Air pollutants have been reported to correlate with several diseases, such as those of the cardiovascular (Zhang et al., 2019; Andersson et al., 2020) and respiratory systems (N. Chen et al., 2020), including COVID-19 (Martelletti et al., 2020). Exposure to air pollutants has been demonstrated to induce pulmonary oxidative stress, leading to

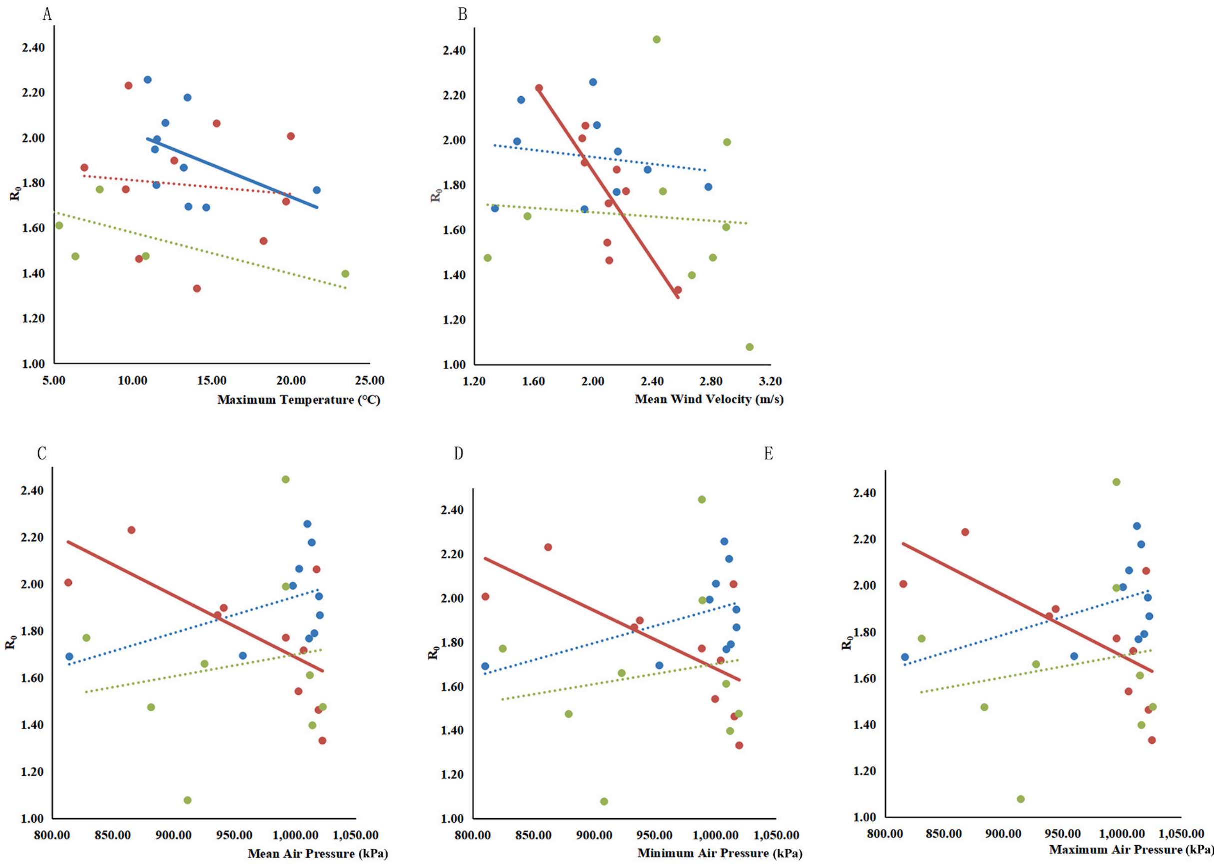

Fig. 2. The trend between R_0 and meteorological factors. A. R_0 and maximum temperature; B. R_0 and mean wind velocity; C. R_0 and mean air pressure; D. R_0 and minimum air pressure; E. R_0 and maximum air pressure. Blue, high flow; red, medium flow; green, low flow. Solid line means significant association between observation variable and COVID-19, dotted line means no significant association between observation variable and COVID-19. . (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

production of free radicals, in turn injurying the respiratory system and reducing viral resistance (Ciencewicki et al., 2007). These correlations were also inherent to our study, showing regional characteristics (Ogen et al., 2020), analogous to the climate factors noted above. Subgroup analysis showed that frequent flow group CO, CO_24 h and R_0 were positively correlated,while NO_2, NO_2_24 h and R_0 were negatively correlated. No correlation was found between the air quality factors and R_0 in the medium flow group or the low flow group.

The production of CO is closely related to the incomplete combustion of fossil fuels, and is a ubiquitous environmental gaseous pollutant (Wu et al., 2005). Increased CO concentrations in the air were accompanied by increased R_0. Previous studies have indicated that CO exposure is associated with respiratory symptoms (Zhao et al., 2019; North et al., 2019; Lawin et al., 2018). Therefore, COVID-19 as a respiratory disease may be associated with high level CO exposure. CO exposure is associated with increased concentrations of endogenous CO, producing carboxyhemoglobin (COHb) and airway inflammatory diseases (Burnett et al., 1998; Zayasu et al., 1997). Recent studies have shown that high environmental CO concentrations trigger reactive oxygen species (ROS) generation and impaired myoglobin function (Piantadosi et al., 1995, 2008). In contrast, it has been reported that ambient CO is negatively- (Tian et al., 2014) or not-correlated with respiratory diseases (Chen et al., 2011), contradicting our findings. However, existing research cannot determine the association between ambient CO levels and human health, and further research on this issue is warranted.

However, different from CO, we observed a negative relationship between NO_2 and COVID-19. In published studies, most results have shown no significant relationship with COVID-19; only a few found a positive correlation between NO_2 and COVID-19 confirmed cases or death (Ogen et al., 2020; Zhu et al., 2020). In contrast, our study focused on the transmissibility of this virus, which has not been found to correlate with NO_2 yet. NO_2 was found to be negatively correlated with laboratory-confirmed influenza (Liu et al., 2018), corroborating in part our results. In addition, NO has been shown to inhibit the replication cycle of the severe acute respiratory syndrome coronavirus (SARS CoV) *in vitro* (Akerström et al., 2005). Thus, a similar mechanism may exist for NO_2 and the novel Coronavirus. Additional research is needed to determine the biological mechanisms associated with this phenomenon.

Our study is divided into three subgroups of population movement between January10 to 24, 2020. No correlations were found between air quality and R_0 in the medium and low flow subgroups. This may reflect the fact that the population that exported from Wuhan was the main infection source in other cities and provinces (Z. L. Chen et al., 2020), causing frequent flow groups to have a larger R_0 (Spearman correlation analysis results suggest that R_0 is positively correlated with different flow areas $r_s = 0.392$, $P = 0.035$). On the other hand, although the improvement of air quality may reduce the R_0, the impact caused by the flow of people may be sufficiently great, and therefore mask the impact in air quality of the improvement. Further it may contribute to the impression that R_0 is rising although the environmental conditions are improving,(reduced CO and NO_2 levels, etc. (Dutheil, 2020, NASA, 2020; Tobías et al., 2020).

5. Limitations

The present study has several limitations. First, exposure to meteorological environment or air pollution at individual level is difficult to obtain and quantified. The results are presented at the group level,

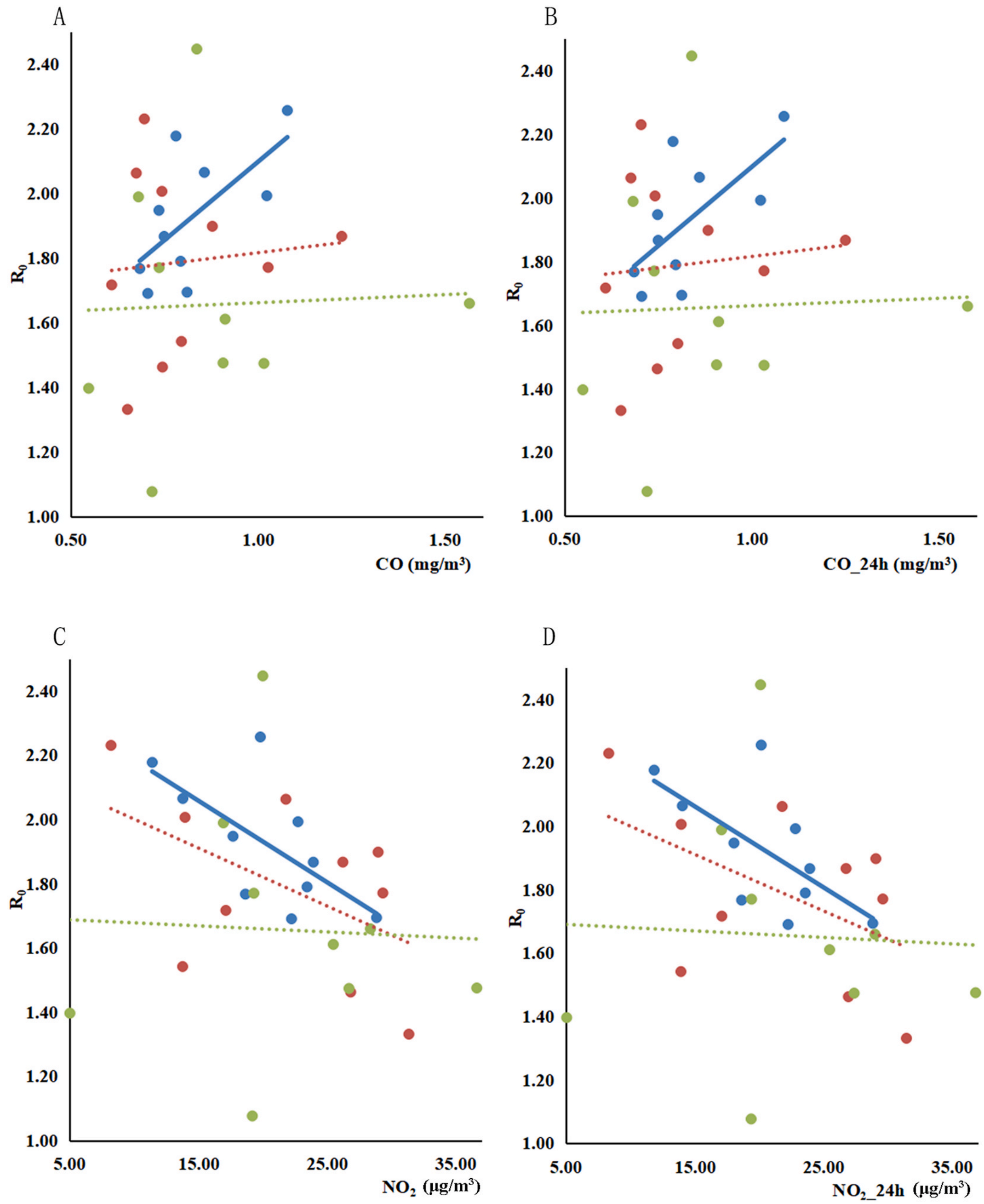

Fig. 3. The trend between R_0 and air quality factors. A. R_0 and CO; B. R_0 and CO_24 h; C. R_0 and NO_2; D. R_0 and NO_2_24 h; Blue, high flow; red, medium flow; green, low flow. Solid line means significant association between observation variable and COVID-19, dotted line means no significant association between observation variable and COVID-19. . (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

which may lead to an ecological fallacy, which arises when an inference is made about an individual based on analyses of group data, to which a given individual belongs. However, considering the current urgency in understanding the novel coronavirus, ecological studies are necessary and invaluable tools. Second, since COVID-19 is caused by the virus SARS CoV-2, more factors are needed to be investigated, such as viral resistance, population mobility, population immunity level, public interventions, medical resources, among others. It is noteworthy, public health interventions implemented by the Chinese government such as traffic restriction, social distancing measures, home isolation and centralized quarantine, extensive health education, as well as rigorous measures in public places, played an important role in mitigating the spread of COVID-19 (Pan et al., 2020; Maier et al., 2020). Considering that all provinces have quickly adopted first-level response measures to the virus, we believe the impacts of these interventions were comparable across provinces. Nevertheless, this study aimed to highlight the impact of air pollutants and meteorological parameters on COVID-19, thus it is important and acceptable to focus on these factors. Furthermore, we have selected the most representative indicator R_0 to describe the transmission capacity, and as one of the main indicators of infectious disease, we have partially considered population mobility by conducting subgroup analysis. Finally, the information on comorbidities in these populations were not collected in our study, which should also be considered in the observed differences between regions. However, this study is just a preliminary analysis. For sounder conclusions, additional studies will require analysis over a more protracted time with bigger data sets. Overall, this study has shown that meteorological factors such as relative humidity, air pressure, temperature, and air pollutants such as CO and NO_2 may affect the transmission of COVID-19, differing among various provinces. Nonetheless, we emphasize the need for further investigation on the transmissibility of COVID-19 and its relationship to meteorological factors and air pollutants.

6. Conclusion

We conducted an observational study on the correlation between COVID-19 and ecological indicators such as meteorological parameters and air quality, reflecting the most comprehensive study to date on the role of meteorological parameters and air quality factors in COVID-19. We conclude that high carbon monoxide concentration is a risk factor, whilst higher temperatures, increased air pressure and better ventilation may reduce the transmissibility of the novel coronavirus. The effect of meteorological parameters and air pollutants varies in different Chinese provinces and should be considered in future studies on COVID-19 transmissibility.

Author statement

Shaowei Lin: Software, Writing - original draft. Donghong Wei: Software, Writing - original draft, Investigation. Yi Sun: Software, Writing - original draft, Investigation. Kun Chen: Data curation, Investigation. Le Yang: Data curation, Investigation. Bang Liu: Data curation, Investigation. Qing Huang: Data curation, Investigation. Monica Maria Bastos Paoliello: Writing- Reviewing and Editing. Huangyuan Li: Conceptualization, Methodology, Writing- Reviewing and Editing. Siying Wu: Conceptualization, Methodology, Writing- Reviewing and Editing. All authors contributed to critical revision of the final manuscript and approved the final version of the manuscript.

Declaration of competing interest

The authors declare that they have no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoenv.2020.111035.

Consent for publication

Not applicable.

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