The impact of meteorological factors on COVID-19 of California and its lag effect

Haitao Wei | Shihao Liu | Yan Liu | Bang Liu | Xiyun Gong

1The School of the Geo-Science & Technology, Zhengzhou University, Zhengzhou, China
2Joint Laboratory of Eco-Meteorology, Zhengzhou University, Chinese Academy of Meteorological Sciences, Zhengzhou University, Zhengzhou, China
3The First Affiliated Hospital of Zhengzhou University, Zhengzhou, Henan, China

Correspondence
Xiyun Gong, The First Affiliated Hospital of Zhengzhou University, Zhengzhou, Henan 450001, China.
Email: zzu_gongxy@163.com

Funding information
National Key R&D Program of China (Grant No. 2018YFB0505000).

Abstract
As of March 30, 2021, COVID-19 has been circulating globally for more than 1 year, posing a huge threat to the safety of human life and property. Understanding the relationship between meteorological factors and the COVID-19 can provide positive help for the prevention and control of the global epidemic. We take California as the research object, use Geodetector to screen out the meteorological factors with the strongest explanatory power for the epidemic, then use partial correlation analysis to study the correlation between the two, and finally construct a distributed lag non-linear model (DLNM) to further explore the relationship between the dominant factor and COVID-19 and its lag effect. It turns out that temperature has a greater impact on COVID-19 and the two have a significant negative correlation. When the temperature is lower than 50°F, it has a significant promotion effect on the epidemic, and the relative risk (RR) increases approximately exponentially as the temperature decreases. The delayed effect of the cold effect on the epidemic can be as long as 15 days. This study has shown that more attention should be paid to epidemic prevention and control when the temperature is low, and the delay effect of temperature on the spread of the epidemic cannot be ignored.

KEYWORDS
California, COVID-19, distributed lag non-linear model, Geodetector, meteorological factors, partial correlation analysis

1| INTRODUCTION

Respiratory diseases are mostly caused by pathogenic microorganisms such as viruses and bacteria invading people's nasal cavity, throat and other organs. Due to its strong transmission ability, complex transmission route and difficult treatment, respiratory diseases have become one of the world's leading fatal diseases (Lim et al., 2013; Lozano et al., 2013; Zumla et al., 2014). In December 2019, a respiratory disease caused by the ‘new coronavirus’ was discovered in Wuhan, Hubei, China. On February 11, 2020, the World Health Organization (WHO) officially named the ‘new coronavirus’ as ‘COVID-19’. Since then, COVID-19 has swept the world and caused a global respiratory infectious disease. As of March 30, 2021, the cumulative number of confirmed cases worldwide has exceeded 100 million, and the cumulative number of deaths has exceeded 2.5 million. The explosive and highly contagious nature of COVID-19 has caused great harm to human beings.
Respiratory diseases are mainly affected by environmental factors and social factors (D’Amato et al., 2014; Fares, 2013). Since the 21st century, people have been threatened by a global pandemic of respiratory infectious diseases many times. The severe acute respiratory syndrome (SARS) pandemic in 2003, the influenza A (H1N1) pandemic in 2009 and the Middle East respiratory syndrome (MERS) pandemic in 2012 all caused huge disasters to people around the world. In order to reduce the harm when such disasters occur again, people have conducted extensive research on pandemics, and the relationship between meteorological factors and pandemics is one of them. In the study of these pandemics, it is found that SARS, H1N1 and MERS cases are related to meteorological factors such as daily average temperature, daily average humidity, daily average wind speed and sunshine hours before the onset of the disease (Altamimi & Ahmed, 2019; Cai et al., 2007; Gardner et al., 2019; Tan et al., 2005; Zhao et al., 2016).

SARS-CoV-2 is a coronavirus like the other two viruses, SARS-CoV and MERS-CoV. This type of virus has a wide range of hosts in nature and brings great harm to animal and human health. SARS-CoV-2 has a stronger transmission and infection ability than SARS-CoV and MERS-CoV (Li et al., 2020). The host infected by SARS-CoV-2 will not show obvious symptoms in the early stage but will show symptoms such as fever, cough and shortness of breath after the incubation period, which threatens the life of the host (Chen et al., 2020).

After the SARS and MERS pandemics, people have carried out extensive research on respiratory diseases caused by coronavirus (Doremalen et al., 2020; Song et al., 2019). Starting from the survival time of the virus in the environment, some scholars found that the survival time of coronavirus was significantly affected by the environmental temperature and humidity. Low temperature and low humidity environment are more conducive to virus stability (Casanova et al., 2010; Chan et al., 2011; Lin et al., 2006). Some studies on the epidemic situation from the way of transmission have shown that the main ways of transmission of the coronavirus are droplet transmission and contact transmission. Maintaining a certain social distance and paying attention to personal hygiene can effectively prevent the spread of the disease. Other studies have shown that medical conditions, economic levels, population density all have a certain impact on the spread of diseases (O’Sullivan & Phillips, 2019; Rajakaruna et al., 2017). COVID-19 spreads faster and more widely around the world, so many scholars have conducted research on the transmission mechanism and its influencing factors. Ghinai et al. (2020) recorded the first case of human-to-human transmission in the United States, indicating that human-to-human transmission may be caused by prolonged close contact with an infected person. Other scholars have found that the COVID-19 virus can be transmitted by droplets and aerosols, and the aerosol containing the virus within 1 m has significant infectivity (Anderson et al., 2020; Liu et al., 2020; Santarpia et al., 2020). Meanwhile, Zhang et al. (2020) and Kang et al. (2020) found live viruses in the patient’s faeces and proposed that COVID-19 may be transmitted through faeces-oral transmission. Kitajima et al. (2020) also detected COVID-19 in wastewater. In addition to studying transmission routes, some meteorologists and environmentalists have done a lot of research on the relationship between meteorological environmental factors and epidemics. It can be summed up as: it is considered to be related to the season (Byun et al., 2021; Carleton & Meng, 2020; Kistler et al., 2020), to environmental pollution (Zhu et al., 2020), to geographical location (Oktorie & Berd, 2020; Whittemore, 2020), and to temperature and humidity. However, there are many inconsistent results in these studies, among which the relationship between temperature and epidemic is highly controversial. Some studies have reported the promotion of low temperature on the spread of the epidemic (Bolaño-Ortiz et al., 2020; Kodera et al., 2020; Méndez-Arriaga, 2020), but other studies believe that low temperature can inhibit the spread of the epidemic (Ahmadi et al., 2020; Bashir et al., 2020) or temperature is not related to the spread of the epidemic (Yao et al., 2020). The main reason for this controversy may be that the time series of different studies are too short (does not include the complete seasonal cycle) or the study area is too single (the study area is just a county or city). Besides, most studies on the relationship between meteorological factors and the COVID-19 epidemics have not controlled the influence of social factors and lack discussion on the lagging influence of meteorological factors.

Therefore, we integrate temporal and spatial correlations, combined with temporal and spatial analysis methods, and take the confirmed cases of COVID-19 in 58 counties in California from March 11, 2020, to March 30, 2021 as the research object. First, we use Geodetector to explore the impact of different meteorological factors on the spread of the epidemic and select the most significant factors. Then, partial correlation analysis is used to determine the correlation between specific meteorological factors and COVID-19 cases. Finally, DNLM is used to study the relationship between meteorological factors and the COVID-19 and its lag effects. Relevant research makes up for the shortcomings of research time series and ignoring the lag of influencing factors, and provides a reference for California and the global epidemic prevention and control.
2 | DATA AND METHOD

2.1 | Overview of the study area

California is located in the western United States, with a total area of about 410,000 square kilometres. It is the most economically developed and most populous state in the United States. California is distributed in a long strip, with the Pacific Ocean to the west, Nevada and Arizona to the east, Oregon to the north, and Baja California, Mexico to the south. The geographical conditions of California are complex and changeable. The southeastern and northeastern ends of the state are a desert, and to the west of the desert is the Sierra Nevada. The Central Valley formed by the Coastal Mountains and the Sierra Nevada occupies the main agricultural production area in California. California's population is mainly distributed in the Central Valley or around San Francisco and Los Angeles along the western coast. Affected by geographical conditions, the climatic conditions of different regions in California vary significantly. Desert areas are arid and rainless, with large temperature differences between day and night; coastal areas have a Mediterranean climate, with hot and dry summers and mild and rainy winters; mountain areas are cold in winter and mild in summer (Figure 1).

2.2 | COVID-19 and meteorological data

We drew a diagram of the mechanism to more clearly show the influencing factors of COVID-19 (Figure 2). The case data in this article come from the tableau website (https://www.tableau.com/), and the data include the daily new cases from March 11, 2020 to March 30, 2021 and cumulative confirmed cases 3,666,394 in California. Weather data are obtained from the weather station in each county (usually an airport weather station) and downloaded from the underground weather database (https://www.wunderground.com/). The data include daily minimum temperature, average temperature, maximum temperature, maximum relative humidity, average relative humidity, minimum relative humidity and average wind speed. Moreover, we also collected the 2010 census data of California counties (http://www.census.gov/) and government response index (GRI). GRI comprehensive presents three types of policy requirements, including containment and closure policies, economic policies, and health system policies (such as school closing, workplace closing, stay at home requirements, income support, testing policy, etc.); we obtained California GRI data from GitHub Covid-policy-tracker (https://github.com/OxCGRT/covid-policy-tracker/) to exclude The impact of other non-pharmacological interventions.

FIGURE 1  California's annual average temperature in 2020  FIGURE 2  The impact mechanism of COVID-19
2.3 | The research method

2.3.1 | Spatial autocorrelation analysis

Spatial autocorrelation analysis is an analysis method to study whether the observed value of a space unit correlated with the observation value of its neighbouring unit, and it is a measure of the degree of aggregation of the observation value of the space unit (Yang et al., 2018). It can be used to evaluate the spatial patterns of COVID-19 and determine whether they are spatially related (Han et al., 2021). Spatial autocorrelation analysis is divided into global autocorrelation and local autocorrelation. Among them, the global Moran’s I proposed by P. Moran (1950) is usually used to measure the global spatial autocorrelation. The calculation formula is as follows:

\[
I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\left( \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \right) \sum_{i=1}^{n} (x_i - \bar{x})^2}, \quad i \neq j.
\]  

In the formula, \( n \) is the total number of spatial units, \( x_i \) and \( x_j \) are the attribute values of the elements \( i \) and \( j \) in the spatial units, \( \bar{x} \) is the average value of \( x \), and \( w_{ij} \) is the weight representing the spatial relationship between the elements \( i \) and \( j \). The value range of global Moran’s \( I \) is \([-1, 1]\). At a given significance level, a positive value represents a positive correlation in the overall distribution. The larger the value, the stronger the correlation and the more similar the properties; the negative value represents the overall distribution is negatively correlated: the greater the absolute value, the greater the spatial difference. When its value is 0, there is no spatial correlation and the observation objects are randomly distributed in space.

Compared with global spatial autocorrelation, local spatial autocorrelation is used to calculate and analyse the degree of spatial correlation between each spatial object in the region and its neighbours, calculate and analyse the difference of local characteristics in the distribution of spatial objects, and reflect the spatial heterogeneity and instability in the local region. Commonly used methods are local Moran’s \( I \) and Getis – Ord \( Gi* \). This article uses the local Moran’s \( I \) to detect hot spots and analyses the local autocorrelation of the epidemic distribution. The calculation formula is as follows:

\[
I = \frac{n(x_i - \bar{x}) \sum_{j=1}^{n} w_{ij} (x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}, \quad i \neq j.
\]

The meaning of the parameters in the formula is the same as that of the global Moran’s \( I \).

2.3.2 | Geodetector

The core idea of the Geodetector is: if an independent variable has an important influence on a dependent variable, then the spatial distribution of the independent variable and the dependent variable should be similar (Wang et al., 2010; Wang & Xu, 2017). Among them, differentiation and factor detection detect the spatial differentiation of \( Y \) and the extent to which a certain factor \( X \) explains the spatial differentiation of attribute \( Y \), which is measured by the \( q \) value (Wang & Xu, 2017). This paper mainly uses differentiation and factor detectors to study the relationship between daily new cases and meteorological factors in California counties. The expression is as follows:

\[
q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma^2_h}{N \sigma^2} = 1 - \frac{SSW}{SST},
\]

\[
SSW = \sum_{h=1}^{L} N_h \sigma^2_h, \quad SST = N \sigma^2.
\]

In the formula, \( L \) is the stratification of variable \( Y \) or factor \( X \), that is, classification or partition; \( N_h \) and \( N \) are the number of units in layer \( h \) and the whole area respectively; \( \sigma^2_h \) and \( \sigma^2 \) are the variances of \( Y \) values of layer \( h \) and the whole area respectively; \( SSW \) and \( SST \) are within sum of squares and total sum of squares. \( q \) is the detection power index of the factors affecting the differentiation of new cases in each county every day, and the value range is \([0, 1]\), the larger the value, the stronger the explanatory power of the stratification factor to \( Y \), and the \( q \) value of 0 indicates that the factor \( X \) has no relationship with \( Y \).

2.3.3 | Partial correlation analysis

There may be multiple correlations between variables in Pearson correlation analysis, and other variables may affect the correlation between the two variables involved in the calculation. Partial correlation analysis controls other variables and calculates the correlation coefficient after excluding the influence of other variables (Brown & Hendrix, 2014). After selecting \( \xi \) as the control variable, the formula for calculating the partial correlation coefficient between \( X \) and \( Y \) is as follows:

\[
\rho_{XY(\xi)} = \frac{\rho_{XY} - \rho_{X\xi} \rho_{Y\xi}}{\sqrt{1 - \rho^2_{X\xi}} \sqrt{1 - \rho^2_{Y\xi}}},
\]

where \( \rho_{XY} \) is the correlation coefficient between \( X \) and \( Y \), \( \rho_{X\xi} \) is the correlation coefficient between \( X \) and \( \xi \), and \( \rho_{Y\xi} \) is the correlation coefficient between \( Y \) and \( \xi \).
Among them, $\rho_{XY}$, $\rho_{X \xi}$, $\rho_{Y \xi}$ represent the Pearson correlation coefficients of $X$ and $Y$, $X$ and $\xi$, $Y$ and $\xi$, respectively.

### 2.3.4 | Distributed lag non-linear model (DLNM)

DLNM can simultaneously express non-linear exposure-response correlation and delay effects. Its core idea is to construct a cross-base and incorporate it into the model as an independent variable (Gasparrini et al., 2010). This method is widely used to study the relationship between environmental factors and diseases (Moghadamnia et al., 2018; M. Xu et al., 2015; Q. Xu et al., 2018; Ye et al., 2016). We use the daily average temperature as the dependent variable to establish a cross-base and incorporate it into the model while controlling other factors such as the time trend, day of the week effect, daily average wind speed and GRI. The model formula is as follows:

$$\log[E(Y_t)] = \alpha + cb(\text{temp}) + \text{ns}(\text{time, df}) + \text{ns}(\text{wind, df}) + \text{ns}(\text{humidity, df}) + \text{GRI} + \text{Dow},$$

where $Y_t$ is the number of new COVID-19 cases on day $t$; $\alpha$ is the intercept of the model; $cb$ is the DLNM cross-basis matrix; temp is the daily average temperature; ns is the natural spline function; time is the time variable; wind is daily average wind speed; df is the degree of freedom; Dow is the day of the week effect. The degree of freedom in the model is determined by Akaike’s information criterion (AIC).

### 3 | RESULTS AND ANALYSIS

#### 3.1 | Descriptive analysis

As of March 30, 2021, California has a total of 3,666,394 confirmed cases. The number of newly confirmed cases increased rapidly from November 2020 to February 2021. During the study period, the average temperature in California had a clear pattern, and the average temperature was less than 60°F after November 11; the average relative humidity and average wind speed changed greatly in each stage without an obvious pattern (Figure 3).

By dividing the cumulative number of confirmed diagnoses by the number of populations, we get the prevalence of each county. The visualized result is shown in Figure 3. It can be found that counties with higher prevalence are concentrated in the south of California, with Los Angeles as the centre, and neighbouring counties all show higher prevalence. In the north, except for Lassen, the prevalence of other counties is relatively low, and the risk of epidemic spread has been reduced to a certain extent.

#### 3.2 | COVID-19 spatial distribution characteristics

In order to further study the spatial distribution characteristics of COVID-19 in California, GeoDa is used to
perform global spatial autocorrelation analysis and local spatial autocorrelation analysis of the epidemic. The results of global spatial autocorrelation are shown in Table 1. The number of Monte Carlo simulations is 9999, the global Moran's $I$ is 0.331, and the $Z$-value is greater than 2.58, the $p$-value is less than 0.01, and the result is significant. This shows that the distribution of the new crown epidemic in California is significantly clustered.

The global spatial autocorrelation index reflects the overall spatial correlation of the prevalence in California, but it cannot reflect the specific spatial relationship between different counties. Therefore, we use local spatial autocorrelation to analyse the relationship of the prevalence among different counties in California. From the results of the local spatial autocorrelation (Figure 4), we can find that the counties with high–high (H–H) correlation of confirmed cases include Fresno ($p = 0.05$), Imperial ($p = 0.05$), Kern ($p = 0.05$), Kings ($p = 0.05$), Los Angeles ($p = 0.05$), Orange ($p = 0.01$), Riverside ($p = 0.01$), San Bernardino ($p = 0.05$), San Diego ($p = 0.01$) and Tulare ($p = 0.05$). These counties are mainly located in the southern part of California, with a developed economy, a high level of urbanization, and a large population. Moreover, these areas contain many well-known universities with high population density and mobility, and it is easy to form high-value gathering areas.

Low–low (LL) associations include Del Norte ($p = 0.05$), Humboldt ($p = 0.01$), Mendocino ($p = 0.05$), Siskiyou ($p = 0.01$), Tehama ($p = 0.05$) and Trinity ($p = 0.05$). These counties are mainly located in the northern part of California. The population and confirmed cases in this area are relatively small, and population mobility is low, so low-value clusters are formed. There are also two low-high cluster counties (Inyo($p = 0.01$) and San Luis Obispo($p = 0.05$)) and two high-low cluster counties (Lassen($p = 0.01$) and Yuba($p = 0.05$)). Their prevalence is significantly different from the surrounding counties, thus forming independent low-/high-value areas.

3.3 | The impact of meteorological factors on COVID-19

We use Geodetector to study the impact of meteorological factors on the new confirmed cases. We select daily maximum temperature (MAX_T), average temperature (AVG_T), minimum temperature (MIN_T), maximum relative humidity (MAX_H), average relative humidity (AVG_H), minimum relative humidity (MIN_H) and daily average wind speed (AVG_W) as the influence factors (Gupta, 2020; Runkle et al., 2020; Shi, Dong, Yan, Li, et al., 2020a; Shi, Dong, Yan, Zhao, et al., 2020b). The natural breakpoint method is used to classify different impact factors and convert them into type variables.

Considering statistical significance, we excluded counties (Alpine, Mariposa, Modoc, Plumas, Sierra and Trinity) with a cumulative number of confirmed cases of less than 1000. Figure 5 shows the visualization results of differentiation and factor detection in the other 52 counties. It can be found that the regularity of temperature influencing factors is relatively obvious, and AVG_T has a greater degree of influence in most of the 52 counties. Except for Marin, which is significant at the 10% level, other counties are significant at the 1% level, which shows that the detection results are credible.
and temperature has a significant impact on the epidemic. Among the humidity influencing factors, the most influential factor has large changes and the law is not obvious. Among them, MAX_H has the greatest influence in 13 counties, AVG_H has the greatest influence in 28 counties, and MIN_H has the greatest influence in eight counties. In addition, there are three counties that have insignificant humidity influencing factors. Among them, Mono is located in east-central California and the cumulative number of confirmed cases is relatively low at 1243, which is easily affected by extreme values, making the statistical results insignificant; Santa Cruz is in the midwest part of California and is adjacent to the sea, which makes the humidity value often maintain a high level, so it shows little impact on the changes in daily new cases; Shasta is in the middle of northern California. Among the six neighboring counties, the cumulative number of confirmed cases in three counties is less than 1000. The humidity factors in the other three counties have a significant impact on the changes in the daily newly diagnosed cases. Therefore, Shasta's lack of significant influence of humidity factor on the new confirmed cases may be an accident. The influence degree of AVG_W in 52 counties is generally small and not significant, but in Del Norte, Los Angeles, Napa, San Diego and other counties, the influence of AVG_W cannot be ignored, so this factor is also included as a variable in the subsequent distribution lag non-linear model (Figure 6).

### 3.4 Partial correlation analysis

According to the results of the geographic detector, in order to exclude the influence of other factors, we selected the 10 counties with the most confirmed cases, and performed partial correlation analysis with AVG_H, AVG_W and GRI as the control variables to determine the correlation...
between AVG_T and COVID-19. The results showed that the correlation coefficients of all counties were less than 0, and all counties except Alameda passed the 1% significance level test ($p < 0.01$), indicating that the results are statistically significant, and AVG_T has a significant negative correlation with COVID-19 (Table 2).

### Table 2 Partial correlation analysis results

| City      | Alameda | Fresno | Kern     | Los Angeles | Orange | Riverside | Sacramento | San Bernardino | San Diego | Santa Clara |
|-----------|---------|--------|----------|-------------|--------|-----------|------------|----------------|-----------|-------------|
| Correlation Coefficient ($r$) | -0.056 | -0.150 | -0.442 | -0.397      | -0.232 | -0.445    | -0.495     | -0.444         | -0.304    |
| Significance Level ($p$)     | 0.271  | 0.003  | 0        | 0           | 0      | 0         | 0          | 0               | 0         |

### Table 3 Temperature factor characteristics

| City             | Maximum | Minimum | Mean | Standard Deviation | 10% Quantile | 75% Quantile | 90% Quantile |
|------------------|---------|---------|------|--------------------|--------------|--------------|--------------|
| AVG_T Alameda    | 85.4    | 43.2    | 59.7 | 8.0                | 49.5         | 64.8         | 69.6         |
| Fresno           | 95.7    | 41.3    | 66.0 | 14.5               | 48.5         | 79.8         | 85.8         |
| Kern             | 94.9    | 32.1    | 66.5 | 14.7               | 49.1         | 81.1         | 86.4         |
| Los Angeles      | 84.0    | 49.2    | 62.7 | 6.3                | 54.8         | 67.0         | 70.6         |
| Orange           | 89.5    | 46.3    | 64.5 | 8.4                | 54.0         | 70.3         | 75.3         |
| Riverside        | 93.1    | 41.1    | 64.9 | 11.2               | 51.5         | 74.5         | 79.5         |
| Sacramento       | 92.5    | 40.8    | 62.5 | 12.4               | 47.1         | 73.3         | 79.1         |
| San Bernardino   | 92.5    | 41.9    | 64.0 | 11.0               | 50.6         | 72.8         | 77.8         |
| San Diego        | 85.4    | 52.3    | 66.2 | 7.6                | 56.9         | 72.0         | 76.3         |
| Santa Clara      | 85.5    | 43.1    | 60.9 | 9.0                | 49.5         | 68.0         | 71.7         |

3.5 | Temporal and spatial responses of meteorological factors based on DLNM

DLNM can simultaneously represent non-linear exposure-response correlation and delay effects. In order to further explore the impact of meteorological factors on the new confirmed cases, AVG_T was selected as the main influencing factor, combined with wind speed, humidity, time series, day of the week effect and GRI as confounding factors to establish a model.

3.5.1 | Temperature factor characteristics

The characteristics of temperature factors in 10 counties are shown in Table 3. During the study period, the variation range of daily average temperature in each county was different. The two counties with the largest variation range were Kern and Fresno, where the daily mean temperature range was 32.1–94.9°F and 41.3–95.7°F and the standard deviations were 14.7 and 14.5, respectively. The two counties with the smallest range were Los Angeles and San Diego, ranging from 49.2 to 84.0°F and 52.3 to 85.4°F, with standard deviations of 7.6 and 8, respectively. This shows that the selected study area has significant temperature changes during the study period. In addition, the maximum temperature of the selected different study areas during the entire study period is 95.7°F, and the minimum temperature is 32.1°F, which can eliminate the influence of extreme weather on the experiment and make the experimental results more reliable.

3.5.2 | The overall impact of temperature on the delayed effect of the spread of the epidemic

In this paper, the DNLM based on Poisson distribution is used to study the relationship between AVG_T and the daily newly confirmed cases in California. Considering that the impact of meteorological factors on the disease generally has a lag and the incubation period of COVID-19 is generally within 14 days, we set the maximum lag days to 15 days (Kong, 2020; Lauer et al., 2020).

Use AVG_T as the reference temperature to draw a three-dimensional correlation diagram of DLNM. It can be found that AVG_T has a non-linear relationship with the number of new cases per day when the lag is 0 days. Alameda, Kern, Los Angeles, Orange, Riverside and San Bernardino showed similar patterns. Their cooling effect is obvious, and relative risk (RR) > 1 at low temperature promotes the increase of daily cases and this effect has a certain lag. The shapes of Fresno, San Diego and Santa
Clara are similar, and they all show the short-term and immediate promotion of high temperature on new daily cases (Figure 7).

Figure 8 shows the overall impact of AVG\_T on the cumulative lag effect of newly confirmed cases; the grey area in the figure is the 95% confidence interval. We can find that the cumulative hysteresis effect of AVG\_T in Alameda, Kern, Los Angeles, Orange, Riverside, San Bernardino and San Diego on new daily cases is similar: the overall distribution is in an ‘anti-J’ pattern, and as the temperature rises, RR showed a downward trend, and the RR reached the maximum and minimum, respectively, when AVG\_T was the lowest and the highest. Moreover, all counties show that RR responds more quickly to temperature when the temperature is lower (the temperature is less than the 10% quantile). When the temperature drops to about 50°F, RR will increase rapidly as the temperature continues to drop, showing a significant promotion effect on the increase in daily cases. In the higher temperature part (temperature greater than
90% quantile), RR response to temperature becomes flat, and in the higher temperature part, the RR of these seven counties are less than 1, indicating that high temperature inhibits the increase in daily cases. Fresno, Sacramento and Santa Clara's AVG_T have similar cumulative hysteresis effects on new daily cases: RR has experienced a process of first decreasing with temperature changes, then becoming larger and then decreasing. When the
temperature is low, the RR's trend is similar to that of the other seven counties, all showing rapid response to lower temperatures. Fresno and Santa Clara reached the maximum RR of 3.473 (95% CI: 2.239–5.388) and 2.531(95% CI: 1.434–4.465) at the lowest temperature (41.3 and 43.1°F). Sacramento’s RR reached its peak when the temperature was 47.3°F (1.748, 95% CI: 1.366–2.119), and when the temperature was lower than 45.9°F, RR decreased slowly with the continuous decrease of the temperature, but its value was always greater than 1,
which did not affect the promoting effect of lower temperature on the epidemic. When the temperature is higher, Fresno, Sacramento and Santa Clara are significantly different from the other seven counties. The main manifestation is that RR is also greater than 1 in a certain higher temperature range, that is, the higher temperature in a certain range also shows a promoting effect. When AVG_T is 86.1°F, Fresno’s RR reaches a peak of 1.463 (95% CI: 0.992–2.160);
when $AVG_T$ is 80.9°F, Sacramento's RR reaches a peak of 1.235 (95% CI: 0.741–2.057); when $AVG_T$ is 72.0°F Santa Clara's RR reached a peak of 1.056 (95% CI: 0.816–1.367). After that, as the temperature increased, the RR value of each county began to decrease. After the temperature reached 94.5°F, 86.5 and 74.8°F, the RR value was less than 1, and higher temperatures began to show an inhibitory effect on the epidemic.

In order to further explore the hysteresis effect of low temperature and high temperature on the daily new cases in each county, $AVG_T$ at 5% quantile and 95% quantile of each county was selected to analyse the hysteresis effect. Figure 9 shows the hysteresis effect of $AVG_T$ at the 5% quantile of each county. It can be found that when the temperature is low, the difference in the hysteresis effect of each county mainly occurs during the lag period of 0–6 days. Among them, Alameda, Kern, Los Angeles, Riverside, San Bernardino and Santa Clara have similar lag effects. They all have a larger RR value when lagging for 0 days. The RR values are 1.112 (95% CI: 1.270–1.065), 1.110 (95% CI: 1.008–1.222), 1.145 (95% CI: 1.067–1.231), 1.136 (95% CI: 1.009–1.768), 1.136 (95% CI: 0.959–1.345), 1.050 (95% CI: 0.902–1.222); within 0–2 days of lag, the RR rapidly drops to a trough value of 0.967 (95% CI: 0.888–1.051), 0.986 (95% CI: 0.930–1.045), 0.966 (95% CI: 0.935–0.998), 0.874 (95% CI: 0.731–1.045), 0.965 (95% CI: 0.870–1.072), 1.006 (95% CI: 0.909–1.113); within 3–6 days of lag, RR rises at a faster rate and reaches a peak of 1.061 (95% CI: 1.014–1.109), 1.074 (95% CI: 1.042–1.106), 1.023 (95% CI: 0.999–1.047), 1.095 (95% CI: 1.019–1.177), 1.038 (95% CI: 0.982–1.097), 1.066 (95% CI: 1.011–1.123), at this time the hysteresis effect has an obvious performance. Sacramento and San Diego have similar lag effects between 0 and 6 days of lag. At 0 days of lag, the RR of these two counties are at their minimum values of 0.922 (95% CI: 0.717–1.186) and 0.974 (95% CI: 0.843–1.126), within 1–3 days of lag, the RR rises rapidly to a peak of 1.038 (95% CI: 0.915–1.178) and 1.034 (95% CI: 0.994–1.076), and then the RR value lags 4–6 days, slowly decreasing again. Fresno's lagging effect of low temperature from 0 to 6 days slowly decreases with the increase of the number of lag days. The RR reaches the maximum value of 1.103 (95% CI: 0.866–1.405) at the lag of 0 days, and the minimum RR of the lag 6 days reaches 1.021 (95% CI: 0.982–1.061). The RR of Orange decreases rapidly within 0–4 days of lag, and reaches a trough value of 1.000 (95% CI: 0.954–1.047) after 4 days of lag. After that, the RR rises slowly as the number of lag days increases. Within 7–15 days of lag, the lag effect of the 10 counties is roughly the same. RR is still at a large value after 15 days of lag. It is believed that temperature still contributes to the epidemic, which shows that the hysteresis effect of low temperature may be up to 15 days.

Figure 10 shows the lag effect of $AVG_T$ at 95% quantile in each county. It can be found that a higher $AVG_T$ has a significant impact on the daily new cases at a lag of about 0–3 days, and then the effect of higher $AVG_T$ gradually disappears with the increase of the lag days, indicating that the lag effect of high temperature on the daily new cases is about 2–3 days.

4 | DISCUSSION

As of March 30, 2021, the global outbreak of COVID-19 has exceeded 1 year, and the cumulative number of confirmed cases worldwide has exceeded 100 million, and the epidemic in most countries has experienced a complete seasonal cycle. This article uses spatial autocorrelation, Geodetector, partial correlation analysis and DLNM to explore the temporal and spatial distribution of the California epidemic and the relationship between meteorological conditions and daily new cases.

The study on the temporal and spatial distribution of the California epidemic found that the distribution of the epidemic is positively correlated as a whole, with the global Moran's $I$ being 0.331 at the 99% significance level. The results of local spatial autocorrelation show that the distribution of epidemics in California is quite different from north to south. Southern California has a significant high–high clustering phenomenon and a significant low–low clustering in the north, which has a lot to do with the geographical, economic, cultural and demographic differences between the north and south of California. Los Angeles County in Southern California has a population of more than 10 million, of which Los Angeles City has a population of more than 3.5 million. It is the most densely populated and most diverse place in the United States. In addition, Los Angeles is also the largest industrial centre in the western part of the United States, and its cultural and entertainment industry also has a great influence, which makes it have close contacts with other surrounding counties and cities, and increases the risk of the spread of the epidemic within and between counties, thus forming the phenomenon of high–high clustering. Northern California has a small population and no counties with strong influence like Los Angeles, which makes the number of confirmed cases in the counties of northern California smaller, resulting in a low–low clustering situation.

Studies have found that compared with humidity and wind speed, temperature has a more significant impact on the outbreak in California, which is similar to the results obtained by some previous studies (Gao et al., 2020; Guo et al., 2020; Shi, Dong, Yan, Li, et al., 2020a; Shi, Dong, Yan, Zhao, et al., 2020b). However, there are
also studies that believe that humidity is the best factor affecting the spread of the epidemic, which may be related to the different geographical locations of the study area (Runkle et al., 2020). The results of partial correlation analysis showed that under the condition that the influence of AVG_H, AVG_W and GRI remains unchanged, there is a significant negative correlation between AVG_T and daily new cases. Through DNLM research, it is found that this negative correlation is nonlinear. The lower temperature promotes the spread of the epidemic and the lag time can be up to 15 days. The results of eight counties show that when the temperature is lower than 50°F, the RR of new cases increases rapidly with the decrease of temperature, and the RR reaches the maximum when the AVG_T is the lowest. This is because, on the one hand, the COVID-19 virus exhibits a high degree of stability in a cold environment, so when the temperature is low, the COVID-19 virus can survive in the environment for a longer time, which increases the risk of epidemic spread (Eslami & Jalili, 2020; Lv et al., 2020). On the other hand, people are more willing to stay indoors and close doors and windows when the temperature is low, which is not conducive to air circulation. Studies have shown that in a closed space with poor air circulation, even if they are far apart, inhalation of aerosols from an infected person may cause infection (Doremalen et al., 2020; Liu et al., 2020). Meanwhile, a lower temperature will reduce the body’s immunity and increase the risk of infection (Appenheimer & Evans, 2018). In addition, COVID-19 is a type of coronavirus, and high temperature can reduce its stability (Riddell et al., 2020). Therefore, high temperature mainly inhibits the spread of the epidemic. When the temperature is higher than 80°F, the RR is generally less than 1, and the RR is slowly reduced as the temperature rises. However, the results of Fresno and Sacramento indicate that high temperature may also play a short-term and immediate role in promoting the development of the epidemic. This is contrary to the results of many studies. It may be because the factors affecting the spread of the epidemic are very complicated. In addition to weather conditions, factors such as personal protection, government measures and personal physical fitness also play a vital role. At higher temperatures, people may relax their vigilance and reduce the wearing of protective tools such as masks for their comfort, thereby increasing the risk of infection (Chernozhukov et al., 2020).

Limited by experimental data, this paper cannot conduct experiments on cases stratified by age and gender, and cannot reveal the impact of temperature on people of different ages and genders and the hysteresis effect. Besides, the study area of this paper is limited to California, which has a Mediterranean climate. Therefore, more research is needed on the impact of other climatic conditions on the spread of the epidemic.

5 CONCLUSION

The spatial distribution of the California epidemic is positively correlated as a whole, but there are obvious differences in local areas. Among them, there is a significant high–high clustering phenomenon in southern California and a significant low–low clustering phenomenon in the north. The impact of meteorological factors on the epidemic situation, compared with humidity and wind speed, shows temperature has a greater impact on the spread of the epidemic and a negative correlation overall. When the temperature is low, the risk of transmission of the epidemic is greater, and the lag effect of low temperature can be as long as 15 days. High temperature has a certain inhibitory effect on the spread of the epidemic, but if self-protection is reduced, it may also increase the risk of infection. Therefore, it is impossible for us to completely rely on changes in meteorological conditions to overcome the epidemic. Being vigilant and actively doing personal protection is the best way to overcome the epidemic.

CONFLICT OF INTEREST

We declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Haitao Wei: Conceptualization (lead); supervision (equal); writing – review and editing (equal). Shihao Liu: Formal analysis (lead); methodology (equal); writing – original draft (lead). Yan Liu: Supervision (equal); writing – review and editing (equal). Bang Liu: Investigation (equal). Xiyun Gong: Conceptualization (equal); writing – review and editing (equal).

ORCID

Xiyun Gong https://orcid.org/0000-0001-5581-8940

REFERENCES

Ahmadi, M., Sharifi, A., Dorosti, S., Ghoushchi, S.J. & Ghanbari, N. (2020) Investigation of effective climatology parameters on COVID-19 outbreak in Iran. The Science of the Total Environment, 729, 138705.

Altamimi, A. & Ahmed, A.E. (2019) Climate factors and incidence of Middle East respiratory syndrome coronavirus. Journal of Infection and Public Health, 13, 704–708.

Anderson, E., Turnham, P., Griffin, J.R. & Clarke, C.C. (2020) Consideration of the aerosol transmission for COVID-19 and public health. Risk Analysis, 40, 902–907.

Appenheimer, M.M. & Evans, S. (2018) Temperature and adaptive immunity. Handbook of Clinical Neurology, 156, 397–415.
Ghinai, I., McPherson, T.D., Hunter, J.C., Kirking, H. & Team, I.C. (2020) Correlation between climate indicators and COVID-19 pandemic in New York, USA. *The Science of the Total Environment*, 728, 138835.

Bolaño-Ortiz, T., Camargo-Caicedo, Y., Puliafito, S., Ruggeri, M.F., Bolaño-Diaz, S., Pascual-Flores, R. et al. (2020) Spread of SARS-CoV-2 through Latin America and the Caribbean region: a look from its economic conditions, climate and air pollution indicators. *Environmental Research*, 191, 109938.

Brown, B. & Hendrix, S. (2014) Partial correlation coefficients. Wiley StatsRef: Statistics Reference Online.

Byun, W.S., Heo, S.W., Jo, G., Kim, J.W., Kim, S., Lee, S. et al. (2014) Comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the global burden of disease study 2010. *The Lancet*, 380, 2224–2260.

Carleton, T.A. & Meng, K. (2020) Causal empirical estimates suggest COVID-19 transmission rates are highly seasonal. medRxiv.

Casanova, L., Jeon, S., Rutala, W., Weber, D. & Sobsey, M. (2010) Effects of air temperature and relative humidity on coronavirus survival on surfaces. *Applied and Environmental Microbiology*, 76, 2712–2717.

Chan, K., Peiris, J., Lam, S.Y., Poon, L., Yuen, K. & Seto, W. (2011) The effects of temperature and relative humidity on the viability of the SARS coronavirus. *Advances in Virology*, 2011, 1–7.

Chen, N., Zhou, M., Dong, X., Qu, J., Gong, F., Han, Y. et al. (2020) Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. *Lancet (London, England)*, 395, 507–513.

Chernozhukov, V., Kasahara, H. & Schrimpf, P. (2020) Causal impact of masks, policies, behavior on early Covid-19 pandemic in the U.S. *Journal of Econometrics*, 220(1), 23–62.

D’Amato, G., Cecchi, L., D’Amato, M. & Annesi-Maesano, I. (2014) Climate change and respiratory diseases. *European Respiratory Review*, 23, 161–169.

Doremalen, N.V., Bushmaker, T., Morris, D.H., Holbrook, M., Gamble, A., Williamson, B.N. et al. (2020) Aerosol and surface stability of SARS-CoV-2 as compared with SARS-CoV-1. *The New England Journal of Medicine*, 382, 1564–1567.

Eslami, H. & Jalili, M. (2020) The role of environmental factors to transmission of SARS-CoV-2 (COVID-19). *AMB Express*, 10, 92.

Fares, A. (2013) Factors influencing the seasonal patterns of infectious diseases. *International Journal of Preventive Medicine*, 4, 128–132.

Gao, M., Zhou, Q., Yang, X., Li, Q., Zhang, S., Yung, K. et al. (2020) Nonlinear modulation of COVID-19 transmission by climate conditions. *Meteorological Applications*, 28(2).

Gardner, E., Kelton, D., Poljak, Z., Kerkhove, M.V., Dobbschuetz, S. V. & Greer, A. (2019) A case-crossover analysis of the impact of weather on primary cases of Middle East respiratory syndrome. *BMC Infectious Diseases*, 19, 113.

Gasparrini, A., Armstrong, B. & Kenward, M.G. (2010) Distributed lag non-linear models. *Statistics in Medicine*, 29, 2224–2234.

Ghinai, I., McPherson, T.D., Hunter, J.C., Kirking, H. & Team, I.C. (2020) First known person-to-person transmission of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in the USA. *Lancet (London, England)*, 395, 1137–1144.

Guo, C., Bo, Y., Lin, C., Li, H., Zeng, Y., Zhang, Y. et al. (2020) Meteorological factors and COVID-19 incidence in 190 countries: an observational study. *The Science of the Total Environment*, 757, 143783.

Gupta, D. (2020) Effect of ambient temperature on COVID-19 infection rate. SSRN.

Han, Y., Yang, L., Jia, K., Li, J., Feng, S., Chen, W. et al. (2021) Spatial distribution characteristics of the COVID-19 pandemic in Beijing and its relationship with environmental factors. *The Science of the Total Environment*, 761, 144257.

Kang, M., Wei, J., Yuan, J., Guo, J., Zhang, Y., Hang, J. et al. (2020) Probable evidence of fecal aerosol transmission of SARS-CoV-2 in a high-rise building. *Annals of Internal Medicine*, 173, 974–980.

Kisler, C., Jump, R., Sloane, P. & Zimmerman, S. (2020) The winter respiratory viral season during the COVID-19 pandemic. *Journal of the American Medical Directors Association*, 21, 1741–1745.

Kitajima, M., Ahmed, W., Bibby, K., Carducci, A., Gerba, C., Hamilton, K. et al. (2020) SARS-CoV-2 in wastewater: state of the knowledge and research needs. *The Science of the Total Environment*, 739, 139076.

Kodera, S., Rashed, E. & Hirata, A. (2020) Correlation between COVID-19 morbidity and mortality rates in Japan and local population density, temperature, and absolute humidity. *International Journal of Environmental Research and Public Health*, 17(15).

Kong, T. (2020) Longer incubation period of coronavirus disease 2019 (COVID-19) in older adults. *Aging Medicine*, 3, 102–109.

Lauer, S., Grantz, K., Bi, Q., Jones, F.K., Zheng, Q., Meredith, H. et al. (2020) The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application. *Annals of Internal Medicine*, 172, 577–582.

Li, X., Jiang, J., Wang, D., Deng, J., He, K. & Hao, J. (2020) Transmission of coronavirus via aerosols and the influence of environmental conditions on its transmission. *Environmental Science, 42*, 3091–3098. https://doi.org/10.13227/j.hjkx.202010033

Lim, S., Vos, T., Flaxman, A., Danaei, G. & Ezzati, M. (2013) A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the global burden of disease study 2010. *The Lancet*, 380, 2224–2260.

Lin, K., Fong, D.Y., Zhu, B. & Karlberg, J. (2006) Environmental factors on the SARS epidemic: air temperature, passage of time and multiplicative effect of hospital infection. *Epidemiology and Infection*, 134(2), 223–230.

Liu, Y., Ning, Z., Chen, Y., Guo, M., Liu, Y., Gali, N.K. et al. (2020) Aerodynamic analysis of SARS-CoV-2 in two Wuhan hospitals. *Nature*, 582, 557–560.

Lozano, R., Naghavi, M., Foreman, K., Lim, S. & Murray, C. (2013) Global and regional mortality from 235 causes of death for 20 age groups in 1990 and 2010: a systematic analysis for the global burden of disease study 2010. *The Lancet*, 380, 2095–2128.

Lv, Q., Liu, M., Qi, F., Gong, S., Zhou, S., Zhan, S. et al. (2020) Sensitivity of SARS-CoV-2 to different temperatures. *Animal Models and Experimental Medicine*, 3, 316–318.

Méndez-Arriaga, F. (2020) The temperature and regional climate effects on communitarian COVID-19 contagion in Mexico.
throughout phase I. The Science of the Total Environment, 735, 139560.

Moghadamnia, M.T., Ardalan, A., Mesdaghinia, A., Nassafi, K. & Yekaninejad, M.S. (2018) The effects of apparent temperature on cardiovascular mortality using a distributed lag nonlinear model analysis: 2005 to 2014. Asia-Pacific Journal of Public Health, 30(4), 361–368.

Moran, P. (1950) Notes on continuous stochastic phenomena. Biometrika, 37, 17–23.

Oktorie, O. & Berd, I. (2020) Spatial model of COVID 19 distribution based on differences an climate characteristics and environment of according to the earth latitude. Sumatra Journal of Disaster, Geography and Geography Education, 4(1), 17–21.

O’Sullivan, T. & Phillips, K. (2019) From SARS to pandemic influ-enza: the framing of high-risk populations. Natural Hazards (Dordrecht, Netherlands), 98, 103–117.

Rajakaruna, S., Liu, W., Ding, Y. & Cao, G. (2017) Strategy and technology to prevent hospital-acquired infections: lessons from SARS, Ebola, and MERS in Asia and West Africa. Military Medical Research, 4, 32.

Riddell, S., Goldie, S., Hill, A., Eagles, D. & Drew, T. (2020) The effect of temperature on persistence of SARS-CoV-2 on common surfaces. Virology Journal, 17, 145.

Runkle, J., Sugg, M., Leeper, R., Rao, Y., Matthews, J. & Rennie, J. (2020) Short-term effects of specific humidity and temperature on COVID-19 morbidity in select US cities. The Science of the Total Environment, 740, 140093.

Santarpia, J., Herrera, V., Rivera, D.N., Ratnesar-Shumate, S., Reid, S., Denton, P.W. et al. (2020) The infectious nature of patient-generated SARS-CoV-2 aerosol. medRxiv, 10(1).

Shi, P., Dong, Y., Yan, H., Li, X., Zhao, C., Liu, W. et al. (2020a) The impact of temperature and absolute humidity on the coronavirus disease 2019 (COVID-19) outbreak - evidence from China. medRxiv.

Shi, P., Dong, Y., Yan, H., Zhao, C., Li, X., Liu, W. et al. (2020b) Impact of temperature on the dynamics of the COVID-19 outbreak in China. The Science of the Total Environment, 728, 138890.

Song, Z., Xu, Y., Bao, L., Zhang, L., Yu, P., Qu, Y. et al. (2019) From SARS to MERS, thrusting coronaviruses into the spotlight. Viruses, 11(1).

Tan, J., Mu, L., Huang, J., Yu, S., Chen, B. & Yin, J. (2005) An initial investigation of the association between the SARS outbreak and weather: with the view of the environmental temperature and its variation. Journal of Epidemiology and Community Health, 59, 186–192.

Wang, J. & Xu, C. (2017) Geodetector: principle and prospective. Acta Geographica Sinica, 72(1), 116–134.

Wang, J., Li, X., Christakos, G., Liao, Y., Zhang, T., Gu, X. et al. (2010) Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. International Journal of Geographical Information Science, 24, 107–127.

Whittemore, P.B. (2020) COVID-19 fatalities, latitude, sunlight, and vitamin D. American Journal of Infection Control, 48, 1042–1044.

Xu, M., Yu, W., Tong, S., Jia, L., Liang, F. & Pan, X. (2015) Non-linear association between exposure to ambient temperature and children’s hand-foot-and-mouth disease in Beijing, China. PLoS ONE, 10, e126171.

Xu, Q., Li, R., Rutherford, S., Luo, C., Liu, Y., Wang, Z. et al. (2018) Using a distributed lag non-linear model to identify impact of temperature variables on haemorrhagic fever with renal syndrome in Shandong Province. Epidemiology and Infection, 146, 1671–1679.

Yang, S., Xing, X., Dong, W., Li, S., Zhan, Z., Wang, Q. et al. (2018) The spatio-temporal response of influenza a (H1N1) to meteorological factors in Beijing. Acta Geographica Sinica, 03, 460–473.

Yao, Y., Pan, J., Liu, Z., Meng, X., Wang, W. & Kan, H. (2020) No association of COVID-19 transmission with temperature or UV radiation in Chinese cities. The European Respiratory Journal, 55, 2000517.

Ye, Q., Fu, J., Mao, J. & Shang, S. (2016) Haze is a risk factor contributing to the rapid spread of respiratory syncytial virus in children. Environmental Science and Pollution Research, 23, 20178–20185.

Zhang, Y., Chen, C., Zhu, S., Shu, C., Wang, D., Song, J. et al. (2020) Isolation of 2019-nCoV from a stool specimen of a laboratory-confirmed case of the coronavirus disease 2019 (COVID-19). China CDC Weekly, 2, 123–124. https://doi.org/10.46234/ccdcw2020.033

Zhao, X., Cai, J., Feng, D., Bai, Y. & Xu, B. (2016) Meteorological influence on the 2009 influenza a (H1N1) pandemic in mainland China. Environmental Earth Sciences, 75, 1–9.

Zhu, Y., Xie, J., Huang, F. & Cao, L. (2020) Association between short-term exposure to air pollution and COVID-19 infection: evidence from China. The Science of the Total Environment, 727, 138704.

Zumla, A., Al-Tawfiq, J., Enne, V., Kidd, M., Drosten, C., Breuer, J. et al. (2014) Rapid point of care diagnostic tests for viral and bacterial respiratory tract infections—needs, advances, and future prospects. The Lancet. Infectious Diseases, 14, 1123–1135.

How to cite this article: Wei, H., Liu, S., Liu, Y., Liu, B., & Gong, X. (2022). The impact of meteorological factors on COVID-19 of California and its lag effect. Meteorological Applications, 29(1), e2045. https://doi.org/10.1002/met.2045