On Interesting Correlation between Meteorological Parameters and COVID-19 Pandemic in Saudi Arabia

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Summary
The recent outbreak of COVID-19 pandemic cases around the globe has affected Saudi Arabia with around 15, 00,000 confirmed cases within the initial 4 months of transmission. The present investigation analyzed the relationship between daily COVID-19 confirmed cases and meteorological parameters in seventeen cities of KSA. We used secondary published data from the Ministry of Health, KSA daily dataset of COVID-19 confirmed case counts. The meteorological parameters used in the present investigation are temperature, humidity, dew point, and wind speed. Pearson correlation and Spearman rank correlation tests were utilized for data analysis. The incubation period of COVID-19 varies from 1 day to 14 days as per available information. Therefore, an attempt has been made to analyze the effects of meteorological factors with bins of 1, 3, 7, and 14 days. The results suggested that the highest number of correlations (15 cities) was observed for temperature (maximum, minimum, and average) and humidity (12 cities) (minimum and average). The dew point showed relationships for 7 cities and wind showed moderate correlations only for 2 cities. The study results might be useful for authorities and stakeholders in taking specific measures to combat the Covid-19 pandemic.

Keywords:
Covid-19; Temperature; Humidity; Dew point; Wind speed; Saudi Arabia

1. Introduction

Coronavirus disease 2019 (COVID-19) is a pandemic that was firstly found in Wuhan City, Hubei Province, China, in December 2019. The World Health Organization (WHO) has declared COVID-19 as pandemic after it spread across the globe, and there are about 10,101,998 confirmed cases and 501,644 total deaths as on June 28, 2020, worldwide (World Health Organization, 2020). Saudi Arabia reported the first case of the COVID-19 pandemic in the first week of March 2020. As of June 27, 2020, it has increased to 178,504 cases in 13 provinces and the number of deaths was 1511 (Ministry of Health, 2020). As of June 27, 2020, there were around, 475,153 (54%) recovered cases worldwide, with mortality of 5, 01,644 (4.96%). In Saudi Arabia, there are around 122,128 (68.41%) recovered cases, with mortality of 1511 (0.84%) persons. The data suggest that Saudi Arabia's response to the pandemic is quite effective to date. The highest number of cases is reported in Riyadh city with around 45000, which is around 25% of Saudi Arabia.

COVID-19 affects people differently; infected people can develop mild to moderate illnesses including difficulty in respiration [15]. Recent studies suggested that COVID-19 is spreading through human-to-human transmission [3] [10] [19]. In addition to human-to-human transmission, meteorological parameters are some main predictors of coronavirus spread [5] as temperature, humidity, and wind speed are important factors for the spread of infectious diseases [19] [21]. Recent studies examined the relationships between meteorological factors and COVID-19 infection in different parts of the world. Chen [4] found the relationship between meteorological parameters (wind speed, temperature, and relative humidity) and the COVID-19 cases worldwide. Latest studies found a correlation between meteorological factors and COVID-19 number of cases [2] [11] [12] [18] [19] [22]. Sahin [12] suggested that the analysis of different cities with extended time series could provide more insight of the relationship between meteorological parameters impact on COVID-19 spread. The main goal of the current research is to analyze the relationship between meteorological parameters (temperature, humidity, dew point and, wind speed) with COVID-19 confirmed cases in seventeen cities of Saudi Arabia. An attempt has been made in the present study to investigate the effect of incubation period with respect to meteorological parameters as Sahin [12]. Each meteorological factor is analyzed on four-time bins, namely on the same day of the case (1D), within 3 days (3D), within 7 days (7D), and within 14 days (14D) of the case.

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2. Materials and methods

2.1 The data

The data of COVID-19 confirmed cases (ncases) of 17 cities was collected from the official website of the Ministry of Health - Kingdom of Saudi Arabia (https://COVID19.moh.gov.sa/). The location map of 17 cities under investigation showed in Fig 1. Fig. 2 showed the cities with the highest ncases as of June 22, 2020. Among all cities maximum number of cases were reported in Riyadh followed by Jeddah, Makkah, Madinah, Dammam, Al Houfuf, Khobar, Ta'if, Al Jubayl, Al Qatif, Dhahran, Buraydah, Diriyah, Khamis Mushait, Al Mubarraz, Tabuk, Ha'il. These 17 cities contained nearly 89% of the total ncases in Saudi Arabia.

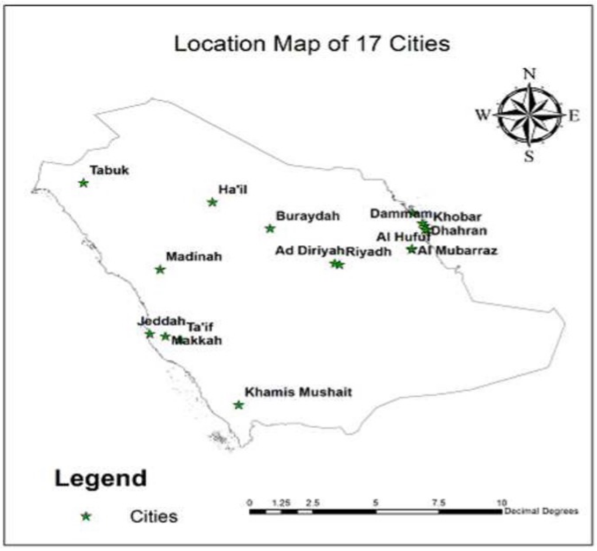

Figure 1: Location map of 17 cities in Saudi Arabia

The weather data includes maximum, minimum and average temperatures (Tmax, Tmin, Tavg), maximum, minimum, and average dew points (DPmax, DPmin, DPavg), maximum, minimum and average humidity (Hmax, Hmin, Havg), and maximum, minimum and average wind speed (WSmax, WSmin, WSavg). The weather data was downloaded from the wunderground website https://www.wunderground.com/. The data was available for 8 cities (Riyadh, Jeddah, Makkah, Madinah, Dammam, Buraydah, Tabuk, and Ha'il. The weather data of Al Mubarraz and Al Houfuf was collected from Al Ahsa station. From the location map shown in Fig. 1 it is evident that cities such as Khobar, Al Jubayl, Al Qatif and Dhahran are close to Dammam, therefore the weather data of Dammam is used for these 4 cities. Similarly, the weather data of Diriyah and Taif was taken from Riyadh and Makkah stations respectively. Meteorological data of Khamis Mushait or nearby station data was unavailable on underground website therefore only Tmax, Tmin, Tavg data was collected from accuweather website https://www.accuweather.com/. Fig. 3 shows the Tavg of 10 cities from March 1, 2020 to June 22, 2020. Riyadh is showing higher Tavg (84^{o} F) and Tabuk is showing lower Tavg (76^{o} F) from March 1, 2020 to June 18, 2020. Fig. 4 showed the dew point of nine cities from March 1, 2020 to June 22, 2020. Dew point is the temperature at which the air is saturated or 100 % relative humidity. Dew point depends on the amount of moisture in the air. Jeddah is showing higher DPavg (62.91^{o} F) and Tabuk is showing lower DPavg (30.54^{o} F) from March 1, 2020 to June 18, 2020. The primary reason could be that Jeddah is located at seashore. Fig. 5 shows the average humidity of nine cities from March 1, 2020 to June 22, 2020. Jeddah is showing higher Havg (51.93 %) and Buraydah is showing lower Havg (22.6%) from March 1, 2020 to June 18, 2020. Fig. 6 shows the average wind speed of nine cities from March 1, 2020 to June 22, 2020. Hail is showing higher WSavg (12.88 mph) and Tabuk is showing lower WSavg (4.04 mph) from March 1, 2020, to June 18, 2020. The population of the cities was also analyzed with the ncases in all 17 cities.

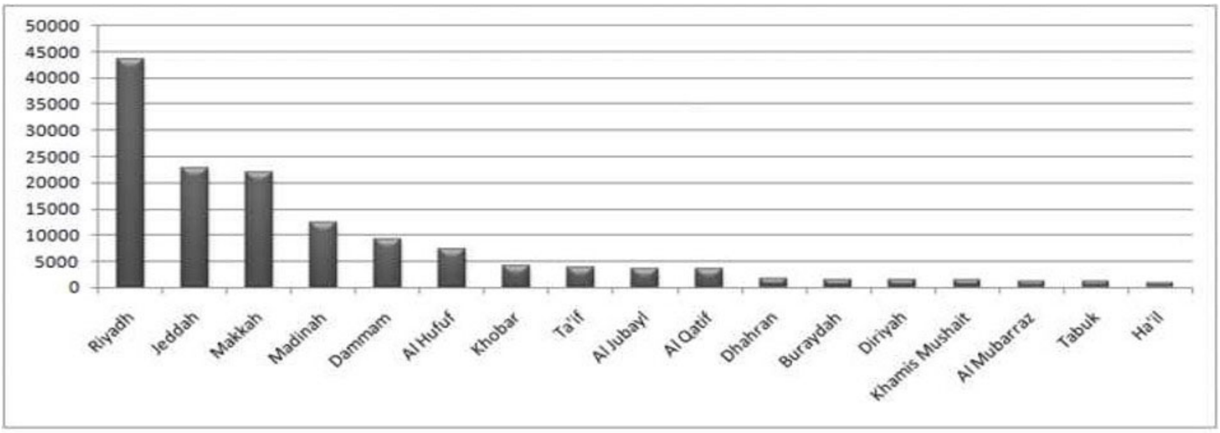

Figure 2: Total number of confirmed cases in 17 cities of Saudi Arabia as of June 22, 2020.

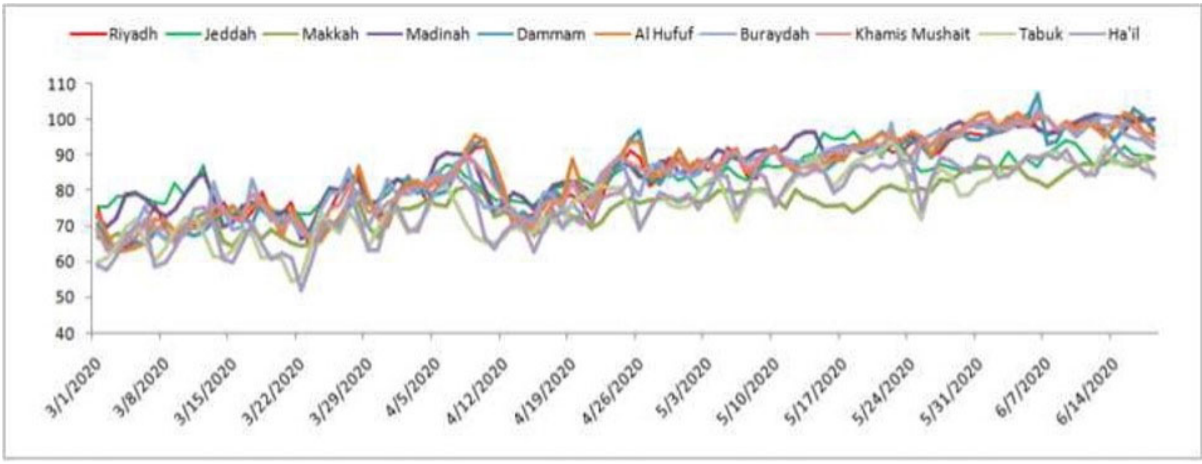

Figure 3: Tavg of 10 cities from March 1, 2020, to June 18, 2020, X-axis shows the dates and Y-axis shows the temp in °F

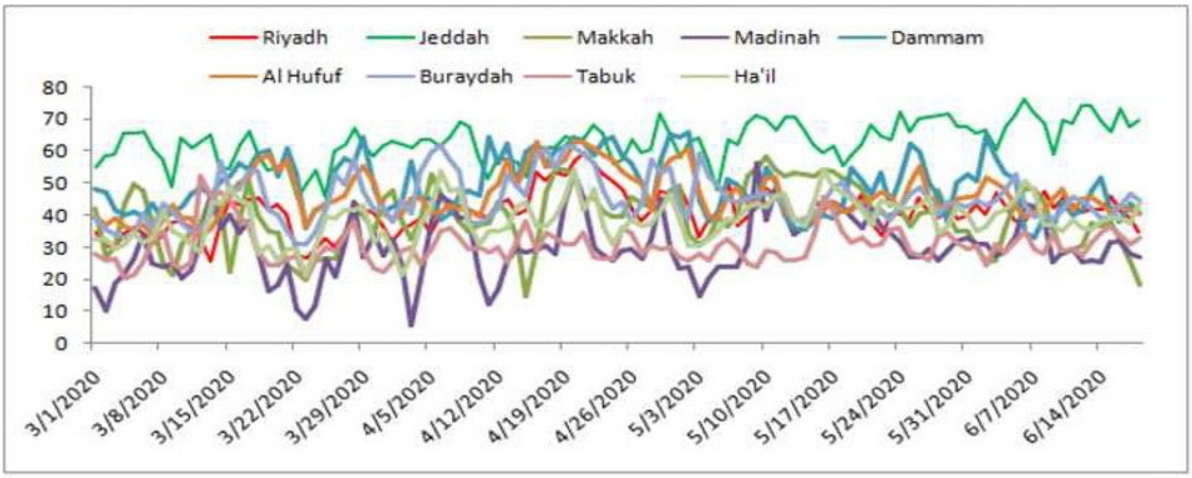

Figure 4: DPavg of nine cities from March 1, 2020, to June 18, 2020, X-axis shows the dates and Y-axis shows the dew point in °F

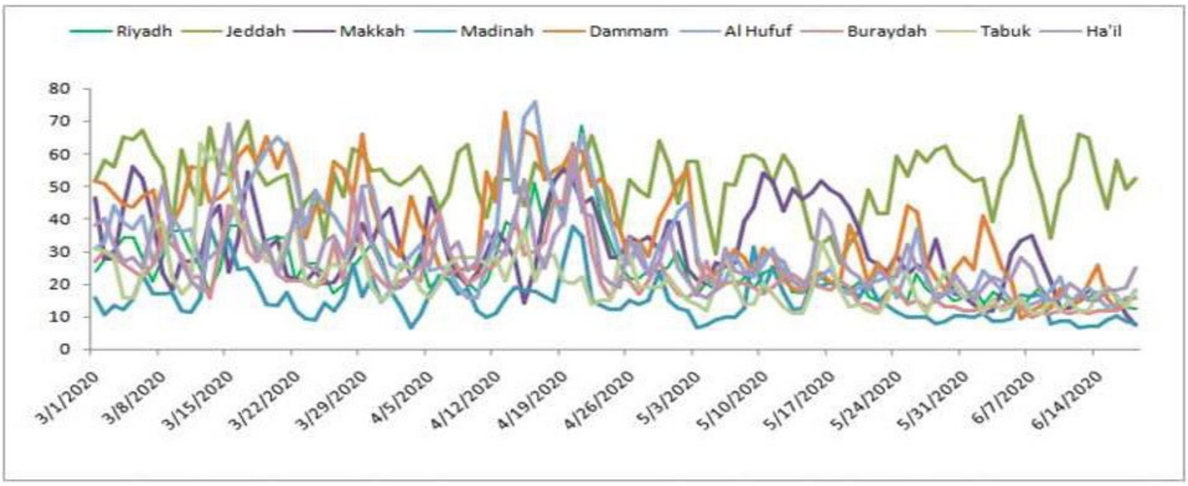

Figure 5: Havg of nine cities from March 1, 2020, to June 18, 2020, X-axis shows the dates and Y-axis shows the humidity in %

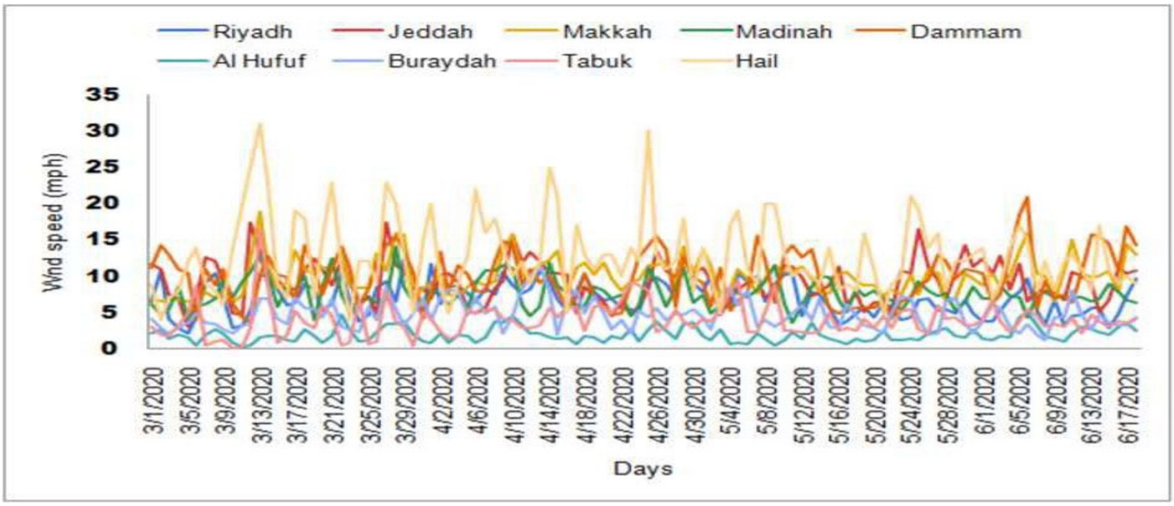

Figure 6: WSavg of nine cities from March 1, 2020, to June 18, 2020, X-axis shows the dates and Y-axis shows the wind speed in mph.

2.2 Data Analysis

To understand the relationship of between ncases and meteorological factors the Spearman's rank correlation coefficient and Pearson Product Moment Correlation Coefficient (PPMCC) is implemented.

2.2.1 Spearman's correlation test

Spearman's rank correlation coefficient (ρ) was applied to examine the correlation between meteorological factors and ncases. This test defines the correlation between two variables based on a monotonic function. The data analyzed in the present research work is not normally distributed; therefore, correlation coefficients were derived using the following Eq. 1.

$$\rho = 1 - 6\frac{\sum di^2}{n(n^2-1)} \tag{1}$$

where *di* represent the difference between a pair of ranks and n represents the number of observations.

2.2.2 Pearson Product Moment Correlation Coefficient (PPMCC)

The PPMCC formula for computing correlation coefficient is as shown in Eq. 2.

$$R = \frac{N\sum XY - \sum X \sum Y}{\sqrt{[N\sum X^2 - (\sum X)^2]\,(N\sum Y^2 - (\sum Y^2)}} \tag{2}$$

where N is the number of pairs of data, and X, Y are parameters.

3. Results and Discussion

Temperature shows the highest correlation among all other meteorological factors with ncases. Table 1 and Table 2 present the result of Spearman's correlation analysis and Pearson correlation analysis respectively. As already mentioned, the four main meteorological parameters are considered in the study are temperature, humidity, dew point, and wind speed. Meteorological parameters are analyzed for four-time bins viz. 1D, 3D, 7D and 14D.

Table 1: Spearman correlation coefficients (Correlation is significant at the 0.01 level, 2-tailed)

City/Values	Time Bin	Tmax	Tavg	Tmin	DPmax	DPavg	DPmin	Hmax	Havg	Hmin	WSmax	WSavg	WSmin
Riyadh	1D	0.80	0.81	0.72	0.13	0.18	0.21	-0.51	-0.60	-0.57	-0.36	-0.40	-0.16
Riyadh	3D	0.82	0.82	0.73	0.10	0.16	0.21	-0.55	-0.63	-0.60	-0.36	-0.44	-0.19
Riyadh	7D	0.79	0.80	0.70	0.17	0.19	0.19	-0.49	-0.58	-0.55	-0.30	-0.38	-0.14
Riyadh	14D	0.78	0.80	0.76	0.33	0.24	0.15	-0.38	-0.54	-0.51	-0.19	-0.20	-0.04
Jeddah	1D	0.63	0.77	0.72	0.55	0.44	0.26	-0.07	-0.08	-0.02	-0.08	-0.05	-0.13
Jeddah	3D	0.57	0.73	0.68	0.57	0.46	0.28	0.03	0.00	0.05	-0.05	-0.02	-0.11
Jeddah	7D	0.57	0.69	0.68	0.59	0.52	0.36	0.10	0.05	0.10	-0.02	0.05	-0.06
Jeddah	14D	0.57	0.62	0.59	0.54	0.46	0.29	0.07	-0.04	0.01	-0.05	0.04	0.02
Makkah	1D	0.40	0.38	0.46	0.36	0.46	0.44	0.24	0.29	0.19	0.08	0.02	0.10
Makkah	3D	0.49	0.44	0.37	0.28	0.35	0.32	0.12	0.14	0.04	-0.01	0.01	0.09
Makkah	7D	0.48	0.45	0.42	0.27	0.27	0.27	0.04	0.07	-0.01	0.08	0.06	0.16

Makkah	14D	0.55	0.55	0.51	0.12	0.21	0.19	-0.12	-0.04	-0.10	0.02	0.04	0.14
Madinah	1D	-0.04	-0.08	-0.09	0.26	0.15	-0.01	0.29	0.26	0.10	-0.05	-0.22	-0.05
Madinah	3D	-0.09	-0.09	0.00	0.16	0.15	0.14	0.16	0.18	0.20	0.31	0.22	0.05
Madinah	7D	-0.22	-0.16	-0.03	0.10	0.07	-0.07	0.13	0.17	0.15	-0.06	0.02	-0.02
Madinah	14D	-0.08	-0.10	-0.17	-0.30	-0.32	-0.34	-0.17	-0.21	-0.26	-0.15	-0.06	0.05
Dammam	1D	0.44	0.43	0.21	-0.40	-0.49	-0.40	-0.50	-0.54	-0.51	-0.15	-0.13	-0.04
Dammam	3D	0.39	0.44	0.26	-0.34	-0.33	-0.31	-0.44	-0.46	-0.41	0.02	0.02	0.06
Dammam	7D	0.49	0.54	0.42	-0.07	-0.06	-0.03	-0.33	-0.36	-0.28	0.08	0.10	0.16
Dammam	14D	0.46	0.46	0.41	0.19	0.11	0.01	-0.06	-0.17	-0.25	-0.14	-0.16	-0.13
Al Hufuf	1D	0.58	0.58	0.56	-0.12	-0.06	-0.08	-0.44	-0.46	-0.41	0.16	0.00	0.00
Al Hufuf	3D	0.62	0.63	0.60	-0.14	-0.06	0.08	-0.48	-0.48	-0.40	0.08	-0.04	0.00
Al Hufuf	7D	0.60	0.62	0.67	-0.16	-0.14	-0.04	-0.55	-0.56	-0.46	0.11	0.02	0.00
Al Hufuf	14D	0.73	0.75	0.74	-0.01	0.00	0.08	-0.55	-0.61	-0.56	0.07	0.05	0.00
Khobar	1D	0.54	0.57	0.36	-0.43	-0.47	-0.42	-0.59	-0.62	-0.53	0.14	0.14	0.17
Khobar	3D	0.55	0.58	0.37	-0.29	-0.30	-0.28	-0.51	-0.52	-0.47	-0.04	-0.07	0.10
Khobar	7D	0.53	0.61	0.40	-0.20	-0.21	-0.13	-0.43	-0.45	-0.36	-0.07	-0.07	0.08
Khobar	14D	0.47	0.54	0.51	0.21	0.13	0.05	-0.08	-0.18	-0.23	-0.03	-0.06	-0.05
Ta'if	1D	0.54	0.56	0.55	0.05	0.04	0.03	-0.11	-0.13	-0.18	0.13	0.03	0.05
Ta'if	3D	0.64	0.58	0.55	0.17	0.16	0.14	-0.03	-0.07	-0.20	0.06	-0.07	0.11
Ta'if	7D	0.72	0.68	0.61	0.14	0.11	0.13	-0.15	-0.16	-0.23	0.17	0.04	0.11
Ta'if	14D	0.67	0.73	0.65	0.08	0.15	0.17	-0.17	-0.15	-0.22	-0.03	-0.11	0.08
Al Jubayl	1D	0.26	0.24	0.19	-0.30	-0.37	-0.36	-0.37	-0.40	-0.37	-0.14	-0.13	0.06
Al Jubayl	3D	0.31	0.28	0.19	-0.07	-0.12	-0.14	-0.19	-0.22	-0.23	-0.10	-0.15	0.00
Al Jubayl	7D	0.26	0.24	0.12	-0.02	0.00	0.00	-0.16	-0.12	-0.12	-0.11	-0.10	0.09
Al Jubayl	14D	0.11	0.18	0.24	0.31	0.25	0.18	0.14	0.11	0.06	-0.14	-0.12	-0.06
Al Qatif	1D	0.59	0.66	0.47	-0.37	-0.44	-0.37	-0.56	-0.62	-0.55	0.08	0.09	0.07
Al Qatif	3D	0.61	0.68	0.47	-0.41	-0.45	-0.40	-0.59	-0.67	-0.60	0.08	0.13	0.14
Al Qatif	7D	0.61	0.66	0.43	-0.26	-0.34	-0.30	-0.50	-0.59	-0.54	0.02	-0.04	-0.08
Al Qatif	14D	0.61	0.60	0.46	-0.04	-0.11	-0.18	-0.29	-0.43	-0.45	-0.04	-0.13	-0.12
Dhahran	1D	0.55	0.59	0.35	-0.41	-0.50	-0.45	-0.56	-0.64	-0.56	0.05	0.00	-0.03
Dhahran	3D	0.56	0.58	0.37	-0.27	-0.34	-0.34	-0.44	-0.52	-0.51	-0.06	-0.04	0.01
Dhahran	7D	0.57	0.61	0.37	-0.31	-0.37	-0.30	-0.57	-0.61	-0.53	-0.03	-0.02	0.03
Dhahran	14D	0.59	0.61	0.50	-0.15	-0.25	-0.25	-0.43	-0.54	-0.51	-0.03	-0.05	-0.03
Buraydah	1D	-0.32	-0.33	-0.38	0.27	0.18	0.10	0.36	0.39	0.30	0.10	0.12	0.00
Buraydah	3D	-0.48	-0.45	-0.41	0.04	0.10	0.05	0.41	0.44	0.38	0.23	0.36	0.00
Buraydah	7D	-0.40	-0.44	-0.47	0.06	0.09	0.07	0.40	0.45	0.34	0.17	0.14	0.00
Buraydah	14D	-0.49	-0.46	-0.37	-0.03	0.01	0.02	0.32	0.41	0.40	0.08	0.15	0.00
Diriyah	1D	0.47	0.49	0.42	-0.26	-0.29	-0.25	-0.49	-0.51	-0.44	-0.16	-0.17	-0.08
Diriyah	3D	0.46	0.51	0.50	-0.27	-0.11	0.05	-0.44	-0.45	-0.32	-0.27	-0.20	-0.05
Diriyah	7D	0.37	0.42	0.42	-0.22	-0.15	-0.11	-0.34	-0.40	-0.28	-0.14	-0.03	0.03
Diriyah	14D	0.38	0.39	0.33	0.12	0.09	0.01	-0.16	-0.23	-0.17	-0.19	-0.14	-0.01
Al Mubarraz	1D	0.26	0.40	0.51	-0.28	-0.17	-0.22	-0.35	-0.42	-0.13	0.43	0.44	0.00
Al Mubarraz	3D	0.48	0.60	0.65	-0.12	0.00	0.03	-0.37	-0.51	0.05	0.14	0.34	0.00
Al Mubarraz	7D	0.64	0.69	0.64	-0.06	0.08	0.11	-0.33	-0.46	-0.21	0.12	0.35	0.00
Al Mubarraz	14D	0.68	0.73	0.59	0.09	0.25	0.37	-0.17	-0.36	-0.26	0.17	0.35	0.00
Tabuk	1D	0.50	0.52	0.52	-0.03	-0.04	0.05	-0.49	-0.49	-0.35	0.16	0.20	-0.13
Tabuk	3D	0.48	0.49	0.48	0.22	0.16	0.20	-0.26	-0.32	-0.18	0.06	0.10	0.00
Tabuk	7D	0.47	0.46	0.44	0.05	0.01	0.15	-0.37	-0.43	-0.15	-0.13	-0.06	0.00
Tabuk	14D	0.42	0.42	0.42	-0.05	-0.08	0.03	-0.35	-0.38	-0.30	0.11	0.18	0.00
Ha'il	1D	0.63	0.61	0.48	-0.18	-0.25	-0.22	-0.33	-0.45	-0.47	0.15	0.14	0.03
Ha'il	3D	0.43	0.47	0.31	-0.34	-0.46	-0.40	-0.43	-0.53	-0.47	-0.12	-0.12	-0.01
Ha'il	7D	0.52	0.47	0.19	-0.35	-0.38	-0.40	-0.43	-0.49	-0.54	-0.24	-0.23	-0.09
Ha'il	14D	0.47	0.56	0.45	-0.28	-0.36	-0.31	-0.55	-0.62	-0.52	0.09	0.10	0.02
Khamis	1D	0.57	0.48	0.68									

Mushait				
Khamis Mushait	3D	0.66	0.75	0.75
Khamis Mushait	7D	0.60	0.72	0.71
Khamis Mushait	14D	0.46	0.58	0.57

Table 2: Pearson correlation coefficients (Correlation is significant at the 0.01 level, 2-tailed)

City/Values	Time Bin	Tmax	Tavg	Tmin	DPmax	DPavg	DPmin	Hmax	Havg	Hmin	WSmax	WSavg	WSmin
Riyadh	1D	0.72	0.72	0.60	-0.01	0.00	0.05	-0.46	-0.47	-0.43	-0.19	-0.39	-0.22
Riyadh	3D	0.71	0.72	0.61	-0.01	0.04	0.10	-0.48	-0.47	-0.42	-0.22	-0.46	-0.23
Riyadh	7D	0.74	0.76	0.65	0.07	0.07	0.05	-0.47	-0.47	-0.45	-0.14	-0.41	-0.18
Riyadh	14D	0.74	0.75	0.65	0.21	0.13	0.03	-0.40	-0.45	-0.43	-0.08	-0.27	-0.08
Jeddah	1D	0.61	0.74	0.68	0.59	0.45	0.28	-0.13	-0.11	0.02	-0.05	-0.08	-0.14
Jeddah	3D	0.56	0.68	0.64	0.58	0.46	0.27	-0.05	-0.05	0.05	0.05	-0.03	-0.08
Jeddah	7D	0.51	0.65	0.64	0.58	0.50	0.35	0.01	-0.01	0.10	0.08	0.07	-0.02
Jeddah	14D	0.56	0.64	0.58	0.52	0.42	0.23	-0.04	-0.14	-0.04	-0.06	0.02	0.02
Makkah	1D	0.38	0.37	0.44	0.31	0.43	0.44	0.19	0.27	0.25	0.11	-0.03	0.10
Makkah	3D	0.48	0.44	0.39	0.27	0.33	0.34	0.09	0.13	0.10	0.04	-0.06	0.09
Makkah	7D	0.48	0.48	0.46	0.27	0.32	0.33	0.05	0.11	0.05	0.05	0.01	0.17
Makkah	14D	0.54	0.56	0.53	0.20	0.26	0.22	-0.11	-0.03	-0.10	0.04	-0.05	0.04
Madinah	1D	-0.05	-0.11	-0.11	0.30	0.19	0.03	0.29	0.23	0.03	-0.01	-0.24	-0.02
Madinah	3D	-0.07	-0.08	0.01	0.15	0.16	0.21	0.15	0.21	0.24	0.30	0.20	0.09
Madinah	7D	-0.22	-0.16	-0.06	0.12	0.14	0.03	0.17	0.26	0.19	-0.11	0.03	-0.02
Madinah	14D	-0.07	-0.10	-0.17	-0.30	-0.27	-0.24	-0.17	-0.19	-0.13	-0.14	-0.04	0.01
Dammam	1D	0.41	0.40	-0.08	-0.42	-0.49	-0.45	-0.51	-0.51	-0.46	-0.13	-0.12	-0.02
Dammam	3D	0.39	0.45	0.10	-0.29	-0.31	-0.33	-0.43	-0.40	-0.36	0.05	0.11	0.12
Dammam	7D	0.47	0.53	0.08	-0.01	-0.05	-0.11	-0.29	-0.34	-0.29	0.10	0.13	0.16
Dammam	14D	0.43	0.45	0.38	0.19	0.08	-0.07	-0.06	-0.19	-0.29	-0.16	-0.18	-0.12
Al Hufuf	1D	0.49	0.49	0.47	-0.17	-0.09	-0.13	-0.39	-0.32	-0.24	0.20	0.01	0.00
Al Hufuf	3D	0.53	0.55	0.55	-0.16	-0.09	-0.04	-0.43	-0.38	-0.27	0.07	0.00	0.00
Al Hufuf	7D	0.49	0.49	0.47	-0.17	-0.09	-0.13	-0.39	-0.32	-0.24	0.20	0.01	0.00
Al Hufuf	14D	0.67	0.69	0.68	-0.09	-0.10	-0.02	-0.52	-0.51	-0.40	0.11	0.13	0.00
Khobar	1D	0.49	0.54	0.00	-0.38	-0.47	-0.46	-0.59	-0.58	-0.47	0.21	0.19	0.16
Khobar	3D	0.52	0.58	0.21	-0.31	-0.35	-0.31	-0.53	-0.50	-0.42	0.04	0.07	0.24
Khobar	7D	0.52	0.63	0.26	-0.20	-0.23	-0.18	-0.44	-0.44	-0.34	0.00	0.07	0.25
Khobar	14D	0.49	0.53	0.47	0.20	0.13	-0.01	-0.08	-0.18	-0.21	-0.02	-0.04	-0.06
Ta'if	1D	0.38	0.49	0.54	-0.20	-0.13	-0.03	-0.25	-0.23	-0.14	0.11	0.24	0.37
Ta'if	3D	0.57	0.54	0.48	0.08	0.03	0.02	-0.14	-0.16	-0.20	0.04	-0.16	0.06
Ta'if	7D	0.38	0.49	0.54	-0.20	-0.13	-0.03	-0.25	-0.23	-0.14	0.11	0.24	0.37
Ta'if	14D	0.55	0.60	0.50	0.06	0.05	0.01	-0.17	-0.22	-0.29	0.04	-0.10	0.03
Al Jubayl	1D	0.14	0.12	0.06	-0.22	-0.29	-0.26	-0.25	-0.30	-0.30	-0.15	-0.14	-0.02
Al Jubayl	3D	0.14	0.13	0.08	0.02	0.01	0.02	-0.04	-0.06	-0.12	-0.12	-0.15	-0.01
Al Jubayl	7D	0.14	0.14	0.07	0.08	0.11	0.09	-0.08	-0.03	-0.06	-0.01	0.06	0.18
Al Jubayl	14D	-0.04	0.02	0.11	0.34	0.29	0.19	0.28	0.25	0.15	-0.25	-0.17	-0.07
Al Qatif	1D	0.49	0.56	-0.02	-0.36	-0.42	-0.41	-0.56	-0.53	-0.41	0.17	0.17	0.19
Al Qatif	3D	0.50	0.62	0.32	-0.34	-0.37	-0.30	-0.52	-0.52	-0.40	0.12	0.22	0.30
Al Qatif	7D	0.52	0.58	0.04	-0.19	-0.26	-0.29	-0.40	-0.45	-0.38	-0.03	0.02	0.04
Al Qatif	14D	0.55	0.58	0.47	0.16	0.04	-0.10	-0.12	-0.28	-0.34	0.00	-0.06	-0.04
Dhahran	1D	0.41	0.48	-0.03	-0.30	-0.41	-0.41	-0.49	-0.51	-0.37	0.23	0.18	0.10
Dhahran	3D	0.45	0.51	0.15	-0.20	-0.27	-0.29	-0.39	-0.40	-0.35	0.10	0.15	0.27
Dhahran	7D	0.44	0.50	0.18	-0.29	-0.33	-0.26	-0.47	-0.47	-0.35	-0.16	-0.06	0.10

Dhahran	14D	0.51	0.56	0.45	0.05	-0.06	-0.14	-0.21	-0.34	-0.36	0.00	0.00	0.02
Buraydah	1D	0.34	0.34	0.36	-0.27	-0.22	-0.11	-0.34	-0.33	-0.28	-0.12	-0.13	0.00
Buraydah	3D	0.50	0.46	0.41	-0.09	-0.12	-0.06	-0.35	-0.34	-0.33	-0.21	-0.34	0.00
Buraydah	7D	0.39	0.44	0.46	-0.07	-0.07	-0.03	-0.31	-0.30	-0.27	-0.18	-0.15	0.00
Buraydah	14D	0.50	0.46	0.34	-0.02	-0.04	-0.04	-0.26	-0.30	-0.32	-0.08	-0.15	0.00
Diriyah	1D	0.40	0.39	0.28	-0.26	-0.32	-0.30	-0.38	-0.37	-0.34	-0.09	-0.24	-0.18
Diriyah	3D	0.37	0.40	0.36	-0.29	-0.19	-0.02	-0.36	-0.34	-0.28	-0.17	-0.25	-0.09
Diriyah	7D	0.30	0.34	0.30	-0.23	-0.24	-0.16	-0.33	-0.33	-0.27	0.01	-0.07	-0.03
Diriyah	14D	0.30	0.35	0.31	0.04	0.01	-0.07	-0.17	-0.19	-0.16	-0.16	-0.10	0.02
Al Mubarraz	1D	0.13	0.24	0.39	-0.29	-0.19	-0.27	-0.31	-0.32	-0.13	0.50	0.30	0.00
Al Mubarraz	3D	0.40	0.52	0.56	-0.17	-0.07	-0.09	-0.38	-0.44	0.04	0.18	0.29	0.00
Al Mubarraz	7D	0.51	0.56	0.57	-0.07	0.02	0.04	-0.35	-0.39	-0.14	0.11	0.27	0.00
Al Mubarraz	14D	0.62	0.69	0.62	0.05	0.14	0.23	-0.20	-0.31	-0.24	0.21	0.40	0.00
Tabuk	1D	0.34	0.33	0.34	0.20	0.12	0.13	-0.13	-0.18	-0.14	-0.06	-0.12	0.00
Tabuk	3D	0.42	0.41	0.37	0.26	0.18	0.17	-0.19	-0.23	-0.13	-0.04	0.00	0.00
Tabuk	7D	0.37	0.37	0.34	-0.03	-0.06	0.05	-0.33	-0.34	-0.03	-0.10	-0.03	0.00
Tabuk	14D	0.30	0.30	0.29	-0.07	-0.12	-0.11	0.10	-0.28	-0.19	0.01	0.03	0.00
Ha'il	1D	0.50	0.47	0.25	-0.16	-0.25	-0.19	-0.27	-0.38	-0.36	0.10	0.04	-0.06
Ha'il	3D	0.35	0.41	0.11	-0.29	-0.41	-0.38	-0.39	-0.44	-0.37	-0.13	-0.13	0.01
Ha'il	7D	0.46	0.42	0.06	-0.21	-0.30	-0.35	-0.31	-0.38	-0.42	-0.22	-0.21	-0.04
Ha'il	14D	0.39	0.45	0.33	-0.29	-0.33	-0.29	-0.49	-0.50	-0.39	0.09	0.09	0.09
Khamis Mushait	1D	0.70	0.10	0.56									
Khamis Mushait	3D	0.59	0.67	0.67									
Khamis Mushait	7D	0.55	0.61	0.63									
Khamis Mushait	14D	0.38	0.54	0.52									

3.1 Temperature

Interestingly 15 out of 17 cities showed significant correlation of temperature with ncases. The rate of change of the temperature shows a significant increasing trend in all 17 cities, the Tavg change was ranging between 0.27^{o} F to 0.35^{o} F per day, during the period of study. The results indicated that the temperature shown good correlation on all 4-time bins viz. on the same day, within 3 days, within 7 days and within 14 days. Riyadh showed an increase in ncases from 36 on March 21, 2020 to around 43000 on 21 June 2020 with observed Tavg ranging of 67.9^{o} F to 101.1^{o} F an increase of 50 % during the observation period. Jeddah showed an increase in ncases from 5 on March 21, 2020 to around 22000 on 21 June 2020 with observed Tavg changing from 76.26^{o} F to 90^{o} F, an increase of 18 % during the observation period. In case of Spearman coefficient 15 out of 17 cities shown significant positive correlation (SPC) with Tmax, Tmin and Tavg. Madinah does not show any significant correlation (SC) and Buraydah shown significant negative correlation (SNC) (Table 1). In case of Pearson coefficient 16 out of 17 cities showed SPC with Tmax, Tmin and Tavg (Table 2). The correlation coefficients for temperature and ncases observed in current investigation are higher ranging from 0.4 to 0.81 compared to other studies (e.g., Sahin [12] have spearman r value of −0.483; Tosepu et al. 2020 have spearman r value of 0.392.). The difference is likely because of the extended time series and different temperature regime.

3.2 Dew point

DPmax and DPavg showed with ncases SPC for Jeddah and Makkah. On the other side Dammam, Al Khobar, Al Qatif, Dhahran and Hail showed SNC with DPmax, DPmin and DPavg. Jeddah showed SPC for maximum and average dew points for all 4-time bins i.e., same day, within 3 days, within 7 days and within 14 days. Makkah showed SPC for DPmin and DPavg on 1D. Dammam showed SNC with DPmax, DPmin and DPavg for all 4-time bins. Al Khobar, Al Jubayl and Dhahran showed SNC with DPmax, DPmin and DPavg on 1D time bin. Al Qatif and hail showed SNC with DPmax, DPmin and DPavg on 1D, 3D and 7D.
Sahin (2020) found significant correlation (-0.3 to -0.4) between dew point cases. Present investigation found the range of correlation coefficients are between -0.4 to -0.59 for some cities and Jeddah and Makkah showed the spearman correlation coefficients value between 0.57 for maximum dew (all time bins) and 0.46 for the average dew on 1D.

3.3 Humidity

Humidity also showed significant correlation with ncases for 12 cities out of 17 cities. The relationship between humidity and ncases is the most on 1D time bin. 11 cities showed SNC of humidity with ncases except Buraydah which showed SPC. Riyadh, Dammam, Al Houfuf, Al Khobar, Al Qatif Dhahran and Hail showed SPC in all 4 time bins (i.e. 1D, 3d, 7D and 14D). Al Jubayl showed SPC for Havg on the same day. On contrary Buraydah showed SPC with Hmax, hmin and Havg for 3 time bins except on the 1D. The major reason could be that the Hmax, Hmin and Havg of Buraydah showed inconsistent trend. In other words the humidity of Buraydah have indicated an increasing trend from March 20, 2020 to April 19, 2020 followed by an inconsistent decreasing trend afterwards till June 20, 2020. In the observation period Diriyah, Al Mubbarraz and Tabuk showed significant correlation on 1D, 3d, 7D and 14D with humidity. Literature suggests that an increase in humidity can suppress the number of infected cases. Basher [2] found the positive correlation of ncases with temperature and negative correlation with relative humidity in New York City, USA. Liu [11] found that humidity is negatively correlated to the increase of ncases. Gupta [7] indicates a negative correlation between humidity and ncases in India. Wu [20] indicated a negative correlation between daily relative humidity and ncases in Chinese cities. Wu [20] suggested that the ncases probably decrease with rise in temperature and humidity. Several previous epidemiological investigations suggested a negative correlation between humidity and virus diseases [9] [11]. Therefore, the relationship between humidity and ncases in present investigation are in agreement with other studies.

3.4 Wind Speed

Wind is an important meteorological parameter for the spread of infectious diseases [6]. The wind speed showed significant correlation only in two cities. Riyadh showed SNC with WSavg on two-time bins (1D and 3D). Second city which showed SPC with WSmax and WSavg on 1D is Al Mubbarraz. Wind speed showed positive correlation with ncases over Oslo, Norway [13] in Turkey [12] and in New York, USA [2]. Pani [14] found no correlation of WS with ncases over Singapore.

Different factors can influence the spread of COVID-19, including meteorological variables, population of the city, and medical treatment [19]. The goal of the current investigation was to assess the impact of meteorological parameters on COVID-19 transmission. A positive correlation was observed between temperature and the ncases, which states that increasing temperatures does not indicate any significant decrease in ncases. It is evident that the effect of temperature on human health can vary between different regions [8]. The findings of current investigation are in line with other studies which suggested that there is a positive correlation between temperature and ncases. Auler [1] suggested that high temperature and humidity may not reduce the spread of COVID-19 in tropical regions. Tosepu [18] observed that Tavg showed SPC with ncases($r = 0.392$). Bashir [2] found that Tmin and Tavg are positively correlated with the spread of ncases in New York city. Gupta [7] found positive correlation between temperature and ncases in India. Pani [14] suggested that Tavg, Tmin have shown SPC with ncases over Singapore. Xie [22] also found that there is no indication that ncases would suppress with increase in temperature. On the contrary, some studies found that the COVID-19 spread is negatively correlated with the temperature [11] [12] [16] [19]. The major reason of this contradiction may be that COVID-19 is in a stage of rapid transmission through community transmission [17]. Therefore, the effect of meteorological parameters alone is not sufficient to fully understand the COVID-19 transmission. The population of the cities showed a very high correlation with ncases with r value of 0.91. In other words, the population is directly proportional to ncases.

4. Limitations

Despite the interesting findings of the meteorological factors with ncases, this study has some limitations. COVID-19 is in a stage of rapid transmission and high infectivity [17]. Probably, the impact of meteorological parameters with ncases is not sufficient fully to inhibit the pattern and behavior of current pandemic. Some other factors need to be investigated such as human to human transmission, mobility or migration of population etc. There may be governing processes and unknown variables that control the pandemic's need to be researched. In view of different opinion about the role of temperature on COVID-19 spread, there is a requirement of considering more number of regions including different temperature and climatic regimes.

5. Conclusions

The current study analyses the correlation of meteorological parameters (temperature, humidity, dew point, and wind speed) on 4 time bins (on the same day, within 3 days, within 7 days and within 14 days) with COVID-19 cases of 17 cities in Saudi Arabia. The population showed a high correlation with the COVID-19 number of cases with r value of 0.91. It was observed that the highest number of correlations (15 cities) was found with temperature (maximum, minimum and average) and humidity (12 cities) (minimum and average). The dew point showed relationships for 7 cities and wind showed moderate correlations only for 2 cities. The future scope of this research is to include more number of parameters such as effect of virus resistivity at different temperatures and different altitudes, wind direction, air quality parameters (AOD, PM2.5, PM 10 etc.), solar radiation, and including

more number of regions having different temperature and climatic regimes.
The future scope of the present investigation is to utilize the advanced deep learning models including [23-27] for other semi-arid regions of the world [28-32].

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