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How Climate Variables Influence the Spread of SARS-CoV-19 in the United States

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Abstract: During the 2020 Coronavirus pandemic, several scientific types of research investigated the causes of high transmissibility and deaths caused by SARS-CoV-2. Among the spreading factors of the disease, it is known that there is an association between temperature and infected people. However, the studies that identified this phenomenon explored an association relationship, which is weaker and does not allow the identification of which variable would be the cause. This study aimed to analyze the impact of temperature variations and other climatic variables on the infection rate of COVID-19. Data were extracted from weather stations in the United States, which were segregated by county and day. Daily COVID-19 infections and deaths per county were also collected. Two models were used: the first model to analyze the temperature and the number of infected cases and the second model to evaluate the variables of temperature, precipitation, and snow in relation to COVID-19 infection. Model 1 shows that an increase in temperature at time zero caused a decrease in the number of infected cases. Meanwhile, a decrease in temperature after the temperature shock was associated with an increase in the number of cases, which tended to zero overall. A 1% increase in temperature caused a 0.002% decrease in the number of cases. The results suggested a causal relationship between the average temperature and number of CODIV-19 cases. Model 2, which includes temperature, precipitation, and snow shows that an increase in temperature resulted in a 0.00154% decrease response. There was no significant effect of increased precipitation and snow on the infection rate with COVID-19.

Keywords: SARS-CoV-2; temperature; precipitation; snowfall

1. Introduction

On 30 January 2020, the World Health Organization (WHO, Geneva, Switzerland) declared that the spread of a new type of coronavirus, SARS-CoV-2, [1] was a public health emergency of international interest [2]. This virus was first identified in patients with pneumonia in the city of Wuhan, Hubei province, China, in December 2019 [3]. Due to its rapid transmissibility, it gained prominence in the world scientific community [4].

The transmissibility of SARS-CoV-2 is unknown precisely, but some studies indicate that the most common form is from respiratory secretion or droplet [5,6], and may also happen from contact between contaminated surfaces (glass, plastics, stainless steel) and the mucous membrane [6]. Usually, the transmission of respiratory viruses occurs when there are symptoms [5]. However, asymptomatic

people can also transmit the virus [6]. Consequently, transmissibility can occur at the beginning of the disease and even with mild symptoms or no symptoms at all.

Coronavirus is one of the viruses responsible for seasonal severe acute respiratory syndromes (SARS) in humans [7]. This virus has a high mortality rate; indeed, in 2003, the mortality rate associated with SARS was approximately 10% in the city of Hong Kong, and, 34% mortality rate (858 deaths) in Saudi Arabia in 2012 [8].

The clinical presentation of the novel coronavirus disease 2019 (COVID-19) caused by SARS-CoV-2 ranges from a mild, or asymptomatic, presentation to severe and fatal respiratory disease [3]; however, the exact spectrum of presentation of the disease is not yet clear. Nevertheless, countries that were exposed to other types of coronavirus in the past have valuable lessons to share based on experiences with previous pandemics, such as that observed in Hong Kong in 2003 and in the Middle East in 2012.

The spread of COVID-19 has already reached pandemic proportions, affecting more than 100 countries [9]. Therefore, a global response is imperative and extremely necessary in order to prepare health systems worldwide to face this unprecedented challenge [10]. Although containment and prevention measures have reduced the number of new cases in several countries, these measures are not as effective in other countries [11,12].

Indeed, the spread of COVID-19 in countries such as France, Italy, China, United States, and Iran has demonstrated that this novel virus can overwhelm healthcare resources even in countries with a sufficient supply [9,13]. It is estimated that 30% of the exposed population will have no symptoms, 55% will have mild to moderate symptoms, 10% will be in serious condition, and 5% will need intensive care [14].

The United States has become one of the countries most affected by COVID-19, presenting cases in all 50 states [1]. According to the Centers for Disease Control and Prevention (CDC), on 19 April 2020, the country recorded more than 37.2 thousand deaths and 720.6 thousand cases, becoming the country with the highest number of deaths caused by the disease [15].

The US government has implemented extraordinary measures to limit viral transmission, including social isolation, in order to minimize the likelihood of uninfected people coming into contact with infected people [1]. Currently, the capacity of the national health system to respond to the needs of those who are already infected is of great concern [1].

For accurate estimation of the capacity of the health care network to respond to COVID-19, it is essential to construct models that assist in the prediction of cases and deaths. Such models can assist in the decision-making process for the allocation of human, financial, and material resources.

Three aspects can affect the epidemiology of communicable diseases: the transmitting agent, the host, and the environment [16]. The environmental variable has been identified as an important characteristic to be considered. Studies have already begun to identify associations between environmental variables and transmissibility [17,18].

In this context, the present study aimed to assess the impact of average temperature and climatic variables on the transmission of COVID-19. To achieve this, we aimed to assess a possible causal relationship between climatic variables and the number of cases of COVID-19 in the United States.

In our study, we collected the daily temperature in each county of the United States for an in-depth analysis of the impact of the environment on the number of people infected with SARS-CoV-19. This data was obtained directly from local weather stations. We then evaluated the number of infections per county-day, which made it possible to analyze causality. Such information has not yet been studied, as prior research was limited to assessing associations and correlations between these variables.

Therefore, we aimed to assess the impact of variations in temperature, precipitation, and snow on the infection rate, allowing treatment providers to adopt contingency approaches, such as measures of social isolation and construction of field hospitals, based on the climatic variations in specific regions of the US.

2. Materials and Methods

The objective of this study was to evaluate the impact of increased temperature in the USA and climate variables on infection rate with COVID-19. The data collection was performed as shown.

2.1. Data Collection

The average temperatures were collected from an application programming interface [19] (API) of the National Centers for Environmental Information (NCEI) [20]. Considering that the first registered case occurred in the province of Wuhan on 8 December 2019, we choose to adopt the beginning date of 1 December 2019. The adoption of this initial date does not interfere with the final results of the model. Thus, data were collected for the interval between 1 December 2019 to 6 April 2020. Data collection was divided into three stages, as shown in Table 1.

Table 1. Climate data extraction process.

	Step 1	Step 2	Step 3
Source	USDA Natural Resources Conservation Service (USDA, Washington, DC, USA, 2020)	National Centers for Environmental Information (NCEI, Asheville, NC, USA) (NOAA, Washington, DC, USA, 2020)	Consolidated USDA (Washington, DC, USA) and NCEI (Asheville, NC, USA) data
Application	Nodejs (OpenJS Foundation, San Francisco, California, 2020)	C# [2]	Excel, CSV
Data	Counties FIPS [1]	Daily Average Temperature by county	Daily Average Temperature by county FIPS [1]

[1]—Federal Information Processing Standard; [2]—Computer programming language. It is developed by Microsoft (Microsoft Corporation, Albuquerque, NM, USA) (See https://docs.microsoft.com/en-us/dotnet/csharp/).

Overall, we collected 7.3 million records of climate indicators for a total of 3141 counties. One file per US state was created, totaling 50 files.

Information on infection rate was obtained from the Centers for Disease Control and Prevention [21]; however, this information did not allow for daily targeting by county. In a complementary way, we used data from The New York Times case count, [22] which consolidates information on infection rate based on each county's Federal Information Processing Standard Publication (FIPS) code [23,24].

2.2. Data Analysis

For the VAR model, all variables must be stationary. Before performing the estimation, we performed a unit root test to assess the stationarity of the series. An augmented Dickey–Fuller (ADF) test was performed, and the results suggested that the variables number of cases, precipitation, and snowfall are stationary, and the average temperature is unit root. Subsequently, we set the average temperature as the first difference.

The objective of this study was to evaluate the impact of increased temperature in the USA and climate variables on infection rate with COVID-19. For this purpose, we used a vector regression model that can be described with the following Equation (1):

$$y_t' A_0 = \sum_{l=1}^{p} y_{t-1}' A_l + \varepsilon_t' \text{ for } 1 \leq t \leq T \tag{1}$$

where y_t is $n \times 1$ vector of endogenous variables; A_0 is $n \times n$ matrix of parameters; A_l is $n \times n$ parameters of lagged variables, for $1 \leq l \leq p$; ε_t is $n \times 1$ vector of structural disturbances; "p" is the lag order; "T" is the sample size. However, the structural model presented in (1) is not determined. To solve

this, we transformed Equation (1) to a reduced form by multiplying with A^{-1}, and we obtained the following Equation (2):

$$y'_t = y'_{t-1}B + u'_t \tag{2}$$

where $B = FA^{-1}u'_t = \varepsilon'_t A^{-1}$ and $E[u'_t u_t] = \Omega = (AA')^{-1}$ is the residual variance-covariance matrix.

According to Sims [25], Equation (1) should be identified by restricting the cotemporary effects matrix A_0 through Cholesky decomposition. In this study, it is assumed that average temperature has a contemporaneous effect on number of cases, suggesting that temperature is the most exogenous variable in the system. For the second model with all climate variables, the Cholesky decomposition assumes that average temperature has a contemporaneous effect on all variables.

The empirical model is estimated based on the following Equation (3):

$$y_t = (TAVG_t, CASES_t)' \tag{3}$$

where $TAVG_t$ is the average temperature in Fahrenheit and $CASES_t$ is the total number of COVID cases registered in the USA in logarithmic form. The model to be estimated is based on the following Equation (4):

$$\begin{bmatrix} 1 & 0 \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} TAVG_t \\ CASES_t \end{bmatrix} = [F] \begin{bmatrix} TAVG_{t-1} \\ CASES_{t-1} \end{bmatrix} + C\xi \tag{4}$$

For the model with climate variables, the empirical model is estimated based on the following Equation (5):

$$y_t = (TAVG_t, PRCP_t, SNOW_t, CASES_t)' \tag{5}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{12} & 1 & 0 & 0 \\ a_{13} & a_{23} & 1 & 0 \\ a_{14} & a_{24} & a_{34} & 1 \end{bmatrix} \begin{bmatrix} TAVG_t \\ PRCP_t \\ SNOW_t \\ CASES_t \end{bmatrix} = [F] \begin{bmatrix} TAVG_{t-1} \\ PRCP_{t-1} \\ SNOW_{t-1} \\ CASES_{t-1} \end{bmatrix} + C\xi \tag{6}$$

where $PRCP_i$ is the average precipitation and $SNOW_t$ is the average snow precipitation. Exogenous variables were used to estimate Equations (4) and (6). The exogenous variables were constant and a temporal dummy variable indicated that March was the month with the greatest number of infected cases.

After estimating the vector autoregression (VAR), we established the reduced form of Equation (2) as dependent on the residuals u_t, and the parameters estimated were used to identify changes in the variables to temperature shock in u_t. The results of this procedure are denominated variance decomposition and impulse response functions.

The variance decomposition indicates the contribution (forecast error variance) of each endogenous variable to the other variables in the model [26]. The impulse response function determines the degree to which an endogenous variable can be explained by exogenous temperature shocks represented by other variables. In the current estimated model, variance decomposition indicates the degree to which variance in the number of infected cases can be explained by temperature and all other climate variables used in the model average. The impulse response function indicates the degree to which the number of COVID-19 cases results from an increase in temperature, rainfall, and snow fall.

3. Results

Based on the Akaike criterion, the results indicated that the VAR structure has one lag for both models. Table 2 shows the results of the Granger causality test, which uses only the number of cases as the dependent variable. The results of this test show that the average temperature Granger-causes number of infected cases considering 10% of significance. The same result is observed in Model 2 and the null hypothesis that the Precipitation and Snow Granger-causes number of infected cases could not be rejected.

Table 2. Granger causality test for the number of COVID-19 cases.

	Model 1		Model 2	
	F-Stat	**Significance**	**F-Stat**	**Significance**
Average Temperature	3.4155	0.0686391	3.4556	0.0671830
Precipitation	-	-	1.9191	0.1702955
Snow	-	-	1.0645	0.3056946
Number of cases	19,666.4837	0.0000000	19,660.8558	0.0000000

Table 3 shows the variance decomposition for the number of cases. For Model 1 at step one, 2.4% of the variation in the number of cases is due to the average temperature. In the long run (steps 30 and 40), as much as 5% of the variation in the number of cases can be explained by the average temperature. For Model 2, the results are the same, and precipitation and snow fall do not affect the number of cases. This suggests that in all daily variations in the number of cases, at least 5% is due to temperature.

Table 3. Variance decomposition for number of cases.

	Model 1		Model 2			
Step	**Average Temperature**	**Cases**	**Average Temperature**	**Precipitation**	**Snow**	**Cases**
1	2.406	97.594	1.278	0.129	0.287	98.306
10	3.911	96.089	5.192	0.390	2.403	92.015
20	4.780	95.220	5.935	0.514	2.582	90.969
30	5.051	94.949	6.163	0.552	2.638	90.648
40	5.173	94.827	6.266	0.569	2.663	90.502

Figure 1 shows the impulse response function after estimating the VAR. The blue line represents the confidence bands estimated using the Monte Carlo simulation. For Model 1, the results show that an increase in temperature at time zero causes a decrease in the number of infected cases. Subsequently, a significant response was observed seven days after the temperature shock. The number of cases tends to zero in the long run. At t = 0, a 1% increase in temperature causes a 0.002% decrease in the number of cases. The results suggest a causal relationship between the average temperature and number of COVID-19 cases.

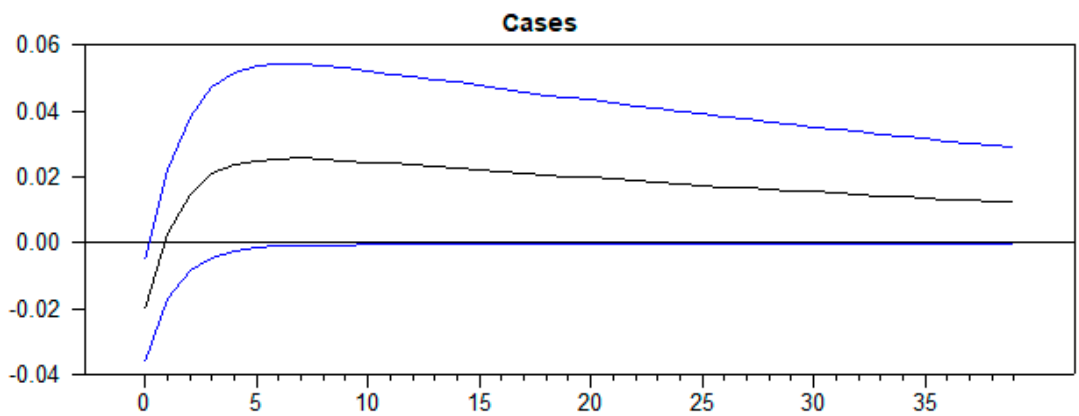

Figure 1. Response to average temperature increase in Model 1.

Figures 2–4 show the impulse response function considering temperature shocks for all climate variables in Model 2: temperature increase, precipitation increase, and snow fall increase. Figure 2 shows that temperature increase caused a 0.00154% decrease response at t = 0 shock, and the response behavior is the same as that presented in Model 1.

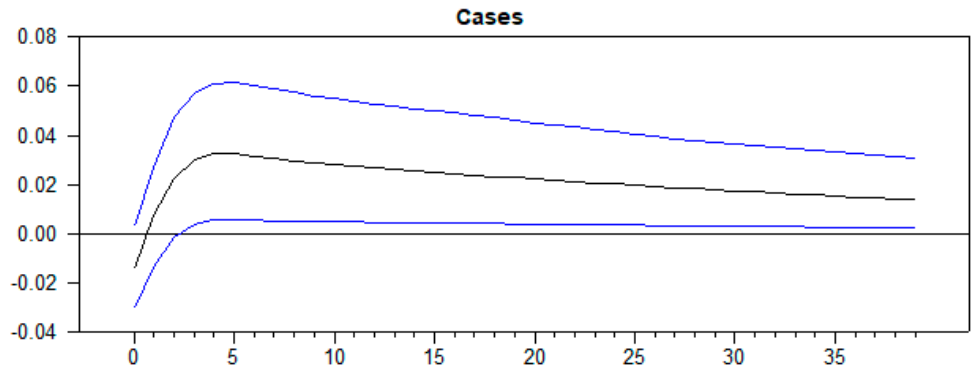

Figure 2. Response to average temperature increase in Model 2.

Figures 3 and 4 show that there is no significant response in the number of infected cases with increased precipitation and snow.

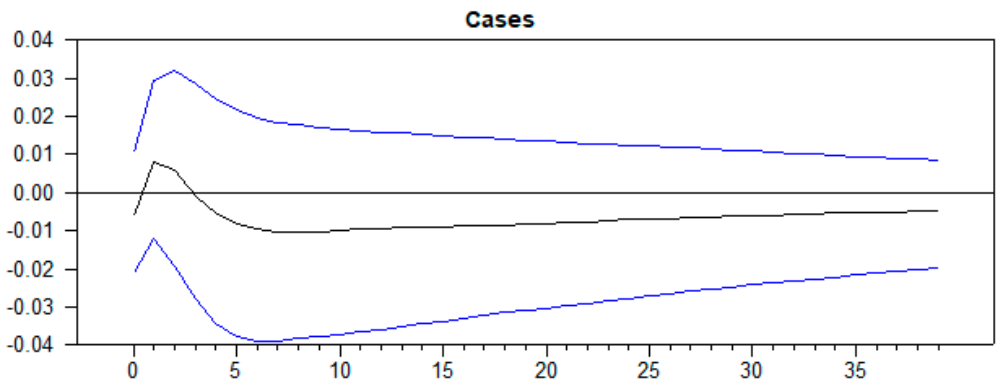

Figure 3. Response to average temperature increase in Model 3.

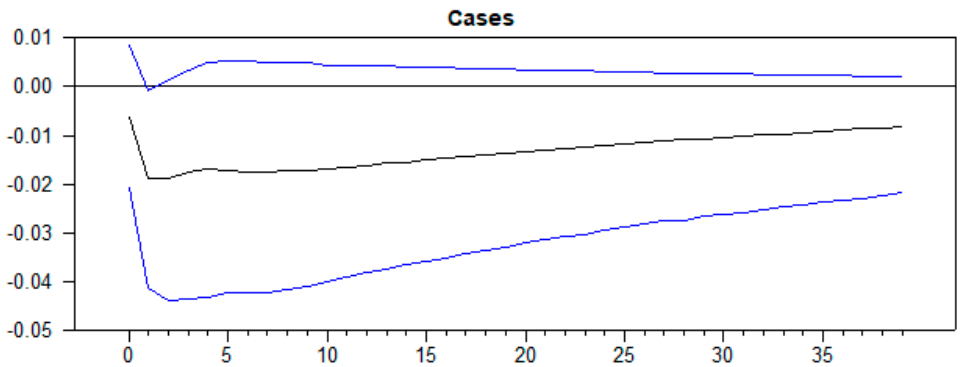

Figure 4. Response to average temperature increase in Model 4.

The overall findings are limited due to lack of information by terrestrial weather stations on some variables of interest, such as humidity and solar incidence. Therefore, we suggest that future studies attempt to include all potentially relevant variables, such as humidity and sunlight.

4. Discussion

The present study aimed to explore a possible causal relationship between average temperature and the number of COVID-19 infections in the United States. A climate database of US county was used. This allowed for the compensatory reduction caused by the adoption of the average values for all variables.

The results of our model suggest that there is a relationship between average temperature and COVID-19 infections. According to the model, the average temperature is responsible for 5% of

infections variation. In a pandemic, where the number of infected cases corresponds to millions of people [27], this percentage can have a significant impact on the variation of the number of people infected.

The average temperature was responsible for 5% of COVID-19 infections. In a pandemic, where the number of infected cases corresponds to millions of people [27], this percentage can have a significant impact on the absolute number of people infected.

Researchers have already observed a negative association between temperature and transmissibility of the virus [17,28]. Chan et al. [29], for example, evaluated the stability of the coronavirus at different temperatures and humidity. The authors showed significantly reduced viability at higher temperatures and high humidity [29]. These results are in line with the findings of the present study, specifically regarding the relationship between increased temperature and virus transmissibility.

Research on other respiratory diseases, such as influenza and severe acute respiratory syndrome (SARS) [30] have highlighted the importance of climatic variables in the transmission of these diseases. In addition, the marked change in ambient temperature was associated with a greater transmission capacity of SARS [31,32].

In our research, the model using number of COVID-19-related deaths was also tested; however, the result did not indicate a direct influence of climatic variables on the number of COVID-19-related deaths. However, it can be deduced that temperature has an indirect influence on deaths since estimates show that the global mortality rates of COVID-19 are 5.7% of those infected with the virus [33].

A review of the literature on climate and virus transmission indicated that the methodology adopted was aimed at searching for correlations. However, association-based conclusions are less robust, decreasing the accuracy of the results. This is due to the fact that spurious associations can arise when many variables in complex studies are studied simultaneously [34]. Furthermore, the association between variables does not necessarily imply causality [34].

In our study, we sought to obtain more robust and accurate results; therefore, we chose to perform causality tests, followed by the use of autoregressive vectors, thus allowing us to assume that the average temperature effectively influences the number of people infected with COVID-19, and, indirectly, the number of disease-related deaths. The results of the VAR estimation suggest a causal relationship between temperature and number of cases. When precipitation and snowfall data were incorporated in the model, the results did not change.

The results of this study do not provide information to help determine whether the cause of the increase in COVID-19 transmission that is observed in decreased temperatures could be due to strengthening of the virus or weakness of the host. Indeed, studies have indicated that the influence of temperature on human health can vary depending on geographic region or latitude [35,36].

5. Conclusions

Based on the results identified by the VAR model, it is possible to verify the existence of causality between the variables in our model. Indeed, it is possible to assume that there is not a mere association, but a cause and effect relationship exerted by the average temperature on the number of infected individuals. Our data will allow for the adoption of measures that respond to climatic variation of the seasons and derived weather forecasts relative to COVID-19 transmission.

The findings indicate of an association between these two variables, allowing for the measurement of the number of infected people derived from temperature variation. Such findings will allow treatment providers to adopt customized measures for each region or season for reducing COVID-19 transmission.

It was not possible to obtain information on all climate variables by county. Thus, data such as UV rays, humidity, and precipitation could not be incorporated into the model. Therefore, we indicate the absence of these control variables as a limitation to the study.

Our results support both the increase or reduction in the service capacity and the adoption of social distance actions adjusted for each region or climate profile.

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