Investigating of climate factors associated with the number of COVID-19 incidences in Saudi Arabia

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Abstract: This study investigates the possible association between the climate variables of daily average temperature (°C), relative humidity (%), wind speed (mph), air pressure (mmHg), and the number of COVID-19 incidents in five main cities in Saudi Arabia. Furthermore, other non-climate factors that might influence the number of COVID-19 incidents, such as region, day type, and conducted number of COVID-19 tests (massive testing levels), are included in the model. A negative binomial regression model is applied to study the association between the climate and non-climate factors affecting COVID-19 cases for 75 days with an average temperature range of (18–36)°C. Results show significant findings that the only climate factor affecting the COVID-19 numbers is the average daily temperature. The regression model shows a significant positive association between average daily temperature and the COVID-19 incidents by increasing 6.1% in the number of COVID-19 cases for each extra 1°C average temperature increase.

Keywords: COVID-19 spread in warm weather; COVID-19 and climate; negative binomial regression; data mining; indoor climate and COVID-19; high temperature; Saudi weather; massive tests and spread of COVID-19; humidity effect on COVID-19; COVID-19 cases predictions.

Reference to this paper should be made as follows: Alkabaa A.S. (2021) 'Investigating of climate factors associated with the number of COVID-19 incidences in Saudi Arabia', *Int. J. Environment and Health*, Vol. 10, Nos. 3/4, pp.195–212.

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1 Introduction

In December 2019, a novel viral infection spread in Wuhan, China. Since then, it has been determined as a zoonotic coronavirus from the family of Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) (Lu et al., 2020) and Medial East Raspatory Syndrome (MERS) coronavirus (Zaki et al., 2012) and named COVID-19. The World Health Organization (WHO) has declared COVID-19 as a pandemic affecting the entire globe on March 11, 2020 (WHO, 2020a). Its rate of contagion has increased exponentially and caused a pandemic fear and large-scale quarantines, isolations, travel restrictions, and social-distancing. To control the pandemic, most countries have been applying new rules and policies to reduce the cases of COVID-19 incidents at any given time (flattening the curve) or even decrease the mortality rate. Moreover, several studies from different fields are being conducted and analysed to understand and identify the COVID-19 symptoms, transmission behaviour, and potential treatments. On May 19, 2020, WHO reported 4,735,622 confirmed cases of COVID-19, including 316,289 deaths all over the world (WHO, 2020b). On the other hand, experts are concerned that many cases were not declared or identified. The number of confirmed cases and deaths are varied across different countries. Given these variations of confirmed cases based on different countries and their climate, it seems rational to consider several important weather factors such as temperature, humidity, wind speed, and air pressure, which are associated with the COVID-19 incidents (Bi et al., 2007; Casanova et al., 2010; Chan et al., 2011; Tan et al., 2005; Doremalen et al., 2013).

Viruses can be transmitted by means of several variables, including weather variables such as temperature, humidity, wind speed, and air pressure (Dalziel et al., 2018; Yuan et al., 2006; Adnan et al., 2021). Climate changing patterns are highly associated with pneumonia's mortality rates (Bull, 1980). The prevalence of COVID-19 is correlated seasonally with humidity and temperature (Sajadi et al., 2020; Wang et al., 2020). The spread of COVID- 19 from Wuhan city in China addresses a significant correlation between disease prevalence and weather conditions. Another study by Ma et al. (2020) and Poole (2020) shows that the humidity and temperature might substantially influence the COVID-19's mortality. A study by Tan et al. (2005), Van et al. (2013) and Li et al. (2020) finds the real correlation between the spread of respiratory syncytial virus (RSV) and SARS and climate variables is significant. A regression model proposed by Yuan et al. (2006) describes how the effects of temperature, humidity, and wind speed reduce SARS spread. Climate factors are likely to be indirectly associated with the transmission of respiratory viruses, but the exploration of non-climate factors is critical.

It is essential to shade the light and infer to the readers that how the mechanism of impatient high temperature and other environmental factors can affect cells and gene expression to stimulate the receptor of COVID-19 in the blood system (Ahmadi Hedayati, 2020). Climate variables are likely to be indirectly associated with transmission of respiratory viruses, but exploration of non-climate factors is extremely important.

This research aims to investigate the possible association between different weather factors and the number of COVID-19 cases in Saudi Arabia. Other important variables such as region, day type, and mass testing, are included in the investigation and the model. Additionally, a negative binomial regression model on the confirmed cases of COVID-19 across different Saudi Arabian provinces is applied.

The findings from this study will help to understand the COVID-19 transmissibility behaviours, based on the influence of climate factors, and to guide the implementation of prioritised prevention and control measures. Moreover, the climate of Saudi Arabia is generally classified as desert, and very hot in the summer. Therefore, the results of this study are significant when the summer and warm weather arrive in other countries during the pandemic.

2 Materials and method

2.1 Study area

The study area includes five major cities in Saudi Arabia that have varieties of weather factors. The specific selection of these areas considered various weather, geographical, and population factors. Table 1 shows the locations, latitudes, populations, and averages of climate variables throughout these five cities' study.

Table 1 Study area of COVID-19 cases and averages of climate variables

City	*Location*	*Latitude*	*population*	*Averages of environmental variables* Temp. (°C)	Humd. %	W.S. (mph)	Pres. (hg)
Riyadh	On a desert plateau in the country's centre	24.7136° N, 46.6753° E	5,236,901	28.14	26.91	12.12	941.59
Jeddah	West of the country and on Red sea	21.4858° N, 39.1925° E	3,456,259	28.38	50.44	14.47	1008.69
Madinah	Mid north west of the country	24.5247° N, 39.5692° E	1,152,991	29.05	16.69	12.29	937.27
Dammam	East of the country and on Gulf sea	26.4207° N, 50.0888° E	1,244,009	28.18	40.48	15.41	1007.47
Taif	Southwest of the country	21.2841° N, 40.4248° E	884,597	23.69	34.12	16.25	853.41

2.2 Data gathering

Data of the confirmed cases of COVID-19 are collected daily from the Ministry of Health in Saudi Arabia (https://covid19.moh.gov.sa/) and King Abdullah Petroleum Studies and Research Center (https://datasource.kapsarc.org/pages/eechartbook/). The first confirmed case of COVID-19 was detected in Saudi Arabia on March 02, 2020. Therefore, the spread of COVID-19 started after three months from the source of the virus, in Wuhan China, in late December 2019. Table 2 summarises the counts of COVID-19 incidence for the study period of this research as of May 27, 2020.

The data in Table 2 describes that the highest number of cases are in Riyadh, followed by Jeddah, Medina, Dammam, and Taif. These five cities represent approximately 60 % of the total cases in Saudi Arabia. It is notable that Riyadh is highest rate of infection in Saudi Arabia, with 22.6% of the total confirmed cases in the country. According to the COVID-19 Community Mobility Report by Google, Riyadh appears the highest mobility rate in Saudi Arabia. It represents a percentage of + 27% in the residents' mobility (COVID-19 Google Community Mobility Report reports in May 2020- Saudi Arabia). Namely, Riyadh's high number of mobility percentages may provide some explanations for the maximum number of COVID-19 incidents in this city compared to other cities in the country (Tosepo et al., 2020). The median incubation period of COVID-19 is reported to be four days (Guan et al., 2020; Li et al., 2020; Nishiura et al., 2020); therefore, all explanatory variables involved in the model are lagged four days later.

Table 2 Number of COVID-19 incidences in each city as of 27 May, 2020

City	*COVID-19 incidences*
Riyadh	17,762
Jeddah	13,140
Madinah	9350
Dammam	4915
Taif	1667

2.3 Climate data

Climate data are gathered for the study period of March 2020 to May 2020 for each city, from weather underground (https://www.wunderground.com/). Average climate variables involve daily averages of temperature (°C), relative humidity (%), wind speed (mph), and air pressure (mmHg).

2.4 Non-climate data

Since the first confirmed case of COVID-19 in Saudi Arabia, several rules and policies have been applied to control and limit the virus spread. Specifically, the government closed all schools, mosques, businesses, malls, and banned all domestic and international flights.

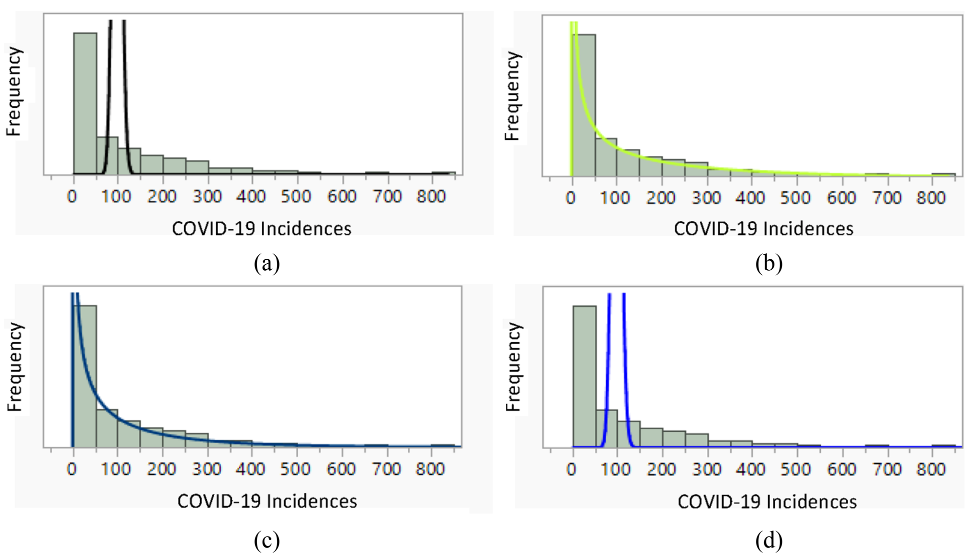
Other vital factors are essential for the statistical model in addition to the potential influence of the climate variables on the number of COVID-19 incidence. The proposed model should account for all possible factors that may affect the number of COVID-19 incidence to improve the model's reliability and credibility. Region variable is introduced in the statistical models as a nominal variable, and coded as (1 = Damam, 2 = Jeddah, 3 = Madinah, 4 = Riyadh, and 5 = Taif)

Variables of non-climate, for each city, are day types and mass COVID-19 tests. The data are obtained from the Ministry of Health, official news, and the Ministry of the Interior (https://www.moi.gov.sa/). Table 3 describes these factors in more detail. It is important to mention that mass testing levels gradually increased from March to May. The Ministry of Health imports new testing resources and applies COVID-19 testing in more affected areas. Moreover, the factor of day types (weekdays and weekends) is included in the model to investigate the possible increase of social gathering during weekends, and hence it might be reflected in the COVID-19 confirmed cases.

Table 3 Non-climate factors

Factor name	*Factor classification*	*Factor representation*
Region	Categorical – Nominal	1 = Dammam
		2 = Jeddah
		3 = Madinah
		4 = Riyadh
		5 = Taif
Day type	Categorical – Nominal	0 = weekdays
		1 = otherwise
Massive test level	Categorical – Ordinal	0 = No COVID-19 tests on site
		1 = COVID-19 tests < 5000
		3 = expanded COVID-19 tests > 15000

Figure 1 Fitting different discrete probability distribution curves on the confirmed COVID-19 incidences histogram: (a) fitting a binomial distribution curve on the COVID-19 incidences histogram; (b) fitting a beta binomial distribution curve on the COVID-19 incidences histogram; (c) fitting a NB distribution curve on the COVID-19 incidences histogram and (d) fitting a Poisson distribution curve on the COVID-19 incidences histogram (see online version for colours)



2.5 *Statistical modelling and analysis*

The daily numbers of confirmed COVID-19 cases at each city are non-negative integers such as 0, 1, 2, 3, and 4. At first glance, these numbers are assumed to follow Poisson distribution and therefore, the best cause and effect model is Poisson regression. From the statistical distribution analysis, however, the probability distribution of the daily numbers of confirmed COVID-19 cases at each city should be tested for the best distribution family. The histogram in Figure 1 depicts fitting curves from several discrete probability distributions. It can be seen that the best fitting distribution curve is for the negative binomial in Figure 1(b). Consequently, the quantitative and graphical testing procedures show that the best-fitting probability distribution on the confirmed number of COVID-19 cases is the negative binomial regression model. For more information regarding negative binomial regression, the readers are guided to Agresti (2018) and McCullagh and Nelder (1989).

2.6 *Negative binomial regression model*

The negative binomial distribution is applied to the non-negative integer values. Unlike the Poisson distribution, it includes one more term that is called overdispersion. It also intends to model a regression when the count data's variance is larger than its mean. The negative binomial results are a type of mixture of Poisson distributions that do not make the variance = mean assumption about the data.

Negative binomial regression is a model of generalised linear models (GLMs) for counts expressing the mean parameter λ in terms of independent variables x_j. That is, the confirmed number of COVID-19 cases is described by the factors of weather and other additional non-climate variables considered in this study. The negative binomial regression equation is represented in equation (1).

$$\log(\mu) = \left(\alpha + \sum_{j=1}^{k} \beta_j x_{ij} \right) \qquad i = 1, 2, \ldots, n \tag{1}$$

where link function $\log(\mu)$ models the log of the mean of the response variable μ, which is the number of daily COVID-19 cases. The log function uses non-negative integer numbers. Thus, the log function applies when μ is positive, such as with count data. The variable n expresses number of cases, α is the constant term or the intercept, x_{ij} denotes the ith level of variable x_j, and β_j represents the coefficient for each j factor.

The interpretation of the negative binomial regression equation (1) is that a one-unit increase in x has a multiplicative effect of e^{β} on λ: The mean μ at $x + 1$ equals μ at x multiplied by e^{β}. In other words, if there is no effect from an explanatory variable, a coefficient β will be equal 0, then $e^{\beta} = e^{\circ} = 1$ and the multiplicative factor is 1. Thus, the mean μ of the number of COVID-19 cases does not change as x changes. In contrast, if $\beta > 0$, then $e^{\beta} > 1$, and the mean μ increases as x increases, whereas if $\beta < 0$, the mean decreases as x increases.

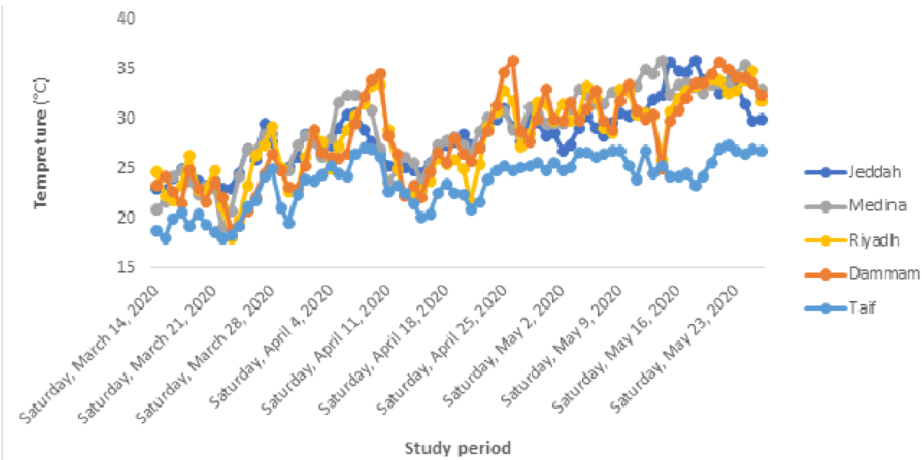
In modelling and analysing the dependent (daily number of covid-19 cases) and independent variables (climate and non-climate variables) in this study, the following model is represented in equation (2):

$$\begin{aligned} \log(\text{Num.of. COVID19}) = {} & \beta_0 + \beta_1 * (\text{temp}) + \beta_2 * (\log\_\text{humid}) \\ & + \beta_3 * (\log\_\text{windsped}) + \beta_4 * (\log\_\text{presr}) \\ & + \beta_5 * (\text{Regin}) + \beta_6 * (\text{Day\_type}) + \beta_7 * (\text{Massiv\_test}) \end{aligned} \tag{2}$$

3 Results and discussion

A negative binomial regression model is applied in this study to investigate potential causes and effects of weather and non-climate variables on the counts of COVID-19 incidents in five main cities in Saudi Arabia. The study covers the period from 14 March to 27 May, 2020, with a total of 370 observations. Figure 2 shows the variation patterns of the daily average temperatures in the five cities, which presents the coverage of different climate regions in the study.

Figure 2 Variations in daily average temperatures in five main cites in Saudi Arabia from the period of 14 March to 26 May, 2020 (see online version for colours)



Descriptive statistics for COVID-19 incident counts and weather factors are summarised in Table 4. The number of days (N) is 370, which is a time series dataset that would be the number of days i.e., 74 days by five locations, with the average COVID-19 incidence being 123.35. The average daily temperature, relative humidity, wind speed, and air pressure are 27.49°C, 33.73%, 949.69 mmHg, and 4.47 mph.

Table 4 Descriptive statistic of COVID-19 confirmed cases and weather variables across all five cities

		N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
Response	Cases	370	0	856	123.3541	164.5445
Weather variables	Temperature (°C)	370	18	36	27.4924	4.23131
	Humidity (%)	370	6.6	72.8	33.7351	15.64695
	Wind speed(mph)	370	5.7	27.9	14.113	4.47184
	Pressure (mmHg)	370	851.3	1014.3	949.69	57.22557

The Omnibus test with likelihood ratio = 640.02 and p-value equals 0.000 shows that the model of all the weather and non-climate factors collectively improve the regression model over the term of intercept only in the model is statistically significance.

After identifying all the independent variables that provide a statistically significant model, it is crucial to investigate which variables from the weather and non-climate variables are statistically significant and affect the number of COVID-19 incidents. The test of model parameter effects in Table 5 presents the statistical significance of each variable in the model. Specifically, the weather variable of temperature is statistically significant, with p-value = 0.023 < 0.05 and the number of COVID-19 incidents in Saudi Arabia. All other climate variables of humidity, wind speed, and pressure, however, are not statistically significant and have no impact on the number of COVID-19 cases. Therefore, from the statistical viewpoint, the effect of the temperature within the range of (18-36)°C is significant. Even though the temperature variable is statistically significant, its p-value < 0.05, it is important that the p-value of the temperature is close to the alpha level of 5%, which does not demonstrate a strong impact of temperature on the number of COVID-19 incidents. In other words, this statistical result should be interpreted in caution due to the nature of uncertainty and confounding data and the variables considered in the research.

Table 5 Test of parameter effects

Source	*Type III*		
	Wald Chi-Square	*df*	*p-value*
(Intercept)	0.778	1	0.378
Day-type	0.566	1	0.452
Region	122.540	4	0.000
Mass-testing-level	188.939	2	0.000
Temperature	5.207	1	0.023
Humidity	0.007	1	0.933
Wind Speed	1.502	1	0.220
Pressure	0.965	1	0.326

The non-climate variables of region and mass testing level are statically significant, with *p*-values of 0.000 < 0.05 for both variables. The factor of day-type does not influence the number of the COVID-19 cases in this study.

The parameter estimates of the effect of each variable in the model are shown in Table 6. The temperature variable has a coefficient estimate of 0.059, representing a positive association between the temperature and COVID-19 incidence. The exponent value, in 'Exp(B)' column, of the coefficient estimate for temperature is 1.061, representing a 6.1% increase in the number of COVID-19 incidents for each extra temperature increase. This finding supports the results of Tan et al. (2005) that the ideal ecological temperature related to SARS cases is 16–28°C, based on records gathered from Hong Kong, Guangzhou, Beijing, and Taiyuan. Moreover, the study by Tosepu et al. (2020) uses the Spearman-rank correlation test to show among different climate variables that the temperature ranges from 24.6–31.4°C and is correlated significantly with COVID-19 cases with a correlation coefficient of $r = 0.392$. Besides, Altamimi and

Ahmed (2020) show that more than half of the MERS-COV cases found to peak in August 2015 with high-temperature raising. A recent study by Auler et al. (2020) addresses a positive association between COVID-19 incidents and average temperatures of 27.5°C and relative humidity near 80% in Brazil (Tropical country).

Table 6 Parameter estimates

			Hypothesis test			*Exp(B)*
Parameter	*B*	*Std. Error*	*Wald Chi-Square*	*df*	*p-value*	
(Intercept)	–32.325	34.5279	0.876	1	0.349	9.149E-15
[Day-type = 1.00]	–0.089	0.1183	0.566	1	0.452	0.915
[Day-type=.00]	0[a]					1
[Region = TIF]	4.149	5.2724	0.619	1	0.431	63.343
[Region = RYD]	3.509	2.2541	2.423	1	0.120	33.399
[Region = MDN]	3.133	2.3809	1.731	1	0.188	22.940
[Region = JED]	0.891	0.1729	26.534	1	0.000	2.437
[Region = DMM]	0[a]					1
[Mass-testing-level = 3.00]	2.255	0.1738	168.260	1	0.000	9.533
[Mass-testing-level = 1.00]	1.700	0.1610	111.436	1	0.000	5.473
[Mass-testing-level=.00]	0[a]					1
Temperature	0.059	0.0264	5.207	1	0.023	1.061
Humidity	0.000	0.0056	0.007	1	0.933	1.000
Wind Speed.	–0.016	0.0133	1.502	1	0.220	0.984
Pressure	0.033	0.0339	0.965	1	0.326	1.034

*set at zero because this is a reference category

Figure 3 displays how changes in temperatures affect the number of COVID-19 cases. Besides, Figure 4 shows the climate variations for different climate variables of Temperature (maximum, minimum) (°C), Avg. Relative Humidity (%), and Avg. Wind Speed (mph) for all regions.

From Table 6, the variable of mass-testing-level = 3, is statistically significant with a p-value of 0.000 higher COVID-19 cases (estimated coefficient of 2.255) than no mass testing conducted in the field (mass-testing-level = 0), the reference category. Thus, the exponent values of the coefficients (the 'Exp(B)' column) is 9.553, which means that the number of COVID-19 cases will be 9.533 times greater than no mass testing conducted in the field (mass-testing-level = 0). The COVID-19 incidence in Jeddah is statistically significant, with a p-value equal to 0.000 and higher by 2.43 times of COVID-19 incidences than in Dammam. In contrast, the variable of day-type (weekday and weekend) has no impact on COVID-19 incidence across all regions. In other words, the number of COVID-19 incidences is not different based on day types.

Figure 3 Relationship between the average temperature and confirmed number of COVID-19 cases across different cities in Saudi Arabia (see online version for colours)

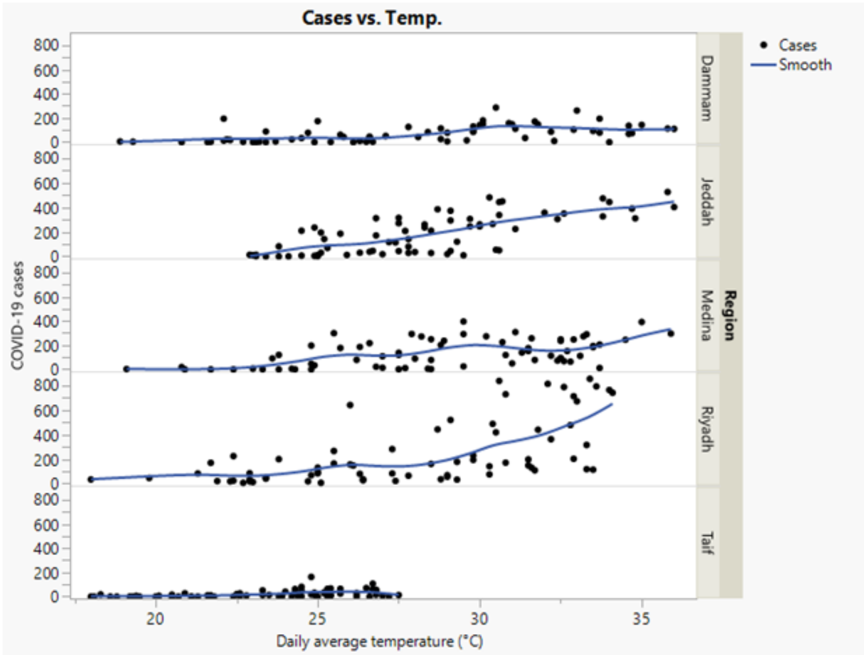
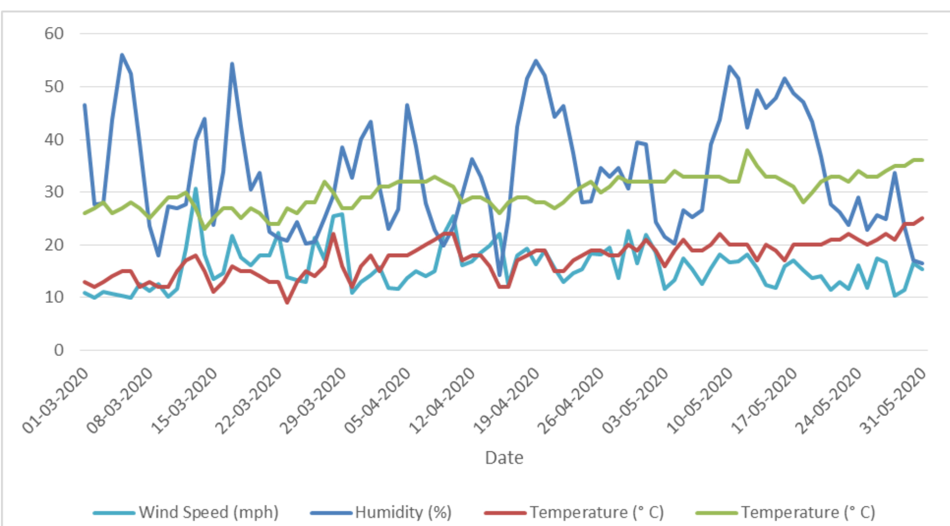
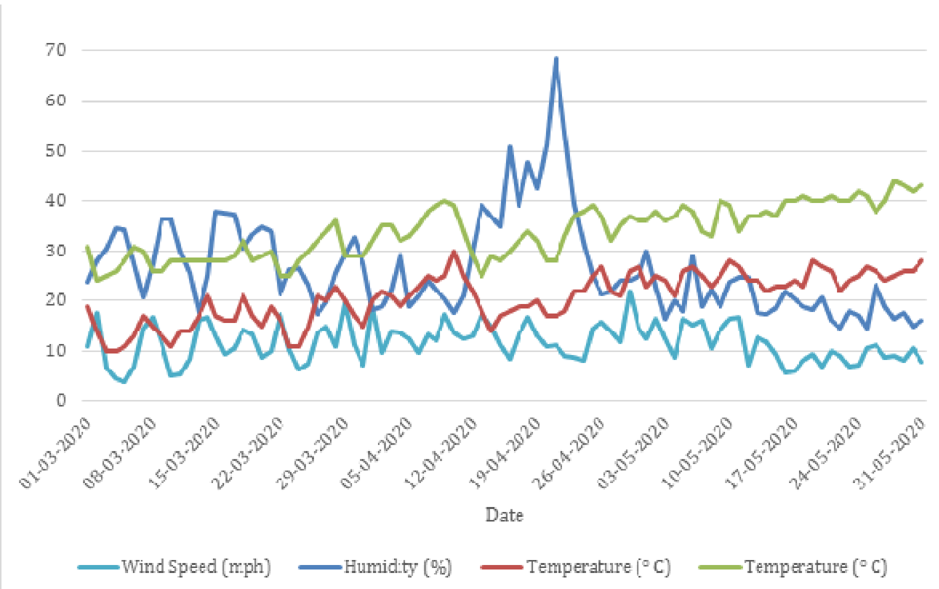


Figure 4 Climate variables of temperature (maximum, minimum) (°C), avg. Relative humidity (%), and avg. Wind speed (mph) for all regions: (a) climate variability in Jeddah from March to May, 2020; (b) Climate variability in Riyadh from March to May, 2020; (c) climate variability in Dammam from March to May, 2020; (d) climate variability in Medina from March to May, 2020 and (e) climate variability in Taif from March to May, 2020 (see online version for colours)

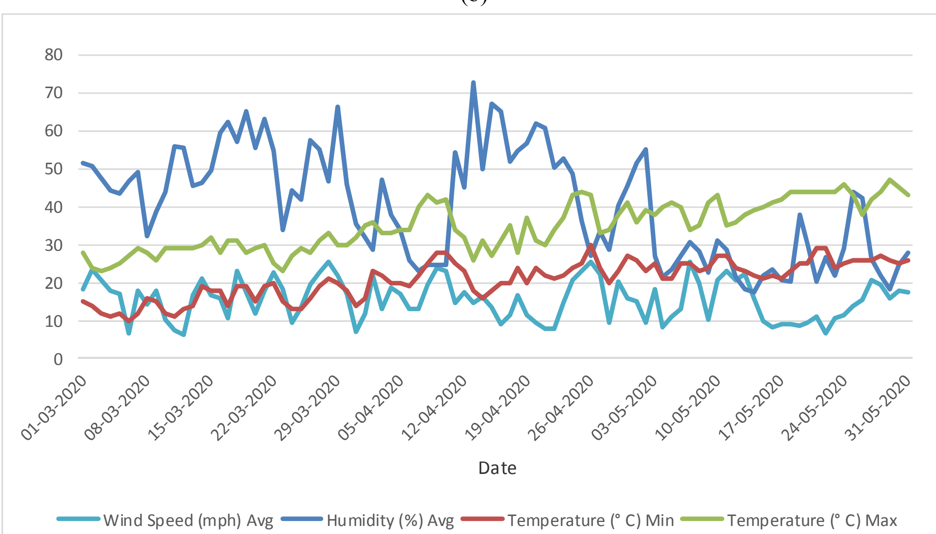


(a)

Figure 4 Climate variables of temperature (maximum, minimum) (°C), avg. Relative humidity (%), and avg. Wind speed (mph) for all regions: (a) climate variability in Jeddah from March to May, 2020; (b) Climate variability in Riyadh from March to May, 2020; (c) climate variability in Dammam from March to May, 2020; (d) climate variability in Medina from March to May, 2020 and (e) climate variability in Taif from March to May, 2020 (see online version for colours) (continued)

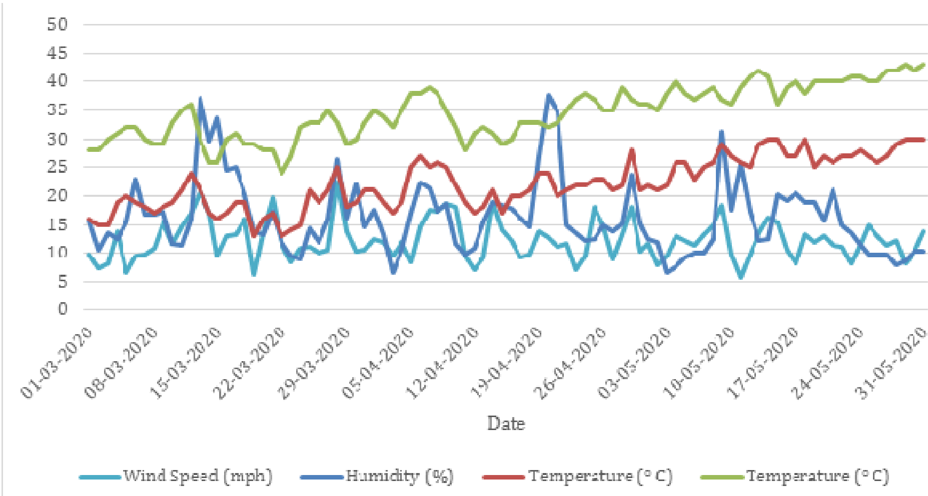


(b)

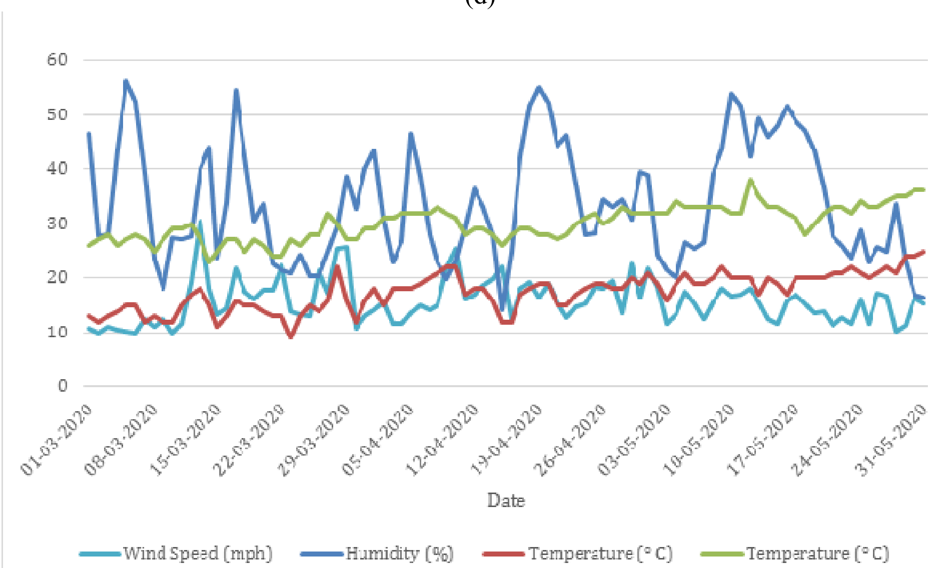


(c)

Figure 4 Climate variables of temperature (maximum, minimum) (°C), avg. Relative humidity (%), and avg. Wind speed (mph) for all regions: (a) climate variability in Jeddah from March to May, 2020; (b) Climate variability in Riyadh from March to May, 2020; (c) climate variability in Dammam from March to May, 2020; (d) climate variability in Medina from March to May, 2020 and (e) climate variability in Taif from March to May, 2020 (see online version for colours) (continued)



(d)



(e)

To explore the differences between regions and COVID-19 cases, Table 7 displays the significant differences between each pair of regions regarding COVID-19 incidences and tests whether each difference between regions is due to chance variation. Although the parameter estimates in Table 6 shows a significance difference (p value 0.000) in the COVID-19 incidences between Jeddah and Taif, this is not the result in Table 7 of pairwise comparisons (p value 0.778, adjusted by the least significant difference). The p values shown in Table 6 are unadjusted for multiple comparisons. The pairwise comparisons report that Riyadh has a statistically significantly more COVID-19 incidents than Dammam by mean difference of 249.77. Besides, Riyadh has a statistically significantly larger COVID-19 incidents than Jeddah by mean difference of 242.96. The other regions of Taif and Medina are not statistically significant (p value < 0.05) compared to Riyadh.

Table 7 Pairwise comparisons between regions and COVID-19 incidences

(I) Region	*(J) Region*	*Mean Difference (I-J)*	*Std. Error*	*df*	*Sig.*	*95% wald confidence interval for difference*	
						Lower	*Upper*
Dammam	Jeddah	–6.8057	14.58655	1	0.641	–35.3948	21.7834
	Medina	–202.9120	105.09246	1	0.054	–408.8894	3.0654
	Riyadh	–249.7709[a]	90.23811	1	0.006	–426.6343	–72.9074
	Taif	–867.9615	3036.12263	1	0.775	–6818.6525	5082.7296
Jeddah	Dammam	6.8057	14.58655	1	0.641	–21.7834	35.3948
	Medina	–196.1063	118.97876	1	0.099	–429.3004	37.0877
	Riyadh	–242.9652[a]	103.77637	1	0.019	–446.3631	–39.5672
	Taif	–861.1558	3050.58886	1	0.778	–6840.2001	5117.8885
Medina	Dammam	202.9120	105.09246	1	0.054	–3.0654	408.8894
	Jeddah	196.1063	118.97876	1	0.099	–37.0877	429.3004
	Riyadh	–46.8588	44.32023	1	0.290	–133.7249	40.0072
	Taif	–665.0494	2937.24803	1	0.821	–6421.9498	5091.8509
Riyadh	Dammam	249.7709[a]	90.23811	1	0.006	72.9074	426.6343
	Jeddah	242.9652[a]	103.77637	1	0.019	39.5672	446.3631
	Medina	46.8588	44.32023	1	0.290	–40.0072	133.7249
	Taif	–618.1906	2953.37268	1	0.834	–6406.6947	5170.3135
Taif	Dammam	867.9615	3036.12263	1	0.775	–5082.7296	6818.6525
	Jeddah	861.1558	3050.58886	1	0.778	–5117.8885	6840.2001
	Medina	665.0494	2937.24803	1	0.821	–5091.8509	6421.9498
	Riyadh	618.1906	2953.37268	1	0.834	–5170.3135	6406.6947

[a]The mean difference is significant at the 0.05 level.

In short, several studies suggest that a high temperature of 38°C leads to inactivation of the coronavirus transmissibility comparing to a low temperature of 4°C and negative correlation between low temperature and COVID-19 cases (Casanova et al., 2010; Chan et al., 2011; Xie and Zhu, 2020; Qi et al., 2020; Livadiotis, 2020; Srivastava, 2020; Doremalen et al., 2013).

However, these studies were conducted in the winter or cold environments, with a maximum average temperature of 26.9°C and different geographical locations (Xie and Zhu, 2020). To the best of the author's knowledge, no studies in the literature attempt to investigate the effects of climate factors on COVID-19 incidences in the Saudi Arabian climate (desert area). Consequently, the temperature can be classified as an essential factor, and further studies in different locations and climates are highly demanded. For the presented datasets, COVID-19 transmission in Saudi Arabia is found to be associated with higher mean temperatures. It is more important to mention that high temperature leads to an increase in indoor gathering rate and activities, such as in shopping malls, workplaces, etc. Several studies by Lee and Chang (2000) and Morgan and De Dear (2003) show indoor average temperatures are generally within the range of 17.2–24°C, which in some way can support the research that claims a positive association between COVID-19 transmission and the low outdoor temperature.

4 Conclusion

This study investigates the possible association between the number of COVID-19 cases and climate factors using a negative binomial regression model. Also, non-climate factors choice in this model increases the reliability and accuracy of the research's contributions. To the best of the author's knowledge, this is the first study to consider the daily mean temperature values from 18°C to 36°C for an extended period of more than two months across different cities in Saudi Arabia with a total of 46,834 COVID-19 confirmed cases. The results show that average daily temperature has a positive association with the number of COVID-19 cases by increasing 6.1% the number of COVID-19 cases for each extra 1°C of temperature increase. Even though our results show that mean temperature is significantly associated with newly confirmed cases with a p-value of 0.023, this finding should not be considered a highly significant result of high temperature. In other words, it provides an important clue as to the temperature factor when considering the COVID-19 cases. The high temperature may be confounded by indoor and outdoor activities in which increase social gatherings and finally lead to a high possibility of COVID-19 transmissibility and cases. It is essential to mention that when colder weather reveals, as in the US and Europe, the COVID-19 cases will be larger than high temperature raises in these countries. The high temperature in these countries encourages people to increase outdoor activities. Hence no social gathering in an indoor environment, and that is not the situation in Saudi Arabia.

In other words, climate variables are potentially associated with mechanisms of viral transmission, mainly where human-to-human or animal transmission occurs. For example, colder or hotter and humid weather may influence human exposures by encouraging more time spent indoors, where the respiratory viral transmission can occur. However, the viral transmission would not happen on its own without an infected human host being exposed to an uninfected susceptible host.

Further research needs to explore the correlation between the contribution of high temperature and indoor activity on viral transmission.

It is important to mention that wearing masks and gloves, and social distancing rules that governments enforce may control and impact COVID-19 cases even in high or low temperatures. Although countries' responding methodologies, policies, and procedures to control and limit the spread of COVID-19, their efforts may mislead and can confound the real association between environmental conditions and virus propagation (Briz-Redón and Serrano-Aroca, 2020). Consequently, every statistical model of COVID-19 incidences must be construed with caution (Royal Statistical Society, 2020).

Declaration of competing interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

The data that support the findings of this study are openly available as mentioned in the reference section.

Author contributions

The contribution of the author is for the whole manuscript.

Ethical approval

The author declares that there is no ethical violation in this manuscript. Also, this manuscript does not contain data belonging to others (human or animal).

Consent to participate

The author has confirmed that this has not been published elsewhere and is currently not considered to be published elsewhere.

Consent to publish

The author agrees that the article can be published in Int. J. of Environment and Health (IJENVH).

Acknowledgements

The author would also like to acknowledge that this work is not funded by any organisation.

Significance statement

COVID-19 disease has been declared by the World Health Organization (WHO) as a pandemic affecting the entire global on March 11, 2020 (WHO, 2020a). This research aims to model and investigate the potential effect of different climate factors on the number of COVID-19 incidence in the environment and desert climate as in Saudi

Arabia. Association between the speed of infection spread and climate variables is considered the most critical factor affecting the number of COVID-19 cases. The research's results find a significant correlation between COVID—19 and temperature; one Celsius degree increases the COVID-19 cases by 6.1%. Future studies should investigate the correlation between the spread of the corona various and among diverse indoor climates such as shopping malls, places of worship, schools, etc.

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