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

**Mohammad Nayeem Hasan**

**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 investigate 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, 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 all over the world (1). In late December 2019, a flu-like symptom detected in Wuhan, China (1) which was caused by the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and spread it all over the world, because the transmission rate is very high (2). On March 11, 2020, The World Health Organization (WHO), announced the disease known as COVID-19 (3). Coronavirus is a positive (+) sense RNA virus (4). In a previous study, we got that SARS-CoV survived at low ambient temperature and relative humidity on surfaces over 5 days but quickly vanished at 40 °C and higher humidity (5). Early studies had shown that environmental factors significantly affecting on the growth and activity of respiratory viral disease (6)(7)(8)(9). There is a significant relationship between climate conditions especially the temperature and the incidence rate of MERS-CoV was reported in Saudi Arabia (10).

On March 8, 2020, the first corona case was identified in Bangladesh. On March 18, the first corona patient death due to coronavirus (1). The case fatality rate (CFR) of COVID-19 is defined as the proportion of death due to the specific disease and it varies greatly in different countries. There is no study is reported so far on whether and how the meteorologicalconditions can affect the COVID-19 mortality (11). 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. Here we study to find out the relation between the meteorological factors and the CFR of coronavirus in Bangladesh. As no other study before about the relationship between meteorological variables and spreading of COVID-19 CFR. The findings of the present study will add more knowledge into the evidence on the climatic implications of COVID-19 from a megacity of developing country context**.**

**Methods**

Here, we used three time series (i.e. Simple Exponential Smoothing (SES), Auto-Regressive Integrated Moving Average (ARIMA), and Automatic forecasting time-series model (Prophet)). Finally, we developed beta-regression model of explanatory variables to identify whether the weather variables have any relationship between the country’s CFR of COVID-19. 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. All analyses were doing by using the statistical software R.

**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 (12).

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

We calculated total CFR COVID-19 case as the number of deaths per 100 COVID-19 confirmed cases. There is a fraction between total case and death case, we considered the term as reported CFR or simply as rCFR (13).

**Meteorological factors**

We also included different types of weather data parameters based on a daily scale such as Rainfall (mm), Relative humidity (%), Temperatures (°C), Surface pressure (kPa), Dew point (°C), and velocity of wind (m/s) at 10 m height (Maximum Wind Speed) were collected from NASA Prediction of Worldwide Energy Resources website (NASA, 2020).

**Time series model to predict the trend**

We used three time-series models, including SES, ARIMA, and Prophet to identify the global trend of rCFR for COVID-19. We selected all these time series models because the outcome variable (cumulative rCFR) is dependent on the previous records and all these models can take this into account. Using the time series models with the reported COVID-19 data, we forecasted trends for the prospective 30 days and visualizing in the figure. SES was used as a benchmark to compare the performance of other models.

**Simple Exponential Smoothing (SES):**

Simple exponential smoothing is one of the most widely used methods for forecasting procedures (14)(15). SES is a short-term used for forecasting model that define data fluctuates around a relatively stable mean (16). The SES model for this study had been carried out using R package ‘fpp2’.(17)

**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 interpret a perfect model by using the structure of the data itself.(18) This model shows that the time series values are linearly related and defines the extract prediction by deleting high-frequency noise from the data.(19) The benefit of ARIMA models is the ability to dynamically oriented analysis which using recent data and make future prediction.(20). The ARIMA model for this study had been carried out using R package ‘forecast’(21).

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

We also used a construe automatic forecasting time-series model called ‘Prophet’ using R package “prophet” to predict the 10-days fatality rate and distinguished with rCFR.(24) The Prophet model doesn’t want the temporal dependence of the irregular observations are allowed in the data set and the model fits very quickly(25).The benefit is, it collect missing data also and manages outliers well generally.(26) (27) .

**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 (34). 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).

**Outcome and predictor variables**

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

**Statistical analysis**

Here, we analysed that the COVID-19 cases has changed over time (**Fig. 3**). We also find out that the COVID-19 cases reached highest peak at July 28, 2021 (cases = 16230) and then the trend started to decline. We segregated the whole data with this peak and rename pre-peak cases period from 25th January, 2021 to 28th July, 2021, and post-peak cases period from 29th July, 2021 to 25th January, 2022, as the cases are lower in this period. Not only used time-series model to identify the reason behind the rCFR of COVID-19 in that period. We tried to find out the relationship between the rCFR of COVID-19 and explanatory variables vary over time or they remain the same in four period through regression model. Here we applied the beta regression model separately for each dataset to investigate the association between possible explanatory variables and tried to get which variables affecting most in these periods.

**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 (35,36). The benefits of beta-regression model is explanatory variables for reporting that the incidence rate ratios (IRRs) after adjusting them for environmental factors like temperature, precipitation, relative humidity, wind speed and dew in Bangladesh country (37). In this study the beta regression models had been carried out using R package ‘betareg’ (31).

**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% in 25th March, 2020 and then gradually declined. However, the rCFR was not remain same in two periods. In 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 are 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 value). 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 regional cumulative rCFR of COVID-19 for each model are shown in **Fig. 3.**

**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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Among the meteorological factors, in pre-peak period, the highest variation is observed in the relative humidity at 16.04, followed by rainfall at 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. Additionally, out of all the variables, average temperature, dew, relative humidity are negatively skewed. In post-peak period, the highest variation is observed also in the relative humidity at 14.51, followed by rainfall at 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. Additionally, out of all the variables, average temperature, dew, relative humidity and surface pressure are negatively skewed (**Table 2**).

**Table 2.** Descriptive statistics

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Wind Speed | Average Temperature | Dew | 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 with 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 remain almost same on post-peak cases period (IRR 0.97 [0.97-0.98]), but, surface pressure showed 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 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 | 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:**

Researchers have previously focused their attention on the association between the incidence of certain illnesses and meteorological conditions. The effects of temperature, humidity, rainfall, wind speed, and dew on morbidity, mortality, and case fatality rates were investigated. Previous research has looked at the links between viral diseases and meteorological conditions as well as non-infectious illnesses and weather conditions. Murphy et al. (2004), for example, discovered significant seasonal fluctuation in atrial fibrillation hospitalizations and mortality (38). In terms of the impact of weather conditions on the transmission of prior epidemics/pandemics, research on the association between meteorological parameters and infectious illnesses (such as avian influenza A/H5N1, SARS-CoV, and MERS-CoV) have been carried out.

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 the month of August (pre-peak cases period). Wind speed, dew, and rainfall was a negative relationship after the month of July (post-peak cases period).

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. According to Lin et al. (2006), the probability of increased daily incidence of SARS-CoV (2003 pandemic) was 18 times greater 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). (39) Chan et al. looked studied the stability of the SARS coronavirus in different meteorological situations (2011). (40) 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 longer periods of time. As a result, the environmental conditions of tropical nations (e.g., Malaysia, Indonesia, and Thailand) are not suitable to the virus's long-term existence.

In our study, we found negative relation of rainfall and COVID-19 rCFR. However, several studies established the positive association between rainfall and transmission of influenza (Gomez Barroso et al. 2017; Lopez et al. 2014; Mahamat et al. 2013). (49)(50)(51) The data suggests 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 (da Silva et al. 2020; Jones and Brosseau 2015). (52)(53). Airborne transmission by aerosols, however, is very virulent and dominating (Zhang et al. 2020).(55) Aerosol viruse survival and infectivity are affected by ambient stress temperature (Jayaweera et al. 2020). (56) 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) (Van Doremalen et al. 2020). (57) 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 (sabbir). 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 other studies (S. Gupta et al., 2020; Li et al., 2020; Ma et al., 2020; J. Wang et al., 2020; Y. Wu et al., 2020) found similar results that there exists an association of COVID-19 with relative humidity and pressure. (Sabbir). However, Shi et al. (2020) obtained opposite findings that there was no significant correlation between COVID-19 incidence and absolute humidity.

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. (59)(60)(61)

**Limitation:**

Data from COVID-19, reports from the World Health Organization and other sources, have been gathered publically available. The data available to the public may contain underreported numerator values (COVID-19 deaths) or denominator values (COVID-19 cases). Day testing, air pollution, number of cases imported, immunity to the populations, population migrations, human mobility, social behaviour, economic and cultural conditions might confuse COVID-19's transmission, since the study has not taken account of these elements. 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. The cumulative rCFR was generated that tends to sous-estimate the risk of mortality since the future fatalities are not included in the dataset. Both are universal rCFR restrictions estimated in most investigations employing COVID-19 regional data. One of the main assumptions is that towards the latter stage of the pandemic younger people get infected with COVID-19. We were not, however, able to assess if the population's median age changed over time and whether the rCFR decreased.

**Conclusion:**

The cumulative rate of rCFR from COVID-19 (regional Bangladesh part) rose until the 15th weeks of epidemiology (7-14 April 2020) 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 precipitation, relative humidity, temperature, wind speed and dew. While the precipitation and dew factors are favourably linked to the rCFR and the relative humidity, wind and temperature are adversely linked. 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 which 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 with 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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**Tables and figures**