Impact of climate indicators on the COVID−19 pandemic in Saudi Arabia

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Abstract

The novel coronavirus (COVID−19) outbreak has left a major impact on daily lifestyle and human activities. Many recent studies confirmed that the COVID−19 pandemic has human-to-human transmissibility. Additional studies claimed that other factors affect the viability, transmissibility, and propagation range of COVID−19. The effect of weather factors on the spread of COVID−19 has gained much attention among researchers. The current study investigates the relationship between climate indicators and daily detected COVID−19 cases in Saudi Arabia, focusing on the top five cities with confirmed cases. The examined climate indicators were temperature (°F), dew point (°F), humidity (%), wind speed (mph), and pressure (Hg). Using data from Spring 2020 and 2021, we conducted spatio−temporal correlation, regression, and time series analyses. The results provide preliminary evidence that the COVID−19 pandemic spread in most of the considered cities is significantly correlated with temperature (positive correlation) and pressure (negative correlation). The discrepancies in the results from different cites addressed in this study suggest that non-meteorological factors need to be explored in conjunction with weather attributes in a sufficiently long-term analysis to provide meaningful policy measures for the future.

Keywords: COVID-19; Coronavirus; Climate indicators; Correlation tests; Temperature; Dew point; Humidity; Wind speed; Pressure.

Acknowledgment

The authors wish to acknowledge the support of King Fahd University of Petroleum and Minerals and The Hong Kong Polytechnic University, Hong Kong SAR.

1. Introduction

On March 11, 2019, the World Health Organization (WHO) has declared Coronavirus disease 2019 (COVID-19) as a global pandemic (Cucinotta and Vanelli, 2020). COVID-19 is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (Bashir et al., 2020a; Cucinotta and Vanelli, 2020). This viral infectious disease has been initially recognized in December 2019 in Wuhan, China. The virus then spread all over the world, resulting in more than 184.3 million reported cases and about 3.99 million deaths as of July 7, 2021 (Coronavirus disease (COVID-19) – World Health Organization). Clinical studies show that COVID-19 severely patients are suffering from pneumonia and breathing difficulties (Holshue et al., 2020). Furthermore, according to the WHO, the usual signs and symptoms of COVID-19 infection are cough, fever, and shortness of breath (Bashir et al., 2020a; Holshue et al., 2020; Tosepu et al., 2020). This epidemic has stimulated researchers to explore the impacts of COVID-19 on different aspects of human life. The socio-economic changes and environmental consequences of COVID-19 spread have been studied (Bashir et al., 2020; Mofijur et al., 2021). Other studies focused on investigating the association between COVID-19 spread and environmental pollution indicators such as $PM_{2.5}$, PM_{10}, NO_2, CO, O_3, and SO_2 in different countries and cities such as Germany (Bilal et al., 2020), Bahrain (Qaid et al., 2021), South America (Bilal et al., 2021), and New York City (Magazzino et al., 2021).

In Gulf Cooperation Council (GCC) Countries, the total number of COVID-19 cases reached up to 800,000 by June 30, 2020 (Eltoukhy et al., 2020; World Bank, 2020). Saudi Arabia faced a significant spread of the disease with around 206,000 confirmed COVID-19 cases. Among these cases, 143,000 and 1,885 have been recorded as recoveries and deaths due to COVID-19, respectively. Qatar ranks second with around 109,305 cases. The above list is followed by countries like Oman, Kuwait, the United Arab Emirates, and Bahrain. Till June 30, 2020, around 610,000 people in GCC countries have recovered from COVID-19, accounting for about 76% of all cases; while around 20,000 cases have died due to the virus. This study focuses only on Saudi Arabia as the study data was available and easily accessible. Other GCC countries were not included in the study due to significant differences in response and control policies to the pandemic.

In Saudi Arabia, the first confirmed COVID-19 case was reported on March 2, 2020. As of June 30, 2020, the number of confirmed COVID-19 cases has reached up to 206,000 cases (COVID 19 Dashboard: Saudi Arabia; King Abdullah Petroleum Studies and Research Center website - KAPSARC Data Portal). The top five cities with total confirmed COVID-19 cases were: Riyadh (46,653 cases), Jeddah (25,178 cases), Makkah (24,755 cases), Al-Madinah (13,858 cases), and Dammam (12,449 cases) (King Abdullah Petroleum Studies and Research Center website - KAPSARC Data Portal). Consequently, Saudi Arabia is ranked 13th among the worldwide infected countries. On the other hand, Saudi Arabia has one of the lowest fatality rates among the infected countries in the world, at about 0.9%.

Recent studies have confirmed that COVID-19 has a human-to-human transmission nature (Lai et al., 2020). Therefore, almost every country in the world, including Saudi Arabia, has taken firm regulations to control the spread of COVID-19. This includes decreasing the chances of direct contact between humans by imposing social distancing between people. Among the precautionary regulations applied in Saudi Arabia are the following: the closure of borders and international flights, the closure of the two holy cities, Makkah and Al-Madinah, the transition to online education, the suspension of all sport activities, the imposition of a nationwide curfew, and the limitation of Hajj season to only 10 thousand people during 2020, compared to an average of 2 million in previous years.

The pandemic has motivated many researchers to explore the different factors that affect the spread rate of COVID-19. Many recent studies claimed that many factors contribute to the spread of COVID-19

(Doremalen et al., 2013; Şahin, 2020). In this regard, the effects of the meteorological parameters on the viability, transmissibility, and range of propagation of COVID-19 are examined by many recent studies (Bashir et al., 2020a; Fu et al., 2021, p. 19; Şahin, 2020; To et al., 2021; Tosepu et al., 2020; Yuan et al., 2021). McClymont and Hu (2021) presented a recent literature review of the effect of weather indicators on COVID-19 transmission. The meteorological factors, which were considered in recent studies to examine their correlation with the number of COVID-19 cases, include:

I) Temperature (Abdelhafez et al., 2021; Alkhowailed et al., 2020; Auler et al., 2020; Bashir et al., 2020a; Bilal et al., 2021; Briz-Redón and Serrano-Aroca, 2020; Dalal and Pandey, 2021; Fernández-Ahúja and Martínez, 2021; Fu et al., 2021; Hariharan, 2021; M. M. Iqbal et al., 2020; Menebo, 2020; Pani et al., 2020; Şahin, 2020; Shahzad et al., 2020; Shi et al., 2020a; Sobral et al., 2020, p. 2; To et al., 2021; Tosepu et al., 2020; Yuan et al., 2021),

II) Humidity (Abdelhafez et al., 2021; Alkhowailed et al., 2020; Auler et al., 2020; Bashir et al., 2020a; Basray et al., 2021, 2021; Dalal and Pandey, 2021; Fu et al., 2021; Hariharan, 2021; Pani et al., 2020; Şahin, 2020; Shi et al., 2020a; Tosepu et al., 2020; Yuan et al., 2021),

III) Rainfall (Auler et al., 2020; Bashir et al., 2020a; Basray et al., 2021; Fernández-Ahúja and Martínez, 2021; Menebo, 2020; Sobral et al., 2020, p. 2; Tosepu et al., 2020),

IV) Wind speed (Abdelhafez et al., 2021; Alkhowailed et al., 2020; Bashir et al., 2020a; Coccia, 2021; Dalal and Pandey, 2021; Hariharan, 2021; Menebo, 2020; Pani et al., 2020; Şahin, 2020; Yuan et al., 2021),

V) Dew point (Alkhowailed et al., 2020; Dalal and Pandey, 2021; M. M. Iqbal et al., 2020; Pani et al., 2020; Şahin, 2020),

VI) Pressure (Abdelhafez et al., 2021; Alkhowailed et al., 2020; Fernández-Ahúja and Martínez, 2021; Pani et al., 2020; Xie and Zhu, 2020), among other meteorological factors.

Table 1 summarizes the most recent studies that explore the effect of the meteorological factors on the number of COVID-19 cases.

Table 1: Explored effect of meteorological factors on the number of COVID-19 cases.

Reference	Studied environmental factors*						Country (or city) of application
	T	H	R	W	D	P	
Bashir et al. (2020a)	√	√	√	√			USA (New York)
Shi et al. (2020a)	√	√					China
Briz-Redón and Serrano-Aroca (2020)	√						Spain
Sobral et al. (2020)	√		√				All countries
Shahzad et al. (2020)	√						China
Tosepu et al. (2020)	√	√	√				Indonesia
Gupta et al. (2020)	√	√					USA
Auler et al. (2020)	√	√	√				Brazil
Shi et al. (2020b)	√						China
Şahin (2020)	√	√		√	√		Turkey (9 cities)
Yao et al. (2020)	√	√					China
Runkle et al. (2020)	√	√					USA

Menebo (2020)	√		√	√			Norway (Oslo)
Prata et al. (2020)	√						Brazil
M. M. Iqbal et al. (2020)	√				√		Entire world
N. Iqbal et al. (2020)	√						China (Wuhan)
Méndez-Arriaga (2020)	√		√				Mexico
Bashir et al. (2020b)							USA (California)
Pani et al. (2020)	√	√		√	√	√	Singapore
Wu et al. (2020)	√	√					166 countries
Liu et al. (2020)	√	√					China (30 provincial capital cities)
Xie and Zhu (2020)	√					√	China (122 cities)
Ma et al. (2020)	√	√					China (Wuhan)
Qi et al. (2020)	√	√					China
Li et al. (2020)	√			√			China (Wuhan and XiaoGan)
Yuan et al. (2021)	√	√		√			127 countries
Coccia (2021)				√			Italy
Fernández-Ahúja and Martínez (2021)	√		√			√	Spain
Hariharan (2021)	√	√		√			Delhi, India
Basray et al. (2021)	√	√	√				Pakistan (5 cities)
Abdelhafez et al. (2021)	√	√		√		√	Jordan
Ali et al. (2021)				√			Pakistan
Bilal et al. (2021)	√	√	√				USA (10 states)
Dalal and Pandey (2021)	√	√		√	√		Asia
Khursheed et al. (2021)	√	√					Italy
Selcuk et al. (2021)	√	√		√	√	√	Turkey (81 provinces)
Nottmeyer and Sera (2021)	√	√					England
To et al. (2021)	√						Canada (4 provinces)
Kulkarni et al. (2021)	√	√	√	√			India
Qaid et al. (2021)	√	√		√			Bahrain
Alkhowailed et al. (2020)	√	√		√	√	√	Saudi Arabia (5 major cities)
This study	√	√		√	√	√	**Saudi Arabia (Top 5 infected cities)**

* Studied environmental factors key: T: Temperature, H: Humidity, R: Rainfall, W: Wind speed, D: Dew point, P: Pressure.

Saudi Arabia has a desert climate with scant rainfall and extreme heat during the day, with an average temperature of 113° F (45° C) during the summer. It is clear from the summary of literature presented in Table 1 that research on the effect of climate factors on the propagation of COVID-19 in Saudi Arabia is scarce. Alkhowailed et al. (2020) analyzed the effect of meteorological parameters on the spread of COVID-19 in Saudi Arabia by investigating the Spearman correlation test using JASP statistical software during Spring 2020 and 2021. The current study aims at investigating the impact of climate indicators such as temperature, humidity, wind speed, dew point, and pressure on the daily confirmed COVID-19 cases in Saudi Arabia’s top five affected cities across 2020 and 2021. This study makes the following contributions:

1. It is focused on multidimensional aspects: to the best of our knowledge, our work is among the firsts to conduct spatio‒temporal correlation, regression, and time series analyses on COVID-19 in the Kingdom of Saudi Arabia.

    a. The spatial aspect of our analysis is identified by the consideration of several geographical locations in the Kingdom of Saudi Arabia with various weather conditions.
    b. The temporal aspect investigates both the autocorrelation of COVID−19 cases as well as their correlation with weather factors across 2020 and 2021.
2. It provides insights on potential factors for the disease spread: discovering the correlation between the climate factors and the spread of COVID-19 may provide useful information to medical authorities and the general public to control the spread of COVID-19.

The paper is organized as follows: Section 2 presents the data collection. Section 3 provides the conducted correlation analysis. Section 4 discusses the regression analysis of the weather and COVID−19 data. Finally, Section 5 concludes the paper.

2. Data collection

The data, which was used in this study can be classified into two sets: the data of daily cases infected by COVID−19 and the meteorological data. The first set was collected from the official website of King Abdullah Petroleum Studies and Research Center (https://datasource.kapsarc.org/), which reports daily COVID−19 cases discovered by the Ministry of Health. The second data set includes daily records of basic meteorological parameters in Saudi Arabia, such as average temperature, average dew point, average humidity, average wind speed, and average pressure, obtained from the online database archives of the Weather Underground (http://www.wunderground.com/). This online weather database is a well-known and a trustworthy platform that has been used as the main source of weather data in many recent research studies (Pani et al., 2020; Şahin, 2020). It should be noted that the data is collected during spring of 2020 and 2021. Note that this study was based on five major Saudi cities, namely: Riyadh, Jeddah, Makkah, Madinah, and Dammam. These cities were selected for two reasons: first, they are among the top Saudi cities affected by COVID−19. Second, these cities are of diverse climate conditions, so using these cities facilitate discovering different associations between COVID−19 cases and climate factors.

3. Correlation analysis

3.1 Methodology

Existing studies in the literature investigate the correlation between the number of infected cases and climate factors. This article differs in its approach by conducting a spatio-temporal analysis, which assesses the correlation within different geographic locations and across two time periods (2020, 2021). To select an appropriate correlation test, the normality of the change in climate factors should be checked. It was then found that the conditions for normality were not fulfilled. This observation led to the use of the non-parametric Spearman correlation test in our study (Menebo, 2020; Şahin, 2020; Tosepu et al., 2020). In the correlation test, two indicators are calculated: the r-coefficient to indicate whether the correlation is positive or negative, and the p-value to reveal the significance of the correlation (Nabhan et al., 2021). Note that the correlation tests were conducted with a 95% significance level.

3.2 Results and findings

This section presents the correlation analysis results of our study, which are summarized in Table 2. This study considered the following climate indicators (i.e. average temperature (°F), average dew Point (°F), average humidity (%), average wind speed (mph), and average pressure (Hg)) in the top five Saudi Arabian cities of confirmed COVID−19 cases (i.e. Riyadh, Jeddah, Makkah Madinah, and Dammam).

Table 2: Detailed correlation results in the considered cities.

Madinah

2020			2021		
Climate indicator	**r-coefficient**	**p-value**	**Climate indicator**	**r-coefficient**	**p-value**
Avg. Temperature	0.1613	0.1107	Avg. Temperature	0.7032	0.0000
Avg. Dew	0.1848	0.0671	Avg. Dew	0.0483	0.6475
Avg. Humidity	0.1033	0.3089	Avg. Humidity	-0.4182	0.0000
Avg. Wind	-0.0314	0.7579	Avg. Wind	-0.0598	0.5709
Avg. Pressure	-0.0711	0.4846	Avg. Pressure	-0.4781	0.0000

Jeddah					
2020			2021		
Climate indicator	**r-coefficient**	**p-value**	**Climate indicator**	**r-coefficient**	**p-value**
Avg. Temperature	0.6975	0.0000	Avg. Temperature	0.6653	0.0000
Avg. Dew	0.5011	0.0000	Avg. Dew	0.5242	0.0000
Avg. Humidity	-0.0550	0.5644	Avg. Humidity	0.0019	0.9859
Avg. Wind	-0.1144	0.2299	Avg. Wind	-0.1843	0.0787
Avg. Pressure	-0.5407	0.0000	Avg. Pressure	-0.6888	0.0000

Riyadh					
2020			2021		
Climate indicator	**r-coefficient**	**p-value**	**Climate indicator**	**r-coefficient**	**p-value**
Avg. Temperature	0.8150	0.0000	Avg. Temperature	0.4120	0.0000
Avg. Dew	0.0743	0.4429	Avg. Dew	0.4080	0.0001
Avg. Humidity	-0.6241	0.0000	Avg. Humidity	-0.1510	0.1509
Avg. Wind	-0.3929	0.0000	Avg. Wind	-0.2274	0.0293
Avg. Pressure	-0.4739	0.0000	Avg. Pressure	-0.3514	0.0006

Dammam					
2020			2021		
Climate indicator	**r-coefficient**	**p-value**	**Climate indicator**	**r-coefficient**	**p-value**
Avg. Temperature	0.7311	0.0000	Avg. Temperature	0.4343	0.0000
Avg. Dew	-0.3104	0.0009	Avg. Dew	0.0458	0.6647
Avg. Humidity	-0.6757	0.0000	Avg. Humidity	-0.2985	0.0038
Avg. Wind	0.0250	0.7933	Avg. Wind	-0.1019	0.3336
Avg. Pressure	-0.7242	0.0000	Avg. Pressure	-0.3230	0.0017

Makkah	
2020	2021

Climate indicator	r-coefficient	p-value	Climate indicator	r-coefficient	p-value
Avg. Temperature	0.4785	0.0000	Avg. Temperature	0.6615	0.0000
Avg. Dew	0.2936	0.0017	Avg. Dew	0.1401	0.1828
Avg. Humidity	0.0458	0.6316	Avg. Humidity	-0.1318	0.2103
Avg. Wind	-0.0044	0.9633	Avg. Wind	0.3072	0.0029
Avg. Pressure	-0.0555	0.5609	Avg. Pressure	-0.1137	0.2805

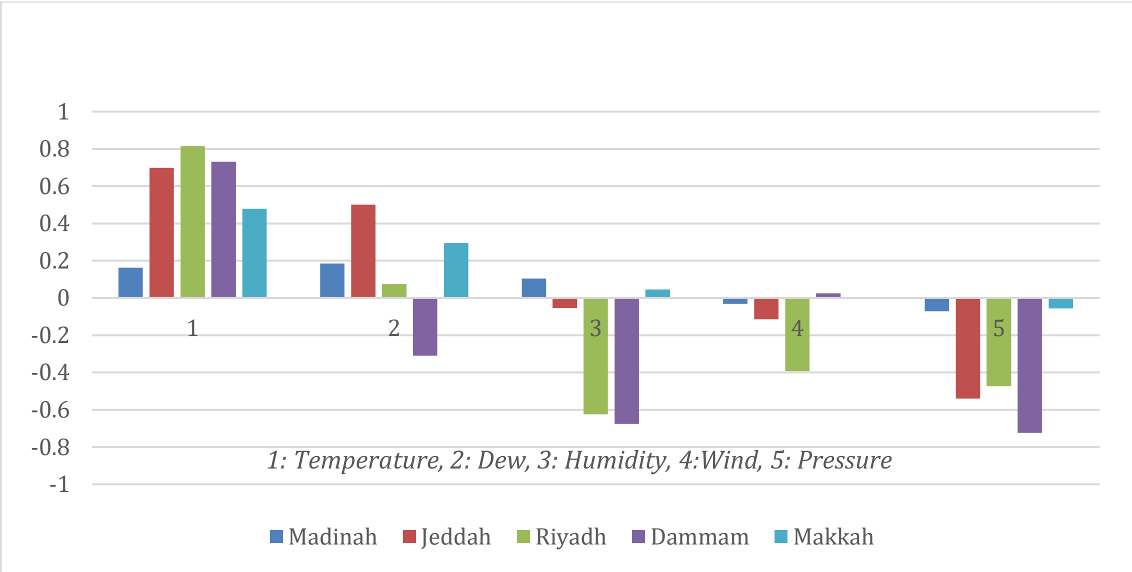


Figure 1 (a): Spearman *r*-coefficient values for the five weather factors across the five cities in 2020.

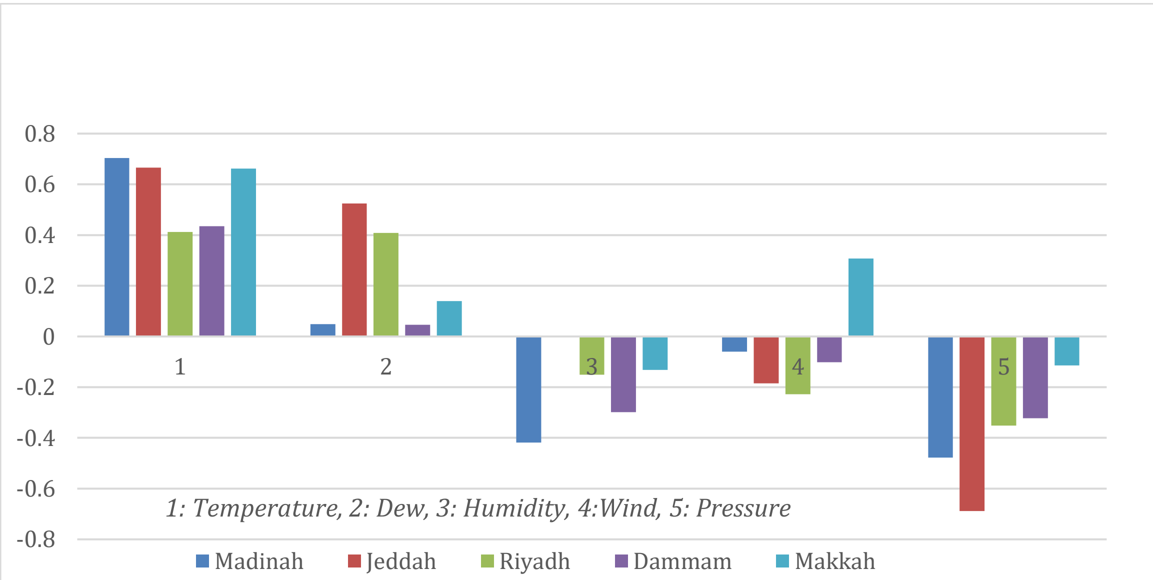


Figure 1 (b): Spearman *r*-coefficient values for the five weather factors across the five cities in 2021.

Figure 1 (a and b) demonstrates the correlation coefficient values for the five different cities in 2020 and 2021. The figure shows that the average temperature is the climate factor with the highest positive correlation coefficient among other factors in most cities during 2020 and 2021, which agrees with the results of Tosepu et al. (2020). This is followed by the pressure, except that it is negatively correlated.

On the other hand, humidity and wind had the lowest correlation coefficient values in 2020 and 2021, which is consistent with the finding of Şahin (2020). Location-wise, Makkah and Madinah had the lowest r-coefficient values in 2020; Dammam had the lowest r-coefficient values in 2021.

Table 3 extracts from Table 1 the factors that are consistently significant throughout 2020 and 2021, by measuring the similarity of correlation values. It shows that Madinah has no weather factors that are consistently significant; Jeddah, Riyadh, and Dammam have three consistently significant weather factors, while Makkah has only one. The letters represent a similarity index between the correlation coefficient of the corresponding city's weather factor and the number of cases throughout 2020 and 2021; where (A) similar, (B) relatively similar, and (C) not similar. For instance, Table 1 indicates that the correlation coefficient value for the temperature in Jeddah in 2020 is like that of 2021 (Category A). The (C) corresponding to the pressure in Dammam indicates that the correlation coefficients throughout 2020 and 2021 appear to be different yet significant.

Table 3: Similarity analysis between the values of the significant weather factors for the years 2020 and 2021

	Madinah	**Jeddah**	**Riyadh**	**Dammam**	**Makkah**
Climate indicator					
Avg. Temperature		A	C	C	B
Avg. Dew		A			
Avg. Humidity				C	
Avg. Wind			B		
Avg. Pressure		B	B	C	

Most of the observations presented in this section need extra investigation to find the reasons behind these findings. To address this, our analysis was extended to include regression analysis, as presented in the next section.

4. Regression analysis of the weather and COVID−19 data

Based on correlation analysis, this section presents some proposed statistical models to quantify the impact of the different climate factors on the total of COVID−19 cases.

- *Scatter plot matrices*

To conduct an initial investigation for the data, a scatter plot matrix of all-weather data was created. The scatter plot matrix identified two data attributes. First, the plot matrix demonstrates collinearity between regressors representing the same weather factor (e.g. minimum, average, and maximum temperature values). This is natural due to the natural relation between such variables. To remove redundant regressors, this study uses only the average as a representative regressor for each weather factor (e.g., using average temperature/dew/pressure/etc… only). Second, the scatter plot matrix for Jeddah averages data, which is shown in Figure 2, indicates a potential linear relationship between the total number of COVID−19 cases and both the average temperature and the average dew point. Therefore, linear regression could be a potential tool for subsequent analysis.

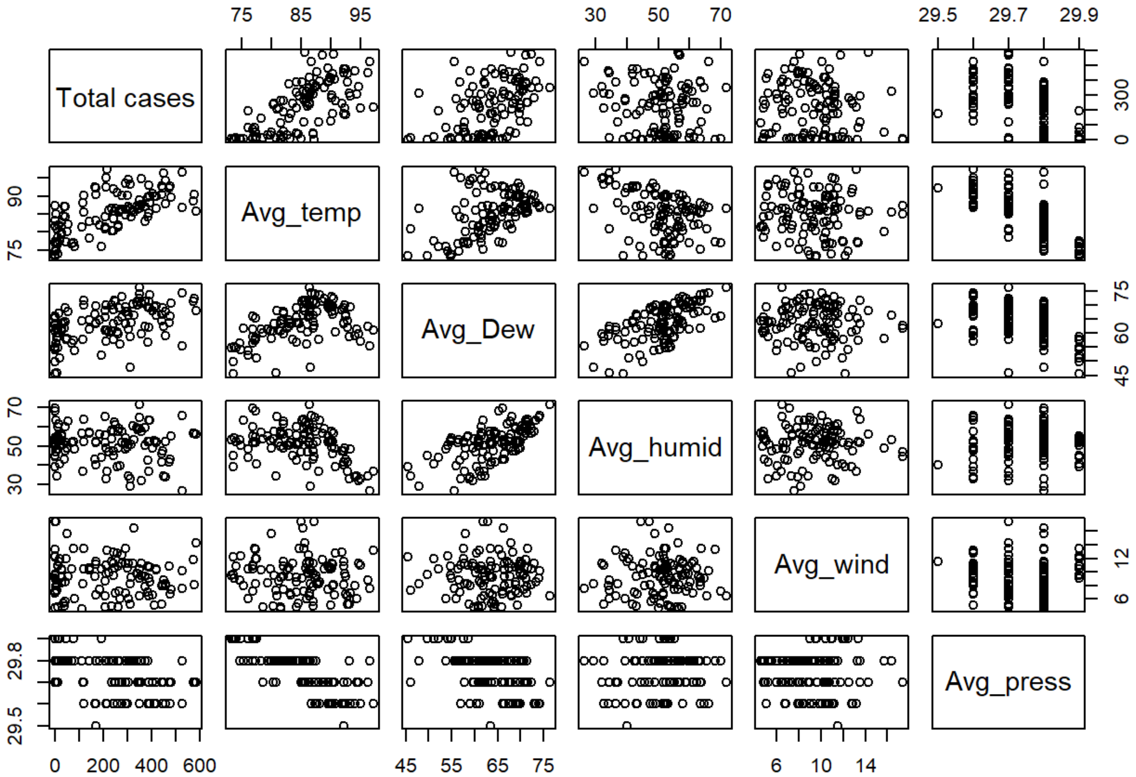


Figure 2: Scatter plot matrix for COVID−19 cases and weather data in the city of Jeddah

- *Preliminary regression analysis of the total COVID−19 cases and 2020−2021 weather data*

To investigate the suitability of linear regression, separate regression analyses were conducted for the five cities, as regression is one of the most efficient ways to capture the relationship between a response variable and one or multiple predictors (Eltoukhy et al., 2018; Eltoukhy et al., 2019). All models, except for Madinah, were found significant (Based on their P-values). The model adequacy analysis indicated strong positive autocorrelation in the residuals, while the remaining model assumptions did not suggest significant violation (QQ plots, residuals vs. fitted values plots, residuals vs. regressors plots, and scale location plots). Figure 3 illustrates the residuals autocorrelation for the city of Jeddah.

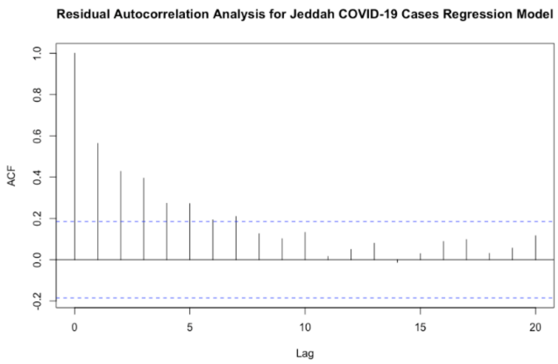


Figure 3 (a): Residual autocorrelation function (ACF) for Jeddah city data

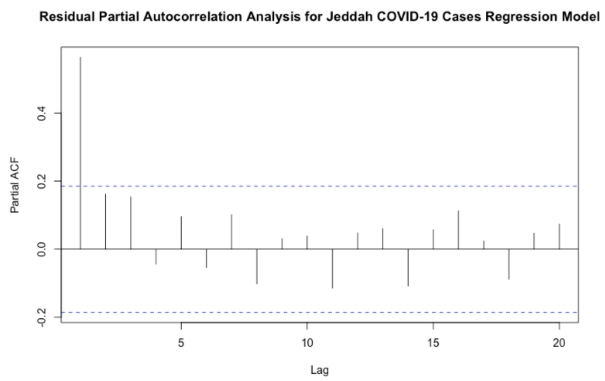


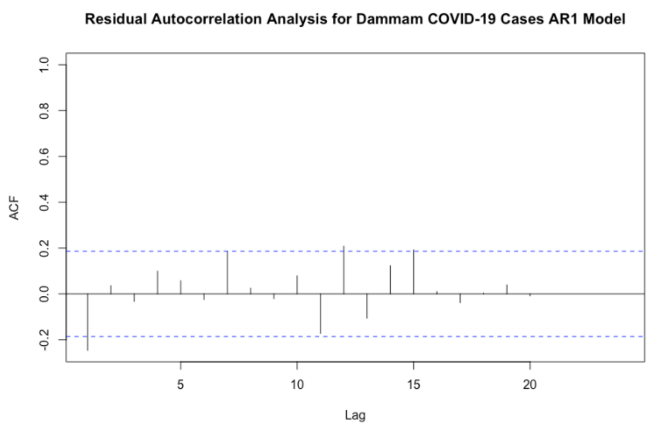
Figure 3 (b): Residual partial autocorrelation function (PACF) for Jeddah city data

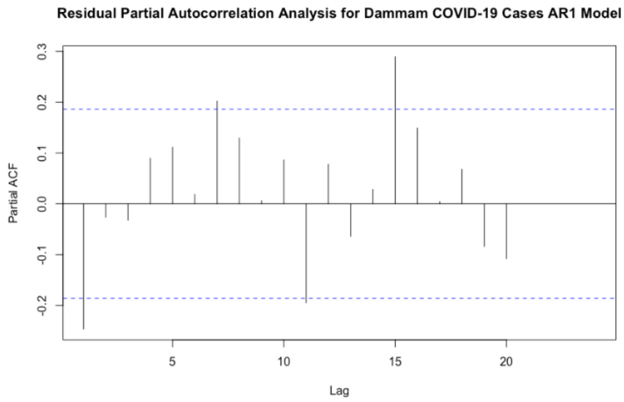
According to Figure 3 (a and b), there is a gradual decrease in the residual autocorrelation function (ACF) and a sharp drop in the partial autocorrelation function (PACF) after lag 1. This suggests that time series analysis with an autoregressive model with lag 1 (AR1) may be applicable to model and analyze the data.

A subsequent combined regression model, with cities as the categorical variables, was fit. Initially, the model did not include Madinah, because its regression model was not found to be significant. The remaining cities were found to be significantly different from each other, except Makkah; the residual analysis suggested the same observations obtained from the individual models.

- *Time series analysis of the total COVID−19 cases and weather data*

This section discusses the results of a time series analysis of the data to address the previously mentioned residual autocorrelation. An AR1 model was fit to each of the main cities (Dammam, Jeddah, and Riyadh). The analysis indicated that the three AR1 models were significant, confirming the suspected correlation between successive daily COVID−19 cases. While Figure 4 (a and b) indicates that the autocorrelation was adequately addressed, the residuals of the AR1 models did not seem to be normally distributed (Figure 4, c). This suggests that something is missing in the model. In the next Section, we incorporate the Lag 1 data in the weather factors regression model to potentially attain a more adequate model.





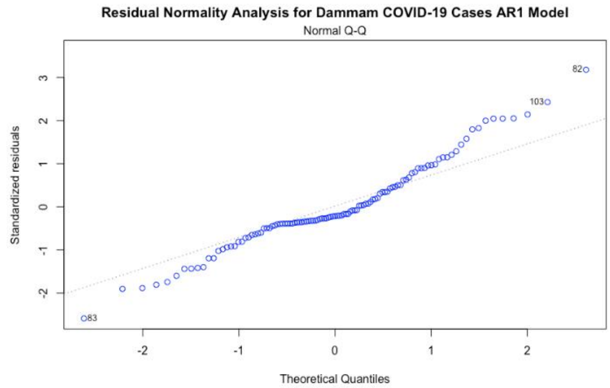


Figure 4: Dammam city's AR1 model residuals (a) ACF, (b) PACF, and (c) Normal Q-Q plot

- *Combined time series and regression analysis for individual cities*

This section presents the results of the "all possible regressors" for the 2020 and 2021 data. The analysis was conducted across cities and years. Mallows' Cp-statistic and the adjusted coefficient of determination (R^2_adj) (Montgomery and Runger, 2018) are two statistical indices that are ubiquitously used to measure model adequacy while also considering the complexity to avoid overfitting the model. In general, a higher R^2_adj represents a better-fitting model, and vice versa for the Cp-statistic. Both measures were utilized to select the best two models from the resulting possible combinations of each city (Tables 3 – 6). Each table indicates the city/year and the best two regression models with the selected regressors indicated by their p-values. For instance, Model 2 of Dammam in the year 2020 indicates that the lag 1 time series data and the pressure were both significant, but the humidity was insignificant (p-value = 0.25642). In the remainder of the analysis, we use the word consistent to refer to factors that appear to be significant over both periods or across several regions. Based on Tables 4-7, we can conclude that lagged data is consistently significant, and temperature, to some extent, is consistently significant to the model. Chronologically, Tables 4 and 5 indicate that Makkah and Jeddah cities demonstrate consistently significant weather indicators. In contrast, Dammam and Riyadh had both inconsistent weather factors in 2020 and 2021 (Tables 3 and 6). Finally, it was found that the residual analyses of the given models were satisfactory.

Table 4: Regression analysis for Dammam data 2020, 2021 (best two models out of all possible regressors)

	p-values							
2020	lagged	temperature	pressure	dew	humidity	wind	Cp	R^2_adj
Model 1	<2e-16		0.00143				0.7	0.7329
Model 2	3.21e-15		0.01018		*0.25642*		1.3	0.7337

2021								
Model 1	**0.00088**			**0.003368**	**0.000684**		***5.58***	***0.307***
Model 2	**0.00256**			**0.001199**	**0.000725**		***4.19***	***0.3258***

Table 5: Regression analysis for Jeddah data 2020, 2021 (best two models out of all possible regressors)

	p-values							
2020	lagged	temperature	pressure	dew	humidity	wind	Cp	R^2_adj
Model 1	4.03e-16	0.0237					1.94	0.712
Model 2	1.59e-15			0.00936	0.03406		2.25	0.714
2021								
Model 1	**2.09e-15**			**0.0250**	**0.0665**		**4.59**	**0.8274**
Model 2	**9.52e-13**			**0.00483**	**0.01286**	**0.08430**	**3.59**	**0.8314**

Table 6: Regression analysis for Makkah data 2020, 2021 (best two models out of all possible regressors)

	p-values							
2020	lagged	temperature	pressure	dew	humidity	wind	Cp	R^2_adj
Model 1	<2e-16	0.055					2.39	0.6507
Model 2	1.18e-15	0.00928			0.07723		1.29	0.6576
2021								
Model 1	**5.26e-12**	**0.00616**	**0.067641**		**0.01987**		**4.31**	**0.6826**
Model 2	**0.00456**	**0.00477**		***0.14079***	**0.03447**		**4.12**	**0.687**

Table 7: Regression analysis for Riyadh data 2020, 2021 (best two models out of all possible regressors)

	p-values							
2020	lagged	temperature	pressure	dew	humidity	wind	Cp	R^2_adj
Model 1	<2e-16	0.01204				0.00478	2.53	0.8573
Model 2	<2e-16			0.01770	0.00778	0.01018	3.39	0.8575
2021								
Model 1	**<2e-16**	***0.346***					***-0.94***	***0.8814***
Model 2	**<2e-16**	***0.384***				***0.811***	***1.01***	***0.8802***

- *Combined cities, time series, and weather factors regression analysis 2020, 2021*

In this section, data from different cities is combined into a single regression model, to represent the time series data, weather factors. The main purpose is to determine the persistently significant regressors. Madinah and Makkah were excluded because their models did not indicate significance in terms of weather factors and R^2_adj values. In addition to the lagged number of cases, the regression analysis indicated that temperature and pressure were systematically significant, supporting the findings of the correlation analysis (Section 3). Temperature was found to be positively correlated to the total number of COVID-19 cases during 2020 and 2021 in all cities. A similar result was found in Asia, Jordan, and Pakistan (Basray et al. (2021), Abdelhafez et al. (2021), Dalal and Pandey (2021)). Contrary to our findings, certain studies conducted in Turkey, China, and Italy found negative associations between temperature and COVID-19 cases (Şahin (2020), Qi et al. (2020), and Khursheed et al. (2021)). Pressure was less frequently addressed in the literature, and our findings indicate a negative correlation between pressure and the total number of COVID-19 cases, which is consistent with the finding of Abdelhafez et al. (2021), who conducted their study in Jordan. It is noteworthy to mention that the variability in the results can be attributed to many other important factors that were not addressed. For example, Bashir et al. (2020a) suggested investigating the effects of social distancing, people's endurance, the availability of health facilities, and personal hygiene.

The other factors were city/year dependent. Furthermore, this is supported by constructing a model based on all cities' data with temperature and pressure. Table 8 summarizes the results of the regression analysis, which supports our findings regarding the impact of the factors representing the Lag 1 number of cases, temperature and pressure.

Table 8: Combined cities model (the year 2020 data)

Coefficient	Estimate	p-value
Intercept	-5343.4075	0.059754
Lag 1 three cities cases	0.8522	< 2e-16
Average temperature	4.6754	0.000999
Average pressure	166.9131	0.071316
Jeddah	13.6509	0.426642
Riyadh	366.1052	0.040742

Aside from a slightly higher variability in the residuals for the high fitted values of Riyadh (Figure 5); the residual analysis of the combined model was satisfactory.

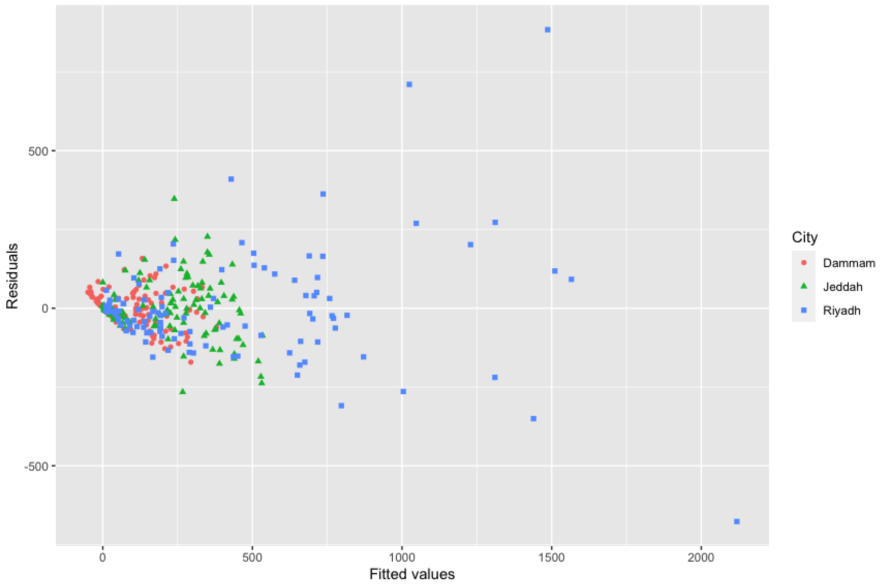


Figure 5: Residuals versus fitted values for the 2020 combined cities model

For the 2021 data, it was not possible to construct an adequate combined regression analysis model. For instance, Figure 6 demonstrates that the variability of the residuals is affected by the cities. Given the inconsistency between the findings from 2020 and 2021, one can conclude that other unaccounted for factors may influence the total number of cases.

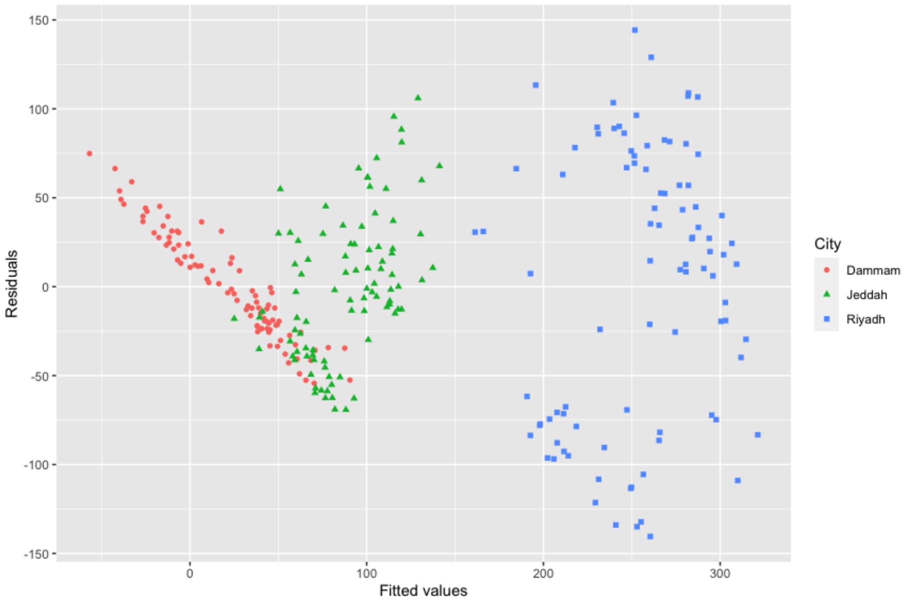


Figure 6: Residuals versus fitted values for the 2021 combined cities model

5. Conclusions

This study examined the relationship between the number of cases infected by COVID−19 and the climate factors in the top five affected cities in Saudi Arabia; Riyadh, Jeddah, Makkah, Al-Madinah, and Dammam are among these cities. This study considers most climate factors reported in the literature. This includes temperature (°F), dew point (°F), wind speed (mph), and pressure (Hg). Since most of the climate factors are not normally distributed, the Spearman test was adopted to assess the correlation. Compared to other similar studies, this study is among the first to conduct spatio−temporal correlation, regression, and time series analyses. Spatially, we studied numerous geographical locations of different weather conditions within the Kingdom of Saudi Arabia. Temporally, we examined both the autocorrelation of COVID−19 cases and their correlation with weather factors across 2020 and 2021.

The results showed that the significance and correlation strength between the number of COVID−19 cases and the weather factors varied across geographic locations and time periods. However, the correlation and time series regression analysis indicated that the lagged number of COVID−19 cases, temperature, and pressure were systematically significant. The discrepancies between some of the results that were reported in the literature and ours suggest that the effect of weather factors on COVID-19 cases varies according to other non-meteorological factors. Moreover, the spatio-temporal aspect was inconsistent among the different studies. Some studies were limited to one or two cities, while others spanned more than one country. In addition, the data collected in the studies were frequently limited to a small-time period, where weather conditions were not expected to change significantly. To provide effective insights on the disease spread, non-meteorological factors need to be explored in conjunction with weather attributes in a sufficiently long-term analysis. A non-exhaustive list of such factors includes population density, pollution, lockdown policies, and other sociodemographic patterns.

Note that one should carefully interpret the results of the regression analysis in this study. While most individual models were found to be significant, this does not imply that they are accurate for prediction. This is because there are potentially other non−meteorological factors that might be correlated with the number of COVID−19 cases. For example, dynamic quarantine policies were imposed in reaction to the spread of the disease within different areas. Furthermore, the rapid advancement in medical treatment, especially vaccine administration, likely affected the spread of COVID−19 in 2021. However, due to the novelty of the vaccine and the lack of adequate data regarding its distribution and efficacy, such factors were out of the scope of this study. Ultimately, the development of more comprehensive models for predicting the future number of COVID−19 cases in Saudi Arabia remains an interesting direction for future research.

Ethical Approval and Consent to participate

Not applicable

Consent for Publication

Not applicable

Authors Contributions

Mohammad A. M. Abdel-Aal brought the idea of the paper. Abdelrahman E. E. Eltoukhy conducted the correlation test. Mohammad A. Nabhan conducted the regression and time series analysis. Mohammad M. AlDurgam wrote the result part. All the authors participated in writing the manuscript. Besides, all authors read and approved the final manuscript.

Funding

There is no fund used in this paper.

Competing Interests

The authors declare that they have no competing interests

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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