# Relationship between Climatic Variables and Reproduction Number (R0) of Confirmed COVID-19 Cases

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Research Article

# Relationship between climatic variables and Reproduction number ($R_0$) of confirmed COVID-19 cases

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## Abstract

Most transmittable diseases appear in a specific season and the effect of climate on COVID-19 is of special interest. This study aimed to investigate the relationship between climatic variables and R0 of COVID-19 cases in one hundred areas around the world. The daily confirmed cases COVID-19 and climatic data of each area per day from January 2020 to March 2021 are utilized in the study. The GWR and MLR methods were used to identify the relationship between R0 of COVID-19 cases and climatic variables. The MLR results showed a significant (p-value < 0.05) weak inverse relationship between R0 of COVID-19 cases and wind speed, but a positive significant (p-value < 0.01) relationship with precipitation. It implies that lower COVID-19 cases were recorded with high wind speed and low precipitations. Based on GWR, R0 of COVID-19 infection against principal climatic variables has found statistically significant using Monte Carlo p-value test and the effect of climatic variables on COVID-19 infection appears to vary geographically. However, besides climatic variables, many socio-economic factors could influence the virus transmission and will be considered in future studies.

**Keywords:** Coronavirus; Geographically Weighted Regression (GWR); Global; Relationship; SARS-CoV2

## 1. Introduction

The corona virus (COVID-19) emerged in China between end of 2019 and early 2020. Since then it rapidly spread to other countries around the world, and the World Health Organization announced COVID-19 pandemic (Bukhari and Jameel, 2020; Wu *et al.*, 2020). The number of confirmed cases and casualties of SARS-CoV2 is exceeded the number of SARS-CoV1 and MERS-CoV casualties (Johns Hopkins University, 2021). It seemed

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definitely in the future the pandemic would strike unrich countries. Currently, climatic variables have not recognized as the effective drivers of the COVID-19, and the sensitivity of the virus to climate not evident. (Rodó et al., 2021)

Most transmittable diseases appear in a specific season, for instance, influenza is not readily transmitted in hot and humid situations and shows seasonality in the regions with a temperate climate where the peak of infections happens during winter (Bukhari and Jameel, 2020; Sajadi *et al.*, 2020). Likewise, SARS-CoV1 and MERS-CoV also showed seasonal patterns and correlations with temperature. The peak of the first one occurred during the spring while the second one was transmitted in the warm climate during spring and summer seasons (Caspi *et al.*, 2020). The people stay more in indoor in winter, which can assist the spread of diseases; and vitamin D levels in people tend to drop in winter, which may reduce the immunity (Chen *et al.*, 2021). It may be one reason for the more quickly spread of infectious diseases in winter.

Even though cultural, and population density are influencing the growth and spread of COVID-19, the effect of climate on the virus is of special interest (Caspi *et al.*, 2020) and cannot be neglected. Visual assessment of the global maps of COVID-19 infection display that the disease fewer prevalent in hot and humid countries that lie on the Equator (Chen *et al.*, 2021). At the local scale, Ahmadi et al. (2020) detected that COVID-19 infection in Iran is high in cities with low degrees of wind speed, humidity, and solar radiation. Rasul and Ibrahim (2020) assessed the influence of climatic variables and sociodemographic characteristics on COVID-19 infections in Iraqi cities. In China, Wang et al. (2020) used linear regression to reveal that high temperature and high humidity significantly decreased the spread of COVID-19 in 100 cities. Many research carried out about the relationship between COVID-19 disease and climatic variables have been on the local scale. However, further research is essential to assess influence of climatic elements on the virus in different climatic zones at the global scale in different regions.

R nought or zero ($R_0$) refers to the number or the basic reproduction number or the effective reproduction number ($R_e$). It describes the average number of people each infected person will infect where there is no pre-existing immunity in the community, based on three factors: the duration, the likelihood of infection and the frequency of contact (Mahase, 2020). $R_0$ is an exponent of the spread of a virus, firstly used to evaluate the capability of an infectious disease to occupy society. Secondly to locate the fraction of the society which have to be vaccinated (Dharmaratne *et al.*, 2020).

This study aimed to investigate the relationship between climatic variables and $R_0$ of detected COVID-19 cases by comparing the transmission performance of the virus in small regions around the world. The novel contribution of this research is the quantitative analysis of relationships between SARS-CoV2 spread and principal climatic elements at the large scale using multivariate regression method. The research aims to support policymakers through the monitor and improving climate-related health in cities, states, and small countries.

## 2. Methods and Data

### 2.1. Data

One hundred states (e.g. states of the US, Canada, China and Australia), provinces and small countries (smaller than 20,000 $km^2$; e.g. Malta, Qatar, Fiji, Lebanon, Kuwait and Gambia ) are selected for this study. The reason for select small regions in all countries COVD-19 infection data in the city scale is not available so large countries that only COVID-19 data at the countries scale available ignored.

Data of daily confirmed COVID-19 from January 2020 to March 2021 in selected areas were downloaded from Humdata.org (2020). Daily data of weather components (air temperature, relative humidity, atmospheric pressure, visibility and wind speed) across weather stations in the study areas were obtained using "worldmet" package of R programming (Carslaw, 2020). Surface meteorological data of regions weather stations were downloaded by worldmet package from the NOAA Integrated Surface Database (ISD).

### 2.2. Statistical analysis

To make an accurate rate of transmission, only those data after 30 cases of COVID-19 in each region is used in the R0 production (Smit *et al.*, 2020). The basic R0 transmissibility projected by Cori et al. (2013) framework is used to estimate each COVID-19 patients spread to how many individuals. The method generates robust analytical speculates of R. When the result of R0 is higher than 1, means the virus spreads fast and a larger spread with higher number of R0 values(Team, 2014). This tool estimates $R_t$ from time series of cases and therefore reproducing R0 of the endemic (Cori *et al.*, 2013).

Association between R0 of the daily confirmed cases of COVID-19 of selected regions and daily weather variables were assessed. We converted the hourly data of downloaded weather stations to daily data before data

analyses. Geographically weighted regression (GWR) and Multiple Linear Regression (MLR) approaches were used to quantify the linear and spatial regression analyses.

Statistical process was performed in R programming (e.i. spgwr (2020) and sp (2021) packages). GWR multivariate regression was performed and preferred over univariate regression because in multivariate regression it is possible to quantify the partial contributions of each variable and robust the assessment correlation between R0 of COVID-19 infection and explanatory climatic variables. GWR is localized regression that suggested by Brunsdon et al. (1996) which assess non-stationary variables (Zhou and WANG, 2011). The model stated as (Equation 1) and MLR expressed as (Equation 2).

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (1)$$

where $(u_i, v_i)$ implies the coordinates of the $i$th point in space, $\beta_0$ and $\beta_k$ are parameters to be estimated, and $\varepsilon_i$ is the random error term at point $i$.

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \quad (2)$$

where $y$ dependent variable, $b_0$ y-intercept, $x$ explanatory variables, $b_n$ slop for $x_n$.

# 3. Results and Discussion:

The research aimed to display the influence of climatic variables on COVID-19 at states and country levels around the world. Results of this association assist researchers' better compruence condition of the new virus. Based on the daily climatic variables and R0 of confirmed COVID-19 cases analyses, the results are as follows.

**3.1. Relationship of R0 of COVID-19 infection and climatic variables at global**

Based on MLR method, only precipitation and wind speed significantly correlated with lag7 of R0 COVID-19 infection. In particular, wind speed negatively correlated with COVID-19 infection and increasing wind speed could potentially decrease COVID-19 infection by 0.016 per unit. In contrast, precipitation and ws found to have positively correlated with COVID-19 infection, meaning an increase in rainfall could increase COVID-19 infection by 0.008 per mm unit (Table 1).

**Table 1**: Statistics of regression between climatic variables and lag7 R0 of COVID-19 based on the Multiple Linear Regression method.

|  | Estimate | Std.Error | tvalue | Pr(>|t|) |
|---|---|---|---|---|
| Intercept | -7.133151 | 3.209931 | -2.22 | 0.0263 * |
| Wind speed | -0.016102 | 0.009561 | -1.68 | 0.0922 . |
| Average temperature | -0.002282 | 0.001980 | -1.15 | 0.2492 |
| Precipitation | 0.008256 | 0.003130 | 2.64 | 0.0084 ** |
| Rh | 0.001559 | 0.001504 | 1.04 | 0.3000 |
| Air pressure | 0.000101 | 0.000464 | 0.22 | 0.8276 |

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

**3.2. Relationship between R0 of COVID-19 infection and climatic variables at local**

R0 of COVID-19 infection against principal climatic variables has found statistically significant using Monte Carlo p-value test (Table 2). Generally, GWR method showed negative relationship against wind speed, air temperature and air pressure while positive against precipitation and relative humidity to R0 infection of COVID-19. However, this negative relationship got changed to positive in some points in particular to maximum.

Regarding the spatial variation of regression, the effect of wind speed, temperature, humidity, precipitation and air pressure on convid-19 infection appears to vary geographically. Figure 1 displays that increasing air temperature leads to decreasing R0 of COIVID-19 in America and some part of Europe (negative regression) while increasing infection in East and south of Asia, Africa, Australia and UK (positive regression, Figure 1a). High wind speed lead to increase infection in Asia, Australia and Caribbean Islands (positive regression) between 0 to 0.07 while decreasing infection in Europe between 0 to 0.08 (negative regression, Figure 1b). Relative humidity has been found to negatively related to infection in Europe while opposite in Asia and America. At the global scale, air pressure was found negative with infection and positive for Australia and Africa (Figure 1d). Precipitation was found to have negative influence on R0 of Covid-19 except in Europe  (Figure 1e). Based on Brunsdon, Forheringham and Charlton (2002) ANOVA test, the GWR (SS residuals = 49865, AICc = 33514.041) provides a statistically significant (p-value 0.3) improvement over an OLS (SS residuals = 50431, AICc = 33591.833). Figure 2 shows GWR based predicted R0 of COVID-19 infection, standard error of predicted R0 and localR2. High pred_se

observed in East of Asia. Figure 3 displays that predicted and observed R0 statistically significantly correlated and predicted R0 based on GWR has less rmse (2.12) than predicted rmse based on OLS (2.13).

**Table 2**: Summary statistics of GWR coefficient parameter estimates between daily climatic variables and lag7 R0 of COVID-19.

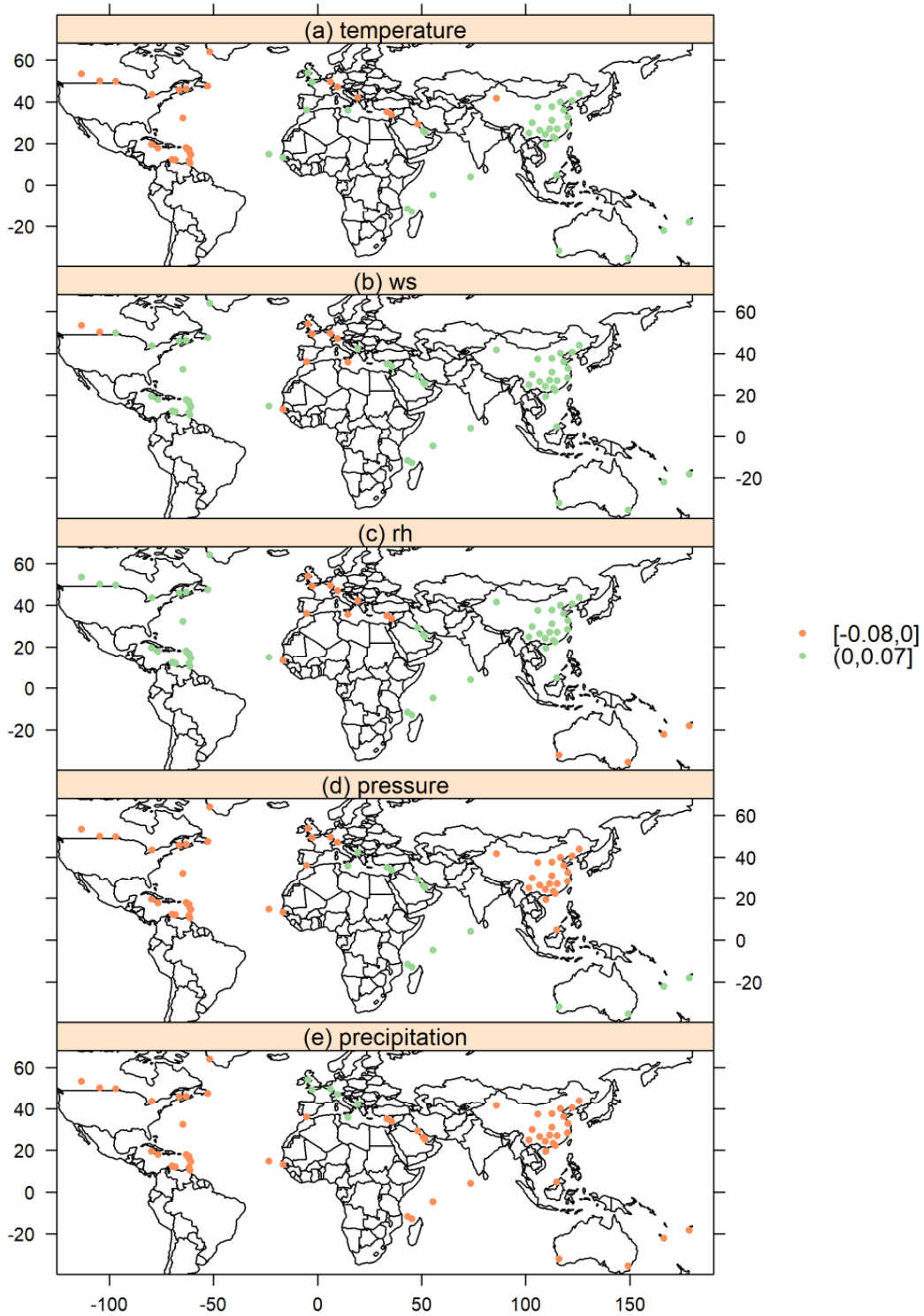| | Min. | Median | Max | Global | Monte Carlo p-value |
|---|---|---|---|---|---|
| **Intercept.** | -62.7119 | -5.2736 | 2.2711 | -7.133 | 0.00 |
| **Wind speed** | -0.078 | -0.0026 | 0.006 | -0.016 | 0.25 |
| **Average temperature** | -0.016 | -0.0027 | 0.022 | -0.002 | 0.03 |
| **rh** | -0.0047 | 0.0065 | 0.0139 | 0.002 | 0.00 |
| **Precipitation** | -0.00137 | 0.0058 | 0.0627 | 0.008 | 0.00 |
| **Air pressure** | -0.00053 | -0.0002 | 0.00137 | 0.0001 | 0.11 |

Figure 1: GWR based relationship between lag7 R0 of confirmed cases of COVID-19 with air temperature (a), wind speed (b), relative humidity (c), air pressure (d), and precipitation (e).
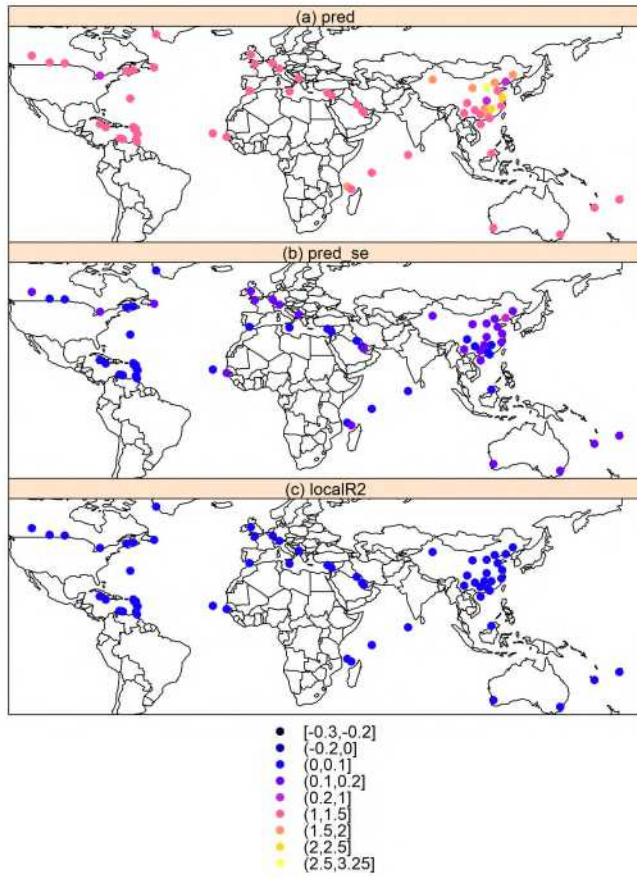
Figure 2: GWR based predicted R0 of COVID-19 infection (a), standard error of predicted R0 (b), and localR2 (c).
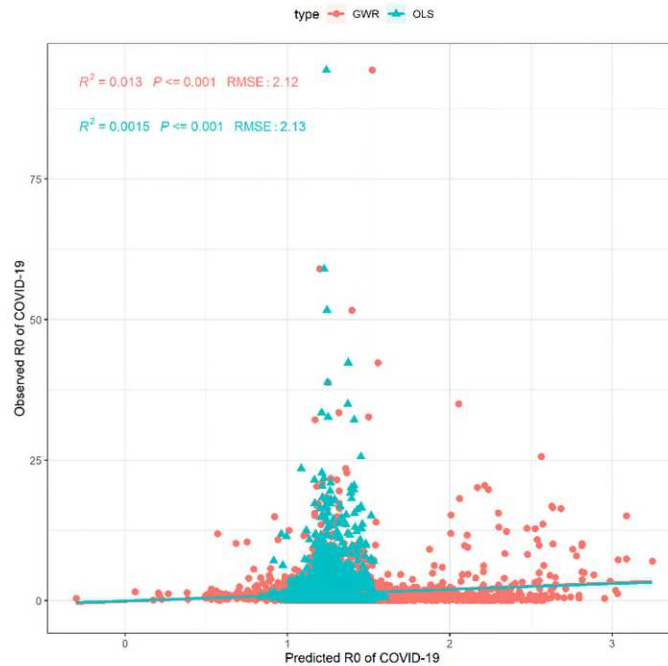
Figure 3: Validation of predicted R0 of COVID-19 infection based on OLS and GWR methods.

# 4. Conclusion

Our results reported that based on MLR method precipitation and wind speed are the main significant climatic drivers with R0 of COVID-19 cases both at state and country levels. This result is in agreement with Sajadi et al. (2020) where a close relationship between COVID-19 R0 cases and climatic drivers exists. Based on GWR, R0 of COVID-19 infection against principal climatic variables has found statistically significant and the effect of climatic variables appears to vary geographically. Previous studies focusing on socio-economic parameters have shown that population density, hospital, diabetes and aged patients have been found to be the main drivers controlling the R0 of COVID-19 cases. The combined effects of socio-economic and climatic parameters would be explored in future research to sustaine cities, countries and society to sustaine healthy community in cities and countries.

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**Conflicts of Interest:** The authors declare no conflict of interest.

**Availability of data and material:** produced and used data available online on GitHub:

https://github.com/Azad77/Relationship_Climate_and_R0_Covid19

**Code availability:** All source codes are publicly available on GitHub:

https://github.com/Azad77/Relationship_Climate_and_R0_Covid19

**Ethics approval:** Not applicable, because this article does not contain any studies with human or animal subjects.

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**Consent for publication:** Not applicable. Used Covid-19 data is open access available at: Humdata.org (2020).

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