**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). Then, it quickly spread throughout the country and infecting many other countries severely (2). On March 11, 2020, The World Health Organization (WHO), announced the disease known as COVID-19 (3). The transmission rate is very high, then the COVID-19 has spread globally in more than 200 countries. On February 25, 2021, the WHO reported 111,999,954 confirmed cases and 2,486,679 deaths globally (World Health Organization 2021).

Early studies had shown that environmental factors significantly affecting on the growth and activity of respiratory viral disease (4)(5)(6)(7). In China, the November of 2002, the emergence of severe acute respiratory syndrome (SARS) coronavirus outbreak was detected 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 (8). There is a significant relationship between climate conditions especially the temperature and the incidence rate of MERS-CoV was reported in Saudi Arabia (9).

Coronavirus is a positive (+) sense RNA virus (Patrick, 22/9/2006). It contains four fundamental basic proteins, which are the spike (S), layer (M), envelope (E), and nucleocapsid (N) proteins, all of which are encoded inside the 3′ conclusion of (10)(11). The M protein is the most abundant auxiliary protein within the virion (11).

The recent studies said that the temperature can be affected on the transmission of COVID-19 infection (12). The SARS-CoV-2 reported that there is a long resistance period at 4 ° C but it reduced to 5 minutes when the temperature increased to 70 ° C (13). Many studies found that the influence of the temperature factor on the transmission of COVID-19 in different geographical regions, but the relations are still unclear (3)(14)(15)(16)(17). Recent research found that 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 said that by Wu et al. (2020)(12) a negative relation between meteorological parameters and daily reported new COVID-19 cases and deaths. This is reasonable to say that the climate conditions may also have a significant impact on COVID-19 transmission in Bangladesh.

Bangladesh is a member country of the World Health Organization located and it stands on the eastern side of the South Asia region (18), the country’s climate is different 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 (19). Around 75% of rainfall occurs in the monsoon season (May-September) with an annual average of 2428 mm (19). 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). As COVID-19 continuously spread rapidly throughout Bangladesh, studying the relationship between climatic variables especially temperature and COVID-19 spread could bring useful recommendations in the upcoming months for decision-makers and the public. However, there is no study is reported so far on whether and how the temperature conditions can affect the COVID-19 spreading (20). Here we study to find out the relation between the temperature and the spreading of coronavirus in Bangladesh. Because the temperature is one of the vital elements in climates and no study before about the relationship between temperature and spreading of coronavirus. We analyzed the data between April 8, 2020, to December 12, 2020, and find out the affecting rate depending on the temperature in Bangladesh. 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 five time series and two trending analysis (i.e 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. We used the Mann-Kendall (M-K) trend analysis to identify existence of any trend and the direction of the trend (increasing or decreasing) by Sen’s slope analysis. Finally, we developed beta-regression model of explanatory variables to identify whether the variables have any relationship between the country’s case-fatality rates (CFR) of COVID-19. All these different analysis approaches helped us to make a specific conclusion on the global trend of COVID-19 CFR and factors affecting the CFR of COVID-19 in different phase of pandemic. All analyses were doing by using the statistical software R.

**COVID-19 Data**

The fundamental COVID-19 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 (21). The ARIMA, SES, ARIMAX, BSTS, M-K and Prophet models were appearing for the full dataset.

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

We calculated total rCFR 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 (22).

**Time series model to predict the trend**

Here, we used five time-series model to define the relation between COVID-19 and the temperature 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 ARIMA and Prophet models. We used M-K and Sen’s slope analysis to different between every day or every week total drift (expanding or diminishing) of COVID-19 rCFR.

**Simple Exponential Smoothing (SES):**

Simple exponential smoothing is one of the most widely used methods for forecasting procedures (23)(24)(my1). SES is a short-term used for forecasting model that define data fluctuates around a relatively stable mean (25). The simple exponential smoothing equation is

*Ft*+1 = *α yt* + (1 *−α*) *Ft*

here yt 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(24). The SES model for this study had been carried out using R package ‘fpp2’.(26)

**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(27). This model shows that the time series values are linearly related and defines the extract prediction by deleting high-frequency noise from the data.(28)

The benefit of ARIMA models is the ability to dynamically oriented analysis which using recent data and make future prediction.(29). For this studies R package ‘forecast’ had been using f eliminating or the ARIMA model (30).

**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 (31)(32). The equation of the ARIMAX is (31)(33)



and the variable calendar effect equation is (33)



**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 (34). 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 (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. The error term for any unexpected changes of the analysis that the model does not allow for (36)(37) .

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

We applied weekly cumulative rCFR data and performed the M-K trend test to identify the trend of COVID-19 rCFR.(38)

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.(38). It can calculated 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.(39)

In addition, the Sen’s slope test was exerted to determine the changes in COVID-19 rCFR in both periods.(40) M-K and Sen’s slope trend analysis are using by R package ‘trend’.(41)

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

Bayesian structural time series (BSTS) model is a statistical technique according to use the time series data, like forecasting, now casting, inferring causal impact and other applications (43). 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 studies the R package ‘forecast’ had been using for eliminating or the BSTS model (44).

**Empirical evaluation**

The ARIMA and Prophet 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 (42). 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 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 several factors data from the ….

**Statistical analysis**

Here, we analysed that the rCFR of COVID-19 has changed over time (**Fig. 1**). We also find out that the rCFR reached a peak at 17th epidemiological week (22-28 April 2020, considering 1st January 2020 as the start of epidemiological week) and then the trend turned into decline. 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 country-level explanatory variables vary over time or they remain the same in two period through regression model. We divided this dataset into two half one until it reaches a peak (1-17th week) and termed as “before peak rCFR” or simply as “pre-peak period” and another with 18th – 53rd week (December 29-31, 2020) and termed as “after peak rCFR period” or simply as “post-peak period”. Here, we got the trending of rCFR value is different in both periods, then 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 the both periods separately.

**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 (45,46). The benefits of beta-regression model (46) is explanatory variables of two different periods (Pre and post peak)and reported that the incidence rate ratios (IRRs) after adjusting them for population density (per square kilometrer),the prevalence of obesity and the stage of the epidemic in Bangladesh country(47). In this study the beta regression models had been carried out using R package ‘betareg’.(41)

**Result:**

More than 170.2 million cumulative confirmed cases and 3.53 million deaths had been documented globally and the global rCFR of COVID-19 is reported as 2.04 % as of May 31st, 2021. The weekly global cumulative rCFR of COVID-19 reached a peak at 7.23% during the 17th Epidemiological week (April 22-28, 2020). In Bangladesh, the rCFR value is positioned around 1.57%. However, the daily cumulative rCFR for Bangladesh reached a peak at 10.37% by April 7th,2020. The top two divisions with COVID-19 rCFR are Mymensingh (2.50%), and Barisal (2.50%) (**Fig. 2**). The peak of the COVID-19 rCFR was dominated by different regions at different time frames. In a nutshell the rCFR value of 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 percent, 0.02, and 0.01 respectively (Table 1 and Fig. 3). 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 99.20 percent and 97.46 percent, 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 fall 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 for the week 1-15th (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. (48) 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.

We used five time-series models using real-time data to discover worldwide changes in COVID-19 CFR reported on a daily or weekly basis and found a downward trend since May 2020. We discovered a growing trend for daily rCFR (Bangladesh Region) values of COVID-19 until the 15th week (pre-peak period, which ends on April 14th, 2020) at 7.23 percent, and then a substantial dropping trend until the 73rd week (post-peak period) at 2.04 percent using the M-K trend test (May 29-31, 2021). We discovered a substantial decreasing trend of COVID-19 rCFR using a more robust time series model (ARIMA, Prophet, ARIMAX, BSTS, and SES). he ARIMA and BSTS models beat the benchmark SES, Prophet, and other models among five time-series models, which is likely due to the fact that the SES and Prophet approaches were originally created to solve business-related challenges. (42)(49)

This study investigates the relationship between local climatic conditions and COVID-19 rCFR at the local level in Bangladesh, considering many potential confounding variables. 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. There is a substantial yet modest relationship between climatic factors and daily rCFR. The lack of association might be ascribed to epidemic advancement, longer time series data, and COVID-19 counts' nonlinear character. 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). 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 show 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). (50) Chan et al. looked studied the stability of the SARS coronavirus in different meteorological situations (2011). (51) 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. (52) They stated that incorporation of one or any combination of the meteorological parameters as inputs in models did not improve the performance of any model compared with the corresponding univariable model.

MERSCoV (epidemic in 2012) is 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. (53) 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. (12) 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. (20) If the average temperature is less than 25,8°C, every 1°C increase in the number of cumulative confirmed daily COVID-19 instances was associated with a decrease of −4,8951 percent. According to Shi et al. (2020), the incidence of COVID-19 in China reduces as the temperature rises.(54) Increased temperature and relative humidity dramatically decreased COVID-19 transmission in 100 Chinese cities, according to Wang et al. (2020).(55) 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.(56)(57) 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). (58) 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 who 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). (59)(60)(61) 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). (62)(63) 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 on multiple ways (Wei et al. 2020).(64) Airborne transmission by aerosols, however, is very virulent and dominating (Zhang et al. 2020).(65) Aerosol viruse survival and infectivity are affected by ambient stress temperature (Jayaweera et al. 2020). (66) 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). (67) 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 community level, local policies such as the social distance and the amount of vulnerable people might influence the transmission of COVID-19. Kraemer et al. (2020) demonstrated that intervention measures decreased SARS-CoV-2 transmission in Wuhan, taking human movement as a surrogate for social separation. (68) Moreover, the control of SARS-CoV2 transmission accounted for a large part of severe local control measures (social insulations and cleanliness). Rubin et al. (2020) found significant social distance related with the lower transmission of SARS-CoV-2 in the United States. (69) There was also a comparable discovery in the UK (Hadjidemetriou et al. 2020). (70) In all, 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.(64)(71)

The COVID-19 rCFR is connected with many parameters that are strongly predictorous for precipitation, relative moisture and dew. The collection of small variable elements might potentially be used to drive, but were not included, environmental factors including contaminants, population density, indigenous population immunity and a water pollution index. We detect decreasing rCFR patterns comparable with findings from the early and later phase pandemic data based on hospital-based investigations. (72)(73) Superficials In New York the rate of death among hospitalized patients fell 18%-20% in 3-4 months, representing 25,6% in March and 7,6% in June 2020. (72) In England, the mortality rate at Intensive Care Unit and High Intensive Unit decreased substantially among the patients admitted in May compared to those admitted in March (9% and 11.2%, respectively). (73)

The rCFR is steadily declining over time and additional factors, including meteorological factors are sure to be associated. However, the decline in 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. (74)(75)(76)

Overall, from 21 July 2020 to the publication of this document the COVID-19 case increases with more than 200,000 instances each day (May 31st, 2021). In Bangladesh, however, from April 14, 2020 rCFR is declining. The decreased rCFR of COVID-19 might be somewhat abnormal, as COVID-19 trials are growing, (77) enabling more mild and asymptomatic patients to be detected that were previously excluded. In Germany, for example, the average daily test number in April 2020 was 22,829, and in August 2020 the figure is 117,423.(34)

While our study suggests a dropping regional (Bangladesh) RCFR owing to COVID-19 the rCFR is not to be confused with the rate for infection fatality, or IFR in any nation (in other words, a lower risk of dying when being infected). RCFR remains high and/or growing in many nations. In Yemen, (78) for example, while the world rCFR is estimated at 2.20 percent by 31 December 2020, it has a rCFR exceeding 28.9 percent.(34) The severity of the disease also does not decrease from our data. A SARS-CoV-2 investigation showed that the virus was replaced by D614 by a mutation of the G614 spike and became the dominant version of the virus worldwide. (79) The mutation is probably linked to the increased infectivity but is not known about the pathogenicity of the variation. (79) Further study is needed on the pathogenicity of the virus at the host level.

**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. Whereas our data cannot establish whether IFR is also decreasing while this study reveals a dropping rCFR rate.

**Conclusion:**

The cumulative rate of case fatality reported (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. While greater testing helps to identify more asymptomatic and mild illnesses, our study has revealed that there are low rCFR tests specifically during the post-peak period (weeks 15-73). 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 favorably 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.

**Reference**

1. Kushal SA, Amin YM, Mubassara L, Alam MM, Chakraborty PA. Managing SARS-CoV-2 outbreak challenges in psychiatric hospitals of Bangladesh. Public Heal Pract [Internet]. 2020 Nov;1:100041. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2666535220300409

2. Auler AC, Cássaro FAM, da Silva VO, Pires LF. Evidence that high temperatures and intermediate relative humidity might favor the spread of COVID-19 in tropical climate: A case study for the most affected Brazilian cities. Sci Total Environ [Internet]. 2020 Aug;729:139090. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0048969720326073

3. Bashir MF, Ma B, Bilal, Komal B, Bashir MA, Tan D, et al. Correlation between climate indicators and COVID-19 pandemic in New York, USA. Sci Total Environ [Internet]. 2020 Aug;728:138835. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0048969720323524

4. Tan J, Mu L, Huang J, Yu S, Chen B, Yin J. An initial investigation of the association between the SARS outbreak and weather: with the view of the environmental temperature and its variation. J Epidemiol Community Health [Internet]. 2005 Mar;59(3):186–92. Available from: http://www.ncbi.nlm.nih.gov/pubmed/15709076

5. Bi P, Wang J, Hiller JE. Weather: driving force behind the transmission of severe acute respiratory syndrome in China? Intern Med J [Internet]. 2007 Aug;37(8):550–4. Available from: http://doi.wiley.com/10.1111/j.1445-5994.2007.01358.x

6. van Doremalen N, Bushmaker T, Munster VJ. Stability of Middle East respiratory syndrome coronavirus (MERS-CoV) under different environmental conditions. Eurosurveillance [Internet]. 2013 Sep 19;18(38). Available from: https://www.eurosurveillance.org/content/10.2807/1560-7917.ES2013.18.38.20590

7. Park J, Son W, Ryu Y, Choi SB, Kwon O, Ahn I. Effects of temperature, humidity, and diurnal temperature range on influenza incidence in a temperate region. Influenza Other Respi Viruses [Internet]. 2020 Jan 21;14(1):11–8. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1111/irv.12682

8. Riddell S, Goldie S, Hill A, Eagles D, Drew TW. The effect of temperature on persistence of SARS-CoV-2 on common surfaces. Virol J [Internet]. 2020 Dec 7;17(1):145. Available from: https://virologyj.biomedcentral.com/articles/10.1186/s12985-020-01418-7

9. Altamimi A, Ahmed AE. Climate factors and incidence of Middle East respiratory syndrome coronavirus. J Infect Public Health [Internet]. 2020 May;13(5):704–8. Available from: https://linkinghub.elsevier.com/retrieve/pii/S187603411930351X

10. van der Hoek L, Pyrc K, Jebbink MF, Vermeulen-Oost W, Berkhout RJM, Wolthers KC, et al. Identification of a new human coronavirus. Nat Med [Internet]. 2004 Apr;10(4):368–73. Available from: http://www.ncbi.nlm.nih.gov/pubmed/15034574

11. Fehr AR, Perlman S. Coronaviruses: An Overview of Their Replication and Pathogenesis. In 2015. p. 1–23. Available from: http://link.springer.com/10.1007/978-1-4939-2438-7\_1

12. Wu Y, Jing W, Liu J, Ma Q, Yuan J, Wang Y, et al. Effects of temperature and humidity on the daily new cases and new deaths of COVID-19 in 166 countries. Sci Total Environ [Internet]. 2020 Aug;729:139051. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0048969720325687

13. Chin AWH, Chu JTS, Perera MRA, Hui KPY, Yen H-L, Chan MCW, et al. Stability of SARS-CoV-2 in different environmental conditions. The Lancet Microbe [Internet]. 2020 May;1(1):e10. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2666524720300033

14. Liu J, Zhou J, Yao J, Zhang X, Li L, Xu X, et al. Impact of meteorological factors on the COVID-19 transmission: A multi-city study in China. Sci Total Environ [Internet]. 2020 Jul;726:138513. Available from: https://linkinghub.elsevier.com/retrieve/pii/S004896972032026X

15. Ma Y, Zhao Y, Liu J, He X, Wang B, Fu S, et al. Effects of temperature variation and humidity on the death of COVID-19 in Wuhan, China. Sci Total Environ [Internet]. 2020 Jul 1;724:138226. Available from: http://www.ncbi.nlm.nih.gov/pubmed/32408453

16. Xie J, Zhu Y. Association between ambient temperature and COVID-19 infection in 122 cities from China. Sci Total Environ [Internet]. 2020 Jul;724:138201. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0048969720317149

17. He, Zonglin, Yiqiao Chin, Jian Huang, Yi He, Babatunde O. Akinwunmi, Shinning Yu, Casper J. P. Zhang and WM. Meteorological factors and domestic new cases of coronavirus disease (COVID-19) in nine Asian cities: A time-series analysis. medRxiv [Internet]. 2020; Available from: https://www.medrxiv.org/content/10.1101/2020.04.15.20066613v1.article-info

18. Zahirul Islam M, Rutherford S, Phung D, Uzzaman MN, Baum S, Huda MM, et al. Correlates of Climate Variability and Dengue Fever in Two Metropolitan Cities in Bangladesh. Cureus [Internet]. 2018 Oct 1; Available from: https://www.cureus.com/articles/14701-correlates-of-climate-variability-and-dengue-fever-in-two-metropolitan-cities-in-bangladesh

19. Rahman MR, Lateh H. Climate change in Bangladesh: a spatio-temporal analysis and simulation of recent temperature and rainfall data using GIS and time series analysis model. Theor Appl Climatol [Internet]. 2017 Apr 9;128(1–2):27–41. Available from: http://link.springer.com/10.1007/s00704-015-1688-3

20. Prata DN, Rodrigues W, Bermejo PH. Temperature significantly changes COVID-19 transmission in (sub)tropical cities of Brazil. Sci Total Environ [Internet]. 2020 Aug;729:138862. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0048969720323792

21. Max Roser, Hannah Ritchie EO-O and JH. Coronavirus Pandemic (COVID-19) - Statistics and Research - Our World in Data. 2020.

22. Mohammadpour S, Torshizi Esfahani A, Halaji M, Lak M, Ranjbar R. An updated review of the association of host genetic factors with susceptibility and resistance to COVID-19. Journal of Cellular Physiology. 2020.

23. de Livera AM, Hyndman RJ, Snyder RD. Forecasting time series with complex seasonal patterns using exponential smoothing. J Am Stat Assoc. 2011 Dec;106(496):1513–27.

24. Ostertagová E, Ostertag O. Forecasting using simple exponential smoothing method. Acta Electrotech Inform [Internet]. 2012 Jan 1;12(3). Available from: http://www.aei.tuke.sk/papers/2012/3/12\_Ostertagová.pdf

25. Maistor SI, Negrea R, Mocan ML, Turi A. Aspects of forecasting for the european automotive industry. In: Advances in Intelligent Systems and Computing. Springer Verlag; 2016. p. 981–92.

26. Data T, All D, Athanasopoulos G, Ggally S, Utf- E, Gpl- L, et al. Package ‘fpp2.’ 2020;1–23.

27. Dyer O. Covid-19: Remdesivir has little or no impact on survival, WHO trial shows. BMJ. 2020 Oct;371:m4057.

28. Adhikari R, Agrawal RK. An Introductory Study on Time Series Modeling and Forecasting. 2013 Feb;

29. Papastefanopoulos V, Linardatos P, Kotsiantis S. COVID-19: A Comparison of Time Series Methods to Forecast Percentage of Active Cases per Population. Appl Sci. 2020 Jun;10(11):3880.

30. Hyndman R, … GA-O https://cran. r, 2020 U. Package “forecast” Title Forecasting Functions for Time Series and Linear Models Description Methods and tools for displaying and analysing univariate time series forecasts including exponential smoothing via state space models and automatic ARIMA modelli. sunsite.icm.edu.pl. 2020.

31. Kongcharoen C, Kruangpradit T. Autoregressive Integrated Moving Average with Explanatory Variable (ARIMAX) Model for Thailand Export. 2013.

32. Adhikari R, Agrawal RK. An Introductory Study on Time Series Modeling and Forecasting. 2013 Feb 26; Available from: http://arxiv.org/abs/1302.6613

33. Anggraeni W, Vinarti RA, Kurniawati YD. Performance Comparisons between Arima and Arimax Method in Moslem Kids Clothes Demand Forecasting: Case Study. Procedia Comput Sci [Internet]. 2015;72:630–7. Available from: http://dx.doi.org/10.1016/j.procs.2015.12.172

34. Letham B. Package “prophet” Title Automatic Forecasting Procedure. 2019;1–16.

35. Kumar N, Susan S. COVID-19 Pandemic Prediction using Time Series Forecasting Models.

36. Samal KKR, Babu KS, Das SK, Acharaya A. Time series based air pollution forecasting using SARIMA and prophet model. In: ACM International Conference Proceeding Series. New York, New York, USA: Association for Computing Machinery; 2019. p. 80–5.

37. Hasan MN, Haider N, Stigler FL, Khan RA, McCoy D, Zumla A, et al. The Global Case-Fatality Rate of COVID-19 Has Been Declining Since May 2020. Am J Trop Med Hyg [Internet]. 2021 Apr 21; Available from: https://www.ajtmh.org/view/journals/tpmd/aop/article-10.4269-ajtmh.20-1496/article-10.4269-ajtmh.20-1496.xml

38. Yue S, Pilon P. A comparison of the power of the t test, Mann-Kendall and bootstrap tests for trend detection / Une comparaison de la puissance des tests t de Student, de Mann-Kendall et du bootstrap pour la détection de tendance. Hydrol Sci J. 2004 Feb;49(1):21–37.

39. Wang F, Shao W, Yu H, Kan G, He X, Zhang D, et al. Re-evaluation of the Power of the Mann-Kendall Test for Detecting Monotonic Trends in Hydrometeorological Time Series. Front Earth Sci. 2020 Feb;8:14.

40. Sen PK. Estimates of the Regression Coefficient Based on Kendall’s Tau. J Am Stat Assoc. 1968;

41. Pohlert. Package “trend.” Package “trend.” 2020. p. 1–18.

42. Kourentzes N, Petropoulos F. Forecasting with multivariate temporal aggregation: The case of promotional modelling. Int J Prod Econ. 2016 Nov;181:145–53.

43. Almarashi A, Khan K. Bayesian Structural Time Series. Nanosci Nanotechnol Lett. 2020 Jan 1;12:54–61.

44. Jun S. Bayesian structural time series and regression modeling for sustainable technology management. Sustain. 2019;11(18).

45. Cribari-Neto F, Zeileis A. Beta regression in R. J Stat Softw. 2010 Apr;34(2):1–24.

46. Ferrari SLP, Cribari-Neto F. Beta regression for modelling rates and proportions. J Appl Stat. 2004 Aug;31(7):799–815.

47. James G, Witten D, Hastie T, Tibshirani R. Springer Texts in Statistics An Introduction to Statistical Learning.

48. Murphy NF, Stewart S, MacIntyre K, Capewell S, McMurray JJV. Seasonal variation in morbidity and mortality related to atrial fibrillation. Int J Cardiol [Internet]. 2004 Nov;97(2):283–8. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0167527304003663

49. Papastefanopoulos V, Linardatos P, Kotsiantis S. COVID-19: A Comparison of Time Series Methods to Forecast Percentage of Active Cases per Population. Appl Sci [Internet]. 2020 Jun 3;10(11):3880. Available from: https://www.mdpi.com/2076-3417/10/11/3880

50. LIN K, YEE-TAK FONG D, ZHU B, KARLBERG J. Environmental factors on the SARS epidemic: air temperature, passage of time and multiplicative effect of hospital infection. Epidemiol Infect [Internet]. 2006 Apr 7;134(2):223–30. Available from: https://www.cambridge.org/core/product/identifier/S0950268805005054/type/journal\_article

51. Chan KH, Peiris JSM, Lam SY, Poon LLM, Yuen KY, Seto WH. The Effects of Temperature and Relative Humidity on the Viability of the SARS Coronavirus. Adv Virol [Internet]. 2011;2011:1–7. Available from: http://www.hindawi.com/journals/av/2011/734690/

52. Biswas PK, Islam MZ, Debnath NC, Yamage M. Modeling and Roles of Meteorological Factors in Outbreaks of Highly Pathogenic Avian Influenza H5N1. Viboud C, editor. PLoS One [Internet]. 2014 Jun 2;9(6):e98471. Available from: https://dx.plos.org/10.1371/journal.pone.0098471

53. van Doremalen N, Bushmaker T, Munster VJ. Stability of middle east respiratory syndrome coronavirus (MERS-CoV) under different environmental conditions. Eurosurveillance [Internet]. 2013;18(38):20590. Available from: http://dx.doi.org/10.2807/1560-7917.ES2013.18.38.20590

54. Shi P, Dong Y, Yan H, Zhao C, Li X, Liu W, et al. Impact of temperature on the dynamics of the COVID-19 outbreak in China. Sci Total Environ [Internet]. 2020 Aug;728:138890. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0048969720324074

55. Wang J, Tang K, Feng K, Lv W. High Temperature and High Humidity Reduce the Transmission of COVID-19. SSRN Electron J [Internet]. 2020; Available from: https://www.ssrn.com/abstract=3551767

56. Luo W, Majumder M, Liu D, Poirier C, Mandl K, Lipsitch M, et al. The role of absolute humidity on transmission rates of the COVID-19 outbreak. medRxiv. 2020;1–7.

57. Yao Y, Pan J, Liu Z, Meng X, Wang W, Kan H, et al. No association of COVID-19 transmission with temperature or UV radiation in Chinese cities. Eur Respir J [Internet]. 2020 May;55(5):2000517. Available from: http://erj.ersjournals.com/lookup/doi/10.1183/13993003.00517-2020

58. Jinjarak Y, Ahmed R, Nair-Desai S, Xin W, Aizenman J. Accounting for Global COVID-19 Diffusion Patterns, January–April 2020. Econ Disasters Clim Chang [Internet]. 2020 Oct 4;4(3):515–59. Available from: http://link.springer.com/10.1007/s41885-020-00071-2

59. Gomez-Barroso D, León-Gómez I, Delgado-Sanz C, Larrauri A. Climatic Factors and Influenza Transmission, Spain, 2010–2015. Int J Environ Res Public Health [Internet]. 2017 Nov 28;14(12):1469. Available from: http://www.mdpi.com/1660-4601/14/12/1469

60. Lopez D, Gunasekaran M, Murugan BS, Kaur H, Abbas KM. Spatial big data analytics of influenza epidemic in Vellore, India. In: 2014 IEEE International Conference on Big Data (Big Data) [Internet]. IEEE; 2014. p. 19–24. Available from: http://ieeexplore.ieee.org/document/7004422/

61. Mahamat A, Dussart P, Bouix A, Carvalho L, Eltges F, Matheus S, Miller M.A, Quenel P VC. Climatic drivers of seasonal influenza epidemics in French Guiana. J Infect [Internet]. 2013;67(2):141–7. Available from: http://www.labex-ceba.fr/publication/climatic-drivers-of-seasonal-influenza-epidemics-in-french-guiana-2006-2010/

62. da Silva PG, Nascimento MSJ, Soares RRG, Sousa SIV, Mesquita JR. Airborne spread of infectious SARS-CoV-2: Moving forward using lessons from SARS-CoV and MERS-CoV. Sci Total Environ [Internet]. 2021 Apr;764:142802. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0048969720363312

63. Jones RM, Brosseau LM. Aerosol Transmission of Infectious Disease. J Occup Environ Med [Internet]. 2015 May;57(5):501–8. Available from: https://journals.lww.com/00043764-201505000-00004

64. Wei J-T, Liu Y-X, Zhu Y-C, Qian J, Ye R-Z, Li C-Y, et al. Impacts of transportation and meteorological factors on the transmission of COVID-19. Int J Hyg Environ Health [Internet]. 2020 Sep;230:113610. Available from: https://linkinghub.elsevier.com/retrieve/pii/S1438463920305563

65. Zhang Z, Xue T, Jin X. Effects of meteorological conditions and air pollution on COVID-19 transmission: Evidence from 219 Chinese cities. Sci Total Environ [Internet]. 2020 Nov;741:140244. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0048969720337657

66. Jayaweera M, Perera H, Gunawardana B, Manatunge J. Transmission of COVID-19 virus by droplets and aerosols: A critical review on the unresolved dichotomy. Environ Res [Internet]. 2020 Sep;188:109819. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0013935120307143

67. van Doremalen N, Bushmaker T, Morris DH, Holbrook MG, Gamble A, Williamson BN, et al. Aerosol and Surface Stability of SARS-CoV-2 as Compared with SARS-CoV-1. N Engl J Med [Internet]. 2020 Apr 16;382(16):1564–7. Available from: http://www.nejm.org/doi/10.1056/NEJMc2004973

68. Kraemer MUG, Yang C-H, Gutierrez B, Wu C-H, Klein B, Pigott DM, et al. The effect of human mobility and control measures on the COVID-19 epidemic in China. Science (80- ) [Internet]. 2020 May 1;368(6490):493–7. Available from: https://www.sciencemag.org/lookup/doi/10.1126/science.abb4218

69. Rubin D, Huang J, Fisher BT, Gasparrini A, Tam V, Song L, et al. Association of Social Distancing, Population Density, and Temperature With the Instantaneous Reproduction Number of SARS-CoV-2 in Counties Across the United States. JAMA Netw Open [Internet]. 2020 Jul 23;3(7):e2016099. Available from: https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2768570

70. Hadjidemetriou GM, Sasidharan M, Kouyialis G, Parlikad AK. The impact of government measures and human mobility trend on COVID-19 related deaths in the UK. Transp Res Interdiscip Perspect [Internet]. 2020 Jul;6:100167. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2590198220300786

71. Méndez-Arriaga F. The temperature and regional climate effects on communitarian COVID-19 contagion in Mexico throughout phase 1. Sci Total Environ [Internet]. 2020 Sep;735:139560. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0048969720330771

72. Leora I. Horwitz, Simon A. Jones, Robert J. Cerfolio, Fritz Francois, Joseph Greco, Bret Rudy VOPAP. Trends in Covid-19 risk-adjusted mortality rates in a single health system. medRxiv. 2020;

73. Dennis JM, McGovern AP, Vollmer SJ, Mateen BA. Improving Survival of Critical Care Patients With Coronavirus Disease 2019 in England: A National Cohort Study, March to June 2020\*. Crit Care Med [Internet]. 2021 Feb 26;49(2):209–14. Available from: https://journals.lww.com/10.1097/CCM.0000000000004747

74. Iftikhar H, Rind M. Forecasting daily COVID-19 confirmed, deaths and recovered cases using univariate time series models: A case of Pakistan study. medRxiv [Internet]. 2020;2020.09.20.20198150. Available from: https://doi.org/10.1101/2020.09.20.20198150

75. Green MS, Peer V, Schwartz N, Nitzan D. The confounded crude case-fatality rates (CFR) for COVID-19 hide more than they reveal—a comparison of age-specific and age-adjusted CFRs between seven countries. Di Gennaro F, editor. PLoS One [Internet]. 2020 Oct 21;15(10):e0241031. Available from: https://dx.plos.org/10.1371/journal.pone.0241031

76. Dexamethasone in Hospitalized Patients with Covid-19. N Engl J Med [Internet]. 2021 Feb 25;384(8):693–704. Available from: http://www.nejm.org/doi/10.1056/NEJMoa2021436

77. Liang L-L, Tseng C-H, Ho HJ, Wu C-Y. Covid-19 mortality is negatively associated with test number and government effectiveness. Sci Rep [Internet]. 2020 Dec 24;10(1):12567. Available from: http://www.nature.com/articles/s41598-020-68862-x

78. Dureab F, Al-Awlaqi S, Jahn A. COVID-19 in Yemen: preparedness measures in a fragile state. Lancet Public Heal [Internet]. 2020 Jun;5(6):e311. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2468266720301018

79. Korber B, Fischer WM, Gnanakaran S, Yoon H, Theiler J, Abfalterer W, et al. Tracking Changes in SARS-CoV-2 Spike: Evidence that D614G Increases Infectivity of the COVID-19 Virus. Cell [Internet]. 2020 Aug;182(4):812-827.e19. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0092867420308205