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Analysis of the correlation between SARS-CoV-2 transmission and meteorological parameters in Bangladesh

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Abstract

Introduction: Since COVID-19 has been characterized as a worldwide epidemic, multiple studies have suggested that weather may have a role in virus transmission. This research aims to examine the correlation between meteorological parameters and SARS-CoV-2 transmission, as well as to forecast cumulative COVID-19 cases in Bangladesh.

Methods: In this study, an average incubation period of 5-6 days was used to examine the real effect of environmental parameters on SARS-CoV-2 transmission. Therefore, considering the incubation period and reporting time a standard 7-day shift in meteorological parameters from the daily COVID-19 cases was applied to measure the actual correlation. In this regard, the non-parametric correlation test (Spearman's Rank Correlation) was performed where 95% ($p < 0.05$) and 99% ($p < 0.01$) confidence intervals were considered as an acceptance criterion.

Results: This work found a significant positive correlation ($p < 0.01$) for COVID-19 cases with minimum temperature, average temperature (only for division-specific analysis), wind speed, rainfall, humidity, and cloud. Furthermore, a significant negative correlation ($p < 0.01$) was found with atmospheric pressure and sun hours. However, the impact of maximum temperature (except for some divisions) or UV index was significantly low.

Discussion: Our findings showed that the strength of the correlation coefficient is higher for the test positivity rate rather than the confirmed case count. However, to forecast the cumulative cases of COVID-19, ARIMA (Autoregressive Integrated Moving Average) may be considered the best-fitting model according to AIC (Akaike Information Criterion) and performs slightly better than Holt's exponential smoothing model. Additionally, this study represents the comparative analysis between predicted and actual Coronavirus-19 cases during December 2021 to show how close the predicted result is to the selected model.

Take-home message: In this study, the overall analysis indicates that COVID-19 outbreaks in Bangladesh are more likely to hit massively during the pre-monsoon (March to May) season and the monsoon (June to October) season than in winter (November to February). These findings might be useful for decision-makers and authorities to know more about the seasonal impact of the outbreak and plan accordingly before the country enters a new weather season.

Keywords: Bangladesh; Correlation; Forecasting; COVID-19; Meteorological Factors.

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INTRODUCTION

The 2019 novel coronavirus (Coronavirus 19), officially named Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), was first identified in Wuhan, China, on December 31, 2019, and is the virus responsible for a serious life-threatening disease known as COVID-19 (Coronavirus Disease 2019). The World Health Organization (WHO) declared the COVID-19 outbreak as a Public Health Emergency of International Concern on 30 January 2020, and as a pandemic on 11 March 2020 [1]. This disease has emerged as one of the greatest threats to human health, due to its high morbidity and mortality worldwide causing economic, social, and political disruption [2,3]. The COVID-19 pandemic has overburdened healthcare systems in most countries and has led to massive economic losses. As of 5 September 2022, the number of COVID-19 infections had exceeded 600 million cases, with the pandemic affecting over 230 countries and territories and resulting in over 6.5 million deaths globally [4].

Bangladesh, like the rest of the affected countries, has not been shielded from the COVID-19 pandemic. The first COVID-19 cases in Bangladesh were reported on March 8, 2020. Until 05 September 2022, a total of 2,012,376 diagnosed cases causing over 29,326 deaths have been reported in Bangladesh [5]. According to the global comparison of COVID-19 cases, Bangladesh is listed in the top 50 countries with the maximum number of cases [4].

SARS-CoV-2 transmission typically occurs by respiratory droplets, the average incubation period is 6.4 days, and presenting symptoms typically include fever, cough, dyspnea, myalgia, or fatigue. While most of the patients tend to have mild illnesses, a minority of patients develop severe hypoxia requiring hospitalization and mechanical ventilation [6–9]. Before the establishment of an effective vaccine and therapeutic management of the patients with anti-viral agents, and immunomodulatory therapy with steroids and various cytokine blockers [10–13], non-pharmaceutical infection prevention and control (IPC) measures including lockdown measures (i.e., closure of schools and businesses, movement restrictions, international travel restrictions, and geographical area quarantines) have been considered as reliable "weapons" in the fight against the virus [14–19]. SARS-CoV-2 is constantly evolving and spreading through asymptomatic carriers [20–22]. Asymptomatic COVID-19 infection and person-to-person transmission are highly prevalent and may depend on the varying viral incubation period among individuals [23,24]. COVID-19 spreads primarily with contact routes and respiratory droplets, but the airborne transmission of COVID-19 has been recognized, too [25-28]. The virus was identified in aerosol up to three hours after aerosolization, four hours on iron, twenty-four hours on paper, and two to three days on stainless steel and plastic [29]. Healthcare capacity, existing poverty, and environmental factors may affect COVID-19 mortality and transmission [30,31].

In addition to this, political and social issues, geographical considerations, and environmental determinants may all affect the COVID-19 outbreak. Due to the virus's ability to remain viable in the air for several hours, meteorological parameters such as wind, humidity, and temperature, along with the density of the population, have been considered indicators of the virus's viability, transmission, and range of spreading [32,33].

Bangladesh has three major climatic seasons: the hot and humid pre-monsoon (March to May) season, the monsoon (June to October) season, and the dry winter (November to February) season [34]. The impact of COVID-19 seemed to be less severe in Bangladesh than in other Southeast Asian countries, despite the country's large population and one of the largest population densities in this geographical area. This might be due to an insufficient number of testing centers in the country [35], yet weather conditions in Bangladesh could play a role in the SARS-CoV-2 transmission. For this reason, the importance of environmental determinants in the current COVID-19 pandemic should not be overlooked.

Since the outbreak of COVID-19, professionals worldwide have been conducting studies on the virus's propagation and utilizing a variety of forecasting models to assist concerned authorities in making better decisions and adopting necessary control measures. However, pandemic viruses can act differently; numerous studies have studied the relationship between meteorological variables and the COVID-19 outbreak. In one of the first studies on the influence of humidity and temperature in China, Liu et al. [36] investigated a generalized linear model with negative binomial distribution to find the city-specific effects of meteorological parameters on daily confirmed cases. According to their findings, ambient temperature, diurnal temperature range, and absolute humidity are all negatively related to an increase in COVID-19 transmission, with each 1 °C rise in ambient temperature and diurnal temperature range resulting in a significant decrease in daily confirmed case counts. In another study carried out in Mainland China, Qi et al. [37] fitted a generalized additive model to measure the province-specific analysis. The study found that humidity and temperature are both negatively linked with daily positive cases, which is consistent with previous research [34]. However, this study noted that these relationships are not uniform across Mainland China. In a USA-based study, Bashir et al. [38] performed the Kendall and Spearman rank correlation tests for data analysis. Their result estimated that minimum and average temperatures are positively correlated with the transmission of SARS-CoV-2 in New York City. They also found a significant correlation between virus transmission and low air quality. In another study, focused on Jakarta, Indonesia, Tosepu et al. [39] found that only the average temperature is positively related to the COVID-19 outbreak ($r = 0.392$; $p < 0.01$). In Mozambique, Southern Africa, Edgar, et al. [40] performed a Pearson correlation test showing a negative correlation between temperature and the number of infection cases. In another study where a panel regression model analyzed the effect of weather variables on the growth rate of SARS-CoV-2 in 3,235 regions across 173 countries, Carleton et al. [41] showed that ultraviolet rays (UV) affect daily virus growth rates, which is reduced by a standard increase in UV. In India, Sharma et al. [42] showed that minimum temperature, maximum temperature, average temperature, and humidity are strongly correlated with SARS-CoV-2 confirmed cases ($r = 0.93$, 0.94, 0.83, and 0.30, respectively). In a study including the top 20 affected countries in the world, Sil and Kumar [43] used the Gutenberg-Richter's relationship to estimate the association between SARS-CoV-2 confirmed cases and environmental factors including temperature, humidity, wind speed, cloud cover, and precipitation. They found that only temperature increases contribute greatly to the reduction in infection growth rate. In Bangladesh, Haque and Rahman [44] found that high humidity and temperatures significantly minimize the transmission of SARS-CoV-2. Their study suggests that the summer and the rainy season in Bangladesh can potentially minimize the COVID-19 outbreak. In another study carried out in Dhaka, Bangladesh, Mofijur et al. [45] revealed that only minimum ($r = 0.427$; $p = 0.01$) and average temperatures ($r = 0.472$; $p = 0.02$) are positively correlated with new COVID-19 cases. Furthermore, they identified a negative association between the air quality index and the SARS-CoV-2 incidence in Dhaka city. On the contrary, no significant correlation between maximum temperature, precipitation, wind speed, or humidity with SARS-CoV-2 dynamics was found. In India, Anne and Jeeva [46] suggested that the ARIMA model is effective for predicting the next 10 days of cumulative confirmed cases. In another study using the ARIMA model in India, Tandon et al. [47] forecasted the confirmed cases and concluded that the exponential increase of infection cases is expected to significantly increase in the next few days. Ceylan [48] also proposed the ARIMA model to build and forecast the epidemiological trend of SARS-CoV-2 cases in Italy, Spain, and France for improving resource allocation and proper management. Their result showed that the best fit model for Italy and France was ARIMA (0, 2, 1) model, whereas ARIMA (1, 2, 0) model was the best model for Spain. In India, Sharma, and Nigam [49] analyzed the growth curve of the COVID-19 outbreak using exponential and polynomial regression, ARIMA, exponential smoothing, and Holt-Winters models. The final result reported that ARIMA (5, 2, 5) model is the best fit model for predicting COVID-19 cases, with an accuracy of 97.38%, and the Holt-Winters model with an accuracy of 97.11%.

Based on the above-mentioned works, it seems that meteorological factors may potentially affect SARS-CoV-2 transmission. However, these studies have several shortcomings, because of short study periods and a low number of observations. Moreover, research focused primarily on temperature, wind speed, rainfall, and humidity, excluding the confounding effect of other meteorological parameters such as UV index, atmospheric pressure, cloud cover, and sun hours, which may also affect SARS-CoV-2 transmissibility. Additionally, most of the studies concentrated solely on the correlations between weather indicators and COVID-19 cases, without illustrating the virus growth trend. With these premises, this study aimed to determine the correlation between meteorological parameters and SARS-CoV-2 transmission in Bangladesh, to estimate through time series forecasting models the trend of SARS-CoV-2 cumulative cases.

METHODS

Study procedure

Bangladesh is the 8th most populous country in the world, with over 163 million people living in an area of 1,47,570 square kilometers, placing it as one of the world's most densely populated countries. It is subdivided into eight administrative divisions namely Dhaka, Chittagong, Khulna, Rajshahi, Sylhet, Rangpur, Barisal, and Mymensingh. Dhaka is the capital city of Bangladesh, with a population of over 20 million [50]. This study focused on both divisions and the country as a whole.

Data collection and processing

Both daily and monthly data on COVID-19 cases and deaths have been gathered from the Directorate General of Health Services (DGHS) website [51], which includes confirmed cases and test positivity rate (TPR in %) for each division and all the country. From the daily confirmed cases, cumulative confirmed cases were calculated. Meteorological data for each division were collected from "World Weather Online" [52], which is a freely accessible weather website. Then, these data were statistically assembled to provide country-level information. For daily analysis, eight meteorological parameters, such as maximum temperature (°C), minimum temperature (°C), average temperature (°C), wind speed (km/h), rainfall (mm), humidity (%), cloud (%), and atmospheric pressure (millibar or mb) were collected. The monthly average value for those parameters and two additional parameters, such as average UV index and average sun hours (hr), were also collected for monthly analysis.

To ensure consistency among all the divisions, the study period for division-specific analysis was carried out from 1 May 2020 to 30 November 2021, since the COVID-19 outbreak started across all the divisions at different times. The study period for all the countries ranged from 8 March 2020 to 30 November 2021.

In this study, an average incubation period of 5-6 days was used to examine the real effect of environmental parameters on SARS-CoV-2 transmission. Thus, considering the average incubation period, testing, and reporting time, a standard 7-day shift in meteorological parameters from the daily COVID-19 cases was applied to adjust and picture the actual correlation for daily analysis. However, lag lengths differ between individuals and places around the world.

COVID-19 case forecasting

Forecasting gives meaningful and trustworthy information about past, current, and expected future events. To forecast the COVID-19 cumulative cases in Bangladesh, forecasting models were trained using data from 8 March 2020 to 31 October 2021. Additionally, data from 1 November to 30 November 2021 were utilized to analyze the models' performance. Finally, a short-term forecast was made for the upcoming month (December 2021) of winter.

Statistical analysis

Since the data in this analysis were not normally distributed, a non-parametric correlation test (i.e., the Spearman's rank correlation test) was performed to examine the relationship between meteorological parameters and SARS-CoV-2 transmission. Spearman's correlation coefficient measures the magnitude and direction of the monotonic relation between two variables. The formula for Spearman's rank correlation coefficient (r_s) can be written as [53]:

$$r_s = 1 - 6\frac{\sum d_i^2}{n(n^2 - 1)}$$

Here, 'd_i' is the difference in rank between two observations and 'n' denotes the total number of observations. The '$+r_s$' refers to a positive correlation, and the '$-r_s$' refers to a negative correlation. The correlation strength [54] for the value of r_s is shown in Table 1.

Table 1. Correlation strength for the value of r_s.

Correlation Strength	$\boldsymbol{r_s}$
Very Strong	0.90 to 1.00
Strong	0.70 to 0.89
Moderate	0.40 to 0.69
Weak	0.20 to 0.39
Very Weak	0.00 to 0.19

As an acceptance criterion for the correlation between meteorological parameters and SARS-CoV-2 cases, 95% ($p < 0.05$) and 99% ($p < 0.01$) confidence intervals were adopted. The analyses were conducted in Python (version: 3.9.6) using Pandas and SciPy libraries.

Time series forecasting model

Time series forecasting is a strategy for predicting future events by evaluating past trends, with the premise that future trends will be similar to past trends. To forecast the future, models are fitted to historical data. Time series forecasting is required for prediction problems with a time component since it gives a data-driven solution for efficient and timely planning. In this study, two-time series forecasting models have been studied to model and forecast the cumulative confirmed cases in Bangladesh.

ARIMA (Auto Regressive Integrated Moving Average) model

A time series is essentially a collection of observed data points that are sorted in time. Auto-Regressive Integrated Moving Average (ARIMA) is a widely used time series model because it uses changing trends, periodic changes, and random disruptions into consideration. The ARIMA model is frequently termed as ARIMA (p, d, q), where 'p' is the rank of autoregression (AR), 'd' is the integration (I) which denotes the degree of difference, and 'q' denotes the order of the moving average (MA) [55]. These three terms are discussed below:

An Auto-Regressive (AR) model is one in which Y_t is determined only by its lags. This means, Y_t is a function of its lags, which can be stated by the equation given below:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} + \cdots + \beta_p Y_{t-p} + \varepsilon_t$$

Where, Y_{t-1} is the initial lag of the time series, β_1 is the first lag coefficient predicted by the model, and the intercept term α is determined by the model as well.

Similarly, a Moving Average (MA) model is one in which Y_t is solely determined by the lagged forecast errors, which can be addressed by the equation given below:

$$Y_t = \alpha + \varepsilon_t + \varphi_1\varepsilon_{t-1} + \varphi_2\varepsilon_{t-2} + \varphi_3\varepsilon_{t-3} + \cdots + \varphi_q\varepsilon_{t-q}$$

Where φ is the MA parameter and the error terms are the AR model errors for the relevant lags. The errors ε_t , ε_{t-1} and ε_{t-2} result from the equations given below:

$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} + \cdots + \beta_0 Y_0 + \varepsilon_t$$

$$Y_{t-1} = \beta_1 Y_{t-2} + \beta_2 Y_{t-3} + \beta_3 Y_{t-4} + \cdots + \beta_0 Y_0 + \varepsilon_{t-1}$$

$$Y_{t-2} = \beta_1 Y_{t-3} + \beta_2 Y_{t-4} + \beta_3 Y_{t-5} + \cdots + \beta_0 Y_0 + \varepsilon_{t-2}$$

Therefore, by merging the AR and MA models, the constructed ARMA model can be expressed as follows:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} + \cdots + \beta_p Y_{t-p} + \varepsilon_t + \varphi_1\varepsilon_{t-1} + \varphi_2\varepsilon_{t-2} + \varphi_3\varepsilon_{t-3} + \cdots + \varphi_q\varepsilon_{t-q}$$

In summary, the projected ARMA model is just a constant value with a linear mix of lags (p) and lagged forecast errors (q).

Finally, the parameter 'd' is used for differencing (I) to make the time series stationary. When statistical features such as mean and variance stay constant across time, then it is called a stationary time series. To avoid over-difference in the series, it is necessary to choose the value of 'd' carefully. Because, a series that is over-differenced can still be stationary, which in turn will impact the parameters of the ARIMA model. The following equation expresses the principle of first-order differencing by calculating the difference between consecutive observations:

$$Y_t' = Y_t - Y_{t-1}$$

The optimal ARIMA (p, d, q) model is the one with the lowest value across all the measures. Now, the objective is to find the optimal value of 'p', 'd', and 'q' to fit the ARIMA model. This can be accomplished by following these steps:

At first, to find the value of 'd', the ADF (Augmented Dickey-Fuller) test [56] can be applied. The ADF test is a basic statistical test used to verify stationarity. It is a unit root test for stationarity. The ADF test's null hypothesis is that the time series is non-stationary. Due to the non-stationarity ($p = 0.95$) of the time series, it is differenced and calculated by the differences between subsequent observations. As the p-value (0.08) after first order differencing is more than 0.05, a second order differencing is required. The p-value (0.02) after second order differencing is less than 0.05, hence the null hypothesis is rejected, and the dataset does not have any unit root which makes it stationary. Thus, the optimal value of 'd' is 2. Table 2 illustrates the ADF test summary.

Table 2. ADF test summary.

Order (d)	ADF	p-Value	Stationary
0	-0.13	0.95	No
1	-2.67	0.08	No
2	-3.14	0.02	Yes

Now, in the second step, to find the optimal value of 'p' and 'q' with 'd = 2', AIC (Akaike Information Criteria) [57] can be used. This information criterion can be utilized to choose the best-fitted model. The goal is to select the model with the lowest AIC value from different combinations of ARIMA (p, d, q) values. From Table 3, using the grid search method specifying 'd = 2', the best-fit model is ARIMA (2, 2, 3) with the lowest AIC value of 9546.971. The analyses were conducted in Python (version: 3.9.6) using Pandas, pmdarima, and statsmodels libraries.

Table 3. AIC value for different ARIMA models.

ARIMA (p, d, q)	**AIC**
ARIMA (0, 2, 0)	9632.404
ARIMA (0, 2, 1)	9634.269
ARIMA (0, 2, 2)	9622.565
ARIMA (0, 2, 3)	9607.807
ARIMA (0, 2, 4)	9603.234
ARIMA (0, 2, 5)	9605.056
ARIMA (1, 2, 0)	9634.295
ARIMA (1, 2, 1)	9631.18
ARIMA (1, 2, 2)	inf
ARIMA (1, 2, 3)	9605.254
ARIMA (1, 2, 4)	9600.937
ARIMA (2, 2, 0)	9627.963
ARIMA (2, 2, 1)	9610.503
ARIMA (2, 2, 2)	9564.733
ARIMA (2, 2, 3)	9546.971
ARIMA (3, 2, 0)	9616.803
ARIMA (3, 2, 1)	9606.375
ARIMA (3, 2, 2)	9547.109
ARIMA (4, 2, 0)	9611.328
ARIMA (4, 2, 1)	9604.566
ARIMA (5, 2, 0)	9591.458

Holt's exponential smoothing model

Holt's forecasting is a technique for forecasting the behavior of time series data. Holt's approach applies exponential smoothing (ES) to numerous historical data to anticipate "typical" values for the present situation and future. Exponential smoothing is a term that refers to the process of "smoothing" a time series using an exponentially weighted rolling average [58]. A new time series s_t can be defined from a given time series, x_t where s_t is a simple smoothed version of x_t. Thus, the equation for single exponential smoothing becomes:

$$s_t = \alpha x_t + (1 - \alpha) s_{t-1}$$

Where, $\alpha \in (0, 1)$ specifies the smoothing factor for the data. Now, in the case of Holt's double exponential smoothing (also known as Holt's exponential smoothing), suppose raw observations to be indicated by x_t , smoothed values by s_t , and b_t indicates the best approximation of trend at time t. Therefore, the equations for double exponential smoothing become:

$$s_t = \alpha x_t + (1 - \alpha)(s_{t-1} + b_{t-1})$$

$$b_t = \beta (s_t - s_{t-1}) + (1 - \beta) b_{t-1}$$

Where, $\alpha \in (0, 1)$ specifies the smoothing parameter for the data and $\beta \in (0, 1)$ specifies the smoothing parameter for the trend. The m-step ahead forecast method, F_{t+m} , can be expressed as follows:

$$F_{t+m} = s_t + mb_t$$

The analyses were conducted in Python (version: 3.9.6) using Pandas and statsmodels libraries.

Performance evaluation

Testing the accuracy of a model involves comparing actual values with the predicted values. The ARIMA and Holt's exponential smoothing models were evaluated for predictive accuracy using the popular performance metric, namely Root Mean Square Error (RMSE) [59]. It is equal to the square root of the mean of the squared differences between the estimated and observed values. A lower RMSE value suggests that the data is better suited. The analyses were conducted in Python (version: 3.9.6) using Pandas and sklearn libraries. The equation for the performance metric can be expressed as follows:

$$RMSE = \sqrt{\sum_{t=1}^{N} \frac{(\hat{y_t} - y_t)^2}{N}}$$

Where, y_t denotes the actual data at time t, $\hat{y_t}$ denotes a prediction of y_t , and N is the number of observations.

This study considered daily data for division-specific correlation analysis, and monthly data for country-level analysis and visualization. In addition to this, both confirmed cases and the test positivity rate (TPR in %) were considered for correlation analysis with meteorological parameters. We considered a tendency for less testing during the holidays and festive seasons, resulting in a lower number of positive cases. For example, Friday is a weekly holiday in Bangladesh, and the daily positive case report on Saturday has been always lower than on the other days of the week. As a result, the test positivity rate is important for presenting a realistic image of the scenario in the most optimal way.

RESULTS AND DISCUSSION

Division-specific analysis

The Spearman's rank correlation of COVID-19 confirmed cases and test positivity rate (TPR) with meteorological parameters on a daily basis is shown in Table 4. For this investigation, a standard 7-day lag of meteorological factors was used.

Table 4. Division-Specific Correlation analysis on a daily basis.

Division	Target Variables	Maximum Temp.	Minimum Temp.	Average Temp.	Wind Speed	Rainfall	Humidity	Cloud	ATM Pressure
Dhaka	Cases	0.10*	0.28**	0.27**	0.38**	0.28**	0.35**	0.38**	-0.43**
	TPR	0.16**	0.46**	0.37**	0.47**	0.34**	0.34**	0.43**	-0.56**
Chittagong	Cases	0.05	0.29**	0.21**	0.48**	0.32**	0.39**	0.38**	-0.47**
	TPR	0.17**	0.50**	0.39**	0.58**	0.42**	0.48**	0.47**	-0.58**
Khulna	Cases	0.13**	0.60**	0.43**	0.49**	0.50**	0.47**	0.56**	-0.70**
	TPR	0.20**	0.68**	0.51**	0.54**	0.49**	0.44**	0.54**	-0.73**
Rajshahi	Cases	0.18**	0.49**	0.38**	0.44**	0.54**	0.45**	0.54**	-0.64**
	TPR	0.26**	0.60**	0.46**	0.52**	0.54**	0.40**	0.53**	-0.70**
Sylhet	Cases	0.13**	0.55**	0.41**	0.56**	0.44**	0.40**	0.52**	-0.61**

	TPR	0.06	0.64**	0.41**	0.62**	0.54**	0.48**	0.60**	-0.66**
Rangpur	Cases	0.03	0.51**	0.30**	0.48**	0.53**	0.52**	0.55**	-0.64**
	TPR	0.04	0.51**	0.31**	0.49**	0.53**	0.47**	0.55**	-0.62**
Barisal	Cases	0.10*	0.49**	0.39**	0.54**	0.43**	0.40**	0.48**	-0.60**
	TPR	0.08	0.53**	0.40**	0.53**	0.46**	0.43**	0.51**	-0.63**
Mymensingh	Cases	0.12**	0.52**	0.41**	0.57**	0.53**	0.46**	0.57**	-0.62**
	TPR	0.10*	0.51**	0.39**	0.54**	0.49**	0.40**	0.53**	-0.59**

**, * indicates a 1% and 5% level of significance respectively

As shown in Table 4, the maximum temperature showed a very weak (r = 0.10 to 0.18) positive correlation with COVID-19 daily case count and very weak (r = 0.10 to 0.17) to weak (r = 0.20 to 0.26) positive correlation with test positivity rate (TPR) in some divisions. On the contrary, minimum temperature showed a moderate (r = 0.46 to 0.68) positive correlation with daily cases (except in Dhaka & Chittagong) and TPR. For average temperature, the study found a mix of weak (r = 0.21 to 0.39) to moderate (r = 0.40 to 0.51) positive association for both daily case count and TPR. For wind speed, the study found a moderate (r = 0.44 to 0.62) positive correlation for both positive cases (except in Dhaka) and TPR. In the case of rainfall, humidity, and cloud, the study also found a moderate (r = 0.40 to 0.60) positive association between daily case count (except in Dhaka & Chittagong) and TPR (except in Dhaka for Rainfall & Humidity). And finally, atmospheric pressure showed a moderate (r = −0.43 to −0.66) negative correlation for both daily case count and TPR in most of the divisions. For Khulna, it was strongly negative in both daily case count (r = −0.70) and TPR (r = −0.73), and for Rajshahi, it was strongly negative only with TPR (r = −0.70). All of these correlation coefficients (r) were statistically significant at a 1% level, except for maximum temperature. The strength of the coefficient (r) was better for the test positivity rate (TPR) compared to the daily case count in most of the scenarios.

Country-level analysis

The Spearman's rank correlation of COVID-19 confirmed cases and test positivity rate (TPR) with meteorological parameters on a monthly basis is shown in Table 5. The monthly average values of the meteorological parameters were considered with the monthly cases and monthly test positivity rate.

Table 5. Country-Level Correlation analysis on a monthly basis.

Target Variables	Maximum Temp.	Minimum Temp.	Average Temp.	Wind Speed	Rainfall	Humidity	Cloud	ATM Pressure	UV Index	Sun Hours
Cases	-0.13	0.58**	0.21	0.57**	0.59**	0.61**	0.65**	-0.63**	-0.27	-0.61**
TPR	-0.06	0.70**	0.35	0.71**	0.69**	0.63**	0.71**	-0.71**	-0.11	-0.67**

**, * indicates a 1% and 5% level of significance respectively

As shown in Table 5, maximum temperature observed a very weak negative correlation and average temperature observed a weak positive correlation with positive case count and test positivity rate (TPR). Both were statistically non-significant at any level (1% or 5%). On the contrary, minimum temperature observed a moderate positive correlation with confirmed cases (r = 0.58) and a strong positive correlation with TPR (r = 0.70). For wind speed and cloud, the study found a moderate positive correlation with confirmed cases (r = 0.57, r = 0.65, respectively) and a strong positive correlation with TPR (r = 0.71). In the case of rainfall and humidity, the study found a moderate positive correlation for both confirmed cases (r = 0.59, r = 0.61, respectively) and TPR (r = 0.59, r = 0.63, respectively). Atmospheric pressure showed a moderate negative correlation with confirmed case count (r = −0.63) and a strong negative correlation with TPR (r = −0.71). Similarly, sun hours also showed a moderate negative correlation for both confirmed case count (r = −0.61) and TPR (r = −0.67).

However, the UV index showed a weak negative correlation with SARS-CoV-2 confirmed cases and a very weak negative correlation with TPR. But those were not statistically significant at any level. All of these correlation coefficients (r) were statistically significant at a 1% level for those of moderate and strong correlation scenarios. The strength of the coefficient (r) was higher for the test positivity rate (TPR) compared to the COVID-19 confirmed case count in all of those statistically significant cases.

Graphical analysis

For graphical analysis, this study considered the monthly data at the country level for better understanding and visualization. As from Table 5, the values of correlation coefficient (r) were higher for test positivity rate (TPR) in almost all the scenarios, therefore test positivity rate (%) was chosen to visualize the association with the meteorological factors. The combination (bar & line) graphs are illustrated as follows:

Temperature

Figure 1 shows that, among the three temperature variables, only the minimum temperature was strongly related to the TPR. It followed the pattern of the TPR better than the other two temperature variables over the months. It also indicates that the TPR was higher in June, July, and August when the minimum temperature was between 26 °C to 27 °C. On the other hand, TPR was in the lower range when the minimum temperature was between 18 °C to 22 °C.

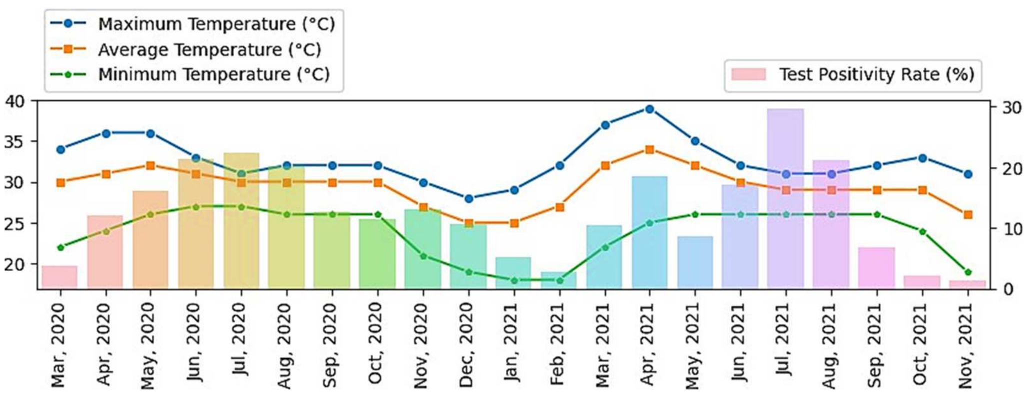

Figure 1. Positive association between TPR and minimum temperature.

Wind speed

Figure 2 reveals that the TPR increased with high wind speed, and declined with low speed. This could be because a high wind speed makes it easier for the virus to spread in more locations and, then, infect more people in those locations.

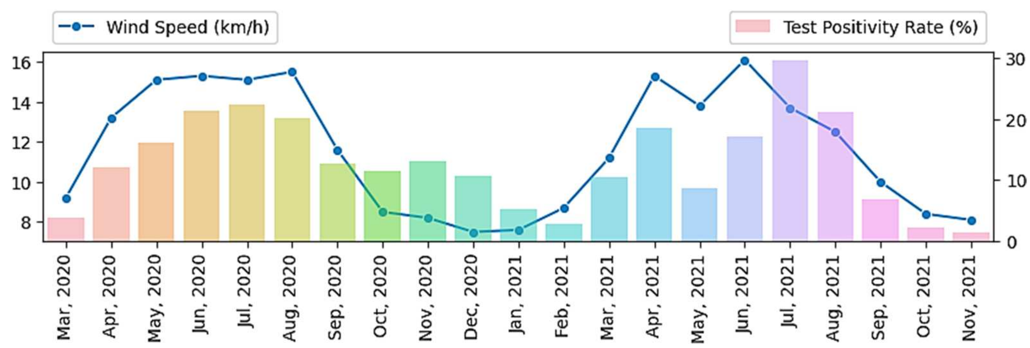

Figure 2. Positive association between TPR and wind speed.

Rainfall

Figure 3 shows a similar trend between TPR and rainfall as for wind speed. Because, an increased rainfall might reduce the evaporation of respiratory droplets, allowing them to stay more freely on the surfaces. As a result, this increases the likelihood of infection by touching those surfaces with hands.

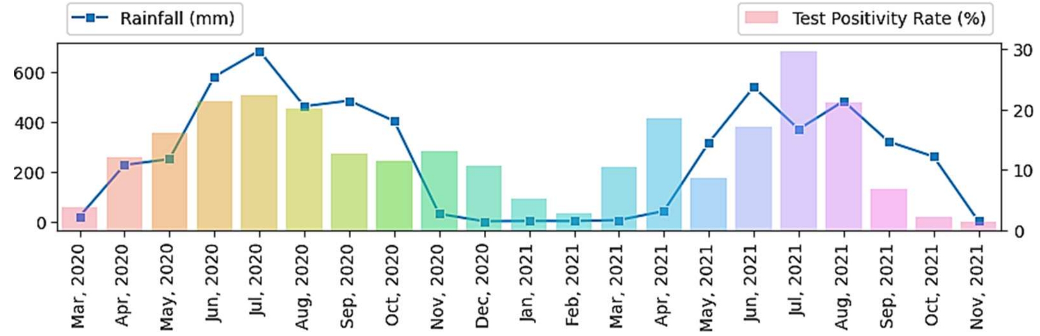

Figure 3. Positive association between TPR and rainfall.

Humidity

Figure 4 also shows a positive trend between humidity and TPR, as for wind speed and rainfall. This might be the reason that, when the air is humid, there is so much water vapor in it that there is no place for anything else, so droplets cannot evaporate into the air as they should.

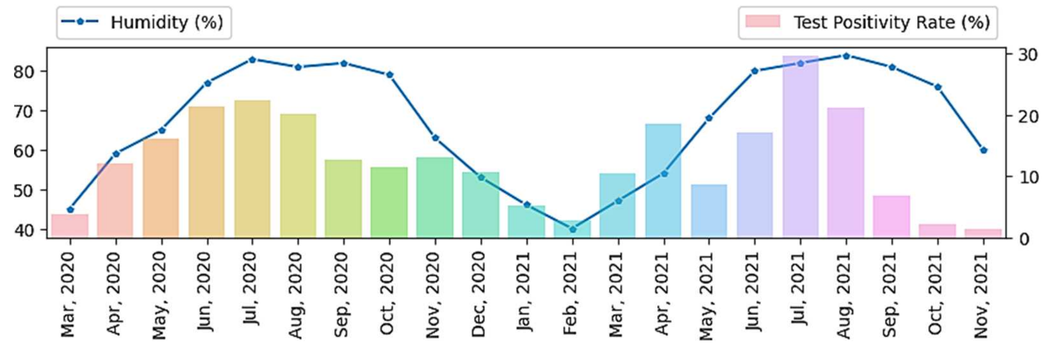

Figure 4. Positive association between TPR and humidity.

Cloud

Though Figure 5 depicts a positive pattern between TPR and clouds, like wind speed, rainfall, and humidity, it might have an indirect influence rather than the direct one. Because cloudy weather indicates the possibility of storms and rain, which in turn accelerate the wind speed, both wind speed and rainfall were positively associated with a greater amount of test positivity rate.

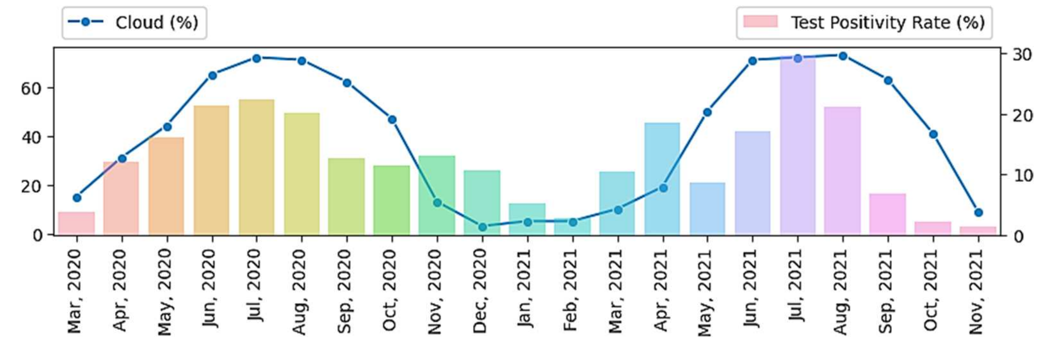

Figure 5. Positive association between TPR and cloud.

Atmospheric pressure

Figure 6 illustrates that TPR was higher when the atmospheric pressure was lower and vice versa. Similar to the cloud, it might also have an indirect influence rather than a direct one. The atmospheric pressure is a good indicator of the weather. Low atmospheric pressure usually brings high wind speeds, cloudiness, and rainfall to an area. As a result, high wind speeds allow droplets to easily move to different areas, while rain allows them to stay on the surface longer.

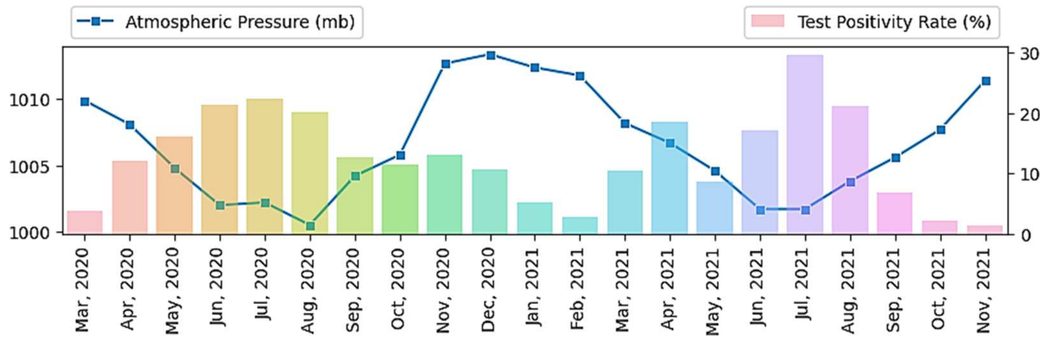

Figure 6. Positive association between TPR and atmospheric pressure.

Sun hours

Figure 7 indicates that TPR was lower when sun hours were higher. Because of the low wind speed and humidity in the dry season, there is an increased likelihood for the droplets to stay in the same place for a long period, where the sun rays can easily dry them before further transmission.

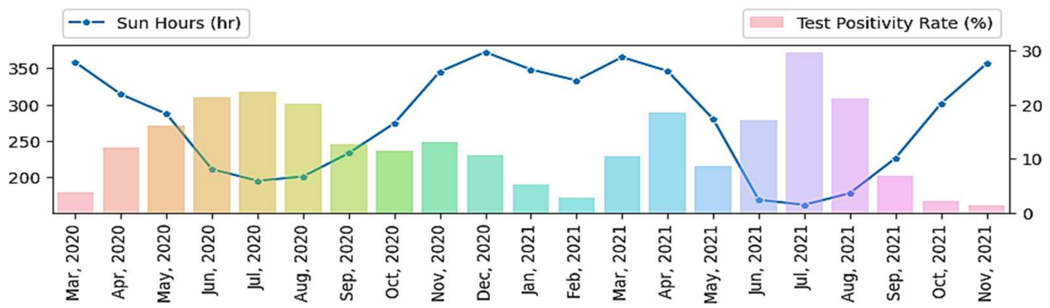

Figure 7. Negative association between TPR and higher sun hours.

UV index

Figure 8 does not show any clear pattern between the UV index and test positivity rate. Here, the UV index fluctuated irregularly, revealing no clear pattern to conclude the relationship with the test positivity rate.

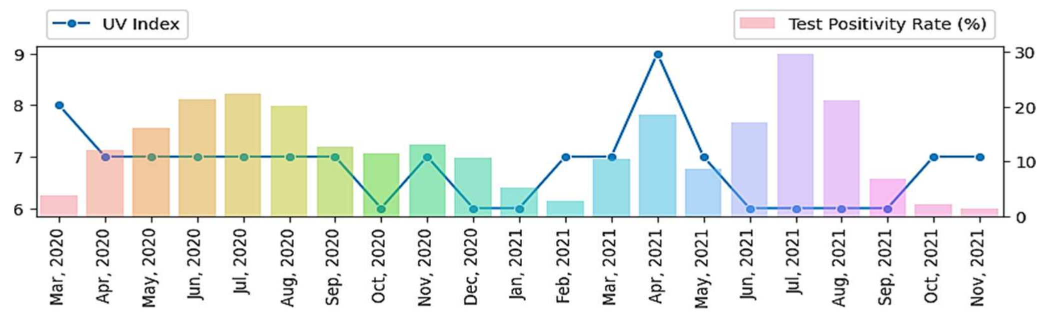

Figure 8. Unclear association between TPR and UV index.

Forecasting using ARIMA model

ARIMA (2, 2, 3) model was employed to forecast the cumulative SARS-CoV-2 cases in Bangladesh. In Figure 9, the model's predictions for the test data period were plotted against the original test data. The calculated RMSE for this prediction was 187.

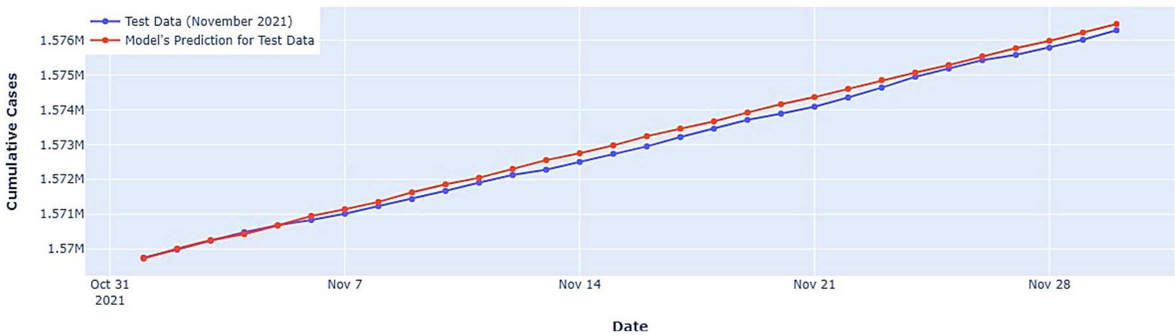

Figure 9. ARIMA model's prediction for test data.

From Figure 10, the forecasted trend indicates that COVID-19 cases were not expected to rise considerably in the second month (December 2021) of winter in Bangladesh. It is also evident from the graph that the growth trend for the first two months of the winter (November and December) season of 2021 is almost identical to the growing trend for the winter season of 2020.

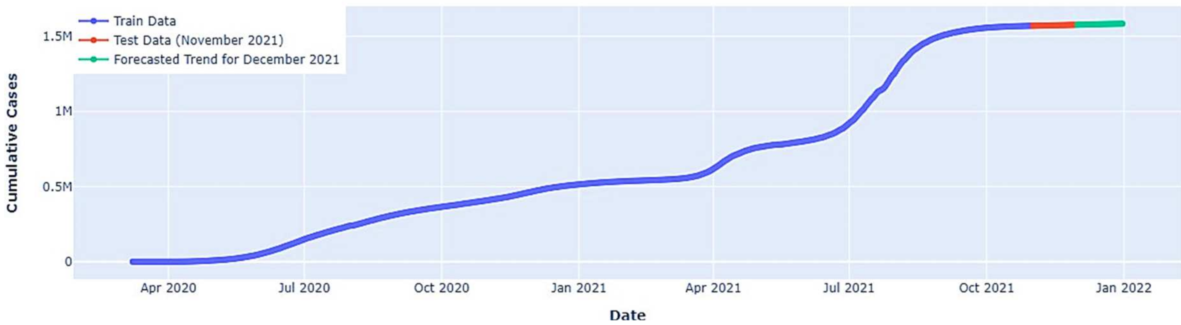

Figure 10. Forecasting COVID-19 cases using the ARIMA model.

Forecasting using Holt's ES model

In Figure 11, Holt's exponential smoothing model's predictions for the test data time range were plotted against the original test data. The calculated RMSE for this prediction was 214.

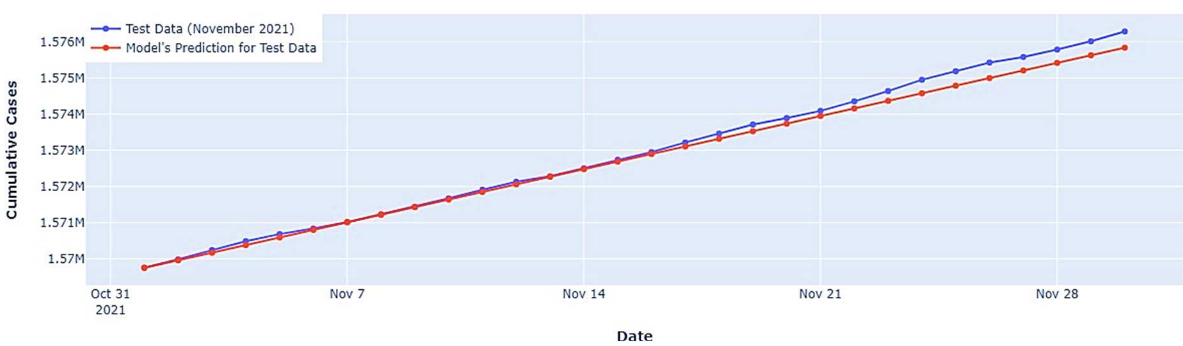

Figure 11. Holt's ES model's prediction for test data.

As shown in Figure 12, the forecasted trend indicates a similar future to ARIMA, which means that COVID-19 outbreaks are unlikely to increase significantly in December 2021. Therefore, analyzing the trend, it is evident that the upcoming months of winter will not be as vulnerable as the monsoon season in Bangladesh.

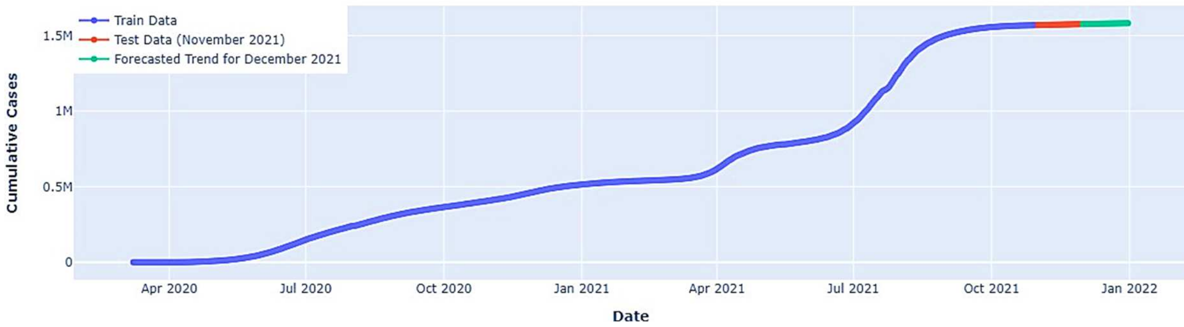

Figure 12. Forecasting COIVD-19 cases using Holt's ES model.

Relationship between present and forecast

The actual and forecasted SARS-CoV-2 cases in Bangladesh, which were forecasted by the studied models were quite similar for the month of December 2021. According to Figure 13, the ARIMA forecasted trend follows a similar pattern to the actual cumulative cases and performs better than Holt's ES model.

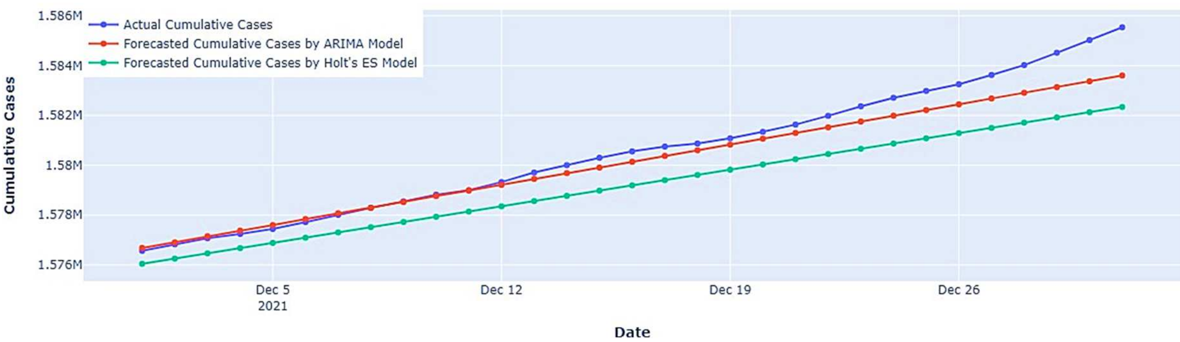

Figure 13. COVID-19 scenario in Bangladesh (December 2021).

Table 6 also shows the actual cumulative cases for December 2021 and the forecasted cumulative cases based on the ARIMA and Holt's ES models. This relationship between actual cases and forecasted values demonstrates how effectively the models forecasted the future. As a result, these forecasting models will be very useful in anticipating future scenarios as well as analyzing the nature of the COVID-19 epidemic and similar types of outbreaks in the future.

Table 6. Relationship between present and forecast.

Date	Actual Cumulative Cases	Forecasted Cumulative Cases	
		ARIMA Model	Holt's ES Model
01/12/21	1576566	1576680	1576045
02/12/21	1576827	1576905	1576254
03/12/21	1577070	1577152	1576464
04/12/21	1577246	1577379	1576674
05/12/21	1577443	1577597	1576884
06/12/21	1577720	1577837	1577094
07/12/21	1578011	1578075	1577304
08/12/21	1578288	1578293	1577514
09/12/21	1578550	1578523	1577724

10/12/21	1578819	1578766	1577933
11/12/21	1578996	1578990	1578143
12/12/21	1579325	1579213	1578353
13/12/21	1579710	1579453	1578563
14/12/21	1580005	1579686	1578773
15/12/21	1580302	1579907	1578983
16/12/21	1580559	1580140	1579193
17/12/21	1580750	1580378	1579403
18/12/21	1580872	1580603	1579612
19/12/21	1581083	1580830	1579822
20/12/21	1581343	1581068	1580032
21/12/21	1581634	1581298	1580242
22/12/21	1581986	1581522	1580452
23/12/21	1582368	1581756	1580662
24/12/21	1582710	1581991	1580872
25/12/21	1582985	1582216	1581082
26/12/21	1583253	1582446	1581291
27/12/21	1583626	1582682	1581501
28/12/21	1584023	1582911	1581711
29/12/21	1584518	1583137	1581921
30/12/21	1585027	1583372	1582131
31/12/21	1585539	1583604	1582341

CONCLUSION

This study suggests that weather conditions may play a crucial role in COVID-19 transmission. According to our findings, in Bangladesh, the pre-monsoon (March to May) season and the monsoon (June to October) season might be more sensitive to COVID-19 outbreaks than the winter (November to February) season. As a result, policymakers and health officials should consider weather season as a relevant environmental determinant of the SARS-CoV-2 spread in the country and plan accordingly the subsequent infection and control measures.

Our study is not without limitations, because it did not take into account some key factors in the relationship with meteorological parameters that might have influenced the core relationship, such as countrywide lockdown and the testing capacity in terms of population, immunity, personal hygiene attitudes, etc. Therefore, a much larger number of influencing variables are needed to perform a detailed breakdown in future studies. Additionally, future research could also examine causal relationships among the variables through correlation analyses. Finally, a multivariate model including vaccines administered, lockdown period, capacity of testing, etc., along with other social and environmental (e.g., air quality) influencing factors, should be analyzed in the future.

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