How Is COVID-19 Affected by Weather? Metaregression of 158 Studies and Recommendations for Best Practices in Future Research

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ABSTRACT: Because many viral respiratory diseases show seasonal cycles, weather conditions could affect the spread of coronavirus disease 2019 (COVID-19). Although many studies pursued this possible link early in the pandemic, their results were inconsistent. Here, we assembled 158 quantitative empirical studies examining the link between weather and COVID-19. A metaregression analysis was performed on their 4793 correlation coefficients to explain these inconsistent results. We found four principal findings. First, 80 of the 158 studies did not state the time lag between infection and reporting, rendering these studies ineffective in determining the weather–COVID-19 relationship. Second, the research outcomes depended on the statistical analysis methods employed in each study. Specifically, studies using correlation tests produced outcomes that were functions of the geographical locations of the data from the original studies, whereas studies using linear regression produced outcomes that were functions of the analyzed weather variables. Third, Asian countries had more positive associations for air temperature than other regions, possibly because the air temperature was undergoing its seasonal increase from winter to spring during the rapid outbreak of COVID-19 in these countries. Fourth, higher solar energy was associated with reduced COVID-19 spread, regardless of statistical analysis method and geographical location. These results help to interpret the inconsistent results and motivate recommendations for best practices in future research. These recommendations include calculating the effects of a time lag between the weather and COVID-19, using regression analysis models, considering nonlinear effects, increasing the time period considered in the analysis to encompass more variety of weather conditions and to increase sample size, and eliminating multicollinearity between weather variables.

SIGNIFICANCE STATEMENT: Many respiratory viruses have seasonal cycles, and COVID-19 may, too. Many studies have tried to determine the effects of weather on COVID-19, but results are often inconsistent. We try to understand this inconsistency through statistics. For example, half of the 158 studies we examined did not account for the time lag between infection and reporting a COVID-19 case, which would make these studies flawed. Other studies showed that more COVID-19 cases occurred at higher temperatures in Asian countries, likely because the season was changing from winter to spring as the pandemic spread. We conclude with recommendations for future studies to avoid these kinds of pitfalls and better inform decision-makers about how the pandemic will evolve in the future.

KEYWORDS: Climate change; Climatology; Seasonal cycle; COVID-19; Regression analysis; Shortwave radiation; Statistics

1. Introduction

Coronavirus disease 2019 (COVID-19) is an infectious disease caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), and it has caused a devastating pandemic since December 2019. As of 1756 UTC 24 August 2021, the World Health Organization COVID-19 Dashboard (<https://covid19.who.int>) displayed more than 0.212 billion confirmed cases and a death toll of 4.44 million globally.

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Because other viruses exhibit seasonally varying infection rates (e.g., [Moriyama et al. 2020](#)), it is natural to speculate that SARS-CoV-2 also might exhibit such seasonality for two main reasons.

First, SARS-CoV-2 is mainly transmitted through respired droplets and close human-to-human contact (e.g., [Fathizadeh et al. 2020](#); [Greenhalgh et al. 2021](#)). Its transmission is similar to that of other respiratory viruses such as influenza, and these respiratory viruses display seasonal patterns in their incidence (e.g., [Audi et al. 2020](#); [Moriyama et al. 2020](#)), being more common in winter (e.g., [Reichert et al. 2004](#); [Rucinski et al. 2020](#)). Second, both laboratory and epidemiological studies confirmed that the survival and transmission of coronavirus-related infections [e.g., Middle East respiratory syndrome coronavirus

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(MERS-CoV) identified in Saudi Arabia in 2012; SARS-CoV from 2002 to 2003] varied with weather conditions, with the virus being more stable at lower air temperature (hereinafter, just *temperature*) and humidity and being less stable at higher temperature and humidity (e.g., [Chan et al. 2011](#); [van Doremalen et al. 2013](#)). Thus, if a relationship exists between COVID-19 and weather, then the spread of COVID-19 could be modulated by seasonally varying weather variables (e.g., [Carlson et al. 2020](#); [Smit et al. 2020](#); [Engelbrecht and Scholes 2021](#); [Kronfeld-Schor et al. 2021](#)).

This hypothesized seasonality and the urgency of the pandemic has resulted in a large number of studies to investigate the effects of weather on COVID-19 spread on all six permanently inhabited continents within just the first 20 months since the pandemic started. However, the results have not been consistent, as has been noted by others (e.g., [Briz-Redón and Serano-Aroca 2020](#); [Zaitchik et al. 2020](#); [Kerr et al. 2021](#); [McClymont and Hu 2021](#); [WMO COVID-19 Task Team 2021](#)). For example, some studies have found that an increase in temperature (e.g., [Menebo 2020](#); [Zoran et al. 2020](#)) or relative humidity (e.g., [Auler et al. 2020](#); [Nottmeyer and Sera 2021](#)) accelerated the spread of COVID-19, whereas other studies have found that a decrease in temperature (e.g., [Demongeot et al. 2020](#); [Liu et al. 2020](#)) or relative humidity (e.g., [Ahmadi et al. 2020](#); [Wu et al. 2020](#)) accelerated the spread. Even studies performed using data from the same country have produced different results. For instance, in the United States, [Adhikari and Yin \(2020\)](#) suggested that temperature and relative humidity were significantly and positively associated with COVID-19 confirmed cases; [Wang et al. \(2021\)](#) suggested that increases in temperature and relative humidity significantly suppressed spread; and [Chien and Chen \(2020\)](#) and [Doğan et al. \(2020\)](#) suggested that increases in temperature reduced the risk of COVID-19, whereas increases in relative humidity significantly increased the risk. Such heterogeneous findings prevent us from understanding the true effects of weather conditions, if any, on the spread of the pandemic.

Our motivation for this article stems from these heterogeneous findings. We wondered whether a systematic and quantitative exploration of the literature could help us to understand the reasons for these inconsistent findings. To do this, we identified 158 empirical studies published on or before 31 March 2021 that investigated the weather effects on COVID-19 spread. Specifically, we wondered whether the statistical analysis methods employed in the original studies, the geographical regions and countries from which the data were analyzed, and eight different weather variables (e.g., temperature, relative humidity, precipitation, wind speed, air pressure, absolute humidity, dewpoint temperature, solar energy) could explain the spread of COVID-19 (e.g., deaths, confirmed cases). A metaregression approach was conducted to analyze the statistical analysis method, region, and weather variables, what we call the *modeling factors* in our research study. A metaregression approach uses a set of rigorous statistical methods to review and to evaluate the empirical evidence from diverse studies, to establish evidence-based practice, and to help to understand the heterogeneity of research results (e.g., [Stanley et al. 2008](#); [Lazzaroni and van](#)

[Bergeijk 2014](#); [Gurevitch et al. 2018](#)). Metaregression has been used in the past to summarize the effects of environmental conditions on mortality. For instance, [Achilleos et al. \(2017\)](#) used metaregression to examine the association between short-term exposure to PM_{2.5} and adult mortality, and [Luo et al. \(2019\)](#) used metaregression to investigate the effects of temperature on mortality in China. Consequently, metaregression is a suitable approach to address the purpose of this study. Because the global pandemic continues, the accurate determination of the weather effects on the spread of COVID-19 is a pressing issue. Thus, this article contributes to the literature by providing a metaregression analysis based on the evidence of weather effects on COVID-19 spread, to help to explain the reasons for the inconsistent results in these 158 previous studies.

The rest of this article is organized as follows: [Section 2](#) presents the process of data collection of the empirical evidence obtained from current studies. The process resulted in 158 studies and 4793 correlation coefficients. [Section 3](#) describes the statistical analysis methods used by these studies. [Section 4](#) presents the relationships between weather variables and COVID-19 spread by region. [Section 5](#) introduces the metaregression approach, describes the modeling factors, and presents the metaregression results. [Section 6](#) discusses the results produced by different statistical analysis methods, region, and weather variables based on [sections 4 and 5](#). [Section 7](#) summarizes the results and provides recommendations for best practices in future research on the effects of weather on COVID-19. Table S1 in the online supplemental material lists the 158 studies.

2. Data and methods

The studies involved in this article were identified and selected through a four-step process ([Fig. 1](#)). First, an initial search was conducted by searching scientific-literature databases for specified keywords ([Fig. 1](#)). The databases were Google Scholar, ScienceDirect, Web of Science, Taylor and Francis Online, and Springer. Searches in Google Scholar and ScienceDirect were organized by “relevance,” and results beyond the first 300 results were neglected because lower-ranked literature led to literature of little relevance. We used keywords for the COVID-19 pandemic including “COVID-19” and “coronavirus,” and keywords denoting weather including “weather,” “meteorological,” and “climate.” The studies selected in the search criteria started in 2019 and ended on 31 March 2021, and they included published articles in peer-reviewed journals, typescripts on preprint servers (e.g., medRxiv and arXiv), working papers, and conference abstracts. We excluded studies in languages other than English. Using these search criteria, we identified 1075 initial studies. Because these 1075 studies were obtained from different databases, duplicates inevitably existed. Second, the lists of the 1075 studies were merged and obvious duplicates were removed, resulting in 767 studies.

Third, the metaregression analysis requires quantitative information on the correlation coefficients presented in each of the different studies. Specifically, to be included in our

FIG. 1. The process of study identification and selection. (top) The scientific-literature databases and keywords used to build the database of published studies. (bottom) The four-step process involved in identifying relevant studies for this article, where N represents the number of studies at each step.

metaregression analysis, the candidate study must have met both of these inclusion criteria: 1) the study must be relevant to the academic subject of the relationship between weather and COVID-19 spread, including cumulative cases, new confirmed cases, or deaths, and 2) the study must be an empirical study in humans and have obtained quantitative values of statistical correlations. We read the title, abstract, and even the full text of each study, when necessary, to ensure that each study met the inclusion criteria. The inclusion criteria produced 146 studies and excluded the other 621 studies. Because the purpose of this article is to explore the relationship between weather and COVID-19, studies such as the biology of COVID-19 and changes in the weather or air-quality conditions during the pandemic were excluded from further exploration. Fourth, we searched the reference list of each of these 146 studies to find studies that were not identified in the database searches performed earlier. Another 12 studies were identified, increasing the number of studies to 158. As of 31 March 2021, the 158 studies in our article consisted of 143 peer-reviewed journal articles and 15 preprints. The identification and selection process were performed independently and verified jointly by the lead author and two other individuals. The 158 studies meeting our selection criteria are listed in Table S1 in the online supplemental material. Of these 158 studies, 36 (23%) were published by one journal, Elsevier's *Science of the Total Environment*.

For the purposes of the analysis in the present article, four characteristics were determined for each study: statistical analysis methods used, research regions investigated, weather variables analyzed, and whether time-lagged effects were involved between weather and the COVID-19 cases or

deaths. Statistical methods used to obtain empirical estimates included correlation tests (i.e., Pearson test, Spearman test, Kendall test) and regression analysis (e.g., multiple linear regression, generalized linear model, generalized additive model, polynomial regression model). Some studies examined the effects of weather on COVID-19 spread in different regions, countries, or cities, including countries on all six permanently inhabited continents. The eight weather variables were temperature, relative humidity, precipitation (the variable for precipitation in 157 studies was precipitation amount, and only 1 study used precipitation rate), wind speed, air pressure, solar energy (i.e., insolation, sunshine hours, ultraviolet index), absolute humidity, and dewpoint temperature. These data originated from surface observing station networks in 147 studies and from ERA5 reanalyses in 10 studies. Also, the time lags for the various studies varied from 0 days to as many as 70 days.

For each of the 158 studies, relevant correlation coefficients were extracted. Of these 158 studies, 4793 correlation coefficients were collected, and 4281 of those also reported effects of weather on COVID-19 spread at least at a 5% significance level (a p value of less than 0.05 is considered a statistically significant relationship with 95% confidence intervals). We did not specify the significance levels at different levels (i.e., 10%, 5%, and 1% significance levels) because correlation coefficients with 5% significance level were reported by most studies. Furthermore, some studies even set the default standard at 5% significance level; thus, it was difficult to judge whether the reported correlation coefficients were also significant at a 1% significance level. These 4793 correlation coefficients included 3614 correlation coefficients extracted from

correlation tests (i.e., 2052 Pearson coefficients, 1283 Spearman coefficients, 279 Kendall coefficients) and 1179 correlation coefficients derived from regression models. For the weather variables, 2033 correlation coefficients were associated with temperature, 1241 correlation coefficients were associated with relative humidity, 773 correlation coefficients were associated with precipitation, 445 correlation coefficients were associated with wind speed, and 162 correlation coefficients were associated with air pressure. Absolute humidity, solar energy, and dewpoint temperature were associated with 100 correlation coefficients each.

3. Description of statistical analysis methods

Various statistical analysis methods were used to evaluate the effects of weather on COVID-19 spread. The correlation coefficients obtained from the 158 studies were derived from correlation tests and regression analysis. Correlation tests are the most commonly used methods to examine the statistical relationship between variables. Specifically, the Pearson correlation test is a parametric statistical test that measures the linear correlation between variables, whereas Spearman and Kendall correlation tests are nonparametric statistical tests used to evaluate the degree of relationship between variables. All three correlation tests yield a correlation coefficient between -1 and 1 , where -1 and 1 represent total negative and positive correlations, respectively, and 0 means no correlation. Although Spearman and Kendall correlation tests can examine the nonlinear relationship between two variables, the correlation coefficients obtained only reflect monotonic correlations.

Regression models can also be divided into linear and nonlinear. The linear regression models were widely used to investigate the association between COVID-19 spread and weather, including the ordinary least squares regression model (e.g., Pan et al. 2021), negative binomial regression model (e.g., Sehra et al. 2020), and generalized linear model (e.g., Lorenzo et al. 2021). On the other hand, nonlinear models might be better methods because of the nonnormality of the data. The generalized additive model is a combination of the generalized linear model and the additive model, which is the main nonlinear regression model to produce both linear and nonlinear results on the associations between weather and COVID-19 spread. Although the linear relationship in generalized additive models can be obtained and explained by regression coefficients, the nonlinear results in the 16 studies using generalized additive models are presented graphically, making it difficult to obtain quantitative information from them. Therefore, only the linear relationship obtained with the generalized additive model was shown in our analysis, which used the available correlation coefficients in the original studies.

Additionally, 4 of the 158 studies used polynomial regression models to explore the nonlinear effects of weather on COVID-19 spread. Although there are only four such studies and the resulting number of correlation coefficients is small, they provided new insights to capture the nonlinear relationships between weather and COVID-19 spread. Thus, we discuss these studies individually here. First, Fang et al. (2020)

used a generalized estimated equation model to investigate the relationship between temperature, relative humidity, and COVID-19 spread in mainland China, and they found an inverted U-shaped relationship between relative humidity and COVID-19 infections. Second, Xu et al. (2021) found a U-shaped relationship with outdoor ultraviolet-radiation exposure using infection data from Australia, Canada, China, Iran, and the United States. They found that low/moderate ultraviolet radiation was associated with decreased COVID-19 spread, whereas higher ultraviolet radiation was associated with increased spread. Third, Zhang et al. (2020) introduced a quadratic regression model to capture the nonlinear relationship between temperature and COVID-19 spread in China. Fourth, Gao et al. (2021) also used a quadratic regression model to explore relationships between weather and COVID-19 in 45 countries. They found a local maximum between COVID-19 spread and mildly warm conditions.

The above description showed that correlation tests and regression analysis (including linear regression and nonlinear regression analysis) were the most commonly used statistical analysis methods for assessing the associations between weather and COVID-19 spread. However, there were only a few studies using nonlinear methods, and the 21 coefficients produced by these studies were difficult to analyze. Thus, only empirical evidence for the relationship between COVID-19 spread and weather based on correlation coefficients derived from correlation tests and linear regression analysis were further analyzed in the present article.

4. Association between weather variables and COVID-19 spread by region and the effect of time-lagged weather

After removing the 21 regression coefficients derived from nonlinear regression models, there were 4772 correlation coefficients remaining. We then grouped the 4772 correlation coefficients into positive correlations and negative correlations based on the association between COVID-19 spread (e.g., death, confirmed cases) and the eight weather variables (Fig. 2). From the distribution of all correlation coefficients, the effects of the eight weather variables could be summarized as follows:

- For the 2026 coefficients for temperature, 1016 were negative correlation coefficients (meaning that temperature was inversely proportional to COVID-19 spread in 1016 of those statistical analyses) and 1010 were positive correlation coefficients (meaning that temperature was directly proportional to COVID-19 spread in 1010 of those statistical analyses). Of those 1016 and 1010 correlation coefficients, 586 and 588 were associated with statistically significant relationships at the 5% level (Fig. 2b).
- For relative humidity, wind speed, air pressure, absolute humidity and solar energy effects, more negative correlation coefficients were reported than positive ones for both the entire population and those with statistical significance.
- For precipitation and dewpoint temperature effects, more positive correlation coefficients were reported than negative

FIG. 2. The population distribution of all correlation coefficients according to correlation tests and regression analysis (blue bars represent the number of negative correlation coefficients, and red bars indicate the number of positive correlation coefficients): (a) all of the correlation coefficients and (b) the subset of the data in (a) that is statistically significant.

ones for both the entire population and those with statistical significance.

These results mean the linear relationship between eight weather variables and COVID-19 spread is different based on the population distribution of all 4772 correlation coefficients. Considering that these results are obtained based on different study regions, we might hypothesize that there is an optimal geographic latitude or weather range for COVID-19 spread. In this optimum, the weather would be associated with increased COVID-19 spread; outside this optimum, the weather would be associated with decreased COVID-19 spread.

To test this hypothesis, the effects of the weather in six regions were examined next: Africa, Asia, Europe, North America, South America, and Oceania (Fig. 3). Interestingly, the results of this analysis found different results across the six regions.

- For African countries, more negative correlation coefficients than positive ones were reported between temperature, relative humidity, solar energy, and COVID-19 spread.
- For Asian countries, more negative correlation coefficients than positive ones were reported between relative humidity, air pressure, and solar energy, whereas more positive correlation coefficients than negative ones were reported between temperature, precipitation, wind speed, absolute humidity, dewpoint temperature, and COVID-19 spread.
- For European countries, more negative correlation coefficients than positive ones were reported between temperature, relative humidity, absolute humidity, solar energy, dewpoint temperature, and COVID-19 spread.
- For North American countries, more negative correlation coefficients than positive ones were reported between temperature, relative humidity, solar energy, and COVID-19 spread, whereas more positive correlation coefficients than negative ones were reported between precipitation, wind speed, and COVID-19 spread.

- For South American countries, more negative correlation coefficients than positive ones were reported between temperature, relative humidity, precipitation, wind speed, solar energy, and COVID-19 spread.
- For Oceanian countries, more negative correlation coefficients than positive ones were reported between temperature, relative humidity, solar energy, and COVID-19 spread.

For the purposes of this study, Asia, Europe, and North America are considered the Northern Hemisphere regions; South America is the Southern Hemisphere region. Because Oceania and Africa are in both hemispheres, they are not included in either the Northern or Southern Hemisphere regions. Thus, Southern Hemisphere regions reported more negative correlation coefficients than the Northern Hemisphere regions for both the entire population and those with statistical significance, especially for temperature. In the early stage of the rapid outbreak of COVID-19, the Southern Hemisphere was in the transition from summer to autumn, and the temperature was gradually decreasing. In contrast, the Northern Hemisphere was in the transition from winter to spring, and the temperature was gradually increasing. Therefore, the resulting difference in temperature effects between the Southern and Northern Hemisphere regions may be related to the timing of the outbreaks relative to their seasonal cycles. This result shows the value in separating out the various countries by geographical region for some types of analysis.

The results described above reflect the distribution of 4772 correlation coefficients. These bulk results, however, do not consider the quality of the original studies. One example of where the quality of the study needs to be considered pertains to the lagged effect between the weather and COVID-19 spread. Specifically, well-designed studies need to consider lags between the day of the infection (and its weather) and the day of the case being reported that are due to both the incubation period and the delay in virus detection. The incubation period averages 4–5 days (e.g., Guan et al. 2020; Li et al.

FIG. 3. The empirical distribution of COVID-19 spread and weather in different geographic regions according to correlation tests and linear regressions: (a) Africa, (b) Asia, (c) Europe, (d) North America, (e) South America, and (f) Oceania. Blue bars represent the number of negative correlation coefficients, and red bars indicate the number of positive correlation coefficients. Dashed horizontal lines separate the effects of weather variables. For each variable, the upper solid bars represent the number of all of the correlation coefficients, and the lower hatched bars represent the subset of the upper number that is statistically significant (at the 5% level).

FIG. 4. The empirical finding distribution of significant correlation coefficients (at the 5% level) according to whether correlation coefficients involved time-lagged effects (blue bars represent the number of negative correlation coefficients, and red bars indicate the number of positive correlation coefficients): (a) the correlation coefficients with lagged weather effects and (b) the correlation coefficients without lagged weather effects.

2020; Linton et al. 2020) but can fall within the range of 2–14 days (Linton et al. 2020). Also, during the incubation period, patients are asymptomatic and less likely to be tested so that there are lags caused by the time it takes for symptoms to appear, time it takes to be tested, time to be hospitalized, and the time to record COVID-19 test results into the official government databases (e.g., Pellis et al. 2021). Thus, the time-lagged effects between the weather on the day of the infection spread within an individual and the spread of COVID-19 using official databases needs to be considered. Not doing so means that these studies would be examining the weather on the day the COVID-19 cases were reported and not the weather on the day that the infection took place. Consequently, studies that omit lagged weather effects cannot contribute to addressing the relationship between weather and COVID-19 spread.

In the 158 studies, only 78 studies (49%) involved lagged weather effects in their research, whereas 80 studies (51%) did not report their assumed time lag between the date of infection and the date of reporting, which would render these 80 studies ineffective. Of those 36 studies published in *Science of the Total Environment*, 21 (58%) were published with zero lag. Most of the 78 studies tested one or more lags between 0 and 14 days (Table S1 in the online supplemental material). However, our dataset is too small to conduct robust statistical analysis of various weather effects by separating studies into categories based on the number of lagged days (such as 1–3 days, 4–7 days, 7–10 days, and more than 10 days). The research outcomes tended to report more negative and significant correlation coefficients than positive ones between temperature, relative humidity, and absolute humidity with COVID-19 spread considering the lagged weather effects (Fig. 4a), in comparison with those correlation coefficients with no consideration of lagged weather effects (Fig. 4b). Furthermore, for temperature, air pressure, absolute humidity, and dewpoint temperature, the results are reversed for the correlation coefficients with (Fig. 4a) and without (Fig. 4b) time-lag effects. These differing results depending on whether time lags are

accounted for indicates the importance of including this effect in the analysis. Also, when studies without time-lag effects are removed, all eight correlations with solar energy were negative.

As before, we consider the effects of the weather in the six regions, but this time only those with statistically significant results (Fig. 5). Although the number of correlation coefficients is made smaller by excluding studies without declared time lags, the associations become much stronger by removing such studies that failed to address time lags. We find the following results:

- For temperature, Asian countries reported more positive and significant correlation coefficients, whereas countries in other regions reported more negative and significant correlation coefficients.
- For relative humidity, African, European, North American, South American, and Oceanian countries reported more negative and significant correlation coefficients than for Asian countries.
- For precipitation and wind speed, Asian countries reported more positive and significant correlation coefficients, whereas South American countries reported more negative and significant correlation coefficients.
- For absolute humidity and dewpoint temperature, European countries reported more negative and significant correlation coefficients than for the other regions.
- For other weather variables, there were too few reported correlation coefficients to make any claims.

These results mean that the effects of weather on COVID-19 are different across these regions in terms of different weather variables and geographical regions based on 2777 correlation coefficients involving time-lagged effects. Also, Southern Hemisphere regions reported more negative correlation coefficients than Northern Hemisphere regions with lagged weather effects, both for the entire population and for statistically significant results.

The above statistical analyses revealed that, although a large number of studies had assessed the effects of weather on

FIG. 5. The empirical distribution of significant correlation coefficients (at the 5% level) based on time-lagged effects in different geographic regions (blue bars represent the number of negative correlation coefficients, and red bars indicate the number of positive correlation coefficients): (a) Africa, (b) Asia, (c) Europe, (d) North America, (e) South America, and (f) Oceania.

COVID-19 spread, the results were inconsistent, as has been previously recognized (e.g., [Briz-Redón and Serrano-Aroca 2020](#); [Zaitchik et al. 2020](#); [Kerr et al. 2021](#); [McClymont and Hu 2021](#); [WMO COVID-19 Task Team 2021](#)). Nevertheless, we were able to produce the following principal conclusions from this part of our analysis.

First, half of the studies omitted lagged weather effects. Such studies fail to address the incubation period of the virus, or the time it requires to diagnose, report, and record the case in official databases. Therefore, such flawed studies are ineffective at addressing the relationship between weather and COVID-19 spread.

Second, the weather effects were inconsistent across various study regions ([Figs. 3 and 5](#)). Countries in South America and Oceania reported more negative associations with the weather than countries in other geographic regions. In contrast, countries in Asia reported more positive correlation coefficients for temperature, whereas other regions reported more negative correlation coefficients for temperature, likely reflecting the temperature change from winter to summer during the early stage of the rapid outbreak of COVID-19 in Asian countries.

Third, despite these regional differences for some weather variables described above, higher solar energy was reported with less COVID-19 spread in all geographic regions ([Figs. 3, 4a, and 5](#)), meaning the effects of solar energy may have seasonal implications on COVID-19 spread. These results motivate us to examine whether information about how the original studies were conducted (including their statistical analysis methods, geographical regions, and weather variables) could explain the reasons for these inconsistent research results about weather and the spread of COVID-19. Thus, the next section introduces a method called metaregression analysis to account for these modeling factors.

5. Metaregression analysis

The metaregression approach used in this article is described in [section 5a](#), including a multinomial logit model and a multiple linear regression model, as well as a description of the modeling factors. In [section 5b](#), we present the metaregression results based on all correlation coefficients, and then present the metaregression results based on correlation tests and linear regression analysis separately.

a. Metaregression analysis method

One way to examine empirical findings from previous studies is to use metaregression, which is a statistical approach to identify the key factors that may influence the investigated research outcomes (e.g., [Palmatier et al. 2006](#)). Metaregression analysis contains a large collection of analysis results from individual studies for the purpose of integrating research findings ([Glass 1976](#)). A key assumption of this approach is that each study provides the relationship between research findings and different modeling factors, and when the research findings across studies are aggregated, the statistical association between the differences of the research outcomes and the modeling factors can be observed (e.g., [Zhou and Chen 2021](#)). Thus, each correlation coefficient derived from

the 78 studies that included nonzero time-lagged effects was taken as one single observation containing information on the nature of the modeling factor and COVID-19 spread. When all of the correlation coefficients across the 78 studies were aggregated, the statistical associations became apparent.

Based on the metaregression analysis, we used the same six geographical regions in [section 4](#) and analyzed the relationship between weather and COVID-19 separately within these six regions. Moreover, a rather large number of studies were performed on a small number of countries. Specifically, studies using data from India had 380 correlation coefficients, those from the United States had 332 correlation coefficients, those from China had 329 correlation coefficients, and those from Bangladesh had 217 correlation coefficients. These four countries accounted for 45.3% of the total number of 2777 correlation coefficients that included time-lagged effects. Therefore, these top four countries with correlation coefficients were also included in the metaregression analysis to explore the relationship between the weather and COVID-19 spread.

The metaregression analysis contained three steps. First, we included all correlation coefficients that included time-lagged effects collected from both correlation tests and linear regression analysis to analyze the influence of weather on the spread of COVID-19 from the perspective of geographical regions, top four countries, and weather variables based on the multinomial regression model. Second, the degree of correlation can be judged by the absolute value of significant correlation coefficients derived from correlation tests. Thus, in the second step, on the one hand, we used the multinomial regression model to analyze the factors that could affect the positive and negative relationship; on the other hand, we used the multiple linear regression model to find out the modeling factors that could affect the degree of correlation based on the absolute value of significant correlation coefficients. Third, we used the multinomial regression model to similarly analyze the factors that could affect the positive and negative relationships based on correlation coefficients derived from regression analysis. Then, we used the absolute value of the significant coefficients of the first-order term to perform multiple linear regression analysis to find out the factors that could affect the strength of the linear relationship. The descriptive statistics of modeling factors that we incorporated in the metaregression analysis are shown in [Table 1](#).

Before performing the metaregression analysis, we first conducted the correlation test to prevent the evaluation results from being distorted or from being difficult to evaluate because of the high correlation between the modeling factors. In other words, when performing regression analysis, the included variables were required to be independent and uncorrelated. If the variables included were highly correlated, the evaluation results would be inaccurate. Thus, we first used the least absolute shrinkage and selection operator (LASSO) dimension reduction method proposed by [Tibshirani \(1996\)](#) to screen the essential factors from among all kinds of modeling variables, solve the collinearity problem, and establish an optimal subset of independent variables, thereby improving the model structure. Then, we adopted a multinomial logit model to explore the relationship between variation in the research outcomes and modeling factors. To explain heteroscedasticity and study dependency, we

TABLE 1. Description and basic statistics of research findings and modeling factors.

Variable	N	N(1)	Mean	Std dev	Description
Research findings					
Positive and significant	2566	514	0.20	0.40	1 if the obtained coef was positive and significant (0 otherwise)
Negative and significant	2566	694	0.27	0.44	1 if the obtained coef was negative and significant (0 otherwise)
Positive and insignificant	2566	715	0.28	0.45	1 if the obtained coef was positive and insignificant (0 otherwise)
Negative and insignificant	2566	643	0.25	0.43	1 if the obtained coef was negative and insignificant (0 otherwise)
Research regions					
Africa	2777	388	0.14	0.35	1 if African countries were explored (0 otherwise)
Asia	2777	1101	0.40	0.49	1 if Asian countries were explored (0 otherwise)
Europe	2777	689	0.25	0.43	1 if European countries were explored (0 otherwise)
North America	2777	379	0.14	0.34	1 if North American countries were explored (0 otherwise)
South America	2777	678	0.24	0.43	1 if South American countries were explored (0 otherwise)
Oceania	2777	172	0.06	0.24	1 if Oceanian countries were explored (0 otherwise)
Research countries					
India	2777	380	0.14	0.34	1 if India was explored (0 otherwise)
United States	2777	332	0.12	0.32	1 if the United States was explored (0 otherwise)
China	2777	329	0.12	0.32	1 if China was explored (0 otherwise)
Bangladesh	2777	217	0.08	0.27	1 if Bangladesh was explored (0 otherwise)
Statistical analysis methods					
Kendall	2777	96	0.03	0.18	1 if Kendall test was adopted (0 otherwise)
Spearman	2777	630	0.23	0.42	1 if Spearman test was adopted (0 otherwise)
Pearson	2777	1479	0.53	0.50	1 if Pearson test was adopted (0 otherwise)
Regression	2777	572	0.21	0.40	1 if regression technique was adopted (0 otherwise)
Weather variables					
Temperature	2777	1185	0.43	0.50	1 if the investigated weather variable was temperature (0 otherwise)
Relative humidity	2777	712	0.26	0.44	1 if the investigated weather variable was relative humidity (0 otherwise)
Precipitation	2777	570	0.21	0.40	1 if the investigated weather variable was precipitation (0 otherwise)
Wind speed	2777	211	0.08	0.27	1 if the investigated weather variable was wind speed (0 otherwise)
Air pressure	2777	54	0.02	0.14	1 if the investigated weather variable was air pressure (0 otherwise)
Absolute humidity	2777	62	0.02	0.15	1 if the investigated weather variable was absolute humidity (0 otherwise)
Dewpoint temperature	2777	47	0.02	0.13	1 if the investigated weather variable was dewpoint temperature (0 otherwise)
Solar energy	2777	42	0.02	0.12	1 if the investigated weather variable was solar energy (0 otherwise)

estimated the multinomial logit model with robust standard errors by studying clustering. The multinomial logit model for metaregression analysis was specified as follows:

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \cdots + \beta_k x_{kij} + u_{ij}, \quad (1)$$

where y_{ij} is the i th estimated effect drawn from study j and includes four categories. Based on the 5% significance level, $y_{ij} = 1$ means that the reported estimate is positive and significant at least at 5%, $y_{ij} = 2$ means that the reported estimate is negative and insignificant at least at 5%, $y_{ij} = 3$ means that the

FIG. 6. The summary of the metaregression results in a graphical format. Red indicates a positive and significant effect between the modeling factor and COVID-19 spread, blue indicates a negative and significant effect between the modeling factor and COVID-19 spread, and gray indicates that the modeling factor was omitted by the LASSO regression.

reported estimate is positive and insignificant, and $y_{ij} = 4$ means that the reported estimate is negative and insignificant. Also, x_{kij} is the modeling characteristic variable k in the estimated effect i drawn from study j , β_k is the regression coefficient to be estimated, which reflects the influence of the characteristic variable k on y_{ij} , β_0 is the constant term of y_{ij} , which means the value given to all the modeling characteristic variables equals zero, and u_{ij} is the error term. The multiple linear regression model for metaregression analysis was specified as follows:

$$\text{coefficient}_{ij} = \beta_0 + \beta_{01}x_{1ij} + \beta_{02}x_{2ij} + \cdots + \beta_{0k}x_{kij} + \varepsilon_{ij}, \quad (2)$$

where coefficient_{ij} is the estimated correlation coefficient i drawn from study j , β_{0k} denotes the regression coefficient to be estimated, β_{00} is the constant term, and ε_{ij} is the error term.

b. Results

We show the metaregression results separately through three steps, including the metaregression results based on all correlation coefficients that included time-lagged effects collected from both correlation tests and linear regression analysis, correlation coefficients only derived from correlation tests, as well as correlation coefficients only derived from regression analysis. The positive/negative and significant results of the metaregression results are summarized graphically in Fig. 6.

This summary reveals a significant difference caused by different statistical analysis methods (Fig. 6). First, based on all correlation coefficients with time-lagged effects, we find the following three results: 1) Countries in Africa, Asia, and North America tended to report positive and significant associations between weather and COVID-19 spread. 2) The

United States tended to report negative and significant associations. 3) Studies using temperature, air pressure, and dewpoint temperature as the weather variables tended to report positive and significant associations. Second, based on correlation coefficients from correlation tests with time-lagged effects, we find the following three results: 1) Countries in Africa, Asia, Europe, and North America tended to report positive and significant associations. 2) India tended to report positive and significant associations. 3) Studies using absolute humidity as the weather variable tended to report negative and significant associations. Third, based on correlation coefficients from linear regression analysis with time-lagged effects, we find these three results: 1) Countries in Europe tended to report positive and significant associations. In contrast, countries in South America tended to report negative and significant associations. 2) Bangladesh tended to report negative and significant associations. 3) For weather effects, if temperature, relative humidity, precipitation, wind speed, air pressure, and dewpoint temperature were used as weather variables, then the research outcomes tended to report positive and significant associations.

These results mean the research outcomes depended on the analysis methods employed in each study. Specifically, studies that used correlation tests produced research outcomes that were functions of the study location (e.g., positive and significant associations in countries from Africa, Asia, Europe, and North America), whereas studies that used linear regression produced research outcomes that were functions of the analyzed weather variables (e.g., positive and significant associations for temperature, relative humidity, precipitation, wind speed, air pressure, and dewpoint temperature effects). Also, the effects of modeling factors have yielded consistent results

TABLE 2. Metaregression results on the estimated effects of weather on COVID-19 spread based on all correlation coefficients including time-lagged effects. The standard errors are shown in parentheses, and they are clustered by studies. Also, one, two, and three asterisks stand for 10%, 5%, and 1% levels of significance, respectively.

Variables	Multinomial logit model—marginal effects			
	Positive and significant	Negative and significant	Positive and insignificant	Negative and insignificant
Africa	0.278*** (0.095)	−0.020 (0.133)	−0.121* (0.072)	−0.136** (0.066)
Asia	0.386*** (0.059)	−0.266** (0.114)	0.025 (0.079)	−0.145** (0.066)
Europe	0.190** (0.084)	0.003 (0.066)	−0.052 (0.065)	−0.142*** (0.048)
North America	0.411*** (0.134)	−0.239*** (0.064)	0.025 (0.095)	−0.198*** (0.068)
South America	−0.146*** (0.019)	0.238** (0.109)	−0.011 (0.068)	−0.081 (0.052)
Oceania	−0.124*** (0.038)	−0.103 (0.112)	−0.116** (0.045)	0.343*** (0.096)
United States	−0.053* (0.029)	0.242** (0.113)	−0.195*** (0.064)	0.006 (0.091)
India	0.045 (0.054)	−0.036 (0.102)	−0.025 (0.075)	0.016 (0.060)
China	−0.053* (0.031)	0.287 (0.196)	−0.230*** (0.080)	−0.004 (0.122)
Bangladesh	0.023 (0.070)	0.170 (0.136)	−0.137 (0.103)	−0.057 (0.076)
Temperature	0.251* (0.141)	−0.092 (0.167)	−0.164 (0.171)	0.006 (0.058)
Relative humidity	0.059 (0.079)	−0.166 (0.122)	−0.096 (0.144)	0.204** (0.088)
Precipitation	0.222 (0.168)	−0.321*** (0.057)	0.042 (0.159)	0.056 (0.111)
Wind speed	0.390 (0.240)	−0.147 (0.096)	−0.244** (0.117)	0.001 (0.138)
Air pressure	0.737*** (0.151)	−0.225*** (0.051)	−0.268*** (0.098)	−0.245*** (0.039)
Absolute humidity	0.308 (0.305)	0.081 (0.252)	−0.281*** (0.099)	−0.109 (0.105)
Dewpoint temperature	0.600** (0.249)	−0.014 (0.248)	−0.274*** (0.096)	−0.311*** (0.018)
Solar energy	−0.103*** (0.038)	0.014 (0.132)	−0.287*** (0.091)	0.376*** (0.128)
Control variable	2.86×10^{-4}	-6.37×10^{-4}	-7.62×10^{-5}	4.27×10^{-4}
(Observed days)	(2.67×10^{-4})	(1.02×10^{-3})	(6.28×10^{-4})	(5.46×10^{-4})
N	2491	2491	2491	2491

despite these different statistical analysis methods. For instance, countries in Africa, Asia, and North America tended to report positive and significant associations based on all correlation coefficients and correlation coefficients only from correlation tests. In contrast, using temperature, air pressure, and dewpoint temperature as the weather variables tended to yield positive and significant associations based on all correlation coefficients and correlation coefficients only from linear regression analysis.

Tables 2–4 describe the three-step metaregression analysis results in detail. First, based on all 2491 correlation coefficients that included time-lagged effects, the LASSO regression analysis showed that 16 associated modeling factors can be included in the further regression analysis and the variables for South America and China were omitted due to the

collinearity problem. The reason why 2491 valid correlation coefficients were obtained instead of 2777 observations is that some of the original studies did not provide sufficient information on the specific modeling factors they used. For example, some studies did not mention the significance level (e.g., Ghosh et al. 2020; Lin et al. 2020; Daneshvar et al. 2021); other studies either did not mention the number of observation days or time period (e.g., Wu et al. 2020; Metelmann et al. 2021; Pan et al. 2021). Thus, these correlation coefficients were excluded from the metaregression analysis. This method shows that similar results can be obtained to those described in section 4. Specifically, countries in Africa, Asia, and North America tended to report positive and significant associations between COVID-19 and weather (Table 2). In contrast, the

TABLE 3. Metaregression results on the estimated effects and strength of weather on COVID-19 spread based on correlation coefficients from correlation tests including time-lagged effects. South America, United States, and temperature were not included because of collinearity. The standard errors are shown in parentheses, and they are clustered by studies. Also, one, two, and three asterisks stand for 10%, 5%, and 1% levels of significance, respectively.

Variables	Correlation coef	Multinomial logit model—marginal effects			
		Positive and significant	Negative and significant	Positive and insignificant	Negative and insignificant
Africa	0.010 (0.030)	0.567*** (0.173)	−0.175** (0.087)	−0.240** (0.095)	−0.152** (0.082)
Asia	−0.028 (0.032)	0.642*** (0.137)	−0.321*** (0.073)	−0.152 (0.100)	−0.169** (0.071)
Europe	−0.106 (0.067)	0.452** (0.194)	−0.182** (0.066)	−0.140 (0.103)	−0.130* (0.073)
North America	−0.037 (0.039)	0.741*** (0.153)	−0.241*** (0.040)	−0.253** (0.114)	−0.247*** (0.044)
Oceania	0.804** (0.230)	−0.096*** (0.034)	−0.302*** (0.040)	−0.146*** (0.033)	0.544*** (0.031)
India	−0.121 (0.074)	0.264* (0.140)	−0.118 (0.079)	−0.114 (0.111)	−0.032 (0.091)
China	−0.035 (0.130)	−0.103*** (0.038)	0.258 (0.268)	−0.246*** (0.075)	0.090 (0.182)
Bangladesh	−0.108 (0.150)	0.142 (0.148)	−0.068 (0.113)	−0.055 (0.136)	−0.020 (0.113)
Relative humidity	0.038 (0.021)	−0.156*** (0.039)	−0.071 (0.173)	0.003 (0.116)	0.224*** (0.062)
Precipitation	−0.032** (0.011)	−0.058*** (0.019)	−0.236*** (0.062)	0.212*** (0.029)	0.082 (0.060)
Wind speed	−0.285*** (0.075)	−0.063 (0.041)	−0.004 (0.082)	−0.116 (0.142)	0.183 (0.137)
Air pressure	−0.242** (0.067)	0.160 (0.099)	−0.002 (0.106)	0.142 (0.087)	−0.301*** (0.027)
Absolute humidity	−0.125 (0.101)	−0.052 (0.033)	0.696*** (0.118)	−0.468*** (0.035)	−0.175** (0.083)
Dewpoint temperature	−0.259* (0.097)	−0.002 (0.062)	0.451 (0.333)	−0.112 (0.285)	−0.338*** (0.028)
Solar energy	−0.022 (0.122)	−0.107** (0.042)	0.315 (0.192)	−0.298*** (0.107)	0.090 (0.188)
Control variable (Observed days)	6.97×10^{-4} (6.08×10^{-4})	5.64×10^{-4} (4.38×10^{-4})	-1.06×10^{-3} (1.13×10^{-3})	1.30×10^{-4} (8.74×10^{-4})	3.62×10^{-4} (7.30×10^{-4})
Constant	0.569*** (0.058)				
R^2	0.376				
N	911	2004	2004	2004	2004

probability of reporting positive and significant associations was lower for countries in Oceania. Moreover, the United States tended to report negative and significant associations. For weather effects, if evaluation models in the original studies used temperature, air pressure, and dewpoint temperature as weather variables, the research outcomes tended to report positive and significant associations, and the probability of reporting positive associations was lower if solar energy was used as the weather variable. These results mean different geographic regions and weather variables could influence the investigated research outcomes between weather and COVID-19.

Second, for those studies using correlation tests, when the LASSO regression analysis is repeated only for those 2004 correlation coefficients, 15 associated modeling factors were

identified, and the variables of South America, United States, and temperature were omitted due to the collinearity problem. The metaregression results were reported in Table 3. First, countries in Africa, Asia, Europe, and North America tended to report positive and significant associations. In contrast, the probability of reporting positive associations was lower for countries in Oceania. Second, India tended to report positive and significant associations, and the probability of reporting positive associations for China was lower. Third, for weather variables, if relative humidity and precipitation were used as weather variables, then the research outcomes tended to report insignificant associations, and, if absolute humidity was used as the weather variable, the result outcomes tended to report negative associations. Also, the significant degree of

TABLE 4. Metaregression results on the estimated effects and strength of weather on COVID-19 spread based on correlation coefficients from regression analysis including time-lagged effects. The standard errors are shown in parentheses, and they are clustered by studies. Also, one, two, and three asterisks stand for 10%, 5%, and 1% levels of significance, respectively.

Variables	Correlation coef	Multinomial logit model—Marginal effects			
		Positive and significant	Negative and significant	Positive and insignificant	Negative and insignificant
Africa	−13.286** (4.586)	−0.177** (0.085)	−0.481*** (0.085)	0.994*** (0.006)	−0.336*** (0.063)
Asia	−5.499 (3.821)	0.008 (0.040)	−0.680*** (0.189)	0.950*** (0.030)	−0.277 (0.193)
Europe	−1.250 (2.911)	0.905*** (0.109)	0.044 (0.055)	−0.998*** (0.002)	0.049 (0.063)
North America	−2.854 (4.135)	−0.093 (0.090)	−0.743*** (0.123)	1.000*** (5.920 × 10 ^{−5})	−0.164* (0.086)
South America	10.274** (3.525)	−0.492*** (0.131)	0.773*** (0.091)	−0.005 (0.012)	−0.276** (0.108)
Oceania	−6.399** (1.833)	−0.616*** (0.122)	−0.155*** (0.056)	0.999*** (0.001)	−0.228*** (0.078)
United States	−4.479 (4.137)	0.091 (0.101)	0.252 (0.210)	0.003 (0.014)	−0.347** (0.162)
India	0.834 (3.411)	−0.022 (0.073)	−0.415*** (0.109)	0.022 (0.021)	0.414*** (0.126)
China	−3.003 (2.644)	−0.089 (0.103)	−0.014 (0.156)	−0.013 (0.018)	0.117 (0.141)
Bangladesh	11.278 (7.245)	0.010 (0.121)	0.540*** (0.098)	−0.216*** (0.049)	−0.333*** (0.083)
Temperature	3.543* (1.709)	0.302** (0.151)	−0.442* (0.245)	0.022*** (0.007)	0.118 (0.150)
Relative humidity	0.298 (0.946)	0.379** (0.133)	−0.507** (0.135)	0.020** (0.008)	0.108 (0.099)
Precipitation	4.383 (3.492)	0.299* (0.158)	−0.425*** (0.062)	0.146*** (0.055)	−0.019 (0.155)
Wind speed	9.147 (5.942)	0.677*** (0.088)	−0.348*** (0.050)	0.034 (0.046)	−0.363*** (0.071)
Air pressure	29.610 (18.642)	0.685*** (0.141)	−0.390*** (0.054)	−0.019*** (0.003)	−0.276* (0.152)
Absolute humidity	4.491 (2.695)	0.174 (0.269)	−0.315*** (0.054)	0.105 (0.086)	0.036 (0.214)
Dewpoint temperature	9.853** (2.967)	0.749*** (0.046)	−0.346*** (0.053)	−0.013*** (0.003)	−0.391*** (0.044)
Solar energy	5.920 (3.195)	−0.285*** (0.051)	−0.260*** (0.097)	−0.019*** (0.003)	0.564*** (0.094)
Control variable (Observed days)	0.060 (0.032)	−2.26 × 10 ^{−4} (9.52 × 10 ^{−4})	1.09 × 10 ^{−3} (7.82 × 10 ^{−4})	−1.55 × 10 ^{−4} (1.41 × 10 ^{−4})	−7.12 × 10 ^{−4} (1.17 × 10 ^{−3})
Constant	2.184 (2.628)				
R ²	0.237				
N	274	487	487	487	487

correlation tended to be weak between precipitation, wind speed, air pressure, dewpoint temperature, and COVID-19 spread. Moreover, the probability of reporting positive associations was lower if solar energy was used as the weather variable. These results mean the effects of geographical regions were more significant than other modeling factors in influencing research outcomes based on correlation coefficients from correlation tests.

Third, for those studies using regression analysis, the LASSO regression analysis showed that all the modeling

factors can be included in the regression analysis based on the 487 correlation coefficients. The metaregression results were reported in Table 4. First, countries in Europe tended to report positive and significant associations. In contrast, countries in South America tended to report negative and significant associations, and the significant strength of the linear relationship between COVID-19 and weather tended to be strong for countries in South America. Second, Bangladesh tended to report negative and significant associations. Third,

for weather variables, most of the weather variables tended to report positive and significant associations, including temperature, relative humidity, precipitation, wind speed, air pressure, and dewpoint temperature. Also, if dewpoint temperature was used as the weather variable, then the significant strength of the linear relationship tended to be strong. However, the probability of reporting positive associations was still lower if solar energy was used as the weather variable. These results mean the effects of weather variables were more significant than other modeling factors in influencing research outcomes based on correlation coefficients from regression analysis.

6. Discussion

Although the weather effects on COVID-19 spread have been investigated by 158 previous studies in a short period of time since the outbreak of the pandemic, their results were inconsistent. This article, for the first time, investigated the relationship between weather and COVID-19 in the extant literature (up until 31 March 2021) through an overview and a metaregression analysis based on 4793 separate and previously published correlation coefficients with the goal of identifying consistencies among the studies.

First, different statistical analysis methods caused significant differences in research outcomes on the associations between COVID-19 and weather. Regression-based approaches are relatively effective in controlling for other potentially confounding factors (e.g., [McNamee 2005](#)). In contrast, correlation tests (i.e., Pearson test, Spearman test, Kendall test) can only explore the relationship between the two variables being studied (e.g., [Shih and Fay 2017](#)), with no consideration of confounding factors. Specifically, the effect of weather conditions on the spread is likely to be sensitive to some possible confounding factors in quantitative studies, including social and economic conditions (e.g., population density and public awareness) and public health policies (e.g., lockdown, travel restrictions, and vaccination).

In addition, human behavior also may display seasonal cycles that facilitate or inhibit the spread of the virus. For instance, the school cycle for children and university students often occurs in the local cool season, thereby facilitating the daily cycle of indoor social mixing at day and return to family homes at night that can encourage the spread of the virus. Also, people tend to stay indoors when it is especially cold or hot, depending on the local climate and the prevalence of heating/cooling systems in local housing. If the time people spent indoors is not accounted for, interpreting the results of these kinds of studies will be challenging. Thus, recognizing the weather effects on COVID-19 spread involves more than just knowing the weather conditions.

Second, we found differences in the association between weather and COVID-19 by geographic region. For instance, countries in Africa, Asia, Europe, or North America were more likely to report positive weather effects, whereas countries in South America were more likely to report negative weather effects. Globally, positive temperature effects were found, especially for Asian countries. There are two confounding effects

that merit discussion, including the impact of the rapid outbreak of COVID-19 pandemic in the early stages and the climate of Asia. In many Asian countries, in particular, the pandemic took off in the early months of 2020, and these regions were experiencing the seasonal change from winter to spring (e.g., [Karapiperis et al. 2020](#)). As the temperature (and solar radiation) increased, the COVID-19 transmissibility also increased during the rapid outbreak of the pandemic. Thus, some studies showed that the COVID-19 spread was positively associated with temperature and may have conflated the rise in the number of COVID-19 cases with the seasonal increase in temperature. Therefore, the confounding effects of the positive associations between rising temperatures and the COVID-19 spread may have been clearer in Asia than other regions.

Third, our study found higher solar energy was associated with less COVID-19 spread. In the metaregression analysis in [section 5b](#), using solar energy as the weather variable lowered the probability of reporting positive associations. Also, the results show a remarkable consistency with only higher solar energy being reported with less COVID-19 spread in all regions ([Fig. 5](#)). Although ultraviolet radiation may also influence human behavior such as time spent indoors or socializing, both laboratory and epidemiological studies confirmed that the negative effects of solar energy on COVID-19 are expected because of the characteristics of ultraviolet radiation. First, previous studies showed the link between ultraviolet radiation and COVID-19. For example, ultraviolet radiation from simulated sunlight has been shown to deactivate the SARS-CoV-2 virus residing on surfaces ([Ratnesar-Shumate et al. 2020](#)) and in the air ([Schuit et al. 2020](#)). Also, ultraviolet radiation was associated with reduced daily COVID-19 growth rates from an empirical study based on the number of COVID-19 cases from 173 countries and ultraviolet radiation from a global reanalysis ([Carleton et al. 2021](#)). Second, solar energy is a main source of vitamin D for humans (e.g., [Moan et al. 2008](#)), and vitamin D promotes the normal operation of the human immune system (e.g., [Kamen and Tangpricha 2010](#); [Lanham-New et al. 2020](#)) and also appears to inhibit pulmonary inflammatory responses (e.g., [Hughes and Norton 2009](#)). In addition, vitamin D has also been supported scientifically to be protective in preventing COVID-19 infections (e.g., [Grant et al. 2020](#)), although administering high doses of vitamin D as has been proposed (e.g., [Ebadi and Montano-Loza 2020](#)) is not recommended ([Lanham-New et al. 2020](#)). Thus, the increased dose of solar energy in the transition from winter to summer may be associated with fewer COVID-19 infections because of the role of UV radiation and vitamin D.

One aspect that we could not investigate with the published literature was the inclusion of the small number of reported correlation coefficients of the nonlinear regression analysis. As the pandemic continues to spread, investigations between weather and COVID-19 continued after the deadline of our literature search period (i.e., after 31 March 2021). Although most of these newer studies still draw findings from linear analysis (e.g., [Chakraborty et al. 2021](#); [Versaci et al. 2021](#)), nonlinear regression analysis is also becoming increasingly popular (e.g., [Sera et al. 2021](#)). In this case, it would be feasible to perform metaregression analysis on the correlation coefficients collected from the nonlinear regression model in

future research. For example, the coefficients obtained from quadratic regression models can be divided into estimated effects of U-shaped and inverted U-shaped according to the direction of the quadratic regression coefficients. Also, the absolute value of quadratic coefficients can also be used to analyze the strength of the relationship of quadratic curve analysis. In fact, that the stability of the virus may be maximum at moderate temperatures (i.e., very low and very high temperatures may make the virus inactive) argues for a nonlinear model and may explain why linear models for temperature fail to produce definitive results (e.g., Fig. 2). In addition, although the metaregression approach used in this article accounted for the effects of weather variable on COVID-19, the effects of air quality (e.g., particulate matter, ozone, carbon monoxide, and nitrogen dioxide) were not investigated, an opportunity for future research.

7. Summary and recommendations

Trying to determine the effect of the weather on COVID-19, especially given all the confounding effects and the inadequacies of the available datasets, is difficult enough. Trying to do so during the phase of rapid growth and spread of the pandemic in its early stages would be next to impossible. Clearly, the exponential growth of COVID-19 cases due to the rapid growth of the pandemic likely has overwhelmed more subtle effects due to the influence of the weather on COVID-19 (e.g., Engelbrecht and Scholes 2021). However, as the pandemic evolves, a scenario is likely to develop where the virus exhibits seasonality (e.g., Merow and Urban 2020). Thus, understanding the effects of weather on the spread of COVID-19 is critical for identifying current and future adaptation strategies. The scientific literature to date provides contrasting evidence for the effect of the weather on the spread of COVID-19, with some studies indicating that weather conditions can promote the spread of COVID-19, whereas others indicating that weather conditions can mitigate its spread.

We conducted a metaregression analysis to examine the effects of weather on COVID-19 spread, arriving at four major findings:

- First, more than half of the 158 studies did not consider the time lag between infection and reporting, rendering these studies ineffective. The cumulative lags between the weather on the day of transmission between individuals and when that case is recorded must be included in any such study. These lags include the incubation period within an individual, the time required for symptoms to appear, the time required to diagnose the disease, and the time for the case to be recorded in official databases.
- Second, correlation tests and regression analysis are commonly used statistical methods for assessing the associations between weather and COVID-19 spread. However, these two statistical methods resulted in different research outcomes. Specifically, studies using correlation tests produced research outcomes that were functions of the geographic regions, whereas studies using linear regression produced research outcomes that were functions of the analyzed weather variables.
- Third, the effects of the weather on COVID-19 were inconsistent across different geographic regions. Countries in Africa, Asia, Europe, or North America were more likely to report positive weather effects, whereas countries in North America were more likely to report negative weather effects. Specifically, Asian countries were especially more likely to report positive temperature effects than other regions, likely because the growth in COVID-19 cases in these countries paralleled the seasonal increase in temperature in the transition from winter to spring.
- Fourth, despite the effects of many of the weather variables being inconsistent across the six geographic regions we studied, negative associations between solar energy and COVID-19 spread were found in all geographic regions, possibly due to the benefits of ultraviolet radiation and vitamin D on reducing COVID-19 spread.

Our research, which has investigated 158 studies examining the relationship between weather and the spread of COVID-19, has led to several important results that will inform those performing such research in the future. In this way, we offer the following five recommendations for implementing best practices in the future.

First, it is crucial that all future studies include a time lag between the stimulus on the day of infection (i.e., the weather) and the outcome (i.e., the COVID-19 case being recorded in the official database). Prior case studies suggested the mean incubation period is 4–5 days (e.g., Guan et al. 2020; Li et al. 2020; Linton et al. 2020), with a range of 2–14 days (e.g., Linton et al. 2020), which may also depend on the age of the person (e.g., Tan et al. 2020). Then, the mean period between symptom onset and case confirmation is 4 days with a range of 2–7 days (Nie et al. 2020). Also, there is a time required to record the case in official databases, which may vary due to the detection techniques of virus and speed of information transmission. Therefore, analysts should be cautious when overly specifying the lags in future modeling efforts. Some flexibility in selecting the lag is required (e.g., Runkle et al. 2020; Yuan et al. 2021).

Second, regression analysis is a more preferred statistical analysis method to employ than correlation coefficient tests because regression analysis can separate out some confounding factors from the weather. There are a number of obvious confounding factors (e.g., economic development, age structure, public health policies, population concentration, public awareness, vaccination, and human behavior) that affect the spread of the pandemic and should be controlled and considered for investigations between weather and COVID-19 spread. It is difficult to control for all confounding factors. What we recommend here is to provide reference for future studies. The data of socioeconomic condition (i.e., gross regional product per capita and age structure), lockdown level, travel restrictions, and number of vaccinations is often public and is relatively easier to obtain and control in regression analysis. The application of merging multisource methods may provide a powerful tool and new insight to address the data of confounding factors that are not available. For instance, remote sensing and agent-based modeling may provide new information on population mobility and human-behavior simulation during the study period, and online

surveys or field surveys may be able to assess the level of public awareness by asking the public whether they are willing to maintain social distancing or to wear masks.

Third, the real relationship between the weather and COVID-19 is not necessarily linear. For example, studies of the viability of the virus have shown the value in nonlinear regressions (e.g., Fang et al. 2020; Xu et al. 2021; Zhang et al. 2020; Gao et al. 2021). Prior studies also found nonlinear relationships between other diseases and weather (e.g., Talmoudi et al. 2017). Thus, it is imperative to investigate the nonlinear responses. We also encourage future metaregression analyses using a projected larger number of nonlinear correlation coefficients.

Fourth, the mean number of observed days in all the 158 studies was 94 days (Table S1 in the online supplemental material). The time period was short and sensitive (e.g., middle of the cold or warm season, during the transition seasons when daily changes are changing more rapidly). As the pandemic progresses, future studies have the means to investigate longer periods of record. In addition, the pandemic first appeared in December 2019 and then broke out globally in just a few months. Thus, the rapid growth of the outbreak in its early stages would overwhelm the subtle effects of weather changes. Moreover, care should be taken to avoid conflating effects that have independent causes (e.g., rapid growth in COVID-19 at the same time as seasonal changes).

Fifth, the multicollinearity between weather variables should be eliminated before regression analysis and to secure sufficient robustness in the research outcomes. For instance, relative humidity was one of the most commonly used weather variables in these previous studies, in part because it is easy to understand and common in weather forecasts. Unfortunately, the relative humidity depends upon the temperature. Absolute humidity is another measure of the amount of water vapor in the air, which is related to relative humidity and temperature. Thus, the problem is that these three variables are correlated (e.g., Davis et al. 2016), which means multivariable methods that assume independence are inappropriate when using these interrelated variables together. We used the LASSO method to eliminate the multicollinearity between modeling factors, but that is not the only way. We recommend that authors of future studies check the degree of correlation between the included variables and screen out the independent and effective variables for analysis before starting to conduct further analysis.

In conclusion, should the COVID-19 pandemic evolve from a phase in which rapid outbreaks happen to a phase dominated by cycles (e.g., Charters and Heitman 2021), perhaps modulated by seasonality (e.g., Engelbrecht and Scholes 2021), then the kind of research that has been proposed in this article will become even more important. Thus, it is imperative on the research community to make the best use of our collective research efforts, ensuring that the investment of time, money, and effort goes toward rigorous research that will provide the greatest insight into the outbreak. In that way, avoiding the pitfalls of previous research projects, which are documented in this study, and following the best-practice recommendations that we propose will be the surest way to provide guidance to inform decision-makers in public health and public policy to make decisions to bring the COVID-19 pandemic under control.

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Data availability statement. The datasets and code used during the current study can be found online (<http://doi.org/10.48420/c.5677333>).

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