Association between meteorological factors and daily new cases of COVID-19 in 188 countries: A time series analysis

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HIGHLIGHTS

- We used time series analysis to study the relationship between meteorological factors and the transmission of COVID-19.
- Global prevalence figures of COVID-19 and meteorological data for a whole year were analyzed.
- We use a distributed lag linear model to study the lag effect of meteorological factors on the incidence of COVID-19.

GRAPHICAL ABSTRACT
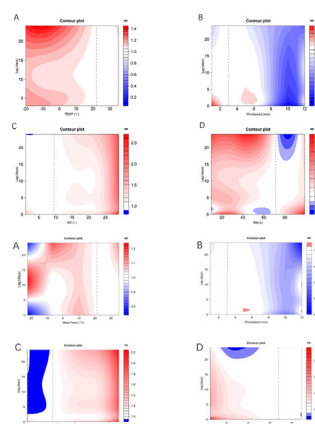
ABSTRACT

By 31 December 2020, Coronavirus disease 2019 (COVID-19) had been prevalent worldwide for one year, and most countries had experienced a complete seasonal cycle. The role of the climate and environment are essential factors to consider in transmission.

We explored the association between global meteorological conditions (including mean temperature, wind speed, relative humidity and diurnal temperature range) and new cases of COVID-19 in the whole past year. We assessed the relative risk of meteorological factors to the onset of COVID-19 by using generalized additive models (GAM) and further analyzed the hysteresis effects of meteorological factors using the Distributed Lag Nonlinear Model (DLNM).

Our findings revealed that the mean temperature, wind speed and relative humidity were negatively correlated with daily new cases of COVID-19, and the diurnal temperature range was positively correlated with daily new cases of COVID-19. These relationships were more apparent when the temperature and relative humidity were lower than their average value (21.07°C and 66.83%). The wind speed and diurnal temperature range were higher than the average value (3.07 m/s and 9.53 °C). The maximum RR of mean temperature was 1.30 under −23 °C at lag ten days, the minimum RR of wind speed was 0.29 under 12 m/s at lag 24 days, the maximum RR of range of temperature was 2.21 under 28 °C at lag 24 days, the maximum RR of relative humidity was 1.35 under 4% at lag 0 days. After a subgroup analysis of the countries included in the study, the results were still robust.

As the Northern Hemisphere enters winter, the risk of global covid-19 remains high. Some countries have ushered in a new round of COVID-19 epidemic. Thus, active measures must be taken to control the source of infection, block transmission and prevent further spread of COVID-19 in winter.

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1. Introduction

Since the first case of Coronavirus disease 2019 (COVID-19) raised concerns in Wuhan, China, in late December 2019 (WHO, 2020a), which was caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), COVID-19 spreads rapidly throughout the globe due to its highly contagious nature (Lotfi and Rezaei, 2020). By 26 January 2021, COVID-19 had been prevalent worldwide for one year, and almost all countries had experienced a complete seasonal cycle. Over 99 million cases and 2135 thousand deaths had been reported worldwide, and more than 200 countries and regions had been affected (WHO, 2021).

The relationship between viral infection and meteorological conditions had been of interest in the past. It is inferred that SARS-CoV-2 transmission is also likely to be influenced by Climatological, Meteorological and Environmental (CME) factors, such as temperature, humidity, and PM2.5 (Scientific Committee, 2020). Previous studies have investigated that climate parameters may be important factors that could influence the transmission of COVID-19 (Mecenas et al., 2020). There is still debate on the subject of the impact of meteorological factors on transmission of COVID-19. Some global or regional studies have reported a negative association between temperature and the number of confirmed COVID-19 cases, including China (Liu et al., 2020; Shi et al., 2020), Japan (Kodera et al., 2020), Mexico (Méndez-Arriaga, 2020), and other countries. Other studies have also observed positive correlations (Menebo, 2020), no correlations (Yao et al., 2020) or non-linear correlations (Xie and Zhu, 2020). Our previous study found that temperature and humidity were inversely correlated with daily new cases and deaths of COVID-19 in 166 countries (excluding China) as of 27 March 2020 (Wu et al., 2020). With the extension of the time range, the northern hemisphere transitions from winter to summer. In another study, we revealed that temperature, relative humidity, and wind speed were nonlinearly correlated with daily new cases of COVID-19 in 127 countries as of 31 August 2020. They may be negatively correlated with the daily new cases of COVID-19 over 127 countries when temperature, relative humidity and wind speed were below 20 °C, 70% and 7 m/s, respectively (Yuan et al., 2020).

The inconsistencies may be attributed to the relatively small sample size, short study period, and differences in previous study regions. Nowadays, COVID-19 had been prevalent worldwide for more than one year, and both the northern and southern hemispheres had experienced a complete seasonal cycle. It is essential to conduct ecological studies on a global scale to analyze spatial differences in the spread of COVID-19 and interpret it in terms of associated changes in temperature, humidity or other environmental factors, which may be helpful to predict the disease dynamics and communicate accurately science-based information to inform interventions such as vaccine campaigns and social distancing regulations.

In this study, we used the generalized additive models (GAM) and the Distributed lag non-linear model (DLNM) to explore the association between global meteorological conditions (mean temperature, wind speed, relative humidity and diurnal temperature range) and new cases of COVID-19 in the whole past year (up to 31 December 2020) in 188 countries and find appropriate models for the prediction of SARS-COV-2 transmission and to provide scientific information for decision-making and action.

2. Method

2.1. Data collection

As of 31 December 2020, more than 200 countries and regions worldwide had reported cases of COVID-19 to WHO. After excluding 19 countries and areas that lacked daily new cases of COVID-19, 188 countries were included in this research, including 54 African countries, 45 Asian countries, 46 European countries, 23 North American countries, 8 Oceanian countries and 12 South American countries (Attachment 1). (See Fig. 1.)

We obtained the daily new cases of COVID-19 in 188 countries, new confirmed cases of COVID-19 per 1,000,000 people, HDI (human development index, that is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and have a decent standard of living), population density and GRSI (Government Response Stringency Index: composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest response)) from "Our world in data."

Daily meteorological data and environmental data as of 31 December 2020 in 188 countries, including daily mean temperature, daily maximum temperature, daily minimum temperature, dew point temperature, precipitation, and wind speed, were obtained from NOAA.

2.2. Establishment of model

We used two stages to analyze the relationship between meteorological factors and the number of daily new cases.

The GAM is a combination of the generalized linear model and the additive model. GAM uses a connection function to establish the relationship between the expectation of the response variable and the non-parametric predictor variables (Peng et al., 2006a; Talmoudi et al., 2017), which is useful to explore the non-linear relationship between weather factors and health outcomes. In this study, a log-linear GAM was used to analyze the associations between meteorological factors and daily new cases of COVID-19 (Peng et al., 2006a).

In the first stage, we estimated associations of meteorological variables with daily new cases using GAM. We assumed that the daily new cases of COVID-19 approximately followed the Poisson distribution. Besides, the number of daily new cases and observations of meteorological factors belongs to time series data. Given the data characteristics, a model was established between the logarithm of expected daily new cases, meteorological factors, and other explanatory variables (median age, GRSI and population density of each country) by applying a GAM with a Gaussian distribution family (Hastie and Tibshirani, 1990). We calibrated the model using temporal trends as a mixed factor. Considering that the number of daily new cases has a non-linear tendency over time, penalty splines were used in the Poisson autoregression model to control the time trend (Peng et al., 2006b). Classified index variables were used to correct the weekly effect of the model for possible confounding effects on Saturday and Sunday. The model was defined as follows:

$$log\,Y_t = \alpha + s(MV_t, df) + s(GRSI_t, df) + PD_i + HDI_i + COUNTRY_i \\ + DOW + s(day_t, df) \qquad (5)$$

In formula (5), $log(Y_t)$ is the log-transformed of the number of COVID-19 daily new cases on day_t (added one to avoid taking the logarithm of zeros); α is the intercept; MV_t is different meteorological variables (including mean temperature, wind speed, relative humidity and diurnal temperature range) on day_t; $GRSI_t$ is government response stringency index of COVID-19 of each country on day_t; $s()$ refers to a thin plate spline function, which is based on the penalized smoothing spline; PD_i is a variable of population density of $country_i$; HDI_i is a variable of HDI of $country_i$; $COUNTRY_i$ is a categorical variable for country; DOW is a categorical variable indicating the date of the week; day_t is the number of days appearing COVID-19 cases in each country for capturing day fixed effect; df is the degree of freedom.

The impact of meteorological factors on health usually has a lag effect. Besides, considering that the incubation period of COVID-19 is generally 1–14 days, and individual cases can reach 24 days, it is a reasonable choice to analyze the lag effect of meteorological factors on daily new cases of COVID-19. Since GAM only considers the impact within a specific period, if the exposure level of several consecutive days is simply introduced into the model without considering the characteristics of lag distribution, high

Attachment 1
Countries and continents included in the study.

Continent	Countries ($n = 188$)
Africa ($n = 54$)	Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo, Cote d'Ivoire, Democratic Republic of Congo, Djibouti, Egypt, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe
Asia ($n = 45$)	Afghanistan, Armenia, Azerbaijan, Bahrain, Bangladesh, Bhutan, Brunei, Cambodia, China, Georgia, India, Indonesia, Iran, Iraq, Israel, Japan, Jordan, Kazakhstan, Kuwait, Kyrgyzstan, Laos, Lebanon, Malaysia, Maldives, Mongolia, Myanmar, Nepal, Oman, Pakistan, Palestine, Philippines, Qatar, Saudi Arabia, Singapore, South Korea, Sri Lanka, Syria, Taiwan, Tajikistan, Thailand, Timor, Turkey, United Arab Emirates, Uzbekistan, Yemen
Europe ($n = 46$)	Albania, Andorra, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Moldova, Monaco, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Russia, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom, Vatican
North America ($n = 23$)	Antigua and Barbuda, Bahamas, Barbados, Belize, Canada, Costa Rica, Cuba, Dominica, Dominican Republic, El Salvador, Grenada, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Trinidad and Tobago, United States
Oceania ($n = 8$)	Australia, Fiji, Marshall Islands, New Zealand, Papua New Guinea, Samoa, Solomon, Vanuatu Islands
South America ($n = 12$)	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela

collinearity is bound to occur, which leads to the deviation of the analysis results that cannot be ignored.

DLNM is based on the ideas of traditional models such as generalized linear models and generalized additive models. It introduces a cross-basis process and describes the dependent variable's distribution in the independent variable dimension and the lagging dimension to simultaneously evaluate the lag effect and non-linear effects of the exposure factor (Gasparrini, 2011).

Thus, in the second stage, we use DLNM to establish a cross-basis matrix of meteorological factors and the maximum number of lag days(24 days). According to the GAM model of the first stage, we substitute meteorological factors with different lag levels to observe the overall exposure-lag-reaction process.

2.3. Calculation of variables

2.3.1. Calculation of diurnal temperature range

The diurnal temperature range refers to the difference between the maximum temperature and the minimum temperature in a day. The calculation formula is as follows:

$$RT = MAXT - MINT\ (°C) \tag{1}$$

In formula (1), RT donates the diurnal temperature range; MAXT donates maximum temperature; MINT refers to the minimum temperature.

2.3.2. Calculation of absolute humidity

Absolute humidity refers to the mass of water vapour per unit volume of air. Calculated as follows:

$$AH = \rho = 217E/T(g/m^3) \tag{2}$$

In formula (2), AH donates the absolute humidity; E (hPa) donates the actual vapour pressure, the essential vapour pressure E can be calculated from the dew point temperature and the actual temperature respectively by adopting the modified Magnus formula (Wu et al., 2020), the formula is as follows:

$$E = E_0 \times e^{\frac{At}{B+t}} \tag{3}$$

E_0 denotes saturation vapour pressure at a reference temperature T0 (273.15 K) which equals 6.11 Mb; A is a constant of 17.43, and B is a constant of 240.73.t(°C) is the actual temperature or dew point.

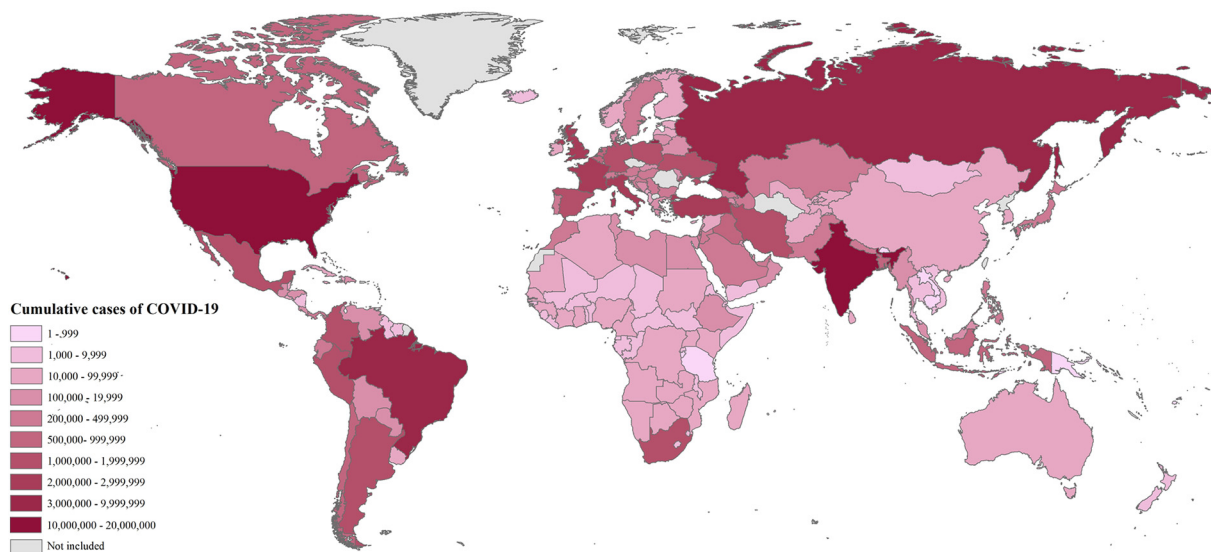## Cumulative cases of COVID-19 in 188 countries

Fig. 1. The cumulative cases of COVID-19 in the study area as of 31 December 2020.

2.3.3. Calculation of relative humidity

The relative humidity is the absolute humidity ratio to the saturated absolute humidity at the same temperature and pressure. The calculation formula is as follows:

$$RH = \frac{E}{E_w} \times 100\% \qquad (4)$$

In Eq. (4), RH donates the relative humidity, E(hPa) donates the actual vapour pressure, Ew (hPa) donates the saturated vapour pressure of pure horizontal liquid level (or ice surface) corresponding to the dry-bulb temperature t (°C). E and Ew both can be calculated by Eq. (3).

3. Statistical analysis

The descriptive analyses, mean, standard deviation, quartiles (P25, median, P75), minimum, and maximum were used to describe the distribution of new cases of COVID-19 and meteorological variables. There were some missing values for meteorological variables. Thus, we used the Kalman smoothing method to attribute the values by R package "imputeTS."

To reduce the confounding effects and avoid collinearity in the models, we used two approaches for analyzing the data. First, we used complete pairwise observations to compute Pearson's correlation coefficients among the daily incidence of COVID-19 and meteorological variables. Second, we accessed the associations between meteorological factors and daily new cases of COVID-19 with the use of time-series approaches. We first estimated associations between meteorological factors and daily new cases using quasi-Poisson GAM. Then we use DLNM to observe the relationship between meteorological factors and daily new cases of different lag days. We observed the effects of weather variables under different lag time dimensions by single-variable and multiple-variables analysis. This comparison can help identify whether other variables modify the effects (Wu et al., 2020). We also used the multiple-variables DLNM to perform subgroup analysis on the northern and Southern Hemispheres. We fitted the exposure-lag-response curves of different meteorological factors in the Northern and the Southern Hemispheres.

We used R software version 4.0.3 (R Foundation for Statistical Computing) to perform all statistical analyses. $P < 0.05$ is considered statistically significant.
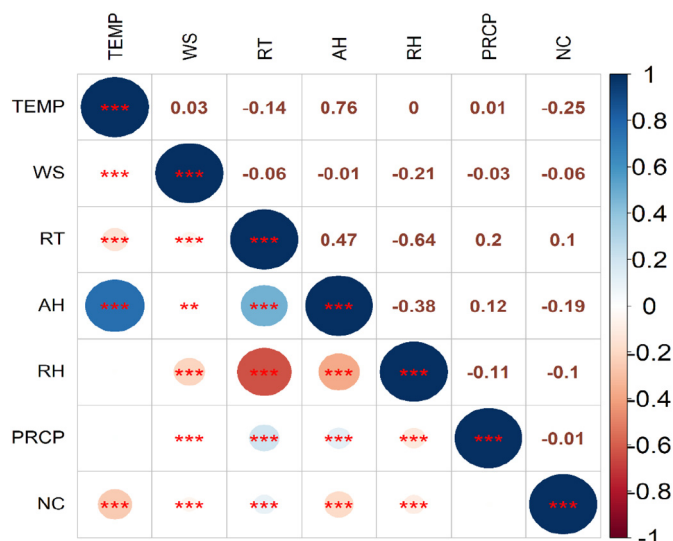
4. Results

4.1. Descriptive statistics

We performed a descriptive analysis of the meteorological conditions in 188 countries. Globally, as of 31 December 2020, the average number of daily new cases was 1495, the mean temperature was 21.07 °C, the mean diurnal temperature range was 9.53 °C, relative humidity is 66.83%, absolute humidity was 13.30 g/m³, the wind speed was 3.07 m/s, and the precipitation was 2.57 mm³ (Table 1).

Fig. 2. Pearson correlation coefficients between meteorological variables and daily incidence of COVID-19. TEMP: mean temperature; WS: wind speed; RT: diurnal temperature range; AH: absolute humidity; RH: relative humidity; PRCP: precipitation. *$0.01 < P \le 0.05$; **$0.001 < P \le 0.01$; $P \le 0.001$.
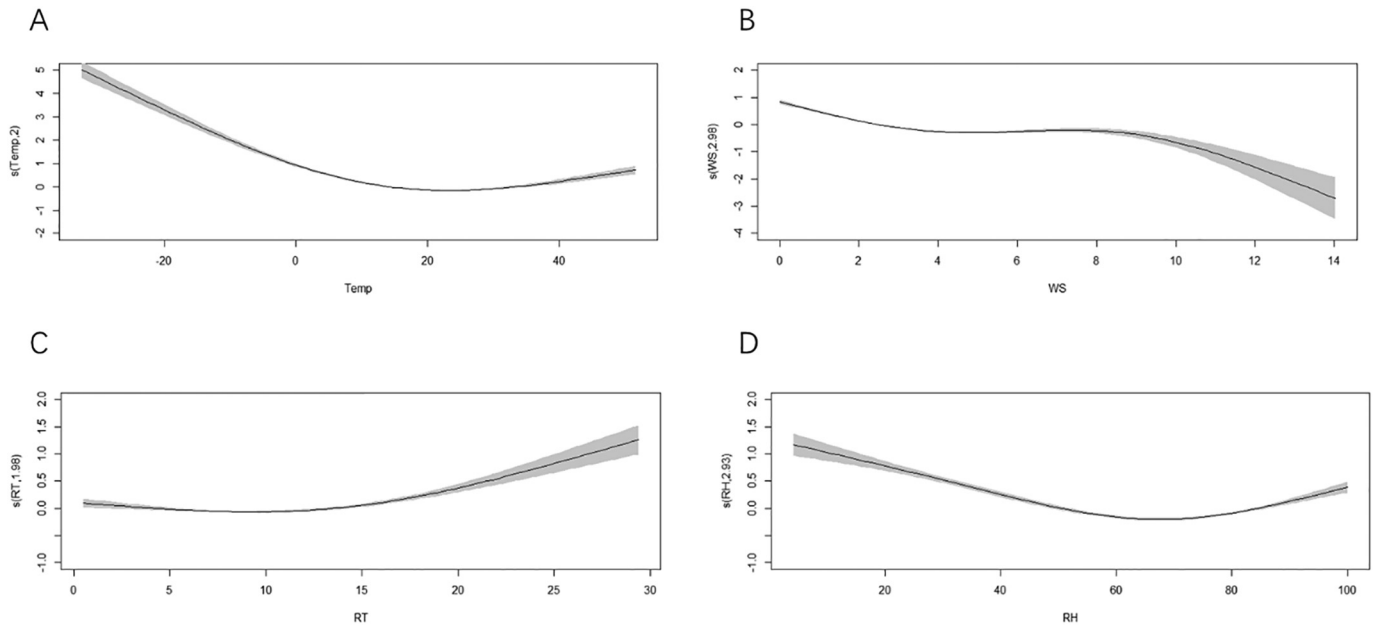
4.2. Pearson correlation analysis of meteorological factors and the new cases per million

To reduce the confounding effects and avoid collinearity in the models, we used complete pairwise observations to compute Pearson's correlation coefficients among meteorological variables and the incidence of COVID-19. (Fig. 2). Temperature($r = -0.25$), wind speed ($r = -0.06$), absolute humidity ($r = -0.19$) and relative humidity ($r = -0.10$) were negatively correlated with the number of daily new cases of COVID-19. In contrast, the diurnal temperature range was positively correlated with the incidence of COVID-19 ($r = 0.1$). There was no statistical significance between precipitation and daily incidence of COVID-19, and there was high collinearity between temperature and absolute humidity. Thus we did not treat precipitation and absolute humidity as covariates in the subsequent model.

4.3. Relationship between meteorological factors and COVID-19

First, we used GAM to conduct single-variable analyses for different meteorological variables. The results were shown in Fig. 3. Wind speed and diurnal temperature range were linearly correlated with the number of daily cases, among which wind speed was negatively correlated with the number of daily cases. In contrast, the diurnal temperature range was positively correlated with the number of daily cases. Temperature and relative humidity were nonlinearly correlated with the number of daily cases. When the temperature was below 21 °C, and the relative humidity was below 64%, the temperature and relative

Table 1
Descriptive statistics for weather conditions in 188 countries.

Variables	Mean	SD	Min	P25	P50	P75	Max
Daily new cases	1495	8239.20	0	1	41	441	249,524
Mean temperature (°C)	21.07	8.81	−23.22	15.39	23.22	42.94	51.61
Diurnal temperature range (°C)	9.53	4.37	0.44	6.28	9.00	12.00	29.39
Relative humidity (%)	66.83	18.41	4.15	56.36	71.02	80.48	100.00
Absolute humidity(g/m³)	13.30	6.50	0.21	7.74	12.25	19.81	36.20
Wind Speed (m/s)	3.07	1.67	0.00	1.94	2.75	3.88	12.44
Precipitation (mm)	2.57	19.27	0.00	0.00	0.00	0.25	484.89

SD: standard deviation; Min: minimum; P25: 25th percentile; P50: 50th percentile; P75: 75th percentile; Max: maximum.
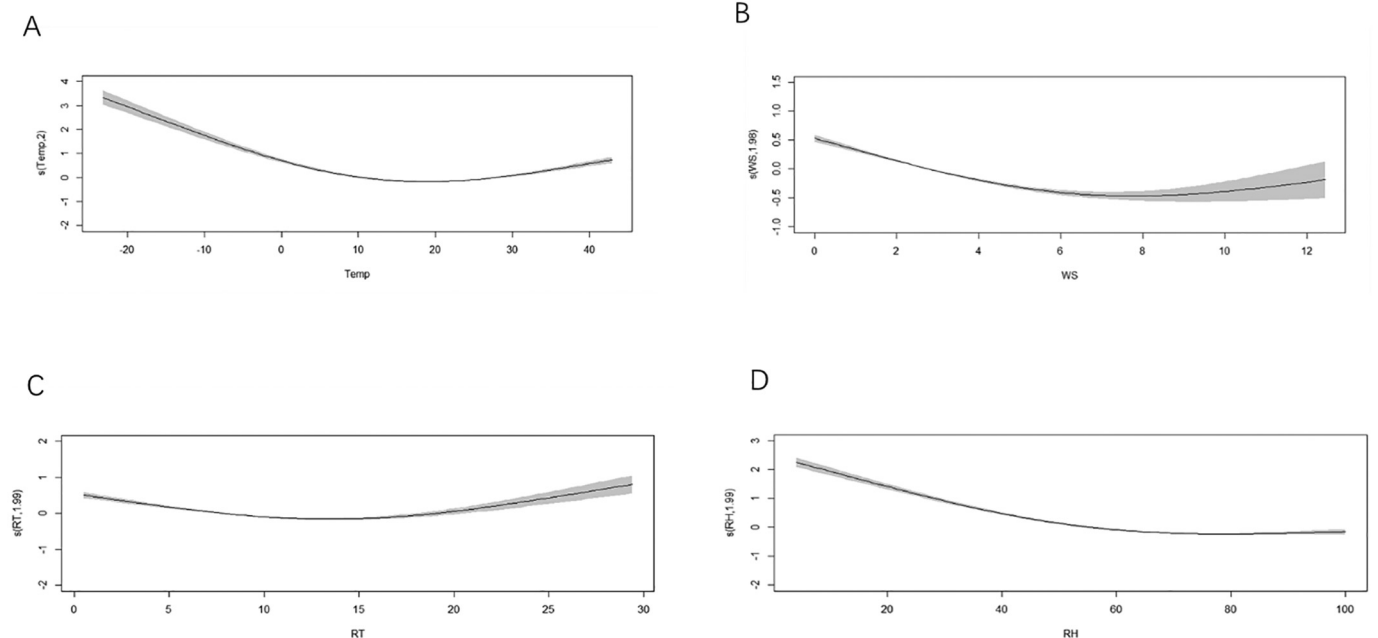
Fig. 3. Exposure-response curves for the effects of meteorological variables on daily new cases of COVID-19 in the single-variable model using GAM. The x-axis is the meteorological parameters. The y-axis indicates the contribution of the smoother to the fitted values.Temp: temperature; WS: wind speed; RT: diurnal temperature range; RH: relative humidity.

humidity were negatively correlated with the number of daily cases. A weak positive correlation appeared when the temperature is above 21 °C, and the relative humidity was above 64%.

Then we used GAM to conduct multiple-variables analysis on these four meteorological variables(Fig. 4). In general, temperature, wind speed and relative humidity were broadly negatively correlated with the number of daily new cases. In contrast, the diurnal temperature range was positively correlated with the number of daily new cases. This correlation was more apparent when the temperature is lower than 21 °C, the wind speed was higher than 7 m/s, relative humidity is lower than 64%, and the diurnal temperature range was higher than 12 °C. At temperatures above 21 °C and wind speed above 6 m/s, there were weak positive correlations.

Fig. 5 showed the result of using DLNM to analyze the univariate of the meteorological factors. The exposure-response relationship curves showed essentially linear associations between COVID-19 and lag meteorological conditions in the DLNM model. The reference level is set as the corresponding variable's median value (the dotted line's position in the figure, RR = 1). In general, when the mean temperature and relative humidity were lower than their average value, the relative risk is higher than when they were higher than the average value. When the wind speed and diurnal temperature range were lower than the average value, the relative risk was lower than when they were higher than the average value.

The range of relative risks was 0.16–1.38 for mean temperature. When the daily mean temperature is lower than the total mean temperature (21.07 °C), the risk of COVID-19 will increase with the decrease of

Fig. 4. Exposure-response curves for the effects of meteorological variables on daily new cases of COVID-19 in the multiple-variables model using GAM. The x-axis is the meteorological parameters. The y-axis indicates the contribution of the smoother to the fitted values. Temp: temperature; WS: wind speed; RT: diurnal temperature range; RH: relative humidity.
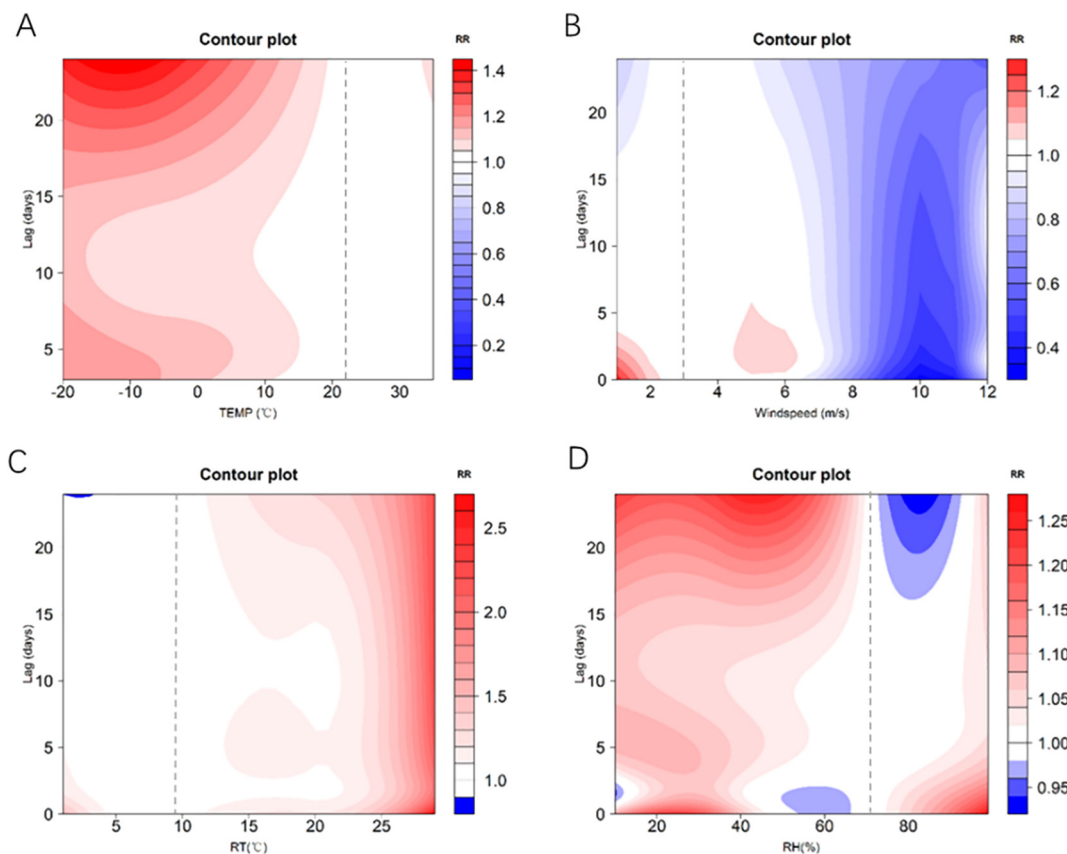
Fig. 5. Contour plots of the exposure–response relationship for the association between daily new cases of COVID-19 and meteorological variables in the single-variable model. A: mean temperature B: wind speed: wind speed C: diurnal temperature range D: relative humidity The Y-axis is the lag days ranging from 0 to 24. The X-axis is the range of the observed values of each variable. The color gradient represents the relative risk (RR). The red color gradient represents higher strength of RR, above 1, and the blue gradient represents lower strength of RR, below 1. The white color represents no difference, at RR = 1.

the daily mean temperature. The risk range was 0.34–1.25 for wind speed. The relative risk of COVID-19 decreased with increasing wind speed at wind speeds higher than 3 m/s. The range of relative risks was 0.90–2.65 for the diurnal temperature range. When the diurnal temperature range was higher than 9.53 °C, the risk of COVID-19 will increase with the daily diurnal temperature range. When the temperature, wind speed and diurnal temperature range were lower than the average, there was no apparent change in the relative risk of COVID-19. The range of relative risks was 0.93–1.27 for relative humidity. When the relative humidity was lower than 66.83%, the risk of COVID-19 will decrease with the increase in relative humidity. When the relative humidity was higher than 66.83%, the relative risk would vary with the number of lag days.

The exposure-response relationship curves showed essentially linear associations between COVID-19 and lag meteorological conditions in the multiple-variables model (Fig. 6). In general, when the mean temperature and relative humidity were lower than their average value, the relative risk was higher than when they were higher than the average value. When the wind speed and diurnal temperature range were lower than the average value, the relative risk was lower than when they were higher than the average value. When the mean temperature and humidity were lower than the average value, the relative risk will decrease as the temperature and relative humidity increase. When it is higher than the average value, there was no significant change. When the wind speed and diurnal temperature range were higher than the average value, as the diurnal temperature range increases, the relative risk has decreased and increased, respectively. When it was lower than the average value, there was no significant change.

The range of relative risks was 0.75–1.30 for mean temperature, 0.29–1.19 for wind speed, 0.96–1.35 for relative humidity, 0.91–2.21

for the diurnal temperature range. The maximum RR of mean temperature was 1.30 under −23 °C at lag 10 days, the minimum RR of wind speed was 0.29 under 12 m/s at lag 24 days, the maximum RR of range of temperature was 2.21 under 28 °C at lag 24 days, the maximum RR of relative humidity was 1.35 under 4% at lag 0 days.

4.3.1. Subgroup analyses

The 188 countries in the study were divided into two subgroups according to their respective hemispheric regions, the Southern ($n = 40$) and the Northern ($n = 148$). Multiple-variables DLNM models were used to analyze the two subgroups in the northern and southern hemispheres.

Expose-lag-response curves were shown in Figs. 7 and 8. The results of the research were still robust. In the Southern Hemisphere, the change trends of mean temperature, wind speed, and relative humidity were consistent with the multiple-variables model results in 188 countries. While in the diurnal temperature range, no significant relationship between the diurnal temperature range and the relative risk was observed. In the northern hemisphere study, it was found that with the changes in wind speed, diurnal temperature range, and relative humidity, the risk of disease was consistent with the results of 188 countries. When the temperature lags 0–5 days, it was found that as the temperature increased, it was found that the relative risk increased with the mean temperature increases.

5. Discussion

As of 31 December 2020, COVID-19 had been prevalent worldwide for more than one year, and both the northern and southern hemispheres had experienced a complete seasonal cycle. Many countries
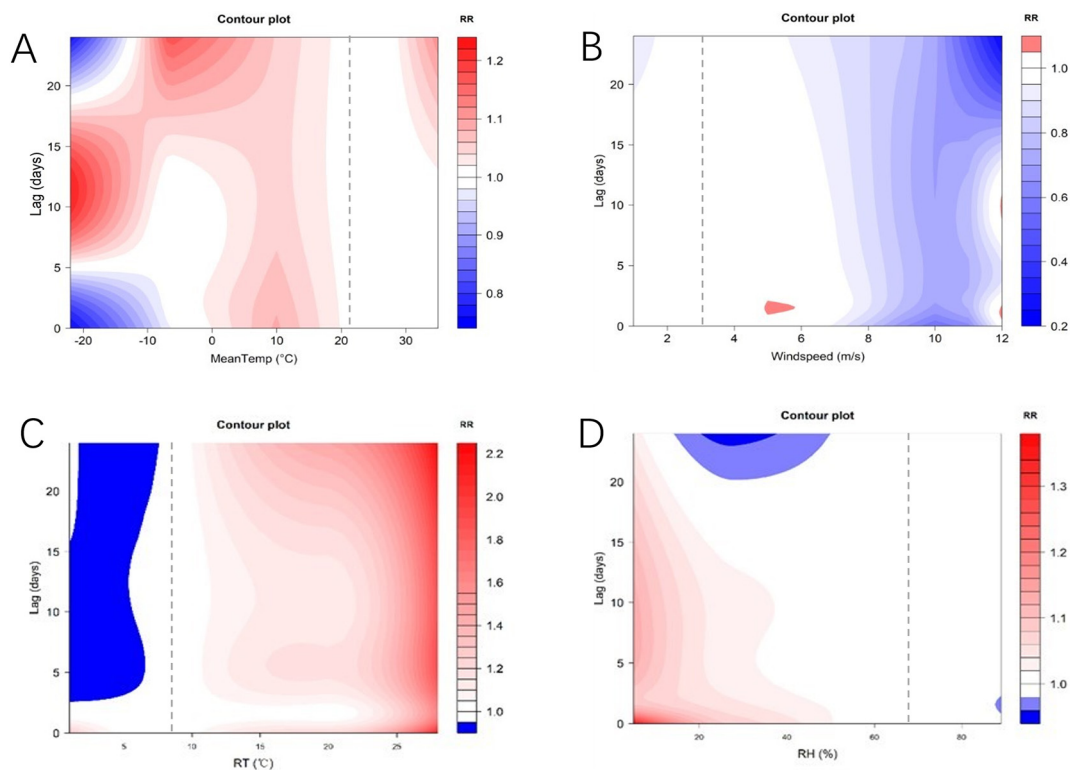
Fig. 6. Contour plots of the exposure-response relationship for the association between daily new cases of COVID-19 and meteorological variables in the multiple-variables model. A: mean temperature B: WIND speed: wind speed C: diurnal temperature range D: relative humidity The Y-axis is the lag days ranging from 0 to 24. The X-axis is the range of the observed values of each variable. The color gradient represents the relative risk (RR). The red color gradient represents higher strength of RR, above 1, and the blue gradient represents lower strength of RR, below 1. The white color represents no difference, at RR = 1.

have taken active prevention and control measures to deal with the COVID-19 epidemic in the past year (WHO, 2020b), but there were still more than 600,000 confirmed cases every day (WHO, 2021). Our study demonstrated the effects of meteorological variables on COVID-19 as of 31 December 2020 and found that the mean temperature, wind speed and relative humidity were negatively correlated with daily new cases of COVID-19. The diurnal temperature range was positively correlated with daily new cases of COVID-19. These relationships were more apparent when the temperature and relative humidity were lower than their average value(21.07°Cand 66.83%, respectively). The wind speed and diurnal temperature range were higher than the average value(3.07 m/s and 9.53 °C). After a lag analysis of different days for meteorological factors, the results were still robust.

Our previous study involved data of COVID-19 cases in 166 countries (excluding China) as of 27 March 2020 for analysis and found that temperature and humidity were negatively correlated with daily new cases and deaths of COVID-19 (Wu et al., 2020). With the extension of the time range, the northern hemisphere transitions from winter to summer. In another study, we included data on new cases and deaths in 127 countries as of 31 August 2020. We revealed that temperature, relative humidity, and wind speed were nonlinearly correlated with daily new cases. They may be negatively correlated with the daily new cases of COVID-19 over 127 countries when temperature, relative humidity and wind speed were below 20 °C, 70% and 7 m/s, respectively (Yuan et al., 2020).

Several studies on the relationship between meteorological factors and the global spread of COVID-19 have reported a negative correlation between temperature and COVID-19 morbidity or mortality (Rouen et al., 2020; Notari, 2021; Guo et al., 2021). Studies in other specific regions have also reached similar conclusions. Similar conclusions can be found in studies in China (Liu et al., 2020; Shi et al., 2020; Qi et al., 2020),

Japan (Kodera et al., 2020), Mexico (Méndez-Arriaga, 2020), Turkey (Şahin, 2020), Germany (Biktasheva, 2020) and other places. Significant negative correlations were found in several cities in Latin American cities (Bolaño-Ortiz et al., 2020) and in the United States (Li et al., 2020a). We observed an overall negative correlation between temperature and COVID-19 incidence on a global scale. The number of daily new cases of COVID-19 sharply decreased as the mean temperature was lower than 21 °C, was not significant when the temperature was below 21 °C. Inconsistencies in study results may be caused by differences in the study time range, study methods and study regions. The effect and delay effect of low temperature on COVID-19 need to be further studied and confirmed.

Some studies have reported correlations between COVID-19 and humidity in different regions and globally. Some have reported negative correlations between COVID-19 and humidity (Bashir et al., 2020), while some studies have reported no significant correlations (Pan et al., 2021), and some have shown non-linear correlations. We observed the higher relative humidity was generally associated with a lower risk of COVID-19 incidence as relative humidity was lower than 66.8%.

There is relatively little information on the correlation between COVID-19 incidence and wind speed/diurnal temperature ranges globally. Most previous studies have shown that higher wind speeds are generally associated with a lower risk of COVID-19 (Xie and Zhu, 2020; Şahin, 2020; Pani et al., 2020). Some studies have observed no significant association (Adekunle et al., 2020). A few studies in China reported the relationship between COVID-19 and diurnal temperature range and found that the increase of diurnal temperature range was associated with decreased daily confirmed case counts (Liu et al., 2020). Some did not observe a significant association between diurnal temperature range and the incidence of COVID-19 (Li et al., 2020b). Further studies on this topic are warranted.
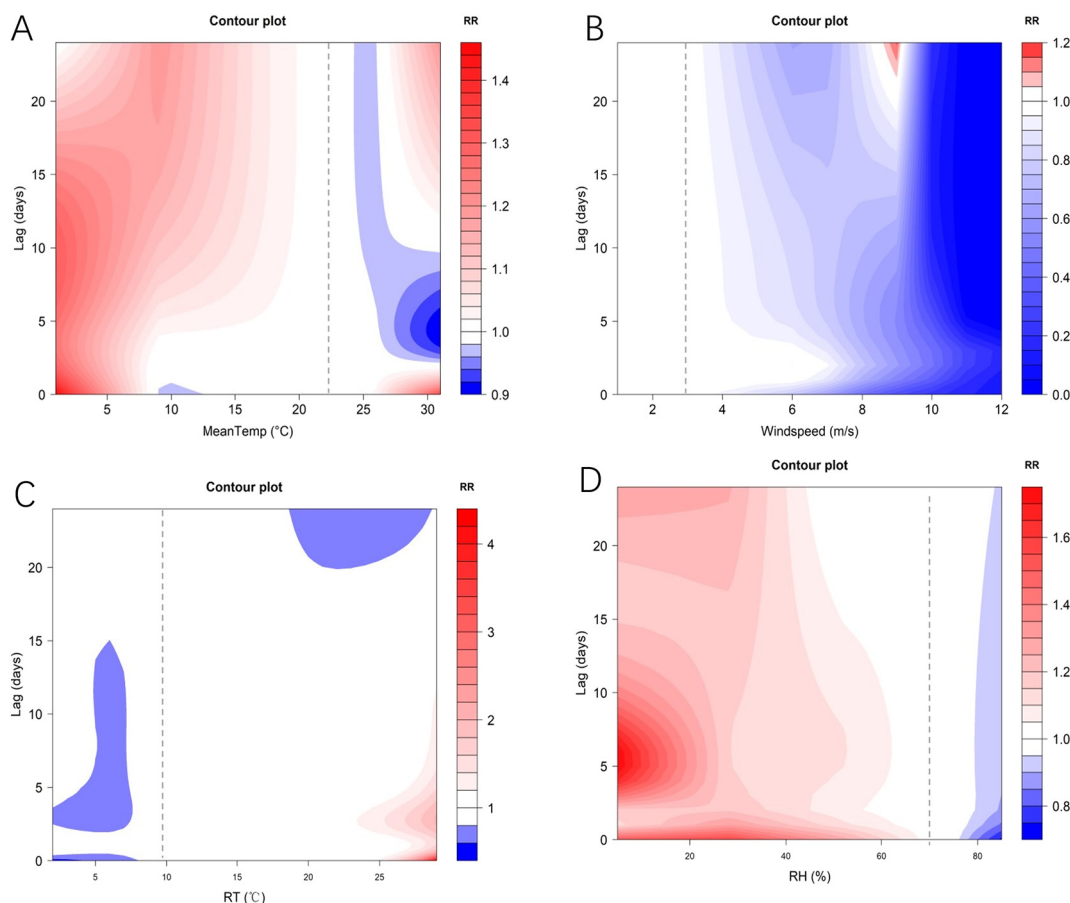
Fig. 7. Contour plots of the exposure-response relationship for the association between daily new cases of COVID-19 and meteorological variables in the Southern Hemisphere. A: mean temperature B: wind speed: wind speed C: diurnal temperature range D: relative humidity The Y-axis is the lag days ranging from 0 to 24. The X-axis is the range of the observed values of each variable. The color gradient represents the relative risk (RR). The red color gradient represents higher strength of RR, above 1, and the blue gradient represents lower strength of RR, below 1. The white color represents no difference, at RR = 1.

The underlying mechanism of the association between meteorological factors and COVID-19 incidence remains unclear. The mechanism by which climate factors influence disease transmission and infection may be related to the virus's ability to survive under external environmental conditions before infection (Mecenas et al., 2020). Changes in host physiological susceptibility, immune system function, social behavior and weather conditions were also thought to play a role (Mecenas et al., 2020). It is supposed that high temperature and humidity have a combined effect on the inactivation of coronaviruses. In contrast, the opposite weather condition can support prolonged survival time of the virus on surfaces and facilitate the transmission and susceptibility of the viral agent (Chan et al., 2011). Thus, cold and dry weather may trigger an impairment of the local and systemic antiviral defence mechanisms, leading to increased host susceptibility to the respiratory viruses in winter (Moriyama et al., 2020). Previous literature suggested that low wind speeds may promote a longer permanence of the infected aerosol particles in the air, thus favouring the transmission of SARS-CoV-2 (Coccia, 2021). Higher wind speeds may blow away the droplets and reduce the concentration of infected aerosol particles (Guo et al., 2021; Coccia, 2021). Diurnal temperature differences may increase the number of influenza cases by affecting susceptibility to SARS-CoV-2 (Imai et al., 1998; Togias et al., 1985; Graudenz et al., 2006).

The advantages of this study were as follows. The time range of this study was one full year after the outbreak of COVID-19, and the seasonal characteristics of COVID-19 can be observed more clearly. Second, the data of this study were time-series data, and the GAM model and DLNM model were used to systematically evaluate the correlation and lag effect between meteorological factors and COVID-19. Third, this study was the first study to compare the differences in the association between meteorological factors and COVID-19 cases in the northern and southern hemispheres.

Some limitations of our study should be noted. First, this is an ecological study, and we cannot infer the effect of individual exposure levels from meteorological conditions across large geographical areas on the risk of infection. Then, the meteorological parameters of each country were obtained from a single site, which may affect the statistical analysis. Third, the effects of policies and measures on COVID-19 transmission were not assessed in our study.

6. Conclusion

As the northern Hemisphere enters winter, WHO assessed the global risk level as very high due, in part, to recent reports of new SARS-CoV-2 variants (WHO, 2005). This study mainly aims to contribute the community research by investigating the association between COVID-19 and meteorological parameters over 188 countries by using statistical approaches. The results show that the epidemic situation in Northern Hemisphere countries may increase with the decrease in temperature in the next few seasons, so we should keep vigilant and take active measures. Although COVID-19 is likely to be less prevalent in the Southern Hemisphere during the summer months, as COVID-19 transmission is influenced not only by meteorological factors, the epidemic still requires vigilance. We should take advantage of summer opportunities to prepare for better control of the disease in winter. This research will be a useful supplement to help healthcare policymakers understand the weather dependency of COVID-19 over these countries.
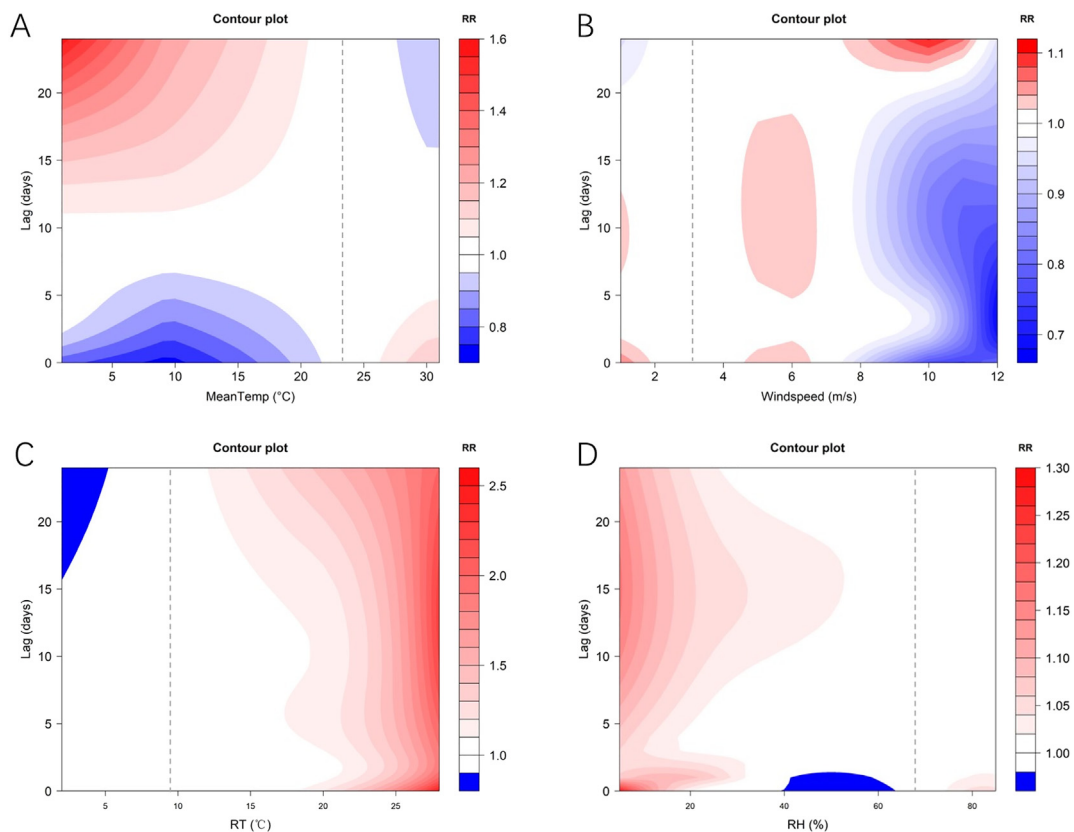
Fig. 8. Contour plots of the exposure-response relationship for the association between daily new cases of COVID-19 and meteorological variables in the Northern Hemisphere. A: Mean temperature B: Wind speed: wind speed C: diurnal temperature range D: relative humidity The Y-axis is the lag days ranging from 0 to 24. The X-axis is the range of the observed values of each variable. The color gradient represents the relative risk (RR). The red color gradient represents higher strength of RR, above 1, and the blue gradient represents lower strength of RR, below 1. The white color represents no difference, at RR = 1.

Ethical approval and consent to participate

Not applicable.

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CRediT authorship contribution statement

Jie Yuan: Writing – original draft, Methodology, Software, Data curation. **Yu Wu:** Writing – review & editing. **Wenzhan Jing:** Writing – review & editing, Visualization. **Jue Liu:** Supervision, Methodology. **Min Du:** Data curation, Investigation. **Yaping Wang:** Investigation. **Min Liu:** Conceptualization, Funding acquisition, Project administration, Supervision.

Declaration of competing interest

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

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