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Research article

Non-linear effects of meteorological factors on COVID-19: An analysis of 440 counties in the americas

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ABSTRACT

Background: In the last three years, COVID-19 has caused significant harm to both human health and economic stability. Analyzing the causes and mechanisms of COVID-19 has significant theoretical and practical implications for its prevention and mitigation. The role of meteorological factors in the transmission of COVID-19 is crucial, yet their relationship remains a subject of intense debate.
Methods: To mitigate the issues arising from short time series, large study units, unrepresentative data and linear research methods in previous studies, this study used counties or districts with populations exceeding 100,000 or 500,000 as the study unit. The commencement of local outbreaks was determined by exceeding 100 cumulative confirmed cases. Pearson correlation analysis, generalized additive model (GAM) and distributed lag nonlinear model (DLNM) were used to analyze the relationship and lag effect between the daily new cases of COVID-19 and meteorological factors (temperature, relative humidity, solar radiation, surface pressure, precipitation, wind speed) across 440 counties or districts in seven countries of the Americas, spanning from January 1, 2020, to December 31, 2021.
Results: The linear correlations between daily new cases and meteorological indicators such as air temperature, relative humidity and solar radiation were not significant. However, the non-linear correlations were significant. The turning points in the relationship for temperature, relative humidity and solar radiation were 5 °C and 23 °C, 74 % and 750 kJ/m^2, respectively.
Conclusion: The influence of meteorological factors on COVID-19 is non-linear. There are two thresholds in the relationship with temperature: 5 °C and 23 °C. Below 5 °C and above 23 °C, there is a positive correlation, while between 5 °C and 23 °C, the correlation is negative. Relative humidity and solar radiation show negative correlations, but there is a change in slope at about 74 % and 750 kJ/m^2, respectively.

1. Introduction

Since March 11, 2020, when it was officially declared a global pandemic by the World Health Organization (WHO) [1], COVID-19 has shown several rounds of peaks associated with mutated strains such as Alpha, Delta and Omicron. As of October 6, 2023, there have been over 771 million reported infections and over 6.9 million deaths globally [2]. On May 5, 2023, the WHO declared that COVID-19

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was no longer a Public Health Emergency of International Concern (PHEIC). However, it is important to note that COVID-19 remains a global health threat due to its continued mutation and associated risks [3].

The spread of COVID-19 is influenced not only by factors such as population density, individual lifestyle habits and mobility, specific restrictions imposed by governments, vaccination rates, and individual susceptibility, but also by meteorological factors [4–6]. The relationship between the spread of epidemics and meteorological factors has drawn significant interest from specialists and scholars in the past [7–12]. Many infectious respiratory diseases, including those caused by other coronaviruses and influenza, exhibit marked seasonality, peaking during the winter months, partly due to meteorological conditions affecting virus survival and human immunity [11]. As COVID-19 began to spread, environmental scientists recognized that the world faced a perilous upper respiratory viral disease, potentially sensitive to seasonal weather conditions. Laboratory studies have demonstrated that SARS-CoV-2 viruses survive better in cold, dry, and low UV radiation conditions [13–17]. In August 2020, the World Meteorological Organization (WMO) established a working group to investigate the relationship between climatic, meteorological, and environmental (CME) factors and the risk of COVID-19 transmission and to develop a unified template [18–20]. However, there is still no consensus on the impact of meteorological factors on the spread of COVID-19. For example, the most studied factor, temperature, is considered to be positively correlated with daily new cases [21–25]. However, others consider it to be negatively correlated [26–35], and still, some find no significant correlation [36–38]. Therefore, it is essential to conduct more comprehensive and systematic research on the impact of meteorological factors on the spread of COVID-19.

Sorting through the existing studies, it was found that the reasons for the disagreement may be related to different data and research methods. For example, too short time series, too small regional scope or too large study unit may lead to biased analysis results. Additionally, the discrepancy may be related to the analysis methods used; for example, many early studies used methods such as linear correlation analysis to examine the relationship between the two variables, without considering the non-linear relationship and lagged effects between them. Other studies have failed to correct for the discrepancies that existed in the data reported from

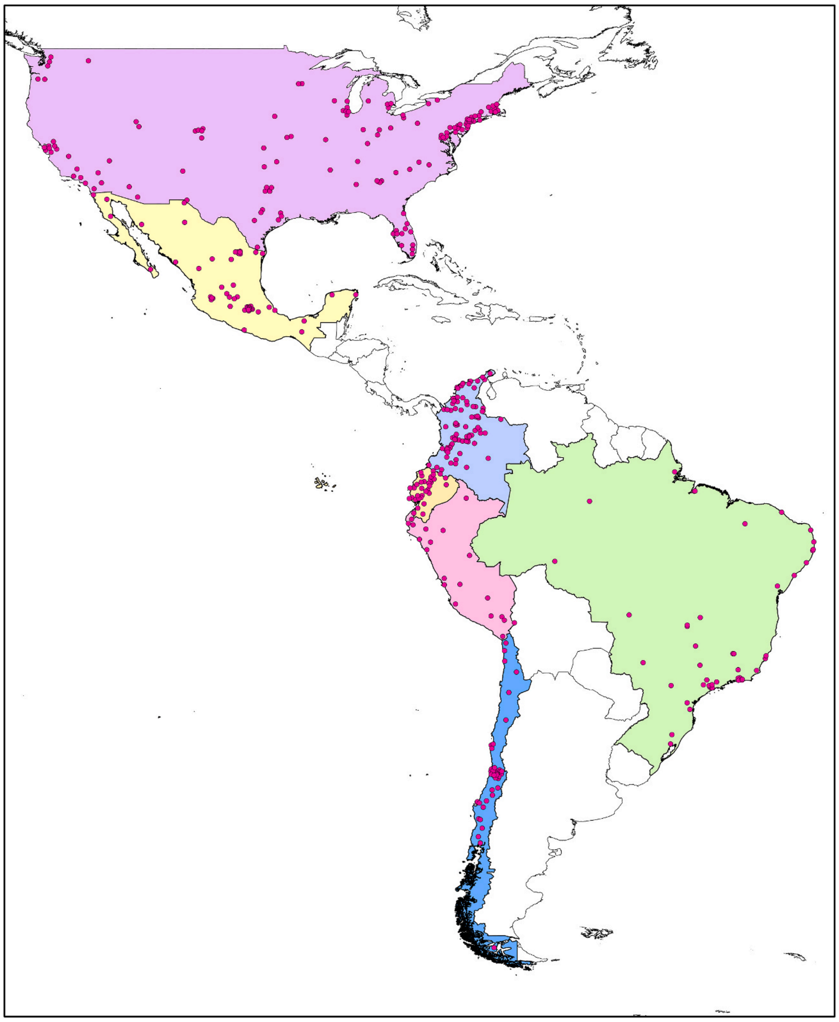

Fig. 1. Location and distribution of 440 counties (districts) across 7 countries in the Americas.

different regions, all of which may lead to uncertainty in the analysis results. Recently, an increasing number of studies have used non-linear time series analysis methods, such as GAM [5,23,38–44] and DLNM [28,44–46]. However, these studies encompass analyses at the country [43,44], state [5,26,40] or city [23,28,38,39,41,45,46] level. In studies with a country or state as the unit of analysis, the regional scope is relatively large, and acquiring data on meteorological indicators and their representativeness is prone to significant errors. In contrast, conducting a study at the city level would be easier to integrate and would offer greater representativeness. However, the diverse sizes of cities in present studies pose challenges for data consistency, while the spatial and temporal representativeness of most analyses is hindered by their concentration on single countries, spatial unevenness, and periods less than one year.

This study examines the relationship between daily new cases over a two-year period (January 1, 2020 to December 31, 2021) and meteorological factors (temperature, relative humidity, solar radiation, precipitation, surface pressure and wind speed) across 440 counties (districts) in seven countries in the Americas. Using two models, GAM and DLNM. The study area encompasses 101 latitudes and altitude ranging from 1 m to 3399 m above sea level, cover different climate types from tropical to boreal and from humid to arid. Temperature varies from −27 °C to +38 °C, relative humidity from 2 % to 99 %, daily precipitation from 0 mm to 344 mm, solar radiation from 12 kJ/m^2 to 1485 kJ/m^2, surface pressure from 62 kPa to 103 kPa and wind speed from 0 m/s to 12 m/s. The comprehensive two-year analysis covers the latitude and altitude range of most human activities and the primary climate types, ensuring the representativeness and reliability of the results.

2. Materials and methods

2.1. Study area and period

To mitigate potential significant statistical errors, we selected counties (districts) with populations exceeding 100,000 (in countries with smaller populations such as Colombia, Ecuador, Chile, and Peru) or those exceeding 500,000 (in countries with larger populations such as the United States, Mexico, and Brazil) as our research units. Ultimately, we selected 440 counties(districts) across seven countries in the Americas (Fig. 1). The study period spanned from January 1, 2020 to December 31, 2021.

2.2. Data collection and processing

Data on daily new cases and meteorological indicators for the 440 counties (districts) were sourced from the Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE) Unified COVID-19 Dataset [47]. The database contained data from four administrative levels: country, state, county and district. Given that the length of the time series of daily new cases varied across countries, all data within the specified time range (Table 1) was selected. Since each county (district) had small daily new cases at the beginning of the pandemic, the starting point of each pandemic was chosen as the time when cumulative cases reached 100 to minimize errors. Time series data for daily mean air temperature, relative humidity, surface pressure, surface downward solar radiation, total precipitation, and wind speed were extracted at the county or district level from the database. Raw meteorological data were obtained from the fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global climate (ERA5). ERA5 incorporates surface observations, satellite measurements and model output to provide continuous gridded maps of meteorological variables with a spatial resolution of $0.25^\circ \times 0.25^\circ$ [48].

2.3. Statistical analysis

We used GAM to evaluate the association between meteorological factors and daily new cases. A GAM [49] is a generalized linear model with a linear predictor involving a sum of smooth functions of covariates [50]. This aids in uncovering the non-linear relationship between meteorological factors and COVID-19 spread by using a link function to establish the relationship between the expected value of the response variable and the non-parametric predictor variables [51,52]. In this study, the relationship between meteorological factors and daily new cases was examined using log-linear GAM, assuming that daily new cases approximately followed a quasi-Poisson distribution. In addition, given the time-series nature of the observed data, the relationship between the log-expectation of daily new cases and meteorological factors was modelled using a GAM with a Poisson family of distributions [53].

Table 1
COVID-19 basic data information. The last column represents the pattern of the daily number of reported COVID-19 cases in each country over a week.

Country	Spatial resolution	Number of Counties/Districts	Time range	Statistic
United states	2nd AL (county)	139	2020.1.22–2021.12.31	Saturday and Sunday are few
Mexico	2nd AL (municipality)	58	2020.1.4–2021.4.8	Saturday and Sunday are few
Colombia	2nd AL (municipality)	88	2020.3.1–2021.12.31	Sunday is few
Ecuador	2nd AL (canton)	31	2020.3.1–2021.12.31	Monday and Sunday are few
Peru	3rd AL (district)	21	2020.3.1–2021.12.31	Monday is few
Chile	2nd AL (municipality)	57	2020.3.2–2021.7.26	Only available on Monday and Friday
Brazil	2nd AL (municipality)	46	2020.3.29–2021.12.31	Monday and Friday are few

AL: administrative level.

The effect of time trends was considered and included as a confounding factor in the model calibration. As daily new cases showed a non-linear trend over time, a natural cubic spline function was used to control for the effect of time trend [51]. In addition, classification variables were used to correct for week effects in the model to identify possible confounding effects within a week. Some regularity was observed in the distribution of daily new cases throughout the week, and unlike other common epidemics, the week effect for COVID-19 exhibited distinct statistical characteristics. Peaks in daily new cases were no longer confined to weekends, and there were variations among countries. For example, daily new cases were generally lower on Saturdays and Sundays in the United States, while in Chile, they were only reported on Mondays and Fridays. The model was defined as follows:

$$log\ Y_t = ns(MV_t, df) + ns(Date_t, df) + County_i + Dow + \alpha \tag{1}$$

In equation (1), $logY_t$ is the logarithmic transformation of the daily new cases on day t; α is the intercept; MV_t represents the meteorological factors on day t, including temperature, relative humidity, solar radiation, surface pressure, precipitation and wind speed; ns represents the natural cubic spline function; $County_i$ represents the classification variable for counties or regions to account for differences between them; *Dow* represents a categorical variable indicating the day of the week; $Date_t$ represents the length of the time series for each county (district) to capture the daily fixed effects; *df* represents the degrees of freedom of the spline function and the time trend, which experts recommend to take as 3 and 14, respectively.

Meteorological factors usually have a lagged effect on health outcomes. Considering the typical incubation period of 1–14 days for COVID-19 and the 1–7 days between case onset and test reporting, analyzing the lagged effect of meteorological factors on daily new cases is a reasonable approach. Traditional GAM only considers effects within a given time period, and simply introducing exposure levels for consecutive days while ignoring the characteristics of the lagged distribution can result in high covariance problems and biased results. To address this problem, we introduced DLNM, which was based on the concept of GAM and employed crossover basis functions to capture the distribution of the dependent variable across both independent and lagged dimensions. DLNM enables a comprehensive assessment of both the lagged and non-linear effects of exposure factors, resulting in a more thorough analysis of the influence of meteorological factors on COVID-19 [54,55]. The model was defined as follows:

$$log\ Y_t = cb(MV_t, lag, fun, vardf, lagdf) + ns(Date_t, df) + County_i + Dow + \alpha \tag{2}$$

In equation (2), *cb* represents the cross-basis function; *lag* represents the maximum lag period and takes the value of 21; *vardf* represents the spline function degree of freedom and *lagdf* represents the lag term spline function degree of freedom, both take the value of 3; *fun* represents the natural cubic spline function.

Therefore, we used DLNM to generate cross-basis matrices of meteorological factors and maximum lag days, and plotted exposure–response–lag graphs of each meteorological factor against the risk of COVID-19 infection. These graphs aid in visualizing the effect of meteorological factors on the risk of COVID-19 infection and to identifying potential lagged effects. Relative risk (RR) is employed to represent the risk of COVID-19 infection relative to a reference value (the median value of a given meteorological factor with a reference value of RR = 1), thus better understanding and explaining the role of meteorological factors in the spread of the pandemic.

2.4. Analytical process

First, descriptive statistical analyses were conducted to depict the distribution of daily new cases and meteorological factors, including indicators such as mean, standard deviation, quantile and extreme values. Second, Pearson correlation analysis was employed to evaluate the correlation between the daily new cases and meteorological variables. Finally, GAM and DLNM were used to analyze the relationship between daily new cases and meteorological factors across 440 counties. Additionally, the 440 counties (districts) were categorized into four segments based on latitude (30°–60° in the northern hemisphere, 0°–30° in the northern hemisphere, 0°–30° in the southern hemisphere, and 30°–60° in the southern hemisphere) to facilitate comparative analysis. For these statistical analyses, R 4.2.1 software was employed, GAM and DLNM models were constructed using the ’mgcv’ and ’dlnm’ packages, respectively. A significance level of $p \leq 0.05$ was adopted.

Table 2
Descriptive statistics of daily new cases and meteorological variables in 440 counties (districts).

Variables	Mean	SD	Min	P25	Median	P75	Max
Daily new cases	164	583.32	0	4	37	147	99926
Mean temperature(°C)	18.24	7.66	−27.21	13.34	19.20	24.53	38.83
Relative humility(%)	69.94	17.06	2.18	60.71	74.07	82.94	99.85
Solar radiation(kJ/m^2)	738.15	278.91	11.57	551.48	750.61	928.68	1484.94
Surface pressure(kPa)	93.35	9.42	62.41	89.58	97.81	100.17	103.46
Precipitation(mm)	4.66	10.25	0.00	0.00	0.64	5.07	340.17
Wind speed(m/s)	1.89	1.41	0.00	0.81	1.56	2.62	12.27

SD: standard deviation; Min: minimum; P25: 25th percentile; P75: 75th percentile; Max: maximum.

3. Results

3.1. Descriptive analysis

Descriptive statistical analyses were conducted for daily new cases and meteorological factors across 440 counties (districts) in Americas, based on data up to December 31, 2021 (Table 2). The mean and median values of temperature, relative humidity, solar radiation, surface pressure, precipitation and wind speed were 18.24 °C and 19.20 °C, 69.94 % and 74.07 %, 738.15 kJ/m^2 and 750.61 kJ/m^2, 93.35 kPa and 97.81 kPa, 4.66 mm and 0.64 mm, 1.89 m/s and 1.56 m/s, respectively.

3.2. Pearson correlation analysis

To investigate the relationship between meteorological factors and COVID-19, Pearson correlation coefficients were computed between daily new cases per million and meteorological factors across 440 counties (districts). The results (Fig. 2) indicated weak negative correlations between daily new cases per million and temperature (−0.12) as well as solar radiation (−0.13). However, other factors exhibited mainly insignificant correlations with daily new cases per million. In addition, none of the correlation coefficients among the meteorological factors exceeded 0.5, suggesting a lack of significant collinearity among them. Therefore, the above meteorological indicators could be incorporated into the subsequent model.

3.3. Analysis of GAM

GAM was used to analyze daily new cases and meteorological factors. The model yielded a goodness-of-fit R^2 of 0.369 and a deviance explained(DE) of 64 %. Exposure-response curves (Fig. 3) revealed a significant non-linear relationship between new daily cases and all factors. Temperature (Fig. 3a) exhibited positive association with daily new cases at temperatures below 5 °C and above 23 °C, and a negative association with daily new cases between 5 °C and 23 °C. Relative humidity (Fig. 3b) and solar radiation (Fig. 3c) exhibited an overall negative association with daily new cases, with an increase in the slope of the curve for relative humidity above 74 % and solar radiation above 750 kJ/m^2. Surface pressure (Fig. 3d) showed a positive correlation with daily new cases between 85 kPa and 98 kPa, and a negative correlation with daily new cases above 98 kPa. The overall relationship for precipitation (Fig. 3e) was not significant. Wind speed (Fig. 3f) exhibited a negative correlation with daily new cases below 6 m/s and a positive correlation with daily new cases above 6 m/s, but the relationship was not significant.

3.4. Analysis of DLNM

DLNM analysis was conducted with the same parameters for daily new cases and meteorological factors, and the model fit results are depicted in Fig. 4. The results showed that the R^2 and DE obtained using DLNM (0.398, 65.4 %) were higher than that obtained using GAM (0.369, 64 %), indicating a lag effect between meteorological factors and daily new cases.

Figs. 4 and 5 showed a non-linear relationship and lag effect between COVID-19 transmission and meteorological factors.

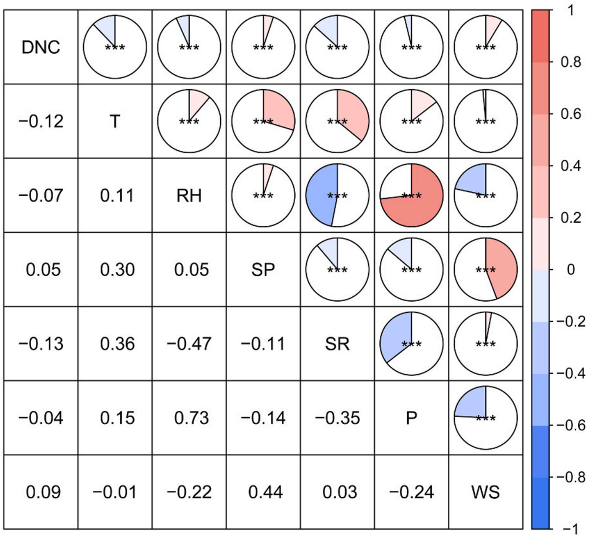

Fig. 2. Pearson correlation coefficients between meteorological variables and daily new cases per million. T: mean temperature; RH: relative humidity; SP: surface pressure; SR: solar radiation; P: precipitation; WS: wind speed; DNC: daily new cases per million. All associations between variables passed the significance test, ***:$p \leq 0.001$.

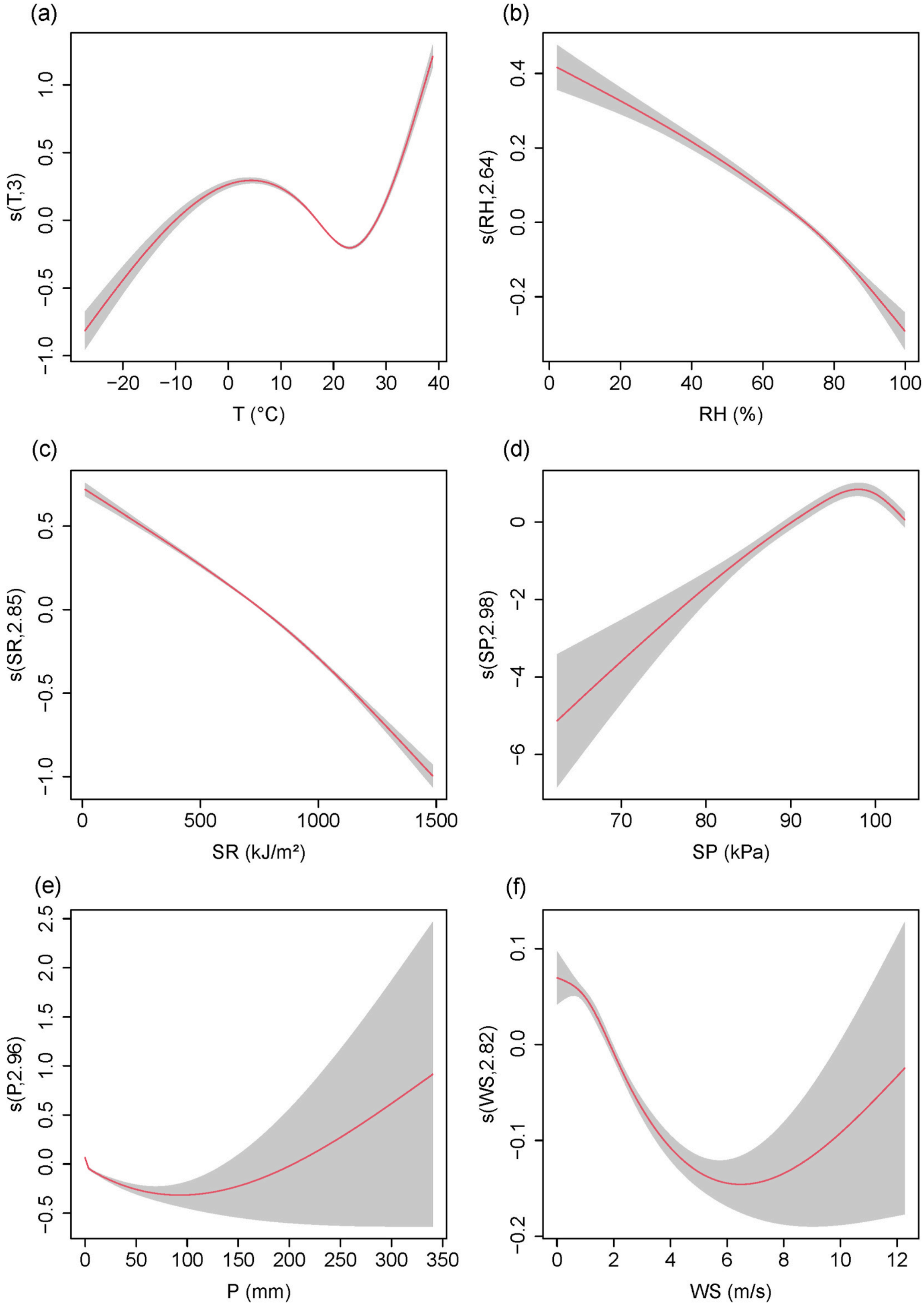

Fig. 3. Exposure–response curves between daily new cases and meteorological factors using GAM. (a) mean temperature; (b) relative humidity; (c) surface pressure; (d) solar radiation; (e) precipitation; (f) wind speed. The X-axis show the meteorological factors; the Y-axis shows the contribution value after fitting using the spline function.

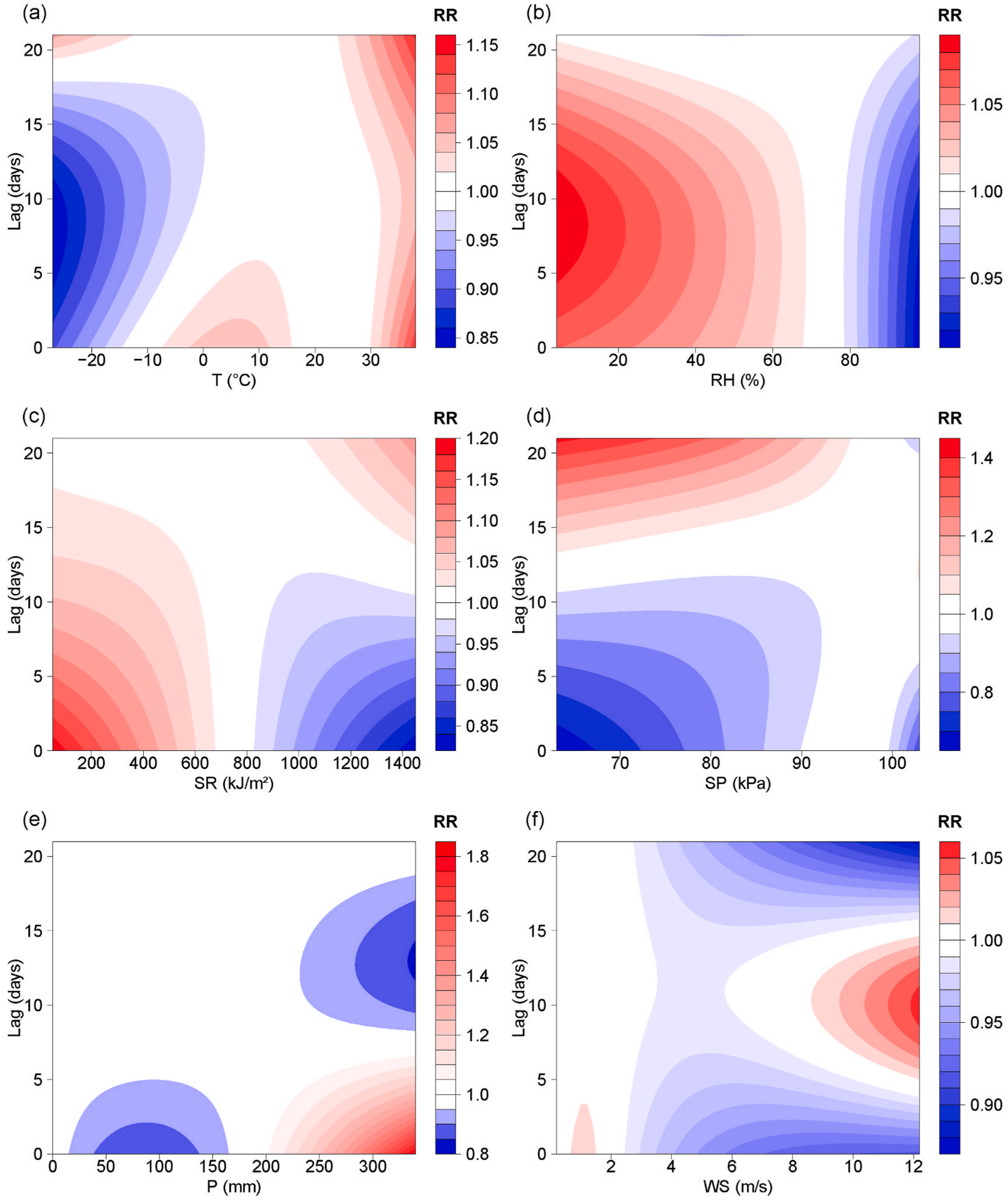

Fig. 4. Contour map of exposure–lag–response relationship between daily new cases and meteorological variables. (a) Mean temperature; (b) relative humidity; (c) surface pressure; (d) solar radiation; (e) precipitation; (f) wind speed. The Y-axis shows the lag days, ranging from 0 to 21. The X-axis shows 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.

Specifically, temperature (Figs. 4–5a) exhibited a little higher risk of infection at around 5 °C during the 0–6 day lag period and the highest risk above 30 °C during the 0–6 and 14–21 day lag periods. Relative humidity (Figs. 4–5b) showed a higher risk of infection at low levels throughout the lag period, with a significant relationship at approximately 8 days lag. Solar radiation (Figs. 4–5c) indicated increased infection risk at low levels, particularly evident at a lag period of 0 days. Conversely, surface pressure (Figs. 4–5d) demonstrated an inverse relationship with COVID-19 infection risk at lag periods of 0–10 days and 15–21 days. The association between precipitation (Figs. 4–5e) and COVID-19 infection risk remained insignificant throughout the lag period. Infection risk was slightly higher under low wind conditions (0–2 m/s, throughout the lag period) and high wind conditions (lag period of approximately 10 days), but the variation in infection risk was minimal (no more than 5 %). However, large confidence intervals under high wind conditions suggested low reliability of the fit (Figs. 4–5f).

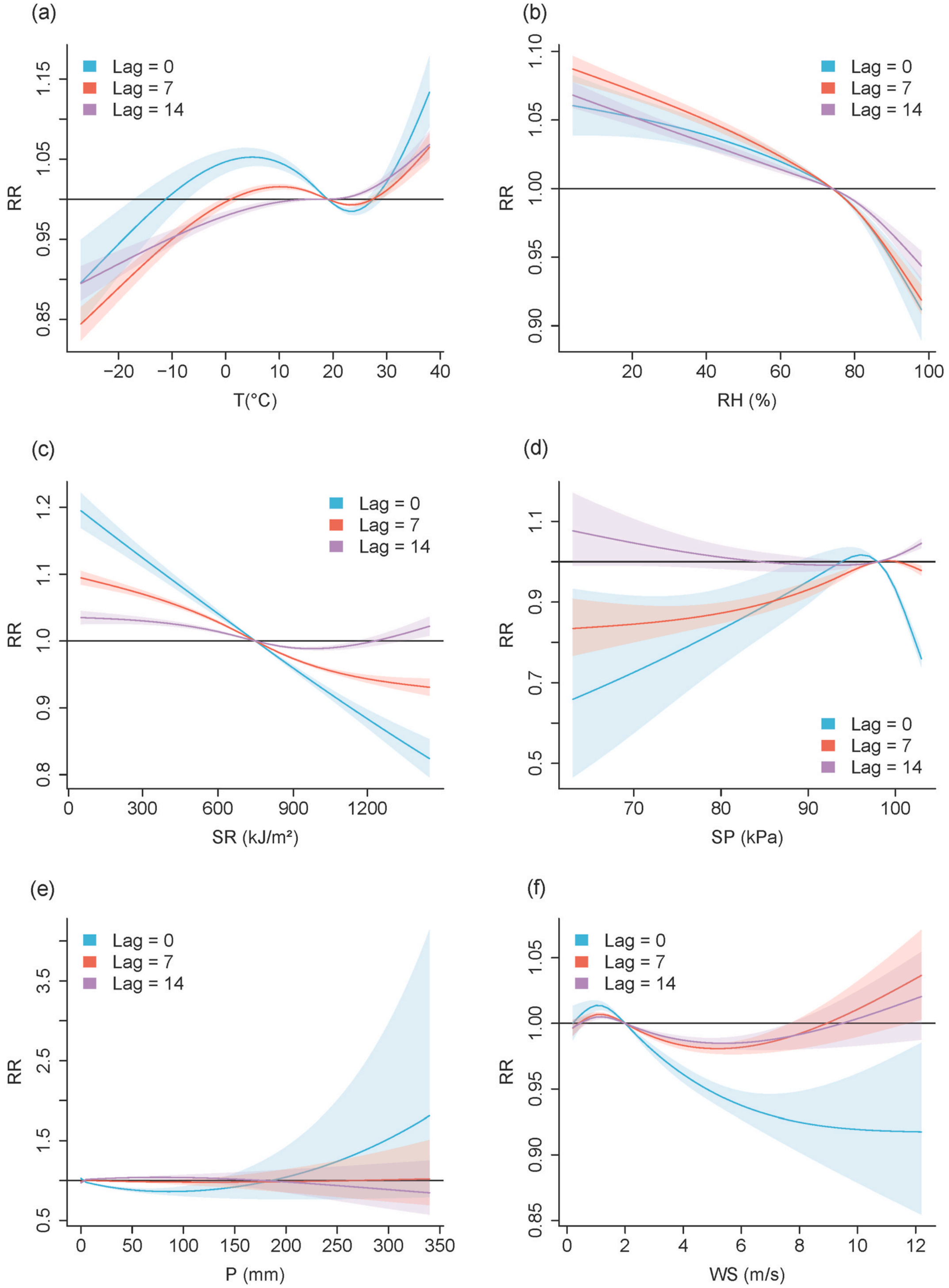

Fig. 5. Exposure–response curve of the relationship between various meteorological variables and daily new cases under different lag conditions. (a) Mean temperature; (b) relative humidity; (c) surface pressure; (d) solar radiation; (e) precipitation; (f) wind speed. The X-axis shows the range of the observed values of each variable. The Y-axis shows relative risk (RR). The blue line represents the situation without lag; the red and purple lines represent the situation with a lag of 7 days and 14 days, respectively.

3.5. Analysis of DLNM by latitude sub-region

For the DLNM analysis, we divided the 440 counties (districts) separately into four regions by latitude: 30°–60° in the northern hemisphere, 0°–30° in the northern hemisphere, 0°–30° in the southern hemisphere, and 30°–60° in the southern hemisphere (Fig. 6). The results indicated that the relationship between the risk of COVID-19 infection and meteorological factors varied across latitudes. However, the model analyses of temperature, relative humidity, and solar radiation demonstrated similar nonlinear relationships and lag effects overall. Specifically, although temperature (Fig. 6a) ranges differed among latitudes, the risk of infection was higher around 0 °C and 30 °C and lower around 20 °C and at extremely low temperatures. In addition, the risk of infection was elevated at low levels of relative humidity (Fig. 6b) and solar radiation (Fig. 6c).

4. Discussions

Most published papers have concluded that temperature was negatively associated with the spread of COVID-19, while a few reported positive associations, and others found no significant relationship. The reasons for these discrepancies may be attributed to the duration of the study period, the geographical scope, the chosen statistical units, and the analytical methodologies employed. Short time series or limited geographical coverage may lead to biased results, and the utilization of linear analytical methods without

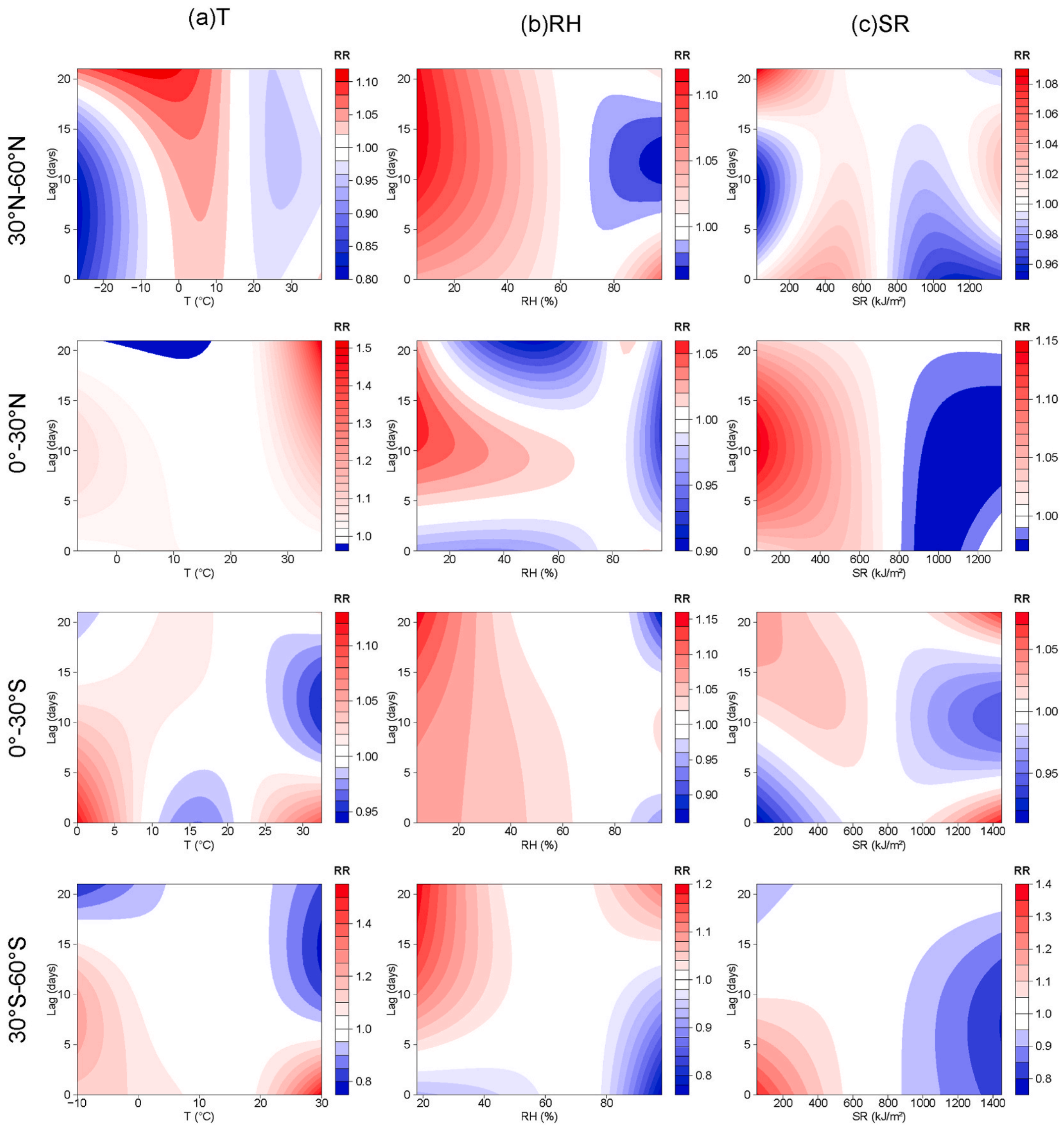

Fig. 6. Contour map of exposure–lag–response relationships between daily new cases and meteorological variables at different latitudes. Only (a) temperature, (b) relative humidity and (c) solar radiation are displayed.

accounting for lagged effects may lead to different results. This study analyzed a broader range of meteorological indicators over a longer time span, employing diverse methodologies while carefully considering lagged effects and possible biases in statistical reporting. The results revealed a non-linear relationship between daily average temperature and daily new cases: a positive correlation below 5 °C and above 23 °C, a negative correlation between 5 and 23 °C. There was a higher risk of infection around 5 °C and above 30 °C, with a lower risk of infection at around 20 °C. Similar results were reported by Yuan et al. [44] and Lyu et al. [56]. An experimental study has demonstrated that the viral activity remained highly stable at 4 °C, however, the virus was fully inactivated within a mere 5 min at 70 °C [57]. Another experimental study investigated the activity of SARS-CoV-2 at different temperatures (10 °C, 22 °C, 27 °C). The findings revealed that the rate of virus inactivation was directly proportional to the temperature [15]. In addition, the effect of temperature on influenza virus emission in simulated silos was studied using guinea pigs as model animals. It was shown that the peak period of virus shedding was approximately 40 h in guinea pigs infected with virus at 5 °C compared with 20 °C. This extended shedding period may increase the efficiency of virus transmission, and the phenomenon may be due to reduced mucociliary clearance and increased stability of the virus in the upper respiratory tract at lower temperatures [58]. The mechanisms through which temperature influences epidemic spread may vary across different temperature ranges. In the 0–30 °C range, temperature may affect viral activity, or viral emission may be the primary factor influencing virus transmission. Although cold temperatures may weaken human immunity by reducing blood supply and immune cell supply to the nasal mucosa. However, in the cold winter months, reduced population mobility may hinder the transmission of SARS-CoV-2, which primarily spreads through contact and droplet. This could explain the lower infection risk observed at temperatures below 0 °C. Above 30 °C, the increasing infection risk may be primarily attributed to human immunity, as high temperatures can weaken both innate and adaptive antiviral immune responses, despite reduced virus activity.

In the published literature, most studies have concluded that humidity was negatively associated with the spread of COVID-19, while a few suggested a positive association, and others found no significant relationship or a more complex relationship. Several studies using similar analytical approach, such as global studies with national or city-based study units [28,39,40,44,46], have reported similar results to the negative correlation found in this paper. However, this study found revealed a sudden change point around 74 % relative humidity, indicating a rapid decrease in risk with increasing humidity above this threshold. Possible mechanisms include: inhalation of dry air impairs mucosal cilia clearance, reducing the ability of ciliated cells to secrete mucus and clear viral particles (innate immune response), leading to a reduction in respiratory defenses. Additionally, the main transmission routes of SARS-CoV-2, such as droplet and contact transmission, have been well-documented, and aerosol transmission has been shown to be another important mode of transmission [59–61]. At low relative humidity, water evaporation leads to the aggregation of aerosol particles, increasing the risk of virus inhalation [58,62].

The majority of studies in the literature have concluded that solar radiation/UV radiation is negatively associated with the spread of COVID-19 [39,44,63–67], consistent with the findings of this paper. However, a global-scale study of 455 cities reported the opposite result [29]. There is a general consensus that stronger solar radiation or UV irradiation can mitigate the spread of COVID-19. Mechanistically, solar radiation can influence virus activity. For example, one experimental study showing that 90 % of viruses in aerosols were completely inactivated within 4.8 min under sunlight at 40 °C and 20 % RH, compared to more than 2h required for virus inactivation in a nighttime environment [68]. Another study found that 99.99 % of SARS-CoV-2 was inactivated within 10s in a deep UV LED lamp (emitting 280 ± 5 nm of UV light, 3.75 mWcm^{-2}) [69]. Additionally Solar radiation also affects human immunity. Reduced sunlight leads to decreased phagocytic activity of granulocytes and monocytes, reduced the production of reactive oxygen species, and decreased synthesis of vitamin D, thereby affecting the innate immune response [11].

Additionally, conducting a sensitivity analysis is necessary to ensure the robustness of the results during the analysis simulation. First, the model results showed similar exposure–response curves with degrees of freedom for the spline (2–10), but setting the degree of freedom too high or too low can result in poorly fitted or overfitted results. Second, the results remained robust when varying degrees of freedom for time trend (4–10) were applied and when week effects were not included. Finally, the results obtained from the sub-regional analysis of 440 counties (districts) remained relatively stable.

5. Conclusions

In order to overcome the issues related to short time series, large study area units, insufficient data representativeness, or linearity of research methods in previous studies, this paper adopts counties (districts) with a population of more than 100,000 or 500,000 as research units. It considers the cumulative confirmed cases exceeding 100 as the onset of a local epidemic. Taking into account weekly effect of COVID-19 data reporting and the lag effect of the response to meteorological indicators, this study employed Pearson correlation analysis, GAM and DLNM to examine the correlation and lag effect between the daily new cases and meteorological factors (temperature, relative humidity, solar radiation, surface pressure, precipitation, wind speed) in 440 counties (districts) across 7 countries in the Americas from January 1, 2020 to December 31, 2021. The analysis is representative and accurate due to the larger temporal and spatial coverage and the utilization of smaller study unit (county level).

The study found that the linear correlation between daily new cases and meteorological indicators such as temperature, relative humidity and solar radiation was not significant, while the non-linear correlation was more significant. Temperature exhibited a positive correlation below 5 °C and above 23 °C and a negative correlation between 5 and 23 °C. Relative humidity and solar radiation exhibited significant negative correlations with daily new cases, a rapid decrease in daily new cases observed relative humidity above 74 % and solar radiation above 750 kJ/m^2. The results of this study provide a new and dependable foundation for investigating the mechanisms driving the development of COVID-19.

There are some different in the respondence of COVID-19 infection to meteorological indicators. Temperature exhibits a little higher risk of infection at around 5 °C during the 0–6 day lag period and the highest risk above 30 °C during the 0–6 and 14–21 day lag periods. Relative humidity shows the best relationship with COVID-19 infection at approximately 7–8 days lag. Solar radiation indicates the best relationship at a lag period of 0 days. Conversely, surface pressure demonstrates an inverse relationship with COVID-19 infection risk at lag periods of 0–10 days and 15–21 days. The association between precipitation and COVID-19 infection risk remains insignificant throughout the lag period. Infection risk is slightly higher under low wind conditions (0–2 m/s, throughout the lag period) and high wind conditions (lag period of approximately 10 days), but the variation in infection risk is minimal (no more than 5 %).

Although they demonstrated similar nonlinear relationships and lag effects overall, there are still some different in different latitudes.

This study has certain limitations. Firstly, although the analysis of the Americas has gained some valuable insights about the impact of meteorological factors on the COVID-19 pandemic, it will be more convincing if it can be verified by the analysis of other regions and even the global pandemic. Secondly, although the analysis has found some differences in the relationship between meteorological factors and COVID-19 pandemic at different latitudes, more in-depth and systematic research is needed to determine how they vary with latitude.

Data availability statement

Data will be made available on request.

Funding details

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CRediT authorship contribution statement

Hao Zhang: Writing – original draft, Software, Methodology, Data curation. **Jian Wang:** Supervision, Project administration, Funding acquisition, Conceptualization. **Zhong Liang:** Writing – review & editing, Validation. **Yuting Wu:** Visualization, Investigation.

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.

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