Econometric analysis of COVID-19 cases, deaths, and meteorological factors in South Asia

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Abstract

The pandemic has affected almost 74 million people worldwide as of 17 December 2020. This is the first study that attempts to examine the nexus between the confirmed COVID-19 cases, deaths, meteorological factors, and the air pollutant namely PM_{2.5} in six South Asian countries, from 1 March 2020 to 30 June 2020, using the advanced econometric techniques that are robust to heterogeneity across nations. Our findings confirm (1) a strong cross-sectional dependence and significant correlation between COVID-19 cases, deaths, meteorological factors, and air pollutant; (2) long-term relationship between all the meteorological variables, air pollutant, and COVID-19 death cases; (3) temperature, air pressure, and humidity exhibit a significant impact on the COVID-19 confirmed cases, while COVID-19 confirmed cases and air pollutant PM_{2.5} have a statistically significant impact on the COVID-19 death cases. In this way, the conclusion that high temperature and high humidity increase the transmission of the COVID-19 infections can also be applied to the regions with greater transmission rates, where the minimum temperature is mostly over 21 °C and humidity ranges around 80% for months. From the findings, it is evident that majority of the meteorological factors and air pollutant PM_{2.5} exhibit significant negative and positive effects on the number of COVID-19 confirmed cases and death cases in the six countries under study. Air pollutant PM_{2.5} provides more particle surface for the virus to stick and get transported longer distances. Hence, higher particulate pollution levels in the air increase COVID-19 transmission in these six South Asian countries. This information is vital for the government and public health authorities in formulating relevant policies. The study contributes both practically and theoretically to the concerned field of pandemic management.

Highlights

- To examine the nexus among the COVID-19 confirmed cases, deaths, meteorological factors, and the air pollutant namely PM_{2.5} in six South Asian countries, from 1 March 2020 to 30 June 2020, employing advanced econometric techniques
- Strong cross-sectional dependence and significant correlation among COVID-19 cases, deaths, meteorological factors, and the air pollutant
- Temperature air pressure and humidity exhibit a significant impact on the COVID-19 confirmed cases in the six countries
- COVID-19 confirmed cases and air pollutant PM_{2.5} have a statistically significant impact on the COVID-19 death cases
- Results assist government and public health authorities in formulating the policies for containing, mitigating, and surveillance of COVID-19 in different countries

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Introduction

A novel and an unknown virus from the family of coronaviruses with pneumonia-like symptoms outbreak as an epidemic in Wuhan city of China (Zhu and Xie 2020) at the end of 2019. This new unidentified virus is a more severe respiratory disorder as it was causing pneumonia, kidney failure, and even death in severe cases (Wang et al. 2020b). Later, the World Health Organization (WHO) announced the COVID-19 outbreak as a pandemic on 11 March 2020, affecting several countries worldwide (WHO 2020). South Asia witnessed the footprints of COVID-19 about a month later than its first reported case in China (Kumar 2020a). The first country to report a confirmed case in this region was Nepal, followed by Sri Lanka and India (Johns Hopkins Coronavirus Resource Center 2020; The Financial Express 2020). The first confirmed case in India was on 30 January 2020 (Reid 2020). As the governments of the countries in this region started lifting lockdowns and other bans, in the wake of frail health infrastructure and low testing, numbers started flooding (Fig. 1), with more than 3,54,000 confirmed cases by 18 June 2020. India became the fourth worst-hit nation globally and top in South Asia (Worldometer 2020; Stout and Alam 2020). Bloomberg's report opines a rise in infections by 17% in India, by 19% in Bangladesh, and 27% in Pakistan (Mangi and Devnath 2020).

Consequently, with the population density at peak levels, the population's significant quantum is below the poverty line, prevalent malnutrition, underdeveloped public health systems,

and facilities justify the COVID-19 study on the South Asian continent meaningful (Sivakumar and Stefanski 2011; Reid 2020). Geographically, the South Asian region has a vast diversity and varied climatic conditions (also evident from the study's climate data) due to the diverse geographical locations (National Geographic Society 2020). These facts trigger curiosity to find out the underlying causes behind the pandemic outbreak. It further indicates that the varying levels of the spread of infection could be caused by many other factors as well viz. the climatic factors, weather conditions, immunity levels of inhabitants, population's previous experience to such other infections, as evidenced by experts in the past (Hashim 2020). Looking at such trends and divergent setups of this region, the research based on COVID-19 spread in South Asia is a worthwhile study (Deccan Herald 2020).

This paper attempts to fill the gap by making an academic contribution in three ways. First, the study of the relationship between meteorological factors and COVID-19 spread needs to be investigated in the light of previous studies that indicated that during winters, the cold weather hampers the body immunity, thereby increasing the risk of catching virus infections and other respiratory diseases. In many previous studies, the issue of winter seasonality has been observed in many respiratory viruses (Lin et al. 2006; Gaunt et al. 2010). Studies also suggest the higher spread of COVID-19 in the cold climate as observed in the spread of seasonal flu by viruses like MERS CoV and SARS CoV (which belong to the coronavirus family of viruses) in a low degree of temperature (Casanova et al. 2010; Bloom-Feshbach et al. 2013). In some of the previous

Fig. 1 Number of COVID-19 Confirmed Cases

literature that studies the impact of temperature on coronavirus infections, the research advocates that increase or decrease in temperature affect the virus's survival (Chan et al. 2011; Van Doremalen et al. 2013). Liu et al. (2020) also find that by the end of March 2020, the spread of the COVID-19 pandemic would be mostly in the locations with low temperatures. A few of the previous works that studied the relationship between meteorological factors and COVID-19 spread indicated that the spread declined as the atmospheric temperature rose (Oliveiros et al. 2020; Wang et al. 2020b). Hence, the experts have raised voices that temperature rise shall have a restraining impact on COVID-19 spread.

Second, existing literature has raised the curiosity to explore the behavior and pattern of COVID-19 spread in regions situated in high-temperature zones. Hence, South Asian countries being in the hot and tropical zone with higher temperatures and sunlight levels appear to be a reasonable hypothesis to examine this association. Additionally, the present study makes a fresh attempt to study a comparatively under-researched market, namely, six South Asian countries, enhancing our research's geographical scope.

Third, research based on examining the relationship between the COVID-19 cases, deaths, meteorological factors, and air pollutants across nations and world regions opine conflicting and contradictory results due to the employment of different methodologies, different variables, and varied datasets. Some indicate temperature and COVID-19 cases to be negatively correlated (Bannister-Meyer et al. 2020; Wang et al. 2020b; Liu et al. 2020). Yet, others show a positive relationship between the variables (Oliveiros et al. 2020). Studies also report the negative linear relationship of confirmed COVID-19 cases up to a specific threshold limit of temperature, but fail to find a declining curve beyond that temperature limit (Prata et al. 2020). Hence, so far, the existing literature has ignored the cross-sectional dependence and heterogeneity between the concerned variables. The present study employs the advanced econometric techniques robust to heterogeneity, and dependencies across nations, have proven to produce more reliable and efficient results (Dogan and Aslan 2017; Dogan et al. 2017; Nathaniel et al. 2019, 2020b; Sharma et al. 2020). Despite their popularity, the literature has not used these methodologies to investigate the effect of such variables on the transmission of COVID-19.

The rest of the paper is organized as follows: the “Literature review” section reviews the relevant literature; the “Methodology” section specifies the model and data, along with the data analysis techniques; the “Results and discussion” section presents the results and the discussion; and finally, the “Conclusions” section concludes the paper with policy implications.

Literature review

The constant rise in COVID-19 cases and deaths across the globe has undoubtedly caught the attention of the researchers and policymakers since its outbreak in December 2019 in Wuhan, China. Extant literature includes earlier studies exploring the various types of viruses viz. SARS and MERS (Chan et al. 2011; Bloom-Feshbach et al. 2013; Van Doremalen et al. 2013).

Majority of studies (Zhu and Xie 2020; Shahzad et al. 2020) are conducted either on China exclusively, or worldwide or on a vast geographical region (Bannister-Meyer et al. 2020; Ficetola and Rubolini 2020; Sethwala et al. 2020; Wu et al. 2020). Besides, other works explore the USA (Gupta et al. 2020) or Brazil in particular (Auler et al. 2020; Prata et al. 2020). Most of the studies that examine the relationship between temperature and COVID-19 spread also include varied meteorological factors and weather parameters such as diurnal temperature, absolute/relative humidity, precipitation, air quality index, wind speed, and other parameters (Table 1). Some studies (Bannister-Meyer et al. 2020; Pawar et al. 2020) exclusively study the nexus between temperature and COVID-19 cases. In addition to investigating the linkage of COVID-19 cases with weather/metrological parameters, limited studies also incorporate certain demographic features viz. population density, intra-provincial movement, and migration scale index, to name a few.

Zhu and Xie (2020) find a positive linear relationship between COVID-19 cases and temperature with a threshold of less than 3 °C. However, some of the recent studies establish a negative correlation between temperature and COVID-19 cases in Wuhan (China) and Northern Hemisphere countries, including New York, Turkey, and Indonesia (Ficetola and Rubolini 2020; Guo et al. 2020; Prata et al. 2020). Consistently, Wu et al. (2020) and Ficetola and Rubolini (2020) also find a negative correlation between temperature, humidity, and COVID-19 cases in 166 countries. Auler et al. (2020) and Gupta et al. (2020) opine that COVID-19 spread in five Brazilian cities where the relative humidity is nearby 79.6% and the temperature is 27.3%. Liu et al. (2020) employ the linear regression model and reveal that an increase in temperature leads to the decline of confirmed COVID-19 cases after controlling population migration. Considering the local climatic conditions with low temperature and low humidity favored the virus transmission, Pawar et al. (2020) ascertain no significant correlation with cases transmitted, deaths, or recovered in China, the USA, Australia, and Canada. Gupta et al. (2020) study 50 states of the USA and find that the spread of COVID-19 is supported by temperature ranging from 4 to 11 °C. The findings suggested by Bannister-Meyer et al. (2020) reveal that warmer weather in the Northern Hemisphere may modestly reduce the rate of spread.

Table 1 Relevant literature

S. no.	Author(s)/years	Region/country(s)	Methodology	Variables	Time period	Findings
1.	Guo et al. (2020)	Wuhan, China	Correlation and regression	CC → Temperature and humidity	January 24 to February 13, 2020	COVID-19 cases negatively correlated with temperature and humidity
2.	Park et al. (2020)	Seoul, Republic of Korea	Lag non-linear model	CC → Temperature, humidity, and diurnal temperature	2010–2016	Influenza incidence significantly increased with low daily temperatures
3.	Zhu and Xie (2020)	122 cities from China	Generalized Additive Model (GAM)	CC → Temperature	January 23 to February 29, 2020	A positive linear relationship between COVID-19 cases and temperature
4.	Bannister-Meyer et al. (2020)	Global	Measures of central tendency and linear and quadratic	CC → Temperature	Cases reported until 29th February 2020	Warmer weather in the northern hemisphere may modestly reduce the rate of spread
5.	Ficetola and Rubolini (2020)	Northern Hemisphere	Best-fitting mixed model	CC → Temperature and humidity	January to March 2020	COVID-19 cases negatively correlated with temperature and humidity
6.	Ahmadi et al. (2020)	Iran	Partial correlation coefficient and Sensitivity analysis.	CC → Population density, intra-provincial movement, and infection days, meteorological factors	February 19 to March 22, 2020	Areas with low values of wind-speed, humidity, and solar radiation are exposed to a high rate of infection that supports the virus's spread/direct relationship of population density with the infection rate, while there is reverse relation between virus outbreak speed, humidity, and solar radiation
7.	Oliveiros et al. (2020)	31 provinces of Mainland China	Linear regression model	CC → Temperature and humidity	January 23 to March 1, 2020	Temperature and humidity variables explain 18% of the variation in disease doubling time, and the remaining 82% may be related to containment measures, general health policies, population density, transportation or cultural aspects
8.	Shi et al. (2020a, b)	31 provincial-level regions in mainland China	M-SEIR model	CC → Temperature and humidity	January 20 to February 29, 2020	Transmission rate decreased with the increase of temperature, leading to a further decrease of infection rate and outbreak scale
9.	Bashir et al. (2020)	New York City	Kendall and spearman rank correlation	CC → Average, Minimum, Maximum Temperature; Rainfall; Wind-speed; Average humidity, Air Quality Index	March 1 to April 12, 2020	Significant association of average and minimum temperature and air quality with COVID-19 cases
10.	Tosepu et al. (2020)	Indonesia	Spearman rank correlation	CC → Minimum, Maximum, Average Temperature and Rainfall	January to March 2020	A significant correlation between average temperature and COVID-19 cases
11.	Ma et al. (2020)	Wuhan, China	Generalized additive model	CC and daily death counts → Temperature, Humidity and Temperature Range	January 20 to February 29, 2020	Positive association of temperature with COVID-19 daily death counts and negative association of COVID-19 cases with relative humidity
12.	Prata et al. (2020)	27 capital cities of Brazil	Linear and Non-linear relation and Generalized Additive model	CC → Temperature	February 27 to April 1, 2020	A negative linear relationship between average temperature and COVID-19 cases
13.		50 US states	Distribution modeling,			

Table 1 (continued)

S. no.	Author(s)/years	Region/country(s)	Methodology	Variables	Time period	Findings
	Gupta et al. (2020)			CC → Weather parameters comprising Temperature and Absolute Humidity	January 1 to April 9, 2020	The spread of COVID-19 cases is supported by temperature ranging from 4 to 11 °C and average humidity in the range 4 to 6 gm.
14.	Wu et al. (2020)	166 countries from Asia (excluding China)	Log-linear Generalized Additive Model	CC → Temperature and Humidity	January 20 to February 29, 2020	A negative relationship between temperature and relative humidity with COVID-19 daily deaths and new COVID-19 cases
15.	Auler et al. (2020)	5 Brazilian cities (São Paulo, Rio de Janeiro, Brasília, Manaus, and Fortaleza) cities	Principal component analyses and canonical correlation, multivariate and linear regression	CC → Meteorological conditions like Rainfall, Humidity, and Temperature.	March 13 to April 13, 2020	Correlation between meteorological factors and COVID-19 cases in a tropical climate
16.	Liu et al. (2020)	30 capital cities of China	Non-linear regression and the meta-analysis	CC → Meteorological Factors such as Temperature, Humidity and Migration Scale Index	January 20 to March 2, 2020	An increase in temperature led to the decline of confirmed COVID-19 cases after controlling population migration. Results favored the transmission of COVID-19 cases in weather having low temperature, low humidity, and mild diurnal temperature range
17.	Şahin (2020)	Turkey	Spearman's correlation	CC → Meteorological parameters- temperature, dew point, humidity, and wind-speed	March 10 to April 25, 2020	Inverse relationship of temperature and humidity with COVID-19 cases and a positive relationship between wind speed with COVID-19 cases
18.	Sethwala et al. (2020)	Global	Notional p-value was calculated by the Wilcoxon test	CC and death counts → Ambient Temperature	January 23 to April 11, 2020	Definitive association with the highest risk of COVID-19 infections occurring around 9 °C
19.	Pawar et al. (2020)	China and countries and regions outside China	Correlation and Multiple Regression Analysis	CC, death and recovered counts → Average Temperature	January 22 to March 16, 2020	No significant correlation between temperature and confirmed COVID-19 cases, deaths, or recovered. Regression model predicts a rise in the number of deaths in China, USA, Australia, and Canada
20.	Kumar (2020a, b)	India	Correlation Analysis	CC → Temperature, Relative Humidity, Aerosol Optical Depth (AOD) and NO ₂ (an air pollutant)	March to April 2020.	A negative association between air pollution and COVID-19 cases in March and positive association in April 2020, a positive association between COVID-19 cases and temperature
21.	Iqbal et al. (2020)	China	Wavelet Coherence Technique	CC → Average Temperature and RMB (Chinese currency) exchange rate	January 21 to March 31, 2020	The insignificance of an increase in temperature to contain or slow down the new COVID-19 cases, while the RMB exchange rate reports a negative but limited impact of the COVID-19 cases
22.	Xu et al. (2020)	China	Poisson regression model	CC → Air Quality and Meteorological Variables	January 29 to February 15, 2020	An increase in AQI levels has a statistically significant impact on COVID-19 cases, and the impact is further enhanced under low relative humidity.

CC, COVID-19 confirmed cases

Concerning the time frame, the period covered in most of the studies pertains either to January 2020–February 2020 or January 2020–March 2020 or February 2020–March, 2020, or March 2020 to mid of April 2020. Very few studies cover the period from January 2020 to April 2020 (Sethwala et al. 2020; Bashir et al. 2020; Gupta et al. 2020). Based on the country/region and the time frame, studies conducted in this area rely on diverse methodologies and techniques to examine the relationship between COVID-19 cases, deaths, and meteorological factors including air pollutants. Regarding the methods used to study the relationship between COVID-19 cases and meteorological factors, the previous studies employ varied techniques ranging from Kendall and Spearman's Rank Correlation (Bashir et al. 2020; Tosepu et al. 2020; Şahin 2020) to generalized additive model (Ma et al. 2020; Prata et al. 2020; Wu et al. 2020) to non-linear regression and meta-analysis (Liu et al. 2020), partial correlation and sensitivity analysis (Ahmadi et al. 2020), principal component analyses, canonical correlation, multivariate, and linear regression analysis (Auler et al. 2020).

Thus, given the trajectory of literature, previous studies failed to account for the nexus between the COVID-19 cases, deaths, meteorological factors, and air pollutants in South Asian countries where there is a wide variation in the climatic conditions. From this context, the South Asian countries appear to be a befitting case for such a study as it falls in the tropical climatic region. Furthermore, unlike the previous studies, this study employs the advanced econometric techniques robust to heterogeneities across nations and has proven to produce more reliable and efficient results (Nathaniel et al. 2019, 2020a, b; Nathaniel 2020; Sharma et al. 2020).

Unlike the previous literature, the present study attempts to examine the relationship between COVID-19 confirmed cases and death cases with the meteorological factors, namely, temperature, humidity, wind speed, air pressure, and an air pollutant, namely PM2.5, using advanced econometrics techniques of panel data regression, including the first-and second-generation unit root tests, and the LM tests (Table 2). Furthermore, the Westerlund cointegration test is applied to test the long-term relationship between the variables, followed by the Granger non-causality test to evaluate the causality

between the concerned variables. Finally, the long-run estimation approach and mean group estimation technique are applied to six emerging South Asian countries' panel data.

Methodology

Model specification and data

The study examines the relationship among COVID-19 confirmed cases, death cases, and meteorological factors, namely, temperature, humidity, wind speed, air pressure, and air pollutant, namely PM2.5. The dataset consists of six South Asian countries spread over 4 months from 1 March 2020 to 30 June 2020. Out of the eight SAARC nations, Bhutan and Maldives are excluded from the study due to low and insignificant cases; hence, the six countries under our study include Afghanistan, Bangladesh, India, Nepal, Pakistan, and Sri Lanka (Table 3). Since the outbreak of the COVID-19 epidemic, the daily, and even 12-hour confirmed cases (mild, moderate, severe, and critical), suspected cases, close contact cases, and deaths were reported to Health Commissions at all stages (county level, municipal, provincial and national) (Xu et al. 2020). Furthermore, the chosen Asian countries have experienced considerable impact of temperature on the number of COVID-19 cases making the panel suitable for econometric analysis (Hashim 2020; Stout and Alam 2020).

After examining the need for the study, the following two econometric models are used to study the relationship among COVID-19 confirmed cases, death cases, and meteorological factors, namely, temperature, humidity, wind speed, air pressure, and an air pollutant, namely PM2.5.

$$Y_{it} = \alpha_0 + \beta_1 T_{it} + \beta_2 AP_{it} + \beta_3 H_{it} + \beta_4 WS_{it} + \beta_5 PM_{it} + \varepsilon_{it} \quad (1)$$

Table 2 Variables under study

S. no.	Variables	Variable code
1.	COVID-19 confirmed cases	CC
2.	COVID-19 death cases	DC
3.	Temperature	T
4.	Air pressure	AP
5.	Humidity	H
6.	Wind speed	WS
7.	Particulate matter 2.5	PM2.5

Table 3 COVID-19 cases in the SAARC member states

Country	Total cases	Total deaths	Recovered
Afghanistan	49,703	2001	38,500
Bangladesh	4,94,209	7129	4,26,729
India	99,32,547	1,44,096	94,56,449
Nepal	2,50,180	1730	2,38,569
Pakistan	4,40,787	8832	3,84,719
Sri Lanka	34,121	157	24,867
Total	1,12,01,547	1,63,945	1,05,69,833

Source: SAARC Disaster Management Centre (2020) as on 16 December 2020

and

$$Y'_{it} = \alpha_0 + \beta_1 Y_{it} + \beta_2 T_{it} + \beta_3 AP_{it} + \beta_4 H_{it} + \beta_5 WS_{it} + \beta_6 PM_{it} + \varepsilon_{it} \quad (2)$$

where Y denotes the daily confirmed COVID-19 confirmed cases and Y' denotes COVID-19 death cases, T denotes temperature (measured in Celsius), AP denotes air pressure (measured in hPa), H denotes humidity (measured in %), WS denotes wind speed (measured in m/s), PM denotes the daily particulate matter 2.5 (measured in $\mu\text{g}/\text{m}^3$), i denotes the country, t denotes the period under study, and ε_{it} denotes the error term. The temperature data of all the countries has been acquired from AccuWeather Global (2020). For all the other meteorological variables, namely, air pressure, humidity, wind speed, and air pollutant PM2.5, the data has been retrieved from the World Air Quality Index Project Team (2020). Additionally, the data for COVID-19 confirmed cases and deaths is extracted from Our World in Data (2020a, b) as of 20 July 2020. To run the aforementioned econometric techniques, the two statistical softwares, namely EViews and Stata are implemented in this study.

Data analysis and techniques

The data analysis technique begins with a summary of the descriptive statistics of the variables proposed in the econometric model. The purpose of descriptive statistics is to define the basic features of the dataset under study. As the data is related to cross country, it becomes imperative to test cross-sectional dependence through the LM tests, namely, Pesaran and Breusch-Pagan. To check and validate the stationarity of the time-series of the data, we employ a second-generation unit root test, namely, the cross-sectionally augmented Dickey-Fuller (CADF) test, and the cross-sectionally augmented Im, Pesaran, and Shin (CIPS) test. Third, the Westerlund Cointegration Test (WCT) is applied to test the long-term relationship between the model variables. Fourth, Dumitrescu and Hurlin (2012) Granger non-causality test is applied considering the COVID-19 confirmed cases and the COVID-19 death cases as the dependent variable, according to the two models proposed in the previous section. Fifth, the long-run estimates are evaluated using the fully modified ordinary least squares (FMOLS), dynamic ordinary least square (DOLS), and the canonical cointegration regression (CCR) estimators. The sixth step involves the estimation of the country-wise mean group and augmented mean group. Furthermore, the steps involved in the panel data analysis are illustrated in Fig. 2.

Cross-section dependence test

In the case of panel data models where the cross-section dimension (N) is small (typically $N < 10$) and the time-series dimension (T) is large, the standard technique must be to treat the equations from the different cross-section units as a single system (Pesaran et al. 2001; Im et al. 2003; Conley and Dopor 2003; Pesaran 2004). The following simple alternative is based on the pair-wise correlation coefficients rather than their squares used in the present study. Initially, it is argued that the hypothesis of “cross-sectional interdependence” is invalid in macroeconomic analysis that has strong inter-economy relationship. The CD (cross-section dependence) tests overcome the panel data issues and ensure robustness and consistency of estimators (Dogan et al. 2020b; Nathaniel et al. 2020a). For this purpose, we applied three CD tests. Consistent with Breusch and Pagan (1980) and Pesaran (2004), this CD test is applied, as shown in the Eq. (3) below:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=0}^{N-1} \sum_{j=i+1}^{N-1} \rho_{ij} \right) \quad (3)$$

where, CD is the cross-sectional dependence; N is the cross-sections in the panel data; T is the time horizon; and ρ_{ij} is the cross-section correlation of error between i and j .

Second-generation root test

The presence of CD indicates that the first-generation tests may be inefficient, triggering the need for second-generation tests. Hence, the study proceeds with the second-generation unit root tests, namely the cross-sectionally augmented Im, Pesaran, and Shin (CIPS) test and the cross-sectionally augmented Dickey-Fuller (CADF) tests. This test validates the stationarity of the time-series data. Furthermore, the CIPS test is proposed by Pesaran (2007), which examines the cross-sectional average and the cross-sectionally augmented Dickey-Fuller (CADF) unit root test, and provides statistics for the variables individually. Hence, this test is useful for identifying the existence of unit roots in heterogeneous panels. As per Pesaran (2007), the following equation (4) depicts the unit root test:

$$x_t = \alpha_{it} + \beta_i x_{it-1} + \rho_i T + \sum_{j=1}^n \theta_{ij} \Delta x_{i, t-j} + \varepsilon_{it} \quad (4)$$

where α_{it} is the intercept; T is the time horizon; Δ is the difference operator; x_{it} are the study variables; and ε_{it} is the error term. Accordingly, to these tests, if a variable(s) is/are not stationary, the first difference of the variable ($x_t - x_{t-1}$) is taken, and the unit root test is applied again. If the variables become stationary at $I(1)$, there will be a need for cointegration test before parameter estimation. Both the tests generate accurate evidence of both CD and heterogeneity (Nathaniel et al. 2020c).

Fig. 2 Steps adopted in panel data analysis

Westerlund cointegration test

The test is enough to allow for dependence both within and between the cross-sectional units (Westerlund 2007). Westerlund (2007) developed four new panel cointegration tests as an extension of Banerjee et al. (1998) based on structural rather than residual dynamics and, therefore, do not impose any common factor restriction. The first two tests are designed to test the alternate hypothesis that the panel is co-integrated as a whole. At the same time, the other two examine the alternative that at least one unit is co-integrated. This test addresses the common factor restriction issue that be-devilled the first-generation cointegration test. It is an error correction model cointegration test that investigates the null hypothesis of no cointegration (Nathaniel et al. 2020c). The test is applied as per the following Eq. (5):

$$\Delta Y_{it} = \delta_i d_t + \alpha_i Y_{it-1} + \lambda'_i X_{it-1} + \sum_{j=1}^{p_i} \omega_{ij} \Delta Y_{it-j} + \sum_{j=0}^{p_i} \gamma_{ij} \Delta X_{it-j} + \varepsilon_{it} \quad (5)$$

where $\omega_i = (\delta_{i1}, \delta_{i2})'$; and $d_t = (1, t)'$ are the error-correction parameter, vector of parameters, and the deterministic components, respectively; d are model residuals; i is the cross-section in the panel data, and t is the time horizon (Nathaniel et al.

2020c). The null hypothesis under these tests states that there does not exist any long-term relationship between the variables.

Granger non-causality test

Dumitrescu and Hurlin (2012) Granger non-causality test with the bootstrap procedure is applied to examine the direction of causality. This technique is well-known for bivariate causality, which involves estimating a linear vector autoregression (VAR) (Yörük et al. 2006). This test helps explore whether the regressor used in the model can predict the number of COVID-19 cases. The null hypothesis states that there exists no causality between the selected variables under study. The DH test supersedes the vector error correction model (VECM) causality as it is robust amidst heterogeneity and CD. The test is composed of two statistics, namely, the Zbar statistics and Wbar statistics, where the latter incorporates the average test statistic and the former displays standard normal distribution (Nathaniel et al. 2020c). The following equation (6) is used to describe the model:

$$y_{it} = \alpha_i + \sum_{k=1}^K \beta_{ik} y_{i,t-k} + \sum_{k=1}^K \gamma_{ik} x_{i,t-k} + \varepsilon_{it} \quad (6)$$

where the intercept and coefficient α_i and $\gamma_i = (\gamma_{i1}, \gamma_{i2}, \dots, \gamma_{ik})$ are fixed. The autoregressive parameter and regression coefficients are respectively, β_{ik} and γ_{ik} . The underlying variables are x and y for k cross-section in t time (Nathaniel et al. 2020b). The lag order of K is assumed identical for all individuals, and the panel must be balanced. The test hypotheses are:

$$H_0 : \beta_1 = 0$$

$$H_0 \begin{cases} \beta_i = 0 \\ \beta_i \neq 0 \end{cases} \forall i = 1, 2, \dots, N \text{ and } \forall i = N + 1, N + 2, \dots, N$$

Long-run estimation approach

To get a fully efficient estimation, the fully modified ordinary least square (FMOLS), dynamic ordinary least square (DOLS), and canonical cointegration regression (CCR) model are tested (Wang and Wu 2012). Such tests are considered for empirical interpretation to verify the serial correlation in the model (Bhattacharya et al. 2016) and present much more robust results (Paramati et al. 2017).

Phillips and Hansen (1990) proposed the FMOLS estimator, and Park (2010) proposed the CCR estimator. According to Montalvo (1995), CCR is a better estimator than FMOLS and DOLS, as it exhibits lesser bias. The CCR results have shown improvement in the root mean squared error from 20 to 200%, specifically in comparison to the FMOLS results, concluding on the need to apply CCR for long-term estimation of accurate results (Zhao et al. 2018).

Mean group estimates

With the presence of cointegration, the augmented mean group (AMG) estimation technique has been applied. Pesaran and Smith (1995) show that mean group estimators produce consistent estimates of the parameters average. Pirotte (1999) shows that the mean group estimators provide efficient long-run estimators. It allows the parameters to be freely independent across the groups and does not consider potential homogeneity between groups. Pesaran et al. (1999) proposed an inter-mediate estimator that allows the short-term parameters to differ between groups while imposing quality of the long-term coefficients between countries. The AMG accounts for CD and heterogeneity which are the two main panel data issues (Dogan et al. 2020b). The individual regression is:

$$y_{it} = \beta_i x_{it} + \delta_{xi} \bar{x}_t + \delta_{yi} \bar{y}_t + e_{it} \quad (7)$$

where,

$$\bar{x}_t = N^{-1} \sum_{i=1}^N x_{it} \quad (8)$$

is the cross-sectional average of the regressors, and

$$\bar{y}_t = N^{-1} \sum_{i=1}^N y_{it} \quad (9)$$

is the cross-sectional average of the dependent variable, while x_{it} and y_{it} are the observables (Nathaniel et al. 2020c; Sharma et al. 2020)

Results and discussion

This section begins with Table 4, which represents the descriptive statistics for the variables under study for the six South Asian countries. The results show that among all the six countries, the maximum number of cases went up to 19,906, with deaths leading up to 2003. The average value for the cases has been 1317, and for the death cases, it has been 32. Among all the meteorological variables under study, humidity witnessed the maximum variation (41), while the lowest variability is observed by temperature (6.143). Over the period under review, the average temperature remained at 25, while the highest mean value is evident in case of air pressure with a value up to 1009. The distribution of the given data for temperature is approximately symmetric, whereas it is highly skewed in the case of COVID-19 cases for all the countries.

Table 5 presents the cross-sectional dependence for both the variables taken under the study. The values of COVID-19 cases, deaths, all the meteorological factors, and the air pollutant are significant at a level of 1%, in all the three statistics, namely, Breusch-Pagan LM, Pesaran scaled LM, and Pesaran CD exhibiting cross-sectional dependence within the panel data, except for the wind speed and humidity. Under the Pesaran CD test, the results for both the raw and logged values of wind speed and humidity are insignificant and statistically significant at 10%, respectively. This further validates that the spread of the COVID-19 cases to spill over to the other countries, possibly due to their geographical location, and being connected through single boundaries. Furthermore, this result validates a strong connection between all the variables for all the six countries under study.

Furthermore, following the presence of cross-sectional dependence between the variables as shown in Table 5, Table 6 indicates the second-generation unit root test (SUT), namely the cross-sectionally augmented Im, Pesaran and Shin (CIPS) test and cross-sectionally augmented Dickey-Fuller (CADF) which are known for their robustness. It also accounts for serial correlation and cross-sectional dependence. For both the CIPS and CADF, all the variables under study report stationarity with a 1% significance level.

Following the time series data to be stationary, Table 7 explains the cointegration test (Westerlund 2007). The

Table 4 Descriptive statistics

Statistics	Wind speed	Humidity	Air pressure	PM 2.5	Temperature	COVID-19 cases	COVID-19 deaths
Mean	5.741	62.614	1009.732	99.363	25.175	1317.620	32.449
Median	3.450	65.500	1010.500	102.000	27.000	109.000	1.000
Maximum	55.100	134.250	1514.750	277.000	37.000	19,906.000	2003.000
Minimum	0.700	67.800	872.850	23.500	4.000	0.000	0.000
Std. Dev.	6.309	41.947	23.220	38.584	6.143	2885.416	102.652
Skewness	2.936	-20.306	12.755	0.709	-0.844	3.552	10.928
Kurtosis	14.615	498.886	313.359	5.109	3.245	17.452	190.122

statistics G_t and G_a present the group mean tests, and the statistics P_t and P_a represent the panel tests. In the case of COVID-19 death cases, all the four statistics, namely, G_t , G_a , P_a , and P_t reject the null hypothesis at 1% level of significance, while in case of COVID-19 confirmed cases, only G_t and G_a statistics reject the null hypothesis at 1% level of significance. Hence, it is evident from the WCT results that the parameters of the model concerning COVID-19 confirmed cases and the long-term relationship may or may not exist, since only two out of the four statistics confirm the same. While in the model concerning the COVID-19 death cases, the statistics prove that all the variables are co-integrated, establishing the long-term relationship between the variables under study.

Table 8 discusses the Dumitrescu and Hurlin (2012), Granger non-causality test with COVID-19 cases and COVID-19 deaths as the dependent variables, resulting in statistically significant values at 1% level in all variables except wind speed and air pressure, exhibiting the existence of causality between the rest of the variables for all the countries

under study. The causality implies that all the five variables have a significant impact on COVID cases and number of deaths in the countries under study. However, air pressure does not exhibit any causality, while wind speed shows statistical causality at a 10% significance level, with COVID-19 cases. It may also be noted that significant statistical causality is evident between COVID-19 confirmed cases and death cases, implying that along with the meteorological factors under study, the spread of the confirmed cases also drives the number of death cases. This result is also confirmed empirically by Achenbach et al. (2020) and Alluri and Nazmi (2020), where the news reports affirm that a rise in the number of infections is further driving the number of death cases across the country. Moreover, among the countries under study, India, Nepal, and Bangladesh report an increase in the number of deaths (per million people) at the same pace as the number of confirmed cases (per million people) in these countries (Our World in Data 2020b).

Table 9 depicts the long-run output elasticities using FMOLS, DOLS, and CCR estimators, considering the

Table 5 Cross-sectional dependence test

Variables		Breusch-Pagan LM	Pesaran scaled LM	Pesaran CD
COVID-19 deaths	Raw values	510.4794***	90.46175***	15.83637***
	Logged values	560.8396***	99.65622***	17.28983***
COVID-19 cases	Raw values	738.8021***	132.1476***	23.38573***
	Logged values	961.8194***	172.8648***	29.90265***
Air pressure	Raw values	223.3484***	38.03903***	6.322383***
	Logged values	218.8524***	37.21818***	6.332646***
Humidity	Raw values	206.8844***	35.03314***	-1.811504*
	Logged values	204.6962***	34.63363***	-1.929408*
PM2.5	Raw values	309.6420***	53.79403***	14.83581***
	Logged values	306.2989***	53.18367***	14.28678***
Temperature	Raw values	643.0120***	114.6588***	22.96039***
	Logged values	639.6424***	114.0436***	23.01592***
Wind-speed	Raw values	107.1441***	16.82314***	-1.157303
	Logged values	98.04697***	15.16223***	-0.590407

Source: Authors' computation

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

Table 6 Second-generation unit root test

Variables	Level	
	CIPS	CADF
COVID-19 deaths	−2.982***	−7.690***
COVID-19 cases	−4.150***	−10.561***
Air pressure	−3.120***	−6.984***
Humidity	−4.014***	−8.024***
PM2.5	−5.879***	−11.130***
Temperature	−5.656***	−10.522***
Wind-speed	−4.902***	−11.218***

Source: Authors' computation

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

COVID-19 confirmed cases and death cases as the dependent variables. The coefficient (Coeff) refers to the beta value (as depicted in the linear form of the models), while the standard error (Std Error) presents an estimate of the standard deviation of the coefficient that is the amount it varies across cases, while in Table 9, the standard errors in column two confirm that the sampling variance around these coefficients is small.

Out of all the independent variables under study, only temperature represents a statistically significant (at 5% and 10% level of significance) and a positive impact on the COVID-19 confirmed cases for the six South Asian countries under study, implying that with an increase in the temperature by 1%, it shall bring a change of 1.15% according to FMOLS, 1.87% according to DOLS, and 1.10% as per CCR, on the COVID-19 confirmed cases. While this result is consistent with the results by Auler et al. (2020), it contradicts the research by Lolli et al. (2020) and Sarkodie and Owusu (2020) which prove that temperature and humidity negatively impact the COVID-19 confirmed cases.

Alternatively, COVID-19 confirmed cases alone indicate a statistically significant (at 1% level of significance) and a positive impact on the COVID-19 death cases, confirming that the rapid spread and an increase in the number of COVID-19 confirmed cases shall lead to a positive impact (increase) by

Table 7 Westerlund cointegration test

Statistic	COVID-19 cases	COVID-19 deaths
Gt	−3.578***	−15.693***
Ga	−4.759***	−18.845***
Pt	2.348	−15.170***
Pa	1.858	−21.048***

Source: Authors' computation

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

Table 8 Dumitrescu and Hurlin (2012) Granger non-causality test

Null	W-stat	Zbar-stat	Prob	Conclusion
COVID-19 confirmed cases as the dependent variable				
AP $\nrightarrow$ CC	1.3612	0.6256	0.5316	No causality
H $\nrightarrow$ CC	4.0802	5.3351	0.0000	Causality
PM2.5 $\nrightarrow$ CC	4.8749	6.7115	0.0000	Causality
T $\nrightarrow$ CC	6.1516	8.9228	0.0000	Causality
WS $\nrightarrow$ CC	2.1253	1.9491	0.0513	Causality
COVID-19 death cases as the dependent variable				
CC $\nrightarrow$ DC	31.6356	53.0624	0.0000	Causality
AP $\nrightarrow$ DC	7.7601	11.7089	0.0000	Causality
H $\nrightarrow$ DC	8.5958	13.1563	0.0000	Causality
PM2.5 $\nrightarrow$ DC	8.695	13.3281	0.0000	Causality
T $\nrightarrow$ DC	16.7789	27.3299	0.0000	Causality
WS $\nrightarrow$ DC	4.8111	6.601	0.0000	Causality

Source: Authors' computation

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

0.027% (according to all the three tests) on the number of death cases (Achenbach et al. 2020).

According to Table 10, with COVID-19 confirmed cases as the dependent variable, the meteorological factors, precisely the temperature, air pressure, and humidity, exhibit a significant impact in the majority of countries, indicating these independent variables to be the most noteworthy, in comparison to the other variables. Furthermore, wind speed exhibits a significant impact on the COVID-19 confirmed cases in Afghanistan and Sri Lanka. In contrast, the air pollutant PM2.5 presents a statistically remarkable impact on all the countries when analyzed overall. For Afghanistan and Bangladesh, all the variables under study exhibit a significant impact on the COVID-19 confirmed cases, with wind speed positively impacting the cases by 38.4728 units in Afghanistan. While in Bangladesh, all the meteorological factors exhibit a negative impact on the COVID-19 confirmed cases, with air pressure reporting the highest negative impact on the confirmed cases, confirming that an increase in air pressure may lead to a decrease in the number of COVID-19 cases. This finding is partially in line with the results opined by Islam et al. (2020) and Mofijur et al. (2020) which report humidity and temperature, to have a significant impact on the COVID-19 cases in Bangladesh, respectively.

Surprisingly, in contrast to recent studies based on India as a sample (Kumar 2020b), which report a significant impact of meteorological factors, namely, temperature and humidity, our study partially contradicts such findings implying that the meteorological factors exhibit causality, but do not exhibit any significant impact on the COVID-19 confirmed cases in India and Pakistan. Alternatively, the result is consistent to the

Table 9 FMOLS, DOLS, and CCR tests

	FMOLS		DOLS		CCR	
	Coeff	Std error	Coeff	Std error	Coeff	Std error
COVID-19 confirmed cases as the dependent variable						
Constant	11,531.08	17,769.15	27,955.02	36,177.68	15,119.52	22,310.82
Air pressure	−13.88762	17.23566	−31.52718	35.29874	−17.09225	21.68139
Humidity	−7.06385	9.63765	−11.65484	18.90936	−9.82036	12.95153
PM 2.5	8.82350	10.66036	7.93988	13.5209	8.29301	11.31995
Temperature	115.2797*	66.3972	187.8721**	78.37695	110.6268*	67.77283
Wind speed	89.91752	65.03535	67.6235	78.59918	88.0056	66.03737
COVID-19 death cases as the dependent variable						
Constant	60.80048	134.3634	−56.28215	240.3768	64.57718	169.1926
COVID-19 cases	.02770 ***	.00118	.02762***	.00122	.02772***	.00120
Air pressure	−.04614	.13062	.04887	.23536	−.04739	.16491
Humidity	−.01606	.07294	.03460	.12468	−.02934	.09825
PM 2.5	−.06902	.08104	−.00026	.08918	−.07852	.08612
Temperature	−.58392	.54956	−.09665	.56088	−.62136	.56115
Wind speed	.80986	.49852	.58055	.52140	.83987	.51415

Source: Authors' computation

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

findings by Babu et al. (2020) which do not report any significant correlation between temperature, humidity, and COVID-19 cases in Delhi, India. Similar case is also evident in the study by Rehman et al. (2020), where the authors opine no relationship of higher temperature and humidity with COVID-19 proliferation in Islamabad, Pakistan. In the case of Sri Lanka, humidity and wind speed exhibit the most noteworthy

impact on the confirmed cases (at 5% and 1% significant level), which is also evident from the results proven by Jayadevan et al. (2021) where 87% humidity in Colombo resulted in a surge in infections across the city. For Nepal, temperature and air pressure exhibit a significant impact (at 1% and 10% level of significance) on the confirmed cases.

Table 10 Augmented mean group estimates

	Overall	Afghanistan	India	Pakistan	Bangladesh	Sri Lanka	Nepal
COVID-19 confirmed cases as the dependent variable							
Constant	−403.2895	15,149.54*	−1428.664	2231.046	24,842.14***	−1938.186	−741.8754*
Air pressure	1.27668	−14.74939*	2.87945	−.56931	−23.92333***	1.75899	1.01854***
Humidity	−4.03854	−4.31352***	−8.36802	−13.44324	−.49381***	.94675**	−1.40090
PM 2.5	−.14815*	−.06786	−1.60843	−7.23588	−.35810	−.15157	−.02126
Temperature	−8.24114	9.20638**	−47.27252	6.72639	−20.80504**	2.94350	−12.22151*
Wind speed	4.49016	38.47283**	13.58836	−16.52518	.52359	8.09523***	−3.62356
COVID-19 death cases as the dependent variable							
Constant	134.7607	351.0873	169.361	−21.866	410.0215**	−54.2986**	−.0102
COVID-19 cases	.00499*	.00939***	−.04570***	.00899***	.00753***	−.00191	.00057**
Air pressure	.01300	−.34394	.10435	.01579	−.39840**	.05152**	−.00014
Humidity	.02609	.05891	−1.4778**	.08708	−.01220***	.00011	.00217
PM 2.5	−.01427***	−.02053	−.48980**	−.02462	−.02070**	−.00149	−.00338
Temperature	.09114	.12542	−5.32041**	.41964	−.06821	.08282***	.01546
Wind speed	.04655	−1.08881**	.18125	−.82921	−.04880	.01983	.03804

Source: Authors' computation

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

Additionally, with reference to Table 10, representing the results for the COVID-19 death cases, COVID-19 confirmed cases and air pollutant PM_{2.5} exhibit a statistically noteworthy impact at 10% and 1% level of significance, respectively. Air pressure reflects a significant impact on the death cases in Bangladesh (negative impact) and in Sri Lanka (positive impact) at 5% level of significance. Humidity reports a negative impact on the death cases in India (at 5% level of significance) and Bangladesh (at 1% level of significance). Furthermore, temperature presents a significant impact on the death cases in India (negative impact at 5% significance level) and in Sri Lanka (positive impact at 1% significance level). Wind-speed reflects a negative impact on the death cases in Afghanistan alone at 5% level of significance. Clearly, in comparison to the COVID-19 confirmed cases, the meteorological variables under study reflect a much more significant impact on the death cases in these six countries.

In addition to the positive impact of COVID-19 confirmed cases (except for India) and negative impact of PM_{2.5} on the death cases in all the countries, this result is consistent to the findings by Fareed et al. (2020), where the authors suggest a notable coherence between the air pollutant PM_{2.5} and mortality in Wuhan, China. In this study, the statistics for Afghanistan report wind speed to reflect a negative impact on the COVID-19 death cases at 5% level of significance; India reports humidity, PM_{2.5}, and temperature to exhibit a significant negative impact on the COVID-19 death cases, which is further validated by a research study conducted by Wu et al. (2020) in 166 countries, where temperature and humidity exhibit negative correlation with the COVID-19 death cases; Pakistan and Nepal do not report any other variable to have an impact on its death cases; in Bangladesh, all the variables except for temperature and wind speed, indicate a statistically significant and positive impact on its death cases, which is in line with the results by Islam et al. (2020), and in the case of Sri Lanka, only temperature and air pressure impact the COVID-19 death cases, with the highest impact being by temperature (0.0828 units).

From the findings, it is evident that majority of the meteorological factors, the air pollutant PM_{2.5} and the number of COVID-19 confirmed cases and death cases exhibit significant negative and positive effects for the six countries under study. Moreover, as the South Asian countries have high population density with lower income levels and less awareness about the disease transmissions, people often break the lockdown for their livelihood. Such situations may be one of the main reasons for the significant relationship between majority of the climatological factors and the confirmed cases. The findings are further consistent with results opined by Auler et al. (2020) for Indonesia, or by Iqbal et al. (2020), where the increase in temperature is insignificant to contain the COVID-19 cases in China, or the research by Zhu and Xie (2020), where the mean temperature

has a positive linear relationship with the number of COVID-19 confirmed cases in China. The same finding suggesting a positive relationship between temperature and confirmed cases is partially consistent with the results proven by Sethwala et al. (2020) and Kumar (2020). However, it contradicts the results proven by Wu et al. (2020), where both temperature and humidity have a negative impact on both the confirmed cases and death cases. Additionally, there are some other studies also that report an inverse relationship (Dogan et al. 2020a; Sarkodie and Owusu 2020; Shi et al. 2020a) or no relationship (Yuan et al. 2021) between temperature and incidence of COVID-19. However, our result is also consistent with the findings by Ficetola and Rubolini (2020), where the authors prove a strong correlation between local climate and COVID-19 cases, warning Southern Hemisphere to be at risk of widespread COVID-19 cases. In this way, the conclusion that high temperature and high humidity increase the transmission of the COVID-19 infections can also be applied to the regions with greater transmission rates, where the minimum temperature is mostly over 21 °C and humidity ranges around 80% for months.

Furthermore, the results affirm positive association between air pressure and COVID-19 confirmed cases. It is in line with the findings by Sahoo (2020). However, some other studies (Ma et al. 2020; Wang et al. 2020a; Wu et al. 2020) find contradictory results that there exists a significant association between COVID-19 cases and air pressure. The study also recommends a significant relationship of the air pollutant (PM_{2.5}) with COVID-19 confirmed cases, which is also consistent to the finding by Sahoo (2020) which substantially explains the effect of nationwide lockdown and the corresponding preventive measures undertaken to control the spread of the virus. Our result, highlighting the significant impact of the air pollutant PM_{2.5} on the COVID-19 death cases, is consistent to the findings by Shakoor et al. (2020), where the authors report similar significant correlation in both China and the USA. This result further suggests that limited anthropogenic activities in the lockdown situation due to this novel pandemic disease led to a significant improvement in air quality by reducing the concentrations of environmental pollutants.

Conclusions

The coronavirus (COVID-19) is a widespread infectious disease that has affected millions of lives around the world since late December in 2019. The pandemic has affected almost 74 million people across the globe as of 17 December 2020 (Worldometer 2020). In such uncertain times, extant literature is inconclusive about the role of the meteorological factors in the COVID-19 spread (Iqbal et al. 2020; Zhu and Xie 2020). This is the first study that attempts to examine the nexus

Fig. 3 Research framework. The Green Arrows signify a statistically significant impact of the variables under study

among the confirmed COVID-19 cases, deaths, meteorological factors, and an air pollutant in six Asian countries, from 1 March 2020 to 30 June 2020 using the advanced econometric techniques that are robust to heterogeneity across nations and prove to provide more reliable and generalizable results (Nathaniel et al. 2020b; Sharma et al. 2020). The COVID-19 originated in Wuhan, China (Lam et al. 2003). Hence, with its origin in South Asia, it becomes vital to consider the immediate neighboring countries of China and examine a comparatively under-researched market, namely, the six emerging Asian countries (Sarkar et al. 2020). Given the climatic differences between Europe and Asia, it seems reasonable to examine if the meteorological factors and the air pollutants are associated with the spread of COVID-19 disease.

Our findings confirm that (1) there is a strong cross-sectional dependence and significant correlation among COVID-19 cases, deaths, meteorological factors, and the air pollutant for all the six South Asian countries under study; (2) there exists a long-term relationship among all the meteorological variables, air pollutant, and COVID-19 death cases, while the same may not be true for the relationship among the meteorological variables, air pollutant, and the COVID-19 confirmed cases under study; (3) there is a causality running between all the variables, except for the relation between air pressure and COVID-19 confirmed cases; (4) temperature, air pressure, and humidity exhibit a significant impact on the COVID-19 confirmed cases in the six countries, and the COVID-19 confirmed cases and air pollutant PM2.5 have a significant positive impact on the COVID-19 death cases; (5) for Afghanistan and Bangladesh, all the variables under study exhibit a significant impact on the COVID-19 confirmed cases (while the impact is negative in case of Bangladesh), and on the other hand, the death cases in Afghanistan are influenced by its confirmed cases and wind-speed, and in Bangladesh, humidity, PM2.5, and temperature exhibit a significant negative impact on the COVID-19 death cases; (6) contradicting a few recent studies, no variable exhibits any significant impact on the confirmed cases in India and Pakistan, while humidity, PM2.5, temperature, and COVID-19 confirmed cases exhibit a significant negative impact on the death cases in India, and only confirmed cases positively

impact the death cases in Pakistan; (7) humidity, PM2.5, and wind speed affect the confirmed cases in Sri Lanka, while all the variables except for humidity and wind speed impact the death cases in the country; and (8) for Nepal, air pressure, PM2.5, and temperature affect the COVID-19 confirmed cases, while the death cases in the nation report to be influenced by COVID-19 confirmed cases and PM2.5 only. The outcomes of the study are also outlined in the form of the framework, as presented in Fig. 3.

Furthermore, any research relating to this pandemic management can result in better understating and assist in taking appropriate measures. Lately, considerable studies have been undertaken to provide information about COVID-19. Thus, considering the results obtained, intersectoral policies and actions are necessary, mainly in countries with cases increasing rapidly. Therefore, protection and prevention measures must be adopted to reduce the transmission and possible collapse of the public health system. Our findings provide support for the role of the meteorological factors in the outbreaks of COVID-19 infection. This information is vital for the government and public health authorities in formulating the policies such as developing inventories to identify pollution sources, design effective responses, constantly monitoring the air quality countrywide, encourage public transport and formulating stringent emission-reduction targets for containing, mitigating, and surveillance of COVID-19 in different countries. Furthermore, such severe air quality scenarios have also gathered the attention of the experts from scientific and academic backgrounds, emphasizing on the need to identify the solutions to handle the air quality scenarios and which sector needs to be controlled. Our results also encourage the utilization of meteorological information as a critical component in the current and future risk-prediction models. Additionally, the experts may rethink 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).

Furthermore, some suggestions for future research should focus on providing results based on experimental and observational studies, and considering how the factors can affect COVID-19 spreading. Also, long-term studies of world

climates can anticipate other possible pandemics. Additionally, this study provides preliminary evidence that the meteorological factors play a role in leading to seasonal variability in the transmission of COVID-19 disease, but this does not imply that they are the primary drivers of the COVID-19 pandemic. Hence, other factors such as relative humidity, air quality index, population density, and socio-economic variables such as demographic factors, public health policy, and human behavior in cold weather may also be considered for future research. The COVID-19 dynamics are also determined by multiple additional factors, including virus, climate, economic development, and urbanization. Also, the dataset in the study includes the data from March 2020 to June 2020; therefore, more recent data could be incorporated to reflect upon a more comprehensive picture about the findings in such similar contexts. Hence, all these factors may also be considered for future research.

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Declarations

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