Spatial interaction between weather and socio-demographic factor as influencing variables for COVID-19 spread in Iraq

Azad Rasul[1] · Sa'ad Ibrahim[2]

Abstract Weather and sociodemographic indicators are important to comprehensively understand rapid spread of COVID-19 at a given spatial scale and spatial analysis is very useful in studying the causes of disease. This study evaluates the influence of weather variables, sociodemographic characteristics and their corresponding records of COVID-19 in Iraq governorates. The assessments of these relationships were based on R_0 estimated from the time series data of COVID-19 infections, and by using geographically weighted regression (GWR) and linear regression modelling. The results showed that global estimates of these relationships from the linear regressions are generally poor. On the contrary, GWR results show spatially varying patterns. Among weather variables, increasing wind speed leads to rising COVID-19 infection. Population density is one of the sociodemographic characteristics that contribute to higher COVID-19 infection. COVID-19 infections, on the other hand, decreased in cities with a good health index and access to piped water. The findings of this study are therefore of great value to policymakers to design appropriate measures to reduce COVID-19 infection. This demonstrates the importance of spatial information methods in quantifying the impact of different variables on disease spread.

1 Introduction

SARS-CoV2 is increasingly recognised as an important, worldwide public health concern. The number of confirmed cases and casualties of SARS-CoV2, on a global scale, has significantly increased. These have drawn the attention of researchers and policy-makers to devise measures against the rapid development of diseases by providing guidance and options for a better healthcare delivery needed to address the prevailing and future challenges [1]. It has been postulated that the peak time of the transmission of these diseases is most peculiar to a specific season and weather conditions, for instance, the peak of SARS-CoV1 occurred during the spring while MERS-CoV was transmitted in the warm climate during spring and summer seasons [2]. In contrast, the transmission of influenza shows seasonality in the regions with a temperate climate where the peak of infections happens during winter [3–5].

The spread of COVID-19 could be influenced by weather and climatic variables and human demographic variables such as population density, culture, and country measures against the disease [2]. On the global scale, association between per country COVID-19 cases and principal climatic variables were examined by previous studies [5]. The research reported a significant weak inverse relationship between R_0 of COVID-19 cases and wind speed. At the local scale, some research were carried out to evaluate the association between COVID-19 disease and climatic variables. For instance, in Iran, a study reported that COVID-19

✉ Azad Rasul
azad.rasul@soran.edu.iq; azad977@gmail.com

Sa'ad Ibrahim
saadarg1@yahoo.com

1 Department of Geography, Faculty of Arts, Soran University, Soran 44008, Iraq

2 Department of Geography, Adamu Augie College of Education, PMB 1012, Argungu, Kebbi State, Nigeria

infection is high in cities with low degrees of wind speed, humidity, and solar radiation [6]. In China, linear regression was used to assess the impact of temperature in the cities. Results indicated that high temperatures and high humidity significantly reduced the spread of COVID-19 in 100 cities [7]. A tropical case study, in Rio de Janeiro, Brazil, concludes that the spread of COVID-19 could be suppressed by high solar radiation [8]. In Jakarta, Indonesia, results display COVID-19 pandemic is weakly positively correlated with average temperature [9].

To date, only weak evidence is provided by peer reviewed published papers confirming that SARS-CoV-2 is more transferrable under lower air temperatures and low absolute humidity. In addition, the reported relationships between SARS-CoV-2 and air pollution, UV, and wind speed are ambiguous. There is, therefore, the need for researchers to critically investigate the influence of environment and weather on the virus and the disease. This means that the impact of weather and climate variables on COVID-19 infection is not only localized but also at experimental stages.

One other question is whether socio-economic and sociodemographic variables of the people may affect the transmission of COVID-19 infection. The influence of these variables on the spread of COVID-19 infection is still not well understood. Examples of these variables are population size, population density, the degree of urbanization and poverty [10]. Despite the fact that different results were reported in the literature about the influence of environmental conditions on the COVID-19, it is still quite imperative to study the influence of the daily weather and sociodemographic elements on the virus in Iraq (at the local scale). In addition, having more observations and dense time series data regarding the new Coronavirus can reveal a pattern that may not have been explored in the past, perhaps by using strict hypotheses and the development of analytical methods and statistical models [10]. The use of GWR for evaluating the relationships between environmental and human factors and COVID-19 has been not been adequately researched.

In this study, we aimed to investigate whether COVID-19 detection is related to weather elements and sociodemographic indicators in Iraqi cities, which is important to comprehensively understand the factors that contribute to rapid spread of the disease at a given spatial scale. Specifically, we evaluated the relationship between weather and climate elements and sociodemographic variables and COVID-19 using GWR and Multiple Linear Regression (MLR). A recent study by Wu and Zhang [11], who explore the spatial-temporal varying impacts on cumulative case in Texas using GWR, emphasized that there is a lack of country level research on COVID-19 GWR modeling. The findings should make an important contribution to policymakers to enable them to prepare measures and strategize against this disease. A novel contribution of the research is the use of GWR methods to examine the role of climate and social factors in the spread and variation of COVID-19 in Iraqi governorates.

2 Materials and methods

2.1 Data

Data of daily the affected people with COVID-19 in each Iraqi governorate were collected from daily announcements of Iraqi Ministry of Health [12]. The data collected started from 24th of February, which is the first day of COVID-19 detection in Iraq to 31st of December 2021. Daily data of weather elements (air temperature, relative humidity, dewpoint, atmospheric pressure, visibility and wind speed) across weather stations in the country were obtained using "worldmet" package of R programming [13]. Surface meteorological data of Iraqi weather stations were downloaded by the package from NOAA Integrated Surface Database (ISD). The sociodemographic data such as health index, density, urbanization and mean years of schooling were downloaded from Global Data Lab, Institute for Management Research, Radboud University [14]. For Covid-19 and socioeconomic variables all 18 governorates of Iraq used in the research, but for climatic variables because of having a huge gap in the climatic data we used 16 Iraqi governorates.

2.2 Statistical analysis

In the R_0 estimations, to make an accurate rate of transmission, only those data after 30 cases of COVID-19 were reported in each governorate was used [10]. The basic R_0 transmissibility projection based on Cori's et al. [15] framework was adopted in this study (Eq. 1). This method generates robust analytical speculates of R. If the result of R_0 is higher than 1, it means the virus is spreading rapidly [16]. This estimate of R_t from time series of cases provides the R_0 of the endemic [15].

Association between R_0 of the daily confirmed cases of COVID-19 of Iraqi governorates 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) methods were applied to quantify the linear and spatial relationships. We examined climatic variables and the new number of Covid-19 infections during the same day for Iraqi governorates. Because maybe the climatic variables do not affect the infection of the virus during the same day we examined this association between the climatic variables and the number of Covid-19 infections after 3 days (lag3), after 7 days (lag7) and after the 14 days (lag14).

Statistical analyses were executed in R programming (e.i. spgwr [17] and sp [18] packages). In this study GWR, multivariate regression was performed and preferred over univariate regression. GWR is localized regression suggested by Brunsdon et al. [19] which assesses non-stationary variables [20]. The model is stated as (Eq. 2) and MLR is expressed as (Eq. 3).

$$R_t = \frac{E[I_t]}{\sum_{s=1}^{t} I_{t-s^{w_s}}} \tag{1}$$

where $E[I_t]$ is the mathematical expectation of the random variabl I_t.

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \epsilon_i \tag{2}$$

where (u_i, v_i) implies the coordinates of the ith point in space, β_0 and β_k are parameters to be estimated, and ϵ_i is the random error term at point i.

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n \tag{3}$$

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

3 Results

3.1 Relationship between daily climatic variables and R_0 of COVID-19 in Iraq

The relationship between daily data of climatic factors and lag7 of the R_0 index of COVID-19 cases in Iraq is depicted in Table 1; Fig. 1. Table 1 indicated that at the global scale, the highest positive regression coefficients with wind speed was on the same day, lag7 and lag14 (0.04) while the highest relationship with air temperature was found on the same day (0.02). With regards to air pressure, the highest coefficient (0.03) was on the same day. Based on GWR at local coefficients, the strongest relationship of wind speed and temperature was on the same day. In general, lag7 performed better than the same day, lag3 and lag14; therefore, we choose lag7 in this research for further analysis.

Based on MLR method and global regression, air pressure ($p = 0.034$) and wind speed ($p = 0.088$) have significant relationship with lag7 of R_0 COVID-19 infection (Table 2). In particular, air temperature and wind speed had a positive relationship with COVID-19 infection and increasing temperature, air pressure and wind speed could potentially increase COVID-19 infection by 0.025, 0.026 and 0.045, respectively, per unit. In contrast, visibility was found to have a negative relationship with COVID-19 infection (Table 2).

Table 1 Summary statistics of GWR coefficient parameter estimates between daily climatic variables and R_0 of COVID-19 in Iraq

		Intercept.	Wind speed	Average temperature	Visibility	Dewpoint	Air pressure	Relative humidity
Sameday	Min.	− 41.198	0.045	0.025	− 0.000022	− 0.046	0.019	− 0.006
	Median	− 23.595	0.052	0.036	− 0.000008	− 0.011	0.024	0.003
	Max	− 19.959	0.058	0.054	− 0.000002	0.024	0.041	0.015
	P-value	0	0	0	0	0	0	0
	Global	− 26.03	0.04	0.02	0.00	0.01	0.03	0.00
lag3	Min.	− 9.428	0.008	-0.008	0.000038	− 0.058	− 0.022	− 0.009
	Median	7.068	0.024	0.008	0.000045	− 0.023	− 0.006	0.002
	Max.	22.505	0.052	0.021	0.000075	0.025	0.010	0.013
	P-value	0.00	0.00	0.31	0.00	0.00	0.00	0.00
	Global	3.09	0.03	0.00	0.00	− 0.01	0.00	0.00
lag7	Min.	− 3.874	0.035	0.009	0.000039	− 0.013	− 0.002	0.001
	Median	− 0.306	0.046	0.011	0.000041	− 0.007	0.001	0.004
	Max.	2.110	0.051	0.013	0.000042	0.004	0.004	0.006
	P-value	0	0	0	0	0	0	0
	Global	− 0.60	0.04	0.01	0.00	0.00	0.00	0.00
lag14	Min.	6.961	0.025	0.012	0.000003	− 0.071	− 0.017	0.001
	Median	11.316	0.033	0.019	0.000013	− 0.031	− 0.011	0.007
	Max.	16.103	0.064	0.049	0.000033	− 0.0003	− 0.006	0.022
	P-value	0	0	0	0	0	0	0
	Global	10.22	0.04	0.01	0.00	− 0.01	− 0.01	0.00

Table 2 Statistics of regression between climatic variables and sameday R_0 of COVID-19 in Iraq based on the Multiple Linear Regression method

	Estimate	Std. error	t value	Pr (>|t|)
Intercept	− 26.031	12.894	− 2.02	0.044*
ws	0.045	0.026	1.71	0.088.
Temp	0.025	0.022	1.14	0.255
Viss	− 0.00001	0.00005	− 0.27	0.784
Dew	0.005	0.022	0.23	0.816
Pre	0.026	0.012	2.12	0.034*
rh	− 0.002	0.009	− 0.27	0.790

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

At local coefficients, the GWR method showed a positive coefficient COVID-19 infection with wind speed (0.02–0.051), temperature (0–0.02), visibility (0–0.01) and relative humidity (rh) in all Iraqi Governorates (Fig. 1). Regarding air pressure and dew point, the relationship varies, as there are positive as well as negative relationships in different cities.

3.2 Relationship between the sociodemographic variables and COVID-19 infection of Iraq

After assessing the relationship between weather variables and R0 of COVID-19 infection in the last section,

we selected a list of sociodemographic variables to analyses how they are associated with a cumulative number of COVID-19 infections in Iraqi Governorates. On a global scale, as Table 3 indicated, COVID-19 infection has a positive relationship with seven of the variables assessed, such as density (*P*-value < 0.01), human development index and the number population of the governorates.

In contrast, negative relationships were observed with four of the sociodemographic variables such as standard of living index, education index, and having piped water. This means the risk of COVID-19 infection reduces in cities with high education index and availability of piped water, compared to cities with a low education index and less availability of piped water. However, based on LMS method the association between sociodemographic variables and COVID-19 infection was only statistically significant with population density (*P* < 0.01).

GWR method shows that the relationship between sociodemographic variables and the number of COVID-19 infections does not strongly vary spatially. Number of population is the only variable that shows a striking difference in terms of the relationship with COVID-19 infection. A negative relationship was found in southern parts of the country. However, a positive GWR coefficient was found in northern Iraq (Table 4; Fig. 2). Regression coefficients of the urbanization, human development index and population density are positive and do not vary significantly around the cities for the entire country.

Fig. 1 GWR of lag7 R_0 of COVID-19 in Iraqi Governorates and daily climatic data. **a** Wind speed, **b** average air temperature, **c** visibility, **d** dewpoint, **e** atmospheric pressure and **f** relative humidity
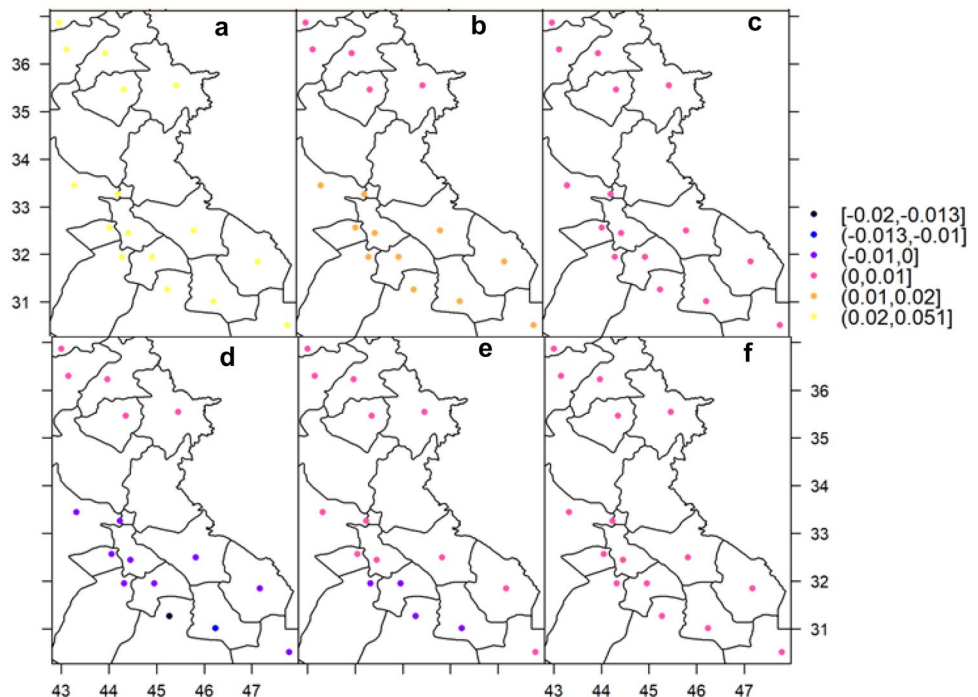
Table 3 Statistics of regression between sociodemographic variables and COVID-19 infection of Iraq based on the Multiple Linear Regression method

	Estimate	Std. error	t value	Pr (>|t|)
(Intercept)	3,759,100	6,276,087	0.60	0.5711
a	3,338,636	4,174,408	0.80	0.4543
b	1,920,829	20,088,989	0.10	0.9269
c	− 4,631,187	8,716,676	− 0.53	0.6143
d	− 1,812,658	1,738,884	− 1.04	0.3374
e	− 53,453	269,636	− 0.20	0.8494
f	51	84	0.60	0.5683
g	− 1021	877	− 0.16	0.2888
h	17,382	22,205	0.78	0.4635
i	24,981	14,402	1.73	0.1335
j	443	1040	0.43	0.6848
k	262	46	5.71	0.0012**

(a) Human Development Index, (b) Health Index, (c) Standard of Living Index, (d) Education Index, (e) Life expectancy, (f) Gross National Income per Capita, (g) % Piped water, (h) % Pop 65+, (i) Population in millions, (j) Urbanization, (k) Density

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

Table 4 Parameter coefficients of the multivariate regression model between sociodemographic variables and COVID-19 infection of Iraq based on the GWR method

	Min.	Median	Max.	*P*-value
Intercept	3,427,005	7,823,990	10,737,878	0.15
a	2,375,934	2,777,869	3,583,718	0.21
b	− 16,469,861	− 7,300,561	10,869,594	0.15
c	− 16,929,701	− 12,069,990	− 6,162,221	0.45
d	− 2,022,902	− 1,711,804	− 1,383,502	0.18
e	− 181,393	69,897	197,090	0.15
f	61	118	168	0.39
g	− 749	96	567	0.56
h	6804	24,594	29,014	0.37
i	19,147	37,745	54,163	0.14
j	6	124	1075	0.22
k	193	226	290	0.15

(a) Human Development Index, (b) Health Index, (c) Standard of Living Index, (d) Education Index, (e) Life expectancy, (f) Gross National Income per Capita, (g) % Piped water, (h) % Pop 65+, (i) Population in millions, (j) Urbanization, (k) Density

4 Discussion

In this study, the correlation between weather and climatic variables (e.g. air temperature, relative humidity, dew point, atmospheric pressure, visibility and wind speed), sociodemographic variables (e.g. human development index, health index, standard of living index, population numbers, urbanization, education index, density etc.) and their corresponding records of the COVID-19 infection were analysed in Iraq. Weather factors and sociodemographic variables can trigger the spread of Coronavirus infection [6, 9, 21].

In general, this research shows that the lag7 of COVID-19's R_0 performed better than the same day, lag3 and lag14. Based on global regression, wind speed significantly ($P = 0.088$) and positively correlated with R0 COVID-19 infection. It is also significantly correlated with air pressure ($P = 0.034$), however, covid-19 infection is not sensitive to air temperature in Iraqi cities because the peak of covid-19 infection occurred during the summer and winter and the regression with temperature is not statistically significant. Local coefficients of COVID-19 infection with wind speed and air temperature based on GWR method show a positive coefficient in all sixteen assessed governorates of Iraq.

A study by Tosepu et al. (2020) who studied the correlation between weather and COVID-19 pandemic in Jakarta, Indonesia found that only average temperature significantly correlated with COVID-19 pandemic ($r = 0.392$, $P < 0.01$). Another study by Bashir et al. (2020) found that both average temperature, minimum temperature and air quality have a significant correlation with COVID-19 epidemic in New York, United State of America (USA). These findings are supporting the view that presently there is no scientific evidence yet that warm weather would reduce COVID-19 epidemic [21, 22].

Furthermore, the relationships between the 11 potential sociodemographic characteristics of the referenced population and their corresponding records of COVID-19 infection were investigated. The results indicated that (based on MLR method) the relationships between sociodemographic variables and COVID-19 infection were statistically significant and strongly positive with population density ($P < 0.01$). Based on GWR this positive association does not vary around the cities in Iraq (Table 3; Fig. 2).

Our result on the relationship between population density and Coronavirus infection is similar to the findings of Rashed et al. (2020) who studied the influence of absolute humidity, temperature and population density on COVID-19 spread and decay durations in Japan, discovered that population density was shown to be a major factor, affecting the spread and decay patterns [23]. Similarly, a study on COVID-19 pandemic which calculates the relative risk of the importation and exportation of the COVID-19 virus from every airport in local municipalities around the world, based on global spatial and mapping information demonstrates that a larger reduction in air travel (in high risk areas) through airports would lead to a gradual decrease in the risk flow. They further emphasized that airport management or government with airports in their jurisdiction should employ stringent countermeasures [24].

One of the most important contributions of this study is that it offers some important insights into the influence

Fig. 2 Relationship of total infection of COVID-19 in Iraqi Governorates and socio-economic variables. (a) Human Development Index, (b) Health Index, (c) Standard of Living Index, (d) Education Index, (e) Life expectancy, (f) Gross National Income per Capita, (g) % Piped water, (h) % Pop 65+, (i) Population in millions, (j) Urbanization, (k) Density
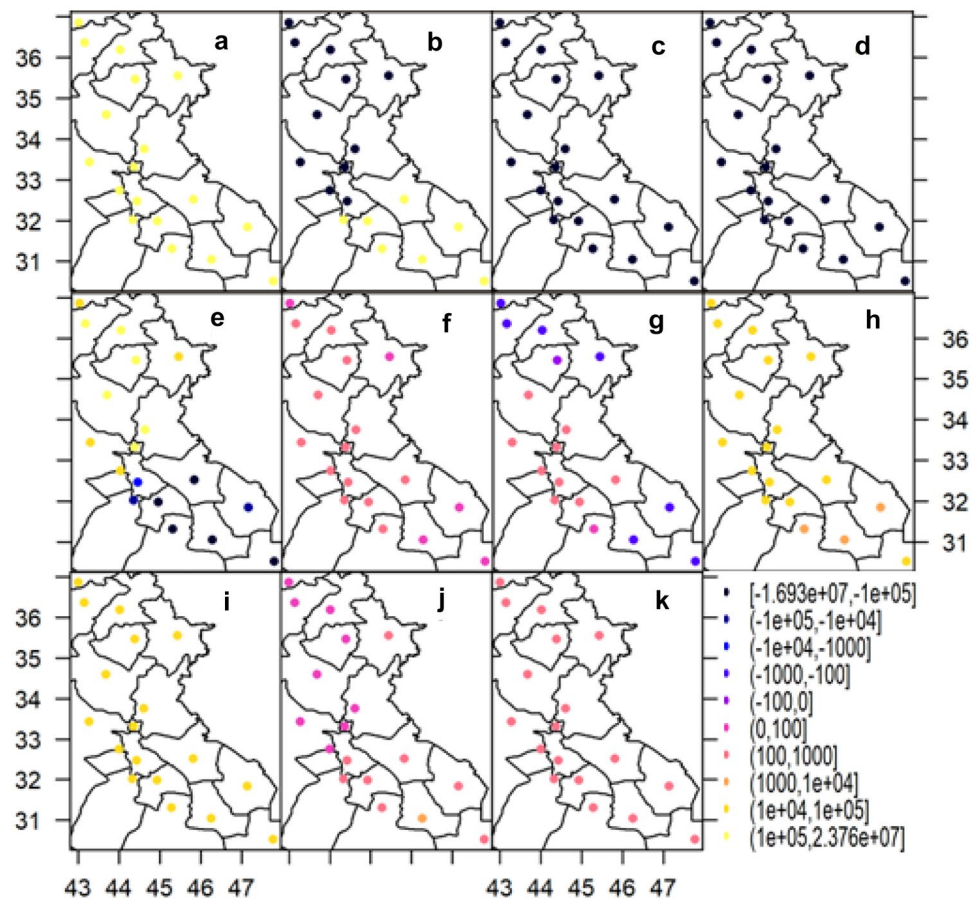
of varied environmental factors, climatic extremity and sociodemographic factors for assessing their influence on COVID-19 infection in Iraq. This is a holistic approach and therefore remarkable at the time policymakers are looking for options to design mitigation policies to contain and prevent this disease. The influence of seasonality on COVID-19 is still uncertain. Some studies have so far postulated that there is a likelihood for a seasonality-sensitive subsequent waves of infections about one year after the initial outbreak [22]. This means that due attention requests to be on policy design in order to flatten the curve. Specifically, there is a requirement to design policies on the most important sociodemographic factors as revealed by this study, such as those on travel restrictions and social distancing.

5 Conclusion

This study set out to evaluate the influence of weather and climate, and sociodemographic variables on COVID-19 infection in Iraq, using the GWR and MLR method. The main findings were that among weather variables increasing wind speed leads to risen COVID-19 infection however covid-19 infection is not sensitive to air

temperature in Iraqi cities because the peak of covid-19 infection occurred during the summer and winter. Among sociodemographic variables, population density leads to more high COVID-19 infection than others ($P < 0.01$). In contrast, COVID-19 infections declined in cities with high health index and access to piped water.

This study recommends to policymakers the need for due attention, proper control and prevention, specifically, there is a need to design or strengthen policies on the most important sociodemographic factors as revealed in this study, such as social distancing. We acknowledged the limitation of our study due to uncertainties arising from the data, for example given the delays in the development of symptoms and testing of the infected persons, which may lead to under-accounting of the confirmed cases.

Data availability 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.

Declarations

Conflict of interest The authors declare no conflict of interest.

Consent to participate Not applicable.

Consent for publication Not applicable.

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

References

1. Eker, S. (2020). Validity and usefulness of COVID-19 models. *Humanities and Social Sciences Communications, 7*(1), 1–5. https://doi.org/10.1057/s41599-020-00553-4
2. Caspi, G., Shalit, U., Kristensen, S. L., Aronson, D., Caspi, L., Rossenberg, O., Shina, A., & Caspi, O. (2020). Climate effect on COVID-19 spread rate: An online surveillance tool. *MedRxiv*. https://doi.org/10.1101/2020.03.26.20044727
3. Bukhari, Q., & Jameel, Y. (2020). *Will coronavirus pandemic diminish by summer*? Available at SSRN 3556998. https://doi.org/10.2139/ssrn.3556998
4. Sajadi, M. M., Habibzadeh, P., Vintzileos, A., Shokouhi, S., Miralles-Wilhelm, F., & Amoroso, A. (2020). *Temperature, humidity, and latitude analysis to predict potential spread and seasonality for COVID-19*. Social Science Research Network. https://doi.org/10.2139/ssrn.3550308
5. Rasul, A., & Balzter, H. (2022). The role of climate in the spread of COVID-19 in different latitudes across the world. *COVID, 2*(9), 1183–1192. https://doi.org/10.3390/covid2090085
6. Ahmadi, M., Sharifi, A., Dorosti, S., Ghoushchi, S. J., & Ghanbari, N. (2020). *Investigation of effective climatology parameters on COVID-19 outbreak in Iran* (p. 138705). Science of the Total Environment. https://doi.org/10.1016/j.scitotenv.2020.138705
7. Wang, J., Tang, K., Feng, K., & Lv, W. (2020). *High temperature and high humidity reduce the transmission of COVID-19*. Available at SSRN 3551767.
8. Rosario, D. K., Mutz, Y. S., Bernardes, P. C., & Conte-Junior, C. A. (2020). Relationship between COVID-19 and weather: Case study in a tropical country. *International Journal of Hygiene and Environmental Health, 229*, 113587. https://doi.org/10.1016/j.ijheh.2020.113587
9. Tosepu, R., Gunawan, J., Effendy, D. S., Lestari, H., Bahar, H., & Asfian, P. (2020). *Correlation between weather and Covid-19 pandemic in Jakarta Indonesia* (p. 138456). Science of the Total Environment.
10. Smit, A. J., Fitchett, J. M., Engelbrecht, F. A., Scholes, R. J., Dzhivhuho, G., & Sweijd, N. A. (2020). Winter is coming: A southern hemisphere perspective of the environmental drivers of SARS-CoV-2 and the potential seasonality of COVID-19. *International Journal of Environmental Research and Public Health, 17*(16), 5634.
11. Wu, X., & Zhang, J. (2021). *Exploration of spatial-temporal varying impacts on COVID-19 cumulative case in Texas using geographically weighted regression (GWR)* (pp. 1–15). Environmental Science and Pollution Research. https://doi.org/10.1007/s11356-021-13653-8
12. moh.gov.iq (2022). The daily epidemiological situation of the new Corona pandemic in Iraq. https://Moh.Gov.Iq/. https://moh.gov.iq/
13. Carslaw, D. (2021). *Worldmet: Import surface meteorological data from NOAA integrated surface database (ISD). R package*.
14. GDL (2022). *Global data lab—innovative instruments for turning data into knowledge*. https://globaldatalab.org/.
15. Cori, A., Ferguson, N. M., Fraser, C., & Cauchemez, S. (2013). A new framework and software to estimate time-varying reproduction numbers during epidemics. *American Journal of Epidemiology, 178*(9), 1505–1512.
16. Team, W. E. R. (2014). Ebola virus disease in West Africa—the first 9 months of the epidemic and forward projections. *New England Journal of Medicine, 371*(16), 1481–1495.
17. Bivand, R., Yu, D., Nakaya, T., & Garcia-Lopez, M. A. (2022). *Package 'spgwr'. 2015*.
18. Pebesma, E., Bivand, R., Rowlingson, B., Gomez-Rubio, V., Hijmans, R., Sumner, M., MacQueen, D., Lemon, J., Lindgren, F., O'Brien, J., & O'Rourke, J. (2022). *sp: Classes and Methods for Spatial Data* (1.5-0). https://CRAN.R-project.org/package=sp.
19. Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis, 28*(4), 281–298.
20. Zhou, X., & WANG, Y. C. (2011). Dynamics of land surface temperature in response to land-use/cover change. *Geographical Research, 49*(1), 23–36.
21. Bashir, M. F., Ma, B., Komal, B., Bashir, M. A., Tan, D., & Bashir, M. (2020). *Correlation between climate indicators and COVID-19 pandemic in New York, USA* (p. 138835). Science of The Total Environment. https://doi.org/10.1016/j.scitotenv.2020.138835
22. Engelbrecht, F. A., & Scholes, R. J. (2020). *Test for Covid-19 seasonality and the risk of second waves*. https://doi.org/10.1016/j.onehlt.2020.100202
23. Rashed, E. A., Kodera, S., Gomez-Tames, J., & Hirata, A. (2020). Influence of absolute humidity, temperature and population density on COVID-19 spread and decay durations: Multi-prefecture study in Japan. *International Journal of Environmental Research and Public Health, 17*(15), 5354.
24. Nakamura, H., & Managi, S. (2020). Airport risk of importation and exportation of the COVID-19 pandemic. *Transport Policy, 96*, 40–47.