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REVIEW ARTICLE

Effects of climate variables on the transmission of COVID-19: a systematic review of 62 ecological studies

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Abstract
The new severe acute respiratory syndrome coronavirus 2 was initially discovered at the end of 2019 in Wuhan City in China and has caused one of the most serious global public health crises. A collection and analysis of studies related to the association between COVID-19 (coronavirus disease 2019) transmission and meteorological factors, such as humidity, is vital and indispensable for disease prevention and control. A comprehensive literature search using various databases, including Web of Science, PubMed, and Chinese National Knowledge Infrastructure, was systematically performed to identify eligible studies from Dec 2019 to Feb 1, 2021. We also established six criteria to screen the literature to obtain high-quality literature with consistent research purposes. This systematic review included a total of 62 publications. The study period ranged from 1 to 8 months, with 6 papers considering incubation, and the lag effect of climate factors on COVID-19 activity being taken into account in 22 studies. After quality assessment, no study was found to have a high risk of bias, 30 studies were scored as having moderate risks of bias, and 32 studies were classified as having low risks of bias. The certainty of evidence was also graded as being low. When considering the existing scientific evidence, higher temperatures may slow the progression of the COVID-19 epidemic. However, during the course of the epidemic, these climate variables alone could not account for most of the variability. Therefore, countries should focus more on health policies while also taking into account the influence of weather.

Keywords Climate variables · COVID-19 · Temperature · Humidity · Ultraviolet ray

Introduction

The current COVID-19 outbreak is a global pandemic caused by the novel coronavirus, which can result in severe acute respiratory syndrome coronavirus 2 and has affected more than 103 million people globally, including 206 countries, and has resulted in over 2 million deaths worldwide as of January 31, 2021 (Dong et al. 2020). The new pandemic has become one of the worst public health crises, arousing considerable concern throughout the world. The new virus is mainly transmitted when people are in close contact, often via small droplets that are produced by coughing, sneezing, and talking, which exposes the virus to the external environment. Usually, instead of remaining in the air for a long period of time, droplets are peculiarly prone to falling to the ground or surfaces (Srivastava 2021). Its mechanism of rapid transmission and virological characteristics have not been fully explored and understood, but we know that, historically, many viruses have possessed different stabilities in different environments and that some infectious diseases have changed with the weather. For example, Middle East respiratory syndrome coronavirus was observed to be more stable under low temperature or low humidity conditions and could still be recovered after 48 h in the laboratory (van Doremalen et al. 2013). Historically, human-to-human transmissions of coronavirus and positive viscous infectious diseases have been mostly reported in subtropical monsoon climates or in winter and spring festivals in the Northern Hemisphere, whereas *Flavivirus* infectious diseases have been mostly detected in tropical regions, as well as in hot and rainy summers and autumns (Wang et al. 2020b). Additionally, the transmission of rotavirus has been shown to peak in December or January in the southwestern USA, but it has also been shown to peak in April

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and May in the Northeast (Mo 2020). At present, some scholars have found that COVID-19 is sensitive to high temperature and humidity conditions in the laboratory. For example, Casanova et al. have found that there was greater survival at low temperatures and low relative humidity for SARS-CoV-2 under laboratory conditions (Casanova et al. 2010). In cell cultures, the new coronavirus was observed to be highly stable at 4°C. Moreover, its survival was found to be related to the concentration of the virus, and the high concentration of the virus could survive for 7 days at 22.5°C, whereas the virus only remained completely alive for 1 day at 37°C (Cui et al. 2021). This in vitro study showed that SARS-CoV-2 obtained from a COVID-19 patient could be rapidly inactivated via irradiation with a deep ultraviolet light-emitting diode (DUV-LED) of 280 ± 5 nm wavelength (Inagaki et al. 2020). These results suggest that the epidemic of COVID-19 may be associated with meteorological variables, such as ultraviolet light and temperature.

Therefore, the exploration of the climate factors affecting the spread of the new coronavirus has become one of the key research issues in academic circles. Various methods, including mathematical models and machine learning algorithms, have been used to identify the epidemiologic relationship between COVID-19 prevalence and weather in different temporal and spatial dimensions. In this systematic review, we comprehensively collected and analyzed the studies involved in the epidemic status of COVID-19 and climate to summarize the methods of ecological studies and the results regarding the association between weather variables and COVID-19 incidence, which could be useful in better predicting the incidence of COVID-19.

Materials and methods

Study selection

A systematic search in Web of Science, PubMed (www.ncbi.nlm.nih.gov/pubmed), and Chinese National Knowledge Infrastructure (www.cnki.net) was conducted to collect publications concerning the correlation between COVID-19 incidence and weather throughout the world. Data that ranged from the start of the pandemic to Feb 1, 2021, were retrieved by means of the keywords “COVID-19” and “wind” or “humidity” or “temperature” or “rainfall” or “precipitation” or “UV” or “weather” or “climate” or “seasonality” in both English and Chinese. Titles and abstracts were scanned for relevance, and further relevant studies were identified from the references. The literature retroactive method was also used to extend the literature search. The last search was performed on Feb 1, 2021.

Inclusion and exclusion criteria

All of the identified studies were subjected to the following six self-established criteria to ensure consistency with the research objectives: (i) new daily, weekly, or monthly confirmed cases of COVID-19 (or other incidence and transmission index that could describe the dynamics of disease) were presented; (ii) meteorological indexes were presented; (iii) the underlying geographical scale information, research period, and temporal data aggregation unit were presented; (iv) the statistical analysis methods that had been used and the results were clearly presented; (v) studies from peer-reviewed dissertations or journals; and (vi) for the included studies, the time range of the data was more than sixty consecutive days, except for the studies concerning spread and decay durations; however, the duration of the studies about China only required more than 30 days. Additionally, the epidemic in China has been generally controlled much better than in other countries. Therefore, epidemiological studies that only provided COVID-19 mortality or admission rate data or studies that did not clearly describe methods or weather indexes were removed, and reviews and comment were also removed. If the studies were repeatedly published, then a dissertation with more detailed information was selected.

Data extraction

The following information was extracted from each included study, which was based on our self-designed information extraction list: first author and publication year, region and period, the type of COVID-19 data, climate indexes (with the lag time considered), temporal data aggregation unit (monthly, weekly, or daily), the statistical method that was used, major results regarding the correlation between climate and COVID-19 activity, and limitations.

To improve the reliability, we adopted the standard Cochrane methods (Cumpston et al. 2019). Two review authors (ZHL and GZL) independently screened for potentially eligible studies by glancing over the titles, abstracts, and full texts; additionally, they created a shortlist and determined final eligibility by using the predetermined inclusion and exclusion criteria. Subsequently, two review authors (ZHL and GZL) independently extracted data from the included studies and entered the data into the well-established data extraction form. We resolved any disagreement with the help of a third review author (WW) who acted as an arbiter. Included publications were considered to be qualified only when the data were extracted and double-checked.

Risk assessment of study bias

In consideration of the PRISMA statement (Moher et al. 2009), the modified criteria from BioMed Central (Wang et al. 2018), the Joanna Briggs Institute (JBI) Critical Appraisal Checklist tool (Mecenas et al. 2020), and the systematic review by Bai et al. (2019), we used the self-designed risk assessment item list (Table S2) to assess the qualities of the included ecological studies. The risks of bias in the included ecological studies were evaluated with twelve risk-biased items that were divided into external validity (items 1 to 3) and internal validity (items 4 to 12), which assessed the domain of selection and the domain of measurement bias and interpretation or extrapolation bias, respectively. For each item, the study was classified as "Yes" or "No", which indicates "Low risk" or "High risk," respectively. Two investigators (ZHL and GZL) negotiated with the help of the principal investigator (WW) and completed the quality assessment.

The resulting interpretation of the risk assessment, which was similar to the previously established standards (Zhang et al. 2019), was as follows: studies with a "No" score ≤30% (1–3) were classified as being low risk, studies with a "No" score 30–60% (4–7) were classified as being moderate risk, and studies with a "No" score >60% (8–12) were classified as being high risk.

Certainty of evidence

The included studies were given a narrative GRADE related to the outcomes and effects of climate variables on the transmission of COVID-19, which was evaluated in this review according to the GRADE guidelines (Balshem et al. 2011). The guidelines consider five aspects for rating the following levels of evidence: design, risk of bias, consistency, directness, and precision of the studies. The levels of evidence were classified as being high, moderate, low, or very low. The outcomes that were evaluated were "association between weather (solar radiation, temperature, humidity, and other climate factors) and transmission of COVID-19."

Results

Study selection

The initial searches identified 346 articles: 102 articles from Web of Science, 235 articles from PubMed, and 9 articles from CNKI. A total of 215 articles that were related to the objective and published online between Dec 2019 and Feb 1, 2021, were identified, including 206 publications in English and 9 publications in Chinese. After reading the titles, abstracts, and full-texts of these articles, only 62 publications (61 in English and 1 in Chinese) were ultimately included in this systematic review and selected for qualitative assessments of bias risk. The literature selection process is shown in Fig. 1.

Characteristics of the included studies

The characteristics of the included studies are presented in Table 1. All of the studies were retrospective observational studies analyzing the association between climate variables with the transmission of COVID-19.

Of these studies, seven studies were global analyses of weather variables—three studies assessed the global distributions at the continent, country, or region level, two studies evaluated the associations in 65 countries and 67 countries, one study selected analyses of 47 affected countries on six continents, and the remaining study analyzed 127 "Belt and Road" countries (not including China). The remaining fifty-five studies were at the province, city, site, county, or community level, including six continents (except for Antarctica). Thirty-three studies focused on the correlation between weather and COVID-19 transmission in Asia: thirteen studies for selected cities or provinces of China but only eight studies from China, nine studies for India, two studies for Pakistan, two studies for Bangladesh, and seven studies for Jordan, Korea, Japan, Singapore, Jakarta of Indonesia, 9 Asian cities, and 4 South Asian countries, respectively. Five studies focused on the correlation in North America, with two studies for the USA and three studies for Ontario of Canada, Canadian, and Victoria of Mexico regions. Seven studies focused on the association in Europe for 4 European countries, Spanish, the original EU-15 countries, the Russian Federation in Europe, 10 European countries, Oslo of Norway, and Italy. Three studies were based in Africa, including Ghana, Lagos of Nigeria, and 16 countries of Africa. Only one study was based in South America (São Paulo in Brazil). Finally, there are six remaining studies: one study that intentionally selected 11 of the most infected cities worldwide and 3 countries, one comparative study concerning China, England, Germany, and Japan, one study selecting the 10 hottest and 10 coldest countries, one study for the top 20 countries with confirmed cases, one study analyzing 9 locations in four continents, and the final study selecting 428 Chinese cities and districts, 18 Italian provinces, and 13 other countries.

All of the included studies focused on many weather factors, including temperature, dew point, temperature range, solar radiation, sunshine duration, humidity, pressure, evaporation, precipitation, wind, and visibility. Lagged effects were considered in 22 studies. The incubation period was considered in 6 studies. Moreover, only one study provided a positive control and a negative control. To avoid potential differences in the absolute number of medical records among the districts (due to different criteria and regulations), a normalization test was conducted (Rashed et al. 2020). Additionally, time series data

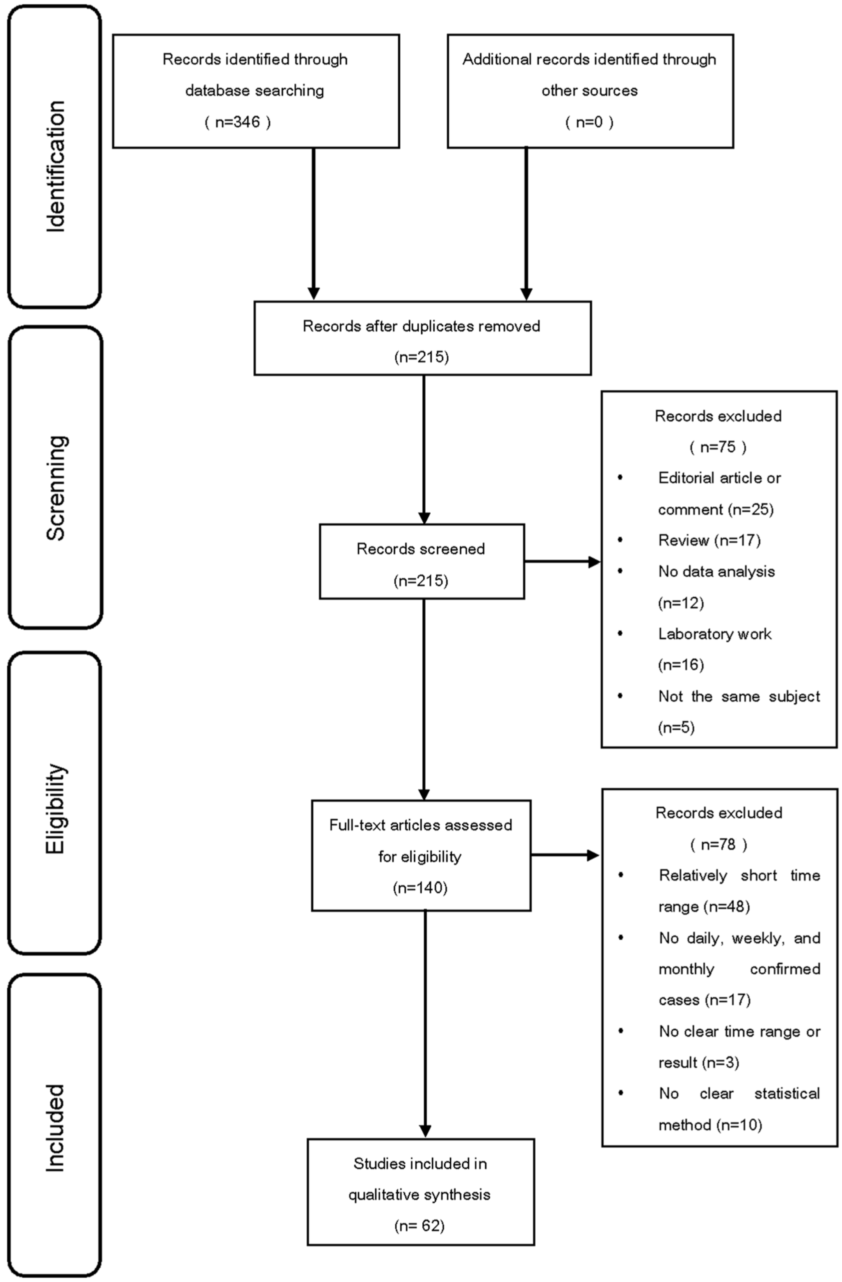

Fig. 1 Flow diagram of study selection.

or COVID-19 data were smoothed by using a sliding window in some studies.

Correlations between climate variables and the transmission of COVID-19

In the 62 included studies, the correlations between major climate variables and the transmission of COVID-19 are presented in Table 2.

Temperature, humidity, and wind were the most popular factors to study. Although the effects of climate variables on COVID-19 activity varied among different country populations, time units, and analytical methods, there were also similar results in the included studies, and especially most of the literature showed that higher temperatures may have largely influenced the spread of coronavirus and suppressed the pandemic. Among the included studies, fifty-eight studies explored the relationship between temperature and COVID-19 transmission, but only one study investigated the heat index, which was found to be positively correlated with the daily basic reproductive number (R_0), growth rate, and doubling time (Adnan et al. 2021). Additionally, another study adopted the mean equivalent temperature and found it to be a noninfluential factor on COVID-19 activity (Jamshidi et al. 2020).

Table 1 Characteristics of the included studies, Dec 2019–Feb 1, 2021

Included studied	Region and period	Type of COVID-19 data and temporal data aggregation unit	Climate indexes (lagged time considered) and temporal data aggregation unit	Statistical methods	Major findings about the correlation between climate variables and COVID-19 transmission of	Limitations
Wang et al. (2020a)	Guangzhou of China; Jan 21 to Feb 26, 2020	Number of new confirmed cases, daily	$T_{(ave,\ max,\ min)}$, RH_{ave}, P, WS_{ave}, AP_{ave}, SD (0–6 days), daily	GAM, Spearman correlation	Negative correlation with $T_{(ave,\ max,\ min)}$, RH_{ave}, P, AP_{ave}, and SD; positive correlation with WS_{ave}	No distinction between imported cases and local cases; no consideration about non-meteorological factors
Fan et al. (2021)	291 cities in the Chinese mainland; Jan 24 to Feb 29, 2020	City-level number of new confirmed cases, daily	T_{ave}, RH_{ave} (lagged effect not indicated), daily	GAM	An inverted U-shaped nonlinear relationship between confirmed cases and RH; a significant negative relationship between T_{ave} and caseload	Not discussed
Adnan et al. (2021)	Major cities of Pakistan; Apr 1 to Jun 5, 2020	Basic reproductive number (R_0), growth rate and doubling time, daily	HI and UVI (lagged effect not indicated), daily	Pearson correlation	Both climate indices show a significant positive correlation to R_0, Td, and Gr	No consideration about non-meteorological factors, incubation period, and lag
He et al. (2021)	9 Asian cities; Jan 20 to Mar 18, 2020	Number of new confirmed cases, daily	$T_{(ave,\ max,\ min)}$, RH_{ave} (0, 1, 3, 5, 7, 14days), daily	GAM and Pearson correlation	Positive correlation with $T_{(ave,\ max,\ min)}$ and RH_{ave}	Three cities didn't have daily new confirmed cases and public health measures were not incorporated into the modeling
Zhang et al. (2021)	1236 regions in the world; from the time when the total regional confirmed cases reach 100 to May 31, 2020	Number of new confirmed cases and R_0, daily	T_{ave}, RH_{ave} (5–14 days), daily	A multivariate regression model, a SIER dynamic transmission model	Negative correlation with T_{ave} and RH_{ave}; weather conditions were not the decisive factor	No consideration about vaccine available
Mehmood et al. (2021)	4 provinces of Pakistan; Jun 1 to Jul 31, 2020	Number of confirmed cases, daily	T_{ave}, RH_{ave}, DP_{ave}, WS_{ave}, AP_{ave} (lagged effect not indicated), daily	GLM, simple linear regression, Pearson correlation	A moderate correlation existed between weather and COVID-19 transmission	No consideration about community interventions, health care system, etc.; ecological fallacy; a challenge to gather PM2.5 and climate factors data at a discrete level
Yang et al. (2021)	4 cities of China; duration of community control	Number of new infected cases, daily	$T_{(ave,\ max,\ min)}$, DTR, RH_{ave}, WS_{ave}, P (lagged effect not indicated), daily	Multiple stepwise regression, Pearson correlation, the lognormal distribution model	T and RH were mainly the driving factors on COVID-19 transmission, but their relations obviously varied with season and geographical location	The result may not be applicable for small scales and arid inland cities
Abdelhafez et al. (2021)	Jordan; Mar 15 to Aug 31, 2020	Number of new confirmed cases, daily	$T_{(ave,\ max,\ min)}$, RH_{ave}, WS_{ave}, AP, SR_{ave} (lagged effect not indicated), daily	Multilayer perceptron, spearman correlation, Sobol sensitivity analysis	In the initial and the second wave, the most effective weather parameters were the SR_{ave} and T_{max}, respectively	Not discussed
Sharif and Dey (2021)	8 cities of Bangladesh; Mar 7 to Aug 14,	Number of new confirmed cases, daily	$T_{(ave,\ max,\ min)}$, RH_{ave}, WS_{ave}, UVI_{ave} (0, 7,	Spearman correlation	T_{ave} had the strongest correlation with the cases	The actual case and fatality number may vary slightly due to the lack

Table 1 (continued)

Included studied	Region and period	Type of COVID-19 data and temporal data aggregation unit	Climate indexes (lagged time considered) and temporal data aggregation unit	Statistical methods	Major findings about the correlation between climate variables and COVID-19 transmission of	Limitations
	2020		14days), weekly and daily			of complete diagnosis of the population
To et al. (2021b)	Ontario of Canada; Jan 1 to Jun 28, 2020	The incidence rates and the effective reproductive number (R_t), daily	1-week averaged UVI (lagged effect not indicated), daily	GLM	1-week averaged UV was significantly associated with a 13% decrease in overall COVID-19 R_t	Underreporting COVID-19 cases; these case-specific data were not available; no consideration about other factors like the populations, and public health policies
Aidoo et al. (2021)	16 major administrative regions of Ghana; Mar 12 to Jul 31, 2020	Number of new confirmed cases, daily	$T_{ave,}$ RH_{ave}, WS_{ave}, AP_{ave} (lagged effect not indicated), daily	GAM	A positive linear relationship with WS and AP, and a non-linear relationship with T and RH	No consideration about government interventions and other variables such as socio-demographical characteristics
Pahuja et al. (2021)	New Delhi of India; Mar 14 to Jun 18, 2020	Number of new confirmed cases, basic reproductive number (R_0), daily; doubling time, weekly	T_{ave} (9, 10days), RH_{ave} and WS_{ave} (10 days), daily and weekly	Pearson correlation, rolling correlation, DLM	The doubling time had a strong positive correlation with T while R_0 had strong negative correlation with T; no significant correlation with RH or WS was observed	No consideration about viral factors, host factors, personal hygiene, and the use of personal protective gears
Byass (2020)	The whole of China excluding Wuhan; Jan to Feb 2020	The number of confirmed cases in the cell-week	P, week mean of daily T $_{(ave,\ max,\ min)}$ at 2m and SR_{max} (lagged effect not indicated), weekly	A Poisson regression model of cell-weeks	Brighter, warmer, and drier conditions were associated with lower incidence	Possible weaknesses around the case data
Mozumder et al. (2021)	11 of the most infected cities worldwide and 3 countries; Jan to May 2020	Number of new confirmed cases, the % change in daily new cases, the specific growth rate, daily	T $_{(ave,\ max,\ min)}$, RH_{ave} (lagged effect not indicated), daily	A generalized regression model, analysis of variance	No significant correlation between T, RH, and the change in number of COVID-19 cases	Not discussed
Shao et al. (2021)	47 countries; Feb 22 to Jun 22, 2020	The effective reproductive number R_t, daily	T_{ave} (3, 7, 14days), daily	Panel data models with fixed effects, Spearman correlation	T can influence the spread of COVID-19 by affecting human mobility	Exposure measurement error and ecological fallacy; a large number of confounders were still not controlled
Diao et al. (2021)	Cities or prefectures from four countries; Jan to Jun 2020	The spread duration (DS) and decay duration (DD), during the period	T $_{(ave,\ max,\ min)}$, AH (lagged effect not indicated), daily	An asymmetric bell-shaped model, multivariable analysis	Spread and decay duration showed highly positive correlation with AH and T_{max}	The daily-increase curves in some cities diverged from the bell-shape used for defining the spread and decay durations, owing to the repetitive sub waves and cluster infections
Fu et al. (2021)	42 provincial regions from 4 European countries; Feb 1	Doubling time (Td), daily	T $_{(ave,\ max,\ min)}$, DRT, AH (cumulative lag: 03, 05, 07, 09, 014), daily	Pearson correlation, DLNM, random effects model of meta-analysis	Both the cold and the dry environment likely facilitated the COVID-19 transmission	No consideration about COVID-19 change trend at global level and other factors like governmental; only paying attention to the Td

Table 1 (continued)

Included studied	Region and period	Type of COVID-19 data and temporal data aggregation unit	Climate indexes (lagged time considered) and temporal data aggregation unit	Statistical methods	Major findings about the correlation between climate variables and COVID-19 transmission of	Limitations
	to Nov 1, 2021					was not enough to reflect the real COVID-19 transmission
Yuan et al. (2021)	127 countries; Jan 1 to Aug 8, 2020	Number of new confirmed cases, daily	T_{ave}, WS_{ave}, RH_{ave} (single-day lag: 0, 1, 3, 7, 14 and cumulative lag: 01, 03, 07, 014), daily	Spearman correlation GAM, piecewise linear regression	T, RH, and WS were nonlinearly and negatively correlated with daily new cases when T, RH, and WS were below 20°C, 70%, and 7 m/s, respectively	Meteorological parameters were obtained from a single site; there would be a difference between the actual number of cases and the number of reported cases; no consideration about population genetics and health infrastructure
Guo et al. (2021)	415 sites from 190 countries; Jan 23 to Apr 13, 2020	The COVID-19 incidence, daily	T_{ave}, WS_{ave}, RH (single-day lag: 0, 7, 14 and cumulative lag: 07, 014), daily	DLNM	The COVID-19 incidence showed a stronger association with T than with RH or WS and the corresponding 14-day cumulative relative risk was 1.28 at 5 °C and 0.75 at 22 °C	Exposure misclassification; the relatively short study period; a narrow range of meteorological factors; the proportion of COVID-19 test in each country or city and other potential confounders were not available
Chen et al. (2020)	428 Chinese cities and districts, 18 Italian provinces, and 13 other countries; Jan 20 to Apr 9, 2020	Number of new confirmed cases, daily	T_{ave}, WS_{ave}, RH_{ave}, VSB (0, 3, 7, 3-7, 14days), daily	Spearman correlation, the short-term model, the single-factor long--term simplified model	Significant correlation of the daily new confirmed case count with the weather 3 to 7 days ago	The prediction became inaccurate and even improper under hot weather and for very large new case count; these factors were not always available for any one certain area; ecological fallacy; no consideration about population mobility and disinfection measures
Tello-Leal and Macías-Hernández (2020)	Victoria of Mexico; Feb 16 to Jun 6, 2020	Number of new confirmed cases, daily and weekly	T_{ave}, RH_{ave}, AH_{ave} (lagged effect not indicated), daily and weekly	Pearson correlation	Negative correlation with T	The study period was relatively short
Hossain et al. (2021)	5 south Asian countries; the first day of	COVID-confirmed cases in each country to Aug 31, 2020	Number of new confirmed cases, daily	$T_{(max,\ min)}$, WS_{max}, SP, RF, RH (-12-12days), daily	The ARIMAX model	Negative correlation with the WS_{max} only in India and Sri Lanka; apart from India, T had mixed effects in four countries
No consideration about wind direction, socio-economic, lifestyle factors, etc.						
Islam et al. (2021)	206 countries or regions the day the first case	Number of new confirmed cases, daily	T_{max}, WS, RH, AH, UVI (7, 14days), daily	Multilevel mixed-effects	No association between COVID-19 cases and 7-day-lagged T_{max}, RH, UVI,	The definition of 'confirmed' cases was not consistent; it was not possible to adjust for temporal

Table 1 (continued)

Included studied	Region and period	Type of COVID-19 data and temporal data aggregation unit	Climate indexes (lagged time considered) and temporal data aggregation unit	Statistical methods	Major findings about the correlation between climate variables and COVID-19 transmission of	Limitations
	reported per region to Apr 20, 2020			negative binomial regression models	and WS, but a positive association with 14-day-lagged T_{max} and a negative association with 14-day-lagged WS	trend of testing rates; the actual daily incidence might be different from the reported values; no consideration about causal association between weather and COVID-19
Jamshidi et al. (2020)	Global to USA County Scale; Jan 1 to Aug 15, 2020	Cumulative cases, COVID-19-infected proportion (%), number of new confirmed cases, the changing rate of the COVID-19-infected cases, daily, weekly or during the period	Mean equivalent temperature (lagged effect not indicated), weekly or during the period	The standardized regression weights, the relative importance analysis	The weather by itself was identified noninfluential factor	Limitations in the data (e.g., spatial resolution, local influences)
Kumar et al. (2020)	67 countries; Jan 22 to April 3, 2020	Number of new confirmed cases, daily	Quartiles of $T_{(ave,\ max,\ min)}$ (lagged effect not indicated), daily	The multivariable two-level negative binomial regression analysis	For the T_{min} category, 28% statistically significant lower incidence was noted for new cases from the countries falling in the second quartile compared with countries falling in the first quartile	Individual city temperature data, including their respective number of cases, age, and sex information for individual case could not be obtained for many countries; the causality of effect cannot be examined with the available epidemiological data
Kulkarni et al. (2021)	46 locations of India; Mar 1 to May 31, 2020	The average R_0 over the entire duration; R_0, daily	T_{ave}, AP_{ave}, WS_{ave}, RH_{ave}, RF_{ave} (-10-10days), daily	Stepwise, backward elimination regression modeling, Pearson correlation	T_{ave} (inversely) and WS_{ave} (positively) were significantly associated with time dependent R_0	All the estimates and associations should only be considered as general patterns rather than definitive evidence; unmeasured confounding could be expected to be operational
Huang et al. (2020)	12 cities of China; Jan 23 to Feb 22, 2020	The new case incidence rate, during the period; number of new confirmed cases, daily	$T_{ave,}$ WS_{ave}, RH_{ave}, P (lagged effect not indicated), daily and during the period	Multiple regression correlation analysis	The new case incidence rate was not correlated with T_{ave}, WS_{ave}, $RH_{ave,}$ and P	There were only twelve cities in this analysis with relatively short period
Sahoo et al. (2021)	Maharashtra of India; Jan 1 to Jul 3, 2020	Number of new confirmed cases; daily	T_{ave}, WS_{ave}, DP, RF (lagged effect not indicated), daily	Kendall rank correlation, the Kendall's tau correlation matrix	Strongly positive correlation with T and DP	Not discussed
Islam et al. (2020)	Bangladesh; Mar 8 to May 31, 2020	Number of new confirmed cases, daily	$T_{(ave,\ max,\ min)}$, DTR, WS, AP, RH, AH (single-day lag: 0–14 and cumulative lag: 01–014), daily	DLNM, Pearson correlation, wavelet transform coherence	Positive correlation with the T (ave, max), WS, RH, and AH	No consideration about more influencing factors (air quality, health-care facilities, gender and age group population, individual data, etc.)

Table 1 (continued)

Included studied	Region and period	Type of COVID-19 data and temporal data aggregation unit	Climate indexes (lagged time considered) and temporal data aggregation unit	Statistical methods	Major findings about the correlation between climate variables and COVID-19 transmission of	Limitations
Singh et al. (2020)	Delhi of India; Mar 14 to Jun 11, 2020	Number of new confirmed cases and cumulative cases, daily	$T_{(ave,\ max\ min)}$, RH, SD, WS, evaporation, RF (lagged effect not indicated), daily	The non-parametric Mann–Kendall test, Pearson correlation	Positive correlation with $T_{(ave,\ max,\ min)}$, RH, WS, and evaporation but no association with SD and RF	No consideration about non-meteorological variables; these results were based on only one city
Nakada and Urban (2020)	59 cities of São Paulo in Brazil; Mar 24 to Jul 6, 2020	The infection rate, daily and during the period	T_{ave}, RH, WS, UV (3, 7, 14days), daily	Spearman correlation, the partial correlation, linear regression	Inversely correlation with T and UV radiation	Not discussed
Awasthi et al. (2020)	Delhi of India; Mar 15 to May 17, 2020	Number of new confirmed cases and cumulative cases, daily	$T_{(ave,\ max\ min)}$, RH_{ave}, WS_{ave}, (lagged effect not indicated), daily	Spearman correlation, linear regression, a Gaussian model	With every 1°C increase in T_{ave}, there was a significant increase in 30 new cases of COVID-19	The relatively short period and narrow temperature range
Lasisi and Eluwole (2021)	The Russian Federation; Mar 21 to May 28, 2020	Number of new confirmed cases, daily	T_{ave}, P (lagged effect not indicated), daily	Spearman correlation, Johansen cointegration analysis	The T_{ave} correlated the most with the number of cases	The relatively short period
Kumar and Kumar (2020)	Mumbai of India; Apr 27 to Jul 25, 2020	Number of new confirmed cases, daily	$T_{(ave,\ max,\ min)}$, $DP_{(ave,\ max,\ min)}$, $RH_{(ave,\ max,\ min)}$, $AH_{(ave,\ max,\ min)}$, $WS_{(ave,\ max,\ min)}$, $SP_{(ave,\ max,\ min)}$ (lagged effect not indicated), daily	Spearman correlation, the Artificial Neural Network model	The RH and SP had the most influencing effect on the active number of COVID-19 cases	Inconsistent results of various states and no any prospective pattern for COVID-19 transmission
Meo et al. (2020b)	16 countries of African, Feb 14 to Aug 2, 2020	The mean values of number of daily cases, cumulative cases, during the period	T_{ave}, RH_{ave} (lagged effect not indicated), during the period	Pearson correlation, Poisson regression	With 1% increase in RH and T, the number of cases was significantly reduced by 3.6% and 15.1%, respectively	Unable to consider other influencing factors, such as socio-economic conditions, population mobility, population immunity, and urbanization
Meo et al. (2020c)	10 European countries; Jan 27 to Jul 17, 2020	The mean values of number of daily cases, cumulative cases, during the period	T_{ave}, RH_{ave} (lagged effect not indicated), during the period	Pearson correlation, linear regression	Positive correlation with T and negative correlation with RH	It was not appropriate to generalize the results globally
Doğan et al. (2020)	New Jersey of the USA; Mar 1 to Jul 7, 2020	Number of new confirmed cases, daily	T_{ave}, RH_{ave} (auto-lags; 2days), daily	Pearson correlation, Spearman correlation, Kendall's rank correlation, the ARDL model	T had a negative correlation, while RH had a positive correlation and lagged effects with daily new cases	No consideration about population density, inter-city movement, and masks in the empirical analysis
Sarkodie and Owusu (2020)	Top 20 countries with confirmed cases; Jan 22 to Apr 27, 2020	Number of new confirmed cases, daily	$T_{(ave,\ max,\ min)}$, DP, WS, P, RH, SP at 2m (lagged effect not indicated) daily	Novel panel estimation techniques	Negative correlation T, RH, DP, WS, P, and SP	Not discussed
Tang et al. (2021)	24 counties of the USA; Apr 17 to		Total UVC dose, total UVB dose, total UVA dose		Negative correlation with the sunlight UV radiation dose in	Higher UV radiation dose did not necessarily correspond to higher

Table 1 (continued)

Included studied	Region and period	Type of COVID-19 data and temporal data aggregation unit	Climate indexes (lagged time considered) and temporal data aggregation unit	Statistical methods	Major findings about the correlation between climate variables and COVID-19 transmission of	Limitations
	Jul 10, 2020	The average percent positive of SARS-CoV-2, weekly and monthly	(lagged effect not indicated), weekly or monthly	Spearman and Kendall rank correlation	census regions 1 and 2 of the USA, while no statistical significance in the other regions	UV radiation intensity; the early data were not available; the data of the USA has not reached a fully seasonal cycle yet
Ladha et al. (2020)	Delhi of India; Apr 1 to May 31, 2020	Number of new confirmed $case_{s}$, daily	$T_{(max, ave)}$, RH_{ave} (lagged effect not indicated), daily	Linear regression	No statistical significance	The result might not represent the whole country; no consideration about other influencing factors like masking, migration of population, etc.
Rouen et al. (2020)	9 locations in four continents; Jan 1 to Apr 17, 2020	Growth rate of daily new cases, daily	T_{max} (lagged effect indicated but days unclear), daily	Spearman correlation, an innovative day-to-day micro--correlation	A negative correlation between T and growth rates with a median lag of 10 days	Not discussed
Ogaugwu et al. (2020)	Lagos of Nigeria; Mar 9 to May 12, 2020	Number of new confirmed cases and cumulative cases, daily	$T_{(ave, max, min)}$, $RH_{(ave, max, min)}$, (7, 14days), daily	Spearman correlation	Weak negative correlation with T and RH; the correlation increased when considering delays	Temperature range was narrow; no consideration about other influencing factors such as public opinion, etc.
Martorell-Marugán et al. (2021)	The Spanish autonomous communities; Mar 7 to Jun 20, 2020	Number of new confirmed cases, daily	T, WS, RF, SR (lagged effect not indicated), daily	DatAC (Data Against COVID-19) tool: Spearman and partial correlation, false discovery rate method	Lockdown, and not T nor SR, was the driving factor of the COVID-19 pandemic	Not discussed
Rendana (2020)	Jakarta of Indonesia, Mar 2 to May 13, 2020	Number of new confirmed cases, daily; total cases, during the period	T, RH, WD, WS, RF, SD (lagged effect not indicated), daily and during the period	Spearman correlation	Negative correlation with WS, T, and SD	Not discussed
To et al. (2021a)	Four Canadian provinces; Jan 25 to May 18, 2020	Effective reproductive number (R_t), daily; cumulative incidence rate, during the period	$T_{(ave, max, min)}$, (lagged effect not indicated), daily	Multiple linear regression	No significant correlation	Ecological fallacy; not a more granular level like cities; this study possibly did not reach a threshold in which the effects of temperature would be more pronounced
Meo et al. (2020a)	10 hottest and 10 coldest countries; Dec 29, 2019, to May 12, 2020	Number of new confirmed cases, cumulative cases, daily and during the period	T_{ave}, RH_{ave} (lagged effect not indicated), daily and during the period	Simple linear regression analysis	Negative correlation with T but positive correlation with RH	Not discussed
Hoang and Tran (2021)	17 cities and provinces of Korea; Feb 24 to	Number of new confirmed cases, daily	T_{ave}, WS_{ave}, RH_{ave}, AP_{ave} (0,7,14,21days), daily	The Kriging predicting model,	Each 1°C increase in T was associated with 9% (lag14)	Data at city-province level; not able to assess the more detailed

Table 1 (continued)

Included studied	Region and period	Type of COVID-19 data and temporal data aggregation unit	Climate indexes (lagged time considered) and temporal data aggregation unit	Statistical methods	Major findings about the correlation between climate variables and COVID-19 transmission of	Limitations
	May 5, 2020			GAM, Pearson correlation	increase of confirmed cases when the temperature was below 8°C	information such as the personal information
Rashed et al. (2020)	16 prefectures of Japan; Mar 15 to May 25, 2020	The spread duration (DS) and decay duration (DD), during the period	$T_{(ave,\ max,\ min)}$, $AH_{(ave,\ max,\ min)}$ (lagged effect not indicated), daily during the spread stage and decay stage	Spearman correlation, partial correlation, linear regression	Negative correlations between the T_{max}, AH_{max}, and the identified durations	Not discussed
Sharma et al. (2020)	India; Jan 29 to Apr 30, 2020	Number of new confirmed cases, daily	$T_{(ave,\ max,\ min)}$, SH_{ave} at 2m (lagged effect not indicated), daily during the spread stage and decay stage	Spearman correlation	High positive correlation with T, but low positive correlation with SH	No consideration about spiritual belief, population density, education, specific health of a person, policies etc.
Malki et al. (2020)	Italy; Dec 12, 2019, to Apr 22, 2020	The number of confirmed cases as of March 16t^{h}, the number of growth rate as of May 17th	Mean of T, RH (lagged effect not indicated), during the period	Machine learning approaches: decision tree, K neighbors regressor, etc.	Negative correlations with T and RH	Not discussed.
Meraj et al. (2020)	3 different ecogeographical regions of India; Mar 9 to May 27, 2020	Number of new confirmed cases, daily	T_{max} (lagged effect not indicated), daily	Pearson correlation, linear regression	Positive correlation with the T_{max} in Rajasthan and Kashmir	Data and time constraints
Ozyigit (2020)	The original EU-15 countries; the day of the 100th case reported to the 60th day for each country	Growth rate of the daily case numbers, daily	T_{ave} (lagged effect not indicated), daily	Panel techniques	A 1 °C increase in T was estimated to reduced COVID-19 transmission by 0.9%	Not discussed
Pani et al. (2020)	Singapore; Feb 24 to May 31, 2020	Number of new confirmed cases, total cases, daily	$T_{(ave,\ max,\ min)}$, $DP_{(ave,\ max,\ min)}$, $RH_{(ave,\ max,\ min)}$, $AH_{(ave,\ max,\ min)}$, $WS_{(ave,\ max,\ min)}$, $SP_{(ave,\ max,\ min)}$, $WV_{(ave,\ max,\ min)}$, (lagged effect not indicated), daily	Spearman correlation, Kendall correlation	T, DP, RH, absolute humidity, and WV showed positive significant correlation with COVID-19 pandemic	Meteorological parameters were taken from one single site; no consideration about peoples' obedience to social-distancing, health infrastructure, personal hygiene, defense mechanisms, subgroup analysis of gender and age, etc.
Li et al. (2020)	Wuhan and Xiaogan of China; Jan 26 to Feb 29, 2020	Number of new confirmed cases, daily	$T_{(ave,\ max,\ min)}$, SD, DRT (lagged effect not indicated), daily	Simple linear association	Inverse correlation with T in both Wuhan and Xiaogan	There were only two cities enrolled and the study period was relatively short
Menebo (2020)				Spearman correlation		

Table 1 (continued)

Included studied	Region and period	Type of COVID-19 data and temporal data aggregation unit	Climate indexes (lagged time considered) and temporal data aggregation unit	Statistical methods	Major findings about the correlation between climate variables and COVID-19 transmission of	Limitations
	Oslo of Norway; Feb 27 to May 2, 2020	Number of new confirmed cases, daily	$T_{(ave, max, min)}$, $WS_{(ave, max)}$, P (0, 5, 6, 14days), daily		Positively correlation with normal temperature and T_{max} but negative correlation with precipitation	No consideration about key factors, like lockdown implementation, testing capacities, sanitization attitudes, etc.
Jiang et al. (2020)	Wuhan, Xiaogan, and Huanggang of China; Jan 25 to Feb 29, 2020	Number of new confirmed cases, daily	T_{ave}, WS_{ave}, RH_{ave} (lagged effect not indicated), daily	Multivariate Poisson regression	Negative correlation with T but positive correlation with RH	No consideration about detailed information of cases and other climate variables; the relatively short study period; a few study cities; imperfect daily reporting practices
Shahzad et al. (2020)	10 most affected provinces of China; Jan 22 to Mar 31, 2020	Number of new confirmed cases, daily	T_{ave} (lagged effect not indicated), daily	The Sim and Zhou'	quantile-on-quantile approach based on a nonparametric quantile regression mode, local linear regression	Positively correlation with T in Hubei, Hunan, and Anhui but negative correlation in Zhejiang and Shandong, and mixed correlation in the remaining five provinces
Not discussed						
Shi et al. (2020)	31 provincial-level regions in mainland China; Jan 20 to Feb 29, 2020	Number of new confirmed cases, the confirmed cases rate, daily	T_{ave} (0, 1, 2, 3, 4, 5days), daily	Locally weighted regression, LOESS, DLNMs, random-effects meta-analysis	Biphasic relationship with T which above about 8 to 10 °C appeared to decrease the incidence of COVID-19 but without time lags	No consideration about virus properties and other factors; the adjustment of diagnostic criteria; a short study period; all confirmed cases including "imported" and "local" cases; time-varying ecological factors
Iqbal et al. (2020)	Wuhan of China; Jan 21 to March 31, 2020	Number of new confirmed cases, daily	T_{ave} (lagged effect not indicated), daily	Continuous wavelet transform, wavelet transform coherence, partial wavelet coherence, multiple wavelet coherence	No significant correlation	Not discussed
Liu et al. (2020)	30 capital cities except Wuhan in China; Jan 20 to Mar 2, 2020	Number of new confirmed cases, daily; total cases, during the period	T_{ave}, AH_{ave}, DTR_{ave} (cumulative lag: 0, 03, 07, 014), daily and during the period	Generalized linear models with negative binomial distribution, random effects meta-analysis	Negative correlation with AH and DTR, and corresponding pooled RRs were 0.80 and 0.90, respectively; for AH, the associations were statistically significant in lag 07 and lag 014	Not discussed
Al-Rousan and Al-Najjar (2020)	All provinces of China, excluding Inner Magnolia and Hong Kong;	Number of new confirmed cases, daily	T_{ave}, RH_{ave}, WS_{ave}, AP, WD, RF, snowfall, snow depth, and shortwave	Pearson correlation, Brown, Holt linear trend model,	Positively correlation with T and short-wave radiation	Not discussed

Table 1 (continued)

Included studied	Region and period	Type of COVID-19 data and temporal data aggregation unit	Climate indexes (lagged time considered) and temporal data aggregation unit	Statistical methods	Major findings about the correlation between climate variables and COVID-19 transmission of	Limitations
	Jan 22 to Mar 1, 2020		irradiation (lagged effect not indicated), daily	simple, and the ARIMA models		
Xie and Zhu (2020)	122 cities of China; Jan 23 to Feb 29, 2020	Number of new confirmed cases, daily	T_{ave}, (the cumulative lag: 0–7, 0–14, 0–21days), daily	GAM, piecewise linear regression	Each 1°C rise was associated with a 4.861% increase in the daily number of confirmed cases when T_{ave} (lag 0–14) was below 3°C	No subgroup analysis by gender and age group; under-reporting may still occur; our data only covered cities in China

Abbreviations: *T* air temperature, T_{ave} average air temperature, T_{max} maximum air temperature, T_{min} average minimum air temperature, *DP* dew point, *HI* heat index, *DTR* daily temperature range, *SD* sunshine duration, *UVI* ultraviolet index, *UV* ultraviolet, *SR* solar radiation, *RH* relative humidity, *AH* absolute humidity, *SH* specific humidity, *WS* wind speed, *WD* wind direction, *AP* air pressure, *SP* surface pressure, *P* precipitation, *RF* rainfall, *GAM* generalized additive model, *GLM* generalized linear model, *DLM* distributed lag model, *DLNM* distributed lag nonlinear model, *ARIMAX* autoregressive integrated moving average with explanatory variables, *ARDL* autoregressive distributed lag, *LOESS* locally weighted regression, *ARIMA* autoregressive integrated moving average

In thirty-seven studies that analyzed relative humidity, fourteen studies did not observe any significant correlations, which was a result that we could not ignore. In addition, another paper included the specific humidity and indicated the existence of a low positive correlation between confirmed cases of COVID-19 and specific humidity. Among twenty-eight studies that analyzed wind speed, only two studies included wind direction, with one study showing that wind direction affected the number of COVID-19 cases (based on wind rose analysis), and the other study indicating that wind direction and wind speed produced minimal effects on the number of confirmed cases in 37.9% and 27.5% of the provinces, respectively, in China. When regarding humidity and wind, we cannot provide a specific conclusion through Table 1.

Similarly, it is not clear how sunlight, pressure, and precipitation were related to COVID-19 activity. In fact, precipitation includes rainfall and snowfall. Only one paper included rainfall, snowfall, and snow depth with rainfall and snow depth imparting minimal effects on the number of confirmed cases in 6% and 24.1% of the provinces, respectively, but no correlation being observed between snowfall rate and the number of confirmed cases in all of the Chinese provinces (Al-Rousan and Al-Najjar 2020). Many coronaviruses are sensitive to ultraviolet light under laboratory conditions, but the effect of ultraviolet light on COVID-19 was undefined at the macrolevel based on the results that 28.5% of the studies about sunlight found no correlation, and the remaining studies were also not relatively consistent. Furthermore, evaporation is not presented in Table 2. Only two studies analyzed evaporation, and both studies showed a positive relationship between confirmed cases and water vapor.

Synthesis of results

We did not perform a meta-analysis because of the heterogeneity of the modeling methods, locations, meteorological indicators, and data processing. Additionally, differing policies, abilities in resisting the disease, test standards, test ranges, and units of measure did not support meaningful comparisons. Hence, only simple and descriptive comparisons and summaries were conducted, beyond the risk of bias and the narrative GRADE of evidence of the results.

Results of risk assessment and certainty of evidence

The PRISMA checklist is provided in Table S1, and the risk bias and assessment results are provided in Table S2. The questions that received more "No" answers indicated the existence of study limitations. Among all of the included studies, 32 studies had a low risk of study bias, and 30 studies had a moderate risk of study bias. For the question of "Were potential confounding factors identified?", only four studies

Table 2 Correlations between major climate variables and the transmission of COVID-19

Climate variables		Positive	Negative	Mixed	None	Total
Temperature	T	15	30	7	6	58
	DP	2	1	1	1	5
	DRT	0	2	0	3	5
Humidity	RH	8	9	6	14	37
	AH	3	4	0	2	9
Sunlight	SD	0	2	0	2	4
	UVI	1	2	0	1	4
	UV	1	2	0	0	3
	SR	1	1	0	1	3
Wind speed		8	10	2	8	28
Pressure	AP	1	3	2	2	8
	SP	0	3	0	1	4
Precipitation		1	3	0	3	7
Rainfall		1	5	1	0	7

Abbreviations: *T* air temperature, *DP* dew point, *DTR* daily temperature range, *RH* relative humidity, *AH* absolute humidity, *SD* sunshine duration, *UVI* ultraviolet index, *UV* ultraviolet, *SR* solar radiation, *AP* air pressure, *SP* surface pressure

provided "Yes" answers (Islam et al. 2021; Sarkodie and Owusu 2020; Shao et al. 2021; Xie and Zhu 2020). For the question of "Were strategies to deal with confounding factors stated?", only three studies provided "Yes" answers (Islam et al. 2021; Shao et al. 2021; Xie and Zhu 2020).

The evaluation of the certainty of the evidence according to GRADE is described in Table 3. The level of certainty of the evaluated outcomes ("Association between weather variables and transmission of COVID-19") was classified as "low" in this systematic review.

Discussion

All of the included studies varied in times, countries, populations, data sources, data processing methods, models, controlling methods, independent variables, and dependent variables, thus leading to different results. This review did not consider COVID-19 mortality, recovery rate, and hospitalization rate, among other factors. The factors influencing these indicators can be more complex, and these indicators cannot clearly describe the prevalence of COVID-19 on a macrolevel. In addition, the included study periods must be longer than 2 months in order to observe a substantial change in the variables (to some extent).

Variable selection

For confirmed cases, little distinction was made between local and imported cases in all of the included studies, but Meyer A used daily local cases of COVID-19 (Meyer et al. 2020). When regarding the choice of outcome variables, the forty-eight selected studies only focused on the incidence rate, the number of new cases, or their proportions, but a small number of studies focused on the case growth rate, the changing rate, or infectivity of the novel coronavirus. Only three studies analyzed the effective reproductive numbers, four studies analyzed the basic reproductive numbers, six studies researched the growth rates, and three studies focused on the doubling times. In addition, two studies focused on the spread duration and decay duration, which could also describe the acceleration of the epidemic.

Influencing factors

There were many possible non-meteorological factors, such as governmental interventions, social contact, population mobility, and coverage rate of COVID-19, that could influence the correlation analysis between meteorological factors and COVID-19 spread. He et al. considered city level and public health measures as being controlling factors in the linear regression (He et al. 2021). Moreover, Zhang et al. included a lockdown variable to explain government intervention in local and cross-regional COVID-19 transmission (Zhang et al. 2021). Panel data models with fixed effects were used to identify the links between daily mean temperature, human

Table 3 Narrative GRADE evidence profile table

Outcomes	Impact	Certainty of the evidence (GRADE)
Association between weather variables and transmission of COVID-19	Among the sixty-two articles evaluated, nine only used Spearman, Pearson correlation, or Kendall rank correlation to explore the association without considering other influencing factors. Other articles included different times and countries. The associations varied with different populations, research periods, sites, lag days, and models even in the same article for the same variable. The effects of weather variables on COVID-19 transmission might be positive, negative, nonlinear, bilateral, or irrelevant	Low

mobility, and transmission rate s(Shao et al. 2021). Additionally, Ladha et al. added the number of COVID-19 tests into the linear regression (Ladha et al. 2020). Fu et al. entered the government response index and other factors into the distributed lag nonlinear models as independent variables (Fu et al. 2021). However, only four studies identified potential confounding factors and conducted strategies to address the stated confounding factors, such as incorporations into the models and inclusions of dew point, cloud cover, precipitation, relative humidity, air pressure, or wind speed for the same period. The hypothesized associations between climatic variables and COVID-19 may change or not be maintained when a range of potential confounding variables are taken into account. It is strange that many studies regarded public opinion, gene mutation, social isolation, universal masking, and other factors as being confounding factors, but this systematic review does not agree with this perception, and we believe that only those factors meeting the definition of confounders are confounding factors (Valente et al. 2017).

Due to the confinement and reduction of socioeconomic activities caused by the pandemic, the air quality in Victoria, Mexico, has improved. Moreover, temperature was moderately to very strongly negatively correlated with all of the air pollution variables, and PM_{10} and $PM_{2.5}$ possessed significant correlations with the cases (Tello-Leal and Macías-Hernández 2020). Hence, we speculated that air quality factors may be confounding factors. Geographic factors, such as elevation, are highly associated with the weather type and can indirectly affect air pressure (Zhang et al. 2021). Furthermore, the sunlight UV radiation dose varies with latitude and season (Tang et al. 2021), but no statistically significant association was found between any geographic characteristic and the R_0 in India (Kulkarni et al. 2021). Therefore, the question as to whether latitude and longitude are confounding factors requires further study.

Another important issue is the direct link between meteorological variables and collinearity problems. Fan et al. performed a multicollinearity test to verify the degree to which weather variables were related to each other and found that multicollinearity was not a primary issue (Fan et al. 2021). Instead of using average daily temperature, Byass adopted the averages of maximum and minimum daily temperatures as a single measure of temperature to avoid collinearity between maximum and minimum temperatures and solar radiation when constructing a multivariable regression model (Byass 2020). To solve the problem that temperature and UV index were highly correlated, two separate models were used to fit for the temperature and the UV index, respectively, and all of the other variables were kept identical (Islam et al. 2021). Some studies were concerned about the relationships between meteorological factors and provided the correlation coefficients. For example, Tello-Leal et al. demonstrated the Pearson correlation coefficient matrix for main variables by using a dataset of the last 4 weeks of the partial lockdown (Tello-Leal and Macías-Hernández 2020). Moreover, Rendana et al. provided the Spearman correlation coefficients between wind speed and other meteorological factors and found that wind speed was positively associated with rainfall and temperature, as well as the fact that the correlation may be influenced by seasonal characteristics (Rendana 2020; Thangariyal et al. 2020).

Interpretation and understanding of the main results

When considering the existing scientific evidence, higher temperatures could slow the progression of the COVID-19 epidemic to a certain extent because high temperatures may reduce the viability, survival, activation, and infectivity of the virus. Fifteen studies believed that low temperature was related to higher morbidity. The possible reason for this effect is that the activity of the crowd is more indoors and windows are usually closed, which may increase the frequency of contact between people when it is cold or windy outside. For other climate variables, their correlations with the epidemic can vary, and there is not a relatively consistent view, due to a small amount of literature. Hence, more studies are needed.

There is an issue that cannot be ignored—variable contributions. There are several studies considering this issue. Diao et al. used the threshold value of the VIF to differentiate between low and high contributions and found a higher population density resulted in longer spread and decay durations, whereas meteorological factors had little effect on the durations (Diao et al. 2021). Malki et al. ranked feature importance through a random forest feature selector algorithm and found that temperature and hours of sunlight were important features for infected cases of COVID-19 cases, and climate factors were more important than demographics, such as population, age, and urban percentage, when inspecting mortality (Malki et al. 2020). Kulkarni et al. estimated the proportional reduction in error by using an established approach to quantify the relative contribution of each covariate with the time-dependent R_0 and found that the contributions of air temperature and wind speed to dampening the R_0 estimate were 3–4 times weaker than that in the countrywide lockdown phases 2–4 (Kulkarni et al. 2021). Hence, governments should take necessary human mobility restrictions and precautionary measures and regard prevention and control of the epidemic as regular.

Strengths and limitations

The greatest strength of our systematic review was that all of the meteorological variables appearing in the included studies were contained, including temperature, humidity, wind, dew point, temperature range, solar radiation, sunshine duration, pressure, evaporation, precipitation, and visibility. In addition, we have provided reference information for global epidemic control and proposed new breakthrough directions for future research. However, we only searched three databases, which could result in biases. The identification of confounding variables, the control of collinearity problems, and the consideration of influential factors were also important limitations of this systematic review. Moreover, there was no consideration of detailed information of cases such as age, weight, personal health status, and other factors. The relatively longer study periods could avoid the bias caused by various ecological factors over time, and more proper processing methods should be explored. Lastly, days of lagging effects and incubation periods need to be distinguished, especially if we want to consider both factors. More investigation is required to address the stated limitations.

Recommendations for future research

In future research, it is better to solve the previously stated limitations as much as possible and to pay more attention to the weathers and not to popular demand. In addition, large-scale multicenter studies may be able to avoid many biases and obtain more concrete results. The optimization of existing models and the addition of prediction models or spatial-temporal models at a more specific and proper level are also good choices. Another essential consideration for future research is vaccine popularization and patient personal information when exploring the correlation between climate factors and the transmission of COVID-19.

Conclusion

In summary, based on a low level of evidence and limited studies, these climate variables alone could not explain most of the variability in disease transmission, but higher temperatures could slow the progression of the COVID-19 epidemic (to a certain extent). It is certain that weather factors, especially temperature, humidity, wind speed, and ultraviolet light, could play an important role in the epidemic, but the contribution of meteorological factors is relatively small compared to factors like lockdown, social interaction, herd immunity, migration patterns, population density, personal hygiene, defense mechanisms, obedience of individuals to policies, and socio-economic level. Therefore, countries should focus more on health policies and vaccines while taking into account the influence of weather on outbreaks.

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Data availability Not applicable.

Declarations

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