Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Meteorological factors, governmental responses and COVID-19: Evidence from four European countries

Shihua Fu a,1, Bo Wang a,1, Ji Zhou b,1, Xiaocheng Xu a, Jiangtao Liu a, Yueling Ma a, Lanyu Li a, Xiaotao He a, Sheng Li c, Jingping Niu a, Bin Luo a,b,d,g,*, Kai Zhang e,f,g

a Institute of Occupational Health and Environmental Health, School of Public Health, Lanzhou University, Lanzhou, Gansu, 730000, People’s Republic of China
b Shanghai Key Laboratory of Meteorology and Health, Shanghai Meteorological Bureau, Shanghai, 200030, People’s Republic of China
c The First Hospital of Lanzhou University, Lanzhou, Gansu, 730000, People’s Republic of China
d Shanghai Typhoon Institute, China Meteorological Administration, Shanghai, 200030, China
e Department of Epidemiology, Human Genetics and Environmental Sciences, School of Public Health, The University of Texas Health Science Center at Houston, Houston, TX, 77030, USA
f Southwest Center for Occupational and Environmental Health, School of Public Health, The University of Texas Health Science Center at Houston, Houston, TX, 77030, USA
g Department of Environmental Health Sciences School of Public Health University at Albany, State University of New York One University Place Rensselaer, NY, 12144, USA

ARTICLE INFO

Keywords:
COVID-19
Meteorological factor
Government response index
DLNM

ABSTRACT

With the global lockdown, meteorological factors are highly discussed for COVID-19 transmission. In this study, national-specific and region-specific data sets from Germany, Italy, Spain and the United Kingdom were used to explore the effect of temperature, absolute humidity and diurnal temperature range (DTR) on COVID-19 transmission. From February 1st to November 1st, a 7-day COVID-19 case doubling time (Td), meteorological factors with cumulative 14-day-lagged, government response index and other factors were fitted in the distributed lag nonlinear models. The overall relative risk (RR) of the 10th and the 25th percentiles temperature compared to the median were 0.0074 (95% CI: 0.0023, 0.0237) and 0.1220 (95% CI: 0.0667, 0.2232), respectively. The pooled RR of lower (10th, 25th) and extremely high (90th) absolute humidity were 0.3266 (95% CI: 0.1379, 0.7734), 0.6018 (95% CI: 0.4693, 0.7718) and 0.3438 (95% CI: 0.2254, 0.5242), respectively. While the DTR did not have a significant effect on Td. The total cumulative effect of temperature (10th) and absolute humidity (10th, 90th) on Td increased with the change of lag days. Similarly, a decline in temperature and absolute humidity at cumulative 14-day-lagged corresponded to the lower RR on Td in pooled region-specific effects. In summary, the government responses are important factors in alleviating the spread of COVID-19. After controlling that, our results indicate that both the cold and the dry environment also likely facilitate the COVID-19 transmission.

1. Introduction

Corona Virus Disease 2019, abbreviated as “COVID-19”, named by the World Health Organization (Wu and McGoogan, 2020; Zu et al., 2020), has been confirmed as an acute respiratory infectious disease caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) infection (WHO, 2020a; Huang et al., 2020; Yu et al., 2020). Due to its fast and wide transmission world-wide, it has been recognized as a global pandemic (WHO, 2020b), which has infected 47,930,397 confirmed cases, including 1,221,781 deaths as of 5:00 pm CEST, November 5, 2020 (WHO, 2020c). Whether this global pandemic is partially influenced by the change of ambient environment is still a hot topic, which needs to be discussed continuously.

Although there is no final conclusion on the meteorological impact over the continuously growing of COVID-19 cases worldwide, it usually indicates that SARS-CoV-2 may be particularly sensitive to weather...
involved the number and time of confirmed cases was considered: doubling time (Td). The Td is defined as the time it takes for the total number of COVID-19 cases to double, which is an index to evaluate the spread rate of the epidemic (Muniz-Rodriguez et al., 2020; Zhou et al., 2020). Considering that the average incubation period of COVID-19 is 7 days (Muniz-Rodriguez et al., 2020; Zhou et al., 2020), we choose 7 days as the interval of the exponential model. Then the equation of Td given by:

\[ Td = \frac{\log 2}{\log \left( \frac{N_{day+7}}{N_{day}} \right) \frac{1}{10}} \]  

(1)

Where day represents the cumulative number of diagnosed on the day of the study, and day+7-represents the cumulative number of diagnosed after an interval of 7 days.

2.1.2. Meteorological data

The daily meteorological data came from the “Wheat-A” data system (http://www.xiaomaiaiyi.cc/). Based on longitude and latitude, the meteorological data of 326 weather stations were matched with regions. Daily meteorological data included average/minimum/maximum temperature, dew-point temperature and average wind velocity. Absolute humidity was calculated indirectly through vapor pressure, using the Clausius–Clapeyron relation (Shaman and Kohn, 2009). Briefly, we first calculated the actual vapor pressure using daily dew-point temperature. Then, absolute humidity (AH) is derived by vapor pressure (Davis et al., 2016), which is described as equations (2) and (3):

\[ e = e_w \exp \left[ \frac{L}{R_h} \left( \frac{1}{T_0} - \frac{1}{\text{Dew point}} \right) \right] \]  

(2)

\[ \text{AH} \ (g/m^3) = \frac{e}{R_h \times T_{	ext{es}}} \times 10^5 \]  

(3)

Where e denotes the actual vapor pressure; \( e_w \) refers to the saturated water vapor pressure (6.112 kPa) at temperature \( T_0 \) (0 °C); \( L \) represents the latent heat of water evaporation (2257 kJ/kg); \( R_h \) is the gas constant of water vapor [287 J/(kg·°C)]; \( T_{	ext{es}} \) means daily ambient temperature (°C); Dew point means daily dew-point temperature (°C).

2.1.3. Fine particles, population density and GRI

Environmental fine particles (PM2.5), population density and GRI data were collected simultaneously. Daily PM2.5 data were downloaded from the “Air Matters” (https://air-matters.com/ch-Hans/index.html). The information about population density was obtained from the European Statistical System (https://ec.europa.eu/eurostat/databrowser/view/demo_r_d3dens/default/map?lang=en), which are available in the supplementary materials. The data on GRI were downloaded from GitHub Covid-policy-tracker (https://github.com/OxCGRT/covid-policy-tracker), which integrated 14 indicators in terms of containment and closure policies, economic policies, and health system policies: School Closures, Workplace closing, Cancel Public Events, Restrictions on gatherings, Public Transportation, Stay at Home Order, Restrictions on Internal Movement, International Travel Controls, Income Support, Debt/contract Relief for Households, Public Information Campaigns, Testing Policy and Contact Tracing (Thomas Hale et al., 2020). The index was adjusted from 0 to 100 (100 = the strictest).

2.2. Statistical analysis

Firstly, we used Pearson correlation analysis to explore the relationship between meteorological factors and daily Td. Then, based on the published research (Runkle et al., 2020), we established DLMN models to evaluate the effects of meteorological factors on the daily Td. Meanwhile, we controlled PM2.5, population density, GRI, residual autocorrelation (Imai et al., 2015) and other confounding factors in the
models. To allow for over-dispersion of COVID-19 in transmission, a quasi-Poisson regression was used as the connection function of the model. The model used three independent research variables: temperature, absolute humidity and diurnal temperature range (DTR). The relative risk (RR) of the Td was estimated by the 90th, 75th, 25th and 10th percentiles values relative to the median of each meteorological factors. This method is suitable for assessing the intermittent changes (e.g., meteorological) in the risk of a rare and acute outcome (i.e., COVID-19 transmission) within a short period (Armstrong et al., 2019; Runkle et al., 2020). We conducted this research using the “dlnm” package in R4.0.1. The modified DLNM models are shown in equations (4)–(6):

\[
\log [E(Y_t)] = \alpha + \beta_1 \sum c_b(Tem, lag) + \eta(PM_{2.5}, df) + \eta(AH, df) + \eta(Wind, df) + \log(Y_{t-1}) + \log(DOP) + GRI_{lag14} + \text{dow} + \text{region},
\]

(eq4)

\[
\log [E(Y_t)] = \alpha + \beta_2 \sum c_b(AH, lag) + \eta(PM_{2.5}, df) + \eta(Tem, df) + \eta(Wind, df) + \log(Y_{t-1}) + \log(DOP) + GRI_{lag14} + \text{dow} + \text{region},
\]

(eq5)

\[
\log [E(Y_t)] = \alpha + \beta_3 \sum c_b(DTR, lag) + \eta(PM_{2.5}, df) + \eta(AH, df) + \eta(Wind, df) + \log(Y_{t-1}) + \log(DOP) + GRI_{lag14} + \text{dow} + \text{region},
\]

(eq6)

Where t is the observation date; j refers to the regions; E(Yt) is the expected value of the Td observed in region j on day t; a is the intercept; βj is the regression coefficient; \( \sum c_b() \) represents the two-dimensional matrix of meteorological factors and lag days and the natural cubic spline function with 3 degrees of freedom was used; We defined 14 days as the maximum lag days; \( \text{ns}() \) denotes the smoother based on normal regression splines; Tem, PM_{2.5}, AH and Wind are the three-day moving average of temperature (df = 6), PM_{2.5} (df = 3), absolute humidity (df = 3) and wind velocity (df = 3), respectively; \( \log(Y_{t-1}) \) is the COVID-19 count of logarithmic conversion on t-1 to control potential sequential autocorrelations; DOP denotes the number of people living on land per unit area; GRI_{lag14} is the GRI at single 14-day-lagged; dow means the day of week was controlled as a categorical variable; region indicates region fixed effects to control for any observable and unobservable characteristics. The meta-analysis was based on R software “meta” package.

As our design of including multiple regions, we further investigated the region-specific effect estimates of meteorological factors on Td under different lag exposure (lag 03, lag 05, lag 07, lag 09, lag 011 and lag 014). The meta-analysis was based on R software “mvmeta” package.

3. Results

In total, 1,508,094 COVID-19 confirmed cases were included in this study from February 1st through November 1st, 2020. The change of COVID-19 new cases exhibited a temporal characteristic, showing two increasing waves till November. The first peak observed in spring (March–May) in these four countries corresponded to shorter Td, while the second increasing wave observed much stronger since August compared with the first one (with a rapid increase since early July in Spain) (Fig. 1). With the latest data, we could find that the confirmed COVID-19 cases were still on the rising trend, which have not reached the peak so far.

3.1. Correlation between the Td and variables

Pearson correlation analysis of daily Td and meteorological factors for four countries from February 1st through November 1st, 2020 were shown in Table. 1, Fig.S1-S3 and Fig.S6-S8. Temperature in four countries had similar patterns, all showed positive associations with Td (\( r_{\text{Germany}} = 0.66, r_{\text{Italy}} = 0.64, r_{\text{Spain}} = 0.47, r_{\text{UK}} = 0.75 \), respectively), similar to the correlation between absolute humidity and the Td (\( r_{\text{Germany}} = 0.55, r_{\text{Italy}} = 0.50, r_{\text{Spain}} = 0.25, r_{\text{UK}} = 0.67 \), respectively). However, the correlations between diurnal temperature range (DTR) and Td were weak in Germany, Italy and Spain (\( r_{\text{Germany}} = 0.07, r_{\text{Italy}} = 0.10, r_{\text{Spain}} = 0.12, r_{\text{UK}} = 0.62 \), respectively), while the correlation in the UK was not statistically significant (\( r_{\text{UK}} = -0.01, p > 0.05 \)). There was a negative correlation between population density and Td in four countries, but the correlation was higher in the UK (Table. 1 and Fig.S4). In linear regression analysis, the GRI at single 14-day-lagged was highly positively correlated with Td (except for Italy) (Table. 1 and Fig.S5), indicating the GRI is an important factor in controlling COVID-19.

3.2. Effects of meteorological factors on Td

Figs. 2 – 4 show the results of the meta-analysis about the RR of Td associated with different percentiles values (10th, 25th, 75th and 90th) of temperature, absolute humidity and DTR at cumulative 14-day-lagged. In the regional analysis, the most significant effect of lower temperature (10th) on Td was found in Italy (RR = 0.0008, 95% CI: 0.0002, 0.0035). In the pooled analysis, compared with the median of each meteorological factors, lower temperatures (10th and 25th) had a greater impact on Td. The RR of temperature in the 10th and 25th percentiles were 0.0074 (95% CI: 0.0023, 0.0237) and 0.1220 (95% CI: 0.0002, 0.0035). The RR of absolute humidity on Td was significant. There was the most significant effect of lower humidity (10th) on Td in Germany (RR = 0.0944, 95% CI: 0.0654, 0.1511). The RR of Td at 10th percentile and 25th percentile were 0.3266 (95% CI: 0.1379, 0.7734) and 0.6018 (95% CI: 0.4693, 0.7718). Meanwhile, the significant effect of extremely high humidity was also observed at the 90th percentile of absolute humidity (RR = 0.3438, 95% CI: 0.2254, 0.5242). However, the effect estimates of DTR on Td were not statistically significant.

3.3. Cumulative lag effects of meteorological factors

Fig. 5 presents the RR for the cumulative effect of Td under different lag exposure (lag 03, lag 05, lag 07, lag 09, lag 011 and lag 014) at 10th and 90th percentiles of temperature, absolute humidity and DTR. Temperature with 10th percentile showed an enhanced cumulative effect on the Td as the lag days change, while temperature with 90th percentile showed a non-significant cumulative effect. The cumulative effect of absolute humidity on Td decreased in the exposure at 10th and 90th percentiles, peaking at cumulative 14 days. The cumulative lag effect of DTR was not significant.
3.4. Multivariate meta-regression analysis and sensitivity analysis

The overall estimates from the region-specific effects are similar to the country-specific effects (Fig. 6), indicating that low temperature and low absolute humidity may be a factor leading to shorter Td in four European countries, resulting in a faster spread of the virus. In the sensitivity analysis, the associations between meteorological factors and the Td of different time intervals (5 and 9 days) were robust. The low temperature and extreme absolute humidity have a greater impact on the COVID-19 Td (Table.S1-S2), indicating that they likely favor the COVID-19 transmission.

4. Discussion

COVID-19 is a widely transmitted respiratory disease, which has been listed as a pandemic by the World Health Organization (WHO, 2020b). Since the outbreak of COVID-19, the arguments over whether the ambient environment could affect its transmission have continuously been a hot topic worldwide. To date, no consistent evidence has been reached with varying study periods, countries/regions with varying climate and weather, and the lack of controlling confounding factors like population density, government intervention policies, etc. To solve these issues, we used the DLMN statistic model to quantitatively evaluate the effects of meteorological factors on COVID-19 transmission during a longer period and controlled the bias from government intervention policies in a form of GRI. Our results indicated that government responses are important factors in controlling COVID-19 pandemic. After controlling government responses and other confounding factors, we found that both the lower temperature and the lower absolute humidity had a greater impact on the COVID-19 case Td.

Although there was a bit difference in the RR in analysis of the association between meteorological factors and Td, but their associations were quit similar, all indicated the positive effect of lower temperature and lower humidity on COVID-19 transmission. This is consistent with those reported in other geographical locations (Bashir et al., 2020; Ma et al., 2020; Tosepu et al., 2020; Xie and Zhu, 2020). With the arriving of winter in these four European countries, the second increasing wave of COVID-19 confirmed cases were much more strong compared to the first one, which better proved that COVID-19 transmission was related to low temperature. An experimental study reported that the SARS-CoV-2 virus was highly stable at 4°C, but sensitive to heat (van Doremalen et al., 2020). At 4°C, there was only around a 0.7 log-unit reduction of infectious titer on day 14, but the time for virus inactivation reduced to 5 min (Chin et al., 2020), when the incubation temperature increased to 70°C. That is, the high temperature is not conducive to the survival of the virus. Besides, it is known that respiratory viruses (such as influenza) can survive longer in a cold environment (Martinez, 2018). Similar virus like SARS-CoV and MERS-CoV were also reported to maintain stronger infectivity at low temperatures on a solid surface, whether it was droplet state or aerosol state (van Doremalen et al., 2013; Casanova et al., 2010; Kim et al., 2007). Besides, the body’s resistance become relatively weak under cold stress (Shaw, 2016), particularly, the phagocytosis function of alveolar macrophage was depressed in an environment with lower temperature (Luo et al., 2017), which may also explain the higher confirmed COVID-19 cases and the shorter Td. Therefore, combined with the more obvious effect of lower temperature in cumulative analysis, our results indicated that the lower temperature is significantly beneficial to the transmission and survival of coronavirus.

Previous studies were usually under a linear regression framework, showing that there was a significant negative correlation between...
humidity and COVID-19 cases (Sarkodie and Owusu, 2020), which need to be confirmed with more precise statistic model. Islam et al. regarded humidity as a driver of SARS-CoV-2 transmission, and a higher COVID-19 transmission rate was reported in specific humidity ranged from 6 to 9 g/kg (Islam et al., 2020; Runkle et al., 2020b). In line with these studies, we found that extreme (high and low) absolute humidity have a greater impact on the COVID-19 Td, which were still robust in pooled analysis for the four European countries. When the humidity in the air is low, the virus forms small aerosol particles, which increases the risk of viral transmission and reduces immunity (Sarkodie and Owusu, 2020). It’s reported that up to 3 h are needed for 2-μm aerosol particles to settle to the ground, while 10 μm aerosol particles only take about 10-min (Marr et al., 2019), the long stay of the virus in the air increase the risk of infection in others. In this study, we found the cumulative effect of lower humidity was obviously significant on Td. This means the longer stable dry environment would promote the long stay of SARS-CoV-2 and shorten the Td, which in turn increases the transmission of COVID-19. In addition, the mucociliary of the nasal cavity and upper respiratory tract have important interception and cleaning functions, but dry air can damage their epithelial structure (Arja I. Hälinen, 2000). To sum up, the dry environment can increase the spread of the virus and facilitate COVID-19 transmission. Also, studies have shown that a considerable number of people infected with COVID-19 suffer from underlying diseases (such as diabetes, hypertension, coronary heart disease, etc.) (Emami et al., 2020). Since extremely high humidity is also a risk factor for chronic diseases like cardiovascular disease in the elderly (Zeng et al., 2017), which may explain why it is also related to the shorter Td. In summary, we believe that a longer sustained dry environment may increase the spread of COVID-19, which need to be stressed in government interventions.

However, previous findings are inconsistent due to a few possible reasons (Xie and Zhu, 2020; Yao et al., 2020; Briz-Redón and Serrano-Aroca, 2020; Jahangiri et al., 2020). Firstly, the temperature range varied greatly with studies due to the short study period. Secondly, many studies are cross-sectional at the national level and there is a large degree of heterogeneity among different countries (Tobías and Molina, 2020). And in some time-series studies, researchers used the temperature of the capital city to reflect the average exposure temperature for one country, which leads to large exposure misclassification. Thirdly, regulations and human behaviors play a great role in the spread speed of COVID-19, e.g., contact tracking, quarantine strategy, the implementation ability of COVID-19 control policy, urbanization rate and the availability of medical resources (Bherwani et al., 2020; Jahangiri et al., 2020; Mukherjee et al., 2020; Bherwani et al., 2020; Jahangiri et al., 2020; Mukherjee et al., 2020). In this study, we conducted the DLMN analysis for a long period (from February 1st through
November 1st, 2020), covering two increasing waves of COVID-19 confirmed cases and controlling factors like population density, GRI, etc. GRI integrates 14 indicators in terms of containment and closure policies, economic policies, and health system policies (including School Closures, Workplace closing, Cancel Public Events, Restrictions on gatherings, Public Transportation, Stay at Home Order, Restrictions on Internal Movement, International Travel Controls, Income Support, Debt/contract Relief for Households, Public Information Campaigns, Testing Policy and Contact Tracing). Thus, our models likely provide better estimates of meteorological factors on the COVID-19 spread by filtering out the impact of regulation and behavior.

A previous study indicated that the impact of environmental factors on virus transmission should be characterized using a dynamic model (such as the susceptible-exposed-infectious-recovered [SEIR] model), because infectiousness estimated from a traditional model is biased by confounding from environmental variables (Shi et al., 2020). However, the SEIR model has some limitations in its application. Firstly, the SEIR model needs to input the daily number of susceptible, exposed, infectious and removed individuals. These detailed data reports are incomplete in many countries or regions. Secondly, the SEIR model may lead to a deviation of output results due to different input parameter estimations (such as contact rate and infection rate) (He et al., 2020). For example, several studies used the SEIR model to evaluate the relationship between meteorological conditions (temperature and relative humidity) and COVID-19 in China, but the results were inconsistent due to the different input parameters of their models (Pan et al., 2021; Guo et al., 2020; Shi et al., 2020). Besides, to allow for over-dispersion of COVID-19 data, some studies used the generalized linear model with negative binomial distribution to fit the relationship between environmental factors and COVID-19 based on R software with “MASS” package (Liu et al., 2020; J Wang et al., 2020). A limitation of the generalized linear model is that it can’t fit the nonlinear-lagged effects between environmental factors and COVID-19. And the previous study showed that both the quasi-Poisson distribution and negative binomial distribution regression model can be used for overdispersal data, and the quasi-Poisson distribution is a better fit to the overall variance-mean relationship (Ver Hoef and Boveng, 2007). Considering the above factors, the DLNM model with quasi-Poisson distribution is the most suitable for this study.

Although we have adjusted population density and GRI, there are still many restrictions that should not be ignored. In this study, our evidence is limited to modeling studies based on parameter assumptions with current incomplete case data. But the transmission of COVID-19 may be affected by many factors, including governmental interventions, social contact, population mobility, population vulnerability and so on. Therefore, this problem should be examined in future.
Secondly, Td is the time needed to double the number of infected people. As an indicator of COVID-19 transmission, it will change with the degree of infection and the implementation of human intervention with the passage of time. Only paying attention to the Td is not enough to accurately reflect the real situation of COVID-19 transmission. Therefore, our research results need to be further discussed.

Thirdly, we only have analyzed the data from four countries covering nine months, which may not be enough to study the COVID-19 change trend at global level. Even so, the conclusion based on the present study at least provides new clues for understanding the relationship between the spread of COVID-19 and temperature and humidity.

5. Conclusion

In summary, the government responses are important factors in alleviating the spread of COVID-19. Our results indicate that both the cold and the dry environment also likely facilitate the COVID-19 transmission after controlling the bias from population density, government response policies, air pollutants and other factors in long study periods covering two increasing waves of COVID-19 in four European countries. This study used data from February 1st to November 1st, which provide strong scientific evidence for the importance of stressing the cold weather effect on COVID-19 transmission with the arriving colder season. In particular, we observed that the confirmed case of COVID-19 are still madly increasing in the Northern Hemisphere, so we strongly suggest to provide more public health resources and governmental interventions on the controlling of COVID-19 in this cold season. Besides, studies covering the entire earth in a longer period are urgently needed to quantify the combined effects of meteorological factors and policy interventions on the spread of COVID-19. By doing that, we hope to find the most effective intervention in controlling the COVID-19, particularly before the vaccinating of an effective vaccine against this tricky virus.

Credit author statement

Shihua Fu, Writing – original draft, Software, Data curation. Bo Wang, Writing – original draft, Software, Data curation. Ji Zhou, Methodology, Supervision, Conceptualization. Xiaocheng Xu, Methodology, Visualization. Jiangtao Liu, Methodology, Visualization. Yueling Ma, Formal analysis. Lanyu Li, Methodology, Visualization. Xiaotao He, Data curation. Sheng Li, Validation. Jingping Niu, Investigation. Bin Luo, Project administration. Bin Luo, Conceptualization, Writing – review & editing. Kai Zhang, Conceptualization, Writing – review & editing.
**Ethics approval and consent to participate**

All data is public, there is no patient contact, and no PIN is required. Therefore, the study does not require ethical approval.

**Consent for publication**

Not applicable.

**Availability of data and materials**

All COVID-19 daily confirmed cases were collected from the official websites of national or regional health departments from February 1st through November 1st, 2020, which are publicly available. The meteorological datasets used and/or analyzed during the current study are not publicly available but are available from the corresponding author on reasonable request. The population density datasets, particulate matter datasets and government response index datasets used and/or analyzed during the current study are available from the open-access websites. For additional details, please see Supplementary data.

---

**Fig. 5.** The cumulative lag effects on the COVID-19 case doubling time with the 10th percentile (a, b, c) and the 90th percentile (d, e, f) of meteorological factors under different lag exposure periods (lag 03, lag 05, lag 07, lag 09, lag 011 and lag 014). Total: a meta-analysis of relative risk across four countries; DTR, diurnal temperature range.

**Fig. 6.** The region-specific effect (lag 014) and the overall estimates effect under different lag exposure periods of temperature (a, d), absolute humidity (b, e) and diurnal temperature range (c, f). DTR, diurnal temperature range.
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.

Acknowledgments

We thank the other participants of the study for their valuable contributions. The authors would also like to thank the investigators and the staff of the public data for making the study possible. This project was supported by the Fundamental Research Funds for the Central Universities, Lanzhou University, China (lzujbky-2020-sp21); the Novel Coronavirus Disease Science and Technology Major Project in Gansu Province (20YF2PA028).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2020.110596.

References

Acharya, R., Porwal, A., 2020. A vulnerability index for the management of and response to the COVID-19 epidemic in India: an ecological study. Lancet Glob Health 8 (9), e1142–e1151. https://doi.org/10.1016/S2214-109X(20)30300-4.

Altamimi, A., Ahmad, A.E., 2020. Climate factors and incidence of Middle East respiratory syndrome coronavirus. Journal of Infection and Public Health 13 (5), 704–708. https://doi.org/10.1016/j.jiph.2019.11.011.

Amuakuwa-Menah, F., Marubash, G., Mubahga, M., 2017. Climate variability and infectious diseases nexus: evidence from Sudan. Infect Dis Model 2 (2), 203–217. https://doi.org/10.1016/j.idm.2017.02.002.

Arja, J., Hålinen, R.O.S.A., 2000. Combined respiratory effects of cold air with SO2( or NO2) in one-hour exposures of hyperventilating Guinean pigs. Inhal. Toxicol. 12 (8), 693–713. https://doi.org/10.1080/08958370050885147.

Amstrong, B., Sera, F., Vicedo-Cabrera, A.M., Abrutsky, R., Åström, O.D.O., Bell, M.L., Chen, B.Y., de Sousa, Z.S.C.M., Correa, P.M., Dan, T.T., 2019. The role of humidity in associations of high temperature with mortality: a multicountry, multicity study. Environ. Health Perspect. 127 (9), 97007 https://doi.org/10.1289/EHP5430.

Bashir, M.F., Ma, B., Bilal, Komal, B., Bashir, M.A., Tan, D., Bashir, M., 2020. Correlation between climate indicators and COVID-19 pandemic in New York, USA. Sci. Total Environ. 728, 138835 https://doi.org/10.1016/j.scitotenv.2020.138835.

Bherwani, H., Gupta, A., Anjum, S., Anbul, A., Kumar, R., 2020. Exploring dependence of COVID-19 on environmental factors and spread prediction in India. npj Climate and Atmospheric Science 3 (1), 38. https://doi.org/10.1038/s41612-020-0114-x.

Briz-Redón, Á., Serrano-Aroca, Á., 2020. A spatio-temporal analysis for exploring the effect of temperature on COVID-19 early evolution in Spain. Sci. Total Environ. 728, 138844 https://doi.org/10.1016/j.scitotenv.2020.138844.

Casanova, L.M., Jeon, S., Rutala, W.A., Weber, D.J., Sobsey, M.D., 2010. Effects of air hand hygiene: A review. Environ. Microbiol. 76 (9), 2712–2717. https://doi.org/10.1111/j.1462-2920.2009.01992.x.

Chen, I., Chen, L., 2020. Meteorological impacts on the incidence of COVID-19 in U. S. 2009 H1N1 pandemic. Environmental and research: research journal. https://doi.org/10.1007/s00470-020-01835-8.

Chin, A.W.H., Chu, J.T.S., Perera, M.R.A., Hui, K.P.Y., Yen, H., Chan, M.C.W., Peiris, M., 2020. COVID-19 transmission in (sub) tropical cities of Brazil. Sci. Total Environ. 729, 138862 https://doi.org/10.1016/j.scitotenv.2020.142272.

Chua, S., Agostino, R., 2020. COVID-19 and climatic factors: a global analysis. Environ. Res. 191, 110119 https://doi.org/10.1016/j.envres.2020.110119.

Cowan, R., Hui, D.L., Yuen, K.Y., 2020. A chronicle of SARS-CoV-2: seasonality, environmental fate, transport, inactivation, and antibiotic resistance. J. Hazard Mater. 124043 https://doi.org/10.1016/j.jhazmat.2020.124043.

Deshpande, S., 2018. The calendar of epidemics: seasonal cycles of infectious diseases. Environ. Health Perspect. 127 (9), 97007 https://doi.org/10.1289/EHP5430.

Dhama, K., Rabaan, A.A., Al-Ahmed, S.H., Haque, S., Sah, R., Tiwari, R., Malik, Y.S., Dhangar, K., 2020c. A chronicle of SARS-CoV-2 Part- I epidemiology, diagnosis, prognosis, transmission and treatment. Sci. Total Environ. 743, 139278 https://doi.org/10.1016/j.scitotenv.2020.139278.

Dong, X., Hu, B., Lei, F., Wang, T., Lu, X., Jiang, J., Jiang, W., 2020. Impact of meteorological factors on the COVID-19 transmission: a multi-city study in China. Sci. Total Environ. 726, 138513 https://doi.org/10.1016/j.scitotenv.2020.138513.

Dubey, P., Aggarwal, V., 2020. Impact of probable interaction of low temperature and ambient fine particulate matter on the function of rats alveolar macrophages. Environ. Toxicol. Pharmacol. 49, 172–178. https://doi.org/10.1016/j.etap.2016.12.011.

Dube, S., Zhao, X., Liu, J., Hu, R., Wang, B., Li, X., He, X., Wang, B., Fu, S., Nia, T., others, 2020. Impact of meteorological factors on the COVID-19 transmission: a multi-city study in China. Sci. Total Environ. 726, 138513 https://doi.org/10.1016/j.scitotenv.2020.138513.

Ebihara, S., Iino, H., 2021. Warmer weather unlikely to reduce the COVID-19 transmission: an ecological study in 202 locations in 8 countries. Sci. Total Environ. 753, 142272 https://doi.org/10.1016/j.scitotenv.2020.142272.

Foti, P., 2018. Infectious diseases nexus: evidence from Sweden. Infect Dis Model 2 (2), 203–217. https://doi.org/10.1016/j.idm.2017.03.003.

Franke, A., 2020. The sensitivity and specificity of climate indicators and COVID-19 pandemic in New York, USA. Sci. Total Environ. 728, 138872 https://doi.org/10.1016/j.scitotenv.2020.138872.

Fukunishi, M., Tukiya, M., Taki, K., Ito, T., Hara, M., Takahashi, K., 2020. Short-term effects of specific humidity and temperature on COVID-19 morbidity in select US cities. Sci. Total Environ. 740, 140093 https://doi.org/10.1016/j.scitotenv.2020.140093.

Galletti, C., 2020. Impact of weather on COVID-19 pandemic in Turkey. Sci. Total Environ. 728, 138810 https://doi.org/10.1016/j.scitotenv.2020.138810.
Sarkodie, S.A., Owusu, P.A., 2020. Impact of meteorological factors on COVID-19 pandemic: evidence from top 20 countries with confirmed cases. Environ. Res. 191, 110101 https://doi.org/10.1016/j.envres.2020.110101.

Shi, P., Dong, Y., Zhao, C., Li, X., Liu, W., He, M., Tang, S., Xi, S., 2020. Impact of temperature on the dynamics of the COVID-19 outbreak in China. Sci. Total Environ. 725, 138436 https://doi.org/10.1016/j.scitotenv.2020.138436.

Tobías, A., Molina, T., 2020. Is temperature reducing the transmission of COVID-19? Environ. Res. 186, 109553 https://doi.org/10.1016/j.envres.2020.109553.

Tosepu, R., Gunawan, J., Effendy, D.S., Ahmad, L.O.A.I., Lestari, H., Bahar, H., Asfian, P., 2020. Correlation between weather and covid-19 pandemic in jakarta, Indonesia. Sci. Total Environ. 725, 138890 https://doi.org/10.1016/j.scitotenv.2020.138890.

Tran, T., Le, T.H., Nguyen, T., Hoang, V.M., 2020. Rapid response to the COVID-19 pandemic: vietnam government’s experience and preliminary success. J Glob Health 10 (2), 020502. https://doi.org/10.7189/Jogh.10.020502.

van Doremalen, N., Bushmaker, T., Munster, V.J., 2013. Stability of Middle East respiratory syndrome coronavirus (MERS-CoV) under different environmental conditions. Euro Surveill. 18 (38) https://doi.org/10.2807/1560-7917.es2013.18.38.20590.

van Doremalen, N., Bushmaker, T., Morris, D.H., Holbrook, M.G., Gamble, A., Williamson, B.N., Tamin, A., Harcourt, J.L., Thornburg, N.J., Gerber, S.I., others, 2020. Aerosol and surface stability of SARS-CoV-2 as compared with SARS-CoV-1. N. Engl. J. Med. 382 (16), 1564–1567. https://doi.org/10.1056/NEJMoa2004973.

Wang, J., Li, W., Yang, B., Cheng, X., Tian, Z., Guo, H., 2020. Impact of hydrological factors on the dynamic of COVID-19 epidemic: a multi-region study in China. Environ. Res. 110474 https://doi.org/10.1016/j.envres.2020.110474.

World Health Organization (WHO), 2020a. Clinical characteristics of covid-19 in China. N. Engl. J. Med. 382 (19), 1859–1862. https://doi.org/10.1056/NEJMoa2005203.

World Health Organization (WHO), 2020b. Director-General’s Opening Remarks at the Media briefing on COVID-19 - 11th March 2020. https://who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020. (Accessed 11 March 2020).

World Health Organization (WHO), 2020c. Coronavirus Disease (COVID-19) Dashboard | WHO Coronavirus Disease (COVID-19) Dashboard. https://covid19.who.int/. (Accessed November 2020).

Yu, F., Du, L., Ojcius, D.M., Pan, C., Jiang, S., 2020. Measures for diagnosing and treating infections by a novel coronavirus responsible for a pneumonia outbreak originating in Wuhan, China. Microb. Infect. 22 (2), 74–79. https://doi.org/10.1016/j.micinf.2020.01.003.

Zeng, J., Zhang, X., Yang, J., Bao, J., Xiang, H., Dear, K., Liu, Q., Lin, S., Lawrence, W.R., Lin, A., others, 2017. Humidity may modify the relationship between temperature and cardiovascular mortality in zhejiang Province, China. Int. J. Environ. Res. Publ. Health 14 (11). https://doi.org/10.3390/ijerph14111383.