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Temperature extreme may exaggerate the mortality risk of COVID-19 in the low- and middle-income countries: A global analysis

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Abstract

We performed a global analysis with data from 149 countries to test whether temperature can explain the spatial variability of the spread rate and mortality of COVID-19 at the global scale. We performed partial correlation analysis and linear mixed effect modelling to evaluate the association of the spread rate and motility of COVID-19 with maximum, minimum, average temperatures and temperature extreme (difference between maximum and minimum temperature) and other environmental and socioeconomic parameters. After controlling the effect of the duration after the first positive case, partial correlation analysis revealed that temperature was not related with the spatial variability of the spread rate of COVID-19. Mortality was negatively related with temperature in the countries with high-income economies. In contrast, temperature extreme was significantly and positively correlated with mortality in the low-and middle-income countries. Taking the country heterogeneity into account, mixed effect modelling revealed that inclusion of temperature as a fixed effect in the model significantly improved model skill predicting mortality in the low-and middle-income countries. Our analysis suggest that warm climate may reduce the mortality rate in high-income economies but in low and middle-income countries temperature extreme may increase the mortality risk.

Key words: temperature extreme; warm climate; low-and middle-income economies; COVID-19; mortality; mixed effect modelling

Introduction

Climate change became one of the major concerns for the world humanity until the first case of COVID-19 has been reported. The direction of thought has now been changed and COVID-19 has become the focal point of discussion, since the pandemic situation caused by COVID-19 posed an unprecedented threat to the world. COVID-19 is a respiratory illness caused by the new corona virus “Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (Gorbalenya et al., 2020; Shereen et al., 2020). According to the world health organization (WHO), the first case of COVID-19 has been reported in December 2019. As shown by the COVID-19 dashboard by the center for systems science and engineering (CSSE) at Johns Hopkins University, COVID-19 caused 346,700 death with a total of 5,519,878 confirmed cases (as of 26th May 2020, 19.00 GMT+6.00) (Dong et al., 2020).

With a start from China, COVID-19 outbreak has been observed in the high latitude (Temperate) region, leading scientists to assume that COVID-19 outbreak and death are linked with low temperature. The first study which tested the effect of temperature and humidity on the COVID-19 associated mortality reported that temperature had a positive link with the mortality in Wuhan, China (Ma et al., 2020). The relationship between ambient temperature and COVID-19 infection has been investigated in China with the hypothesis that warmer weather may reduce the case count of COVID 19 (Xie and Zhu, 2020). Analysing data from 122 cities the study found no evidence of decline in confirmed cases with increasing temperature, rather found a positive association between temperature and COVID-19 confirmed cases ((Xie and Zhu, 2020). The assumption of suppression of COVID 19 due to warmer temperature is probably based on the optimal temperature range of SARS-CoV-2 transmission (13-24 ° C) as confirmed by Anis (2020). It is important to note that this preprint has not been peer reviewed and thus requires caution during interpretation of the results there in. Nevertheless, it is obvious that temperature effect on COVID-19 transmission and mortality is not consistent across the world.

Temperature was negatively associated with the confirmed cases of COVID-19 in Turkey, Brazil and China (Liu et al., 2020; Prata et al., 2020; Şahin, 2020). In contrast to these findings, many studies reported a positive relationship between temperature and COVID-19 transmission in several countries (Bashir et al., 2020; Tosepu et al., 2020; Xie and Zhu, 2020). Some of the recent studies however, reported no significant role of temperature on COVID-19 transmission (Ahmadi et al., 2020; Iqbal et al., 2020; Yao et al., 2020). The available scientific evidence thus provides non-consistent results that call for further studies at the global scale. A country’s socio-economic and environmental factors may also be associated with the confirmed cases. For example, COVID-19 transmission was found to have low sensitivity to temperature and high sensitivity to population size (Jahangiri et al., 2020). These findings highlight importance of socioeconomic and environmental factors to be considered while testing climatic influence on COVID-19 outbreak and mortality. The present study aims at investigating the link between temperature and the spatial variability of COVID-19 spread and mortality at the global scale. We answered the following research questions:

1. Can temperatures explain the spatial variability of the rate of spread and mortality of COVID-19 at the global scale?
2. Does warm climate suppress the rate of spread and mortality of COVID-19?
3. Which socio-economic and environmental factors are linked with the spread and mortality of COVID-19?

Materials and Methods

Data acquisition

The data on total confirmed cases, total death counts, and total test performed in 149 countries were collected from three complementary sources viz: World Health Organization (WHO), COVID-19 dashboard by the center for systems science and engineering (CSSE) at Johns Hopkins University (JHU) and Worldometers.info website. WHO is the leading global organization providing guidelines and reliable information related to COVID-19. Johns Hopkins University has been playing key roles in providing real time data on COVID-19 and has become a reliable data source for the researchers by this time. Worldometer is a United State - based independent digital media run by an international team of researchers, developers, and volunteers. The main goal of this organization is to make world statistics available in a time relevant format to the global audience. It was selected one of the best free reference websites by the world's oldest and largest library association "American Library Association (ALA)". Data was retrieved on 11th May 2020.

Table 1. List of climatic, environmental, socio-economic, and COVID-19 parameters used in the study and their description.

Serial	Parameters used	Description
1	Infected/tested	Rate of spread (%)
2	Mortality	Mortality (%)
3	TempMax	Maximum temperature (° C)
4	TempMin	Minimum temperature (° C)
5	TempAvg	Average temperature (° C)
6	TempMax-Min	Maximum-minimum temperature (° C)
7	ForestArea	Forested area (% of land area)
8	ProtArea	Protected area (%)
9	ThretSp	Threatened species (number)
10	CO_2Emis	CO_2 emission estimates (million tons)
11	PopDen	Population density (per km2, 2019)
12	GDP Growth	Gross domestic product (GDP) growth rate (annual %)
13	PopGrow	Population growth rate (average annual %)
14	HealthExpen	Health expenditure (% of GDP)
15	Age60+	Population age distribution (60+ years old, %)
16	PhysPerTho	Health Physicians (per 1 000 pop.)
17	LifeExped	Life expectancy at birth (years)

The data on the socioeconomic parameters including population density, GDP growth rate, GDP per capita, population growth rate, life expectancy, percentage of population over 60 years, health expenditure, physicians per thousand people and environmental variables including number of threatened species, forested area, CO_2 emission, protected area percentage of the forested area were collected from United nation country database (data retrieved on 13th May, 2020). Daily maximum, minimum and average temperature data for the period from 1st Jan, 2020 to 10th May 2020 were collected from The Weather Channels (https://www.weather.com/) and from the Weather Underground (https://www.wunderground.com/).

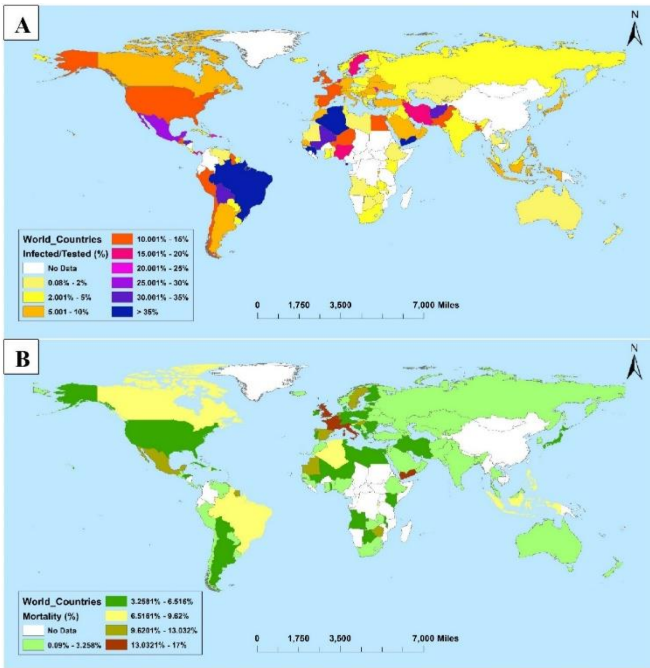

Figure 1. Spatial variability of the rate of spread (A) and mortality (B) of COVID-19 at the global scale.

Data preparation and statistical analyses

We collected data on selected variables (Table 1) from a total of 149 countries. Because a country's health system is linked with the economic condition, we classified the infected countries into two groups: 1. countries with high-income economies 2. countries with low- and middle-income economies. We followed the world bank's country classification 2020 for this grouping. We collected data on number of cumulative tests performed by individual country and the total confirmed cases in each country until 10th May 2020. To parameterize the rate of spread we calculated number of positive cases per 100 tests performed as follows:

Rate of spread (%) = (Total confirmed cases ÷ Total test performed) x 100 %

Calculating the rate of spread in this way instead of using only the total confirmed cases allows to consider the influence of varying number of tests performed by each country on the total confirmed cases. Generally, the cumulative number of confirmed cases has an increasing trend until the positive case becomes zero. This increasing trend does not necessarily mean the rising intensity of the COVID-19 outbreak. Thus, the way we calculated the rate of COVID-19 spread provides an estimate which is independent of the variation of the number of tests performed among the countries. Likewise, mortality was calculated for each country as follows:

Mortality (%) = (Number of total death count ÷ Total infected people) x 100 %.

We calculated the mean value of the daily minimum, maximum and average temperature averaged over the period from 1st January 2020 to 10th May 2020, the common period for which the rate of spread and mortality were calculated. In this way, we made sure that the climatic data is representative of the contemporary pandemic condition. Climatic parameters may cause lag effect of three days on the case count (Liu et al., 2020). We excluded the daily temperature values for the last three days before 10th May 2020 and tested if this affects our results. We found no changes in our overall results due to this lag test.

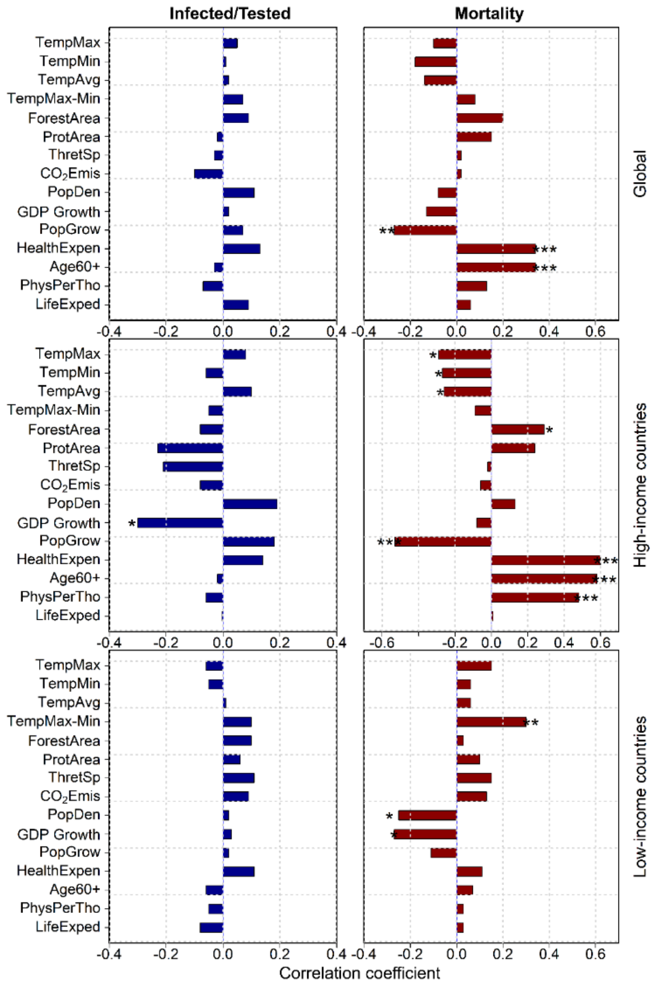

Fig. 2. Results of partial correlation analysis of COVID-19 spread rate and mortality with climatic, environmental, and socioeconomic parameters. For each explanatory variable, the duration after the first positive case was taken as controlling factor. * indicates correlation significant at $p < 0.5$, ** indicates correlation significant at $p < 0.01$, * indicates correlation significant at $p < 0.001$.**

It is likely that the duration after the first positive case may affect the rate of spread and mortality. The case counts and mortality both follow an initial increasing trend until they reach the peak and then decline (Anwar et al., 2020; Jia et al., 2020). It is thus necessary to control the effect of the duration after the first positive case on the rate of spread and mortality. We performed a partial correlation analysis to test the relation of the rate of spread and mortality with a set of explanatory variables listed in Table 1. The advantage of the partial correlation over the traditional bivariate Pearson correlation is that we can rule out the undesired effect of some factors by taking them as controlling factors. In our analyses, we took the duration after the first positive case as a controlling factor which allowed to control the effect of temporal trend on the response variable. Besides, we performed the correlation analysis using 1000 bootstrapped correlations by random extraction with replacement of values. This bootstrapping approach allows to measure the accuracy of the confidence interval to the sample estimates.

Then we performed linear mixed effect modelling with significantly related variables resulted from the partial correlation analysis. It is worth mentioning that health expenditure and physicians per thousand people were highly correlated with 60+ aged people resulting in collinearity problem. As such, these two variables were excluded from the mixed effect models. We ran two sets of mixed effect models for each of the groups of countries (low income countries, and low- and middle-income countries) and all the infected countries together (global). The first sets were run without temperature and the second sets with temperature. Comparing two sets of model's outputs will allow to test if temperature has improved the model performance. Model performance was evaluated by comparing the Akaike information criteria (AIC), model with lower AIC value has better skill for prediction. This mixed effect modelling approach estimates both fixed and random effects and allows to take country heterogeneity into account while testing the effects of explanatory variable on the response variables. We considered temperature, and other response variables as the fixed factors and country Id as the random factors in our mixed effect models.

Before the analyses were performed, the normality of data distribution of all the response and explanatory variables were tested using Kolmogorov-Smirnov and Shapiro-Wilk test. In case of not-normal distribution, data were log-transformed to get a normal distribution. After checking the distribution, the outliers were excluded from the analysis. For example, Algeria and Gavon were left out of the analyses since these countries fell outside the normal range of values. Partial correlation analysis and the normality tests were performed using SPSS version 25.0 (IBM Corp., 2017). Mixed effect modelling was performed using the "lme" function of the "nlme" package in R statistical environment. To evaluate the variation explained by the fixed and random effects together we calculated marginal R^2 using the MuMln package in R (R Development Core Team, 2019)

Results

Both mortality and the rate of spread were low in Asian, Australia and some African countries (Fig. 1). The highest spread rate was observed in Equatorial Guinea (51 %) followed by Guinea-Bissau and Brazil (48%) until 10th May 2020. The highest mortality was observed in Sint Maarten Dutch (~20%) followed by Belgium and Yemen (16%). The lowest spread rate was found in Venezuela, while the mortality was close to zero in Qatar. It is important to note that the countries where either the mortality or the spread rate was zero were excluded from further analyses.

Globally, mortality was negatively related with population growth rate and positively related with the percentage of people over 60 years old (Fig. 2). However, the rate of COVID-19 spread was not associated with any of the climatic, environmental, and socioeconomic parameters. When analysed with the countries having high income economies, the spread rate was negatively linked with GDP growth rate. The mortality in high income countries was associated with multiple climatic, environmental, and socioeconomic parameters (Fig. 2). Temperatures (Max, Min and Avg) were negatively connected with the mortality in high income countries whereas life expectancy and percentage of people over 60 years were positively linked with mortality. In the low- and middle-income countries, the spread rate was not related with any parameters studied but mortality was negatively related with population density and GDP growth rate. The difference between maximum and minimum temperature was positively related with mortality which highlights the influence of extreme weather condition on mortality of COVID-19.

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Table 2. Restricted maximum likelihood parameter estimates and model skills of two sets (with and without temperature) of linear mixed effect models (fixed effects) predicting the effect of temperature on the mortality of COVID 19.

Spatial scale	Models	Estimates	Value	Std.Error	DF	t-value	p-value	AIC	BIC	LogLik	Marginal R^2
Global	Model 1 (Without Temp)	(Intercept)	1.13	0.64	128	1.76	0.08	380	395	-185	0.13
		PopGrow	-0.22	0.10	128	-2.22	0.03				
		Age60+	0.11	0.21	128	0.54	0.59				
	Model 2 (With Temp)	(Intercept)	1.09	0.76	128	1.43	0.16	385	402	-186	0.13
		PopGrow	-0.22	0.10	128	-2.21	0.03				
		Age60+	0.12	0.23	128	0.53	0.59				
		TempMin	0.01	0.09	128	0.09	0.93				
High income conuntries	Model 1 (Without Temp)	(Intercept)	-1.12	1.11	55	-1.02	0.31	173	185	-80	0.41
		PopGrow	-0.23	0.13	55	-1.70	0.09				
		ForestArea	0.01	0.01	55	1.12	0.27				
		Age60+	0.77	0.34	55	2.31	0.03				
	Model 2 (With Temp)	(Intercept)	-1.30	1.71	55	-0.76	0.45	176	190	-81	0.41
		PopGrow	-0.22	0.14	55	-1.65	0.11				
		ForestArea	0.01	0.01	55	1.12	0.27				
		Age60+	0.80	0.38	55	2.08	0.04				
		TempMax	0.04	0.27	55	0.14	0.89				
Low income countries	Model 1 (Without Temp)	(Intercept)	1.87	0.33	82	5.61	0.00	228	240	-109	0.13
		PopDen	-0.12	0.07	82	-1.59	0.12				
		GDPGrowth	-0.11	0.04	82	-2.75	0.01				
	Model 2 (With Temp)	(Intercept)	0.43	0.80	82	0.54	0.59	226	241	-107	0.17
		PopDen	-0.08	0.07	82	-1.09	0.28				
		GDPGrowth	-0.12	0.04	82	-3.02	0.00				
		TempMax-Min	0.60	0.31	82	1.96	0.05				

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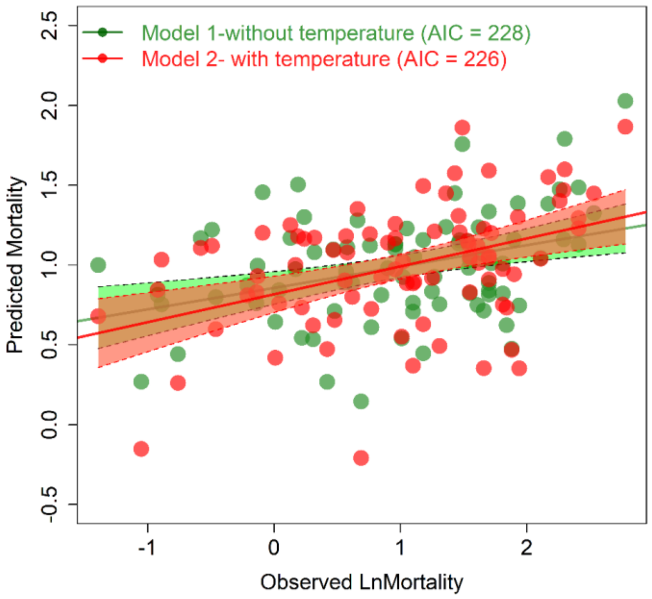

Fig. 3. Comparison of linear mixed effect models without and with temperature predicting mortality rate in the low- and middle-income countries. Shaded areas represent 95% confidence interval.

The mixed effect modelling results revealed that inclusion of temperature in the model significantly improved the model skill predicting mortality in the low- and middle-income countries as observed lower AIC in the model with temperature (Table 2). Globally, temperature did not significantly improve model output of mixed effect models predicting mortality. Likewise, temperature caused no AIC variation between the models with and without temperature in the mortality prediction of high-income countries.

Discussion

The rate of spread and mortality of COVID-19 widely varied across the globe. We analysed a total of 15factors (climatic, socioeconomic and environmental) if they can explain the spatial variability of the spread rate and mortality of COVID-19. Spread rate of COVID-19 was not related with any parameters at the global and regional scale. GDP growth rate was only parameter which significantly and inversely related with the spread rate of COVID-19 in the countries with high income economies. The negative association between GDP growth rate and COVID-19 spread rate may lie in the fact that countries having higher growth rate were able to increase the test facilities rapidly so that infected people were possible to be identified and isolated leading a lower rate of spread. For example, Germany took the rapid initiative of doing more and more test resulting in lower infection as well as low mortality rate.

It was assumed earlier that warmer temperature may suppress the transmission rate of COVID-19. Many studies tested this hypothesis at the local and regional scale and found variable results. With increasing temperature, the confirmed cases were found to be decreased in Brazil, Turkey, and China (Liu et al., 2020; Prata et al., 2020; Şahin, 2020). On the other hand, some studies reported a direct relationship between temperature and COVID-19 transmission (Bashir et al., 2020; Menebo, 2020; Tosepu et al., 2020; Xie and Zhu, 2020).

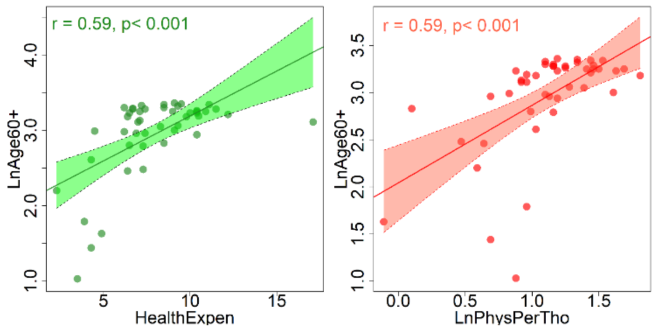

Fig. 4. Relation of health expenditure (% of GDP) and number of physicians per thousand people with percentage of people over 60 years old in countries with high-income economies.

By analysing daily maximum minimum and average temperature for the period from 1st January to 10th May 2020 and the spread rate averaged over the same period for 149 countries, we found no significant relationship between temperature and COVID-19 transmission at the global scale. Our results are however consistent with the findings of some other studies suggesting no influence of temperature on COVID-19 spread (Ahmadi et al., 2020; Iqbal et al., 2020; Yao et al., 2020).

Mortality was negatively related with population growth rate likely because of having high immune system in the countries with high population growth rate. Peoples in a country with high population growth rate are likely to have frequent infection by microorganism which may help develop hard immunity resulting in low mortality rate (Rook et al., 2006). Health expenditure, health physicians per thousand people and population over 60 years were strongly positively related with mortality in high-income countries. The relationship has been slightly dampened but still significant when analysed globally with a non-significant relationship in low- and middle-income countries. People aged over 60 years usually possess weak immune system and become high susceptible to virus infection (Bialek et al., 2020; Montecino-Rodriguez et al., 2013). The improved health system in developed countries increases life expectancy and hence the percentage of 60+ aged people becomes higher which may increase mortality risk in high income countries. This is evident from a very strong positive relationship between health expenditure and % of 60+ aged people globally and in high income countries in our study (Fig. 4).

The negative association of mortality with minimum, maximum and average temperature in the high income countries supports the findings of earlier study that SARS-CoV-2 is more active in low temperature (Anis, 2020; Sajadi et al., 2020). An earlier study also supported this assumption but the case was tested on influenza virus (Lowen et al., 2007). However, in the low- and middle-income countries we observed a positive relationship of temperature with mortality (Fig. 2). This finding is consistent with one of the pioneer studies testing temperature effect on COVID-19 mortality in China (Ma et al., 2020). The variation of this response is likely to be linked with the genetic characteristics of SARS-CoV-2 in different regions. In our study, the difference between maximum and minimum temperature had a positive link with mortality in the low-and middle-income countries. This may imply that very high temperature at daytime and a very low temperature at night (temperature extreme) increase the mortality risk. To confirm this result, we did additional analysis using linear mixed effect modelling. Inclusion of Temperature difference into the mixed effect models improved model performance as we observed significantly lower AIC in the later model. (Table 2, Fig. 3).

Overall, we provide evidence that temperature is not an important factor to explain the spatial variability of COVID-19 transmission at a global scale. However, temperature did explain the spatial variability of mortality particularly in the low-and middle-income countries. A strong positive relation of temperature with mortality in the low-and middle-income countries indicate that warm climate may exaggerate the mortality rate in these regions. In the countries with high-income economies, mortality rate is mainly dependent on the percentage of aged people (60+ years) which is higher in developed countries due to their improved health system.

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