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 impact on the COVID-19 pandemic: A study across eight severely affected regions in South America

Liting Zhu, Xiaobo Liu, Haining Huang, Ricardo David Avellán-Llaguno, Mauricio Manuel Llaguno Lazo, Aldo Gaggero, Ricardo Soto-Rifo, Leandro Patiño, Magaly Valencia-Avellan, Benoit Diringer, Qiansheng Huang, Yong-Guan Zhu.

HIGHLIGHTS

• Eight COVID-19 severely affected regions with varied meteorological factors were included.
• Multiple regression analysis was used to correlate the weather condition and the spread of COVID-19.
• Rt, an indicator to reflect the transmission of infectious diseases, was adopted to analyze the correlation.
• Absolute humidity is negatively correlated to the spread of COVID-19 in the selected regions.
• Decreasing trend of absolute humidity raises the alarming of the potential COVID-19 spread.

GRAPHICAL ABSTRACT

ARTICLE INFO

Article history:
Received 9 June 2020
Received in revised form 3 July 2020
Accepted 9 July 2020
Available online 11 July 2020

Editor: Jay Gan

Keywords:
COVID-19
Meteorological factors
Absolute humidity
South America

ABSTRACT

The role of meteorological factors in the transmission of the COVID-19 still needs to be determined. In this study, the daily new cases of the eight severely affected regions in four countries of South America and their corresponding meteorological data (average temperature, maximum temperature, minimum temperature, average wind speed, visibility, absolute humidity) were collected. Daily number of confirmed and incubative cases, as well as time-dependent reproductive number (Rt) was calculated to indicate the transmission of the diseases in the population. Spearman’s correlation coefficients were assessed to show the correlation between meteorological factors and daily confirmed cases, daily incubative cases, as well as Rt. In particular, the results showed that there was a highly significant correlation between daily incubative cases and absolute humidity throughout the selected regions. Multiple linear regression model further confirmed the negative correlation between absolute humidity and incubative cases. The absolute humidity is predicted to show a decreasing trend in the coming months from the meteorological data of recent three years. Our results suggest the necessity of continuous controlling policy in these areas and some other complementary strategies to mitigate the contagious rate of the COVID-19.

© 2020 Elsevier B.V. All rights reserved.

https://doi.org/10.1016/j.scitotenv.2020.140881
0048-9697/© 2020 Elsevier B.V. All rights reserved.
1. Introduction

Worldwide spread of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) causing coronavirus disease 2019 (COVID-19) infections has brought increased attention and governmental actions to prevent and mitigate the impact of this virus. The confirmed cases have surpassed five million on May 22, 2020, and the death toll is 332,876 (Johns Hopkins, 2020). Researchers have predicted the future of current SARS-COV-2 outbreak, and examined a range of possible transmission scenarios in the next five years. It turns out that the results are not optimistic (Kissler et al., 2020).

Numerous studies have found that droplets produced during speech were intimately connected with person-to-person transmission of the virus (Duguid, 1946; Marr et al., 2019). Meteorological factors can affect the transmission of infectious diseases, including influenza and severe acute respiratory syndrome (Bi et al., 2007; Moriyaama et al., 2020; van Doremalen et al., 2013; Yao et al., 2020). Mechanistically, humidity, visibility, wind speed, air temperature could influence the stability of droplets, a potential carrier of the virus in the environment (Bourouiba, 2020). The change of droplets stability would largely determine the viability and transmission of respiratory viruses (Moriyama et al., 2020). Back in 1960, it was reported that mice that the ability to transmit influenza varied with temperature, relative humidity and season (Schulman and Kilbourne, 1963). Since then, a growing body of researches have reported the effects of temperature, humidity and wind speed on the transmission of respiratory viruses (Lipsitch and Viboud, 2009; Lowen et al., 2008; Marr et al., 2019; Peci et al., 2019).

For COVID-19, there have been several studies showing the impacts of meteorological factors on the transmission from January to April 2020, including China (Liu et al., 2020; Xie and Zhu, 2020), Iran (Ahmadi et al., 2020), Europe and the United States of America (Qasim Bukhari, 2020), Indonesia (Tosepu et al., 2020), and Brazil (Auler et al., 2020). However, different studies produced different results, and the relationship between meteorological conditions and COVID-19 transmissibility is still controversial.

South America is one of the most affected regions by COVID-19. It is worth to modeling the impacts of meteorological factors on the spread of the virus. In this study, eight regions from four countries were selected as they encountered a wide spread of COVID-19. Daily confirmed cases, as well as daily meteorological parameters (average temperature (°C), maximum temperature (°C), minimum temperature (°C), average wind speed (mi/h), visibility (mi), and relative humidity (RH, %)) were collected from National Centers for Environmental Information (https://www.ncei.noaa.gov). Absolute humidity (AH) can represent the actual water vapor content of air irrespective of temperature (T) (Shaman and Kohn, 2009), we calculated the absolute humidity in g/m³ using the Clausius Clapeyron equation as follows, (Iribarne and Goodson, 1973).

\[
\text{AH} = \frac{6.12 \times e^{\left(\frac{17.67 T}{T - 237.3}\right)} \times \text{RH}}{273.15 + T}
\]

The data of daily confirmed cases was obtained directly from the National Health Department or indirectly from several websites as follows, (Ecuador, Feb 23 to May 3, https://www.salud.gob.ec), (Brazil, Mar 29 to May 6, https://covid.saude.gov.br/), (Peru, Apr 16 to May 6, https://covid19.orcebot.com/), (Chile, Feb 29 to May 6, https://en.wikipedia.org/wiki/, which was from Chilean Ministry of Health).

For epidemiological data, the incubation period is defined as the time interval between the earliest date of possible exposure to a source of transmission and the earliest date of symptom onset including cough, fever, and fatigue. According to the situation of each infected patient, Zhong Nanshan et al. found that patients with COVID-19 had an incubation period of up to 24 days with a median of 4 days (Guan et al., 2020). In this study, the number of daily confirmed cases on that day was taken as the number of daily infected cases four days earlier. The daily data of incubative cases (named as daily incubative cases in the survey) was obtained by pushing back the daily confirmed cases by four days, and was used to track the number of new infected persons per day.

In order to curb the epidemic of infectious diseases and develop more effective control interventions, there needs to be a time-dependent indicator to reflect the transmission of infectious diseases in the population, which usually uses time-dependent reproduction number, \(R_t\) (Cowling et al., 2010; Wallinga and Teunis, 2004). \(R_t\) is the number of secondary cases that are infected by a primary case at time \(t\). If the value of \(R_t\) was less than 1, the epidemic could be controlled gradually by maintaining the current prevention and control interventions. If the value was larger than 1, the epidemic will continue to outbreak, indicating that the prevention and control interventions need to be optimized (Thompson et al., 2019).

The computational methods of \(R_t\) have been proposed over many years, and various algorithms have been developed in different statistical software. In this study, we calculated the \(R_t\) using the package of “EpiEstim” in the R software. Which were developed by Cori et al. and were used to estimate the instantaneous reproduction number by using branching processes (Cori et al., 2018). In our study, this method relied on two inputs: a disease incidence time series (the numbers of new confirmed cases at successive times) and the date of confirmed (Wallinga and Teunis, 2004). When setting parameters, for the serial interval, based on the research of the Chinese CDC (Li et al., 2020), we assumed an offset gamma distribution with mean 7.5 days and standard deviation 3.4 days. And the smoothing time was set to 10 days. All the analyses were performed with the using of SPSS 25.0 and R software, version 3.6.2.

2. Materials and methods

2.1. Study area

Eight regions, which have relatively higher records of COVID-19 infections in South American countries, were selected, including Pichincha province (where Quito is located) in Ecuador, Rio de Janeiro, and Fortaleza in Brazil, Lambayeque and Lima in Peru, Santiago, as well as Valparaiso and Antofagasta in Chile (Fig. 1).

2.2. Data collection

Daily meteorological data, including daily average temperature (°C), maximum temperature (°C), minimum temperature (°C), average wind speed (mi/h), visibility (mi) and relative humidity (RH, %) were collected from National Centers for Environmental Information (https://www.ncei.noaa.gov). Absolute humidity (AH) can represent the actual water vapor content of air irrespective of temperature (T) (Shaman and Kohn, 2009), we calculated the absolute humidity in g/m³ using the Clausius Clapeyron equation as follows, (Iribarne and Goodson, 1973).

\[
\text{AH} = \frac{6.12 \times e^{\left(\frac{17.67 T}{T - 237.3}\right)} \times \text{RH}}{273.15 + T}
\]
performed. And we used SPSS 25.0 to assess the associations of meteorological factors with epidemiological data. The Spearman correlation was used for bivariate correlation analysis between epidemiological parameters and meteorological factors with detection level \( \alpha = 0.05 \) (bilateral). Based on the analysis of correlation, we selected the parameters with strong significance to analyze.

Given the spatial scale and geo-social variety of the eight regions investigated by this study, multiple linear regression methods were used to explore the association of meteorological factors with daily incubative cases in the same period. The number of incubative cases were used as dependent variables, and the daily meteorological factors were selected as independent variables. The normalized processing was needed before analysis because of the different units of each parameter, by the common method:

\[
X = \frac{X_n - X_0}{S_n}
\]

where \( X \) is normalized data, \( X_n \) is the raw data and \( S_n \) is the standard deviation of \( X_n \).

Then confirmed whether there was a linear relationship between the independent variables themselves, positive ones were selected to fit into the model. The formula used was as follows:

\[
Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n
\]

In this model, outcome variable, \( Y \), is thought to be a linear function of a set of predictor variables, where \( n \) is the number of predictor variables, \( \alpha \) is a numerical constant that represents an intercept. \( \beta \)'s stand for the partial regression coefficients of \( X \), each \( \beta \) reflects that how \( Y \) will change with the \( X \), which associated with the \( \beta \), when all other \( X \) variables constant (Jaccard et al., 2006). Among them, \( X_s \) stand for the meteorological factors that are significantly associated with epidemiological data. This analysis was performed in R software.
3. Result

3.1. Epidemiological data in the selected regions

All the selected regions were severely affected by the outbreak. The confirmed cases were 614 in Valparaíso until May 2nd, 2294 in Pichincha until May 3rd, 8577 in Rio de Janeiro, 9061 in Fortaleza, 3127 in Lambayeque, 35,299 in Lima, 15,582 in Santiago, 855 in Antofagasta until May 6th. The daily confirmed cases experienced a fast increase in these eight regions, although the increasing trend varied (Fig. 2). Judged by the values of daily confirmed cases and daily incubative cases, the outbreaks in eight regions were in a very tense phase during the study period and all countries have taken relevant preventive and control interventions.

Fig. 3 shows the estimated Rt based on pandemic COVID-19 during the study period. In Pichincha, Ecuador, the Rt reached a peak of 5.9 on March 15 and dropped to around 1 after March 30. In the Brazilian regions of Rio de Janeiro and Fortaleza, Rt decreased from the peaks of 3.7 and 4.6 on April 9, respectively, but remained above 1, with significant fluctuations. In Lambayeque and Lima, Peru, Rt declined to around 2 from the peaks of 3.8 and 2.4 on April 27, respectively, with Lamb showing a steady downward trend, while Lima hit a low of 1.7 on May 4, is suddenly on the rise again. In Valparaíso, Rt declined from a peak of 12.6 on March 23 to around 1 after April 10. In Santiago, Rt peaked at 11.3 on March 16, then declined to around 1 between April 21 and April 27, then rose again after April 28. In Antofagasta, Rt decreased from a peak of 5.6 on March 23, but remained above 1.

Thus, we can also conclude that in Pichincha and Valparaíso, control interventions have been effective as of the time of this study, while Brazil, Peru and two other regions of Chile require more stringent control interventions.

3.2. Daily meteorological factors

The selected regions are located along with the coastal areas in South America. There were a wide variation of daily meteorological factors among the selected regions (Fig. 2). During the study time, daily maximum temperature, minimum temperature, and the average temperature were characterized. The range of daily average temperature in the studied period was 12.5 °C in Valparaíso to 29.1 °C in Fortaleza, the average temperature of eight regions was 20.6 °C. The daily minimum temperatures ranged from 3.9 °C in Santiago to 26.1 °C in Fortaleza, with an average of 16.6 °C. The daily maximum temperature ranged from 16.0 °C in Valparaíso to 35.0 °C in Santiago, with an average of 25.6 °C. The difference between maximum temperature and minimum temperature was between 2.39 °C in Antofagasta and 24.7 °C in Santiago. Average wind speed ranged from 9.9 mi/h in Lima to 17.1 mi/h in Pichincha. The highest average wind speed was 10.7 mi/h in Lambayeque, and the lowest was 0.2 mi/h in Santiago. As far as visibility was concerned, the differences in visibility between the eight regions were not significant, and the average remains between 5 and 8 mi. These eight regions had a wide range of absolute humidity. Fortaleza had the highest average value of 21.15 g/m³, whereas the lowest average level was 8.50 g/m³ in Santiago. In the selected period, the range of absolute humidity was 7.72 to 11.83 g/m³ in Pichincha with the average of 10.54, 13.29 to 19.21 g/m³ in Rio de Janeiro with the average of 15.99, 18.09 to 22.41 g/m³ in Fortaleza with the average of 21.11, 12.81 to 16.37 g/m³ in Lambayeque with the average of 14.20, 12.86 to 14.50 g/m³ in Lima with the average of 13.71, 5.45 to 10.90 g/m³ in Santiago with the average of 8.50, 7.3 to 12.73 g/m³ in Valparaíso with the average of 10.44, 10.13 to 13.45 g/m³ in Antofagasta with the average of 11.83 g/m³. The meteorological range used in this study is wider, compared with previous works (Table S1).

3.3. Correlations between epidemiological factors and daily meteorological factors

Spearman’s Rank Correlation Coefficient was used to correlate the epidemiological factors with the raw data of daily meteorological parameters (Fig. 4). The confirmed cases of most regions (Fig. 4A) were significantly negatively correlated with average daily temperature, except Lambayeque. Confirmed cases in Pichincha and Rio de Janeiro were significantly negatively correlated with absolute humidity, except for Santiago, which was positively correlated (p < 0.05). The cases in Santiago are significantly correlated to all the selected meteorological factors. As shown in Fig. 4B, the number of daily incubative cases had a strong negative correlation (p < 0.05) with absolute humidity (Pichincha r² = −0.350, Rio de Janeiro r² = −0.398, Fortaleza r² = −0.323, Lambayeque r² = −0.566, Lima r² = −0.662, Santiago r² = −0.536, Valparaíso r² = −0.324, Antofagasta r² = −0.616). In contrast, the significant correlation of temperature was observed in specific regions. Average wind speed and visibility were not significantly related to the daily incubative cases. The correlation between meteorological factors and the COVID-19 is not consistent within various studies (Table 1).

There were large differences between the results of the correlation coefficient of daily cases and Rt. As shown in Fig. 4C, the correlation between R and meteorological factors was extremely weak in Pichincha, two regions of Brazil, and Lambayeque, except that in Pichincha which had a significant positive correlation with the average wind speed. In Lima, there were significant negative correlations between R and daily minimum temperature, absolute humidity, while R had a positive correlation with daily maximum temperature. In addition, The R of Santiago had a strong positive correlation with meteorological factors, with the exception of visibility and absolute humidity. In Valparaíso and Antofagasta, R had strong positive correlations with absolute humidity and average temperature, as well as a positive correlation with daily maximum temperature in Antofagasta.

Based on the analysis and comparison of the results of this study, a general relationship between meteorological factors and meteorological factors was found. Of all meteorological factors of this study, daily average temperature and absolute humidity were the strongest correlates of both daily confirmed and incubative cases.

3.4. Model fitting

To determine the quantitative relationship, we screened the meteorological factors with the correlation with daily incubative cases by stepwise multiple linear regression. As shown in Table 2, where Y was the number of incubative cases and Xs stood for the meteorological factors that had linear association with epidemiological data. The models of fitting were different in different areas as the result of the spatial scale and geo-social diversity of the eight regions by this study.

From the results of the model fitting for selected regions, except Valparaíso (adjusted R² = 0.096), the adjusted R² were above 0.1, which means the models included more than 10% of all factors that will affect the change of incubative cases, and these results had a reliable reference value.

The magnitudes of β reflect the influence of the corresponding variable, in Pichincha (β = −0.488), Lima (β = −0.652), and Valparaíso (β = −0.536), the most important parameter of all parameters we selected was absolute humidity, while the most influential factor was average temperature in Rio de Janeiro (β = −2.633), Antofagasta (β = −0.742) and Lambayeque (β = −0.540), maximum temperature in Santiago (β = −0.438), and average wind speed in Fortaleza (β = 0.352). In the fitted models of all regions, except Rio de Janeiro, the variable of X contained absolute humidity, and the β were less than 0, which means negative correlation. Especially in Lima, the value reached −0.652, which means one unit decrease in X means will cause an increase of 0.622 standard deviation of the number of incubative cases. Tables S2–
Fig. 2. Daily changes in the number of confirmed and incubative infections in eight regions since the outbreak of COVID-19. The black line denoted the number of confirmed cases per day, and the gray area indicates the number of incubative cases, with a four-day interval between them. The colored lines represent the meteorological changes over the corresponding time, including the daily average temperature, daily minimum temperature, daily maximum temperature, absolute humidity, average wind speed, and visibility.
S9 shows the significance of each coefficient for each model. Therefore, the results of the multiple regression model further confirmed the negative correlation between absolute humidity and incubative cases, but not in Rio de Janeiro.

We then collected humidity data from the studied regions over the past three years to give a prediction based on the absolute humidity (Fig. 5). In all the regions we selected, absolute humidity had a significant seasonal cycle marked by the low value in the coming months. The situation in this period will not be optimistic from our predictive model with absolute humidity, which is not good news for the epidemic.

### 4. Discussion

The selected eight regions located on both sides of South America have the latitude ranging from 0° to 33°27’ S. The confirmed cases in these regions are among the top ranks in their respective countries that encounter dangerous spread of COVID-19. Furthermore, these locations together are representative of various meteorological factors in the large regions of South America. They have a wide range of absolute humidity from 5.5 to 22.4 g/m³, temperature from 6.0 to 41.6 °C, average wind speed from 0.2 to 16.9 mi/h, visibility from 1.9 to 8.7 mi.

Different from other studies, we used the number of daily incubative cases to indicate how fast the virus is spreading, and Rt to stand for the spread ability of the COVID-19. These daily confirmed cases and incubative cases were used to analyze their correlation with meteorological factors. According to the distribution results of the number of daily confirmed and incubative, the severity of the epidemic can be seen. At the same time, our multiple linear regression models further support this result, which are of great reference value in predicting the daily number of infections.

Conventionally, the spread routes of SARS-CoV, MERS-CoV, and highly pathogenic influenza consist of respiratory droplets and direct contact (Lei et al., 2018; Otter et al., 2016; Zumla et al., 2015), which could also be a transmission route that probably occurs with SARS-CoV-2 as well (Guan et al., 2020). After SARS-CoV-2 droplets expelled from infected hosts, they can be released into the atmosphere through sedimentation and evaporation (Shaman and Kohn, 2009). Droplets have the potential to stay as aerosols in the air (Bourouiba, 2016; Lok, 2016). Humidity and other meteorological factors can favor the spread of aerosols in the environment. Accumulating studies point to the relevance between respiratory diseases and absolute humidity (Ferguson et al., 2010; Lipsitch and Viboud, 2009; Shaman and Kohn, 2009). Our results also confirmed that, like other respiratory diseases, there was a significant association between SARS-CoV-2 infection and absolute humidity. Recent studies with SARS-CoV-2 in China also reported a significantly negative link (Li et al., 2020). In contrast, the correlation is not significant in Jakarta, Indonesia (Tosepu et al., 2020).

Since its first reported case, COVID-19 has spread rapidly, more alarming is that with the advent of winter, other seasonal viruses will also begin to disseminate quickly (Domenech de Celles et al., 2019; Ferguson et al., 2010; Lipsitch and Viboud, 2009; Shaman and Kohn, 2009). In particularly, in the following July, there was a continuing decreasing trend of absolute humidity. Countries must take more stringent interventions to control the epidemic to prevent the virus from entering the more threatening winter outbreak.

There are some limitations of this study. First, the records of some cases may vary due to differences in the timing of the epidemic data from different regions. Second, the incubation period of the virus varies with the host, and we chose the median period to estimate the number of patients infected on a daily basis. Third, the multiple linear model used in this paper is only suitable for determining the trend of meteorological factors to the daily number of infected people. The spread of the...
Fig. 4. Correlation between meteorological parameters and daily confirmed cases (A), daily incubative cases (B) and Rt (C) in the eight regions. The color gradient indicated Spearman's correlation coefficients. The darker red indicates a stronger positive correlation, and darker blue indicates a stronger negative correlation. Data significance was marked by * \( p < 0.05 \), ** \( p < 0.01 \).

Table 1
Summary of correlation studies between meteorological factors and the spread of COVID-19.

| Location           | Average temperature | Minimum temperature | Maximum temperature | Wind speed | Relative humidity | Absolute humidity | Reference                  |
|--------------------|---------------------|---------------------|---------------------|------------|-------------------|-------------------|----------------------------|
| New York           | NA                  | +                   | NA                  | NA         | NA                | NA                | Bashir et al., 2020        |
| China              | –                   | /                   | /                   | /          | /                 | /                 | Li et al., 2020            |
| Brazil             | –                   | /                   | /                   | /          | /                 | /                 | Prata et al., 2020         |
| Turkey             | –                   | /                   | /                   | /          | –                 | /                 | Sahin, 2020                |
| Japan              | –                   | /                   | /                   | /          | /                 | /                 | Takagi et al., 2020        |
| Jakarta, Indonesia | +                   | NA                  | NA                  | NA         | NA                | NA                | Tosepu et al., 2020        |

+, significantly positive correlated; –, significantly negative correlated; NA, no significant correlation; /, no data available in the study.
DIC, daily incubative cases; AT, daily average temperature; Tmin, daily minimum temperature; Tmax, daily maximum temperature; AH, absolute humidity; AWS, average wind speed; Vis, visibility. Detailed parameters of the model are shown in the Supplementary Material.

CRediT authorship contribution statement

Liting Zhu: Conceptualization, Methodology, Visualization, Writing - original draft. Xiaobo Liu: Conceptualization, Methodology, Visualization, Writing. Ricardo David Avellán-Llaguno: Investigation, Visualization. Mauricio Manuel Laguno Lazo: Investigation, Writing - review & editing. Aldo Gaggero: Investigation, Writing - review & editing. Ricardo Soto-Rifo: Investigation, Writing - review & editing. Magaly Valencia-Avellan: Investigation, Writing - review & editing. Benoit Diringer: Investigation, Writing - review & editing. Qiansheng Huang: Conceptualization, Formal analysis, Data curation, Writing - review & editing. Yong-Guan Zhu: Conceptualization, Writing - review & editing.

Declaration of competing interest

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

Acknowledgement

This work was supported by the Strategic Priority Research Program of the Chinese Academy of Sciences (XDA19050202), the Ministry of Science and Technology of the People’s Republic of China (2018YFE0103300), and the Youth Innovation Promotion Association CAS (2018343).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.140881.

References

Ahmadi, M., Sharifi, A., Dorosti, S., Jafari-Zadeh Goushchi, S., Ghanbari, N., 2020. Investigation of effective climatology parameters on COVID-19 outbreak in Iran. Sci. Total Environ. 729, 138705.

Auler, A.C., Cassaro, F.A.M., da Silva, V.O., Pires, L.F., 2020. Evidence that high temperatures and intermediate relative humidity might favor the spread of COVID-19 in tropical climate: a case study for the most affected Brazilian cities. Sci. Total Environ. 729, 139090.

Bashir, M.F., Ma, B., Bilal Komol, 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.

Bi, P., Wang, J., Hiller, J.E., 2007. Weather: driving force behind the transmission of severe acute respiratory syndrome in China? Intern. Med. J. 37 (8), 550–554.

Bourouibia, L., 2016. Images in clinical medicine. A sneeze. N. Engl. J. Med. 375 (8), e15.

Bourouibia, L., 2020. Turbulent gas clouds and respiratory pathogen emissions: potential implications for reducing transmission of COVID-19. JAMA https://doi.org/10.1001/jama.2020.4756.

Corsi, A., Nouvellet, P., Garske, T., Bourouiba, H., Nakoune, E., Jombart, T., 2018. A graph-based evidence synthesis approach to detecting outbreak clusters: an application to dog rabies. PLoS Comput. Biol. 14 (12), e1006554.

Cowling, B.J., Lau, M.S., Hu, L.M., Chuang, S.K., Tsang, T., Liu, S.H., Leung, P.Y., Lo, S.V., Lau, E.H., 2010. The effective reproduction number of pandemic influenza: prospective estimation. Epidemiology 21 (6), 842–846.

Domenach de Celles, M., Arduin, H., Levy-Bruhl, D., Georges, S., Souty, C., Guillermot, D., Watier, L., Opatowski, L., 2015. Unraveling the seasonal epidemiology of pneumococcal meningitis. Proc. Natl. Acad. Sci. U. S. A. 112 (5), 1802–1807.

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 (18).

Duguid, J.P., 1946. The size and the duration of air-carriage of respiratory droplets and droplet-nuclei. J. Hyg. 44 (6), 471–479.

Ferguson, N.M., Shaman, J., Pitzer, V.E., Viboud, C., Grenfell, B.T., Lipsitch, M., 2010. Absolute humidity and the seasonal onset of influenza in the continental United States. PLoS Biol. 8 (2), e1000316.

Guo, W.J., Ni, Z.Y., Hu, Y., Liang, W.H., Ou, C.Q., He, J.X., Liu, L., Shan, H., Lei, C.L., Hui, D.S.C., Du, B., Li, L.J., Zeng, G., Yuan, K.Y., Chen, R.C., Tang, C.L., Wang, T., Chen, P.Y., Xiang, J.
