This paper examines the nexus between the Covid-19 confirmed cases, deaths, meteorological factors, including an air pollutant among the world’s top 10 infected countries, from 1 February 2020 through 30 June 2020, using advanced econometric techniques to address heterogeneity across the nations. The findings of the study suggest that there exists a strong cross-sectional dependence between Covid-19 cases, deaths, and all the meteorological factors for the countries under study. The findings also reveal that a long-term relationship exists between all the meteorological factors. There exists a bi-directional causality running between the Covid-19 cases and all the meteorological factors. With Covid-19 death cases as the dependent variable, there exists bi-directional causality running between the Covid-19 death cases and Covid-19 confirmed cases, air pressure, humidity, and temperature. Temperature and air pressure exhibit a statistically significant and negative impact on the Covid-19 confirmed cases. Air pollutant PM2.5 also exhibits a significant but positive impact on the Covid-19 confirmed cases. Temperature indicates a statistically significant and negative impact on the Covid-19 death cases. At the same time, Covid-19 confirmed cases and air pollutant PM2.5 exhibit a statistically significant and positive impact on the Covid-19 death cases across the ten countries under study. Hence, it is possible to postulate that cool and dry weather conditions with lower temperatures may promote indoor activities and human gatherings (assembling), leading to virus transmission. This study contributes both practically and theoretically to the concerned field of pandemic management. Our results assist in taking appropriate measures in implementing intersectoral policies and actions as necessary in a timely and efficient manner.

Keywords COVID-19 · Temperature · Humidity · Air pressure · Wind speed · Meteorological factors · PM2.5
Most of the research work studying the impact of the Covid-19 has focused on China (Ma et al. 2020; Shi et al. 2020) and the USA (Bashir et al. 2020; Gupta et al. 2020), in particular. There is an immense need to investigate the impact of the virus on other countries. This study focuses on the top 10 adversely affected countries (as of 30 June 2020) (CNA 2020), including Brazil, Chile, India, Iran, Italy, Peru, Russia, Spain, the UK, and the USA. Since these countries include developed as well as developing countries, the results of the study are generalizable.

Epidemiological studies suggest that the spread of historical outbreaks, such as severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome disease (MERS), has been altered by the environmental conditions (Méndez-Arriaga 2020). Casanova et al. (2010) explain that the dry and cold weather conditions facilitate the virus’s transmission and survival. Since the coronavirus belongs to the same family and possesses symptoms like cold, cough, flu, and fever, it must be affected by weather conditions also. Therefore, it is imperative to study different factors, including humidity, temperature, wind speed, and air pressure, and their influence on Covid-19 cases. While most of the studies have investigated the impact of the Covid-19 period on air quality (Dutheil et al. 2020), this study investigates the impact of air quality on Covid-19 cases. Due to the non-availability of Air Quality Index (AQI) data on daily basis for the countries under study, we have used PM2.5 (one of the air pollutants) as a proxy for AQI. Thus, the variables used for this study include the daily number of Covid-19 cases and deaths, air pressure, relative humidity, average air temperature, wind speed, and particulate matter 2.5. The time-series graphs (annexure) for each of the variables per country depict that the number of confirmed cases during the period under study have been the highest for the USA, followed by Brazil and Russia; the number of deaths has been the highest in the USA in April and May, followed by Brazil in June; the temperature has been the highest in India in May, while Peru has also reported higher range of temperature for the period under study; the air pollutant PM2.5 is seen to be the highest in India followed by Iran, while the lowest range is observed to be in Brazil; the highest wind speed is observed in Iran in February followed with the USA in March; the air pressure has been quite similar in every month for each of the top 10 countries under study; the humidity has been highest in almost all the countries while Iran relatively reports the lowest humidity in June. Furthermore, Table 1 presents the latest data on the total number of cases and deaths in the ten countries under study, as of 16 November 2020.

This paper contributes to the existing body of literature in the following three ways. First, it is a comprehensive study considering variables that can potentially affect the transmission of coronavirus. The previous studies have suffered from omitted variable bias. However, Sarkodie and Owusu (2020) examine enough variables, namely dew/frost point, temperature, disaggregate temperature, wind speed, relative humidity, precipitation, and surface pressure against confirmed cases, deaths and recovery cases, spread over a period from January to April 2020 for the top 20 most infected countries. As an extension to this article mentioned above by Sarkodie and Owusu (2020), this study considers all the variables that affect Covid-19 spread across the top ten most infected countries for a period much beyond April 2020. Second, this study focuses on the top ten most affected countries, with an intent to draw much more focused results with few countries under review. The third contribution is using advanced, reliable, and accurate econometric methodologies (Dogan and Aslan 2017; Dogan et al. 2017), making it more rigorous and extensive compared to the previously published studies by employing the novel DCCE approach (Chudik and Pesaran 2015). Despite their popularity, the literature has not used these methodologies to investigate the effect of the variables on the transmission of Covid-19. The advanced econometric methodologies include Panel data analysis through the cross-sectional dependence test, first-generation unit root test and second-generation unit root test, Westerlund cointegration test, Dumitrescu and Hurlin’s (2012) Granger non-causality test, dynamic ordinary least squares (DOLS), fully modified ordinary least squares (FMOLS), canonical cointegrating regression (CCR), augment mean group (AMG) estimations, and the novel dynamic common correlated effect (DCCE) technique.

The rest of the paper is structured as follows. The “Literature review” section presents the review of literature; the “Methodology” section presents the methodology adopted for the study; the “Findings and discussion” section presents the findings and discussions, and the “Conclusions” section concludes the paper.

### Table 1 Number of total cases and total deaths in the ten countries under study, as on 16 November 2020

| S No. | Affected country | Total cases | Total deaths |
|-------|------------------|-------------|-------------|
| 1     | USA              | 11,475,609  | 252,337     |
| 2     | India            | 8,873,994   | 130,552     |
| 3     | Brazil           | 5,864,943   | 165,858     |
| 4     | Russia           | 1,948,603   | 33,489      |
| 5     | Spain            | 1,521,899   | 41,253      |
| 6     | UK               | 1,390,681   | 52,147      |
| 7     | Italy            | 1,205,881   | 45,733      |
| 8     | Peru             | 937,011     | 35,231      |
| 9     | Iran             | 775,121     | 41,979      |
| 10    | Chile            | 532,604     | 14,863      |

Source: Worldometer, (2020)
Literature review

The most frequently studied relationship of Covid-19 is related to meteorological factors and air pollutants as it influences coronavirus transmission, contributing to the spread of Covid-19 (Hazbavi et al. 2020; Islam et al. 2020). The majority of the studies relate temperature with Covid-19 cases and deaths (Covid-19 indicators) and have mixed conclusions with positive/negative or no association between them. Besides temperature, a large number of meteorological factors and weather parameters are included in the study, such as absolute/relative humidity, precipitation, dew point, pressure, air quality index, wind speed and direction, solar radiation, air pollutants, and population density (Table 2).

As the spread of Covid-19 originated from Wuhan, China, in November 2019 (Iqbal et al. 2020), since then, several empirical research investigated China (Chinese provinces), followed by the USA (Adhikari and Yin 2020; Berman and Ebisu 2020; Zangari et al. 2020), Brazil (Rosario et al. 2020; Prata et al. 2020; Auler et al. 2020), and India (Jain and Sharma 2020; Kumar 2020; Sharma et al. 2020d). USA, Brazil, and India have been in the top 3 most affected countries by Covid-19. Al-Rousan and Al-Najjar (2020) and Lin et al. (2020) study the relationship of meteorological factors and Covid-19 in China and have similar observations of the positive association of temperature and pressure with Covid-19 cases. On the contrary, Liu et al. (2020), Ma et al. (2020), and Mandal et al. (2020) found negative correlations between temperature, humidity, and Covid-19 in China. Adhikari and Yin (2020) and Chien and Chen (2020) conduct their study in the USA and found a significant positive link between temperature, humidity, precipitation, and Covid-19 cases. Few studies reported the decline in the level of air pollutants (PM2.5 in all cases) during the Covid-19 period (Berman and Ebisu 2020; Jain and Sharma 2020; Sharma et al. 2020d). Ma et al. (2020) and Wu et al. (2020a, b) confirm the significant linkage of temperature and humidity with Covid-19 deaths. Rosario et al. (2020) exhibit that the increase in wind speed leads to proliferated Covid-19 cases, and Zhu et al. (2020a, b) found that it is not closely related to incubative cases, whereas Zoran et al. (2020) establish an inverse relationship between wind speed and Covid-19 cases.

The rapid increase in the number of Covid-19 affected patients started in January 2020 and was declared a pandemic in March 2020 (WHO 2020). Since then, there is significant research happening worldwide concerning causes, consequences, transmission, etc., of Covid-19. With reference to the time frame, the period covered in most of the studies pertains either to January–February/March 2020 or February–March/April 2020 or March–April 2020. Very few studies cover the period from January–April 2020 (Zoran et al. 2020; Gupta et al. 2020) or some days of May 2020 (Pani et al. 2020; Zhu et al. 2020a). Studies carried out in this field rely upon various methodologies and techniques to examine the relation between Covid-19 and meteorological factors, depending on country/region and the period covered.

Several statistical and scientific models are employed to examine the relations among Covid-19, meteorological factors, and air pollutants, for instance, the generalized additive model (GAM) (Xie and Zhu 2020; Zhu et al. 2020b; Liu et al. 2020), M-SEIR model (Shi et al. 2020), and AERMOD (Sharma et al. 2020d), Spearman’s correlation test (Méndez-Arriaga 2020; Pani et al. 2020; Tosepu et al. 2020) is frequently used to correlate the Covid-19 spread and meteorological indicators. Other analysis techniques included the Wilcoxon test (Sethwala et al. 2020), t-tests (Berman and Ebisu 2020; Jain and Sharma 2020), spatial analysis (Zoran et al. 2020; Briz-Redón and Serrano-Aroca 2020), quantile-on-quantile approach (Shahzad et al. 2020), and wavelet approach (Fareed et al. 2020; Iqbal et al. 2020; Habib et al. 2020). Shi et al. (2020) use the M-SEIR model to explain no significant association between humidity and Covid-19. Iqbal et al. (2020) follow the Wavelet technique to find temperature does not necessarily affect Covid-19 cases.

Existing literature does not present any conclusive results about the association of temperature, wind speed, and humidity with Covid-19. There is a lack of studies examining meteorological factors, including air pressure. Till recently, no paper has been published with the data beyond May 2020 and employing panel data estimation. The present study fills this gap by using panel data analysis to examine the nexus between the Covid-19 (confirmed cases and deaths), meteorological factors (air pressure, humidity, temperature, and wind speed) including an air pollutant (PM2.5) in the world’s top 10 infected countries.

Methodology

Model specification and data

This study examines the nexus between the Covid-19 confirmed cases, deaths, and meteorological factors, including an air pollutant in the world’s top 10 infected countries, which include Brazil, Chile, India, Iran, Italy, Peru, Russia, Spain, UK, and USA (as on 30 June 2020, as per (CNA 2020)). The secondary data is retrieved to apply panel data estimations (that account for the heterogeneity across the nations and provide more reliable and generalizable results) from 1 February 2020 to 30 June 2020. This data relates to Covid-19 confirmed cases and deaths (Worldometer 2020); meteorological factors included in this study are daily air temperature, relative humidity, air pressure and wind speed, and air pollutant PM2.5 (WAQI 2020). We employed Panel data regression over cross-section and time-series data, being a better-modeled technique in handling all the available evidence, which cannot
| Study                  | Country(s)               | Methodology                                                                 | Time period                  | Findings                                                                                                                                                                                                 |
|-----------------------|--------------------------|------------------------------------------------------------------------------|------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Adhikari and Yin (2020) | New York, USA            | Negative binomial regression model                                            | March 1 to April 20, 2020    | Significant and positive association between temperature, O₃ concentration, relative humidity, cloud percentages, and Covid-19 cases; however, none of these are related to death |
| Al-Rousan and Al-Najjar (2020) | 30 Chinese provinces | Pearson's correlation                                                        | January 22 to March 1, 2020 | Temperature, shortwave radiation and pressure are positively correlated with Covid-19 cases. Other variables are provincially distinct, and snowfall has no correlation |
| Auler et al. (2020)    | Brazil                   | Exploratory data analysis, Shapiro-Wilk test, Clausius-Clapeyron equation  | March 13 to April 13, 2020   | High mean temperatures and intermediate relative humidity influence the Covid-19 transmission rate                                                                                                         |
| Berman and Ebisu (2020) | USA                      | Summary statistics and comparisons between pollution concentrations during historical versus current periods done using two-sided t-tests | January 8 to April 21 from 2017 to 2020 | Statistically significant declines in NOₓ and PM2.5 were observed during the Covid-19 period                                                                                                          |
| Bontempi (2020)        | Italy                    | Reported data analysis                                                        | February 10 to March 27, 2020 | It is not necessary that PM10 as a carrier causes Covid-19 transmission                                                                                                                                |
| Briz-Redón and Serrano-Arocía (2020) | Spain                  | Spatio-temporal analysis                                                     | February 25 to March 28, 2020 | Warmer mean, minimum and maximum temperatures does not lead to any reduction in the Covid-19 cases                                                                                                       |
| Chien and Chen (2020)  | USA                      | Generalized additive model (GAM)                                             | March 22, 2020, to April 22, 2020 | Average temperature, minimum relative humidity, and precipitation minimize the Covid-19 risk after some peak value                                                                                     |
| Gupta et al. (2020)    | USA, India               | Distribution modeling - mean, standard deviation                              | January 1 to April 9, 2020   | Covid-19 spread in the USA is significant for states with 4 < AH < 6 g/m³, and temperature in a wider range of 4–11 °C with number of new cases N 10,000                                                                 |
| Iqbal et al. (2020)    | China                    | Continuous wavelet transform (CWT), wavelet transform coherence (WTC), partial wavelet coherence (PWC), and multiple wavelet coherence (MWC) | January 21 to March 31, 2020 | No significant role of temperature in containing Covid-19 cases                                                                                                                                            |
| Jain and Sharma (2020) | India                    | Trend analysis, paired t-test, GIS technique                                  | March to April 2019 and 2020 | Significant decline in all the pollutants except for O₃ during the lock-down phase. Low relative humidity and very high wind speed and temperature lead to dispersion of air pollutants |
| Kumar (2020)           | India                    | Pearson correlation                                                           | March to April, 2020         | Positive association between temperature and Covid-19 cases. Negative association between humidity and Covid-19 cases                                                                                     |
| Zhu et al. (2020)      | 8 South American cities  | Multiple regression analysis: Spearman's correlation coefficient              | February 23 to May 12, 2020  | The association between absolute humidity and incubative cases is negative. There were large differences between the effects of the coefficient of correlation in individual cases and Rt. Average wind speed and visibility were not closely related to daily incubation |
| Lin et al. (2020)      | 20 Chinese provinces     | Mechanism-based parameterisation scheme                                       | January 22 to February 29, 2020 | Higher population density was linearly whereas a lower temperature was exponentially associated with an increased transmission rate of Covid-19                                                                 |
| Liu et al. flu (2020)  | China                    | Generalized linear models, meta-analysis                                      | January 20 to March 2, 2020  | The low temperature climate, moderate diurnal temperatures and low humidity probably contribute to Covid-19 transmission                                                                                   |
| Ma et al. (2020)       | China                    | Generalized additive model (GAM)                                             | January 20 to February 29, 2020 | A positive association is found between daily deaths and DTR and SO₂. Relative humidity and PM2.5 is negatively associated with daily deaths                                                               |
| Mandal and Panwar (2020) | China                  | Univariate analysis and statistical modeling                                  | March 25 to April 18, 2020   | Strong negative correlations with statistical significance exist between MAET and several Covid-19 cases                                                                                                 |
| Méndez-Arriaga (2020)  | Mexico                   | Spearman's non-parametric test                                               | February 29 to March 31, 2020 | Negative association between temperature, atmospheric evaporation and Covid-19 cases while there is a positive association between precipitation and Covid-19 cases |
| Pani et al. (2020)     | Singapore                | Spearman and Kendall's rank correlation tests                                 | March 25 to April 6, 2020    | No significant relationship between temperature and Covid-19 cases. No detectable correlation between precipitation and Covid-19 cases                                                                    |
| Study                     | Country(s)                              | Methodology                                                                 | Time period                          | Findings                                                   |
|--------------------------|-----------------------------------------|----------------------------------------------------------------------------|--------------------------------------|------------------------------------------------------------|
| Prata et al. (2020)      | Brazil                                  | Generalized Additive Model (GAM)                                           | January 23 to May 31, 2020           | Temperature, dew point, relative humidity, absolute humidity, and water vapor show positive significant correlation with Covid-19 cases |
| Rosario et al. (2020)    | Brazil                                  | Spearman’s rank correlation                                                | February 27 to April 1, 2020         | Negative linear relationship between temperature and Covid-19 cases |
| Sarkodie and Owusu (2020)| Top 20 countries                        | CIPS and CADF panel unit root, Granger causality test, split-panel jack-knife method, kernel density estimation | March 6 to April 30, 2020            | Significant correlation between temperature maximum and average, radiation, wind speed and Covid-19 cases |
| Sethwala et al. (2020)   | USA, China, Canada, and Australia        | Wilcoxon’s test                                                            | January 22 to April 27, 2020         | Temperature and humidity have negative impact on COVID-19 whereas wind speed, dew/frost point, precipitation, and surface pressure have a positive impact |
| Sharma et al. (2020, b, c, d) | India                                | Weather research forecasting (WRF) and Air quality dispersion modeling system (AERMOD) | March 16 to April 14 from 2017 to 2020 | Levels of PM2.5, PM10, CO, and NO2 decreased significantly while O3 level increased and SO2 showed negligible changes. Wind speed varies with direction whereas temperature has negligible variations in different regions. |
| Shi et al. (2020)        | 31 Chinese provinces                   | Modified susceptible-exposed-infectious-recovered (M-SEIR) model           | January 20 to January 1 to March 29, 2020 | Negative association between temperature and Covid-19 cases. Average temperature is significantly correlated with Covid-19 pandemic |
| Tosepu et al. (2020)     | Indonesia                               | Spearman-rank correlation test                                              | January 20 to February 4, 2020       | Temperature could significantly change Covid-19 cases to a certain extent |
| Wang et al. (2020)       | Globally 166 countries except China     | Restricted cubic spline function and generalized linear mixture model       | January 20 to February 29, 2020      | Results indicate that mean temperature has a positive linear relationship with the number of Covid-19 cases. Air quality near central China improved significantly. No difference in air quality between 2020 and 2015-2019 is found |
| Wu et al. (2020, b)      | Globally 166 countries except China     | Log-linear generalized additive model, sensitivity analysis                 | As of March 27, 2020                | Both temperature and relative humidity were negatively associated with reported daily cases and deaths |
| Xie and Zhu (2020)       | 122 Chinese cities                     | Generalized additive model (GAM) and piecewise linear regression           | January 23 to February 29, 2020      | Results indicate a significant relationship between air pollution and Covid-19 infection |
| Xu et al. (2020)         | China                                   | Observational analysis                                                     | First 17 weeks from 2015 to 2020     | Strong influence of daily averaged ground levels of concentrations, positively associated with average surface air temperature and inversely related to relative humidity and wind speed on Covid-19 cases |
| Zangari et al. (2020)    | USA                                     | Linear time lag models show                                                | First 17 weeks from 2015 to 2020     | Strong influence of daily averaged ground levels of concentrations, positively associated with average surface air temperature and inversely related to relative humidity and wind speed on Covid-19 cases |
| Zhu et al. (2020)        | 122 Chinese cities                     | Generalized additive model (GAM)                                           | January 23 to February 29, 2020      | Strong influence of daily averaged ground levels of concentrations, positively associated with average surface air temperature and inversely related to relative humidity and wind speed on Covid-19 cases |
| Zoran et al. (2020)      | Italy                                   | Spatial analysis                                                           | January 1–April 30, 2020             | Strong influence of daily averaged ground levels of concentrations, positively associated with average surface air temperature and inversely related to relative humidity and wind speed on Covid-19 cases |

Source: authors’ contribution
be measured in pure cross-section and time-series (Wooldridge 2002). The balanced panel data of 10 countries covering 5 months (the most prolonged period for which data is available) includes two Covid-19-related variables, four meteorological variables, and one air pollutant.

The outbreak of Covid-19 has overgrown, and mortality estimates are also rising. Hence, the study examines the nexus by proposing two models—one, with Covid-19 confirmed cases (as a dependent variable); and two, with Covid-19 death cases (as a dependent variable), with simple functions equated as follows:

$$\text{Covid-19 cases}_{it} = f(\text{AP}_{it}, \text{H}_{it}, \text{T}_{it}, \text{WS}_t, \text{PM2.5}_{it})$$  \hspace{1cm} (1)

$$\text{Covid-19 deaths}_{it} = f(\text{AP}_{it}, \text{H}_{it}, \text{T}_{it}, \text{WS}_t, \text{PM2.5}_{it}, \text{Covid-19 cases}_{it})$$  \hspace{1cm} (2)

where the subscripts $i$ and $t$ denote country and time period, respectively. Here, Covid-19 cases and deaths are the daily number of cases and deaths recorded; AP is the daily air pressure (measured in hPa); H is the daily relative humidity (measured in %); T is the daily average air temperature (measured in Celsius); WS is the daily wind speed (measured in m/s), and PM2.5 is the daily particulate matter 2.5 (measured in $\mu g/m^3$).

Equation (1) can be parameterized as follows:

$$\text{Covid cases}_{it} = \text{AP}_{it}^{\beta_{11}}\text{H}_{it}^{\beta_{21}}\text{T}_{it}^{\beta_{31}}\text{WS}_t^{\beta_{41}}\text{PM2.5}_{it}^{\beta_{51}}$$  \hspace{1cm} (3)

$$\text{Covid deaths}_{it} = \text{AP}_{it}^{\beta_{11}}\text{H}_{it}^{\beta_{21}}\text{T}_{it}^{\beta_{31}}\text{WS}_t^{\beta_{41}}\text{PM2.5}_{it}^{\beta_{51}}\text{Covid cases}_{it}^{\beta_{61}}$$  \hspace{1cm} (4)

### Data analysis and techniques

The data analysis begins with descriptive statistics to study the basic characteristics of the variables in the study. The study then employs econometric techniques including the cross-sectional dependence test, first-generation unit root test, second-generation unit root test, Westerlund cointegration test, Dumitrescu and Hurlin’s (2012) Granger non-causality test, DOLS, FMOLS, CCR, and AMG estimations.

### Cross-sectional dependence test

The interconnections between global economies can lead to cross-sectional interdependence between studied countries. The CSD test, consistent with Breusch and Pagan (1980) and Pesaran (2007), resolves this methodological problem as shown in Eq. (5).

$$\text{CSD} = \sqrt{\frac{2t}{z(z-1)\sum_{j=1}^{z-1} \sum_{i=1}^{t-j+1} pij}}$$  \hspace{1cm} (5)

where CSD is cross-sectional dependence, $z$ is cross-sections in the panel data, $t$ is time horizon, and $pij$ is cross-section correlation of error between $i$ and $j$. Hence, the LM test to study the CSD test in the data series is equated as follows:

$$y_{it} = \alpha_{it} + \beta_{it}x_{it} + \varepsilon_{it}$$  \hspace{1cm} (6)

where $t$ is time horizon and $i$ is the cross-section in the panel. The null hypothesis for both the methods states that there exists cross-sectional independence among the variables under study.

### First- and second-generation unit root test

Following the estimation of cross-sectional dependency, we proceed with second-generation unit root tests, i.e., cross-sectional augmented Im, Pesaran and Shin IPS (CIPS) test (test for each cross-section unit), and cross-sectionally augmented Dickey-Fuller (CADF) unit root test (to provide statistics for the variables individually). Since there exists high cross-sectional dependence in the dataset, the standard panel unit root test could not be applied. The null hypothesis for this method is that the series under study are non-stationary. The unit root test is depicted in Eq. (7) using Pesaran (2007):

$$x_t = \alpha_{it} + \beta_{it}x_{it-1} + \rho_{it}t + \sum_{j=1}^{n} \theta_{ij}x_{it-1,j} + \varepsilon_{it}$$  \hspace{1cm} (7)

where $\alpha_{it}$ is intercept, $t$ is time horizon, $\Delta$ is the difference operator, $x_{it}$ are variables under study, and $\varepsilon_{it}$ is error term.

### Westerlund cointegration test

The Westerlund (2007) cointegration test is further employed to ascertain the long-term linkage among the variables. This test assumes the existence of cross-sectional independence. Since Banerjee et al. (1998) allow for a large degree of heterogeneity among the variables, Westerlund (2007) is employed as an extension to the model and proposed four cointegration tests. The null hypothesis states that the long-term relationship does not exist between the variables. The test is applied as per the below Eq. (8):

$$\Delta Y_{it} = \delta_{it}d_{it} + \alpha_{it}Y_{it-1} + \lambda_{it}\Delta Y_{it-1} + \sum_{j=1}^{n} \alpha_{ij}\Delta Y_{it-1,j} + \varepsilon_{it,j}$$  \hspace{1cm} (8)

where $d_{it}$ is model residuals, $i$ is cross-section in the panel data, and $t$ is time horizon.

### Granger non-causality test

The direction of causality is determined using Dumitrescu and Hurlin’s (2012) Granger non-causality test with the bootstrap procedure. The null hypothesis states that causality between
the selected variables does not exist. Dumitrescu and Hurlin (2012) proposed the following regression Eq. (9):

\[ y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} y_{i,t-k} + \sum_{k=1}^{K} \gamma_{ik} x_{i,t-k} + \epsilon_{it} \] (9)

This equation assumes that the lag order of \( K \) is the same for all individuals and that the panel must be balanced.

**Long-run estimation approach**

The FMOLS and DOLS models are tested to get a fully efficient estimation; (Wang and Wu 2012). The presence of serial correlation, if any, in the model is checked using FMOLS and DOLS. CCR exhibits lesser bias than FMOLS and DOLS and is considered better than them (Montalvo 1995). These cointegration regression tests indicate the impact of all the variables on Covid-19 confirmed cases and death cases as the dependent variables, separately.

**Mean group estimate**

Following the presence of cointegration, we have applied the first-generation estimators for the panel time-series—augmented mean group estimation. The mean group estimator proposed by Pesaran and Smith (1995) does not consider the cross-sectional dependence among the variables and includes a regression for each panel unit (Musaaed et al. 2017). Eberhardt and Teal (2010) introduced an augmented mean group with a long-run cointegrating estimator considering heterogeneity and cross-sectional dependence (Bayar 2016). The individual regression is as follows:

\[ y_{it} = \beta x_{it} + \delta x_{it} + \sum_{p=0}^{P} \gamma_{i} \bar{X}_{t-p} + \sum_{p=0}^{P} \gamma_{j} \bar{Y}_{t-p} + \mu_{it} \] (10)

where \( \bar{X} = Z^{-1} \sum X_i \) is the cross-sectional average of the regressors and \( \bar{Y} = Z^{-1} \sum Y_i \) is the cross-sectional average of the dependent variable.

**Dynamic common correlated effect model**

The literature review highlights that the previous researchers have not considered much of the cross-sectional effects and have majorly worked with homogeneous slopes (Meo et al. 2020). Hence, the panel data estimations with heterogeneous coefficients among cross-sectional units over longer periods have attracted researchers’ attention in the recent past (Pesaran and Smith 1995). In this work, we have applied the dynamic common correlated effect (DCCE) approach introduced by Chudik and Pesaran (2015) to explore the variables’ long-term affiliations. The DCCE model considers cross-sectional dependence and heterogeneity, providing accurate results (Meo et al. 2020). It takes cross-sectional averages and lags the response variable on the model’s right side with explanatory variables. It also helps resolve variabilities (dynamics) by integrating lag-dependent variables into the model (Mensah et al. 2020). Moreover, this technique works well for the small sample size by using the jack-knife correction approach (Chudik and Pesaran 2015). We use the following the equation of the DCCE model as proposed by Chudik and Pesaran (2015):

\[ y_{it} = \alpha_i y_{it-1} + \delta_i x_{it} + \sum_{p=0}^{P} \gamma_{i} \bar{X}_{t-p} + \sum_{p=0}^{P} \gamma_{j} \bar{Y}_{t-p} + \mu_{it} \] (11)

\( \delta_{it} \) refers to the set of independent variables, and \( P_t \) is the limit of lags included in the cross-section averages.

**Findings and discussion**

This section begins with Table 3, presenting the ten most infected countries’ descriptive statistics under study. The Covid-19 confirmed cases are, on average, about 4232 with a maximum number of cases at 54,771, while the total number of deaths is approximately 225 with a maximum number of deaths of 4928. Among the meteorological factors, the highest variation is observed in the air pollutant PM2.5 at 40.673, followed by air pressure at a variation of 34.001. In contrast, the lowest variation is evident in the wind speed at 3.911 for all the ten countries under study. Additionally, out of all the variables, humidity, air pressure, and temperature are negatively skewed. The values for humidity and temperature are the closest to the kurtosis statistical value for normal distribution, i.e., 3. In contrast, the highest deviation from the standard statistical figure is evident in the case of air pressure, followed by wind speed and Covid-19 death cases.

Table 4 presents the cross-sectional dependence for all the variables under study. The statistical values as per the Breusch-Pagan LM test conducted over the raw values of Covid-19 cases, deaths, and all the meteorological factors are significant at 1%. The logged values for PM2.5 and wind speed exhibit significance at 10%, and the temperature does not reveal any significant value. According to the Pesaran scaled LM test, all the variables indicate statistical values at 1% level of significance except for the logged values of PM2.5 and temperature that do not exhibit any significant value. Furthermore, as per the Pesaran CD test, the raw values of all the variables excluding PM2.5 (no significant value) and humidity (statistically significant at 5% level) exhibit a statistically significant value at 1% level. The logged values for PM2.5, humidity, temperature, and wind speed do not exhibit any significant value under the Pesaran CD test. Hence, collectively, all the study variables indicate statistically significant values confirming a strong cross-sectional dependence for the ten countries under study.
Table 5 presents the first and second-generation unit root test for all the variables under study. All the variables under study report stationarity under both IPS and ADF-Fisher’s test (first-generation unit root tests) with statistical values at 1% level of significance. All the meteorological factors show statistically remarkable values under both CIPS and CADF tests, with a 1% level of significance. According to the CIPS values, Covid-19 cases and deaths exhibit statistically significant values at the level of 1% at the first difference, while only Covid-19 death cases represent statistically significant value (at 5%) computed at level. Hence, the degree of significance improves for both the Covid-19 cases and deaths, but the opposite is not true in case of CADF test. Alternatively, as per the CADF test, the values computed at the level for both the Covid-19 confirmed cases and death cases exhibit statistical values at 1% level of significance, while only Covid-19 cases exhibit a statistically significant value at 10% level. Therefore, for all the variables under study, an acceptable level of stationarity is observed, further validating the Westerlund cointegration test.

After the confirmation of the time-series data to be stationary as discussed above, Table 6 explains the Westerlund cointegration test (Westerlund 2007). All the four statistics, namely $G_t$, $G_a$, $P_a$, and $P_t$ reject the null hypothesis at 1% level of significance for both the Covid-19 confirmed cases and deaths. Hence, it is evident that the parameters of both the models indicate that the variables are cointegrated, confirming a long-term relationship between the variables.

Table 7 discusses the Dumitrescu and Hurlin (2012) Granger non-causality test with Covid-19 cases and Covid-19 deaths as the dependent variables. Almost all the variables present statistically significant values at 1% level, with the Covid-19 cases taken as the dependent variable. The results show that bi-directional causalities exist between all the meteorological variables (including the air pollutant PM2.5) and Covid-19 cases, meaning all the variables under study drive

| Variables       | Breusch-Pagan LM | Pesaran scaled LM | Pesaran CD |
|-----------------|------------------|-------------------|------------|
| Covid-19 cases  | Raw values       | 1728.8690***      | 176.4413***| 25.6565*** |
|                 | Logged values    | 165.7510***       | 11.6741*** | 4.9356***  |
| Covid-19 deaths | Raw values       | 1448.2000***      | 146.8562***| 21.3314*** |
|                 | Logged values    | 176.4184***       | 12.7986*** | 7.1736***  |
| Air pressure    | Raw values       | 407.4721***       | 37.1538*** | 5.2383***  |
|                 | Logged values    | 186.0810***       | 13.8171*** | 4.6957***  |
| Humidity        | Raw values       | 356.5339***       | 31.7844*** | 2.3924***  |
|                 | Logged values    | 82.12862***       | 2.8596***  | 0.2379     |
| PM2.5           | Raw values       | 203.8496***       | 15.6901*** | 0.3173     |
|                 | Logged values    | 57.9755*          | 0.3136     | 0.4543     |
| Temperature     | Raw values       | 3477.7480***      | 360.7893***| 4.1820***  |
|                 | Logged values    | 54.0055           | -0.1048    | -0.1804    |
| Wind speed      | Raw values       | 103.0492***       | 5.0648***  | 2.9774***  |
|                 | Logged values    | 58.3650*          | 0.3547***  | 1.2354     |

Source: authors’ computation

*, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively
Covid-19 cases vice-versa. Alternatively, with Covid-19 deaths as the dependent variable, Covid-19 confirmed cases, air pressure, humidity, and temperature exhibit statistically prominent values at 1% level of significance, exhibiting bidirectional causalities with deaths. A unidirectional causality is observed from Covid-19 deaths to PM2.5 towards, and no causal relationship between deaths and wind speed. Our findings are consistent with Sarkodie and Owusu (2020), confirming the strong evidence of causality from confirmed cases to deaths and meteorological factors are good predictors of Covid-19 confirmed and death cases.

With the rapid outbreak globally, most of the infected countries, including India, implemented a country-wide lock-down to reduce the effects of the Covid-19 pandemic and discontinue its transmission. The measures like social distancing and nation-wide lock-down leading to factory and office closures and minimal traffic on roads lead to an improvement in the air quality and climatic conditions across the nations (Shakoor et al. 2020). This improvement is also validated with the causality running from Covid-19 confirmed cases to the meteorological factors, including the air pollutants PM2.5. The findings of bi-directional causalities are confirmed from the extant literature involving empirical research (Chen et al. 2020; Mandal et al. 2020; Tobias et al. 2020; Zangari et al. 2020; Kerimray et al. 2020), which observe that Covid-19 spread has led to lower compositions of air pollutants and more favorable weather conditions.

Table 8 depicts the long-run output elasticities using FMOLS, DOLS, and CCR estimators, considering both the Covid-19 confirmed cases and death cases as the dependent variable.

### Table 5 Panel unit root test

| Variables     | IPS   | ADF-Fisher | CIPS | CADF   |
|---------------|-------|------------|------|--------|
| Covid-19 cases| -9.318*** | 135.168*** | -1.825 (-2.812)*** | -5.279 (-1.501)*** |
| Covid-19 deaths| -14.406*** | 230.317*** | -1.645 (-3.641)*** | -1.501 (-6.504)*** |
| Air pressure  | -22.334*** | 446.182*** | -4.263 (-4.379)*** | -4.347 (-4.519)*** |
| Humidity      | -23.429*** | 474.630*** | -5.456 (-5.106)*** | -5.462 (-5.167)*** |
| PM2.5         | -24.011*** | 489.745*** | -5.886 (-5.289)*** | -6.054 (-6.045)*** |
| Temperature   | -22.269*** | 429.840*** | -4.433 (-4.606)*** | -4.365 (-4.595)*** |
| Wind speed    | -22.981*** | 461.491*** | -5.126 (-5.434)*** | -5.122 (-4.951)*** |

Source: authors’ computation

* *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively

Parentheses denote ΔCIPS or ΔCADF, i.e., at first-level difference

### Table 6 Westerlund cointegration test

| Statistic | Covid-19 cases | Covid-19 deaths |
|-----------|----------------|-----------------|
| $G_t$     | -4.667***      | -12.138***      |
| $G_a$     | -5.849***      | -14.555***      |
| $P_t$     | -3.739***      | -11.576***      |
| $P_a$     | -3.855***      | -14.831***      |

Source: authors’ computation

* *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively

### Table 7 Dumitrescu and Hurlin’s (2012) Granger non-causality test

| Null hypothesis | W-bar | Z-bar | $P$ values |
|-----------------|-------|-------|------------|
| COVID-19 confirmed cases as the dependent variable |       |       |            |
| AP$\leftrightarrow$CC | 3.4586 | 5.4976 | 0.0000 |
| CC$\leftrightarrow$AP | 5.6580 | 10.4156 | 0.0000 |
| H$\leftrightarrow$CC | 2.6860 | 3.7700 | 0.0000 |
| CC$\leftrightarrow$H | 2.6555 | 3.7018 | 0.0002 |
| PM2.5$\leftrightarrow$CC | 2.0112 | 2.2612 | 0.0237 |
| CC$\leftrightarrow$PM2.5 | 3.5575 | 5.7187 | 0.0000 |
| T$\leftrightarrow$CC | 8.9583 | 17.7952 | 0.0000 |
| CC$\leftrightarrow$T | 3.2382 | 5.0047 | 0.0000 |
| WS$\leftrightarrow$CC | 2.3788 | 3.0830 | 0.0020 |
| CC$\leftrightarrow$WS | 3.5769 | 5.7620 | 0.0000 |
| COVID-19 death cases as the dependent variable |       |       |            |
| Null hypothesis | W-bar | Z-bar | $P$ values |
| CC$\leftrightarrow$CD | 21.9771 | 46.9062 | 0.0000 |
| CD$\leftrightarrow$CC | 12.7131 | 26.1914 | 0.0000 |
| AP$\leftrightarrow$CD | 7.0030 | 3.8019 | 0.0001 |
| CD$\leftrightarrow$AP | 4.9130 | 8.7497 | 0.0000 |
| H$\leftrightarrow$CD | 2.2025 | 2.6888 | 0.0072 |
| CD$\leftrightarrow$H | 1.9797 | 2.1908 | 0.0285 |
| PM2.5$\leftrightarrow$CD | 1.4251 | 0.5480 | 0.5837 |
| CD$\leftrightarrow$PM2.5 | 3.5997 | 5.8130 | 0.0000 |
| T$\leftrightarrow$CD | 9.4679 | 18.9347 | 0.0000 |
| CD$\leftrightarrow$T | 4.0616 | 6.8459 | 0.0000 |
| WS$\leftrightarrow$CD | 0.4930 | -1.1337 | 0.2569 |
| CD$\leftrightarrow$WS | 1.6253 | 1.3981 | 0.1621 |

Source: authors’ computation

The symbol $\not{\leftrightarrow}$ represents “does not homogeneously cause”
variables, separately. With Covid-19 confirmed cases as the dependent variable, the air pollutant, namely PM2.5 alone, exhibits a statistically significant and negative impact (at 10% level of significance) on the Covid-19 confirmed cases, as per the FMOLS and CCR statistical values.

Alternatively, with Covid-19 death cases as the dependent variable, Covid-19 confirmed cases reveal a statistically significant and positive impact (at 1% level of significance) on the Covid-19 death cases, according to all the three statistical values under FMOLS, DOLS, and CCR. Additionally, the air pollutant PM2.5 exhibits a statistically significant and negative impact (at 5% level of significance) on the Covid-19 death cases, as per the FMOLS and CCR statistical values.

Hence, air pollutant PM2.5 exhibits a significant negative impact (at 10% and 5% level of significance) on the Covid-19 confirmed cases and death cases in the concerned countries. This finding is consistent with the result by Chen et al. (2020), which states that reduction in the air pollutant serves as a resistance to the continually increasing Covid-19 death cases in China. Also, Fareed et al. (2020) and Wu, Nethery, Sabath, Braun, and Dominici (2020) reveal that exposure to air pollutant PM2.5 leads to massive deaths by Covid-19 in the USA and China, complementing our results.

Table 9 presents the augmented mean group estimates while considering the Covid-19 confirmed cases as the dependent variable. Temperature exhibits a statistically significant impact (at 1% level) on the Covid-19 confirmed cases of all the countries except for Iran, where there is a significant impact but at a 5% level of significance.

Moreover, our results show a positive association of temperature and confirmed cases in countries like Brazil (Rosario et al. 2020), India (Kumar 2020), Iran, and Russia. In contrast, in most countries, it is inversely related, as supported by Wang et al. (2020) and Wu et al. (2020b). Furthermore, air pollutant PM2.5 and air pressure impact the Covid-19 confirmed cases in most countries under study.

All the meteorological variables, including PM2.5, have a strong statistical and significant impact on Brazil’s Covid-19 confirmed cases. The finding is consistent with the results by Auler et al. (2020) and Pequeno et al. (2020) that find a positive linear relationship between the meteorological factors and cases in Brazil, while the results contradict the findings opined by Prata et al. (2020).

In the case of India, all the meteorological variables, including the air pollutant PM2.5, indicate a statistically significant impact (at 1% level of significance) on its Covid-19 confirmed cases. This study serves as an extension to the research by Gupta et al. (2020), which finds no correlation between the vulnerable weather conditions and Covid-19 new cases in India, considering its limited study timeline, while this study includes a more extended timeline. The findings also contradict the results by Kumar (2020), which opine that the cases shall diminish in warmer, humid, and during summer/monsoon regions, as proven by the rising number of cases in India.

Chile reports temperature and wind speed to be statistically significant (at 1% level) and exhibit a negative and a positive impact on its confirmed cases, respectively. Humidity, PM2.5, ...
and temperature reveal a significant impact on the cases in Iran, which is partially consistent with the findings by Ahmadi et al. (2020) that prove humidity, wind speed, and solar radiation exposure support the transmission of coronavirus in Iran. Additionally, the results contradict the findings opined by Jahangiri et al. (2020), finding a low correlation under study impact its death cases.

Except for humidity, all the meteorological factors confirm a statistically significant impact on the Covid-19 confirmed cases in Italy. The findings contradict the results proven by Bontempi (2020) who find no relationship between the particulate matter and the rising Covid-19 cases, while the same is consistent with the results opined by Zoran et al. (2020) who find a significant impact of climatic variables and the cases in Italy. A strong positive association of the concentration of PM2.5 with cases is found in Italy (Lippi et al., 2020).

Alternatively, the findings conclude that air pressure, humidity, and temperature significantly affect the cases in Peru. Air pressure, PM2.5, and temperature have a statistically significant impact (at 1% level of significance) on the rising cases in Russia and Spain (contradicting the result by Briz-Redón and Serrano-Aroca, 2020) which prove no relation between temperature and Covid-19 cases in Spain. The UK exhibits a statistically significant impact by humidity, temperature, and wind speed on its confirmed cases. The former finding is consistent with the results proven by Travaglio, Popovic, Yu, Leal, and Martins (2020) who find low air quality to be associated with the rising Covid-19 cases in England.

The findings report that temperature has a significant negative impact at 1% level of significance on the Covid-19 confirmed cases in the USA, which is also consistent with the findings by Bashir et al. (2020), who opine that average temperature, minimum temperature, and air quality to be significantly associated with the Covid-19 pandemic in the USA.

Table 10 presents the augmented mean group estimates while considering the Covid-19 death cases as the dependent variable. Covid-19 confirmed cases exhibit a statistically significant (at 1% level of significance) and positive impact on the Covid-19 death cases across all the ten countries under study, with the highest impact evident in Italy, where the confirmed cases impact the death cases by 0.1123 units. Out of all the meteorological variables, temperature exhibits a significant negative impact on the death cases in most countries (Wu et al., 2020b) under study, followed by air pressure and humidity (Ma et al., 2020). This finding is consistent with the results by Ma et al. (2020), where the author confirms temperature and humidity as important factors affecting Covid-19 mortality in China.

Countries, namely, India, Spain, and the USA, reveal only temperature and Covid-19 cases to be the essential factors affecting the number of death cases in these countries. This finding contradicts the results by Adhikari and Yin (2020), which confirms no impact by any of the meteorological factors on the death cases in New York, USA, while Brazil and Iran reveal air pressure, in addition to temperature and Covid-19 confirmed cases, to impact its death cases. Similarly, Chile shows wind speed as an essential variable that negatively affects the death cases in the country by 18.45 units. Furthermore, humidity in Italy and Peru has a negative impact on the Covid-19 death cases, as consistent with the results by Fareed et al. (2020). Additionally, UK reveals only air pressure and confirmed cases to have a negative and positive impact on its death cases, respectively. Lastly, Russia exhibits a positive impact of air pressure, humidity, temperature, and Covid-19 confirmed cases, concluding it to be the only country where most of the variables under study impact its death cases.
Considering the issue of endogeneity and cross-sectional dependence (confirmed from the CD test), the study further employs the DCCE model. Table 11 presents the results of the DCCE model. The first part of Table 11 shows the results with Covid-19 confirmed cases as the dependent variable. Consistent with the results proven by the augmented mean group estimation technique, all the variables (except for humidity and wind speed) report a significant impact on the Covid-19 confirmed cases. Overall, temperature and air pressure exhibit a significant but negative impact, implying that an increase in temperature and air pressure shall decrease the number of confirmed cases. Moreover, our results indicate that there is a negative association of temperature and confirmed cases in most countries, which is also supported by Wang et al. (2020) and Wu et al. (2020b). Air pollutant PM2.5 indicates a positive and statistically significant impact, implying that an increase in their levels will ultimately lead to an increase in the number of confirmed cases. Our result is partially consistent with the results by Heneghan and Jefferson (2020), where the authors state that the climatic conditions, including temperature and air pressure have a significant impact on the transmission of the disease. Lolli et al. (2020) also find a negative correlation between temperature and virus transmission, while air pressure exhibits a certain degree of correlation. Hence, it is possible to speculate that cool and dry weather conditions with lower temperature shall contribute to the transmission of the Covid-19 pandemic.

The second part of Table 11 presents the results with Covid-19 death cases as the dependent variable. Similar to the augmented mean group estimation technique, temperature and Covid-19 confirmed cases exhibit statistically significant results. The findings are aligned with Wu et al. (2020b), who opine that temperature is negatively associated with the daily new deaths of Covid-19 worldwide. However, unlike the previous tests, we find air pollutant PM2.5 to positively and significantly impact death cases (at 5% level of significance). This impact of PM2.5 is further validated by Zoran et al. (2020), Magazzino et al. (2020), and Wu, Nethery, Sabath, Braun, and Dominici (2020), who conclude that air pollutant PM2.5 reports a strong positive impact on the Covid-19 death cases. Also, wind speed and humidity do not exhibit any significant impact. This finding partially contradicts the results by Ma et al. (2020) and Sobral et al. (2020), where the authors confirm the significant impact of humidity, and no impact of temperature on Covid-19 death cases, respectively.

| Countries/variables | Constant | Air pressure | Humidity | PM2.5 | Temperature | Wind speed | Covid-19 cases |
|---------------------|----------|--------------|----------|-------|-------------|------------|----------------|
| Overall             | 529.25   | −0.4343      | −0.1614  | 0.0657| −4.5765**   | −0.4067    | 0.0364***      |
| Brazil              | −15320.32***| 16.5607**    | 1.2267   | 0.4780| −13.6685***| −41.8146   | 0.3318***      |
| Chile               | 84.57    | 0.0469       | 0.4234   | 0.1155| −3.7739**   | −18.4571***| 0.0078***      |
| India               | 2784.17  | −2.4807      | −0.7962  | −0.1660| −10.4452*   | −3.7573    | 0.0382***      |
| Iran                | 931.21*  | −0.9071*     | 0.4154   | 0.0796| −1.2489**   | −0.9300    | 0.0407***      |
| Italy               | 1743.83  | −1.1586      | −1.5063**| 0.0215| −3.3447***  | −0.3098    | 0.1123***      |
| Peru                | −2035.72 | 2.6181       | −2.0947***| 0.0830| −18.3167***| −1.0065    | 0.0108***      |
| Russia              | −728.15**| 0.6663**     | 0.6031** | 0.2640| 2.4595***   | 0.5017     | 0.0105***      |
| Spain               | −379.56  | 0.3680       | 0.4440   | −0.0644| −5.2776***  | 2.9427     | 0.0773***      |
| UK                  | 2200.93***| −2.2574***   | −0.0176  | −0.1435| 3.8124      | −0.7229    | 0.0516***      |
| USA                 | 124.51   | −0.0409      | −3.9137  | 3.9048| −0.3409     | 0.0482     | 0.0103***      |

Source: authors’ computation

* *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively

| Table 11 | Dynamic common correlated effect (DCCE) estimation |
|----------|---------------------------------------------------|
| Explanatory variables | Coeff | Std. error |
| Constant | −247.83 | 198.6260 |
| Air pressure | −3.9536*** | 1.2981 |
| Humidity | 0.3085 | 0.2818 |
| PM2.5 | 0.0251*** | 0.0021 |
| Temperature | −0.3675** | 0.1721 |
| Wind speed | 0.2056 | 0.1720 |

COVID-19 death cases as the dependent variable

| Explanatory variables | Coeff | Std. error |
| Constant | −933.80*** | 250.0650 |
| Covid-19 cases | 0.0323** | 0.0141 |
| Air pressure | 1.9540 | 2.6348 |
| Humidity | 0.0343 | 0.5112 |
| PM2.5 | 0.7548** | 0.3782 |
| Temperature | −5.7023** | 2.4512 |
| Wind speed | −2.8108 | 3.6213 |

Source: authors’ computation

** and *** denote statistical significance at 5% and 1% levels, respectively
Conclusions

The coronavirus cases have reached up to 26 million cases and 0.8 million deaths worldwide as of 5 September 2020 (Worldometer 2020). Given the virus’s novelty and the constant increase in the number of cases and deaths, it is imperative to look for the causes behind this widespread pandemic. While there has been progress in managing this disease, the factors apart from age, which affect the severity and mortality of this pandemic, are still not clear (Travaglio et al. 2020). Heneghan and Jefferson (2020) exert that other environmental factors, including air density, air pollution, and daily sunlight, require urgent verification and should be considered for further investigation and testing. Additionally, extant literature highlighted the possible impact of the meteorological factors but has been inconclusive about the role and the degree of influence of such factors on the Covid-19 cases (Iqbal et al. 2020; Xie and Zhu 2020). Given the climatic differences among these most affected ten countries, it seems reasonable to examine the impact of such meteorological factors, including an air pollutant for each of these countries too. This is one of the first studies that take into consideration the nexus between the confirmed Covid-19 confirmed cases, deaths, meteorological factors, including an air pollutant in the world’s top 10 infected countries, from 1 February 2020 through 30 June 2020, using advanced econometric techniques (Sharma et al. 2020a; Nathaniel et al. 2020), including the novel Dynamic Common Correlated Effect (DCCE) model that accounts for the heterogeneity across the nations and provide more reliable and generalizable results (Mensah et al. 2020; Meo et al. 2020).

Our findings confirm a strong cross-sectional dependence between Covid-19 cases, deaths, and the meteorological factors, including air pollutant PM2.5, for all the ten most infected countries under study. The Westerlund (2007) cointegration test confirms a long-term relationship between all the variables under investigation. With Covid-19 cases as the dependent variable, there exists bi-directional causalities running between the Covid-19 cases and all the meteorological factors, namely temperature, wind speed, humidity, air pressure, and PM2.5 (an air pollutant). With Covid-19 death cases as the dependent variable, the bi-directional causality runs between the Covid-19 death cases, and Covid-19 confirmed cases, air pressure, humidity, and temperature. Temperature and air pressure exhibit a statistically significant and negative impact on the Covid-19 confirmed cases. Air pollutant PM2.5 also exhibits a significant but positive impact on the Covid-19 death cases. Simultaneously, Covid-19 confirmed cases and air pollutant PM2.5 exhibit a statistically significant and positive impact on the Covid-19 death cases across the ten countries under study. Hence, it is possible to postulate that cool and dry weather conditions with lower temperature and higher humidity promote indoor activities and human gatherings (assembling), leading to virus transmission.

This study contributes both practically and theoretically to the concerned field of pandemic management. The results herewith provide a better understanding and may assist in taking appropriate measures in implementing intersectoral policies and actions as necessary in a timely and efficient manner. Hence, protection and prevention measures must be adopted to reduce the transmission and possible collapse of the public health system. Such measures shall also encourage e-government initiatives, work-from-home policies for corporates and businesses, improved healthcare sector and facilities, investment in sustainable infrastructure, and better policies for the most vulnerable societies, including the migrants and the daily wage earners. In conclusion, this study provides vital information on the impact of meteorological factors, including an air pollutant, on the rising Covid-19 confirmed cases and death cases. Such information shall lead to a better understanding of the weather parameters responsible for spreading the Covid-19 virus across the most infected countries under study. Lastly, the results may also help the weather forecasting authorities better identify the regions with similar weather conditions that further support the virus’s spread. The present air quality scenarios have gathered all stakeholders’ attention from a scientific, academic, policy decision, and political background, emphasizing the need to identify how to handle future air quality scenarios. Additionally, the experts may rethink and reform the policy measures to reduce the overall impact on the environment and economy together, keeping the policy decisions in line with the sustainable development goals (SDGs).

The study has some limitations. The study has not considered other factors, including demographic variables, personal behaviors, healthcare infrastructure, medical resources, socioeconomic factors, and healthcare sector programs and policies (government response), regulating the transmission of the disease. Therefore, these confounding factors should also be incorporated into such models (as the ones used in this study) and as much as possible empirically tested in future studies. The dataset used for this study is very extensive, but a more extensive dataset, including varying weather conditions, should also be considered by future studies. Also, the dataset included in the study includes the data from February to June; therefore, more recent data could be added to give a more comprehensive picture of the findings.

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Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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