The spread of COVID-19 at Hot-Temperature Places With Different Curfew Situations Using Copula Models

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ABSTRACT

The infectious coronavirus disease 2019 (COVID-19) has become a serious global pandemic. Different studies have shown that increasing temperature can play a crucial role in the spread of the virus. Most of these studies were limited to winter or moderate temperature levels and were conducted using conventional models. However, traditional models are too simplistic to investigate complex, non-linear relationships and suffer from some restrictions. Therefore, we employed copula models to examine the impact of high temperatures on virus transmission. The findings from the copula models showed that there was a weak to moderate effect of temperature on the number of infections and the effect almost vanished under a lockdown policy. Therefore, this study provides new insight into the relationship between COVID-19 and temperature, both with and without social isolation practices. Such results can lead to improvements in our understanding of this new virus. In particular, the results derived from the copula models examined here, unlike existing traditional models, provide evidence that there is no substantial influence of high temperatures on the active COVID-19 outbreak situation. In addition, the results indicate that the transmission of COVID-19 is strongly influenced by social isolation practices. To the best of the authors' knowledge, this is the first copula model investigation applied to the COVID-19 pandemic.

INTRODUCTION

In December 2019, a novel infectious disease termed coronavirus disease 2019 (COVID-19) was discovered in Wuhan city, Hubei province, China. Subsequently, and through human-to human transmission, this virus has caused a global pandemic. COVID-19 is characterized by clinical features similar to those caused by severe acute respiratory syndrome coronavirus (SARS-CoV) and Middle Eastern respiratory syndrome coronavirus (MERS-CoV) infections, such as a fever and dry cough [1].

Previous studies have shown that meteorological variables can affect the transmission and survival of coronaviruses [2], [3]. Earlier research [3] found that MERS-CoV is most active at high temperatures and low humidity.

Notably, recent studies have shown that warm weather and high humidity may be important factors for reducing the spread of COVID-19 (e.g., see [4]). Conversely, some existing studies have found that increasing temperatures will not affect the transmission of COVID-19 (e.g., see [5]). However, most of these studies were limited to winter or low-temperature weather with a small number of observations. Hence, there is still no definitive evidence as to whether there is a negative association between environmental variables and the spread of COVID-19 in extremely hot or cold locations [4]. Besides, most previous studies were performed using traditional models, which are too simplistic and may be unable to deal with complex, non-linear dependency patterns. Thus, further research to understand the activity of COVID-19 under high-temperature conditions is warranted. In addition, such an association should be investigated not only in regard to weather variables, but also by taking into account the lockdown situation at these locations. Presently, copula models have become a favored statistical tool to describe the association between variables. These models have been applied in different areas, including the study of infectious diseases (e.g., see [6]) and environmental science (e.g., see [7]). One important benefit of using a copula model is that one can model the marginal distribution independently from the dependency structures, which are completely captured via the copula function. Another benefit of using a copula model is that the margins do not need to follow the same parametric family. Furthermore, many copula families exist, each with its own capability to describe the unique dependency structure. Hence, various types of associations can be discovered via copula models.

Hence, this study aimed to perform flexible statistical modeling with a copula model to improve our knowledge about the spread of the virus in hot locations with different curfew levels. Specifically, we investigated the impact of high temperatures on the number of confirmed cases in the cities of Riyadh, Jeddah, and Mecca in Saudi Arabia, and these cities were selected for several reasons. First, Saudi Arabia has been strongly affected by MERS-CoV [8], [9], which produces a similar severe respiratory illness as COVID-19. Second, the highest numbers of confirmed cases in Saudi Arabia have been recorded in Riyadh, Jeddah, and Mecca, which are three of the hottest areas in Saudi Arabia. Third, because of the transmission of COVID-19, Mecca and Jeddah have been placed under a series of lockdowns for a long time. Riyadh, however, was only placed under a curfew for a short period. Hence, these cities represent strong to moderate lockdown situations, which could be a factor critical to understanding the effects of high temperatures on the spread of COVID-19. By using the data from these cities and capitalizing on the flexibility of copula models, we aimed to provide clear evidence on the association between high temperatures and confirmed cases of COVID-19.

MATERIALS AND METHODS

Data collection

For this study, the cities of Riyadh, Mecca, and Jeddah were selected for the analysis. Riyadh is the capital city of Saudi Arabia and the city most affected by COVID-19 in this country. Riyadh had 37,244 confirmed cases for the observed period from 13 March 2020 to 15 June 2020. The population of Riyadh estimated for the middle of 2018 based on demographic survey data collected in 2016 was 8,446,866 [10]. Jedda and Mecca are the second most affected cities in Saudi Arabia, with 21,152 and 20,248 confirmed cases, respectively.

Daily counts of confirmed cases for the study period were collected from official reports [11] based on information [12] for Saudi Arabia. The daily average temperature data for the same period time were obtained from the Weather Underground Company [13].

Data analysis

Both the COVID-19 confirmed cases and the average temperature data demonstrated a non-normal distribution for all cities. Fig 1 shows the confirmed cases during the study period, where the new confirmed cases of COVID-19 in Riyadh exceeded 1500 from 08 to 15 June 2020. However, the highest records for Mecca and Jeddah were generally similar and lower than those of Riyadh.

Copula

Copula is a Latin word that means joins or links. A copula function refers to a multivariate function that joins the multivariate distribution functions to their univariate standard uniform margins [14]. Formally, a copula can be defined as follows: copulas [15] are multivariate cumulative distribution functions with uniform marginal distributions on (0,1) such that:

$$C: [0,1]^n \to [0,1], \quad n \ge 2.$$
 (1)



Fig. 1. Plots of the confirmed cases during the study period (from 13 March 2020 to 15 June 2020. (top): Riyadh, (middle): Mecca, (bottom) Jeddah.

Sklar's theorem [16] is the key rule of the copula function, and it can be introduced as follows:

Theorem 0.1 (Sklar's theorem): If F is an *n*-variate distribution function with univariate margins F_1, F_2, \ldots, F_n , then there exists an *n*-variate copula function, C, such that $\forall \mathbf{x} = (x_1, .., x_n)' \in \mathbb{R}^n$:

$$F(x_1, x_2, \dots, x_n) = C(F_1(x_1), F_2(x_2), \dots, F_n(x_n)).$$
(2)

If the margins are continuous, then the copula

$$C(u_1, u_2, ..., u_n) = F(F_1^{-1}(u_1), F_2^{-1}(u_2), ..., F_n^{-1}(u_n))$$
(3)

is unique, where F^{-1} is the inverse function of the margins and $u \in [0,1]^n$. Conversely, if $F_1, ..., F_n$ are the marginal distribution functions and C is a copula function, then the function F (defined by equation (2)) is a joint distribution function with margins $F_1, ..., F_n$.

In accordance with Sklar's theorem (2), a copula models the marginal distributions separately from the dependency pattern, with no restriction on the type of margins.

In this study, we consider an arbitrary number of copula types including the Joe, Gumbel, and Clayton copulas, as well as their rotation types. In addition, we consider the Frank, Gaussian, t-students, and other two-parametric copulas, such as the Joe-Frank (BB8) copula. The following text provides details on some commonly used copula families.

• Frank copula is a one-parametric symmetric Archimedean copula with generator function $\varphi(t) = -\ln[\frac{e^{-\theta t}-1}{e^{-\theta}-1}]$, with $\theta \in (-\infty, \infty) \setminus \{0\}$. The Frank copula can control both the negative and positive dependency pattern, where the strongest dependency occurs at the center of the distribution. However, in the Frank copula, the extremes are independent.

The distribution function of the Frank copula can be given by:

$$C_{\theta}(u_1, u_2) = \frac{-1}{\theta} \ln \left[1 + \frac{(e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}{e^{-\theta} - 1}\right],$$
(4)

and its density function is:

$$c(u_1, u_2) = \theta(e^{-\theta} - 1) \frac{e^{-\theta}(u_1 + u_2)}{e^{-\theta} - 1 + (e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}$$
(5)

• Clayton copula is a one-parametric ($\theta > 0$) nonsymmetric Archimedean copula. It is a lower positive tail dependence copula with generator $\varphi(t) = \frac{1}{\theta}(t^{-\theta} - 1)$. Its distribution is given by:

$$C(u_1, u_2) = [u_1^{-\theta} + u_2^{-\theta} - 1]^{\frac{-1}{\theta}},$$
(6)

and its density function is:

$$c(u_1, u_2) = (1+\theta)(u_1u_2)^{-1-\theta}(u_1^{-\theta} + u_2^{-\theta} - 1)^{\frac{-1}{\theta}-2}.$$
(7)

• Joe copula, in contrast to the Clayton copula, this is a one-parametric upper tail Archimedean copula with generator $\varphi(t) = \ln[1 - (1-t)^{\theta}]$. Its distribution function is:

$$C(u_1, u_2) = 1 - [(1 - u_1)^{\theta} + (1 - u_2)^{\theta} - (1 - u_1)^{\theta} (1 - u_2)^{\theta}]^{\frac{1}{\theta}}$$
(8)

and its density function is:

$$c(u_1, u_2) = [(1 - u_1)^{\theta} + (1 - u_2)^{\theta} - (1 - u_1)^{\theta} (1 - u_2)^{\theta}]^{\frac{1}{\theta} - 2} \times (1 - u_1)^{\theta - 1} (1 - u_2)^{\theta - 1} [\theta - 1 + (1 - u_1)^{\theta} + (1 - u_2)^{\theta} - (1 - u_1)^{\theta} (1 - u_2)^{\theta}].$$
(9)

• Rotated copula refers to a rotation version of asymmetric copulas. This rotation includes 90, 180, and 270 rotation degrees, with arguments $(1 - u_1, u_2), (u_1, 1 - u_2)$, and $(1-u_1, 1-u_2)$, respectively. The 180 rotation degree produces a corresponding survival copula family. However, rotations by 90 and 270 degrees provide corresponding copulas to deal with negative dependencies. For more details on rotated copulas, see for example, [17], [18], [19], and [20].

Pseudo maximum-likelihood method: In this study, we applied the so-called *pseudo maximum-likelihood method (PML)* to estimate the parameters for the selected copula function. *PML* is introduced by [21] as a two-step estimation method. With this method, the margins are estimated non-parametrically via their empirical cumulative distribution function at first, and then, the copula parameter (θ_c) is estimated at the second step. By using *PML*, the copula parameter is estimated by maximizing the copula density, i.e.,

$$L_{\text{MPL}}(\theta_c) = \sum_{i=1}^{n} \log[c(u_{1i}, u_{2i}; \theta_c)],$$
(10)

where $u_1 = \hat{F}_1(x_1; \alpha_1)$ and $u_2 = \hat{F}_2(x_2; \alpha_2)$ are the empirical probability integral transform of variable X_1 and X_2 , respectively. A simulation study of [22] showed that the performance of *PML* is better than that of the full maximum likelihood estimation method and *Inference Function of Margins* of [23] if the margins are unknown, which is the case in almost all real life applications.

A. Goodness-of-fit test

As there is a wide range of copula functions, it is necessary to test the copula shape with the best fit. Therefore, we will use the Akaike Information Criterion (AIC) of [24] and the Bayesian Information Criterion (BIC) of [25] to select the right copula. AIC and BIC can be given by:

$$AIC = -2 \ln L(\hat{\theta}) + 2P, \qquad (11)$$

$$BIC = -2 \ln L(\hat{\theta}) + P(\ln(N)), \qquad (12)$$

where $\hat{\theta}$ is the estimated value of the parameters, and P is the number of the model parameters.

The summary of the full inference steps of copula models used in this study is as follows:

- Transform the continuous variable of the observed data to copula data.
- Calculate the cumulative density function for the discrete variable of the observed data.

- Consider arbitrary types of bivariate copula functions for the assumed model.
- Select the best fit bivariate copula type among all fitted copula functions using AIC and BIC.

RESULTS AND DISCUSSION

Descriptive results

Table I shows the summary statistics for the daily data on temperature and COVID-19 confirmed cases in the cities of Riyadh, Mecca, and Jeddah. With average values of 29.788°C (Riyadh), 24°C (Mecca), and 29.014°C (Jeddah), the temperature in the three cities was very high. Importantly, this study takes into account the daily average temperature, and not the maximum temperature.

TABLE I Summary statistics for the daily average temperature and COVID-19 confirmed cases in the cities of Riyadh, Mecca, and Jeddah. Zeros values indicate no new confirmed cases for the corresponding date during the observation period.

Variable	N	Mean	Standard deviation	Min	Max
Temperature (Riyadh) (°C)	95	29.788	4.947	18	37.4
Temperature (Mecca) (°C)	95	24.983	3.472	18	32
Temperature (Jeddah) (°C)	95	29.014	3.258	22.9	36
Confirm cases (Riyadh)	95	392.042	427.393	2	1,735
Confirm cases (Mecca)	95	213.137	160.938	0	623
Confirm cases (Jeddah)	95	222.653	174.632	0	586

Discussion of the Copula model

This study used a copula model to investigate the relationship between high temperatures and confirmed cases of COVID-19 for three cities in Saudi Arabia. The existing number of copulas is large, and to select the most appropriate fitted model for each city, bicop() function of R ([26]) package [27] was used. As bicop() allows one to consider different selection criteria at each run, it was applied to each data set twice, one with BIC and the other one with AIC. The results of these models are provided in Tables (II, III). Boldfont indicates the selected copula type. Figs (2, 3) present the surface and contour plots for the selected copula families.

		TABLE II			
Selected copula	families (for	each city)	based on	BIC by	bicop()

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014	3.258	22.9	36	2		
2.042	427.393	2	1,735			
				0		



Surface plot of Frank copula ($\theta = 8.51$, $\tau = 0.62$) (Riyadh city)



Surface plot of Survival Joe copula ($\theta=1.92$, $\tau=0.34)$ (Mecca city)



Туре	Parameter (τ)	AIC	BIC
	Riyadh		E' 0
Frank	$\theta = 8.52 \ (\tau = 0.62)$	-102.5	-99 ⁸ 97
	Mecca		(midd fomili
Survival Joe (rotation degree 180)	$\theta = 1.92 \ (\tau = 0.43)$	-35.07	-32.51
	Jeddah		
Frank	$\theta = 7.32 \ (\tau = 0.57)$	-85.52	-82.97

Surface plots of the Frank copulas for Riyadh (top) and Jeddah te), and the Clayton copula for Mecca (Bottom) as the best-fit copula es for each city.

In accordance with Table (II), Frank copulas with a moderate positive dependency ($\theta = 8.51, \tau = 0.62$) and $((\theta = 7.47, \tau = 0.57)$ were selected for Riyadh and Jeddah, respectively. The results indicate that there is a positive relationship between temperature and the spread of COVID-19 in moderate and high temperatures. However, these two



Fig. 3. Contour plots of the Frank copulas for Riyadh (top) and Jeddah (middle), and the Clayton copula for Mecca (Bottom) as the best-fit copula families for each city.

 TABLE III

 Selected copula families (for each city) based on AIC by bicop().

Туре	Parameter (τ)	AIC	BIC
	Riyadh		
BB8 (Joe-Frank)	$\theta = 8 \ (\alpha = 0.7)$	-103.74	-98.63
	Mecca		
tll ¹	7.47 df ²	-39.32	-20.24
	Jeddah		
Frank	$\theta = 7.32 \ (\tau = 0.57)$	-85.52	-82.97

variables became independent at extreme values. Therefore, the results provide clear evidence that SARS-CoV-2 can still remain an active virus in hot places. In the case of Mecca, the survival Joe copula with a low dependency level ($\theta = 1.92$, $\tau = 0.34$) was selected as the most appropriate copula function. With these data, there was only a very weak dependency pattern between high temperatures and confirmed cases at the low values. This relationship reflects the period before the series of lockdowns in the city of Mecca. During the curfew, there was no relationship detected between the spread of COVID-19 and the temperature.

The question that now remains is, do high temperatures affect the transmission of COVID-19? To answer this question, we need to mention some of the main similarities and differences among these cities regarding the (1) temperature, (2) confirmed cases of COVID-19, (3) copula model results, and (4) lockdown situations. First, the temperatures in Riyadh and Jeddah were almost the same and slightly higher than those in Mecca. However, the number of confirmed cases in Riyadh was higher than that in Jeddah and Mecca. In addition, Mecca and Jeddah had almost the same number of confirmed cases. Hence, the same temperature levels were associated with different numbers of new confirmed cases within the three cities. Thus, COVID-19 can spread differently at the same temperature level. Second, the fitted copula models show that the dependency between the temperature and number of COVID-19 cases was very similar for Riyadh and Jeddah, while it was very low for Mecca. Given the first and second points mentioned above, there was another important factor driving the active situation of this new virus, namely, the lockdown situation. During the study period, the cities of Jeddah and Mecca were placed under a lockdown on 29 March 2020 and 30 March 2020, respectively. Then, Mecca was subjected to a 24 hour curfew on 02 April 2020. Later, on 04 April 2020, various areas in Jeddah were placed under a 24 hour curfew. After about one day, Riyadh too was placed under a 24 hour curfew for approximately 18 days. Then, on 25 April 2020, Jeddah and Rivadh were placed under partial curfews, while Mecca still remained under a 24 lockdown. Hence, Mecca experienced a long lockdown period, while duration of curfew in Riyadh was the shortest. These factors may explain the similarity in copula results for Rivadh and Jeddah and the low dependency pattern in the case of Mecca. In consideration of these last findings, we can conclude that high temperatures had only a weak to moderate effect on the transmission of COVID-19 if there was a partial curfew policy in place. However, this effect vanished under the condition of strong social isolation. Hence, even in hot places, COVID-19 can still spread readily when no social distancing is implemented.

CONCLUSION

This study examined the effect of high temperatures on the spread of COVID-19 in hot climates under different curfew situations using copula models. We applied the models to the cities of Riyadh, Jeddah, and Mecca in Saudi Arabia. For Riyadh and Jeddah, which had almost the same average temperature level, the association between temperature and confirmed cases of COVID-19 reflected a moderate positive Frank copula. However, the number of COVID-19 cases in Riyadh was higher than the number in Jeddah. Hence, the transmission of this virus in these two cities may have been affected by the curfew level and not by the high temperature.

In the case of Mecca, which had a temperature level (slightly) less than that of Riyadh and Jeddah, there was a very weak dependency between temperature and the number of COVID-19 cases. However, the number of confirmed cases of COVID-19 in Mecca was very close to the number in Jeddah. In addition, Mecca was under a strong 24 hour lockdown for more than half of the observed data set. Therefore, there is clear evidence that high temperatures are not able to stop the spread of this virus if there is no social isolation. Clearly, lockdowns represent the most effective strategy to prevent the spread of this virus. To the best of our knowledge, this study describes the first copula model fitted to COVID-19 data. The results of this study, derived using copula models, are unlike those derived using existing traditional methods and indicate that the association between COVID-19 and temperature is weak and no substantial decreases in the number of COVID-19 cases can be expected in response to high temperatures.

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