**The trend of Case Fatality Rate and its association between meteorological factors in Bangladesh**

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**Abstract**

Novel coronavirus disease (COVID-19) is an infectious disease that affects the human respiratory tract and is caused by the acute respiratory syndrome coronavirus 2 (SARS-CoV-2). Several meteorological factors and weather elements are directly correlated with the reported case fatality rate (rCFR) of COVID-19 in different groups of people worldwide. This study focused to understand the trend of the rCFR of COVID-19 in Bangladesh and the relation of the trend with meteorological predictors in a different period with the help of the data from the WHO’s daily situation reports dated January 25, 2021, to January 25, 2022. We used the Simple Exponential Smoothing (SES), Auto-Regressive Integrated Moving Average (ARIMA), and Automatic forecasting time-series model (Prophet) model for forecasting our data. The association between the rCFR and meteorological factors were investigated by beta regression models. The daily confirmed cases of COVID-19 in Bangladesh reached a peak at 16230 on July 28, 2021. In the peak of the cases, the country’s rCFR reported at 1.65% which was highest (12.82%) on 25th March 2020 and declined to 1.64% on 25th January 2022. An increasing trend was observed until the highest peak (pre-peak) cases period and then a strong declining trend till 25th January 2022 (post-peak) cases period of cumulative rCFR values of COVID-19. In the pre-peak cases period, the wind speed and surface pressure were found to have a significantly negative relationship with the COVID-19 rCFR. The negative association of rCFR is because the risk of COVID-19 spread might be more in closed places with low wind speed. Moreover, wind speed, average temperature, dew point, rainfall, and relative humidity are also found positive significant relationship in the post-peak cases period with the COVID-19 rCFR. Such a type of critical analysis with the help of an optimum volume of data can help to accurately track the pattern of pandemics.

**1. Introduction**

The novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is pandemic globally everywhere (1–5). A flu-like symptom was discovered in late December 2019 in Wuhan, China, which was caused by the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and quickly spread everywhere in the world due to its high transmission rate (5,6). In March 11, 2020, The World Health Organization (WHO) announced the disease known as COVID-19 (7). Coronavirus is a positive (+) sense RNA virus (8). In a previous study, we got that SARS-CoV survived at low ambient temperature and relative humidity on surfaces over five days but quickly vanished at 40 °C and higher humidity (9). Early studies had shown that environmental factors significantly affecting on the growth and activity of respiratory viral disease (10–13). There is a significant relationship between climate conditions especially the temperature and the incidence rate of MERS-CoV was reported in Saudi Arabia (14).

SARS-CoV-2 is more stable at low relative humidity and lower temperatures, and decays faster at higher relative humidity and temperatures, according to experimental studies. When the virus is exposed to increased relative humidity and temperatures, as well as simulated solar light, the virus becomes even less stable (half-life, 3 min) (15). Animal tests with the influenza virus revealed that transmission was more efficient at 5 degrees Celsius than at 20 degrees Celsius (16). Rainfall and wind speed, among other weather/meteorological factors, influenced the COVID-19 spread rate (17,18). Bashir et al. (2020) observed insignificant role of wind speed in the spread of COVID-19 (19). The activity of the respiratory syncytial virus, influenza, and other viruses is similarly influenced by dew point (20). Wind speed and air pressure have stronger negative association in Asian countries (21).

The first corona case was discovered in Bangladesh on March 8, 2020. On March 18, the first corona patient died due to coronavirus (5). The case fatality rate (CFR) of COVID-19 is defined as the proportion of death due to a specific disease and it varies greatly in different countries. There is no study is reported so far on whether and how meteorologicalconditions can affect COVID-19 mortality (22). As COVID-19 continuously spread rapidly throughout Bangladesh, studying the relationship between the case fatality rate (CFR) of COVID-19 and the meteorological variables could bring useful recommendations in the upcoming months for decision-makers. In this paper, we investigate the relationship between climatic conditions and coronavirus CFR in Bangladesh. As no other study before about the relationship between meteorological variables and spreading of COVID-19 CFR. The findings of this study will add to the evidence on COVID-19's climatic consequences from the perspective of a megacity in a developing country.

**Methods**

Simple Exponential Smoothing (SES), Auto-Regressive Integrated Moving Average (ARIMA), and Automatic Forecasting Time-Series Model (Prophet) were used in this study. Finally, we created a beta-regression model of explanatory factors to see if meteorological factors have any association with the COVID-19 CFR of the country. All these different analysis approaches helped us to make a specific conclusion on the trend of COVID-19 CFR and factors affecting the CFR of COVID-19. The statistical software R was used for all of the analyses.

**COVID-19 Data**

The fundamental COVID-19 related data, including daily new cases, daily new deaths, total deaths, total deaths per million, and total cases from the WHO daily COVID-19 situation reports in Bangladesh was collected from January 25, 2021, to January 25, 2022, for this analysis (23).

**Reported case-fatality rate (rCFR)**

We calculated the total CFR COVID-19 case as the number of deaths per 100 COVID-19 confirmed cases. Because there is a difference between a total case and a death case, we coined the term "reported CFR" or "rCFR" (24).

**Meteorological factors**

We also collected Rainfall (mm), Relative humidity (%), Temperatures (°C), Surface pressure (kPa), Dew point (°C), and wind velocity (m/s) at 10 m height (Maximum Wind Speed) from NASA's Prediction of Worldwide Energy Resources webpage on a daily scale (25).

**Time series model to predict the trend**

To discover the trend of rCFR for COVID-19, we employed three time-series models: SES, ARIMA, and Prophet. All of these time series models were chosen since the outcome variable (cumulative rCFR) is dependent on all meteorological factors. Using the time series models with the reported COVID-19 data, we forecasted trends for the prospective 30 days and visualized them in the figure. SES was used as a benchmark to compare the performance of other models.

**Simple Exponential Smoothing (SES):**

One of the most often utilized strategies for forecasting procedures is simple exponential smoothing (26). SES is a short-term forecasting model that defines data as fluctuating around a steady mean (27–29). The SES model for this study had been carried out using the R package ‘fpp2’ (30).

**Auto-Regressive Integrated Moving Average (ARIMA):**

We used an ARIMA model to forecast the trend of daily cumulative rCFR. The ARIMA model is a statistical, data-oriented analysis that interprets a perfect model by using the structure of the data itself (31). This model shows that the time series values are linearly related and defines the extract prediction by deleting high-frequency noise from the data (32). ARIMA models have the advantage of being able to perform dynamically oriented analysis that uses recent data to predict the future (33). The ARIMA model for this study had been carried out using the R package ‘forecast’ (34).

**Automatic Forecasting time-series model (Prophet):**

We also used a construe automatic forecasting time-series model called ‘Prophet’ using the R package “prophet” to predict the 10-days fatality rate and distinguished it with rCFR (35). The Prophet model doesn’t want the temporal dependence of the irregular observations to be allowed in the data set and the model fits very quickly (36). The benefit is, it collects missing data also and manages outliers well generally (24,37).

**Empirical evaluation**

The time series models are experimentally evaluated by comparing their outcomes to benchmarks in predicting the rCFR. This benchmark permitted us to assess the performance gains made by their counterparts (38). The SES also allows the most appropriate non-seasonal model for each series, allowing for any kind of error or trend component. Here, we analyse and compare the execution of the considered time series models with some commonly utilized measures to assess the prediction significance, including coefficient of determination (R2), root mean square error (RMSE), and mean absolute error (MAE).

**Statistical analysis**

We looked at how the COVID-19 cases have evolved. We also discover that the COVID-19 cases peaked on July 28, 2021 (cases = 16230), after which the trend began to diminish. Because the cases are lower in this period, we separated the entire data with this peak and renamed the pre-peak cases period from 25th January 2021 to 28th July 2021, and the post-peak cases period from 29th July 2021 to 25th January 2022. Not only utilized a time-series model to figure out why COVID-19's rCFR was high at that period. Through a regression model, we attempted to determine whether there is a link between COVID-19 rCFR and explanatory variables that change over time or remain constant throughout two periods. We used the beta regression model independently for each dataset to look into the relationship between various explanatory variables and see which variables had the biggest impact throughout these periods.

**Outcome and predictor variables**

We used rCFR as the outcome variable, we also collected and used several predictors’ data including different types of climate parameters based on a daily scale.

**Beta regression models:**

As the outcome variable (rCFR) varies in an interval of 0 or 1, here we used beta regression models to find out the relation between possible explanatory variables and the rCFR (39,40). The benefits of the beta-regression model are explanatory variables for reporting the incidence rate ratios (IRRs) after adjusting them for environmental factors like temperature, rainfall, relative humidity, wind speed, and dew point in Bangladesh country. We used the variance inflation factor (VIF) value to examine multicollinearity in the dataset with a cut-off value of 5 (41) and thus discarded variables (water vapour and ventilation in the country) from our model those showed multicollinearity. In this study, the beta regression models had been carried out using the R package ‘betareg’ (42).

**Result:**

More than 1.72 million cumulative confirmed cases and 28256 cumulative deaths had been documented in Bangladesh and rCFR of COVID-19 is reported as 1.65% as of January 25th, 2022. The daily cumulative rCFR of COVID-19 reached a peak at 12.82% on 25th March 2020 and then gradually declined. However, the rCFR has not remained the same in the two periods. In the pre-peak cases period the rCFR reached 1.65% and post-peak cases period the rCFR declined to 1.64%. The COVID-19 rCFR was dominated by different divisions at different time frames. According to 25th January 2020, the top two divisions with COVID-19 rCFR are Khulna (3.14%), and Rangpur (2.43%). In a nutshell, the rCFR value of other divisions is Barisal (2.07%), Mymensingh (2.23%), Sylhet (2.23%), and Chittagong (2.24%). The lowest two divisions are Dhaka (1.22%) and Rajshahi (2.02%) according to rCFR (**Fig 1**).

**Fig 1.** The rCFR of COVID-19 in different divisions of Bangladesh

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We discovered a consistent trend between observed and predicted COVID-19 rCFR in the SES model, with R2, RMSE, and MAE values of 959.93%, 0.003, and 0.002 respectively (**Table 1 and Fig. 2**). We discovered a substantial growing trend between observed and predicted COVID-19 rCFR in the ARIMA and Prophet models, with R2, RMSE, and MAE values of 99.98% and 99.12%, 0.002 and 0.001, and 0.011 and 0.006, respectively (**Table 1**). The ARIMA model outperformed the Prophet, and SES models in terms of accuracy (with better R2, RMSE, and MAE values). The ARIMA model has a higher coefficient of determination and smaller errors than the Prophet and benchmark SES models. The COVID-19 rCFR ratio is predicted to rise significantly in the next 30 days, according to both models' forecasts. The forecasting of the regional cumulative rCFR of COVID-19 for each model is shown in **Fig. 2**.

**Table 1.** The summary of Simple Exponential Smoothing (SES), Auto-Regressive Integrated Moving Average (ARIMA), and Automatic Forecasting Time-series Model (Prophet).

|  |  |  |  |
| --- | --- | --- | --- |
| **Method & Period** | **R2** | **RMSE** | **MAE** |
| ***Simple Exponential Smoothing*** | | | |
| Overall | 99.93% | 0.003 | 0.002 |
|  |  |  |  |
| ***Auto-Regressive Integrated Moving Average*** | | | |
| Overall ARIMA (0,2,1) | 99.98% | 0.002 | 0.001 |
| ***Automatic Forecasting time-series model*** | | | |
| Overall | 99.12% | 0.011 | 0.006 |

*RMSE: Root Mean Square Error; MAE: Mean Absolute Error*

**Fig 2.** Top: Observed and predicted daily worldwide daily reported case-fatality rate (rCFR) using a simple exponential smoothing (SES) model. Middle: Observed and predicted daily worldwide daily cumulative rCFR using an auto-regressive integrated moving average (ARIMA) model. Bottom: Observed and predicted daily worldwide daily cumulative rCFR using an automatic forecasting time-series model (Prophet). Black dots = observed data; the blue line = predictive CFR; the shaded area = 95%confidence interval of predicted CFR.

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The highest variance in meteorological parameters is recorded in the pre-peak period, with a variation of 16.04, followed by rainfall with a variation of 10.29. In contrast, the lowest variation is evident in the surface pressure at 0.51 over the country under the study period. Furthermore, average temperature, dew point, and relative humidity are negatively skewed among all variables. The highest variance is likewise found in the post-peak period, with a variation of 14.51, followed by rainfall with a variation of 3.35. In contrast, the lowest variation is evident in the surface pressure at 0.55 over the country under the study period. Furthermore, average temperature, dew point, relative humidity, and surface pressure are all negatively skewed out of all the variables (**Table 2**).

**Table 2.** Descriptive statistics

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Wind Speed | Average Temperature | Dew Point | Rainfall | Relative Humidity | Surface Pressure |
| **Pre-peak period** |  |  |  |  |  |  |
| Mean | 2.18 | 27.42 | 20.20 | 6.57 | 69.09 | 100.63 |
| Median | 2.00 | 28.58 | 20.57 | 1.60 | 67.62 | 100.65 |
| Maximum | 6.41 | 32.90 | 27.30 | 51.59 | 94.12 | 101.73 |
| Minimum | 0.76 | 14.36 | 6.42 | 0.00 | 33.50 | 99.44 |
| Std. Dev. | 1.00 | 4.22 | 5.93 | 10.29 | 16.04 | 0.51 |
| Skewness | 1.09 | -1.49 | -0.49 | 2.10 | -0.12 | -0.04 |
| Kurtosis | 1.89 | 1.51 | -1.10 | 4.44 | -1.12 | -0.69 |
| **Post-peak period** |  |  |  |  |  |  |
| Mean | 2.02 | 25.59 | 20.60 | 7.09 | 77.18 | 100.76 |
| Median | 1.79 | 27.69 | 20.98 | 1.36 | 82.84 | 100.74 |
| Maximum | 6.41 | 32.90 | 27.30 | 93.08 | 95.31 | 101.87 |
| Minimum | 0.59 | 14.36 | 6.42 | 0.00 | 33.50 | 99.27 |
| Std. Dev. | 0.94 | 4.73 | 5.57 | 13.35 | 14.51 | 0.55 |
| Skewness | 1.24 | -0.76 | -0.46 | 3.21 | -1.00 | -0.13 |
| Kurtosis | 2.35 | -0.71 | -1.14 | 12.80 | -0.03 | 0.76 |

The wind speed and surface pressure are significantly negative relation to rCFR of COVID-19 over the country in the pre-peak cases period. The country’s incidence rate ratio (IRR) in the pre-peak cases period of wind speed (IRR: 0.99, 95 percent CI: 0.98-0.99) and surface pressure (IRR 0.97 [0.96-0.98]). However, wind speed remains almost the same in the post-peak cases period (IRR 0.97 [0.97-0.98]), but, surface pressure showed a significantly positive association with rCFR of COVID-19 over the country. Average temperature 1.02 [1.01-1.03]) and relative humidity 1.01 [1.01-1.02]) were significantly positively associated with COVID-19 rCFR. Furthermore, dew point 0.98 [0.97-0.99]) and rainfall 0.99 [0.98-0.99]) were significantly negatively associated with COVID-19 rCFR (**Table 3**).

**Table 3.** Factors associated with reported case-fatality rate (rCFR) of COVID-19 using ARIMAX, BSTS and beta regression model.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variables | Pre-peak Period | | | Post-peak Period | | |
|  | IRR | 95%CI | P-value | IRR | 95%CI | P-value |
| Wind Speed | 0.99 | 0.98-0.99 | <0.001 | 0.97 | 0.97-0.98 | <0.001 |
| Average Temperature | **0.99** | **0.99-1.00** | 0.0621 | 1.02 | 1.01-1.03 | <0.001 |
| Dew Point | 1.00 | 0.99-1.01 | 0.2511 | 0.98 | 0.97-0.99 | <0.001 |
| Rainfall | **1.00** | **0.99-1.00** | 0.989 | 0.99 | 0.98-0.99 | 0.031 |
| Relative Humidity | **1.00** | **0.99-1.01** | 0.687 | **1.01** | 1.01-1.02 | <0.001 |
| Surface Pressure | **0.97** | **0.96-0.98** | <0.001 | **1.03** | **1.02-1.05** | <0.001 |

**Discussion:**

This study investigates the relationship between local climatic conditions and COVID-19 rCFR at the local level in Bangladesh, considering many potential confounding variables. There is a substantial yet modest relationship between climatic factors and daily rCFR. Overall, the findings of the beta regression model and area-aggregated data imply that daily COVID-19 mortality is linked to wind speed and surface pressure before August (pre-peak cases period). Wind speed, dew point, and rainfall was a negative relationship after July (post-peak cases period).

Previously, researchers have focused their attention on the association between the incidence of particular illnesses and meteorological conditions. Temperature, humidity, rainfall, wind speed, and dew point all had an impact on morbidity, mortality, and case-fatality rates were investigated. Previous research has looked at the relationship between viral diseases and weather conditions, as well as the relationship between non-infectious diseases. For example, Murphy et al. (2004) found a considerable seasonal variation in atrial fibrillation hospitalizations and mortality (43). Research on the relationship between meteorological characteristics and infectious illnesses (such as avian influenza A/H5N1, SARS-CoV, and MERS-CoV) has been conducted in order to determine the impact of weather conditions on the transmission of previous epidemics/pandemics.

The findings of our current investigation, which show that temperature has a detrimental influence on COVID-19 mortality, are consistent with past research and confirm the conclusions of other investigations. Lin et al. (2006) found that the chance of an increased daily incidence of SARS-CoV (2003 pandemic) was 18 times higher on days with a lower air temperature than on days with a higher temperature (temperature greater than 24.6°C served as the reference standard) (44). Chan et al. (2011) investigated the SARS coronavirus's stability in various climatic conditions (45). They discovered that high temperatures combined with high humidity have a synergistic impact on SARS-CoV viability inactivation, whereas low temperatures and low humidity enhance viral survival on contaminated surfaces for long periods. As a result, the environmental conditions of tropical nations (e.g., Malaysia, Indonesia, and Thailand) are not suitable for the virus's long-term existence.

Based on data from 166 countries, Wu et al. (2020) found that temperature was adversely connected to daily new cases and fatalities of COVID-19 (46). According to Shi et al. (2020), the incidence of COVID-19 in China reduces as the temperature rises (47). According to Wang et al. (2020), increased temperature and relative humidity dramatically decreased COVID-19 transmission in 100 Chinese cities (48). However, different results were found by Chinese scientists, Luo et al., (2020); Yao et al., (2020), who claimed that higher temperature, humidity, and UV radiation had no effect on COVID-19 incidence (49,50). The majority of the results from earlier research are consistent with our findings. Few researchers used the methodologies that we utilized in this study to examine the COVID-19 pandemic. Jinjarak et al. (2020) analysed the COVID-19 death rate and introduce the relationship with meteorological variables (51). Under the policy interventions, the authors separated nations. They concluded that the pandemic period to the first mortality peak in countries with early more stringent policy actions is longer than in countries that do not have such initiatives.

In our study, we found a negative relation between rainfall and COVID-19 rCFR. However, several studies established a positive association between rainfall and the transmission of influenza (52–55). The data suggest that influenza virus contact or short-range transmission was prevalent in tropical and subtropical regions. Droplets or aerosols formed during cough, snoring, speaking, singing, or breathing can transfer viruses into the air (53). Airborne transmission by aerosols, however, is very virulent and dominating (56). Aerosol virus survival and infectivity are affected by ambient stress temperature (57) The SARS-CoV-2 can remain alive for 3 hours in spray form (< 5 μm) but it shows higher feasibility on plastic and stainless steel, copper, carton, and glass up to 72 hours in droplet form (> 5 μm) (58). The result indicated that the viability of SARS-CoV-2 is reduced substantially due to the lower evaporation rate of the saliva contaminated droplets in high temperature. Similar to our findings, rainfall had reported as a significant negative impact on COVID-19 transmission in India and Pakistan (59). The possible reason for the negative correlation is that rainfall rate contributes to the accumulation and washout process of aerosols and microbial bio-aerosols (Bacteria, viruses, fungi) implying that viruses could not have longer residence times in the atmosphere and, consequently will not able to disperse further. Another hypothetical justification might be that people often stay home on rainy days, which also could reduce the transmission.

We also had positive association of COVID-19 mortality with relative humidity and surface pressure. Some studies (46,48,60,61) found similar results that there exists an association of COVID-19 with relative humidity and pressure (59). However, Shi et al. (2020) obtained opposite findings that there was no significant correlation between COVID-19 incidence and absolute humidity (62).

The rCFR of Bangladesh steadily increasing over time, where it is sharply declining in world data. Additional factors including meteorological factors are sure to be associated. However, the growing of rCFR could be attributable to several reasons, including: the increased number of asymptomatic and mild cases detected by extensive testing, the introduction of dexamethasone and additional medical treatment improvements for seriously ill patients, the acquisition of experiences by health professionals, increased public awareness, protection against infection, potential remedial effects.

**Limitation:**

The data available to the public may contain underreported numerator values (COVID-19 deaths) or denominator values (COVID-19 cases), thus here we used reported CFR. The original scenario of the country may differ for this underreported criteria.Day of testing, air pollution, number of cases imported, population immunity, population migrations, human mobility, and social behavior, as well as economic and cultural conditions, may confuse COVID-19 mortality, as the study did not take all of these factors into account and only looked at meteorological variables. With such limited data, a full scenario may not be present in this study. In addition, one of the main limitations of our study is that our observations are based on data about outside weather. However, SARS-CoV-2 transmission can be affected quite differently by indoor conditions. These criteria should be included while evaluating the combined weather variables and the COVID-19 in Bangladesh in future studies.

**Conclusion:**

The daily COVID-19 confirmed cases rose until the last of July and then began to fall consistently. The growing number of tests and a lowering rate of rCFR for COVID-19 have been proven to be adverse. In this nation, COVID-19 rCFR was substantially linked to climatic parameters, such as rainfall, relative humidity, temperature, wind speed surface pressure, and dew point. While the wind speed and surface pressure are favorably linked to the rCFR the others factors are adversely linked in the pre-peak cases period. All the meteorological factors in this study are favorably linked in the post-peak cases period. More reasons for reducing rCFR need to be examined in greater detail but can be explained by increasing infection among younger patients, by improving healthcare management, or by medicines that can reduce mortality and hospital stays for patients with COVID-19 and by preventing people with co-morbidities. This study reflects an increasing agreement in many national datasets and experiences with the risk variables related to CFR. Further investigations are required to understand the COVID-19 rCFR pattern and the pathogenicity of the virus at the host level.

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