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ABSTRACT

OBJECTIVE: Coronavirus-19 (COVID-19) outbreaks have been reported in a range of climates worldwide, including Bangladesh. There is less evidence of a link between the COVID-19 pandemic and climatic variables. This research article's purpose is to examine the relationship between COVID-19 outbreaks and climatic factors in Dhaka, Bangladesh.

METHODS: The daily time series COVID-19 data used in this study span from May 1, 2020, to April 14, 2021, for the study area, Dhaka, Bangladesh. The Climatic factors included in this study were average temperature, particulate matter ($PM_{2.5}$), humidity, carbon emissions, and wind speed within the same timeframe and location. The strength and direction of the relationship between meteorological factors and COVID-19 positive cases are examined using the Spearman correlation. This study examines the asymmetric effect of climatic factors on the COVID-19 pandemic in Dhaka, Bangladesh, using the Nonlinear Autoregressive Distributed Lag (NARDL) model.

RESULTS: COVID-19 widespread has a substantial positive association with wind speed (r = .781), temperature (r = .599), and carbon emissions (r = .309), whereas $PM_{2.5}$ (r = –.178) has a negative relationship at the 1% level of significance. Furthermore, with a 1% change in temperature, the incidence of COVID-19 increased by 1.23% in the short run and 1.53% in the long run, with the remaining variables remaining constant. Similarly, in the short-term, humidity was not significantly related to the COVID-19 pandemic. However, in the long term, it increased 1.13% because of a 1% change in humidity. The changes in $PM_{2.5}$ level and wind speed are significantly associated with COVID-19 new cases after adjusting population density and the human development index.

KEYWORDS: Nonlinear autoregressive distributed lag (NARDL), dynamic multiplier, Wald test, carbon emissions, particulate matter ($PM_{2.5}$), coronavirus-19 (COVID-19)

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Introduction

The Coronavirus-19 (COVID-19) disease was first discovered in Wuhan, China, where a significant outbreak is caused by the disease's rapid transmission from person to person. Because of COVID-19, the world has seen a health epidemic spread so swiftly across countries, damaging complex health systems, and threatening the whole economy.[1] There are some significant parameters that are responsible for the rapid spread of COVID-19. These can include climate conditions, air quality, air pollution, and population density.[2] Evidence suggests COVID-19-confirmed cases and deaths were shown to be higher in places with high levels of air pollution.[3]

Droplets, person-to-person transmission, infected objects, and airborne transmission are all ways for the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) virus to infect the respiratory system.[4] If virus-carrying droplets or bioaerosols penetrate the human body through coughing or sneezing and reach an uninfected host, they can cause illness. Furthermore, any unprotected contact with an infected object increases the risk of the virus spreading. Another route for COVID-19 transfer is through the inhalation of small airborne particles with a diameter of less than 5 m.[5,6]

Several studies have been carried out to examine if the COVID-19 coronavirus may be transmitted through the environment. Pramanik et al[7] discovered a significant relationship between COVID-19 occurrences and temperature in humid target areas. Temperature, $PM_{2.5}$, and median age have all been reported to play a role in the propagation of COVID-19 in some studies.[2,8-12] There was no correlation between COVID-19 and 7-day lagged meteorological indicators, according to a study by Islam et al[13] that looked into the relationship between weather conditions and COVID-19. Although COVID-19 and 14-day delayed temperature have a positive association, COVID-19 and 14-day lagged humidity have a negative relationship. It should be kept in mind that many diseases are contagious and can be transmitted through epidemiological mechanisms.[9,14-16]

Rosario et al[17] revealed that high sun radiation, temperature, and wind speed all slowed the progression of COVID-19 cases. According to Li et al[18], air pollution had a positive effect on COVID-19 new occurrences, but temperature had a negative effect. Pei et al[19] found a strong correlation between COVID-19 cases and air quality, and COVID-19 cases and air quality, and their findings show a clear relationship between air pollution and temperature, but COVID-19 has a negative connection with carbon monoxide. Pearson correlation analysis was used by Tanis and Karakaya[20] to examine the effects of air pollutants like $PM_{2.5}$, PM_{10}, nitrogen oxides (NO_2), sulfur dioxide

(SO_2), carbon monoxide (CO), ozone (O_3), and SARS-CoV-2 cases. Simultaneously, other literature found a link between weather variables, like temperature and wind speed, and COVID-19 cases. In 3 Chinese cities, Jiang et al[21] evaluated the relationship between air pollutants such as $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 daily meteorological factors of COVID-19. According to the researchers, in all cities, daily COVID-19 incidence was positively associated with PM_{10} and humidity, but negatively associated with PM_{10} and temperature.

The impact of weather-related and climatic variables on the COVID-19 outbreak in Canada was examined by Sarwar et al.[22] They looked at how different meteorological factors influence COVID-19 spread and made the case that weather, and climate change significantly increase COVID-19 infections using key variables like daily COVID-19 cases, carbon dioxide emissions, nitrogen dioxide (NO2), sulfur dioxide (SO2), $PM_{2.5}$, ozone (O3), average temperature, and humidity. According to their argument, the COVID-19 infection rate is significantly increased by weather and climate change.

In Jakarta, Indonesia, Tosepu[23] used the Spearman rank correlation test to evaluate the relationship between climate data such as different situation of temperature, rainfall, humidity, and the daily confirmed cases of epidemic. Air pollution and weather variables are connected to COVID-19 confirmed cases and fatality rates. It can be explained by disparities in medical and health insurance systems, as well as regional policies in different cities and countries, according to Yuan et al[24] and Suhaimi et al.[4] The purpose of our research is to learn more about the COVID-19 virus's propagation in Bangladesh by investigating the methods of climatic factors-to-human transmission and COVID-19-confirmed cases' human-to-human transmission.

Simply expanding the forest canopy is not an effective strategy to reduce carbon emissions.[25] In 2020, fossil CO2 emissions are expected to have decreased by 2.4 billion metric tons because of the global COVID-19 lockdowns, according to new calculations from University of East Anglia researchers (UEA). Compared to 2019, 184 countries' combined carbon emissions decreased by 438 Mt in 2020. The reduction in carbon emissions during the pandemic will not be lasting because it is anticipated that global economic activity will gradually return to its pre-COVID-19 state. Therefore, it is crucial to look into the relationship between carbon emissions and Bangladesh's COVID-19 status.

The relationship between the COVID-19 outbreak and climatic or weather-related factors was investigated separately in the previous literature review. Bangladesh has a tropical monsoon climate and is primarily an air-polluted nation. The COVID-19 pandemic had the biggest negative economic impact on Bangladesh. After Pakistan and India, Bangladesh is the third country in South Asia to be affected. Therefore, it is crucial to investigate how Bangladesh's COVID-19 pandemic is affected by climatic factors and air pollution. As previously indicated, most of the research has focused on the linear association between climatic factors and COVID-19. These variables, on the other hand, exhibit regular oscillations and nonlinear behavior, which have been disregarded in prior investigations. As a result, the nonlinear framework was applied in this study in Dhaka, Bangladesh, to fill in this gap. This study employed correlation measurements to examine the intensity of the association between climatic variables and COVID-19 spreads. This period included the use of Spearman's correlation analysis. To arrive at novel results and recommendations, this study employed correlation measurements, including Spearman's correlation analysis. As a result, we believe our paper will contribute to closing this gap in literature. The study's research objectives are as follows:

- to examine the link between climate variables like temperature, humidity, carbon emissions, wind speed, and $PM_{2.5}$ on COVID-19 confirmed cases in Dhaka, Bangladesh.
- to identify the distribution of COVID-19 confirmed cases asymmetrically or symmetrically linked to climate variables such as temperature, humidity, carbon emissions, wind speed, and $PM_{2.5}$.
- introducing methods can be utilized to halt the spread of the SARS-CoV-2 virus.

Materials and Methods

Data

The time-series data (daily) used for the study area, Dhaka, Bangladesh in this analysis span the dates of May 1, 2020, and April 14, 2021. Meteorological factors, such as average temperature (°C), $PM_{2.5}$ (a proxy for air quality), humidity (%), carbon emissions (per capita), and wind speed (km/h) were selected for the study area. As control variables, 2 non-weather variables are used, such as population mass and the human development index. Table 1 summarizes the definitions and data sources.[13,26,27] IBM Statistical Package for the Social Sciences (SPSS version 19.0) and Eviews 10 were used to carry out the statistical analysis.

Analysis

Correlation analysis. Since we are unsure at first whether the data are normally distributed or not, it is preferable to use non-parametric correlation analysis to determine whether there is a linear relationship between the variables. A previous study conducted using the same data characteristics, shown in Figure 1, revealed the relationship between environmental factors and the transmission of SARS-CoV-2.[28] For empirical investigations, Spearman's non-parametric correlation is used to look at the intensity and direction of the meteorological variables and COVID-19.

Table 1. Definition and sources of the variables.

VARIABLES	INDICATORS	DESCRIPTION	DATA SOURCES
COVID-19 confirmed cases	COVID	Daily confirmed cases	Directorate General of Health Services (DGHS)
Temperature	TEM	Average temperature (in degrees Celsius)	Bangladesh Meteorological Department (BMD)
Humidity	HUM	Average humidity (Measured in percentages)	Bangladesh Meteorological Department (BMD)
$PM_{2.5}$	PM	Average $PM_{2.5}$ (Proxy of air quality)	US Consulate in Dhaka
Carbon emissions	CE	Average carbon emissions (Metric tons per capita)	Bangladesh Meteorological Department (BMD) and World Development Indicators (WDI)
Wind speed	WS	Measured in kilometers per hour	Bangladesh Meteorological Department (BMD)
Population density	PD	per km^2	Worldometer.info and BBS
Human development index	HUMAN	Development index	Globaldatalab .org

COVID-19 confirmed cases, humidity, wind speed, temperature, and $PM_{2.5}$ are all expressed as logarithms.

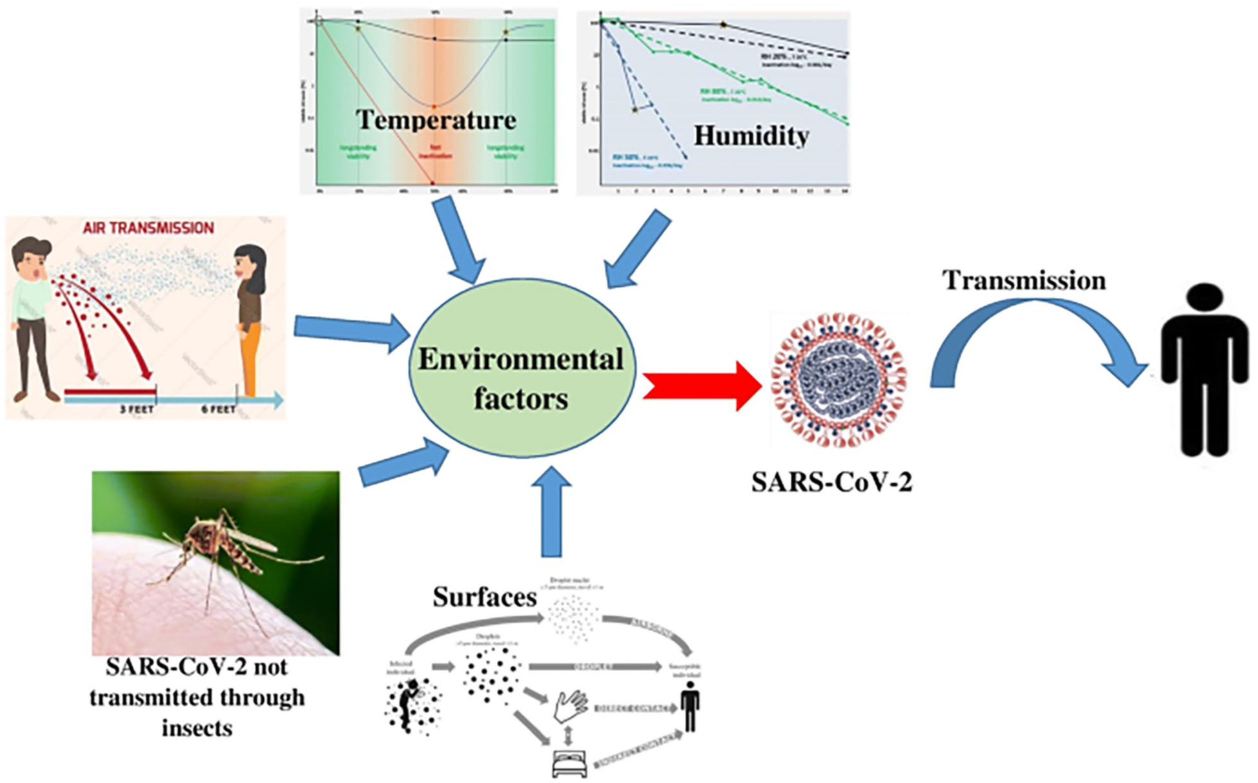

Figure 1. Environmental factors and transmission of SARS-CoV-2.[28]

The formula for calculating the Spearman correlation coefficient is as follows:

$$r_s = 1 - \frac{6\sum_i d_i^2}{n\left(n^2 - 1\right)} \quad (1)$$

Where, n is the total number of observations; d_i = rank of X_i − rank of Y_i.

NARDL model. We used a nonlinear autoregressive distribution lag (NARDL) model to study the long- and short-run nonlinear relations between the COVID-19 and climate variables, as described by Shin et al.[29] Based on the prior work of Ibrahim[30] and Lacheheb and Sirag[31] and considering the nonlinear relationship between temperature, humidity, $PM_{2.5}$, carbon emission, and wind speed in COVID-19 cases, our model will be as follows:

$$
\begin{aligned}
\Delta LNCOVID_t = {} & \beta + \sum_{i=1}^{q}\gamma_0 \Delta LNCOVID_{t-i} + \sum_{i=1}^{p}\gamma_1^{+} \Delta LNTEM^{+}{}_{t-i} + \sum_{i=1}^{p}\gamma_2^{-} \Delta LNTEM^{-}{}_{t-i} + \sum_{i=1}^{p}\gamma_3^{+} \Delta LNHUM^{+}{}_{t-i} \\
& + \sum_{i=1}^{p}\gamma_4^{-} \Delta LNHUM^{-}{}_{t-i} + \sum_{i=1}^{p}\gamma_5^{+} \Delta LNPM^{+}{}_{t-i} + \sum_{i=1}^{p}\gamma_6^{-} \Delta LNPM^{-}{}_{t-i} + \sum_{i=1}^{p}\gamma_7^{+} \Delta CE^{+}{}_{t-i} + \sum_{i=1}^{p}\gamma_8^{-} \Delta CE^{-}{}_{t-i} \\
& + \sum_{i=1}^{p}\gamma_8^{+} \Delta LNWS^{+}{}_{t-i} + \sum_{i=1}^{p}\gamma_9^{-} \Delta LNWS^{-}{}_{t-i} + \theta_1 LNCOVID_{t-1} + \theta_2 LNTEM^{+}_{t-1} + \theta_3 LNTEM^{-}_{t-1} \\
& + \theta_4 HUM^{+}_{t-1} + \theta_5 HUM^{-}_{t-1} + \theta_6 LNPM^{+}_{t-1} + \theta_7 LNPM^{-}_{(t-1)} + \theta_8 CE^{+}_{(t-1)} + \theta_9 CE^{-}_{(t-1)} + \theta_{10} WS^{+}_{(t-1)} \\
& + \theta_{11} WS^{-}_{(t-1)} + \delta_1 LNPD + \delta_2 HUMAN + \varepsilon_t
\end{aligned} \tag{2}
$$

Equation 2 can be included in the NARDL equation with an unrestricted error correction representation. COVID defines COVID-19 daily cases, TEM defines temperature, and PM stands for $PM_{2.5}$, CE stands for carbon emissions, Wind speed is denoted by WS, while humidity is represented by HUM.

Natural logarithms are abbreviated as "LN." Where q and p indicate the lag order and $\beta_1 = \theta_2/\theta_1$, $\beta_2 = \theta_3/\theta_1, \beta_3 = \theta_4/\theta_1$ and $\beta_4 = \theta_5/\theta_1$, $\beta_5 = \theta_6/\theta_1$, $\beta_6 = \theta_7/\theta_1$, $\beta_7 = \theta_8/\theta_1$, $\beta_8 = \theta_9/\theta_1$, $\beta_9 = \theta_{10}/\theta_1$, $\beta_{10} = \theta_{11}/\theta_1$, are long-run asymmetric effects of temperature, humidity, $PM_{2.5}$, carbon emission, and wind speed on COVID-19 cases. Accordingly, $\sum_{i=1}^{8}\gamma_i{}'s$ are measure the short run asymmetric effects of temperature, humidity, $PM_{2.5}$, carbon emission, and wind speed on COVID-19 cases.

Where, the long-term variables are related to β_i. Positive changes TEM^+, HUM^+, PM^+, CE^+ and WS^+ as well as negative changes TEM^-, HUM^-, PM^-, CE^-, and WS^+ respectively, incorporating the nonlinear impact of our study's variables. The decomposition of the NARDL model into a partial sum of positive and negative changes is shown by the x_t in the following equation:

$$x_t = x_o + x_t^+ + x_t^- \tag{3}$$

$$\text{Where, } x_t^+ = \sum_{i=1}^{t}\Delta x_t^+ = \sum_{i=1}^{t} max\left(\Delta x_i, 0\right)$$

$$\text{And } x_t^- = \sum_{i=1}^{t}\Delta x_t^- = \sum_{i=1}^{t} min\left(\Delta x_i, 0\right)$$

We first looked at the order of integration of the chosen variables using the well-known Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Second, we evaluated the existence of a long-run link between variables using a bound testing methodology devised by Pesaran et al[32] and Shin et al.[29] Using the F-test, we checked the null hypothesis $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = \theta_7 = \theta_8 = \theta_9 = \theta_{10} = \theta_{11} = 0$. Third, we demonstrate both long run and short-run asymmetric correlations among the variables using the Wald test. Finally, we show how a 1% difference in the positive and negative lag values of independent variables can cause asymmetric cumulative dynamic multiplier (CDM) effects. Obtaining the CDM of a unit change allows us to assess the asymmetric effect as well in x_{t-1}^+ and x_{t-1}^- on y.

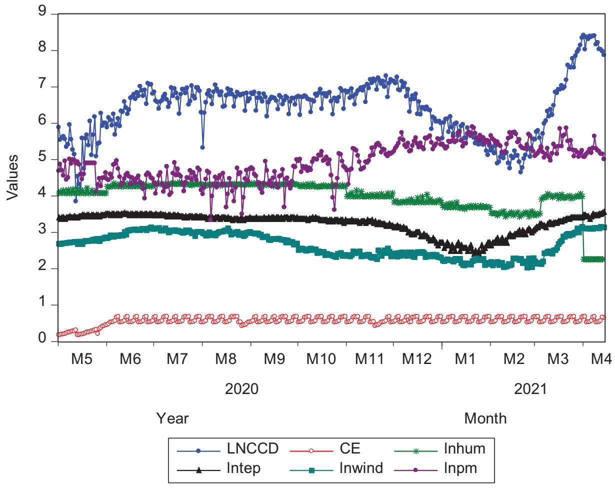

Figure 2. COVID-19 daily-confirmed cases versus climatic factors.

$$m_h^+ = \sum_{j=0}^{h}\frac{\partial y_{t+j}}{\partial x_{t-1}^+} \text{ and } m_h^- = \sum_{j=0}^{h}\frac{\partial y_{t+j}}{\partial x_{t-1}^-}, \text{h}=1,\ 2,\ 3\ldots \tag{4}$$

Findings and Discussion

Supplemental Appendix 1 shows the descriptive statistics, where each variable is normally distributed and has 5% significant levels using the Jarque-Bera test statistic. Figure 2 plots daily confirmed cases against meteorological conditions to highlight each study variable's unique contribution to COVID-19 verified cases. COVID-19 prevalence is intricately tied to climate conditions, as seen in Figure 2.

Table 2 contains the results of the Spearman correlation test. The COVID-19 instances and temperature have a favorable and substantial relationship, according to our study. Temperature and the COVID-19 pandemic have a moderate, an advantageous, and important connection ($r = .599$) at the 1% level of significance, which is consistent with the previous studies in Bangladesh.[2,24,27,33] Some previous studies

Table 2. Test results of Spearman's correlation.

SPEARMAN'S CORRELATION						
VARIABLES	COVID	TEM	HUM	WS	PM	CE
COVID	1					
TEM	0.599***	1				
HUM	−0.087***	0.695***	1			
WS	0.781***	0.841***	0.687***	1		
PM	−0.178***	−0.297***	−0.223***	−0.221***	1	
CE	0.309***	0.301***	0.313***	−0.124***	0.485***	1

***refers correlation is significant at 1% level of significance (2-tailed).

revealed that COVID-19 transmission is decreased at low ambient temperatures[2,12] and that there is a positive and significant connection between temperature and the COVID-19 pandemic.[10,34-36]

COVID-19 has a mild, negative, and significant association with humidity (r = −.087) and a strong, positive, and significant relationship with wind speed (r = .781), according to our data. Hridoy,[26] Pal and Masum,[27] and Pavel[33] discovered a significant relationship between $PM_{2.5}$ and COVID-19. Some other studies[8,10,37,38] have shown that COVID-19 and $PM_{2.5}$ have a negative, weak, and significant relationship at 1% level of significance. Consistent with these studies, we found in Dhaka, Bangladesh, that $PM_{2.5}$ and the COVID-19 outbreak have a significant relationship. According to the study, COVID-19 and carbon emissions had a positive, weak relationship (r = .309). Air pollution and climate variables such as temperature, humidity, carbon emissions, wind speed, and $PM_{2.5}$ have been connected to the increasing number of COVID-19 daily cases in Dhaka, Bangladesh.

The ADF, PP, and KPSS tests were employed for stationary tests in our empirical study, and the findings are summarized in Table 3. The Schwarz information criteria (SIC) were used to find the optimal lag structure. According to the ADF tests, daily COVID-19 confirmed cases are stationary at level, suggesting I (0) according to ADF test, and $PM_{2.5}$ is stationary at level, indicating I (0), whereas all study variables are stationary at the first difference, indicating variables are I (1), according to both tests. We can use the bound testing methods for co-integration to evaluate equation (2) when the I (2) variables. The KPSS test, which is favorable to stationarity for all at first difference series, supports the findings.

By using the traditional VAR model, we optimized the lag, and based on the AIC criterion, we chose lag "1" as the best lag, as shown in Supplemental Appendix 2. Table 4 shows the bound test results of model estimation for the existence of linear and nonlinear co-integration. Because the F-statistic result of 3.258530 is bigger than the necessary lower limit of 2.62, it reveals that there is an inconclusive decision in a linear form

Table 3. Unit root test results.

VARIABLES	LEVEL		FIRST DIFFERENCE	
	ADF	PP	ADF	PP
LNCOVID	−3.501**	−2.523	−6.079**	−30.817**
LNTEM	−0.553	−0.033	−3.012**	−20.467**
LNHUM	−1.547	−2.412	−10.412**	28.943**
LNPM	−2.987	−6.258**	−10.250**	−32.474**
CE	−2.719	−2.369	−10.896**	−7.231**
LNWS	−0.375	−0.566	−22.122**	−30.987**
KPSS test				
Variables	Level		First difference	
LNCOVID	0.435040		0.162501**	
LNTEM	1.017066		0.476468***	
LNHUM	1.283610		0.148905**	
LNPM	1.750468		0.138538**	
CE	1.652322		0.156323**	
LNWS	0.990824		0.231258**	

**refer significant at 5% levels of significance. For optimal lag, order SIC is used, and constant and time intercept are included in level and first difference. The 1% level (0.7390), the 5% level (0.4630), and the 10% level (0.4630) are the KPSS asymptotic critical values (0.3470).

and smaller than the necessary upper limit of 3.79 at 5%. At 5%, the t-statistic result of −3.649323 is higher than the required lower limit of −2.86 and is lower than the required upper limit of −4.19. In a linear approach, the bound test demonstrates that there is an inconclusive decision. On the other hand, the results of the non-linear ARDL specification indicate the long-run existence of cointegration, as the value of the F-statistic, which is 9.763696, exceeds the upper critical constraint of 3.04 at 5%, while the t-statistic value of −9.655781 exceeds the upper critical constraint of −5.03 at 5%.

Table 4. Bounds test results for co-integration.

LINEAR FASHION	VALUE	SIGNIF. (%)	LOWER BOUND, *I*(0)	UPPER BOUND, *I* (1)	DECISION
F-statistic	3.258530	10	2.26	3.35	Inconclusive
		5	2.62	3.79	
		2.5	2.96	4.18	
		1	3.41	4.68	
t-statistic	−3.649323	10	−2.57	−3.86	Inconclusive
		5	−2.86	−4.19	
		2.5	−3.13	−4.46	
		1	−3.43	−4.79	
Nonlinear fashion					
F-statistic	9.763696	10	1.83	2.94	Co integration
		5	2.06	3.24	
		2.5	2.28	3.5	
		1	2.54	3.86	
t-statistic	−9.655781	10	−2.57	−4.69	Co integration
		5	−2.86	−5.03	
		2.5	−3.13	−5.34	
		1	−3.43	−5.68	

The critical values are from the Narayan.[39]

Table 5 shows the NARDL asymmetric estimates. Control variables such as population density have positive and insignificant effects on COVID-19 instances, while another control variable, the human index, has negative and insignificant effects on COVID-19 cases. Table 6 shows the findings of NARDL's short- and long-run estimates. COVID-19 instances are reduced by 1.14% in the short run and increase 1.13% in the long run by a 1% increase in humidity, according to the findings. Reduced humidity, on the other hand, had no influence on COVID-19 instances in the short or long term. COVID-19 is connected to relative humidity, according to other studies.[11,12,26,38] $PM_{2.5}$ has a favorable and positive long-term and short-term effect on COVID-19 daily cases, according to our study. According to the findings, a 1% rise in $PM_{2.5}$ increased COVID-19 instances by 0.124785% in the short run and 0.077525% in the long run, resulting in a 0.077525% increase in COVID-19 cases.

In the short run, there are no significant effects on COVID-19 due to the positive change in carbon emissions, but a 1% increase in carbon emissions reduces the daily cases by 0.489567% in long run. Temperature and wind speed, 2 other study variables, have the highest impact on COVID-19 daily cases. The study findings indicate that a 1% increase in temperature raises COVID-19 incidences by 1.232585% in the short run and 1.525774% in the long run. Reduced temperatures, on the other hand, have no influence on daily cases in the short term but have a favorable and considerable effect on daily cases in the long term. Maximum temperature has a considerable effect on COVID-19 transmission, according to recent studies by Hridoy,[26] Shao et al,[40] Pani et al,[34] and Kumar.[41] This discovery was made, unlike several recent studies that revealed a negative link between temperature and COVID-19 transmission ability.[35,42,43]

In the short run, a 1% increase in wind speed increases COVID-19 instances by 0.147853%, while in the long run; it increases COVID-19 instances by 0.880555%, according to the findings. Reduced wind speed, on the other hand, has no significant influence on everyday instances in the short term but has positive and significant effects in the long term. COVID-19 transmission was shown to be significantly affected by maximum wind speed, which is consistent with earlier studies.[2,26,44-46] According to Li et al,[18] there is no correlation between wind speed and the ability to transmit COVID-19, while Islam et al[2] found a negative correlation. Air pollution and climate variables such as temperature, humidity, carbon emissions, wind speed, and $PM_{2.5}$ are asymmetrically associated with the spread of COVID-19 confirmed cases in Dhaka, Bangladesh, according to our findings.

The current study indicated that temperature and wind speed had a beneficial effect on COVID-19 transmission in

Table 5. NARDL estimate results.

VARIABLE	COEFFICIENT	STD. ERROR	*T*-STATISTIC	PROB.*
C	6.550195**	3.403025	1.924815	0.0051
LNCOVID(−1)	0.546961**	0.066357	8.242647	0.0000
$LNHUM^{+}$	−0.231516**	0.481593	−0.480731	0.0310
$LNHUM^{+}(-1)$	0.744191	0.466428	1.595510	0.1116
$LNHUM^{-}$	−0.060150	0.053389	−1.126632	0.2607
$LNPM^{+}$	0.035122**	0.052463	0.669449	0.0037
$LNPM^{-}$	0.007586	0.052373	0.144854	0.8849
$LNTEM^{+}$	0.691235**	0.132999	5.197307	0.0000
$LNTEM^{-}$	0.293354	0.419602	0.699125	0.0850
$LNTEM^{-}(-1)$	0.974435**	0.471869	2.065057	0.0397
$LNWS^{+}$	0.398926**	0.115926	3.441214	0.0007
$LNWS^{-}$	0.422686**	0.123913	3.411148	0.0007
CE^{+}	−0.221793	0.179287	−1.237085	0.2169
CE^{-}	−0.183127	0.207632	−0.881978	0.3784
LNPD	0.611073	0.486947	−1.254906	0.2104
HUMAN_INDEX	−0.014455	0.317816	−0.045483	0.9637
R-squared	0.899123	Mean dependent var		6.421258
F-statistic	196.0052	Durbin–Watson stat		2.300554

** refer significant at 5% levels of significance.

Table 6. NARDL short run and long run estimates.

SHORT RUN ESTIMATES				LONG RUN ESTIMATES			
VARIABLE	COEFFICIENT	STD. ERROR	*T*-STATISTIC	VARIABLE	COEFFICIENT	STD. ERROR	*T*-STATISTIC
$\Delta LNHUM^{+}$	−1.145121**	0.198547	−0.610733	$LNHUM^{+}$	1.131635**	0.332591	3.402483
$\Delta LNHUM^{-}$	0.451254	0.205747	0.707115	$LNHUM^{-}$	−0.132770	0.112587	−1.179264
$\Delta LNPM^{+}$	0.124785**	0.062527	2.593579	$LNPM^{+}$	0.077525**	0.111697	0.694058
$\Delta LNPM^{-}$	−0.189563	0.055992	−0.567869	$LNPM^{-}$	0.016746	0.114610	0.146110
$\Delta LNTEM^{+}$	1.232589**	0.267766	1.487674	$LNTEM^{+}$	1.525774**	0.182204	8.373991
$\Delta LNTEM^{-}$	0.552147	0.270999	1.670669	$LNTEM^{-}$	2.798413**	0.245814	11.38425
$\Delta LNWS^{+}$	0.147853**	0.233053	1.206260	$LNWS^{+}$	0.880555**	0.236518	3.722987
$\Delta LNWS^{-}$	−0.174859	0.263144	−0.704058	$LNWS^{-}$	0.933002**	0.236349	3.947555
ΔCE^{+}	0.223856	0.278539	0.912895	CE^{+}	−0.489567**	0.430669	−1.136759
ΔCE^{-}	−0.295471**	0.147430	−2.156243	CE^{-}	−0.404219	0.472058	−0.856289

**refers significant at 5% levels of significance.

Dhaka, Bangladesh; this conclusion is consistent with prior research and backs up the findings of Bashir et al[47] and Tosepu.[23] Research from the past supports the positive impact of humidity on COVID-19 transmission in Dhaka.[2,38,48,49]

Table 7. NARDL long run and short Granger Causality results.

VARIABLES	$H_0:\sum\gamma^+=0$ (*F*-TEST)	*P*-VALUE	$H_0:\sum\gamma^-=0$ (*F*-TEST)	*P*-VALUE	ECM (*T* TEST)	*P*-VALUE
LNHUM	4.16396	.0421	16.5677	.0521	0.52611	.0012
LNPM	7.25351	.0974	1.25688	.1030	1.57340	.0341
LNWS	0.50327	.0085	0.03334	.0052	5.62704	.0001
CE	7.76077	.0056	0.22055	.0089	3.25802	.0412
LNTEM	12.9529	.0004	18.6675	.0005	2.07991	.0145

This study supports prior research in that wind speed has a positive impact on COVID-19 transmission.[2,50] This could let virus particles last longer in dirty air, allowing SARS-CoV-2 to spread through a more indirect route.

The NARDL co-integration test validates the presence or absence of asymmetric co-integration among the variables in the model but does not identify causation direction. As a result, we applied positive and negative TEM, HUM, PM, CE, and WS changes to COVID-19 cases to test for Granger causality, and the results are presented in Table 7. The findings demonstrated that COVID-19 instances are caused by positive shocks to the TEM, HUM, CE, and WS in the short run. The negative shock of TEM, HUM, CE, and WS, on the other hand, was found to be the underlying cause of COVID-19 instances in the short term. However, the findings demonstrated that the negative shock of all variables is the fundamental cause of COVID-19 instances in the long term.

The positive change curve will show asymmetric adjustments in COVID-19 cases due to positive TEM changes, whereas the negative change curve has shown negative adjustments in COVID-19 cases due to negative TEM changes. HUM, PM, CE, and WS are all explained in the same way. Negative TEM shocks, positive $PM_{2.5}$ shocks, negative wind speed, and negative HUM shocks had the highest influence on COVID-19 cases, according to all the dynamic multiplier values. According to Figure 3, positive and negative shocks of CE, on the other hand, had the same influence on COVID-19 cases.

Some diagnostic tests were also performed to support the NARDL model's dependability, as shown in Table 8. The NARDL model is reliable because all diagnostic tests demonstrate its accuracy. The adjustment speed, according to our statistics, is −0.45321, indicating a 45% rise in significance in the previous period to attain equilibrium. To confirm the nonlinearities between the variables under examination, the Wald test was performed. Table 8's findings, which show asymmetries between variables at a 5% level of significance, are presented. We performed the CUSUM and CUSUM Square tests to check the model's stability. Figure 4 depicts the outcomes of these tests and demonstrates the stability of the model.

Public health agencies depend on traditional ways to control and monitor the expansion of infectious diseases.[51] Interventions and practices related to water, sanitation, and hygiene are essential for COVID-19 prevention.[52] The ongoing pandemic significantly interacts with the social determinants of environmental health, as evidenced by the significant spread in low-income areas not only in Latin America and Asia but also in the developed world. These factors include low income, inadequate housing, lack of access to safe drinking water and food, unsanitary living conditions, and inadequate infrastructure.[53] This study advises the following key COVID-19 preventative behaviors, despite the introduction of vaccinations as a tool for prevention against COVID-19 and the appropriate use of masks: avoiding crowded or poorly ventilated spaces or wearing a mask in these spaces; practicing proper hand hygiene; maintaining hygiene; cleaning and disinfecting frequently touched objects and surfaces; and maintaining your overall health. In their study, Rao et al,[54] found that instead of getting themselves checked out right away and only getting tested and treated by a doctor when their health deteriorates, people who develop COVID-19 symptoms turn to Google for confirmation and treatment. At that point, hospitalization is the only choice due to the patients' critical conditions. Due to capacity issues and elevated mortality rates, this puts an unsustainable burden on hospitals. In order to forecast COVID-19 waves, mobilize the healthcare system, save lives, and promote frictionless growth, they advise using Google Trends data.

This study has some limitations because COVID-19 transmission can be complicated by factors like the quantity of tests that have been successfully completed, public opposition, internal migration, human behavior, and cultural and economic factors. We were also limited to only looking at Dhaka, Bangladesh. Furthermore, another limitation in this study is that we considered daily COVID-19 cases nationally and considered the climate variables in some specific stations around Dhaka. In future studies, we will consider confounding factors linked to COVID-19′s spread in Bangladesh as a whole. Further research will be needed to generalize the relationship between COVID-19 cases and climate variables.

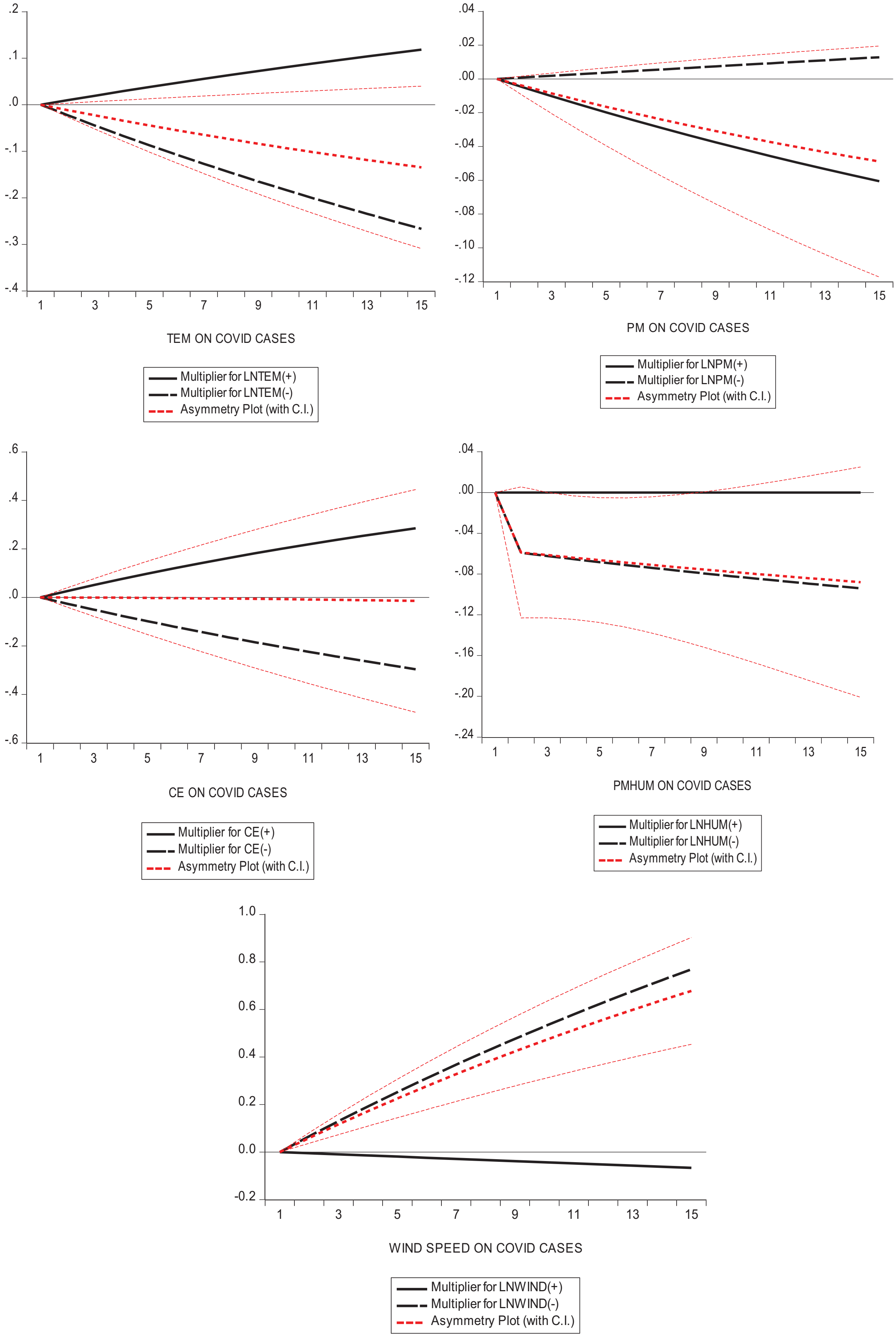

Figure 3. Cumulative dynamic multipliers (CDM) effects on COVID-19 daily cases by climatic parameters.

Conclusion and Policy Suggestions

The importance of meteorological and non-meteorological factors in COVID-19's rapid spread in Dhaka, Bangladesh is highlighted in this paper. Local COVID-19 transmission is closely linked to climate conditions in Dhaka, according to the findings. This study explores the link between temperature, carbon dioxide, humidity, $PM_{2.5}$, wind speed, and COVID-19 in Dhaka, Bangladesh, and offers both intriguing and conflicting results. Two non-climatic factors, such as population density and the Human Development Index, are utilized as control variables. Furthermore, the NARDL findings show that all our study factors had significant asymmetric effects on COVID-19 in Dhaka, Bangladesh, both short- and long term. Increases in temperature are associated with a lower risk of COVID, but humidity has the opposite effect. Increases in wind speed and $PM_{2.5}$ have a favorable effect on COVID instances, according to NARDL studies, whereas a reduction in carbon emissions has a negative effect on COVID instances both in the short and long term. Moreover, decreasing COVID-19 cases can be attributed to increasing wind speed. The spread of COVID-19, however, has been significantly increased with increasing $PM_{2.5}$ levels. New COVID-19 cases have a significant negative relationship with carbon emissions both in the short- and long-term lag non-linear relationship. The Wald test and dynamic multiplier graphs reveal that COVID-19 and climatic factors have an asymmetric connection.

This study suggests that for a sustainable ecosystem, governments, lawmakers, and businesses should reduce harmful gas emissions. The key findings of this study will aid decision-makers in determining the weather and economic factors that influence future pandemic risks. In order to come up with practical solutions to the problems of air pollution and global warming, policymakers and other management authorities will find the study's findings to be very helpful. The results may aid in determining how COVID-19 transmission in Bangladesh is affected by seasonality.

The findings of this study may also be relevant for future research in other nations. More factors relating to COVID-19 incidence should be considered in future studies to further improve accuracy. In our subsequent study, we forecasted COVID-19 waves using Google Trends data to mobilize the healthcare system, save lives, and encourage frictionless growth in the context of Bangladesh. Virus resistance, the number of individuals infected, the size of the city, mobility, cleanliness, the usage of masks and sanitizers, and other COVID-19-related factors must be explored.

Table 8. Diagnostic test and Wald test results.

CointEq(-1)	−0.45321
J-B [prob]	0.1121
R-R [prob]	0.4571
LM (1) [prob]	0.1978
LM (2) [prob]	0.4685
ARCH (1) [prob]	0.6214
ARCH (2) [prob]	0.7142
$TEM_w[X^2,\text{prob}]$	[12.2585, 0.0000]
$HUM_w[X^2,\text{prob}]$	[10.1425, 0.0001]
$PM2.5_w[X^2,\text{prob}]$	[3.2145, 0.0005]
$WS_w[X^2,\text{prob}]$	[7.2145, 0.0001]
$CE_w[X^2,\text{prob}]$	

TEM_W, HUM_W, $PM2.5_W$, $WIND_W$ & CE_W indicates the Wald test result for each variable.

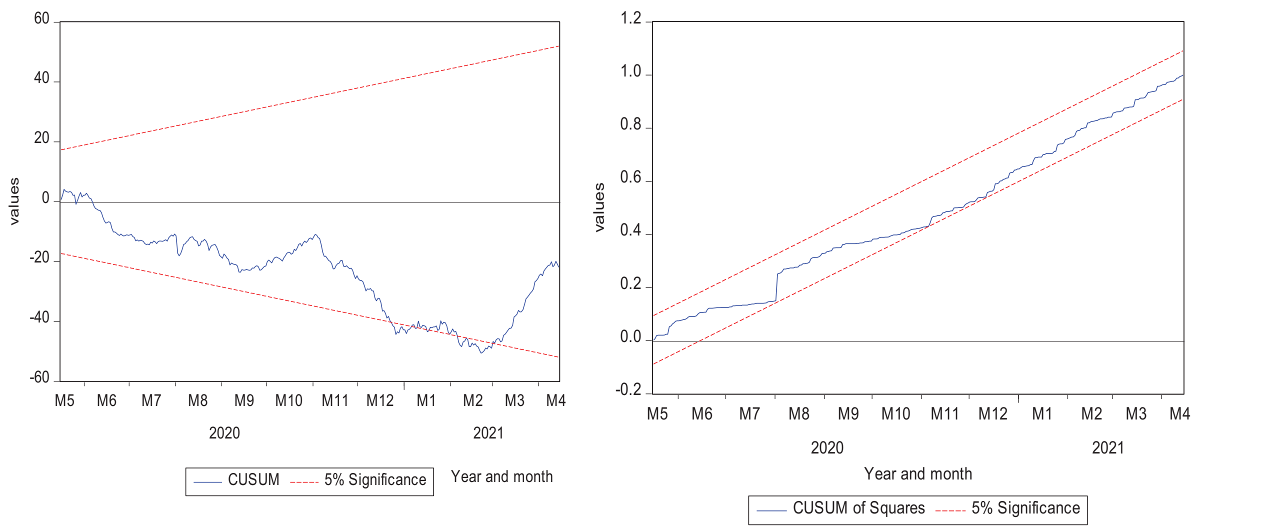

Figure 4. Cumulative sum (CSUM) and cumulative sum square (CSUM squares) test for model stability test.

Author Contributions

The study conceptualization, methodology, software, data analysis and validation were performed by R. Parvin. R. Parvin performed the draft preparation. R. Parvin performed the visualization and reviewed and edited the paper.

Supplemental Material

Supplemental material for this article is available online.

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