Stochastic analysis of the relationship between atmospheric variables and coronavirus disease (COVID-19) in a hot, arid climate

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Abstract
The rapid outbreak of the coronavirus disease (COVID-19) has affected millions of people all over the world and killed hundreds of thousands. Atmospheric conditions can play a fundamental role in the transmission of a virus. The relationship between several atmospheric variables and the transmission of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) are therefore investigated in this study, in which the State of Kuwait, which has a hot, arid climate, is considered during free movement (without restriction), partial lockdown (partial restrictions), and full lockdown (full restriction). The relationship between the infection rate, growth rate, and doubling time for SARS-CoV-2 and atmospheric variables are also investigated in this study. Daily data describing the number of COVID-19 cases and atmospheric variables, such as temperature, relative humidity, wind speed, visibility, and solar radiation, were collected for the period February 24 to May 30, 2020. Stochastic models were employed to analyze how atmospheric variables can affect the transmission of SARS-CoV-2. The normal and lognormal probability and cumulative density functions (PDF and CDF) were applied to analyze the relationship between atmospheric variables and COVID-19 cases. The Spearman’s rank correlation test and multiple regression model were used to investigate the correlation of the studied variables with the transmission of SARS-CoV-2 and to confirm the findings obtained from the stochastic models. The results indicate that relative humidity had a significant negative correlation with the number of COVID-19 cases, whereas positive correlations were observed for cases of infection and temperature, wind speed, and visibility. The infection rate for SARS-CoV-2 is directly proportional to the air temperature, wind speed, and visibility, whereas inversely related to the humidity. The lowest growth rate and longest doubling time of the COVID-19 infection occurred during the full lockdown period. The results in this study may help the World Health Organization (WHO) make specific recommendations about the outbreak of COVID-19 for decision-makers around the world. Integr Environ Assess Manag. 2022;18:500–516. © 2021 SETAC

KEYWORDS: Atmospheric variables, Correlation, Regression, SARS-CoV-2 infection, Stochastic models

INTRODUCTION
The coronavirus disease (COVID-19) is a viral infectious disease that is seriously threatening public health and the economy worldwide. COVID-19 was first identified in Wuhan, China, at the end of December 2019, and is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The clinical symptoms of infection caused by the virus, such as dry cough, fever, pneumonia, dyspnea, and respiratory disorders, can lead to progressive respiratory failure and death in susceptible individuals. At the end of January 2020, the World Health Organization (WHO) declared the outbreak of this virus a public health emergency of international concern, after which it was declared a global pandemic on March 11, 2020. COVID-19 has spread across the globe, with more than 126 million confirmed cases of infection and 2.77 million deaths worldwide as of March 27, 2021 (World Health Organization, 2021). Kuwait is considered a developing country and has been severely affected by this global health crisis. The Ministry of Health for the State of Kuwait declared the first case of SARS-CoV-2 infection on February 24, 2020. More than 226,000 confirmed COVID-19 cases and 1270 deaths occurred in Kuwait as of March 27, 2021 (World Health Organization, 2021). Several vaccines became widely available during the review and post-acceptance of this paper, which has since greatly slowed transmission rates and case numbers where vaccination rates are high (World Health Organization, 2021). Fear became a worldwide phenomenon during the period in which the transmission of the virus peaked because of the limited understanding surrounding its route of transmission. It is therefore important that...
parameters that may play a role in the transmission of SARS-CoV-2 and its spread in the outdoor environment are better understood. Transmission may be affected by various factors including atmospheric variables (such as temperature, humidity, wind speed, visibility, and solar radiation). Thus, understanding the relationship between atmospheric variables and the transmission of SARS-CoV-2 and its spread could be vital in making the best decisions that can minimize or prevent outbreaks of the virus; however, evidence of any possible relationship is still limited.

Previous studies have indicated a relationship between the weather (short-term variation in meteorological conditions) or climate (long-term averages) and the outbreak and transmission of viruses (Casanova et al., 2010; K. Lin et al., 2006; Tamerius et al., 2013; Tan et al., 2005; Van Doremalen et al., 2013; J. Yuan et al., 2006; Lowen and Steel, 2014; Jaakkola et al., 2014). Chan et al. (2011) and Park et al. (2020) investigated the effects of temperature, humidity, and the diurnal temperature range on both the SARS coronavirus and influenza. Their results indicated that high temperatures had a synergistic influence on the inactivation of the SARS coronavirus under high humidity, whereas the incidence of influenza increased under low temperatures and low/high humidity in temperate regions. Another study by Bhimireddy and Bhaganagar (2018) investigated the transport and dispersion of plume in the convective boundary layer conditions for Pure Convective, Neutral regimes. The study’s findings demonstrate that the horizontal transport of the plume scales with the near-surface releases and initial wind conditions for the surface, and the vertical transport scales with atmospheric stability parameters.

ENVIRONMENTAL VARIABLES AND TRANSMISSION OF SARS-COV-2 PANDEMIC

The SARS-CoV-2 outbreak transmission is affected by several environmental variables, for example, weather, climate and atmospheric variables, virus infectivity, host defense mechanism, host behavior, and so forth. Atmospheric variables are essential parameters that are a global primary concern caused by the prevalence of COVID-19 around the world. Studies conducted in 2020 investigated the correlation between the weather or climate variables (e.g., temperature, humidity, wind speed, visibility, rain, and solar radiation) and the number of COVID-19 cases. Several of these studies have concentrated on different cities and countries around the world, for example, the United States and Europe (Bukhari & Jameel, 2020; Gharoie Ahangar et al., 2020), Africa (Adekunle et al., 2020), Russia (Lasisi and Eluwole, 2021), Wuhan, China (Ma et al., 2020), 122 cities in China (Xie & Zhu, 2020), India (Awasthi et al., 2020; Borah et al., 2020; Gupta, Pradhan, et al., 2020), Jakarta, Indonesia (Tosepu et al., 2020), Pakistan (Aslam et al., 2020), Brazil (Aule et al., 2020; Pequeno et al., 2020), Iran (Ahmadi et al., 2020). Preliminary studies that found no relationship between COVID-19 transmission and atmospheric variables (e.g., temperature) were performed by Xie and Zhu (2020), Gupta, Raghuvanshi, et al. (2020), and Yao et al. (2020). Still, some studies found a positive and negative relationship between COVID-19 transmission and atmospheric variables. For example, Zhu, and Liu, Huang, et al. (2020) investigated the meteorological effects on COVID-19 transmission in South America using a multiple linear regression model. The results demonstrated that absolute humidity is negatively correlated with COVID-19 transmission in some regions. Other studies conducted in the USA and other tropical regions by Sobral et al. (2020), J. Lin et al. (2020), Bashir et al. (2020), Melo et al. (2020) and Méndez-Arriaga (2020) assessed the nexus analysis between and the spread of COVID-19 climate variables using the regression models. The aforesaid authors indicated that the humidity and temperature often affect the spread of COVID-19. Esfandi and Jallili (2020) discussed the role and impact of different environmental factors (e.g., humidity, temperature, wind speed, and solar radiation) in the spread of COVID-19. The results demonstrated that the increased temperature and sunlight could facilitate the destruction of COVID-19 and its stability on surfaces. Another study, conducted in 100 countries by Tzampoglou and Loukidis (2020), investigated the impact of climatic factors on the intensity of COVID-19 transmission using statistical models for several countries. The results indicate a significant correlation between atmospheric temperature and COVID-19 transmission and death rates. Another study in Bangladesh by Islam, Hasanuzzaman, et al. (2021) discussed the meteorological impacts of the COVID-19 outbreak using a multiple linear regression model, a Monte Carlo method, a compound Poisson generalized linear model, and a random forest model. Results indicated that high humidity and temperature reduce COVID-19 outbreaks. Asyary and Ver- uswati (2020) demonstrated that exposure to sunlight was significantly correlated with patients’ recovery from COVID-19 in Jakarta, Indonesia. Some studies in India by Kumar and Kumar (2020), Mousavi et al. (2020), Liu et al. (2020), Singh et al. (2020), and Ladha et al. (2020) investigated the association between climatic conditions and COVID-19 transmission in different states of India (e.g., Mumbai, Delhi, Tamil Nadu, Maharashtra, and Gujarat), using the artificial neural network technique, Spearman’s rank correlation model, Mann–Kendall method, Karl Pearson’s correlation analysis, and Sen’s slope estimator. The results found that relative humidity and pressure parameters are more active than the other parameters on the COVID-19 pandemic. The effects of meteorological indicators on COVID-19 cases and infection rates in Pakistan were investigated by Raza et al. (2020) using generalized Poisson regression. This study implies that COVID-19 cases increased with a temperature rise. Another study in Singapore was carried out by Pani et al. (2020) to investigate the relationship of the COVID-19 outbreak with several meteorological parameters using Spearman’s and Kendall’s rank correlation models. The results revealed that temperature, humidity, dew point, and water vapor have a positive correlation with the COVID-19 pandemic. Yang et al. (2021) and Pramanik et al. (2020)
explored whether the relationship of COVID-19 transmission and meteorological factors, with the season and geographical locations using the random forest algorithm, multiple stepwise regression, and Pearson correlations. The results revealed that the lognormal distribution model had the best fit for the changes of COVID-19 infected cases. Fu et al. (2021) studied the influence of governmental responses and meteorological factors on COVID-19 transmission in four European countries (UK, Italy, Germany, and Spain) using the distributed lag nonlinear model. Their results demonstrated that both the dry and cold environments are likely to facilitate COVID-19 transmission. Cacho et al. (2020) and Briz-Redón and Serrano-Aroca (2020a) evaluated the effect of ultraviolet radiation, humidity, and temperature on COVID-19 incidence and the severity across the Spanish cities. Ultraviolet radiation was significantly related to COVID-19 incidence and severity. Neto and Melo (2020) analyzed the correlation between the cases of COVID-19 and population size, and the weather in Brazil’s cities. The analysis revealed a significant positive correlation between humidity and instances of COVID-19. A study conducted by Islam, Bukhari, et al. (2021) discussed the relationship between COVID-19 cases and humidity, temperature, and UV index globally. They found a negative correlation for COVID-19 patients with wind speed. Using data from different outbreak countries (e.g., Italy, UK, France, Sweden, Iran, the United States, Korea, and Australia), Rouen et al. (2020) studied the association between the case growth rate COVID-19 and temperature. They found a negative correlation between temperature variation and daily cases. Şahin (2020) examined the correlation between weather conditions and COVID-19 in Turkey. The results indicated that temperature and wind speed have a positive relationship with the number of COVID-19 cases. A new challenge in sustainable development in Italy by Pirouz et al. (2020) discussed the effect of urban and climate parameters in the correlation between temperature variation and daily cases. Şahin (2020) reported that temperature has a negative linear relationship with the number of COVID-19 cases in Spain’s provinces. They found no consistent evidence of a correlation between the number of COVID-19 cases and temperature at the provincial level in Spain. Another relevant study published by Prata et al. (2020) reported that temperature has a negative linear relationship with the number of confirmed COVID-19 cases. However, Menebo (2020) demonstrated that temperature is positively correlated with SARS-CoV-2 infection, whereas precipitation correlates negatively. Zhu, Liu, Huang, et al. (2020) also investigated the relationship between daily temperature and the number of confirmed SARS-CoV-2 infections in 122 cities in China. They found that daily temperature has a positive linear relationship with the number of COVID-19 cases, with a threshold of 3 °C. Studies by Ma et al. (2020) and Wu et al. (2020) examined the impacts of temperature, diurnal temperature range, and humidity on the mortality of COVID-19 in the Chinese population. They concluded that the mortality of COVID-19 correlates positively with the diurnal temperature range but negatively with humidity. In addition, they demonstrated that the COVID-19 pandemic might be partially suppressed by an increase in the daily temperature and relative humidity. The effects of meteorological conditions, such as temperature, humidity, and rainfall, on the spread of SARS-CoV-2 in a tropical climate were modeled by Auler et al. (2020). They revealed that higher temperatures and humidity favor the transmission of SARS-CoV-2, which differs from the results reported in colder countries. Furthermore, the impacts of atmospheric thermal stability, based on wind speed and air pollution, on the spread of the COVID-19 pandemic were investigated by Coccia (2020) using statistical evidence that supports the hypothesis. Results indicated that high atmospheric stability, with low wind speed, may accelerate the diffusion of SARS-CoV-2 in the atmosphere. A new study by Bhaganagar and Bhimireddy (2020) analyzed the local atmospheric parameters (e.g., atmospheric stability, wind shear, wind speed and direction, air turbulence, air temperature, and moisture content) that enhanced airborne dispersion of coronavirus during March 9–April 6, 2020, in New York City, USA, using Weather-Research-Forecast model coupled with the Lagrangian Hybrid Single-Particle Lagrangian Integrated Trajectory (WRF-HYSPLIT) model. Their study
concluded that atmospheric stability regimes, the transport direction, and the extent of blob spread correlate with the wind shear and temperature gradient, and also with the scales of the horizontal rolls and thermal updrafts and downdrafts.

In hot, arid climates, some studies performed in Iran, Algeria, Pakistan, Mexico, Kuwait, United Arab Emirates, Oman, Ghana, India, Saudia Arabia, and Iraq (Kurdistan region) by Meo et al. (2020), Sasikumar et al. (2020), Alkhowailed et al. (2020), and Amin and Amin (2020) examined the impact of the climate variables on the COVID-19 outbreak. They demonstrated that positive COVID-19 cases increase as humidity, temperature, and wind speed decrease. Another study on a global scale by Iqbal et al. (2020) explored the connection between regional climate parameters and the spread of COVID-19. The results indicated that countries in the colder temperature zone display a faster rise in COVID-19 cases than countries in warmer temperature zones. In contrast, a review of the effect of environmental factors on the spread of COVID-19 was summarized by Azuma et al. (2020), Briz-redon and serrano-aroca (2020b), Kumar et al. (2021), Meccenas et al. (2020), McClymont and hu (2021), and Paraskevis et al. (2020). Some of these studies demonstrated a negative correlation between COVID-19 cases with temperature and a positive correlation with humidity. Another study between Switzerland and the United Arab Emirates by Daneshvar et al. (2021) indicated distinct differences or similarities in the climate impacts on COVID-19 transmission using correlation modeling. The results demonstrated that the impacts of climate on COVID-19 transmission play different roles in the various countries based on climatic regions.

Considering the studies above, conducted by researchers in different cities and countries worldwide using various statistical and modeling techniques, it is clear that much debate remains about the association between the spread and transmission of the COVID-19 pandemic and atmospheric variables. Some studies found no association of the COVID-19 outbreak with atmospheric variables, whereas other studies demonstrated strong and weak, positive and negative associations between the spread of the COVID-19 pandemic and atmospheric variables. Therefore, the association of the COVID-19 outbreak with atmospheric variables is inconsistent and needs more study and time to better understand and evaluate it.

The WHO reported that, currently, there is no conclusive evidence that either meteorological or climate conditions have a strong effect on the transmission of SARS-CoV-2 (World Health Organization, 2020). Thus, proving a relationship between atmospheric variables and COVID-19 outbreaks could be helpful in predicting the pattern of infection over the coming months. However, various parameters may influence the progression of the COVID-19 pandemic. The main objective of this study is, therefore, to investigate the relationship between atmospheric variables (temperature, relative humidity, wind speed, visibility, and solar radiation) and the outbreak of COVID-19 in the State of Kuwait, with a hot, arid climate, using stochastic models. The results will have implications for policy-makers and the public. In this work, stochastic models with a probability density function (PDF) and cumulative density function (CDF) for normal and lognormal distributions were used to model the atmospheric variables and COVID-19 cases. Spearman’s rank correlation and the multiple regression model were used to investigate the correlation between atmospheric variables and the transmission of SARS-CoV-2.

MATERIALS AND METHODS

Site description

The State of Kuwait is situated in the area between 29°30′N and 30°05′N and 46°03′E and 48°35′E in the northeast of the Arabian Peninsula and covers approximately 17,818 km² (Al-Rashidi et al., 2018; Yassin et al., 2018b,c). The climate of Kuwait is characterized as arid with extreme heat and large quantities of airborne dust, low humidity, and little precipitation (Al-Dabbous and Kumar, 2014; Al-Dousari et al., 2019). Kuwait has two primary seasons, namely, summer (during which the temperature ranges between 48 and 54 °C), extending from May to September, and winter, which extends from December to February. In addition, there are two transient seasons—spring, which occurs during March and April, and autumn, which occurs during October and November (Al-Dousari et al., 2020; Yassin et al., 2018a; Yassin et al., 2021). The present study gathered data during spring and summer.

Data collection

Daily data concerning COVID-19 cases and atmospheric variables were collected from February 24 to May 30, 2020, during periods of free movement, partial lockdown, and full lockdown. The period of free movement, during which no restrictions were applied to movement, fell between February 24 and March 21, 2020. Partial lockdown, in which movement was partially restricted, was implemented between March 22 and May 9, 2020, and the full lockdown was enforced between May 10 and May 31, 2020. The daily data for COVID-19 cases in Kuwait were extracted and collected from daily situation reports published by the Ministry of Health for the State of Kuwait (https://corona.e.gov.kw/en).

Data describing the daily atmospheric variables were obtained from weather stations operated by the Directorate General of Civil Aviation (DGCA), Kuwait. Data describing the daily atmospheric variables were collected from weather stations operated by the DGCA, Kuwait. Variables included daily temperature, relative humidity, wind speed, visibility, and solar radiation from February to May 2020. These data are maintained by the meteorology department’s quality control and assured process under the supervision of DGCA. The data processing system uses a nationwide network of fully automatic data collection units (DCU). Each DCU has a meteorological, agro-meteorological, and oceano-graphic sensor suite tailored to its specific application. The DCU units read the sensors in real time and partially process the raw values into meaningful, quality-checked,
1-min values. These values are then communicated back to a central data acquisition system, where the values are further processed into hourly, daily, and monthly statistics. These processed values are displayed on a graphical user interface at the meteorological and display working places. They are also used to generate standard World Meteorological Organization messages, such as SYNOP, SHIP, BUOY, and CLIMAT. The quality monitoring system (QMS) tests, analyses, edits, and monitors these data in the climate database management system (CDMS). CDMS is a relational database that stores meteorological and related data necessary to meet climate data’s present and future needs. The data stored in CDMS form the basis of the climate record. It should be considered that there is a period of latency between the day on which a person becomes infected and the day on which the infection is confirmed; the average duration of this period is 3 days. This 3-day delay was therefore taken into account, meaning that the atmospheric data used described the conditions 3 days before infection was confirmed.

**Stochastic models**

A stochastic model is a tool used to assess the probability distribution of potential outcomes by allowing for random variation in one or more inputs over time. The intensity of COVID-19 cases varied randomly because of changes in the atmospheric conditions. Either the PDF or the CDF was applied as a continuous random variable in the stochastic models, with various applications. As a continuous random variable, the PDF is the density of the probability that a variable has value \( x \). Because the probability of continuous distribution at a single point is zero, this variable is often expressed in terms of integrating two points.

\( x \) is a random variable if the PDF is used, where \( f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-u)^2}{2\sigma^2}} \) is the normal distribution (8).

The lognormal distribution of the PDF is:

\[
f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\ln x-u)^2}{2\sigma^2}}
\]

The lognormal distribution of the CDF is:

\[
F(x) = \frac{1}{2} \left[ 1 + e^{(\ln x-u)/\sigma^2} \right]
\]

where \( \mu \) is the mean of the random variables and \( \sigma \) is the standard deviation.

The random variables (i.e., the intensity of SARS-CoV-2 infection and atmospheric variables = \( \sqrt{(x-\text{mean}(x))} \)) were normalized by their corresponding mean (\( x/\mu \)), where \( x \) and \( \mu \) represent the intensity and mean of the data, respectively. The variable \( x/\mu \) was included in the stochastic model.

**Data analysis**

The infection rate (IR), growth rate (GR), and doubling time (DT) were used to analyze the number of COVID-19 cases during the free movement, partial lockdown, and full lockdown periods. The IR indicates the speed of the spread of COVID-19. The GR indicates the infection cases during the three periods. In contrast, the DT indicates the time taken for a count to double the infection cases for every period. The IR is defined in Equation (12) (Ahmadi et al., 2020; Raza et al., 2020):

**Infection rate (IR)**

\[
\text{IR} = \frac{\text{Then Number of infections}}{\text{The number of those at risk of infection}}
\]

The GR and DT are defined in Equations (13 and 14) (Gupta, Pradhan, et al., 2020; Patel & Patel, 2020):

**Growth rate (GR)**

\[
GR = \frac{Nf}{Ne}^{1/n} - 1
\]

**Doubling time (DT)**

\[
DT = n \cdot \ln(2) / \ln\left(\frac{Ne}{Nf}\right)
\]

where \( Nf/Ne \) is the number of infection cases on the first and last day, and \( n \) is the number of infection days.
Descriptive statistical analyses of the number of COVID-19 cases, IR, and atmospheric variables were performed using minimum, maximum, mean, standard deviation, skewness, and kurtosis distributions. As the data used in this study were not normally distributed, Spearman’s rank correlation \( r_s \) was utilized to examine the correlation between the atmospheric variables and COVID-19 cases. The formula describing the correlation coefficient is defined in Equation (15):

\[
r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}
\]  

(15)

where \( n \) is the number of days and \( d_i \) is a value representing the difference in the number of COVID-19 cases and the atmospheric variables over the period studied.

In addition, a multiple regression model was used to evaluate the relationship between the atmospheric parameters and COVID-19 cases, with the atmospheric parameters as independent variables and COVID-19 cases as the dependent variable. Where multiple regression models are appropriate for the different scenarios in which multiple variables influence a single result. COVID-19 cases \( (Y) \) were modeled as a function of five atmospheric variables \( (X) \): temperature \( (x_1) \), relative humidity \( (x_2) \), wind speed \( (x_3) \), visibility \( (x_4) \), and solar radiation \( (x_5) \) with their corresponding coefficients \( (\beta) \).

The multiple regression model equation can be expressed as:

\[
\hat{Y} = f(X, \beta) + e_i
\]  

(16)

\[
\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1x_1 + \hat{\beta}_2x_2 + \hat{\beta}_3x_3 + \hat{\beta}_4x_4 + \hat{\beta}_5x_5 + e_i
\]  

(17)

A two-tailed \( p \)-value of <0.10 was considered statistically significant for all statistical analyses. The statistical analyses of daily SARS-CoV-2 infections and atmospheric variables were carried out using MATLAB version 2020b.

RESULTS

The predictive performances of the stochastic models described in the previous section: “Stochastic Models” were first estimated. To investigate how infection with SARS-CoV-2 may change with differing atmospheric variables, descriptive statistics, stochastic analyses, and correlation analyses were applied to evaluate the relationship between infection and temperature, humidity, wind speed, visibility, and solar radiation during the three periods of free movement (February 24–March 21, 2020), partial lockdown (March 22–May 9, 2020), and full lockdown (May 10–30, 2020). Table 1 details the number of COVID-19 cases, the number of deaths, and the GR and DT during the periods of free movement, partial lockdown, and full lockdown, provided by the Ministry of Health for the State of Kuwait. In all, SARS-CoV-2 infections numbered 176, 8512, and 17,504 during free movement, partial lockdown, and full lockdown, respectively, and the number of deaths was 0, 58, and 147, respectively. In contrast, the GR was 4.4, 6.5, and 0.26, with the DT at 15.26, 9.59, and 264.62, respectively. This table clearly shows that the GR of infection was 4.4 during the free movement period, but it moves up during the partial lockdown period and then drops during the full lockdown period. Simultaneously, the DT of infection was 15.29 during the free movement period, but it dropped during the partial lockdown period and quickly moved up during the full lockdown period. The fewest COVID-19 cases were reported during the period in which free movement was still allowed, estimated at 176.00. The fewest deaths were also recorded in this period, with a value of 0.00. The lowest GR of infection occurred when the full lockdown was a full restriction, estimated at 0.26. The lowest DT of infection was during the partial lockdown period, with a value of 9.59. Meanwhile, the most cases, the most deaths, the highest GR, and the highest DT of infection were 17,504.00, 147.00, 6.5, and 264.62, respectively, occurring during the full lockdown, except the GT in partial lockdown. Therefore, it is essential to investigate the factors that most influenced SARS-CoV-2 infection in Kuwait during free movement, partial lockdown, and full lockdown periods.

Descriptive statistics analysis

Table 2 provides statistics describing the number of SARS-CoV-2 infections occurring daily, atmospheric variables, and IRs over the three periods under investigation. The relationship between atmospheric variables and COVID-19 cases was statistically evaluated for the three different periods to establish if any correlation between the different variables could be found. The relationships between each atmospheric variable and SARS-CoV-2 infection are as follows.

(a) Temperature

The descriptive analysis listed in Table 2 demonstrates mean temperatures of 19.83, 25.73, and 32.93 °C, respectively, during the periods of free movement, partial lockdown, and full lockdown. The corresponding mean number of infections with SARS-CoV-2 was 6.5, 152.0, and 884.0, respectively. These results suggest that the temperature was correlated with the number of infections occurring during the three periods studied. The number of infection cases and rates increased when the temperature increased. Accordingly, it is possible
that temperature has a significant impact on SARS-CoV-2 infection. Therefore, air temperature is an environmental factor that affects the spread and transmission of the COVID-19 outbreak. The skewness (asymmetry of the probability distribution) and kurtosis (tailedness of the probability distribution) also support this positive relationship. Excess kurtosis was calculated for normal distribution, which is equal to zero. The skewness and kurtosis that were related to temperature decreased during the periods of free movement and partial lockdown, whereas the skewness and kurtosis associated with infection increased. However, the opposite was observed for full lockdown, during which the skewness and kurtosis associated with temperature rose, and the skewness and kurtosis of infection decreased.

(b) Relative humidity
The descriptive analysis in Table 2 indicates the presence of a relationship between relative humidity and SARS-CoV-2 infection. The relative humidity during the periods of free movement, partial lockdown, and full lockdown was 51.28%, 41.30%, and 21.81%, respectively, indicating that a decrease in the relative humidity was related to an increase in infection cases and rates. There appears to be an inverse relationship between relative humidity with COVID-19 cases and infected rates during the three periods. Furthermore, as the skewness and kurtosis of relative humidity increased during the three periods studied, the skewness and kurtosis of COVID-19 cases increased during the periods of free movement and partial lockdown, whereas it decreased during full lockdown.

(c) Solar radiation
The descriptive statistics in Table 2 suggest a relationship between solar radiation and SARS-CoV-2 infection. The amount of solar radiation attainment on the surface during free movement, partial lockdown, and full lockdown was 1230.10, 1437.00, and 1648.10 J/cm², respectively. This indicates the possibility of a direct

| TABLE 2 Descriptive analysis of SARS-CoV-2 infection and atmospheric variables during free movement, partial lockdown, and full lockdown periods |
| --- |
| Variables | Periods | Height*, m | Min. | Max. | Mean | SD | Skewness | Kurtosis |
| Infected cases | Free movement | – | 0.0 | 20 | 6.5 | 5.83 | 0.83 | –0.25 |
| Infected rate (%) | – | 0.0 | 20.6 | 6.7 | 11.44 | 0.83 | –0.25 |
| Temperature (°C) | 2.0 | 17.1 | 22.4 | 19.83 | 1.67 | –0.14 | –1.33 |
| Humidity (%) | 2.0 | 33.60 | 71.80 | 51.28 | 11.95 | 0.11 | –1.24 |
| Wind speed (m/s) | 10.0 | 1.80 | 7.10 | 3.94 | 1.42 | –0.57 | –0.28 |
| Visibility (m) | 2.0 | 250 | 7000 | 3244.4 | 1896.67 | 0.16 | –1.02 |
| Solar radiation (J/cm²) | 2.0 | 528.2 | 1553.0 | 1230.10 | 240.67 | –1.61 | 2.80 |
| Infected cases | Partial lockdown | – | 1 | 641 | 152 | 149.5 | 1.41 | 1.74 |
| Infected rate (%) | – | 18.8 | 33.2 | 26.5 | 3.45 | –0.32 | –0.26 |
| Temperature (°C) | 2.0 | 18.2 | 32.2 | 25.73 | 3.34 | –0.32 | –0.26 |
| Humidity (%) | 2.0 | 19.70 | 64.80 | 41.30 | 13.51 | 0.16 | –1.34 |
| Wind speed (m/s) | 10.0 | 2.10 | 8.60 | 4.06 | 1.49 | 0.88 | 0.27 |
| Visibility (m) | 2.0 | 300.0 | 10000 | 4605.70 | 2672.17 | 0.181 | –1.12 |
| Solar radiation (J/cm²) | 2.0 | 479.2 | 1892.7 | 1437.00 | 315.63 | –1.102 | 0.95 |
| Infected cases | Full lockdown | – | 598 | 1073 | 884 | 152.84 | –0.53 | –0.80 |
| Infected rate (%) | – | 616 | 1106 | 911 | 157.57 | –0.52 | –0.80 |
| Temperature (°C) | 2.0 | 28.70 | 36.90 | 32.93 | 2.22 | 0.001 | –0.51 |
| Humidity (%) | 2.0 | 15.10 | 36.60 | 21.81 | 5.19 | 1.453 | 2.21 |
| Wind speed (m/s) | 10.0 | 2.20 | 7.50 | 4.05 | 1.80 | 0.85 | –0.70 |
| Visibility (m) | 2.0 | 650.0 | 8000.0 | 4478.6 | 2674.72 | –0.17 | –1.58 |
| Solar radiation (J/cm²) | 2.0 | 923.0 | 1889.6 | 1648.1 | 234.71 | –2.07 | 4.27 |

*Sensor Height.
positive relationship between solar radiation and infection cases and rates during the periods of study. Thus, solar radiation had a significant effect on SARS-CoV-2 infection. Moreover, the skewness and kurtosis of solar radiation decreased during the periods of free movement and partial lockdown, whereas the parameters relating to the number of COVID-19 cases increased. The skewness and kurtosis of solar radiation increased during full lockdown, whereas the skewness and kurtosis of infection decreased.

(d) Wind speed and visibility

According to the descriptive statistics results in Table 2, there was no direct relationship between COVID-19 cases and variations in wind speed or visibility. The average wind speed during the three periods was 3.94, 4.06, and 4.05 m/s, respectively, and the visibility was 3244.4, 4605.7, and 4478.6 m, respectively. This indicates that there was an increase in the wind speed and visibility during the periods of free movement and partial lockdown alongside the growth in the number of COVID-19 cases, whereas both factors decreased during full lockdown. These contradictions indicate that there is no consistent association between SARS-CoV-2 infection and wind speed or visibility. The above descriptive analyses revealed the possibility of a relationship between COVID-19 outbreaks and atmospheric variables. The IR for SARS-CoV-2 is directly proportional to the air temperature, wind speed, and visibility but inversely related to the humidity. The importance of each atmospheric variable during each period was therefore further investigated, and the results are discussed in Section: Stochastic Model Analysis.

Stochastic model analysis

The intensity of COVID-19 cases and the atmospheric variables were normalized by the mean (x/μ) in this study. This was applied to clarify the variation in the PDF and CDF shapes that relate the number of infections to changing atmospheric variables. Figures 1–3 show the normal and

FIGURE 1 Normal and lognormal PDFs and CDFs of SARS-CoV-2 infection and atmospheric variables during the free movement period. CDFs, cumulative density functions; PDFs, probability density functions.
lognormal PDF and CDF of SARS-CoV-2 infection and atmospheric variables during the three periods from February 24 to May 30, 2020. The characteristics of the normal and lognormal PDF and CDF for SARS-CoV-2 infection and atmospheric variables during the periods of free movement, partial lockdown, and full lockdown are as follows.

(a) Free movement (without restriction)

Figure 1 shows the normal and lognormal probability density functions (PDFs) and cumulative density functions (CDFs) of both SARS-CoV-2 infection and atmospheric variables during the period in which free movement was allowed. During this period, the normal PDFs of temperature and relative humidity exhibited symmetrical, sharp, and narrow curves, whereas the normal PDFs of infections, wind speed, visibility, and solar radiation exhibited asymmetrical, wide curves. The highest value of the normal PDF was 0.75 for temperature, and the lowest was 0.5, also for temperature. However, the highest and lowest values of the lognormal PDF were associated with temperature and relative humidity, respectively. Figure 1 shows that the normal and lognormal PDFs describing the number of COVID-19 cases were very similar to those of temperature and relative humidity in terms of shape and value. These similarities suggest that temperature and relative humidity had a strong relationship with the SARS-CoV-2 infection during the period of free movement. Figure 1 indicates that the normal PDF and CDF of COVID-19 cases were considerably different from those associated with wind speed, visibility, and solar radiation. This means that wind speed, visibility, and solar radiation had a weak relationship with infection during the period of free movement. One feature to note is that the value and shape of the normal and lognormal CDFs of COVID-19 cases were also similar to those of temperature and relative humidity, which is consistent with previous observations (Figure 1). Moreover, the normal CDFs of infections, temperature, and relative humidity (Figure 1) appear to be higher than those of wind speed, visibility, and solar radiation at $0.5 < CDF < 1.0$. Conversely, the lognormal CDFs of infection, temperature, and relative

FIGURE 2 Normal and lognormal PDFs and CDFs of SARS-CoV-2 infection and atmospheric variables during the partial lockdown period. CDFs, cumulative density functions; PDFs, probability density functions.
humidity were lower than those of wind speed, visibility, and solar radiation at $0.0 < \text{CDF} < 0.5$. Clearly, the CDF of visibility is lower than that of the other variables as $0 < \text{CDF} < 0.5$.

(b) Partial lockdown (partial restriction)

Figure 2 illustrates the normal and lognormal PDFs and CDFs of SARS-CoV-2 infection and atmospheric variables during the partial lockdown. The normal PDFs for infection, temperature, and solar radiation exhibited symmetrical, sharp, and wide curves. The normal PDF of relative humidity was sharp and narrow in the same manner as observed during free movement. The normal PDF curves for wind speed and visibility were asymmetrical, sharp, and narrow, but were wider than those for relative humidity. The curve of the normal PDF of COVID-19 cases was similar to that of temperature and solar radiation in terms of shape and value. The highest and lowest values of the normal and lognormal PDFs for atmospheric variables were observed with relative humidity, which was consistent with the results during free movement. Solar radiation was one the most significant influential atmospheric variables in terms of infection, as seen in Figure 2, because the shape and values of the normal and lognormal PDFs were very close to that of temperature. Therefore, temperature and solar radiation were both influential in SARS-CoV-2 infection. The normal and lognormal CDFs of infection, temperature, and solar radiation were almost identical, which indicates a strong correlation between these three parameters. Figure 2 shows that the effects of solar radiation and temperature on infection were also found to be significant. According to the normal and lognormal PDFs and CDFs, infection with SARS-CoV-2 was mainly affected by temperature and solar radiation during the partial lockdown.

(c) Full lockdown (full restriction)

Figure 3 shows a stochastic model similar to those observed during free movement and partial lockdown.
It is clear that the curves for normal and lognormal PDFs for SARS-CoV-2 infection, wind speed, and visibility during full lockdown were symmetrical, sharp, and narrow. The curves for normal PDFs of temperature, relative humidity, and solar radiation were asymmetrical, sharp, and wider than those for normal PDFs of the other atmospheric variables, with the curve for the normal PDF of solar radiation being the widest. The highest and lowest values of the normal PDF were observed with wind speed. The highest values for lognormal PDF were observed with relative humidity and solar radiation, and the lowest was also associated with solar radiation. The closest values in the normal and lognormal PDFs for the number of infections were associated with temperature. According to Figure 3, the normal and lognormal PDFs of COVID-19 cases were similar to those of wind speed, and those associated with visibility were similar to those of relative humidity. Figure 3 also represents the normal and lognormal CDF analyses, which were similar and consistent with the normal and lognormal PDF analyses. Figure 3 indicates that wind speed and visibility had a greater influence on infection than the other atmospheric variables, whereas the impact of temperature and solar radiation was low. According to the stochastic model analysis shown in Figure 3, wind speed and visibility became the second most influential variables after temperature, whereas relative humidity and solar radiation were found to be the least influential variables affecting SARS-CoV-2 infection at this time.

Correlation statistical analysis

In the present study, Spearman’s correlation coefficient ($r_s$) was used to investigate further the relationship between atmospheric variables and COVID-19 cases over all three periods. Supporting Information figures S1–S5 show the correlation results. According to these figures, a weak significant positive association between SARS-CoV-2 infection and temperature was observed during the period in which free movement was allowed ($r_s = 0.34; p < 0.01$) with a strongly significant positive correlation present during partial lockdown ($r_s = 0.78; p < 0.01$), which means that the number of COVID-19 cases increased as the temperature increased. Meanwhile, there was no significant correlation between COVID-19 cases and temperature during the full lockdown. Figure S2 suggests a significant negative correlation between COVID-19 cases and relative humidity during both partial lockdown ($r_s = -0.50; p < 0.01$) and full lockdown ($r_s = -0.5; p < 0.05$), whereas a significant positive correlation was found during the period of free movement ($r_s = 0.40; p < 0.05$). This indicates that the number of COVID-19 cases increased as the relative humidity decreased during the partial and full lockdowns, and increased during free movement. Figure S3 shows a weakly positive correlation between SARS-CoV-2 infection and wind speed ($r_s = 0.44; p < 0.05$) during the full lockdown period. No significant correlation is observed during free movement and partial lockdown. This means that the number of COVID-19 cases increased as the wind speed increased during the full lockdown. The correlation between SARS-CoV-2 infection and visibility was significantly negative during partial lockdown ($r_s = -0.288; p < 0.05$) and positive during full lockdown ($r_s = 0.50; p < 0.05$), but no significant relationship was found during the period of free movement (Figure S4). Therefore, the number of COVID-19 cases increased as the visibility decreased during the partial lockdown and increased during the full lockdown. According to Figure S5, there was a weakly significant positive correlation between SARS-CoV-2 infection and solar radiation during partial lockdown ($r_s = 0.261; p < 0.05$). No significant relationship was observed in the periods of free movement and full lockdown. Thus, the number of COVID-19 cases increased as solar radiation increased during the partial lockdown. The statistical correlation analysis results are consistent with the descriptive and stochastic model reports in Sections: (Descriptive Statistics Analysis) and (Stochastic Model Analysis).

Multiple regression model analysis

A multiple regression model analyzed the variation in the number of COVID-19 cases by changing the atmospheric variables (temperature, humidity, wind speed, visibility, and solar radiation). The purpose of the regression model was to determine an appropriate mathematical model for the COVID-19 outbreak and to understand how temperature, humidity, wind speed, visibility, and solar radiation affected this outbreak. The regression model was performed to identify the relationship between the atmospheric variables and the number of COVID-19 cases. In this regard, Table 3 summarizes the statistical regression analysis for the periods of free movement, partial lockdown, and full lockdown. The mathematical model describing SARS-CoV-2 infection ($\hat{Y}$) in the period of free movement is:

$$\hat{Y} = -22.85 + 1.239x_1 + 0.207x_2 - 1.301x_3 - 1.7x_4 - 0.0005x_5$$

(18)

The regression analysis indicated that F(5,21) was equal to 2.203 with a $p < 0.10$. The multiple coefficients of determination ($R^2$) of the model were 0.59, with an adjusted $R^2$ value of 0.188 and a standard error of 5.256. The number of COVID-19 cases was therefore significantly correlated with temperature and relative humidity ($p < 0.10$). It can be inferred that the coefficient of temperature and relative humidity was greater than zero. Thus, SARS-CoV-2 infection is positively correlated with temperature and relative humidity, which is consistent with the correlation analysis results in the previous section: Correlation Statistical Analysis. It is clear that the number of COVID-19 cases increased significantly as the temperature and relative humidity increased during the period in which free movement was allowed. No statistical significance was observed in terms of wind speed, visibility, or solar radiation ($p > 0.1$); thus, no significant
correlation is assumed between these three parameters and the number of COVID-19 cases during the period of free movement. The mathematical model of \( \hat{Y} \) for partial lockdown is:

\[
\hat{Y} = -363.42 + 29.162x_1 - 1.908x_2 - 11.306x_3 - 0.001x_4 - 0.049x_5
\]  
(19)

The regression analysis for this period reveals that \( F(5,43) \) is equal to 11.89 with a p-value < 0.01. Meanwhile, the \( R^2 \) of the model is equal to 0.76 with an adjusted \( R^2 \) value of 0.53 and a standard error of 102.307. SARS-CoV-2 infection was significantly correlated with temperature and relative humidity during partial lockdown (p < 0.1). The temperature coefficient was greater than zero, whereas that of relative humidity was smaller than zero; thus, SARS-CoV-2 infection was positively correlated with temperature and negatively correlated with relative humidity during this period. The results in the present study are consistent with the results of the correlation analysis. The mathematical model of \( \hat{Y} \) during full lockdown is:

\[
\hat{Y} = 863.94 + 1.257x_1 - 2.716x_2 + 27.827x_3 + 0.0131x_4 - 0.108x_5
\]  
(20)

Statistical analysis of the regression during full lockdown reveals that \( F(5,20) \) was equal to 2.628 with a p-value < 0.10, but the \( R^2 \) of the model was equal to 0.68 with an adjusted \( R^2 \) value of 0.289 and a standard error of 128.849. During full lockdown, SARS-CoV-2 infection was significantly correlated with relative humidity, wind speed, and visibility (p < 0.1). In this period, SARS-CoV-2 infection was negatively correlated with relative humidity and positively correlated with wind speed and solar radiation during this period. The results are congruent with the results of the correlation analysis.

The multiple regression model results indicated that the effect of atmospheric variables on COVID-19 cases differs in the free movement, partial lockdown, and full lockdown periods. The temperature was the most affecting factor in COVID-19 transmission in partial lockdown. Its contribution in infection cases was more significant than the free movement and full lockdown periods. This may be caused by the seasonal change from winter to spring. The humidity significantly affected the infection cases in the free movement period compared with the other periods. Its contribution was more significant than during the partial and full lockdown periods. This indicates that the decrease in humidity in the hot, arid region might boost COVID-19 transmission. The infection cases' wind speed significantly

| Variables                  | Periods       | Intercept | Temperature | Humidity | Wind speed | Visibility | Solar radiation |
|----------------------------|---------------|-----------|-------------|----------|------------|-------------|-----------------|
| Coefficients Free movement | -22.85        | 1.239     | 0.207       | -1.301   | -1.7E-5    | -0.0005     |                 |
| Standard Error             | 21.748        | 0.711     | 0.101       | 0.956    | 0.001      | -0.081      |                 |
| Multiple R²                | 0.59          |           |             |          |            |             |                 |
| Adjusted R²                | 0.19          |           |             |          |            |             |                 |
| F-statistic                | 2.2           |           |             |          |            |             |                 |
| P-value                    | <0.10         |           |             |          |            |             |                 |
| Coefficients Partial lockdown | -363.42  | 29.162    | -1.908      | 11.306   | 0.001      | -0.049      |                 |
| Standard Error             | 207.21        | 5.499     | 1.016       | 11.054   | 0.005      | 0.050       |                 |
| Multiple R²                | 0.76          |           |             |          |            |             |                 |
| Adjusted R²                | 0.53          |           |             |          |            |             |                 |
| F-statistic                | 11.90         |           |             |          |            |             |                 |
| P-value                    | <0.01         |           |             |          |            |             |                 |
| Coefficients Full lockdown | 863.94        | 1.257     | -2.716      | 27.827   | 0.0131     | -0.108      |                 |
| Standard Error             | 517.043       | 14.304    | 1.961       | 11.259   | 0.0117     | 0.129       |                 |
| Multiple R²                | 0.68          |           |             |          |            |             |                 |
| Adjusted R²                | 0.29          |           |             |          |            |             |                 |
| F-statistic                | 2.63          |           |             |          |            |             |                 |
| P-value                    | <0.10         |           |             |          |            |             |                 |
positively affected the infection cases in the full lockdown period, with a negative effect in the other periods. This may be the result of the full lockdown period being entirely restricted for people and vehicle movement and frequent air convection in spring. The feature of wind speed increases the diffusion rate and spread distance of SARS-CoV-2. In addition, higher wind speed is also helpful for the generation of turbulence within the urban area, which results in the accumulation of novel coronavirus near the surface ground, thus increasing the risk of infection (Yang et al., 2021). The visibility was negatively affected by the COVID-19 infection in the free movement period and positively affected in the other periods because there is no dust during these periods. In contrast, the solar radiation effects were weak during all periods because the sun is mild in these periods. Compared with these periods, temperature and humidity were most directly related to COVID-19 transmission than other atmospheric variables, but their influence varied during the periods. Based on the multiple regression model analysis, ANOVA revealed the significance to be less than 0.10 for the equations of these periods. The $R^2$ increased in the partial lockdown and full lockdown periods. The $R^2$ ranged from 0.59 to 0.68, respectively. $P$-values ranged from 0.01 to 0.10, respectively. This indicates that the ranged from 56% to 76% approximately of the variations in COVID-19 infections can be affected by the atmospheric variables.

**DISCUSSION**

The present study used data describing the conditions in the State of Kuwait during summer and spring 2020, which are characterized by hot and arid weather. The trend of changes in the atmospheric variables provides a better picture of the COVID-19 outbreak in Kuwait. Analysis of the findings in previous sections (Descriptive Statistics Analysis, Stochastic Model Analysis, Correlation Statistical Analysis, Multiple Regression Model Analysis) indicates a significant association between the number of COVID-19 cases and temperature, relative humidity, wind speed, visibility, and solar radiation during the three periods of free movement, partial lockdown, and full lockdown. The findings obtained were compared with those of previous and recent studies that have reported that the coronavirus outbreak is significantly associated with temperature and are consistent with the results of these studies. For example, both Sundell et al. (2016) and Park et al. (2020) reported that influenza is correlated with temperature. Chan et al. (2011) suggested that the coronavirus is correlated with high temperatures, and Casanova et al. (2010) found an association with low temperatures. Recently, Wu et al. (2020) and Sarkodie and Owusu (2020) indicated that the COVID-19 pandemic was suppressed as the temperature increased. Meanwhile, other studies conducted by Menebo (2020), Shahzad et al. (2020), Tosepu et al. (2020), Bashir et al. (2020), Zhu, Liu, Huang, et al. (2020), and Şahin (2020) clearly demonstrated that temperature is positively correlated with outbreaks of COVID-19. The results of both previous and recent studies investigating the link between the coronavirus and temperature are consistent with the present study’s findings, which demonstrated a positive relationship during the periods of free movement and partial lockdown. In contrast, Prata et al. (2020), Bukhari, Massaro, D’agostino, et al. (2020), Ogaugwu et al. (2020), Islam, Bukhari, et al. (2021), Rouen et al. (2020), and S. Lin et al. (2020) found that temperature is negatively correlated with SARS-CoV-2 infection. Relative humidity was also found to be influential in the increasing number of COVID-19 cases during the periods of free movement, partial lockdown, and full lockdown. Studies conducted by Barreca and Shishmack (2012), Soebiyanto et al. (2015), and Tamerius et al. (2013) revealed that influenza is negatively correlated with relative humidity. However, Urashima et al. (2003) indicated that influenza is positively correlated with relative humidity. Recently, Wu et al. (2020), Şahin (2020), Sarkodie and Owusu (2020), Meo et al. (2020), Sasikumar et al. (2020), Alkhawailed et al. (2020), Amin et al. (2020), Zhu, Liu, Huang, et al. (2020), Islam, Bukhari, et al. (2021), and Ahmedi et al. (2020) indicated that the COVID-19 pandemic is inversely associated with relative humidity. This study indicates that SARS-CoV-2 infection was positively correlated with relative humidity during the period of free movement and negatively correlated with relative humidity during the partial and full lockdown. This result in the present study is congruent with other studies by Kumar and Kumar (2020), Mousavi et al. (2020), Liu et al. (2020), Sing et al. (2020), Neto and Melo (2020), and Ladha et al. (2020). Moreover, Şahin (2020) reported that wind speed is positively correlated with the number of COVID-19 cases, which was consistent with our results for full lockdown. However, Bhagangar and Bhimireddy (2020) and Coccia (2020) recently revealed that stable atmospheric conditions result in low wind speeds, low-level turbulence, and cool, moist ground conditions that favor the transmission of the SARS-CoV-2 infection. Their results are consistent with the present study’s findings, which demonstrated a negative relationship during free movement and partial lockdown periods. In addition, the study by Bhagangar and Bhimireddy (2020) revealed a significant contribution of the local meteorological conditions in spreading and transmitting the virus infection. The virus can spread and transfer via 30 min in the atmosphere with a radius of 0.2 km and move a distance of 1.0–2.0 km from the source. Solar radiation was also found to be positively associated with SARS-CoV-2 infection during the full lockdown, which is consistent with the recent findings of Asyary and Veruswati (2020).

**CONCLUSION**

To our knowledge, this study is one of few that have investigated the association between the daily number of confirmed COVID-19 cases and temperature, relative humidity, wind speed, visibility, and solar radiation in a hot, arid climate. Comprehensive analysis of the data was carried out with stochastic models, Spearman’s correlation, and a
multiple regression model. The significant findings of this study indicate a strong relationship between relative humidity and SARS-CoV-2 infection. The number of COVID-19 cases rose as the temperature, wind speed, and visibility increased and decreased as the relative humidity increased. The IR for SARS-CoV-2 is directly proportional to the air temperature, wind speed, and visibility, but it is inversely related to the humidity. The lowest GR and longest DT of the COVID-19 infection were observed in the full lockdown period. The main results for the three periods studied are summarized as follows.

(a) During the period in which free movement was allowed, SARS-CoV-2 infection exhibited a weakly significant positive correlation with temperature and a significant positive correlation with relative humidity.

(b) During the partial lockdown, a strongly significant positive correlation was found between temperature and SARS-CoV-2 infection, whereas a significant negative correlation was observed between SARS-CoV-2 infection and relative humidity. There was also a weak significant positive correlation between COVID-19 cases and wind speed, and a weak significant positive correlation between SARS-CoV-2 infection and solar radiation. A negative correlation was observed between infection with SARS-CoV-2 and visibility.

(c) During full lockdown, there was no significant correlation between COVID-19 cases and temperature. Moreover, a significant negative correlation was obtained between SARS-CoV-2 infection and relative humidity, and a positive correlation was found between SARS-CoV-2 infection and visibility.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHORSHIP CONTRIBUTION

Mohamed F. Yassin: data collection, data curation; author of original paper, Methodology, Results, and Discussion.

Hassan A. Aldashti: data collection; author of Review, Results, and Discussion.

SUPPORTING INFORMATION

The supporting information contains five figures showing the relationship between the infection cases for SARS-CoV-2 and atmospheric variables.

DATA AVAILABILITY STATEMENT

Data, associated metadata, and calculation tools are available from the corresponding author (mohamed_f_yassin@hotmail.com).

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