Interaction of temperature and relative humidity for growth of COVID-19 cases and death rates

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Abstract

Akin to respiratory tract infection diseases, climatic conditions may significantly influence the COVID-19 epidemic. Since the beginning of the COVID-19 pandemic, significant efforts have been made to explore the relationship between climatic condition and growth in number of COVID-19 cases. Contentious findings of either positive, negative, or no association with climatic conditions have been reported in many studies based on some early data on COVID-19 cases over a shorter time span. We integrate COVID-19 datasets with long meteorological time series of 29 countries to explore cross-country variation in COVID-19 cases and death rates with respect to temperature and relative humidity. Our empirical study reveals that temperature and relative humidity jointly influence the growth of COVID-19 cases and death rates. We generate predictive scenarios for changes in daily cases and death rates under different combinations of temperature and relative humidity. Low temperature with low humidity in a temperate climate and high temperature with high humidity in a hot and humid climate are found to surge the growth of COVID-19 cases and death rates. These relationships and our predictive scenarios can be applied to generate early warning for any future outbreak to adopt stringency policies, kick-start economic activities, prepare healthcare service plans, and target vaccination coverage.

1. Introduction

COVID-19 is a SARS-CoV-2 virus induced infectious disease that causes severe acute respiratory syndrome. Akin to other respiratory viruses, human-to-human transmission of this virus mainly occurs through close contact, fomites, respiratory droplets, and contaminated surfaces (Azuma et al 2020, Choi et al 2021). Both temperature and humidity are known to regulate the stability of SARS-CoV-2 for transmission through surface and short-to-long range air drag of aerosol particles (Zhao et al 2020, Morris et al 2021). Thus both the meteorological covariates (temperature and humidity) deemed to contribute significantly in the transmission of SARS-CoV-2.

A respiratory tract infection epidemic is generally found to be correlated with climatic factors such as temperature and relative humidity (Liu et al 2016, Althouse et al 2018, Khan et al 2021). Seasonal patterns of infectious diseases caused by severe acute respiratory syndrome coronavirus (SARS-CoV) and respiratory syncytial virus (RSV) are directly related to air temperature and relative humidity (Tan et al 2005, Moineddin et al 2008, Paynter 2015, Ikaheimo et al 2016). Respiratory diseases account for more than 10% of all disability-adjusted life-years (DALYs) that measures the amount of active and productive life lost. Though an estimate of DALYs is yet to be known for COVID-19 pandemic, however, loss of active and productive life is anticipated to be significant with huge impact on economic activity. Thus, it is important to know the influence of climatic factors on the onset of COVID-19 epidemic for healthcare planning and management. Though most of the studies have explored the effect of climatic variables without an interaction of temperature and relative humidity on the transmission pattern of COVID-19 (Ahmadi et al 2020, Bashir et al 2020, Méndez-Arriaga 2020,
Wu et al (2020), it is highly likely that the interaction of temperature and humidity may also play an important role in explaining the transmission pattern. Therefore, we aim to explore the variation in COVID-19 cases and death rates in response to interactions of climatic factors and control measures.

Since the beginning of the COVID-19 pandemic, a significant effort has been made to establish relationships between COVID-19 transmission and climatic conditions. However, contentious associations with climate conditions are found in some recent studies. For example, positive association with air temperature has been found in several studies in New York (Bashir et al 2020), Oslo (Menebo 2020), China (Xie and Zhu 2020), and in Jakarta (Tosepu et al 2020). On the contrary, negative association with air temperature has been explored in some studies (Méndez-Arriaga 2020, Prata et al 2020, Wu et al 2020). Surprisingly, no association with air temperature has also been supported in some recent studies (Jüni et al 2020, Yao et al 2020). Thus we focus on statements on such contentious relationships between the growth of COVID-19 epidemic and meteorological covariates, and provide an insight based on cross-country variation in climatic patterns.

Akin to the inconsistent association between COVID-19 cases and air temperature, association with relative humidity is also found contentious in different studies. Though negative association with humidity has been explored in some studies (Liu et al 2016, Ahmadi et al 2020, Baker et al 2020, Wu et al 2020), surprisingly, no association between COVID-19 cases and humidity has also been reported (Tosepu et al 2020, Gunthe et al 2022). Most of the studies considered fewer number of cases reported within the first few days during the early stage of the pandemic. Statistical models with short time series are likely to fail to capture enough variation in climatic conditions in the presence of low counts of daily number of COVID-19 cases and deaths. Thus, the time series cross-sectional (TSCS) analysis with more data over a longer time period is preferable to consistently explore the changes in COVID-19 cases and deaths in response to cross-country variation in climatic conditions and control measures.

Both relative humidity and absolute humidity have been considered in lab experiments to explore the stability of influenza and other coronaviruses. Some recent pathological studies on SARS-CoV-2 have demonstrated the relationship of growth of SARS-CoV-2 with temperature and relative humidity (Biryukov et al 2020, Zhao et al 2020, Morris et al 2021). Apart from these two key meteorological factors (temperature and humidity), some other factors such as indoor-outdoor differences in environmental conditions, air drying capacity and wind speed can also affect the transmission of the SARS-CoV-2 (Choi et al 2021, Sera et al 2021). Though low association is explored with climatic covariates such as wind speed and precipitation, population behavior and government interventions are found to be more important drivers of transmission (Sera et al 2021). Thus the joint dynamic effect of temperature and relative humidity on COVID-19 statistics need to be controlled for other exogenous time series that accounts for mobility, government intervention, and healthcare practice.

Exploration of consistent relationships with climatic conditions will provide an insight into early warning for suppression or widespread transmission of SARS-CoV-2 virus. It is crucial for policymakers to make a good balance between the transmission and economic recovery (Varona and Gonzales 2021). An early warning regarding the transmission pattern will equip the policymakers with tools to plan for blocking and reopening businesses during the COVID-19 pandemic. Additionally, an early warning will provide an insight in vaccination program and it will help aid control mechanism for any future widespread transmission. Our current study aims to address the aforementioned issues and therefore makes an attempt to provide original contribution to the literature by (1) establishing strong joint effects of temperature and relative humidity on the growth of COVID-19 cases and death rates, (2) examining the effect of cross-country variations in meteorological covariates and control measures on the growth of daily cases and death rates, and (3) generating predictive scenarios under different climatic conditions to generate early warning for any future outbreak.

To organize remainder of the paper we provide a detailed description of data integration process in section 2. Filtering and data cleaning approaches are described in this section for selection of countries and integrating meteorological data sets with COVID-19 data sets. Statistical properties of integrated data set are discussed and suitable statistical models are determined to explore the cross-country variation in COVID-19 cases and death rates in response to meteorological covariates. In section 3, we explore the joint effects of temperature and relative humidity, and provide predictive scenarios for growth of COVID-19 cases under different climatic conditions. Predictive scenarios of death rates for different combinations of temperature and relative humidity are provided in section 4. We summarize our overall findings and provide concluding remarks in section 5.

2. Data and methods

We have collected both COVID-19 data and meteorological time series data from freely available public domains. Data processing, integration and statistical methods to analyze the integrated data are discussed in this section.
Table 1. Selected countries and weather stations.

| Country   | Weather station                                      | ISO2 code |
|-----------|------------------------------------------------------|-----------|
| Argentina | Ministro Pistarini International Airport             | AR        |
| Bangladesh| Shahjalal International Airport                      | BD        |
| Belarus   | Minsk National Airport                               | BY        |
| Belgium   | Brussels Airport                                     | BE        |
| Bolivia   | Viru Viru International Airport                       | BO        |
| Brazil    | São Paulo–Guarulhos International Airport            | BR        |
| Canada    | Jean Lesage International Airport                    | CA        |
| Chile     | Comodoro Arturo Merino Benitez International Airport | CL        |
| China     | Wuhan Tianhe International Airport                   | CN        |
| Colombia  | El Dorado International Airport                      | CO        |
| Ecuador   | José Joaquin de Olmedo International Airport         | EC        |
| Egypt     | Cairo International Airport                          | EG        |
| France    | Paris Charles de Gaulle Airport                     | FR        |
| Germany   | Düsseldorf International Airport                     | DE        |
| India     | Chhatrapati Shivaji Maharaj International Airport    | IN        |
| Iran      | Tehran Imam Khomeini International Airport          | IR        |
| Italy     | Milan Malpensa Airport                               | IT        |
| Indonesia | Soekarno–Hatta International Airport                 | ID        |
| Kazakhstan| Almaty International Airport                         | KZ        |
| Kuwait    | Kuwait International Airport                         | KW        |
| Mexico    | Mexico City International Airport                    | MX        |
| Netherlands| Amsterdam Airport Schiphol                            | NL        |
| Pakistan  | Jinnah International Airport                         | PK        |
| Peru      | Rodríguez Ballon International Airport               | PE        |
| Portugal  | Lisbon Portela Airport                               | PT        |
| Qatar     | Hamad International Airport                          | QA        |
| Russia    | Vnukovo International Airport                        | RU        |
| Saudi Arabia| Taif International Airport                           | SA        |
| South Africa| O. R. Tambo International Airport                    | ZA        |
| Spain     | Adolfo Suárez Madrid-Barajas Airport                 | ES        |
| Turkey    | Esenboga International Airport                       | TR        |
| Ukraine   | Kyiv International Airport (Zhuliany)                | UA        |
| United Kingdom| London Heathrow Airport                               | UK        |
| United States| John F. Kennedy International Airport               | US        |

2.1. Meteorological data

Our empirical study considers COVID-19 and meteorological time series data of 32 countries. COVID-19 data sets are extracted from https://ourworldindata.org. Time to report the first COVID-19 confirmed case is not unique for all countries. Thus we consider 120 d of data from the date of the first confirmed case in a country. As of 31 July 2020, the average number of confirmed cases across all countries in the first 120 d are computed and countries exceeding this average number of COVID-19 cases are included in this study. Selected countries with weather stations to collect meteorological time series data are shown in table 1. The most affected state of a country is identified based on the number of confirmed cases and the weather station adjacent to the closest international airport is selected to obtain meteorological data. For example, the highest number of COVID-19 cases are identified in North Rhine-Westphalia state in Germany and Düsseldorf is the capital of the state. Meteorological data are then obtained from the Düsseldorf International Airport Weather Station. Similar choices have been made for Italy, Spain, and other countries.

Meteorological time series of average daily temperature and relative humidity are obtained from www.wunderground.com by selecting the weather station. Onset of COVID-19 is also not exactly known for China and limited number of highly regulated tests do not reflect the true transmission scenarios in Bangladesh (Cousins 2020, Wu et al 2020). Daily mean temperature and relative humidity data of selected weather stations in Bangladesh and China were also not available in the open-source database. To ensure reproducible research outcome that reflects the overall climate-induced transmission pattern of SARS-CoV-2, we exclude these two countries from further analysis.

Daily mean temperature and relative humidity of a weather station vary over time. Rolling time series smooths the time series and inclusion of rolling time series enables us to include more lag effects in a model. Thus we compute 7 d rolling means of temperature and relative humidity. A 7 d rolling mean of
Distribution of 7 d rolling means of temperature (RMT) and relative humidity (RMH), 
LDDPM = log(DDPM + 0.5), and 
LDCPM = log(DCPM + 0.5) where DCPM and DDPM are daily cases and deaths per million.

![Figure 1](image-url)
Table 2. Panel unit root test of variables.

| Variable | Test specification | Test statistic | p-value |
|----------|--------------------|---------------|---------|
| $\triangle DCPM$ | Panel mean | $-46.7348$ | $0.0000$ |
| $DPM$ | Panel mean, trend | $-19.2784$ | $0.0000$ |
| $RM$ | Panel mean, trend | $-11.4925$ | $0.0000$ |
| $RMT$ | Panel mean, trend | $-11.2610$ | $0.0000$ |
| $SI$ | Trend | $-3.7505$ | $0.0001$ |

Here, $\triangle DCPM$ is the first difference of daily cases per million (DCPM), and Akaike Information Criterion is used to select the lag length in ADF regression.

daily number of death per million (DDPM), 7 d RMT, 7 d RMH, and $SI$.

2.4. Statistical models

We have explored in table 2 that the panel unit root hypothesis is rejected for all five time series of our interest. Akin to any stationary time series of dynamic nature, $\triangle DCPM$ has dynamic data generating mechanism as the daily number of confirmed cases depend on the previously confirmed cases because of the transmission of virus from infectors to infectees. Thus we may consider dynamic panel model for the time series $\triangle DCPM_{i,t}$ in response to climatic variables $RMT_{i,t}$, $RMH_{i,t}$ and $SI_{i,t}$ where $SI_{i,t}$ is the government induced stringency level (SI) on the $t$th day from the first reported COVID-19 case in the $i$th country ($t = 1,2,\ldots,120$ and $i = 1,2,\ldots,29$). Since $T > N$ in our case, GMM (generalized method of moment) estimation of dynamic panel model is deemed not to be suitable for our data set. So, we apply feasible generalized least square (FGLS) method for TSCS data analysis (Beck 2001, Phillips 2010, Beck and Katz 2011).

In the presence of $q$ exogenous variables $x_{i,t,j} : j = 1,\ldots,q$, the dynamic model with lagged dependent variable can be expressed as:

$$y_{i,t} = \sum_{j=1}^{p} \delta_j y_{i,t-j} + \sum_{j=1}^{q} \delta_j x_{i,t,j} + v_{i,t}, \quad (2)$$

where $i = 1,\ldots,N$ and $t = 1,\ldots,T$.

Inclusion of a 7 d rolling mean as an explanatory variable in a model will essentially include the effect of 7 consecutive days for that variable. We have explored in figure 1 that there are cross-country variations between two climatic variables $RMT$ and $RMH$ as well as variations among COVID-19 cases and death rates. To account for the joint effect of temperature and relative humidity on growth of COVID-19 cases and death rates, we include the interaction effect of $RMT$ and $RMH$ in the FGLS model in equation (2).

As has been explored in section 1, joint effect of temperature and relative humidity on COVID-19 statistics needs to be controlled by other exogenous time series such as population mobility, population density, healthcare, and government intervention. Time series of $SI$ is composed of nine different indicators related to mobility and public health campaign such as school closing, workplace closing, cancelling public events, restrictions on gathering size, closing public transport, stay-at-home requirements, restrictions on internal movement, restrictions on international travel, and public information campaign for healthcare systems (Hale et al 2021). Thus the inclusion of $SI$ time series controls for many factors in the model to explore the interaction effects of meteorological covariates.

Akin to any predictive model, time series models also examine the relationship between the predictor and response variables. Inclusion of time invariant exogenous variable in any time series model does not affect the dynamic relationship between the response and exogenous predictor time series. Application of Granger causality test (Granger 1969, Dumitrescu and Hurlin 2012) shows a significant causal relationship demonstrating that SI time series causes daily changes in cases per million ($\triangle DCPM$) and daily death per million ($DDPM$). Thus the inclusion of SI time series is found to be justified to explain and control the dynamic nature of response variables $\triangle DCPM$ and $DDPM$.

3. Effect of temperature and humidity on growth of COVID-19 cases

As has been discussed in section 2.4 and in equation (2), we apply FGLS to explain the variation in daily changes in number of COVID-19 cases ($DCPM_{i,t}$) in response to climatic conditions and stringency levels. Estimated parameters of the FGLS model are provided in table 3.

It seems that the distance lags in the FGLS model have significant positive effects on the DCPM. The median serial interval of COVID-19 is 5.1 d in Lauer et al (2020) and our FGLS model has also found significant positive coefficients for temporal lags 1–3 of $\triangle DCPM_{i,t}$. Thus our model demonstrates that the changes in daily number of confirmed cases are essentially the combined effect of prior cases reported on the 2nd to the 4th days as $\triangle DCPM_{i,t} = DCPM_{i,t} − DCPM_{i,t-1}$. Thus, the dynamic nature of COVID-19 transmission with a time lag around the serial interval is well demonstrated in our model.

Government enforced stringency level reduces the transmission. The stringency index $SI_{i,t}$ ranges between 0 and 100 reflecting the strictness in control options to reduce the transmission. Implemented stringency does not reduce the transmission immediately, rather it takes enough time to be effective. We examine different time lags for the SIs with different values of $k = 1,2,\ldots,30$ in $SI_{i,t-k}$ and have found that the significant negative effect is achieved only after 24 d. The coefficient of $SI_{i,t-k}$ becomes negative and statistically significant for any $k \geq 25$. This is an indication that the adopted stringency policy takes about more than three weeks for significant reduction of daily changes in number of transmissions. In a recent
study, McKenzie and Adams (2020) have explored a lag response time of 8 d between the stringency policy enactment and activity response. This is essentially a temporal lag between the government stringency action and public response to the stringency policy. Thus a significant reduction in transmission can be achieved with a lag response time of more than 8 d. Our results demonstrate statistically significant effect of SI with a temporal lag of almost 3 weeks in the reduction of number of daily cases per million.

We find that $RMT_{t,0}$, $RMH_{t,0}$, and their interaction $RMT_{t,0} \times RMH_{t,0}$ are highly significant to explain the dynamic nature of $\Delta DCPM_{t,i}$ in the dynamic model shown in table 3. To explore the joint effects of $RMT_{t,i}$ and $RMH_{t,i}$ on $\Delta DCPM_{t,i}$, we fix other variables to some numbers and compute predicted number of cases for a range of $RMT_{t,i}$ and $RMH_{t,i}$. By inserting $\Delta DCPM_{t,i-1} = \Delta DCPM_{t,i-2} = \Delta DCPM_{t,i-3} = 0$ and $SI_{t,25} = 0$ in the FGLS model, we compute predicted change in number of cases for the $t$th day and plot the results in figure 2. It seems that higher degrees of RMT with lower levels of RMH likely to result in lower level of growth in daily confirmed cases. Daily growth in number of cases seems to be low in the region with 7 d RMT over 80 °F and RMH below 75%, and for the combination of RMT below 80 °F and RMH above 75%. It seems that the high temperature with high relative humidity (mimicking hot and humid weather) and low temperature with low relative humidity (mimicking dry winter weather) aggravate the transmission. As the RMT starts moving below 80 °F and RMH starts moving below 75%, growth of daily number cases keeps increasing with the decreasing levels of RMT and RMH.

Climatic factors are found to be correlated with other virus that causes respiratory infection, for example, RSV incidence has a consistent peak during winter months in temperate settings and during rainy season both in tropical and subtropical settings (Paynter 2015). In tropical settings, RSV peak events in Asian, African and South American countries are observed mainly in rainy seasons (Shek and Lee 2003). Thongpan et al (2020) have shown that the RSV activity is positively correlated with the relative humidity and the seasonal profile has a peak during the rainy season in Thailand. Figure 2 supports these results with red shades on the top right corner of the graph corresponding to hot and humid climatic pattern. Thus the SARS-CoV-2 virus activity for COVID-19 is likely to follow a pattern similar to RSV with more incidences in hot and humid weather as well as in dry winter weather.

### 4. Effect of temperature and humidity on death rates

We observe that the DDPM ($DDPM_{t,i}$) for the $t$th day and $i$th country ($t = 1, 2, \ldots, 120$, $i = 1, \ldots, 29$) is stationary as the null hypothesis of panel unit root is rejected by the IPS test shown in table 2. Thus we apply FGLS to explore the effects of cross-country variations in meteorological covariates ($RMT_{t,i}$ and $RMH_{t,i}$) on $DDPM_{t,i}$. Since more COVID-19 infections are likely to result in more hospitalization and more deaths, we include distributed lags for $\Delta DCPM_{t,i}$ in the FGLS model. Country-level demographic factor such as median age of population may also affect the death rates as the COVID-19 mortality is found higher among the older people (Ho et al 2020). Thus we apply FGLS of $DDPM_{t,i}$ with lagged variables $DCPM_{t,i-k}$ for some $k > 0$, $RMT_{t,i}$, $RMH_{t,i}$ and $MAGE_{i}$ (median age of population for the $i$th country). Estimates of FGLS model parameters are provided in table 4.

All coefficients in table 4 are statistically significant and the DDPM depends on daily changes in number of COVID-19 cases per million with temporal lags of 6–10 d, 7 d rolling means of temperature and relative humidity, and median age. In a study on the length of stay in Belgian hospitals, Faes et al (2020)
Table 4. Feasible generalized least square (FGLS) model of daily change in number of deaths per million (DDPMi).

| Variable          | Estimate | z-value | p-value |
|-------------------|----------|---------|---------|
| Intercept         | 3.042    | 30.1792 | 0.0000  |
| RMTi,1            | −0.0883  | −65.2476| 0.0000  |
| RMHi,1            | −0.1185  | −62.7324| 0.0000  |
| RMTi,1 × RMHi,1   | 0.0014   | 62.9957 | 0.0000  |
| △DCPMi,1–6       | 0.0019   | 6.1236  | 0.0000  |
| △DCPMi,1–7       | 0.0025   | 6.3336  | 0.0000  |
| △DCPMi,1–8       | 0.0025   | 6.3336  | 0.0000  |
| △DCPMi,1–9       | 0.0011   | 2.9500  | 0.0032  |
| △DCPMi,1–10      | 0.0011   | 3.4581  | 0.0005  |
| MAGEi             | 0.1619   | 66.0290 | 0.0000  |

Here, p values less than 0.0001 are reported as 0.0000.

showed that the median length of stay in hospital varies between 3–10.4 d. In fact, our FGLS model outputs in table 4 show significant effects of temporal lags of 6–10 d for △DCPM on DDPM. So, the FGLS model in table 4 selects the temporal lags for △DCPM that is reasonably in line with the findings of Faes et al (2020).

The coefficient of the variable MAGE (median age of population) is positive and refers to the increase of 0.1619 deaths per million of population for one year increase of the median age. O’Driscoll et al (2021) have studied the age-specific mortality pattern of COVID-19 among 45 countries and have found that the infection fatality follows a log-linear increase by age among individuals older than 30 years. Thus the results of FGLS panel model shown in table 4 depicts the effects of median age in line with the results obtained in O’Driscoll et al (2021).

Effects of climatic drivers are apparent and have been found significant in the FGLS model shown in table 4. The interaction effect \( RMT_{i,1} \times RMH_{i,1} \) is found highly significant. Hence, we may depict the joint effect of these two climatic covariates by setting the other variables fixed at some levels. For instance, we set \( \Delta DCPM_{i,1–6} = \cdots = \Delta DCPM_{i,1–10} = 0.55 \) and \( MAGE_i = 38 \) (around the mean of the variables for USA) to predict the number of deaths per million in response to different combinations of \( RMT_{i,1} \) and \( RMH_{i,1} \) values. The predicted response surface shown in figure 3 reveals that the COVID-19 death rates are relatively lower for the climatic conditions having low temperature with high relative humidity (temperature below 70 °F and relative humidity above 75%) and high temperature with low relative humidity (temperature above 80 °F and relative humidity below 60%). On the other hand, predicted DDPM is relatively higher for the bottom-left and top-right blocks in figure 3. Consequently, the climatic condition having low temperature with low relative humidity (temperature below 70 °F and relative humidity below 60%) and high temperature with high relative humidity (temperature above 80 °F and relative humidity above 75%) seem to have higher number of deaths per million of population.

Cold and dry conditions in temperate winter likely to increase the transmission of RSV (Paynter 2015, Ikäheimo et al 2016) and our results mimic a qualitatively similar exposition for SARS-CoV-2 virus that is responsible for COVID-19 pandemic. Temperature and relative humidity jointly affect the transmission and so the death rates. In a study in Britain, Bull (1980) reported immediate positive correlation of high humidity and temperature with pneumonia deaths. Historical notes of Sir Leonard Rogers also associated high pneumonia fatality rates with high temperature and high humidity (Rogers 1925). Thus our results are supported by historical notes and research findings for similar other respiratory virus transmission and pneumonia induced death rates. Moreover, our results depict joint effects of temperature and relative humidity on COVID-19 cases and death rates. Not only low temperature and low humidity, but also high temperature and high humidity are found to trigger the growth of COVID-19 cases and death rates. Thus the high temperature with high humidity in tropical climate and low temperature with low humidity in temperate climate can be considered as warning signs for higher degrees of transmission with more COVID-19 cases and deaths.

5. Concluding remarks

Climatic conditions have a significant effect on the growth of daily number of COVID-19 cases and deaths. Though some early studies have reported inconsistent and contentious association (positive or negative or even no association) of COVID-19 cases with meteorological covariates, we have found
significant joint effects of temperature and relative humidity on the growth of COVID-19 cases. Highly significant interaction effect of temperature and relative humidity reveals a nonlinear relationship of COVID-19 cases and death rates with meteorological covariates.

Not only temperature or relative humidity, but also combinations of temperature and relative humidity are found to aggravate or lower the growth of daily cases and death rates. Weekly RMT over 80 °F with rolling mean humidity below 75% or RMT below 80 °F with rolling mean humidity over 75% lowers the growth of COVID-19 cases. On the other hand, weekly RMT below 80 °F with rolling mean humidity below 75% or RMT above 80 °F with rolling mean humidity over 75% aggravates the growth of COVID-19 cases.

Number of cases and death rates are expected to increase for low temperature with low humidity in temperate climates and for high temperature with high humidity in tropical climates. These results can be used to adopt climatic pattern induced stringency policies for regulating onsite businesses to enhance economic activities and vaccinating the vulnerable groups to reduce burdens on healthcare services. Though we have considered long TSCS data, exploration of seasonal profile of COVID-19 requires further research with more data over the years. Moreover, integration of high-resolution gridded data with one-to-one mapping with COVID-19 cases and deaths could better reflect the effect of meteorological covariates. Our time series modeling procedure can be implemented even with the gridded data given that a one-to-one mapping between meteorological time series and time series of a COVID-19 statistic is established within each grid.

**Data availability statement**

The data that support the findings of this study are openly available at [https://ourworldindata.org](https://ourworldindata.org) and [www.wunderground.com](http://www.wunderground.com). Data needed to evaluate the conclusions are presented in the paper. Additional data/code requirement (if any) may be requested from the authors.

All data that support the findings of this study are included within the article (and any supplementary files).

**Ethical statement**

This article does not contain any studies with human participants or animals.

**Conflict of interest**

Authors declare no competing interests.

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