**Mathematical modeling of the correlation between reported case fatality rate (rCFR) of COVID-19 and weather variables in Bangladesh**

**Or**

**The time series modeling of reported case fatality rate (rCFR) of COVID-19 and associated weather variables in Bangladesh**

**Or**

**Comparing the performance of time series models with or without meteorological factors in predicting reported case fatality rate (rCFR) of COVID-19 in Bangladesh**

**Abstract**

Novel coronavirus disease (COVID-19) is an infectious disease that affecting the respiratory system of human beings and is caused by severe 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 on the mathematical modeling of the correlation and prediction of the rCFR of COVID-19 in Bangladesh with the data from the WHO’s daily situation reports dated May 1, 2020 to August 31, 2021. For that, Simple Exponential Smoothing (SES), Auto-Regressive Integrated Moving Average (ARIMA), Autoregressive Integrated Moving Average with Explanatory Variables (ARIMAX), Bayesian Structural Time Series (BSTS), Automatic forecasting time-series model (Prophet) was implied to identify the trend of rCFR for COVID-19 in Bangladesh. According to the analysis performed in this study, the temperature was found to have a negative relationship with the rCFR of the disease. Based on the data from most of Bangladesh, it was found that increased humidity raises the transmission rate of COVID in local people. However, precipitation rate was found positively linked to the COVID rCFR that increases the case fatality rate. Finally, wind speed was surprisingly found to suppress the rCFR inspire of higher transmission. Such type of critical analysis with the help of optimum volume of data can help to accurately track the pattern of pandemics. Such reports and predictions might help to plan and execute preventive measures for local people in respect of certain locality.

**1. Introduction**

The novel coronavirus disease (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is a pandemic all over the world (1). In late December 2019, a flu-like symptom in humans was detected in Wuhan, China which was caused by the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and spread all over the world due to its high transmission rate (2). On March 11, 2020, The World Health Organization (WHO) officially named this disease as COVID-19 (3). On June 21, 2021, the reported confirmed cases was 178.74 million and deaths was 3.87 million globally. In November of 2002, the emergence of severe acute respiratory syndrome (SARS) coronavirus outbreak was detected in China and spreading out itself as the warmer season started from around July 2003 (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 also shown that environmental factors significantly affect the growth and activity of respiratory viral disease (4)(6)(7)(8). There is a significant relationship between climate conditions and the incidence rate of MERS-CoV as reported in Saudi Arabia (9).

Coronavirus is a positive (+) sense RNA virus (10). Recent studies found that temperature may significantly affect the transmission of COVID-19 infection (11). According to a study, there is a long resistance period for SARS-CoV-2 at 4° C, but is reduced to 5 minutes when the temperature increased to 70° C (12). Many studies also found the influence of temperature on the transmission of COVID-19 in different geographical regions, but the relations are still unclear (3)(13)(14)(15)(16). Recent research with 122 cities in China found that each 1° C rise in average temperature (below 3°C) was related to an increase of 4.861 percent in new reported COVID-19 cases per day. A global study by Wu et al. (2020) reported a negative relation between meteorological parameters and daily reported new COVID-19 cases and deaths (11). It is reasonable to say that the climate conditions may also significantly impact COVID-19 transmission in Bangladesh.

[3. The organization should be like this -- intro section should cover a complete literature review with regards to the use of time series techniques and the use of beta regression and its applications.  
  
You must convince the reader and the editor. Thus, everything -- rationale, knowledge gap, literature review, techniques, and their justifications must be in the introduction section.]

On March 8, 2020, the first corona case was identified in Bangladesh. On March 18, the first corona patient death due to coronavirus, and on April 30, 7667 confirmed cases and 168 deaths were reported in Bangladesh (1). Bangladesh is a member country of the World Health Organization located in the eastern side of the South Asia region (17). The country’s climate has diversity at different times. That’s why it is characterized by a humid subtropical climate with a distinct seasonal variation in warm temperature, rainfall, and humidity. The monthly average temperature of the country ranges from 18.85 to 28.75 °C (18). Around 75% of rainfall occurs in the monsoon season (May-September) with an annual average of 2428 mm (18).

The CFR of COVID-19 is defined as the proportion of death due to the specific disease, and it varies greatly in different countries. The case fatality rate (CFR) of COVID-19, which is defined as the proportion of death because of a specific disease among those diagnosed with it, varies greatly in different countries. For example, the CFR of COVID-19 varies from 28.9% in Yemen to 1% in Singapore and Qatar3,4 as of December 31, 2020. There is no study reported in Bangladesh so far on whether and how the climatic conditions can affect the COVID-19 mortality (19). As COVID-19 continuously spread throughout Bangladesh, studying the relationship between the CFR of COVID-19 and the climatic variables, could bring valuable recommendations in the upcoming months for policy-makers and the public. We analyzed nine alternative time series methods were created and compared the data between April 8, 2020, to December 12, 2020, and find out the affecting rate depending on the weather variables in Bangladesh. When it comes to forecasting current cases, the findings show that there is no one-size-fits-all strategy. The present study's findings will add more evidence on the climatic implications of COVID-19 from a megacity of a developing country context**.**

**Methods**

Here, we used five-time series (i.e. Simple Exponential Smoothing (SES), Auto-Regressive Integrated Moving Average (ARIMA), Autoregressive Integrated Moving Average with Explanatory Variables (ARIMAX), Holt–Winters Additive Model (HWAAS), TBAT, DeepAR, N-Beats, Bayesian Structural Time Series (BSTS), Automatic forecasting time-series model (Prophet)) and two trending analysis (i.e. Mann-Kendall (M-K) trend and Sen’s slope) model to identify the trend of CFR for COVID-19 in Bangladesh. We used the Mann-Kendall (M-K) trend analysis to identify the existence of any trend and the direction of the trend (increasing or decreasing). Finally, we developed a beta-regression model of explanatory variables to identify whether the weather variables have any relationship between the country’s rCFR of COVID-19. All these different analysis approaches helped us to make a specific conclusion on the global trend and climatic factors affecting the CFR of COVID-19. All analyses were done using the statistical software R version 3.5.2.2.

**COVID-19 Data**

The fundamental COVID-19 related data, including related data, including precipitation, reality humanity, temperature, due, and wind speed from the WHO daily COVID-19 situation reports in Bangladesh was collected from January 01 to December 31, 2020 for this analysis (20).

**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 (21).

**Time series model to predict the trend**

Here, we used five time-series model to observe the forecasting of rCFR in Bangladesh. We selected all these time series models as the outcome variable (cumulative rCFR) are subordinate to the past records. SES was utilized as a benchmark to compare the execution of the other models.

**Simple Exponential Smoothing (SES):**

Simple exponential smoothing is one of the most widely used methods for forecasting procedures (22)(23). SES is a short-term used for forecasting model that define data fluctuates around a relatively stable mean (24). The simple exponential smoothing equation is

*Ft*+1 = *α at* + (1 *−α*) *Ft*

here it is the actual, known series value at the time t; Ft is the forecast value of the variable Y at the time t; Ft+1 is the forecast value at the time t + 1; α is the smoothing variable(23). The SES model for this study had been carried out using the R package 'fpp2'.(25)

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

We used an ARIMA model to forecast the trend of global weekly cumulative rCFR. The ARIMA model is a statistical, data-oriented analysis that interpret a perfect model by using the structure of the data itself.(26) This model shows that the time series values are linearly related and defines the extract prediction by deleting high-frequency noise from the data.(27)

The benefit of ARIMA models is the ability to dynamically oriented analysis which using recent data and make future prediction.(28). For this studies R package ‘forecast’ had been used for eliminating or the ARIMA model (29).

**Autoregressive Integrated Moving Average with Explanatory Variables (****ARIMAX)**

ARIMA models accept a direct relationship between the time-series values and attempt to exploit these straight conditions in perceptions, in arrange to extricate nearby designs, whereas removing high-frequency commotion. But in this model, the information explanatory variable (X) is added with the ARIMA model for the accurate interpretation which is called ARIMAX (p, d, q)(30)(31).

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

Prophet is a Facebook-developed time series forecasting model. It employs a decomposable time-series model with three key elements: trend, seasonality, and holidays. Prophet uses two models to anticipate trends: a saturating growth model and a piece-wise linear model(32,33).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 rCFR.(34) The Prophet model doesn’t want the temporal dependence of the irregular observations that are allowed in the data set and the model fits very quickly(35).The benefit is, it collect missing data also and manages outliers well generally (36). There are three main factors of the model, i.e., trend, seasonality, holidays. It can be represented as,

*Y (t) = g(t) + s(t) + h(t) + ∈t*

where the model parameters g(t), s(t), h(t), ∈t is piecewise linear curve for modelling non-periodic changes in time series, periodic changes, the effects of holidays with irregular schedules considered in the model by some parameters, respectively. Any unanticipated changes in the analysis that the model does not allow for are represented by this error term. (36)(37) .

**Holt–Winters Additive Model (HWAAS): Exponential Smoothing with Additive Trend and Additive Seasonality:**

The Holt–Winters additive model is a time series forecasting approach for univariate data based on Holt's exponential smoothing. It can handle trend and seasonal variation, and it can be used instead of the popular Box–Jenkins ARIMA family of techniques. The choice of beginning values and their sensitivity to unexpected occurrences or outliers are practical challenges in applying the approach(40–42).

**TBAT:**

The described trigonometric formulation of complex seasonal time series (Trigonometric seasonal formulation, Box–Cox transformation, ARMA errors, and trend component) is the foundation of the TBAT modeling framework. This decomposition has been demonstrated to help identify and extract seasonal components that would otherwise go undetected in a time series plot. The ability to handle the nonlinear characteristics commonly seen in real-world time series data, as well as a wide parameter space with the prospect of improved predictions, are two key advantages(38–42).

**DeepAR:**

DeepAR is a probabilistic forecasting approach based on autoregressive recurrent neural networks. Deeper networks, as described in [59], are typically preferred over shallow and broad neural networks because they allow for more abstract data representations through more complicated transformations. The technique can handle a wide range of likelihood functions, enabling the user to select the one that best suits the data's statistical characteristics(43,44).

**N-Beats:**

N-Beats is a time series forecasting model that uses a deep neural architecture that includes forward and backward residual connections, as well as a deep stack of fully connected layers. The model works in a similar fashion to classic decomposition approaches like the seasonality-trend-level approach. The model is simple to train and may be applied to a wide range of target domains with few, if any, modifications(45,46).

**Mann-Kendall (M-K) trend:**

We applied daily cumulative rCFR data and performed the M-K trend test to identify the trend of COVID-19 rCFR (47). The M-K method is a non-parametric test that provides an indicator of monotonous trend and also indicate that there is a positive or negative trend (47). It can calculate ranks and sequences of time series by dealing with non-normally distributed data, censored data, and time series with missing values rather than the original values (48).

In addition, the Sen’s slope test was exerted to determine the changes in COVID-19 rCFR in both periods.(49) M-K and Sen’s slope trend analysis are using by R package ‘trend’.(50)

**Bayesian Structural Time Series (BSTS):**

Bayesian structural time series (BSTS) model is a statistical technique to follow time series data, like- forecasting, nowcasting, inferring causal impact and other applications (51). It is used for effectively in sustainable technical analysis.(52) The benefit of the Bayesian Structural Time Series (BSTS)model is to understand the causal structure of uncertainties in the data, but the demerit is- it is difficult to illustrate the time factors in the model. For this study, the R package ‘forecast' was used to exclude or the BSTS model was used. (52).

**Empirical evaluation**

The time series models are experimentally evaluated by comparing their outcomes to benchmarks in foreseeing the rCFR. This benchmark allowed us to survey the execution picks up made by their counterparts (53). The SES also allows the most appropriate non-seasonal model for each series, allowing for any kind of error or trend component. Here, we analysed and compared the execution of the considered time arrangement models with a few of the commonly utilized measures to assess the expectation noteworthiness counting coefficient of assurance (R2), root cruel square blunder (RMSE), and cruel outright mistake (MAE).

**Outcome and predictor variables**

We used rCFR as the outcome variable, we also collected and used climetic predictors included different types of climate data parameters based on a daily scale such as Precipitation, Relative humanity, temperature, dew, and wind speed from NASA Prediction of Worldwide Energy Resources website (NASA, 2020).

**Statistical analysis**

Here, we analysed that the rCFR of COVID-19 has changed over time (**Fig. 3**). [NEED TO MENTION THIS IN THE INTRODUCTION SECTION, SOMEHOW TO GIVE AN IMPRESSION OF WHAT WE ARE ACTUALLY GOING TO DO. THIS IS MY THOUGHTS NOW WHICH MAY CHANGE ONCE THE PAPER IS UPDATED]. We also find out that the rCFR reached a lowest peak at 14 April 2021 (CFR = 1.42%) and then the trend started to increase. Not only used time-series model to identify the reason behind the increasing and decreasing trend of COVID-19 rCFR. We tried to find out the relationship between the rCFR of COVID-19 and climatic factors through regression model. Here we applied the beta regression model separately for each dataset to investigate the association between climatic variables and tried to get which variables affecting most in this 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 (54,55). The benefits of beta-regression model is explanatory variables for reporting that the incidence rate ratios (IRRs) after adjusting them for climatic factors like temperature, precipitation, relative humidity, wind speed and dew in Bangladesh country (56). In this study the beta regression models had been carried out using the R package 'betareg' (50).

**Result:**

More than 178.74 million cumulative confirmed cases and 3.87 million cumulative deaths had been documented globally and the global rCFR of COVID-19 is reported as 2.17% as of June 21st, 2021. The daily global cumulative rCFR of COVID-19 had reached a peak at 7.36% on 28th April, 2020. In Bangladesh, the rCFR value is positioned around 1.59%. However, the daily cumulative rCFR for Bangladesh reached a peak at 10.37% by April 7th, 2020 including the top two divisions with COVID-19 rCFR- Mymensingh (2.50%), and Barisal (2.50%) (**Fig. 2**). The peak of the COVID-19 rCFR was dominated by different divisions at different time frames. In a nutshell the rCFR value in other divisions are- Chittagong (2.2%), Dhaka (1.2%), Khulna (2.2%), Rajshahi (1.8%), Rangpur (2.3%), and Sylhet (1.9%).

We discovered a consistent trend between observed and predicted COVID-19 rCFR in the SES model, with R2, RMSE, and MAE values of 95.29%, 0.02, and 0.01 respectively (Table 1) (Fig. 3). We also found a substantial growing trend between observed and predicted COVID-19 rCFR in the ARIMA and Prophet models, with R2, RMSE, and MAE values of 99.20% and 97.46%, 0.91 and 0.02, and 0.44 and 0.01, respectively (Table 1). We detected a modest rising trend between observed and predicted COVID-19 regional rCFR in the ARIMAX and BSTS models, with R2, RMSE, and MAE values of 98.13 percent and 84.78 percent, 0.16 and 0.15, and 0.02 and 0.02, respectively (Table 1). The ARIMA model outperformed the Prophet, SES, BSTS, and ARIMAX 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 10 days, according to both models' forecasts. The forecasting of regional cumulative rCFR of COVID-19 for each model are shown in **Fig. 3.**

In M-K trend analysis, we identified an increasing trend of cumulative rCFR (p < 0.001 and tau = 0.54). Using Sen’s slope test, we found that over the 15-weeks, the slope was 0.008 (95% CI: 0.007 to 0.009). (**Table 1**).

The proportion of precipitation over the country (IRR: 1.01, 95 percent CI: 1.01-1.02) and dew (IRR 1.03 [1.02-1.05]) were both substantially positively linked with COVID-19 rCFR in the beta regression model (Table 2). In the investigated periods, relative humidity, temperature max, temperature min, and wind speed were all somewhat adversely correlated with COVID-19 rCFR (0.99 [0.98-0.99]). (Table 2).

**Discussion:**

Researchers have previously focused their attention on the association between the incidence of certain illnesses and meteorological conditions. The effects of air temperature, humidity, precipitation, 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 (57). 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 investigated 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 incidence is linked to precipitation and dew. Relative humidity, temperature (max), temperature (min), and wind speed all have a negative relationship. However, for all of the sites studied, the beta regression model revealed a substantial negative relationship between COVID-19 and temperature (Dhaka, Chittagong, Sylhet, Rangpur, Rajshahi, Khulna, Barisal and Mymensing). The lack of association might be ascribed to epidemic advancement, longer time series data, and COVID-19 counts' nonlinear character. A larger number of rCFR were observed in these places, which had temperatures between 15-20 °C throughout the observation period. For the most part of Bangladesh, there was a negative correlation between COVID-19 rCFR and humidity. These locations with high humidity (80–90%) reported a higher number of confirmed cases and a lower number of deaths. For the whole country, precipitation was positively linked with COVID-19 rCFR. These places with more than 30 mm of daily precipitation reported a greater incidence of fatality cases. In this location, wind speed was shown to be adversely related to COVID-19 rCFR. With a daily wind speed of 2–6 km/h, a lower number of verified mortality cases were recorded compared to a larger number of confirmed cases.

The findings of our current investigation, which showed that temperature has a detrimental influence on COVID-19 transmission, are consistent with past research and confirm the conclusions of other investigations. COVID-19 and meteorological conditions were the subject of the initial experiments. 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) (58). Chan et al. studied the stability of the SARS coronavirus in different meteorological situations (2011). (59) 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. Biswas et al. (2014) investigated the role of meteorological parameters (air temperature, relative humidity, cloud cover, rainfall, and wind speed) in highly pathogenic avian influenza A/H5N1 outbreaks in Bangladesh between 2007 and 2011. (60)

MERS-CoV (epidemic in 2012) was characterized by a quick decline in viral viability at higher temperatures and greater humidity, according to Doremalen and Munster (2013), implying that MERS-CoV and SARS-CoV have comparable stability characteristics. (61) 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 (11). In the range of less than 25.8°C, Prata et al. (2020) discovered that the connection between the yearly average of temperature compensation and COVID-19 verified cases was almost linear, which became flat above 25.8°C (19). According to Shi et al. (2020), the incidence of COVID-19 in China reduces as the temperature rises (62). Increased temperature and relative humidity dramatically decreased COVID-19 transmission in 100 Chinese cities, according to Wang et al. (2020).(63) 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.(64)(65) The majority of the results from earlier research are consistent with our findings. This research shows that greater air temperatures are correlated with lower COVID-19 CFR values and a shorter pandemic time to the CFR summit. Researchers in few studies utilized the methodologies utilized in this study to examine the COVID-19 pandemic. Jinjarak et al. analysed the COVID-19 pandemic for the first peak of the death rate (2020) (66). In accordance with 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.

Several studies established the positive association between precipitation and transmission of influenza (Gomez Barroso et al. 2017; Lopez et al. 2014; Mahamat et al. 2013). (67)(68)(69) 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). (70)(71) Genetic similarities with SARS-CoV-2 are considered to be possible with respiratory outlets. SARS-CoV-2 as well nevertheless can be spread via droplets, aerosol, and fomites to humans in multiple ways (Wei et al. 2020).(72) Airborne transmission by aerosols, however, is very virulent and dominating (Zhang et al. 2020).(73) Aerosol virus survival and infectivity are affected by ambient stress temperature (Jayaweera et al. 2020). (74) 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). (75) 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.

At the community level, local policies such as the social distance and the amount of vulnerable people might influence the transmission of COVID-19. A beneficial influence of precipitation is discovered on the incidence of COVID-19 daily based on findings collected on the soils. The theory that individuals like when it's raining is attributable to this observation. Local precipitation is also correlated with COVID-19 transmission at the local level (Chattogram, Rajshahi, Bogura). This favorable impact of precipitation is in accordance with and supports the results (Wei et al. 2020; Méndez-Arriaga 2020) in the COVID-19 local-level transmission.(72)(76)

The rCFR of Bangladesh is being increasing steadily 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. (77)(78)(79)

**Limitation:**

Data from COVID-19, reports from the World Health Organization and other sources, have been gathered publicly available. The data available to the public may contain underreported numerator values (COVID-19 deaths) or denominator values (COVID-19 cases). Day of 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 outdoor conditions. 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 week 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 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 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**

**Table 1.** The summary of Simple Exponential Smoothing (SES), Auto-Regressive Integrated Moving Average (ARIMA), Autoregressive Integrated Moving Average with Explanatory Variables (ARIMAX), Bayesian Structural Time Series (BSTS), Automatic forecasting time-series model (Prophet), Mann-Kendall (M-K) trend and Sen’s slope analysis.

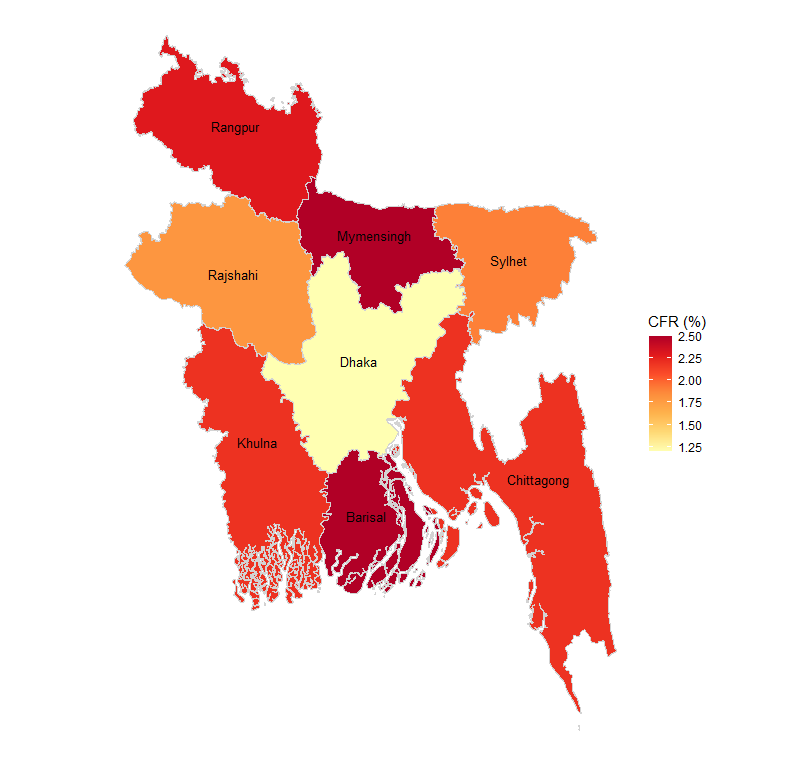
|  |  |  |  |
| --- | --- | --- | --- |
| **Method & Period** | **R2** | **RMSE** | **MAE** |
| ***Simple Exponential Smoothing*** | | | |
| Overall | 95.29% | 0.02 | 0.01 |
|  |  |  |  |
| ***Auto-Regressive Integrated Moving Average*** | | | |
| Overall ARIMA (5,2,1) | 99.20% | 0.91 | 0.44 |
| ***Autoregressive Integrated Moving Average with Explanatory Variables*** | | |  |
| Overall ARIMAX (1,0,1) | 98.13% | 0.16 | 0.02 |
|  |  |  |  |
| ***Bayesian Structural Time Series*** |  |  |  |
|  |  |  |  |
| Overall | 84.78% | 0.15 | 0.02 |
| ***Automatic Forecasting time-series model*** | | | |
| Overall | 97.46% | 0.02 | 0.01 |
| ***Mann-Kendell trend analysis*** | **tau** | **P** | |
|  | 0.54 | <0.001 | |
| ***Sen’s slop test*** | **Sen’s Slope** | **95% CI** | |
|  | 0.008 | 0.007 to 0.009 | |

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

**Table 2.** Factors associated with reported case-fatality rate (rCFR) of COVID-19 using ARIMAX, BSTS and beta regression model.

|  |  |  |  |
| --- | --- | --- | --- |
| Variables | Beta Regression model | | |
|  | IRR | 95%CI | P-value |
| Precipitation | 1.01 | 1.01-1.02 | <0.001 |
| Relative Humidity | **0.99** | **0.98-0.99** | <0.001 |
| Temperature Maximum | 0.99 | 0.98-1.01 | 0.069 |
| Temperature Minimum | **0.98** | **0.97-0.99** | <0.001 |
| Dew | **1.03** | **1.02-1.05** | **<0.001** |
| Wind Speed | **0.99** | **0.98-0.99** | **<0.001** |

**Figure 2.** The rCFR of COVID-19 in different divisions of Bangladesh

**

**Figure 3.**

|  |
| --- |
| E:\Study\ResearchProject\Aminul\Weather\Prophet.tiff |
| Prophet |
| E:\Study\ResearchProject\Aminul\Weather\ARIMA.tiff |
| ARIMA |
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| ARIMAX |
| E:\Study\ResearchProject\Aminul\Weather\BSTS.tiff |
| BSTS |
| E:\Study\ResearchProject\Aminul\Weather\SES.tiff |
| SES |