Novel Evidence Showing the Possible Effect of Environmental Variables on COVID-19 Spread

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Abstract Coronavirus disease (COVID-19) remains a serious issue, and the role played by meteorological indicators in the process of virus spread has been a topic of academic discussion. Previous studies reached different conclusions due to inconsistent methods, disparate meteorological indicators, and specific time periods or regions. This manuscript is based on seven daily meteorological indicators in the NCEP reanalysis data set and COVID-19 data repository of Johns Hopkins University from 22 January 2020 to 1 June 2021. Results showed that worldwide average temperature and precipitable water (PW) had the strongest correlation ($\rho > 0.9$, $p < 0.001$) than common meteorological indicators. The temperature or PW threshold suitable for the spread of COVID-19 may be a key point in the prediction of the next round of its outbreak.

Supporting Information: Supporting Information may be found in the online version of this article.

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Plain Language Summary Climate change has altered life's living environment; humans seem to be able to adapt to climate change within a certain range. This adaptability seems to be human talent, but how about a coronavirus? The impact of environmental variables on coronavirus disease (COVID-19) spread varies between regions. The two meteorological variables that are most likely to affect the distribution of COVID-19 have significant latitude patterns, which means that in areas with higher climate temperatures, the temperature range for the maximum spread of COVID-19 is higher, while in areas with lower climate temperatures, the temperature for the maximum spread of COVID-19 is lower. Perhaps it indicates that the virus also has the ability to adapt to climate change, even more so than humanity. The complete cessation of COVID-19 pandemic requires everyone's efforts.

1. Introduction

Coronavirus disease (COVID-19), which is of unknown origin, was declared a global pandemic on 11 March 2020 (Esakandari et al., 2020; Quintana et al., 2021). The virus causing COVID-19 may spread from person to person through droplets (Esakandari et al., 2020). Aerosol particles with diameters below 5 μm can remain infectious even after being transmitted for a long time over long distances (Dancer et al., 2020; Schijven et al., 2021; WHO, 2020). Although the airborne transmission effect remains under investigation (WHO, 2020), reasonable precautions are needed to ensure safety (Wilson et al., 2020).

Sun et al. compared three epidemics (severe acute respiratory syndrome-associated coronavirus [SARS-CoV], Middle East respiratory syndrome-CoV, and COVID-19) over the past two decades and observed that the local areas were in a state of extreme drought when the diseases were first diagnosed; they speculated humidity as a more critical environmental variable than temperature that determines the onset of a pandemic (Sun et al., 2020). Although the exact mechanism remains unclear, several studies have suggested that high temperature and
humidity may reduce virus toxicity and inhibit the virus spread (Chatziprodromidou et al., 2020; Demongeot et al., 2020). Another evidence supporting these arguments indicates that most respiratory virus outbreaks have seasonal fluctuations (Moriyama et al., 2020; Tamerius et al., 2013). Influenza virus, human CoV, and human respiratory syncytial virus show peak incidences in winter. In summer, strong ultraviolet radiation may inactivate the virus (Gunthe et al., 2020; Sagripanti & Lytle, 2020; Sooryanarain & Elankumaran, 2015). More recent research has suggested that air drying capacity and ultraviolet radiation are the important environmental determinants of COVID-19 seasonality (Choi et al., 2021). Seasonal climate characteristics may also influence the host susceptibility from a physiological view to promote the virus spread (Paraskevis et al., 2021; Tamerius et al., 2013). Particles suspended in the air may serve as carriers for virus transmission. High-concentration particle pollution may be one of the reasons for the rapid spread of COVID-19 and its high mortality rate (Chat-topadhay & Shaw, 2021; Li et al., 2020; Setti et al., 2020; Yao et al., 2020); moreover, meteorological conditions are closely related to air pollution.

However, not all studies have reached a unified conclusion (Kerr et al., 2021). A study of 122 cities in China reported that the average temperature was approximately linearly related to the number of new confirmed cases daily when it was below 3°C. For every 1°C increase, the number of confirmed cases per day increased by 4.861% in the period from 23 January to 29 February 2020 (Xie & Zhu, 2020). Another study covering 166 countries (except China) around the world attained the opposite result and claimed that every 1°C increase in temperature reduced the number of confirmed cases per day by 3.08%; the study period ended on 27 March 2020 (Wu et al., 2020). Jüni et al. (2020) contended that COVID-19 growth is not correlated with latitude and temperature but weakly correlated with humidity (Jüni et al., 2020). Gunthe et al. (2020) believed that the spread of COVID-19 is uncorrelated with humidity but correlated with temperature and ultraviolet intensity (Gunthe et al., 2020). Sun et al. (2020) suggested the opposite (Sun et al., 2020). Several studies reported temperature and humidity as important indicators that affect COVID-19 (Bashir et al., 2020; Bolaño-Ortíz et al., 2020), whereas others found significant lagging correlations between meteorological indicators and the epidemic (Hoang & Tran, 2021; Liu et al., 2020). The above studies seem to only reach a consensus on “The spread of the virus cannot be stopped just by meteorological effect.”

In addition to affecting the virus survival condition and the dynamic mechanism of virus transmission (Gunthe et al., 2020; Sagripanti & Lytle, 2020; Setti et al., 2020; Sooryanarain & Elankumaran, 2015; WHO, 2020), meteorological indicators can restrict or expand the virus spread platform by influencing human activities. Limited by the epidemiological data of COVID-19, as far as we know, previous studies have been highly targeted, often starting from a regional perspective, analyzing COVID-19 trends in a relatively short period, and mostly discussing temperature and humidity variables. Despite their excellent reference value, related studies have not fully analyzed the potential relationship between COVID-19 and meteorological indicators from a relatively long-term and large-scale perspective. This gap may be one of the reasons for the evident differences or contradicting results of various studies. As COVID-19 spread, factual evidence that was inconsistent with the earlier results gradually emerged (Kerr et al., 2021; Paraskevis et al., 2021). Therefore, although the relationship between meteorological indicators and COVID-19 has been relatively extensively studied in the past, a more comprehensive discussion on a prolonged temporal and spatial scale is still needed based on the development and changes in the epidemic. This manuscript selected seven daily meteorological parameters (average temperature, relative humidity [RH], surface air pressure [AP], precipitable water [PW], wind speed [W], daily temperature variation [TV], and daily AP variation) and the number of new confirmed COVID-19 cases/deaths per day and performed correlation analysis with 0, 3, 5, 7, 14, and 21-day lag to analyze the relationship between meteorological conditions and COVID-19 from a global perspective on the timescale of nearly a full year. As a result, we could summarize the patterns of latitude that may affect the coronavirus spread to provide new assistance for humanity to overcome the epidemic as soon as possible.

2. Data and Methods

2.1. Data

The COVID-19 data used in this paper were derived from the COVID-19 Data Repository by the Center for Systems Science and Engineering at Johns Hopkins University (Dong et al., 2020) from 22 January 2020 to 1 June 2021. The daily meteorological data were derived from the NCEP reanalysis data set by the NOAA Physical Sciences Laboratory Data Management; the data included surface temperature, RH, 10 m Gauss W, surface AP,
and PW, whereas the daily TV and daily pressure variation were calculated based on the daily temperature and daily AP, respectively, from 1 January to 1 June 2021 (Kalnay et al., 1996; NOAA, 1994).

2.2. Methods

The Pearson correlation analysis was used to calculate the correlations between meteorological indicators and the number of new confirmed COVID-19 cases and deaths per day. A significance test was also performed. Assuming that two random variables have the number \( N \), their Pearson correlation coefficient is defined as follows:

\[
\rho(A, B) = \frac{1}{N-1} \sum_{i=1}^{N} \left( \frac{A_i - \mu_A}{\sigma_A} \right) \left( \frac{B_i - \mu_B}{\sigma_B} \right)
\]

where \( \mu_A \) and \( \sigma_A \) are the mean and standard deviation of \( A \); respectively; \( \mu_B \) is the mean and \( \sigma_B \) is the standard deviation of \( B \) (Fisher, 1934; MathWorks, 2020).

Quadratic fitting functions between the temperature or PW corresponding to the maximum number of new confirmed cases or deaths on a day and latitude were obtained through the least squares method. The fitting algorithm used \( x \) to construct a Vandermonde matrix \( V \) with \( n + 1 \) columns and \( m = \text{length}(x) \) rows and generated a linear equation set (2); \( p = V'y \) was solved (MathWorks, 2020), and the fitting coefficients were obtained.

\[
\begin{bmatrix}
x_1^n & x_1^{n-1} & \cdots & 1 \\
x_2^n & x_2^{n-1} & \cdots & 1 \\
\vdots & \vdots & \ddots & \vdots \\
x_m^n & x_m^{n-1} & \cdots & 1
\end{bmatrix}
\begin{bmatrix}
p_1 \\
p_2 \\
p_{n+1}
\end{bmatrix}
= 
\begin{bmatrix}
y_1 \\
y_2 \\
y_m
\end{bmatrix}
\]

(2)

We used the coefficient of determination (also called \( R^2 \)) which is given by Equation 3, and adjusted \( R^2 \) which is given by Equation 4 to estimate the fitting effect (Miles, 2014).

\[
R^2 = \frac{SS_{\text{between}}}{SS_{\text{total}}}
\]

where \( SS_{\text{total}} \) refers to the total sum of squares. \( SS_{\text{between}} = \sum (y - \bar{y})^2 \), \( y \) is an outcome variable, \( \bar{y} \) is an average outcome variable. \( SS_{\text{between}} \) is the difference between the total sum of squares and the residual sum of squares, called the regression sum of squares.

\[
\text{Adj. } R^2 = 1 - (1 - R^2) \frac{N - 1}{N - k - 1}
\]

(4)

where \( N \) is the sample size and \( k \) is the number of predictor variables in the analysis. \( R^2 \) and adjusted \( R^2 \) refer to the quality of the fitting function; the closer the value is to 1, the better the fitting effect.

3. Results

3.1. Correlations Between COVID-19 Cases and Meteorological Indicators

3.1.1. Average Correlations Between COVID-19 and Meteorological Indicators of 269 Locations Worldwide

As of 1 June 2021, CoV has invaded 233 countries, areas, or territories, with the number of confirmed cases reaching 170,448,610 and deaths amounting to more than 3,500,000 worldwide (WHO, 2021a). Although 1,638,006,899 vaccine doses have been administered (WHO, 2021b), their effective duration is uncertain due to the high mutation rate of SARS-CoV-2 (the etiological agent of COVID-19; Cohen, 2019; Cui et al., 2019; Dawood, 2020; Del Rio & Camacho-Ortiz, 2020; Masters, 2006; Su et al., 2016; Wang et al., 2021), and patients who recovered after infection are also at risk of reinfection (Ozaras et al., 2020; To et al., 2020). Thus, COVID-19 remains a serious problem for all humanity.
Prior studies generally believed that the incubation period of COVID-19 lasts for 2–14 days (Dawood, 2020), with a median of 5–7 days (Elias et al., 2021; Lauer et al., 2020; Quesada et al., 2021). One of the latest studies estimated that the median incubation period is 7.76 days, and the 90th percentile incubation period is 14.28 days (Jing et al., 2020). Recently, Beijing has required overseas tourists to implement a 21-day quarantine strategy (14 days of medical quarantine monitoring +7 days of home health monitoring; Bikbov & Bikbov, 2021). Based on the characteristics of the COVID-19 incubation period, this paper correlated seven meteorological indicators and the confirmed COVID-19 cases and deaths per day with 0, 3, 5, 7, 14, and 21-day lag. Given that August and September are the boundaries between summer and autumn, to better analyze the potential correlations, this manuscript selected 31 August 2020, as a demarcation point. Pearson correlation analysis was performed on the meteorological indicators and COVID-19 cases in the first half of the year (from 22 January to 31 August 2020), the second half of the year (from 1 September to 31 December 2020), and the near full-year period (from 22 January to 31 December 2020). A significance test was performed. Table 1 shows the global average correlations between meteorological indicators and the number of confirmed COVID-19 cases/deaths. Table S1 in Supporting Information S1 shows the full significance levels.

As shown in Table 1, from 22 January to 31 August 2020, after calculating the average of 269 global locations that reported COVID-19 (hereinafter referred to as global average), the daily average temperature (T) and PW had the strongest positive correlations with confirmed cases ($\rho$ > 0.9, $p < 0.001$); it also showed positive but slightly weaker correlations with daily deaths ($\rho$ > 0.5, $p < 0.001$). The correlations between the daily W and the number of new confirmed COVID-19 cases/deaths were significantly negative ($\rho$ < −0.6, $p < 0.001$). The correlations between the remaining meteorological indicators and the number of confirmed COVID-19 cases/deaths were weak and insignificant ($\rho$ < 0.1). The correlations between daily $T$, PW, and confirmed COVID-19 cases generally increased with the increase in lag days. The correlations between T/PW and the number of COVID-19 non-lag deaths were stronger than those in the lag days. The correlations between W and the number of confirmed COVID-19 cases/deaths increased with the increase in lag days.

From 1 September to 31 December 2020, the daily T, PW, and W were still the variables that had the strongest correlation with confirmed COVID-19 cases/deaths ($\rho$ > 0.55, $p < 0.001$). T/PW were negatively correlated with the number of confirmed COVID-19 cases/deaths ($\rho$ < −0.7, $p < 0.001$), whereas W showed a positive correlation ($\rho$ > 0.5, $p < 0.001$). The correlation coefficients between other meteorological variables and COVID-19 were generally relatively small ($\rho$ < 0.2) and most exceeded the 0.05 significance level. Changes in lag days between various meteorological indicators and the number of new confirmed COVID-19 cases/deaths per day showed no evident pattern.

For nearly a year from 22 January to 31 December 2020, slightly weak correlations were observed between the different meteorological indicators and confirmed COVID-19 cases/deaths ($\rho$ < 0.3), and they were hardly below the 0.05 significance level. The RH and TV that were not significant in the first or second half of the year had the most significant correlations with the number of confirmed COVID-19 cases ($\rho$ < −0.15, $p < 0.01$), and the correlations between T/PW and the number of confirmed COVID-19 cases/deaths lagging 14 and 21 days were weak but significant ($\rho$ > 0.15, $p < 0.001$). Moreover, the correlations between the number of confirmed COVID-19 cases and AP and W were significant with 0, 3, 5, and 7-day lag results ($\rho$ > 0.15, $p < 0.01$).

Although the correlations between the global average W and the number of confirmed COVID-19 cases/deaths were strong over the first two time periods ($\rho$ > 0.55, $p < 0.001$), each location’s correlations were generally weak (see Supporting Information S1). Hence, this paper mainly selected two meteorological indicators that had the strongest correlations with the number of confirmed COVID-19 cases/deaths per day (in the first two time periods, namely, from 22 January to 31 August 2020 and from 1 September to 31 December 2020, $\rho$ > 0.6, $p < 0.001$). Supporting Information S1 provide information on the remaining weak correlations between the meteorological indicators and confirmed COVID-19 cases/deaths around the world.

### 3.1.2. Global Average Temperature, PW, and COVID-19 Trend

Figure 1 shows the distinct trends in daily average temperature, PW, and confirmed COVID-19 cases/deaths in the northern and southern hemispheres in 2020. The mean confirmed COVID-19 cases per day in the northern hemisphere showed a slow increase before September 2020, a gradual increase, and then an explosive increase around November. The death number and temperatures in the northern hemisphere had a special character: the number of deaths per day increased as the temperature rose from January to mid-March 2020 when the temperature was
roughly below 17°C. After mid-March to early October, when the average daily temperature in the northern hemisphere exceeded 17°C, the daily number of deaths dropped slightly and stabilized at about 20 people/day or less. After the temperature dropped to about 17°C, the average number of new deaths per day rose sharply with the increase in new infections. Similarly, when the average daily PW in the northern hemisphere was greater

| Table 1 | Global Average Correlations Between Confirmed COVID-19 Cases/Deaths and Meteorological Indicators |
|---------|--------------------------------------------------|
| ACC     | Period                                           | Lag | T      | RH     | AP      | PW      | W       | TV      | PV      |
|---------|--------------------------------------------------|-----|--------|--------|---------|---------|---------|---------|---------|
| Confirmed COVID-19 cases daily | 22 January to 31 August 2020                   | 0   | 0.95*** | −0.06  | −0.154* | 0.93*** | −0.69*** | −0.05  | −0.06  |
|         |                                                  | 3   | 0.96*** | −0.05  | −0.08  | 0.93*** | −0.73*** | −0.03  | −0.02  |
|         |                                                  | 5   | 0.96*** | 0.00   | −0.05  | 0.94*** | −0.74*** | −0.02  | −0.05  |
|         |                                                  | 7   | 0.96*** | 0.02   | −0.01  | 0.95*** | −0.74*** | 0.01   | 0.00   |
|         |                                                  | 14  | 0.97*** | 0.00   | −0.02  | 0.95*** | −0.75*** | 0.02   | −0.04  |
|         |                                                  | 21  | 0.97*** | −0.02  | 0.02   | 0.95*** | −0.76*** | 0.05   | 0.00   |
|         | 1 September to 31 December 2020                 | 0   | −0.80*** | 0.12   | −0.16  | −0.78*** | 0.62*** | 0.06   | −0.08  |
|         |                                                  | 3   | −0.80*** | 0.14   | −0.11  | −0.75*** | 0.62*** | 0.01   | 0.00   |
|         |                                                  | 5   | −0.80*** | 0.17   | −0.08  | −0.74*** | 0.68*** | 0.00   | −0.10  |
|         |                                                  | 7   | −0.80*** | 0.09   | −0.03  | −0.76*** | 0.63*** | 0.02   | 0.02   |
|         |                                                  | 14  | −0.79*** | 0.10   | 0.15   | −0.75*** | 0.67*** | 0.02   | 0.02   |
|         |                                                  | 21  | −0.79*** | 0.03   | 0.196* | −0.74*** | 0.62*** | −0.05  | 0.01   |
|         | Near full-year 2020                             | 0   | −0.01   | −0.23*** | −0.23*** | 0.04   | 0.26*** | −0.18*** | −0.04  |
|         |                                                  | 3   | 0.03    | −0.22*** | −0.20*** | 0.08   | 0.21*** | −0.20*** | −0.01  |
|         |                                                  | 5   | 0.06    | −0.20*** | −0.17*** | 0.11   | 0.20*** | −0.20*** | −0.05  |
|         |                                                  | 7   | 0.09    | −0.21*** | −0.14*** | 0.12   | 0.15**  | −0.18*** | 0.00   |
|         |                                                  | 14  | 0.19*** | −0.22*** | −0.1    | 0.21*** | 0.06   | −0.16**  | 0.00   |
|         |                                                  | 21  | 0.28*** | −0.28*** | −0.1   | 0.29*** | −0.02  | −0.18*** | −0.01  |
| Confirmed COVID-19 deaths daily | 22 January to 31 August 2020                   | 0   | 0.70*** | −0.08  | −0.20** | 0.61*** | −0.66*** | 0.02   | −0.07  |
|         |                                                  | 3   | 0.70*** | −0.03  | −0.12  | 0.61*** | −0.68*** | 0.00   | −0.06  |
|         |                                                  | 5   | 0.69*** | 0.03   | −0.05  | 0.61*** | −0.66*** | 0.00   | −0.08  |
|         |                                                  | 7   | 0.69*** | −0.02  | 0.02   | 0.60*** | −0.67*** | 0.06   | −0.03  |
|         |                                                  | 14  | 0.68*** | 0.03   | 0.12   | 0.58*** | −0.70*** | 0.10   | −0.06  |
|         | 1 September to 31 December 2020                 | 0   | −0.78*** | −0.01  | −0.28** | −0.81*** | 0.61*** | −0.02  | 0.05   |
|         |                                                  | 3   | −0.78*** | 0.07   | −0.24*** | −0.76*** | 0.62*** | −0.01  | −0.10  |
|         |                                                  | 5   | −0.78*** | 0.06   | −0.12  | −0.77*** | 0.6***  | 0.04   | 0.02   |
|         |                                                  | 7   | −0.78*** | 0.03   | −0.14  | −0.78*** | 0.57*** | −0.01  | 0.02   |
|         |                                                  | 14  | −0.79*** | 0.16   | 0.07   | −0.75*** | 0.62*** | 0.02   | 0.04   |
|         |                                                  | 21  | −0.79*** | 0.04   | 0.20*  | −0.74*** | 0.60*** | 0.03   | 0.00   |
|         | Near full-year 2020                             | 0   | 0.07    | −0.22*** | −0.29*** | 0.07   | 0.09   | −0.14** | −0.01  |
|         |                                                  | 3   | 0.10    | −0.17**  | −0.24*** | 0.10   | 0.05   | −0.15** | −0.07  |
|         |                                                  | 5   | 0.12*   | −0.16**  | −0.16**  | 0.11*  | 0.04   | −0.13*  | −0.05  |
|         |                                                  | 7   | 0.14**  | −0.18*** | −0.13*  | 0.12*  | 0.01   | −0.12*  | −0.01  |
|         |                                                  | 14  | 0.19*** | −0.12*  | −0.01   | 0.18*** | −0.08  | −0.08  | −0.04  |
|         |                                                  | 21  | 0.26*** | −0.17**  | 0.09   | 0.24*** | −0.13*  | −0.08  | −0.02  |

*ACC: average correlation coefficient; T: temperature; RH: relative humidity; AP: air pressure; PW: precipitable water; W: 10 m Gauss wind speed; TV: daily temperature variation; PV: daily air pressure variation.

***Correlation is significant at the 0.001 level. **Correlation is significant at the 0.01 level. *Correlation is significant at the 0.05 level.
than around 28 mm, the average number of new deaths by COVID-19 was stable at about 20 people. The development of COVID-19 in the southern hemisphere was notably different from that in the northern hemisphere. New confirmed cases and deaths per day peaked in June and July, which were the coldest and driest season in the southern hemisphere. However, the decline in the number of confirmed cases per day continued into October, but it then picked up and gradually surpassed its initial growth peak, setting off a new round of peaks. When the southern hemisphere temperature was below 21.3°C and the PW was below 4.6 mm, the average confirmed cases/deaths in the southern hemisphere was the highest. Moreover, the number of deaths peaked sharply on four occasions at the end of June, mid-to-late July, mid-to-early August, and early September. Possibly, these findings offer strong new evidence implying that cold and dry winter weather patterns can influence the development and spread of global diseases, which agree with the conclusions of previous studies (Chatziprodromidou et al., 2020; Demongeot et al., 2020; Moriyama et al., 2020; Sun et al., 2020; Tamerius et al., 2013).

3.1.3. Daily Surface Temperature

As shown in Figure 2, from 22 January to 31 August 2020, Western Eurasia, North Africa, and Central North America all showed significant positive correlations between the confirmed COVID-19 cases and temperature ($\rho > 0.6$, $p \leq 0.05$), and significant negative correlations were found for South America and South Africa ($\rho < -0.6$, $p \leq 0.05$). The correlations between the number of deaths and temperature were slightly weaker, but the geographical distributions of positive and negative correlations were identical. In parts of East Asia and Western Europe where confirmed cases were reported earlier, the negative correlations were weak ($\rho > -0.2$, $p \leq 0.05$), possibly due to the relatively good local epidemic prevention effects, which slowed the natural development momentum of the epidemic.

From 1 September to 31 December 2020, the negative correlations between new confirmed COVID-19 cases/deaths and daily temperature were remarkably significant in the northern hemisphere. $\rho > 0.8$ ($p \leq 0.05$) locations were found in Russia, several European countries, and several North American countries. Saudi Arabia, the southern tip of the African continent, and other regions exhibited significantly positive correlations between COVID-19 cases/deaths and temperature.

Considerably weak correlations between the temperature and the number of new confirmed COVID-19 cases/deaths per day were observed in a near full-year period (22 January–31 December 2020) and no evident pattern was observed in the northern and southern hemispheres. However, more areas with negative correlations were observed than areas with positive correlations in general. Insignificant positive correlations between temperature and COVID-19 cases/deaths appeared in the Sahara Desert-Middle East. No remarkable difference was observed between lagging and non-lagging days.
Figure 2. Correlations between the number of new confirmed coronavirus disease (COVID-19) cases/deaths and daily surface temperature in 269 locations worldwide. “Confirmed Cases” means the number of new confirmed cases daily; “Death Cases” denotes the number of newly confirmed deaths daily; “Lag 0” refers to the confirmed COVID-19 cases/deaths with no lag; “Lag 3, Lag 5, Lag 7, Lag 14, Lag 21” means the confirmed COVID-19 cases/deaths with 3, 5, 7, 14, and 21-day lag, respectively. The color and size of the dots represent the strength of correlations. The larger the dot and the darker the color, the stronger the correlation, and vice versa. The dots are all significant at the 0.05 level, the same as below. (Please see Table S2 for the complete correlation and significance results).
From the perspective of various regions, the correlations between temperature and the number of new confirmed COVID-19 cases/deaths per day were generally significant. Although related to the local epidemic prevention effect, this finding also reflects the influence of meteorological indicators to a certain extent. This result may also explain the different results of previous studies, that is, the situation in each region was heterogeneous and cannot be generalized.

### 3.1.4. Daily PW

As shown in Figure 3, from 22 January to 31 August 2020, apart from the strong correlations in southern North America between the number of new confirmed cases per day and daily PW ($\rho \approx 0.8$, $p \leq 0.05$), the correlations in other regions were weak, and their distributions lacked distinction from the temperature correlation distributions. Distributions of the correlations between the number of new deaths per day and PW were consistent with the distributions of the correlations between confirmed cases and PW. However, the correlations between deaths and PW were weaker than those between the confirmed cases and PW.

From 1 September to 31 December 2020, evident negative correlations were observed between PW and the number of new confirmed COVID-19 cases/deaths per day ($\rho < 0$, $p \leq 0.05$), but they were less than those between the temperature and COVID-19. More locations yielded results beyond the 0.05 significance level. The correlation distributions were irregular, and the positive correlations ($\rho \approx 0.2$, $p \leq 0.05$) in the southern hemisphere were weaker than the negative correlations ($\rho \approx -0.6$, $p \leq 0.05$) in the northern hemisphere. In the case of negative correlations in most regions, India had a relatively strong positive correlation ($\rho \approx 0.6$, $p \leq 0.05$).

The weakest correlations between PW and the number of new confirmed COVID-19 cases/deaths per day were observed from 22 January to 31 December 2020 ($|\rho| < 0.4$, $p \leq 0.05$). Similar to the correlations between temperature and COVID-19, more locations presented weak negative correlations than weak positive correlations across the world. A weak positive correlation belt appeared along the Gulf of Mexico–Sahara Desert–Middle East, approximately a straight band starting at (90°W and 15°N) and ending at (80°E, 40°N), with a width of about 30° latitudes and a northeastward direction. This region is characterized by a tropical desert climate, with dry warmth occurring throughout the year (Beck et al., 2018).

A cold and dry climate promotes the outbreak of diseases (Paraskevis et al., 2021; Sun et al., 2020). Previous studies mostly used humidity as a climate indicator (Auler et al., 2020; Guo et al., 2021; Kerr et al., 2021; Xu et al., 2020). However, we observed that COVID-19 has a stronger correlation with PW than with RH from a long-term perspective on a global scale, which probably represents the atmospheric column water vapor affecting the virus spread more than the humidity near the ground and may provide new insights into the selection of meteorological variables.

### 3.2. Association Between COVID-19 and Latitude

Fittings were conducted by means of the least square method with the local latitude and temperature or PW and by determining the temperature or PW corresponding to the largest number of new confirmed cases/deaths per day in all parts of the world (Figure 4). The results showed a good fitting relationship between the local latitude and the MCT (temperature corresponding to the date of the highest increase in confirmed COVID-19 case), MDT (temperature corresponding to the date of the highest increase in confirmed COVID-19 death), MCPW (PW corresponding to the date of the highest increase in confirmed COVID-19 case), and MDPW (PW corresponding to the date of the highest increase in confirmed COVID-19 death). The fitting functions are shown in Table 2.

The MDT and latitude had the best fitting relationship (Adj. $R^2 \approx 0.76$, $p < 0.001$), followed by latitude-fitted MCT (Adj. $R^2 \approx 0.72$, $p < 0.001$) and MDPW (Adj. $R^2 \approx 0.64$, $p < 0.001$). The fitting effect of the MCPW and latitude was slightly poorer than the others (Adj. $R^2 \approx 0.63$, $p < 0.001$). The MCT, MDT, MCPW, and MDPW showed a distinct pattern of latitude: they decreased with the increase in latitude in the northern and southern hemispheres.

We used data between 1 January and 1 June 2021 to evaluate the fit functions. By finding the top 3% maximum daily confirmed COVID-19 cases and deaths from 1 January to 1 June 2021 in each location, the corresponding temperature and PW were superimposed on the fitting curve and the 95% prediction interval, as shown in Figure 5. It can be seen that most of the top 3% confirmed COVID-19 cases/deaths occurred within the 95% prediction interval of the fitted curves. The temperature prediction effect is the best, but the prediction capacity
for areas above 40°N is limited. On the contrary, the estimation effect of PW is the worst in the range of 0°–20°N, and the estimation of high latitude areas is relatively good. The temperature and PW ranges with the highest risk of COVID-19 infection and death can be calculated from the different latitudes of the fitting functions and may be important in the prediction of the next round of COVID-19 outbreaks.

Figure 3. Correlations between the number of new confirmed coronavirus disease cases/deaths per day and daily precipitable water in 269 locations worldwide.
4. Discussion

From 22 January to 31 August 2020, the strong positive correlations between the temperature/PW and the new confirmed cases/deaths per day in the northern hemisphere and strong negative correlations recorded in the southern hemisphere (|ρ| > 0.6, p ≤ 0.05) belonged to locations that later experienced COVID-19 break out. The numbers of confirmed cases/deaths in these locations were in the natural growth phase. In the same period, the temperature and PW in the northern hemisphere generally increased, but they generally reduced in the southern hemisphere. The effects of climate change were masked by the initial unrestrained interpersonal transmission and social distancing as a decisive factor in guiding infections, resulting in the difficulty of discerning weather impacts (Paraskevis et al., 2021). Conversely, in areas where the epidemic broke out earlier, such as East Asia

![Quadratic fitting curve between maximum coronavirus disease (COVID-19) case temperature (MCT), maximum COVID-19 death temperature (MDT), maximum COVID-19 case precipitable water (MCPW), and maximum COVID-19 death precipitable water (MDPW) and the latitude. The red circles represent the temperature or PW corresponding to the date of the highest confirmed case/death increase. The black curves denote the fitting curve and the gray areas indicate the range of the 95% prediction interval, the same as below.](image)

**Figure 4.** Quadratic fitting curve between maximum coronavirus disease (COVID-19) case temperature (MCT), maximum COVID-19 death temperature (MDT), maximum COVID-19 case precipitable water (MCPW), and maximum COVID-19 death precipitable water (MDPW) and the latitude. The red circles represent the temperature or PW corresponding to the date of the highest confirmed case/death increase. The black curves denote the fitting curve and the gray areas indicate the range of the 95% prediction interval, the same as below.

| Fitting functions | $R^2$   | Adj. $R^2$ | $p$    |
|-------------------|---------|------------|--------|
| MCT = $-0.0092 \times \text{Lat}^2 - 0.0012 \times \text{Lat} + 27.5863$ | (5) | 0.7282 | 0.7251 | <0.001 |
| MDT = $-0.0093 \times \text{Lat}^2 + 0.0127 \times \text{Lat} + 27.4159$ | (6) | 0.7665 | 0.7639 | <0.001 |
| MCPW = $-0.0110 \times \text{Lat}^2 - 0.0392 \times \text{Lat} + 41.6730$ | (7) | 0.6361 | 0.6319 | <0.001 |
| MDPW = $-0.0120 \times \text{Lat}^2 + 0.0371 \times \text{Lat} + 40.6598$ | (8) | 0.6506 | 0.6466 | <0.001 |

**Table 2**

**Fitting Functions**

*Note. MCT and MDT represent the temperature on the days when the number of confirmed cases and the number of deaths were the largest, respectively. MCPW and MDPW denote the PW on the days when the number of confirmed cases and the number of deaths were the largest, respectively. Lat represents the local latitude.*
and parts of Europe, weak negative correlations were observed between the number of new confirmed cases/deaths per day and temperature/PW ($|\rho| < 0.5, p \leq 0.05$). From 1 September to 31 December 2020, the correlations between temperature/PW and confirmed COVID-19 cases/deaths were mostly negative worldwide ($\rho < 0, p \leq 0.05$), and positive correlations only appeared in certain regions, such as the southern tip of the African continent and the Middle East ($\rho > 0, p \leq 0.05$). From the perspective of a nearly full-year period (22 January–31 December 2020), significantly more locations showed the negative correlations of temperature or PW with the number of confirmed cases/deaths than those with positive correlations on a global scale, which may indicate that as temperatures rose and PW increased, the spread of COVID-19 was restricted. Previous studies have suggested the preference of the virus to spread under low-temperature and humidity conditions (Leichtweis et al., 2021; Lowen et al., 2007; Scafetta, 2020); several laboratory research may explain the underlying mechanisms: low-temperature and RH (20%–50%) conditions may promote influenza virus stabilization (Moriyama et al., 2020). Dry air may render the host susceptible to infection, and a high RH will cause exhaled droplets to settle rapidly, thereby limiting the spread of viruses (Lowen et al., 2007). Increased indoor activity in winter promotes close-range infections, and seasonally influenced indoor climate and air exchange rates may be the main drivers for seasonal outbreaks of epidemics (Moriyama et al., 2020).

From 22 January to 31 December 2020, weak negative correlations were observed between the temperature/PW and confirmed COVID-19 cases/deaths per day, but a relatively evident weak positive correlation was recorded in the belt along the Gulf of Mexico-Sahara Desert-Middle East. Positive correlations mean that when the temperatures rose and PW increased, the number of confirmed COVID-19 cases/deaths increased. The belt has a low latitude, a very typical arid climate, and relatively high temperature. Localized climatic conditions indicate that the region has a higher temperature threshold and lower PW threshold than high-latitude areas. If virus activity weakens as temperatures rise (as most research speculates), then the virus should weaken more rapidly in this region than in high-latitude areas. More evident negative correlations should have been observed between COVID-19
and temperature/PW throughout the year. However, the actual situation exhibited the opposite: insignificant positive correlations were detected between the number of confirmed COVID-19 cases/deaths and temperature/PW in this region. Combined with the findings of this study, the temperature corresponding to the highest number of confirmed cases/deaths per day increased significantly as the latitude decreased. Similarly, minimum mortality temperatures or optimal comfort temperatures have latitudinal patterns (Gasparrini et al., 2015; Todd & Valleron, 2015; S. Zhang et al., 2021; Y. Zhang et al., 2020). A possible explanation is the adaptation of humans to environmental changes. Adaptation requires evolution through extremely long genetic mutations, inheritance, and natural selection (Ilardo & Nielsen, 2018); new evidence shows that natural selection has been at work for the past several thousand years, and that human evolution is ongoing (Beauchamp, 2016); viruses may have a stronger adaptive capacity than humans. Previous studies have speculated that one or two climatic zones are suitable for the spread of viruses (Huang et al., 2020). Within a particular latitude and temperature zone, the virus's infectivity will increase (Sajadi et al., 2020; Scafetta, 2020). Perhaps, the maximum transmission capacity of the virus is not confined to a specific temperature and latitude range but varies within different latitude ranges. In addition, specific meteorological ranges can facilitate the highest possible virus transmission. The temperature and PW thresholds for virus outbreaks are low in high-latitude regions and high in low-latitude regions. If supported by further research, this finding will provide a reasonable direction for the prediction of COVID-19 outbreaks.

Although vaccination has been widely promoted, the situation with COVID-19 is still difficult as the virus continues to mutate (Cui et al., 2019; Dawood, 2020; Masters, 2006; Su et al., 2016; Wang et al., 2021). If COVID-19 outbreaks are seasonally dependent, then we need to be vigilant about the second outbreak under suitable climatic conditions and avoid a lax attitude, because such a phenomenon is often more destructive than the first (Engelbrecht & Scholes, 2021). Climate change has driven wildlife closer to people (Ozkan et al., 2021). Bats carry a huge population of coronaviruses; mutations caused by high recombination rates may allow coronaviruses to cross the ethnic barrier between bats and humans, causing potential health threats (Cui et al., 2019; Masters, 2006). Maintaining a proper distance from nature may be the only way to avoid this outcome (Cui et al., 2019).

This research still presented shortcomings, such as the lack of covariates, including the population size, prevention and control policies, human activities, and virus epidemiological characteristics, or other variables that may influence the spread of COVID-19 (Kerr et al., 2021). Limited to the research environment, this research only inferred possible results from a macro perspective, and performing physiological experiments was notably difficult. The collection of field observation data on a large-scale and around the world also presented a challenge. Although the reanalysis data used in this research best reflect the atmospheric conditions, they cannot fully represent the actual meteorological conditions. Using a more appropriate epidemiological model that considers the impact of covariates from multiple angles and levels and searching for the maximum possible transmission threshold of the virus based on different climatic regions may be the direction of future efforts.

5. Conclusions

1. Among the seven meteorological variables (daily temperature, daily PW, daily RH, daily 10 m Gauss W, daily surface AP, daily TV, and daily AP variation), daily temperature and PW had the strongest correlation with the worldwide number of confirmed COVID-19 cases/deaths per day. The correlations between COVID-19 and PW were stronger than those of RH. The use of PW is possibly more reasonable than the usual humidity parameters.

2. Strong positive correlations were observed between the worldwide average (269 locations in total, the same as below) of temperature/PW and the worldwide average confirmed COVID-19 cases per day from 22 January to 31 August 2020 ($ρ > 0.9, p < 0.001$). Significant negative correlations were observed between worldwide average $W$ and average confirmed COVID-19 cases/deaths per day ($ρ < −0.6, p < 0.001$) and the correlations generally increased with the increases in lag days. From 1 September to 31 December 2020, the correlations between worldwide average temperature/PW and confirmed COVID-19 cases and deaths showed a significantly negative relationship ($ρ < −0.7, p < 0.001$), whereas the correlations between worldwide average $W$ and COVID-19 were positive ($ρ > 0.5, p < 0.001$).

3. From 22 January to 31 August 2020, the temperature/PW and the number of confirmed cases/deaths per day were roughly positively correlated in the northern hemisphere and negatively correlated in the southern hemisphere. From 1 September to 31 December 2020, negative and positive correlations were present in the northern and southern hemispheres, respectively. The correlations in the second half of the year (1 September to
31 December 2020) were generally stronger than those in the first half (22 January to 31 August 2020). Weak negative correlations were observed in most locations during the nearly full-year period ($|p| < 0.5$, $p \leq 0.05$), whereas weakly positive correlation locations were distributed in a strip along the Gulf of Mexico-Sahara Desert-Middle East. Outside these regions, the increase in temperature and PW roughly corresponded to the decrease in the number of confirmed COVID-19 cases/deaths per day.

4. The temperature corresponding to the largest confirmed cases/deaths per day increase had a good fitting relationship with the local latitude ($R^2 > 0.72$, $p < 0.001$), which means that the daily temperature of the day corresponding to the largest number of new confirmed cases/deaths increased toward the equator and decreased toward the poles. The corresponding PW changes with latitude had similar patterns, but the fitting effect ($R^2 > 0.63$, $p < 0.001$) was slightly inferior to those of temperature.

Conflict of Interest
The authors declare no conflicts of interest relevant to this study.

Data Availability Statement
Thanks to the NOAA Physical Sciences Laboratory Data Management for providing NECP Reanalysis data products (retrieved from https://psl.noaa.gov/data/gridded/data.necp.reanalysis.html). Thanks to the Center for Systems Science and Engineering at the Johns Hopkins University for operating the COVID-19 Data Repository (retrieved from https://systems.jhu.edu/research/public-health/ncov/).

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