Environmental quality, climate indicators, and COVID-19 pandemic: insights from top 10 most affected states of the USA

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Received: 26 October 2020 / Accepted: 20 January 2021 / Published online: 25 February 2021
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Abstract

In the current context of the COVID-19 pandemic, researchers are working with health professionals to inform governments on how to formulate health strategies. In this study, we examine the correlation between environmental and climate indicators and COVID-19 outbreak in the top 10 most affected states of the USA. In doing so, PM_{2.5}, temperature, humidity, environmental quality index, and rainfall are included as crucial meteorological and environmental factors. Kendall and Spearman rank correlation coefficients, quantile regression, and log-linear negative binominal analysis are employed as an estimation strategy. The empirical estimates conclude that temperature, humidity, environmental quality index, PM_{2.5}, and rainfall are significant factors related to the COVID-19 pandemic in the top 10 most affected states of the USA. The empirical findings of the current study would serve as key policy input to mitigate the rapid spread of COVID-19 across the USA.

Keywords Coronavirus · COVID-19 · Environmental quality index · PM_{2.5} · Temperature

Introduction

The novel coronavirus is a pandemic caused by severe acute respiratory syndrome coronavirus 2 and first reported in Wuhan, China (Sohrabi et al. 2020). Existing literature has

reported that the COVID-19 is mainly transmitted through respiratory droplets, as well as human–human transmission (Arslan et al. 2021; Huang et al. 2020; Ge et al. 2013), and its rapid spread led to World Health Organization (WHO) declaring it as a pandemic (Fofana et al. 2020; Khan et al.

Responsible editor: Lotfi Aleya

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2020). Higher transmissibility of COVID-19, lack of medical facilities, and unstoppable spread have created psychological fear among the general public (Fattorini and Regoli 2020). Like COVID-19, other coronaviruses such as Middle East respiratory syndrome coronavirus (MERS), severe acute respiratory syndrome coronavirus (SARS), and Ebola have caused health emergencies in recent history (Yao et al. 2020). As a consequence, these pandemics caused a large number of deaths, a shortage of medical supplies, and cost billions of dollars to businesses worldwide (Bilal et al. 2021a; Allocati et al. 2016). Recent research shows that several factors including climate and meteorological indicators, i.e., temperature, rainfall, and humidity, affect the spread of COVID-19 (Hemmes et al. 1962). Tan et al. (2005) suggested that the outbreak of SARS in four major cities in China was significantly correlated with temperature resulted in reported cases. Further studies by Iqbal et al. (2020) and Wang et al. (2020) have highlighted that temperature is beneficial to the viral transmission of COVID-19. Although few recent studies contributed to the matter, however, there is still a lack of evidence in the contemporary literature of these indicators and the COVID-19 pandemic. Therefore, it is essential to understand how these meteorological and environmental conditions affect viral outbreaks, such as COVID-19, hence, providing us motivation to analyze the role of environmental and climate variables in the context of COVID-19 spread in the top 10 states of the USA.

The definite diagnosis of COVID-19 ranges between 0 and 60% and maximum temperature in-between 12.2°C and 22.8°C contributes most to such diagnosis (Yao et al. 2020). Additionally, a 1°C increase in maximum temperature reduces the fatality rate by 7.5%. The living environment is greatly affected by temperature, hence making it one of the key determinants to control the developments of infectious diseases (McMichael et al. 2008). According to current scientific studies, the transmission of infectious diseases is higher at lower temperatures because of the human body's vulnerability at such temperatures (Huang et al. 2020). Therefore, there is a consensus that transmission of COVID-19 may slowdown in the coming months due to the arrival of summer.

In the USA, the Washington State was the first territory to report COVID-19 diagnosis on January 15, 2020 (Burke 2020), and lack of federal and state initiatives resulted in the viral outbreak as the USA currently holds the most number of infections and deaths from COVID-19 (Jung et al. 2020). California, Florida, Texas, and New York are states with the most cases. Similar widespread outbreaks in European and Asian countries such as Italy, South Korea, Spain, and France led to WHO declaring COVID-19 as a global pandemic (Cucinotta and Vanelli 2020). However, the USA and the New York state are the epicenters of the COVID-19 in the world due to the higher number of cases and deaths (Bashir et al. 2020b; Doğan et al. 2020). The extant research contribution has been dedicated to examining the impact of climate indicators such as

temperature, humidity, and rainfall. However, the existing research gap suggests that further research is required to provide fresh evidence regarding the combined association between environmental quality and meteorological indicators.

To examine the impact of COVID-19 in the USA, we consider the top 10 states with the most reported cases. The motive behind choosing the top 10 states is the transparency, urbanization, and global economic influence of these top 10 states. Table 1 outlines the top 10 states with most cases and deaths due to COVID-19 in the USA. Furthermore, Figs. 1 and 2 highlight the trend of total cases, daily confirmed cases, total deaths, and daily confirmed deaths from COVID-19 during the timeline of the current research paper.

Data source: Centers for Disease Control and Prevention, USA (October 8, 2020)

Environmental conditions in the USA

Following World War II, industrial sector of USA witnessed rapid growth (Bashir et al. 2021), which not only improved the living standards and purchasing power of its residents but also resulted in lower air quality across the country (Bashir et al. 2020a). According to the World Health Organization (WHO 2019), every year, 7 million people die from exposure to environmental pollutants and due to environmental pollution at least 360,000 die prematurely in the USA alone (McDonald et al. 2016), which is why it is of considerable significance to study the impact of environmental pollution and the outbreak of COVID-19 in the USA. Although, recent studies point out that lockdown strategies have improved the environmental quality in the USA (Parodi and Liu 2020) as well as across the globe (Sardar et al. 2020); however, unlike current research no other study has investigated the impact of environmental pollution's association with COVID-19 over an extended period. The current study not only addresses this gap in existing literature but also further divides the top 10 states into Southern and Northwestern regions to provide a detailed

Table 1 Top ten US states with COVID-19 infections and deaths

No.	State	Cases	Deaths
1	California	840,322	16,251
2	Texas	810,689	16,622
3	Florida	720,117	14,766
4	New York	471,638	32,836
5	Illinois	308,990	9,100
6	Georgia	308,493	7,062
7	Arizona	221,937	5,713
8	North Carolina	221,438	3,691
9	New Jersey	221,438	16,147
10	Tennessee	202,257	2,594

Fig. 1 Total cases and daily confirmed cases—COVID-19

outlook of how meteorological conditions have affected the COVID-19 outbreak in different regions of the USA.

Data and research methodology

Data specification

The current research investigates the top 10 most affected states in the USA from March 2, 2020, to September 17, 2020, to provide a detailed outlook of the effects of the COVID-19 pandemic in the USA. The daily new cases, daily new deaths, and total confirmed cases have been included as dependent variables representing COVID-19 during the same period. Temperature is among the crucial meteorological variables, which has been identified as a crucial indicator in spreading COVID-19 (Bashir et al. 2020a, c). We include an average daily temperature in our research as it is of importance to analyze the impact of temperature given several recent studies have provided inconclusive results (Shahzad et al. 2020; Wang et al. 2020). Humidity is another critical factor in COVID-19 transmission, though further

scientific explanation is required to create better scientific understanding (Fareed et al. 2020; Wu et al. 2020). The environmental quality index (EQI) examines the impact of environmental pollution and the COVID-19 outbreak in the most affected USA states. Moreover, $PM_{2.5}$ is included as it exerts a substantial impact on COVID-19 transmission, especially in highly polluted areas (Bashir et al. 2020a, c). Existing literature suggests that higher environmental pollution is responsible for several health issues. Several recent studies have implied that the risk of contracting COVID-19 is significantly higher where the people are exposed to environmental pollutants (Bilal et al. 2021b; Burke et al. 2020; Iqbal et al. 2020). Data for meteorological indicators have been taken from the National weather service, USA; data for environmental and air pollutants (EQI and $PM_{2.5}$) have been taken from the Environmental Pollution Agency (E.P.A.). At the same time, COVID-19 total confirmed cases and deaths have been taken from the Centers for Disease Control and Prevention. The descriptive statistics of the abovementioned variables including their mean values, minimum, maximum values and measures of dispersions is presented in Table 2.

Fig. 2 Total deaths and daily confirmed deaths—COVID-19

Table 2 Descriptive analysis

Variables	Obs	Mean	Std. dev.	Min	Max	p1	p99	Skew.	Kurt.
totaldeaths	1590	4278.161	6187.375	0.000	25196	0.000	25093	2.172	7.092
Lndeaths	1469	7.212	2.197	0.000	10.134	0.000	10.131	−1.362	4.729
newcases	1590	1904.228	2540.096	0.000	15300	0.000	11126	2.242	7.817
lnnewcases	1540	6.698	1.689	0.000	9.636	0.693	9.317	−1.396	5.978
Lntemp	1590	4.372	0.196	3.526	4.762	3.807	4.700	−1.007	3.817
Lnhum	1590	4.374	0.336	2.639	4.605	3.045	4.605	−2.577	9.409
lnPM _{2.5}	1590	36.000	0.405	33.000	55.000	3.958	5.740	4.567	4.950
Lneqim	1590	3.388	0.015	3.350	3.424	3.353	3.414	−0.654	2.473
Rain	1590	0.117	0.356	0.000	3.21	0.000	1.940	4.685	28.894

Estimation strategy

Kendall and Spearman rank correlation tests

For empirical analysis, Kendall and Spearman rank correlation tests (Alexander 2008) are used to examine the association between environmental parameters and COVID-19. As a non-parametric test, the spearman rank correlation calculates the strength of the link between two variables and can be estimated through the following:

$$\gamma_s = \frac{1-6 \times \sum d_i^2}{n(n^2-1)} \quad (1)$$

where the difference between ranks of two parameters and the number of alternatives is represented through d_i and n respectively. The empirical values of $\gamma_s = -1$ and $+1$ means a negative and positive correlation respectively.

Kendall rank correlation is the second non-parametric test used by the current study to estimate the ordinal association between two variables, where Kendall's tau (τ) evaluates the ordering similarity between different datasets through the following formula:

$$\tau = \frac{[(concor)(discor)]}{0.5 \times n \times (n-1)} \quad (2)$$

In Eq. 2, the number of concordant and discordant pairs is represented by *concor* and *discor*; the total number of pairs is represented by n and the empirical values between $+1$ and -1 bear similar interpretation with spearman's correlation.

The negative binomial regression

We use negative binomial regression as the main analytical tool, which is applied in such a case when the data has several fluctuations, and can reduce any abitalic issues to show the correct impact. Negative binomial regression is part of Poisson regression analytics, where the mean is highlighted

by θ_i , and is considered as homogenous within the classes. Although classes become heterogeneous if we define a definite distribution for θ_i ; hence for empirical estimates, we assume that the mean θ_i follows a gamma distribution with mean $E(\theta_i) = \mu_i$ and variance. $Var(\theta_i) = \mu_i v_i^{-1}$

Also, negative binomial distribution can be shown through marginal distribution if we assume the Poisson distribution $Z_i | \theta_i$ with a conditional mean $E(Z_i | \theta_i) = \theta_i$. Negative binomial distribution's probability density function can be empirically estimated as:

$$\begin{aligned} Pr[Z_i = Z_i] &= \sum Pr(Z_i = Z_i | \theta_i) f(\theta_i)^d \theta_i \\ &= \frac{r(Z_i + V_i)}{r(Z_i + V_i)} \left(\frac{V_i}{V_i + \mu_i} \right)^{V_i} \left(\frac{\mu_i}{V_i + \mu_i} \right)^{Z_i} \end{aligned} \quad (3)$$

where variance parameters can be represented by $VAR(Z_i) = \mu_i + \mu_i^2 V_i^{-1} V_i$ and mean is $E(Z_i) = \mu_i E(Z_i) = \mu_i$.

Quantile regression

Quantile regression, first developed by Koenker et al. (1978), estimates different regression estimates where each estimator refers to the conditional distribution of different quantiles. The primary difference between OLS and regression analysis is that OLS provides regression coefficients as a consequence where the regression line runs through the average dataset; however, quantile regression provides different quantiles based on data distributions. Such empirical estimations allow us to examine the nature of the relationship between independent and dependent variables over the whole data set, hence providing more comprehensive insights. The mathematical form of the quantile regression model is modeled as follows:

$$y_i = x_i' \beta_\theta + \mu_{\theta i}, 0 < \theta < 1 \quad (4)$$

$$Quant_\theta(y_i/x_i) = x_i \beta_\theta \quad (5)$$

where explanatory variables' vector is represented by x ; explained variables are represented by y ; and error term by μ , whose distribution of conditional quantile is equal to zero. The dependent variable's θ th quantile is $Quant_{\theta}(y_i | x_i)$; $\hat{\beta}_{\theta}$ is regression estimator of θ th quantile and is following formula's solution:

$$\min \sum_{y_i \geq x_i' \beta} \theta |y_i - x_i' \beta| + \sum_{y_i < x_i' \beta} (1 - \theta) |y_i - x_i' \beta| \quad (6)$$

Results and discussion

Correlation analysis

We applied the Kendall correlation coefficient and Spearman correlation coefficient as an estimating tool for data analysis, and Table 3 presents the results of correlation analysis. For daily new cases, average temperature, humidity, rainfall, and EQI are significant for the Kendall correlation coefficient, while average temperature, PM_{2.5}, EQI, and rainfall are significant for the Spearman correlation test. And daily new deaths from COVID-19, average daily temperature, PM_{2.5}, EQI, and rainfall is significant for the Kendall correlation test and average temperature, humidity, PM_{2.5}, EQI, and rainfall are significant for the Spearman correlation coefficient.

Results of log-linear binomial analysis

Table 4 provides the empirical estimates of log-linear negative binomial regression to analyze the association between environmental and meteorological indicators and their influence over daily new deaths and daily new cases from most affected regions in the USA. Furthermore, due to significant difference in meteorological conditions, we divide our sample states into the south (Florida, Texas, Georgia, North Carolina, Louisiana) and Northwestern regions (California, Illinois, Arizona, New

Jersey, New York) to create a better understanding of the role of different atmospheric and weather conditions over the COVID-19 outbreak in different geographical locations in the USA (Fig. 3a, b).

The statistical findings suggest that temperature, humidity, PM_{2.5}, EQI, and rainfall are critical determinants in impacting the spread of COVID-19 in the USA. Temperature and humidity have a positive association in daily new cases (model 1), but carry a negative association with daily new deaths (model 2). PM_{2.5} and EQI have a negative association with daily new cases as well as daily fatalities from COVID-19. Finally, rainfall has a negative association with daily new cases (model 1) and new deaths (model 2). To better understand the impact of environmental and meteorological indicators, we divide the top 10 most affected states into the South and Northwestern regions on the basis that both regions have distinct differentiation in climate (temperature) as well as in environmental pollution emitted from industries and transportation sector. Figure 3a and b report the findings through quantile regression. The impact of temperature is positive in both regions but its association decreases at high quantiles for both regions. The impact of humidity is negative at low quantiles but has a marginal positive impact at high quantiles (South region); likewise, humidity has a slight negative impact at high quantiles (Northwestern region). Next, we discuss the findings of environmental pollution indicators and their impact on the COVID-19 outbreak in both regions. PM_{2.5} has a negative association at middle quantiles for both of the regions, whereas EQI negative correlation at low and high quantiles (South region) and has a positive association especially at middle and high quantiles (Northwestern region). Lastly, we report the impact of rainfall, which is a significant meteorological indicator. Rainfall has a significant negative association at middle and high quantiles for the South region, while has a marginally positive association throughout for the Northwestern region.

Table 3 Empirical results for correlation analysis

	Climate variables	Daily new cases	Daily new deaths
Kendall correlation	Temperature average	−0.0656*	0.2557*
	Humidity	−0.0437*	−0.0222
	PM _{2.5}	0.0222	0.0057*
	EQI	−0.0216*	0.1067*
	Rainfall	−0.0105*	0.0093*
Spearman correlation	Temperature average	−0.0976*	0.3796*
	Humidity	−0.0662*	−0.0281*
	PM _{2.5}	0.0333*	0.0095*
	EQI	−0.0333	0.1531*
	Rainfall	−0.0194*	0.018*

*5% level of significance

Table 4 Log-linear negative binomial analysis

Variables	Model 1 (daily new cases)		Model 2 (daily new deaths)			
	Coefficient	Z-statistic	P value	Coefficient	Z-statistic	P value
Temperature	0.0082**	0.8100	0.0180	−0.0081	−1.3400	0.1790
Humidity	0.0111*	1.6300	0.1040	−0.0291***	−6.7800	0.0000
PM _{2.5}	0.0191**	1.5900	0.0110	0.0242***	2.9400	0.0030
EQI	0.0126	0.1400	0.8880	1.5528***	14.7600	0.0000
Rainfall	−0.1900**	−1.9500	0.0510	−0.0233	−0.1900	0.8490
Constant	6.8516**	2.3800	0.0170	−38.3271***	−12.0400	0.0000
Pseudo R ²	0.1672	-	-	0.80	-	-
Further controls	Yes	Yes	Yes	Yes	Yes	Yes

Both models are employed by taking covariates as a function of new cases, and daily fatalities

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$

Previous research work by Vandini et al. (2013) and Tan et al. (2005) examine the early outbreak of infectious diseases to conclude that temperature is one of the key determinants, with low temperature generally means a higher chance of contracting the virus. Shi et al. (2020) analyzed the impact of climate indicators for 31 provinces in China and detailed that temperature is one of the key factors in the spread of COVID-19. Additionally, the USA being the cultural and financial center of the world oversees very high mobility from domestic as well as abroad to seek economic and business opportunities, which contributed to the widespread outbreak in the USA. Another key indicator is humidity; recent research such as Qi et al. (2020) and Ma et al. (2020) concluded that high temperature and humidity reduce the spread of coronavirus and suggested that the arrival of summer could effectively significantly reduce COVID-19. Another important climate indicator is rainfall. Tosepu et al. (2020) analyzed weather indicators' role in affecting COVID-19 in Jakarta, Indonesia, and suggested that higher rainy days influence the spread of COVID-19 cases. Similarly, Lasisi and Eluwole (2021), Şahin (2020), and Ghosh et al. (2020) provided similar findings for the Russian Federation, Turkey, and UK datasets respectively. Our empirical estimates join the strand of recent works Shakoor et al. (2020) and Fareed et al. (2020) for the case of the USA and China.

Another strand of existing literature suggests that long-term exposure to pollution indicators is a significant factor towards higher mortality from COVID-19. Therefore, we included fine particulate matter (PM_{2.5}) to examine its impact on the COVID-19 outbreak. The majority of the pre-existing conditions that increase the risk of death for COVID-19 are the same diseases that are affected by long-term exposure to air pollution. In a recent study, Wu et al. (2020) evaluated the bearing of PM_{2.5} for 300 counties across the USA and discovered that every 1 µg/m³ of PM_{2.5} is linked with a 15% higher likelihood of getting died due to COVID-19. They further

articulated that long-term contact with air pollution means a 20 times higher mortality rate from COVID-19 than any other disease. Likewise, Fareed et al. (2020) also conveyed comparable conclusions for the case of Wuhan China. Cienciewicki and Jaspers (2007) and Sedlmaier et al. (2009) also reported that airborne particulate matter (PM) is responsible for increasingly higher risk of virus diffusion among humans. The environmental quality index serves as a complete environmental indicator for research on human health. Ju et al. (2020) based on investigating the impact of environmental quality towards COVID-19 cases in South Korea concluded that lower environmental quality weakens the human immune system and is the leading contributor in raising the risk of getting infected from COVID-19. In the same way, Dutheil et al. (2020) and Venter et al. (2020) supported similar findings and suggested that higher environmental quality reduces the outbreak of infectious diseases.

Conclusion

North America, especially the USA, became the COVID-19 epicenter, as the COVID-19 infections had an ever-increasing trend, which is why southern and northwestern states in the USA are facing a record number of infections in recent months. The case example of USA states is a unique scenario as not only these states have higher infectious rates but also a higher mortality rate. This is why in the current research paper, we have analyzed the factors behind new daily cases and new daily deaths to provide a comprehensive analysis of factors associated with the COVID-19 outbreak and federal and state response to the pandemic. Current study investigates the impact of air pollution and meteorological conditions in the transmission of COVID-19 in the ten most affected nations from March 2, 2020, until September 17, 2020. We have investigated the difference between environmental and

Fig. 3 **a** Geographical analysis using quantile modelling plot (South region). **b** Geographical analysis using quantile modelling plot (Northwestern region)

meteorological effects between Southern and Western regions, which has not been done before. Our findings indicate

that temperature, humidity, PM_{2.5}, EQI, and rainfall are the

main determinants of COVID-19 spread in most affected American states.

Our findings indicate that higher environmental and air pollution has contributed significantly in the American states, especially southern states, which rely heavily on fossil fuels, which is responsible for environmental degradation in these states. This is why, as a policy recommendation, USA policymakers need to focus further on environmental pollution and strengthen pandemic response strategies to lower the pandemic threat. Furthermore, as it is evident from recent data that the elderly and children as part of vulnerable age groups have higher susceptibility from COVID-19, a well-managed healthcare infrastructure can offer great assistance in lowering the pandemic threat level. We further provide policy recommendations for state and health officials around the world. We recommend that other countries should take insights from the second-wave of COVID-19 infections in southern USA states and should focus simultaneously on improving the healthcare system as well as introducing long-term pollution control policies to prevent environmental degradation further.

Lastly, although currently there are interesting analytical findings, we offer the following limitations in our research work. First, the current study only offers empirical association of environmental and meteorological conditions in the ten most affected states with data categorized with limited frequency; hence, we encourage further research to analyze meteorological and environmental indicators from panel datasets from emerging and industrial economies to provide more significant insights. Also, the inter-regional analysis would help create a better understanding of COVID-19 as a global pandemic. Finally, future research needs to investigate the impact of urban density, population, virus resistance, and health infrastructure; hence, the evolution of COVID-19 research would guide us about the pandemic, causes, and solutions for future health emergencies.

Author contribution Author contribution is as follows: Bilal, Writing—review and editing. Muhammad Farhan Bashir, Writing—original draft, analysis, revision. Khuram Shahzad, Methodology. Bushra Komal, Supervision. Muhammad Adnan Baashir, Project administration. Madiha Bashir, Empirical analysis, Resources. Duojiang Tan, Investigation. Tehreem Fatima, Data curation. Umar Numan, Formal analysis.

Data Availability Research data can be obtained from corresponding author through email

Signature of the corresponding author:

Date of submission: December-29-2020

Declarations

Ethical approval We certify that the manuscript titled “Environmental quality, climate indicators, and COVID-19 pandemic: insights from top

10 most affected states of USA” (hereinafter referred to as “the paper”) has been entirely our original work except otherwise indicated and it does not infringe the copyright of any third party. The submission of the Paper to Environmental Science and Pollution Research implies that the Paper has not been published previously (except in the form of an abstract or as a part of a published lecture or academic thesis), that it is not under consideration for publication elsewhere, that its publication is approved by all authors and that, if accepted, will not be published elsewhere in the same form, in English or any other language, without the written consent of the Publisher. Copyrights for articles published in Environmental Science and Pollution Research are retained by the author(s), with first publication rights granted to Environmental Science and Pollution Research.

Consent to participate We affirm that all authors have participated in the research work and are fully aware of ethical responsibilities.

Consent to publish We affirm that all authors have agreed for submission of the paper to ESPR and are fully aware of ethical responsibilities.

Competing interests The authors have no conflicting interest and are aware of ethical responsibilities.

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