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The effects of air pollution, meteorological parameters, and climate change on COVID-19 comorbidity and health disparities: A systematic review

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ABSTRACT

Keywords: PM2.5, Air quality, meteorological conditions, health disparities, SARS-CoV-2, COVID-19, and epidemic

Air pollutants, especially particulate matter, and other meteorological factors serve as important carriers of infectious microbes and play a critical role in the spread of disease. However, there remains uncertainty about the relationship among particulate matter, other air pollutants, meteorological conditions and climate change and the spread of the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), hereafter referred to as COVID-19. A systematic review was conducted using PRISMA guidelines to identify the relationship between air pollutants and COVID-19. Additionally, the contribution of host related-factors, co-morbidities, and health disparities was discussed. This review found a preponderance of evidence of a positive relationship between PM2.5, other air pollutants, and meteorological conditions and climate change on COVID-19 risk and outcomes. The effects of PM2.5, air pollutants, and meteorological conditions on COVID-19 mortalities were most commonly experienced by socially disadvantaged and vulnerable populations. Results however, were not entirely consistent, and varied by geographic region and study. Opportunities for using data to guide local response to COVID-19 are identified.
1. Introduction

Poor air quality has been reported to exacerbate several environmentally-induced diseases including asthma, chronic obstructive pulmonary lung disease (COPD), pulmonary hypertension, arterial hypertension, arrhythmia, myocarditis, other cardiovascular, and cardiometabolic diseases. Particulate matter has often been implicated as a causative agent in those studies [1-6]. Components of air pollution have been found to alter defense mechanisms of the respiratory system. COVID-19, caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) is most commonly transmitted from person-to-person by droplets, aerosols and fomites [7].

A positive correlation between long-term exposure to high concentrations of air pollutant components, including particulate matter (PM), SO\textsubscript{2}, CO, NO\textsubscript{x}, O\textsubscript{3} and COVID-19 morbidity and mortality has been found in studies carried out across a range of countries, including Spain [8], Italy [8-10], China [11], United States [12], United Kingdom [13] and Canada [14]. Most studies support a positive relationship between particulate matter-associated air pollutants and the rise in autoimmune and respiratory diseases [15-17]. Bioaerosols and aerosols from manufacturing and transport activities have been identified as capable of carrying the Coronavirus, which has a half-life of 1.1 h in aerosols and thus remains stable while it is transmitted through air [18]. The focus of this review was to assess the role of priority air pollutants, meteorological parameters, climate change in the spread of COVID-19 morbidity and mortality. In addition, this review addresses the extent to which COVID-19, air pollutants and meteorological conditions are modified by personal, social, and behavioral factors, co-morbidities and contribute to health disparities [19].

2. Methods

We conducted a systematic review by following the Preferred Reporting Items for Systematic Reviews (PRISMA) guidelines [20] to identify original studies that identified the effects of air pollutants, meteorological conditions and climate change on COVID-19 morbidity, mortality, comorbidities, and health disparities.

2.1. Search strategy

We conducted database searches of Google Scholar, PubMed, OVID, ERIC, SCOPUS, INGENTA and Web of Science between 2019 and 2021 using Covidence software (Covidence Org, Melbourne, Australia). The search strings for each database included combination of the following terms: SARS-CoV-2 OR COVID-19 separated by OR, AND particulate matter OR PM OR PM\textsubscript{2.5} OR PM\textsubscript{10} OR meteorological parameters OR air quality OR air pollution OR air pollutants OR atmospheric pollution OR climate change OR environmental stressors OR mortality OR morbidity. A two-staged screening process was performed by two independent reviewers.

2.2. Eligibility criteria and study selection

Three authors (PDJ, AR, and MA) conducted the systematic review. Initial screening of all databases generated a total of 170,296 articles: Google Scholar (138,970), PubMed (6898), OVID (10,081), ERIC (114), SCOPUS (8366), INGENTA (242) and Web of Science (5625). After 136,240 duplicates were removed, 34,056 articles remained in the search. 1827 records were further excluded by two study authors (AR and MA) because they were from books or book chapters (3), conference proceedings (283), editorials (712), encyclopedia mentions (1), letters to the editor (257), notes (531), and reports (40). The remaining 138,067 records were subjected to title and abstract review by two study authors (PDJ and AR) using the following inclusion criteria: (a) published between March 2000–December 2021; (b) designed as a monitoring study; (c) reported qualitative results or secondary analysis of the data; (d) published in English; and © targeted SARS-CoV-2 or COVID-19. Exclusion criteria used were: (a) articles that focused on how COVID-19 contributed to poverty and change in socio-economic status; (b) articles that discussed the political climate during COVID-19 pandemic; (c) articles that analyzed the issues of healthcare workers; and (d) articles that highlighted impact of lockdown on human activity and comfort. This step eliminated 137,263 articles, resulting in a total of 804 articles. At this stage of the review, 739 additional articles were removed because they lacked a focus on COVID-19 AND environmental stressors (air pollutants, meteorological factors, climate change etc.) After a full text review, 63 articles were included in this systematic review. Fig 1 provides a PRISMA diagram of each step in our systematic review process.

2.3. Data extraction

Data were extracted from all manuscripts included: subject description, study design, sample/sample size, intended outcome, findings and conclusions.

3. Results & discussion

3.1. Factors that influence the spread of COVID-19

A wide array of meteorological factors including particulate matter, air pollution, and heat were identified as positively associated with the spread of COVID-19. Studies identified that reported on the relationship between meteorological parameters and COVID-19 spread in different regions of the world [21–79] are shown in Table 1. The interplay among meteorological factors (air pollution, meteorological parameters, and climate change) and COVID-19 and host-related factors is schematically depicted in Fig. 2.
3.1.1. Role of meteorological factors and air quality (priority pollutants) in COVID-19 incidence and mortality

Particulate matter concentrations are directly impacted by meteorological conditions including temperature, wind, and precipitation [80,81]. A positive association between environmental air pollutants and increased incidence of daily COVID cases and deaths was reported in London [13]. An increase in the hospitalization rate for COVID-affected people over 50 years of age and the high mean concentration of PM$_{2.5}$ was found in Italy. The contribution of global exposure to air-borne PM towards COVID-19 mortality risk has been estimated at 15% [82].

Risk for respiratory virus infections occur in a seasonal manner, reaching a peak in low temperatures [83]. PM serves as an abiotic vector for the spread of these pathogens [84,85]. Since PM is inhalable, the associated viruses are inhaled too. PM$_{2.5}$ has aerodynamic diameter less than or equal to 2.5 μm, and enter the lungs through inhalation. It is then lodged deep into the lungs, paving the way for particle-associated viruses to cause infection.

PM also has been identified previously as a carrier for several bioaerosol components including bacteria, fungi, spores and several viruses and has been greatly implicated in the spread of COVID. Differential deposition of particulate matter under dry and wet conditions which controls the fate of virus-laden droplets, and also UV radiation appear to play a role in the seasonal transmission of COVID-19 [86]. Cold and dry conditions have been found to influence the transmission of COVID-19 in temperate regions, where winters are cool but relatively mild and summers are warm, wet and stormy (Southeast region of the U.S. and large portions of China, Brazil and Argentina), whereas hot and humid conditions prevalent in tropical regions have been found to have an effect on the transmission of COVID-19.

Studies conducted in Singapore, India, and China have found a positive relationship between temperature and the number of COVID-19 cases reported per day [34,35]. A significant positive association between COVID-19 and temperature, relative humidity, absolute humidity and wind speed were found in studies conducted in Thailand [87] and Turkey [88]. Hassan et al. [39] similarly reported a significant correlation between COVID-19 infection rate and water vapor, O$_3$, land surface temperature, rainfall, wind pressure, and wind speed. A modest non-linear association between COVID-19 transmission and weather patterns (temperature, humidity, solar radiation, wind speed and precipitation) was found by Sera et al., [89] in a study conducted in 409 cities and 26 countries.

In contrast, a review conducted by Mecenas et al. [90] found that warm and wet climates reduced the spread of COVID-19. Studies conducted in China [49,91] and Indonesia [44] also found that high temperature and humidity were associated with lower rates of COVID-19. Meanwhile, an ongoing study of viral infections in England by Nichols et al. [92] revealed that transmissibility of coronavirus depends on season, reaching a peak in winter (daily mean temperature below 10 °C, sunshine of less than 5 h/day and relative humidity over 84%), which implies a seasonal increase for COVID-19 infections in countries experiencing similar climate. A study conducted by Christophi et al. [78] reported a 10 °C rise in ambient temperature resulted in 6% lower COVID-19 mortality rates at 30 days after the first reported death in Organization for Economic Co-operation and Development (OECD) countries and the United States. A survey of 2669 U.S. counties revealed that low air temperature, specific humidity and UV radiation were significantly associated with increased SARS-CoV-2 reproduction number. While cold and dry weather and low levels of UV radiation were moderately associated with coronavirus transmissibility, humidity was found to play a greater role [49].

While some of the above-mentioned studies showed a significant relationship between meteorological parameters and COVID-19 incidence, others found no such relationship. Studies that found no association between temperature, relative humidity, and UV irradiance data with transmissibility and incidence of COVID-19 were conducted in China [93,94], Spain [22], South America, Africa [54] and Canada [66]. Using geospatial technology, Singh et al. [95] reported that COVID-19 transmission/mortality is seasonally related to air quality (methane, CO, NO$_2$, SO$_2$, O$_3$) in the USA, India, Brazil, Russia, France, Spain, Argentina, UK, Columbia and Mexico.

Epidemiological and experimental studies previously have shown a positive correlation between airborne toxicants and a variety of viral respiratory infections such as human influenza, avian influenza viruses [96] and children’s respiratory syncytial virus [97]. Epidemiological studies...
Table 1
Relationship among meteorological parameters, air pollutant levels and COVID-19 cases in different parts of the world.

| Study area | Pollutants/environmental parameters studied | Methods employed | Important findings | Reference |
|-----------|---------------------------------------------|------------------|--------------------|-----------|
| Forty-seven (47) provincial capital cities in mainland Spain and the Balearic islands | NO\(_2\) and O\(_3\) levels | In stage I, a time stratified case-crossover design with conditional quasi-Poisson regression model was applied to estimate the city-specific associations between daily NO\(_2\) and O\(_3\) levels and non-accidental mortality. In stage II, a multivariate random-effects meta-analysis was performed to estimate the average association between air pollutants and mortality across cities. | Reductions in NO\(_2\) and O\(_3\) emissions during lockdown measures contributed to less in severity of COVID-19 infections. | [21] |
| Most provinces in the Iberian Peninsula, Spain | Daily temperatures and COVID-19 cases | Temperature data was obtained from weather stations under the control of the State Meteorological Agency. COVID-19 data was downloaded from a publicly available repository. Spatio-temporal modelling techniques and the R programming language were used to analyze the association between temperature and COVID-19 cases. | No consistent evidence has been found regarding the existence of a relationship between the accumulated number of COVID-19 cases and temperature values at the province level in Spain. | [22] |
| France | Temperature and COVID-19 cases | Temperature and COVID-19 spread data were obtained from national and international databases. The epidemic modelling approach was employed to assess the change in the size of population susceptible, infective and recovering individuals due to COVID-19. The COVID cases were correlated with mean temperatures in respective regions using Pearson's correlation coefficient. | High temperatures were found to diminish initial transmission rates of COVID-19. | [23] |
| Eight (8) regions in Northern Italy | PM\(_{2.5}\) levels | PM\(_{2.5}\) data was obtained from the European Environmental Agency's air monitoring database. COVID deaths were determined by a statistical model using negative binomial regression. | A correlation between PM\(_{2.5}\) levels and deaths due to COVID was seen. | [9] |
| Padua, Italy | PM\(_{2.5}\) and PM\(_{10}\) concentrations | PM samples were collected on quartz fiber filters. Samples were analyzed with RT-qPCR for SARS-CoV-2 RNA | No SARS-CoV-2 RNA was found in the outdoor PM, which reveal the low probability of virus airborne transmission through PM. | [24] |
| Italy | PM\(_{2.5}\) and NO\(_2\) levels | Average weekly levels of PM\(_{2.5}\) and NO\(_2\) was extrapolated from the European Environment Agency data. The number of COVID-19 cases was obtained by the Department of Civil Protection. The COVID-19 incidence rates in resident population were obtained from the Italian Institute of Statistics (ISTAT). A linear regression model was used to examine the association between PM\(_{2.5}\) and NO\(_2\) levels and COVID-19 incidence rates. | An increase in PM\(_{2.5}\) and NO\(_2\) concentrations by one unit (1 \(\mu g/m^3\)) corresponded to an increase in COVID-19 incidence rates of 1.56 and 1.24 \(\times 10^4\) people | [25] |
| Emilia-Romagna region, Italy | PM\(_{2.5}\) levels | Indoor temperature, relative humidity, PM\(_{2.5}\) concentrations of air pollutants and the prevalence COVID-19 infections. VOCs, and CO\(_2\) concentrations were measured using passive air sensors. | Mean indoor PM\(_{2.5}\) concentrations peaked in winter compared to spring and summer. The elevated levels of air pollutants and inadequate ventilation indoors close to COVID-19 lockdown raises alarm about the health issues of people as they tend to spend more time indoors during next waves of pandemic. | [26] |
| Lombardi region, Italy | SO\(_2\), NH\(_3\), O\(_3\), NO\(_x\), CO, O\(_3\), PM\(_{2.5}\) and PM\(_{10}\) concentrations | Meteorological data were obtained from the European Centre for Medium-Range Weather Forecasts program. Epidemiological data were collected from the Istituto Superiore di Sanità and Protezione Civile. The Pearson correlation coefficients were calculated between the average concentrations of air pollutants and the prevalence of infected people. | Seasonal weather conditions and concentration of air pollutants seemed to influence COVID-19 incidence. | [27] |
| Lombardi region, Italy | NO\(_2\), O\(_3\), PM\(_{2.5}\), PM\(_{10}\) levels and COVID-19 incidence | Data on demographic, meteorological parameters and COVID-19 incidence and hospitalization records were obtained from the government. | Concentrations of NO\(_2\), O\(_3\), PM\(_{2.5}\) and PM\(_{10}\) relative average humidity, COVID-19 prevalence was positively associated with the case fatality rate. | [10] |
| Lombardi region, Italy | PM\(_{2.5}\), PM\(_{10}\), SO\(_2\), and O\(_3\) concentrations | Air pollution data was gathered from the monitoring stations of the Regional Environmental Protection Agency. Climatic factors such as temperature, relative humidity, wind speed, and precipitation were also analyzed. | While short-term exposure to PM\(_{2.5}\), PM\(_{10}\), and O\(_3\) in some cases seems to be related to an increased incidence of COVID-19 infection, the role of increased susceptibility of the host due to the dysregulation of the immune system. | [29] |
| Fifteen (15) provinces in Italy | PM\(_{2.5}\) concentrations | Data were subjected to Spearman and Pearson correlations between population number, meteorological parameters and COVID-19 cases. The multivariate cross-sectional ordinary least squares (OLS) approach was used to identify the main determinants at regional level, and the Ward's hierarchical agglomerative clustering method was used to build a "taxonomy" of provinces with similar mortality risk of COVID-19. | A significant correlation was found between COVID-19 cases and population number in most of the regions. Also, a significant correlation was found between the number of COVID-19 cases and average daily concentrations of PM\(_{2.5}\) in Lombardy. | [28] |

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| Study area*④ | Pollutants/environmental parameters studied | Methods employed | Important findings | Reference |
|-----------------|---------------------------------------------|-----------------|-------------------|-----------|
| One hundred and seven (107) provinces and twenty (20) regions in Italy | PM$_{2.5}$ concentrations | COVID-19. | Number of positive cases for COVID-19, hospitalization, and mortality data were obtained from the Indian health system. Air pollution data was gathered from the monitoring stations of the Regional Environmental Protection Agency. | [30] |
| | | | An increase in the hospitalization rate in percentage of people over 50 and an increase in the average concentration of PM$_{2.5}$ was noted. | |
| Sixty-nine (69) large cities and thirteen (13) large towns in Italy | PM$_{2.5}$ concentrations | Data on concentrations of PM$_{2.5}$, raditation, temperature and rainfall were obtained from GHS urban center database. Data on COVID-19 cases were collected from the Italian Department of Civil Protection Dataset. A curve estimation model was fitted to estimate the parameters of regression and the coefficient of significance using SPSS software. A heat map analysis was performed using XLSTAT to cluster the contributions of the environmental variables and the COVID-19 cases. | A significant correlation between the first wave of COVID cases and the PM$_{2.5}$ concentrations was found. An inverse correlation between WID-19 cases and temperature was also noted. |
| Three hundred and fifty-five (355) municipalities in Netherlands | PM$_{2.5}$ concentrations | Annual concentrations of PM$_{2.5}$, NO$_2$, and SO$_2$ and COVID-19 incidences, hospital admissions and deaths were obtained from the National Institute for Public Health and the Environment. | A positive relationship between PM$_{2.5}$ concentrations, and COVID-19 cases, hospital admissions and deaths were noted. |
| London, United Kingdom | PM$_{2.5}$, CO and O$_3$ levels | The data was analyzed using “R” language. One-sample Kolmogorov-Smirnov test was used to evaluate the assumptions of Normal and Poisson distributions. Spearman Rho Correlation was used to assess the relationship between various pollutant parameters with the number of cases and deaths. The Poisson regression analysis was performed to predict the number of cases and deaths from pollutant parameters. | A significant increase in number of COVID cases with an increase in PM$_{2.5}$ and O$_3$ levels. |
| Damak, Simara, Kathmandu, Pokhara, Nepalgunj and Surkhet, Nepal | PM$_{2.5}$ and PM$_{10}$ concentrations | Daily PM$_{2.5}$ and PM$_{10}$ concentrations were obtained from the World Air Quality Index project. Mann–Whitney U tests were conducted to test the significance of differences in mean concentration for each site during the lockdown period. The significance of differences in mean concentrations between prior to- and post-lockdown period were also analyzed during Mann–Whitney U test. | During lockdown significant drop in PM$_{2.5}$ and PM$_{10}$ levels was observed. |
| Delhi, Mumbai, Kolkata, and Chennai, India | PM$_{2.5}$, PM$_{10}$, NO$_2$, NH$_3$, SO$_2$, CO, and O$_3$ levels during COVID-19 lockdown | Air pollutant concentrations and air quality index were acquired from the Central Pollution Control Board, Ministry of Environment, Forests, and Climate Change. The Pearson correlation analysis was used to compare the air pollutant concentrations between pre-lockdown and lockdown periods. | The lockdown period showed remarkable improvement in air quality as reflected by the decline in air pollutant concentrations. The pollutants, PM$_{2.5}$ and PM$_{10}$ were found to be highly correlated with air quality index. |
| Mumbai, India | Meteorological parameters and COVID-19 cases | Data on meteorological parameters was used for correlation with COVID-19. The parameters that exhibited significant correlation were subjected to statistical modelling and prediction of COVID-19 infections using Artificial Neural Network technique. | Relative humidity was found to influence the active number of COVID-19 cases. |
| New Delhi, Chennai, Kolkata, Mumbai, and Hyderabad, India | Daily PM$_{2.5}$ concentrations | The PM$_{2.5}$ levels were being measured using Beta Attenuation Monitor 1020. The high-resolution air quality data for the respective cities were obtained from the US Govt. Meteorological data were downloaded from www.ogimet.com. | The average PM$_{2.5}$ levels during the lockdown period were reduced compared to those before lockdown period. During the unlocking period, except for Chennai, all cities showed a reduction in average PM$_{2.5}$ levels compared to concentrations in the lockdown period, with reductions mainly linked with monsoon rains in India. |
| Thirty-two (32) states and union territories, India | Meteorological parameters, PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$ and COVID-19 cases | Data on air pollutants were obtained from an online platform. Meteorological data were obtained from the from Indian Meteorological Department. The COVID-19 case data was obtained from the Ministry of Health and Family Welfare. Spearman’s correlation was used to analyze the correlations between the air pollutants, meteorological factors, and the number of COVID cases. | Significant correlations were found between air pollutants and meteorological factors with COVID cases. |
| Quetta, Karachi, Lahore, Peshawar, and Islamabad, Pakistan | Daily PM$_{2.5}$ and PM$_{10}$ concentrations | PM$_{2.5}$ and PM$_{10}$ samples were collected and their concentrations were measured using Beta-ray Attenuation Mass Spectrometer. The air quality data was obtained from the NASA’s MODIS equipment. The RStudio computational environment was utilized for data analysis. | During the lockdown period, the PM$_{2.5}$ levels decreased from 27 ± 58% in major cities such as Quetta, Lahore, Peshawar, Karachi, and Islamabad |
| Study areaa | Pollutants/environmental parameters studied | Methods employed | Important findings | Reference |
|------------|---------------------------------------------|------------------|-------------------|-----------|
| Dhaka, Bangladesh | Meteorological data, air pollutant levels, and COVID-19 cases | Data on meteorological parameters data were obtained from NASA. Data on PM<sub>2.5</sub>, NO<sub>x</sub>, SO<sub>2</sub>, CO and O<sub>3</sub> were obtained from NASA. The COVID-19 infection/mortality was obtained from the Bangladesh Ministry of Health. Population density data was obtained from Bangladesh Bureau of Statistics. Geographically Weighted Regression (GWR) method was used to assess the association between air pollution, meteorological, and population data with the COVID-19 infection rate. | The levels of PM<sub>2.5</sub>, CO and O<sub>3</sub> showed a strong correlation with COVID-19 infection rate. Similarly, population density and poverty level revealed a significant relationship with COVID-19 incidence in the middle and southern parts of the city, where the population density was high. | [39] |
| Bangladesh | Meteorological data and COVID-19 cases | Data on meteorological parameters were obtained from the Bangladesh Meteorological Department. COVID-19 data was obtained from the Bangladesh Ministry of Health. The compound Poisson generalized linear model was used to determine the relationship between daily meteorological variables, and daily COVID-19 cases. | Humidity and rainfall were found to increase the COVID-19 transmission. | [40] |
| Afghanistan, Bangladesh, India, Nepal, Pakistan, and Sri Lanka | Meteorological parameters and PM<sub>2.5</sub> levels | Data on meteorological parameters and PM<sub>2.5</sub> levels were obtained from the World Air Quality Index Project. Data on COVID-19 infections, and deaths were obtained from Our World in Data platform. To treat the cross-country data, cross-sectional dependence was tested through the Pesaran and Bresh-Pagan tests. To check and validate the stationarity of the time-series of the data, the cross-sectionally augmented Dickey-Fuller test was employed, and the Westerlund Cointegration Test (WCT) was used to test the long-term relationship between the model variables. | A correlation was seen between COVID-19 cases, deaths, meteorological factors, and air pollutant levels. The COVID-19 confirmed cases and PM<sub>2.5</sub> levels showed a statistically significant correlation with COVID-19 deaths. | [41] |
| Singapore | Meteorological parameters and COVID-19 infections | Meteorological parameter data were obtained from the online database archives of the Weather Underground. Daily cases of new COVID-19 infections, recovery rate, and deaths were obtained from the Ministry of Health. Spearman and Kendall rank correlation tests were employed to examine the associations between COVID-19 and meteorological parameters. The PM<sub>2.5</sub> concentrations were measured using US-EPA FEM BAM-1020 Beta Attenuation Mass Monitor. COVID case numbers were obtained from the health ministry. | Meteorological parameters showed positive significant correlation with COVID-19 pandemic. | [42] |
| Bangkok, Thailand | Concentrations of PM<sub>2.5</sub> and COVID-19 numbers | Weather data was obtained from the meteorological department. COVID-19 case data was obtained from the Ministry of Health. Spearman rank correlation test was employed to assess the relationship between weather and daily covid-19 incidence. | The lockdown policy and work from home arrangement brought a significant reduction in PM<sub>2.5</sub> concentrations and the number of cases in COVID-19 hotspot areas. | [43] |
| Jakarta, Indonesia | Meteorological parameters and COVID-19 incidence | Weather data was obtained from the meteorological department. COVID-19 case data was obtained from the Ministry of Health. Spearman rank correlation test was employed to assess the relationship between weather and daily covid-19 incidence. | A significant correlation between temperature and COVID-19 incidence was noted. | [44] |
| Hanoi, Vietnam | PM<sub>2.5</sub>, NO<sub>x</sub>, O<sub>3</sub>, and SO<sub>2</sub> levels during COVID-19-induced lockdown | PM<sub>2.5</sub> samples were collected using high volume air samplers equipped with appropriate filters. Additional data on other air pollutants were collected from Northern Center for Environmental Monitoring. Precipitation, temperature, and solar radiation data were obtained from the European Centre for Medium Range Weather Forecasts. Principal Component Analysis was done to determine sources of elements in PM<sub>2.5</sub> using SPSS. | The concentrations of PM<sub>2.5</sub>, NO<sub>x</sub>, O<sub>3</sub>, and SO<sub>2</sub> concentrations were reduced by 55.9, 75.8, 21.4 and 60.7% respectively during partial lockdown compared to historical values. | [45] |
| Wuhan, China | PM<sub>2.5</sub>, and O<sub>3</sub> concentrations and COVID-19 cases | Air quality data was obtained from the China National Environmental Monitoring Center. The Community Multiscale Air Quality modeling system of USEPA was used to simulate the spatial and temporal variation of air pollutants during lockdown period. | PM<sub>2.5</sub> concentration showed a significant decrease during lockdown, while O<sub>3</sub> levels were found to increase which was attributed to wind direction. | [46] |
| Fourteen (14) provinces in China | PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, NO<sub>x</sub>, and O<sub>3</sub> concentrations and COVID-19 cases | Pollutant data were obtained from the China Air Quality Online Monitoring and Analysis Platform. The number of COVID cases, discharges, and deaths during the epidemic period were obtained from the Urban Health Commission. | Long-term exposure to air pollutants showed a significant relationship with COVID-19 case fatality rate. | [47] |
| One hundred and twenty-two (122) cities in China | Meteorological factors and COVID-19 cases | Meteorological data were collected from National Meteorological Information Center. COVID-19 case data were obtained from health commissions in respective provinces or cities. The generalized additive model was used to explore the nonlinear relationship between | Mean temperature showed a positive linear relationship with the number of COVID-19 cases with a threshold of 3 °C. | [48] |

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### Table 1 (continued)

| Study area* | Pollutants/environmental parameters studied | Methods employed | Important findings | Reference |
|-------------|---------------------------------------------|------------------|-------------------|-----------|
| Wuhan, China | Meteorological parameters, air pollutant concentrations and deaths due to COVID-19 | meteorological factors and COVID-19 outcomes. Meteorological parameters and PM$_{2.5}$, PM$_{10}$, O$_3$, CO, SO$_2$, NO$_x$, NO$_2$ levels data were obtained from Shanghai Meteorological Bureau and Ministry of Ecology and Environment, respectively. After performing descriptive statistics, the Generalized Additive Model was used to analyze the associations between meteorological factors and the daily death counts of COVID-19. Data on meteorological parameters, PM$_{2.5}$, PM$_{10}$, O$_3$, CO, SO$_2$, NO$_x$, NO$_2$ were obtained from the air quality index platform website. The daily COVID-19 incidence was obtained from the Health Commission of Hubei Province. In addition to descriptive statistics, the multivariate Poison regression models were used to evaluate the association of air pollutants and meteorological parameters with COVID-19 incidence in 3 cities. | The COVID-19 deaths were found to be negatively associated with relative humidity, PM$_{2.5}$, and PM$_{10}$. Increase in diurnal temperature was found to be significantly associated with increased COVID-19 mortality. | [49] |
| Wuhan, Xiaogan and Huanggang, China | Meteorological parameters, air pollutant concentrations and COVID-19 outbreak | The PM$_{2.5}$ and humidity were found to be strongly associated with an increased risk of COVID-19, PM$_{10}$ and temperature were found to be strongly associated with a decreased risk of COVID-19. | [50] |
| Thirty (30) provinces in China | Meteorological parameters and COVID-19 infections | Meteorological parameters served as input variables. The number of confirmed, fatal, and recovered COVID-19 cases were used as output variables. Four time series models, including Brown, Holt linear trend model, Simple, and Autoregressive Moving Average (ARIMA) models, were employed to predict the spread of COVID-19 infections in each province separately. | Increasing temperature and short-wave radiation showed an increase in the number of confirmed COVID-19 cases, mortality rate, and recovered cases. | [51] |
| Wuhan, Daegu in China, Tokyo in Japan, and Mumbai in India | Meteorological parameters, air pollutant concentrations and COVID-19 infection and recovery cases | Air pollutant concentrations were obtained from the EPA Air Quality Open Data Platform. Temperature and humidity data were obtained from respective countries. Data on COVID-19 confirmed and recovery cases were obtained from the John Hopkins COVID-19 real-time data source. A Pearson correlation was used to compare the relationship between temperature and humidity with confirmed and recovered cases of COVID-19. Epidemic curve modelling was done using the MATLAB program. | PM$_{2.5}$ levels followed by PM$_{10}$ were significantly reduced during lockdown. A negative correlation between both humidity and temperature with spread of the virus was noted. | [52] |
| Saitama, Chiba, Tokyo, Kanagawa, Osaka, Hyogo, and Fukuoka, Japan | Meteorological parameters and COVID-19 outbreak | COVID-19 case data was obtained from the J.A.G JAPAN Corporation. Demographic and income data was obtained from the government. Meteorological data were obtained from Japan Meteorological Agency. Weighted random-effects regression analysis was used to determine the association between the logarithm of the rate ratio of COVID-19 and the exposure variables. | No association between COVID-19 and parameters such as precipitation, wind speed, humidity, NO, NO$_2$, O$_3$, and PM$_{2.5}$. On the other hand, COVID-19 was found to be significantly associated with increase in daily temperature suggesting person-to-person contact during outing on a sunny day was found to promote the transmission of virus. | [54] |
| USA | Meteorological parameters and COVID-19 incidence | Meteorological data were obtained from the National Oceanic and Atmospheric Administration Center. Data of COVID-19 cases were collected from the WHO daily COVID-19 situation reports. | The temperature and humidity increases were found to suppress the COVID-19 incidence. | [12] |
| Twenty-seven (27) State Capital Cities, Brazil | Temperature and COVID-19 incidence | Meteorological and demographic data were collected from the National Institute of Meteorology and Brazilian Institute of Geography and Statistics respectively. COVID-19 case data was obtained from the Ministry of Health. In addition to descriptive statistics, a generalized additive model already built in SAS, was used to calculate the relationships between the temperature data and the number of total confirmed COVID cases. | Temperatures had a negative linear relationship with the number of confirmed cases. | [55] |
| Arequipa, Peru | PM$_{2.5}$, PM$_{10}$, and COVID-19 cases | The PM$_{2.5}$ and PM$_{10}$ concentration was recorded using Dustmate Particle Collector. The meteorological data were obtained from the nearby airport. The COVID case data was obtained from the government. | A positive correlation between PM$_{10}$ concentration and the number of COVID cases was seen after a delay of 15 days (post-exposure). A negative correlation between wind speed and the number of COVID cases was observed. A significant decrease in the levels of PM$_{2.5}$ and PM$_{10}$ during lockdown was noted. | [56] |
| Environmental conditions in California, Texas, Florida, New York, Illinois, Georgia, Arizona, North Carolina, New Jersey, and Tennessee, USA | Temperature, humidity, environmental quality index (EQI) and PM$_{2.5}$ | Daily meteorological parameter data were collected from the National weather service, USA. Daily data for EQI and PM$_{2.5}$ were taken from the EPA. Kendall and Spearman rank correlation tests were used to examine the association between environmental parameters and COVID-19. | Temperature, humidity, PM$_{2.5}$, EQI, and rainfall were the main determinants of COVID-19 spread in the most affected American states. | [57] |
| Study area* | Pollutants/environmental parameters studied | Methods employed | Important findings | Reference |
|------------|---------------------------------------------|-----------------|-------------------|-----------|
| Bronx, Kings, Nassau, New York, Queens, Richmond, Rockland, Suffolk, and Westchester counties, New York, USA | Concentrations of PM$_{2.5}$ and O$_3$ | Meteorological data were obtained from the Applied Climate Information System (ACIS) maintained by the US National Oceanic and Atmospheric Administration (NOAA) Regional Climate Centers. The association between PM$_{2.5}$ and ozone with the number of new cases of COVID-19, and meteorological parameters were processed using a Hierarchical Mixed Linear Model for COVID-19 Mortality. | A weak association between PM$_{2.5}$ and ozone concentrations with COVID-19 infected cases was found. | [58] |
| New York City, USA | PM$_{2.5}$, CO, NO$_x$, SO$_2$, and O$_3$ concentrations | The air pollutant data before- and after lockdown was collected from EPA. The EPA-established air quality index was calculated by the non-linear aggregated method. | A significant decline in the concentrations of PM$_{2.5}$ and NO$_x$ but an increase in O$_3$ concentration was noted during lockdown compared to pre-COVID-19. | [59] |
| New York City, USA | Meteorological parameters, air quality and COVID-19 incidence | Data for climate parameters were obtained from National weather service, USA. COVID-19 case data was obtained from the New York City health department, Kendall and Spearman rank correlation tests were used to examine the correlation between climate parameters and COVID-19 cases. | Average temperature, minimum temperature, and air quality were found to be significantly associated with the spread of COVID-19 in New York city. | [60] |
| Forty-eight (48) core-based statistical areas representing all the major cities from the fifty (50) states across USA | PM$_{2.5}$ concentrations | Mean PM$_{2.5}$ concentrations for the study areas were obtained from EPA. Daily data on meteorological parameters were obtained from NOAA. Three statistical models (mixed effects model, random slope model, and functional concurrent regression model) were used to evaluate the effect of lockdown on PM$_{2.5}$ concentration levels while accounting for region specific heterogeneity and adjusting for local weather effects. | A statistically significant reduction in levels of PM$_{2.5}$ in most of the regions during the lock-down period was noted. | [61] |
| California, USA | PM$_{2.5}$, CO, and O$_3$ | Daily data on meteorological parameters, wildfire pollutants, PM$_{2.5}$, CO, and O$_3$ levels was obtained from EPA, California Air Quality data, and Bay Area Air Quality Management District. Air quality including pollutant data was obtained from the California Air Resources Board's Air Quality and Meteorological Information System. COVID-19-related hospitalizations and fatalities were obtained from EMR inpatient and mortality records. Correlations among freeway, non-freeway and total near-roadway air pollution as well as among regional PM$_{2.5}$ and NO$_2$ across shorter- and longer-term periods were assessed using Pearson correlation coefficients. | The California wildfire caused an increase in ambient concentrations of PM$_{2.5}$, CO which showed a temporal association with an increase in the incidence and mortality of COVID-19. Near-roadway air pollution (NRAP), particularly non-freeway exposure in Southern California, may be associated with an increased risk of COVID-19 severity and mortality among infected patients. Regional PM$_{2.5}$ and NO$_2$ exposures showed significant association with NRAP and COVID-19 severity and mortality, after adjusting for regional air pollutant exposures. | [62] |
| California, USA | PM$_{2.5}$ and NO$_2$ levels | Daily data on meteorological parameters, wildfire pollutants, PM$_{2.5}$, CO, and O$_3$ levels was obtained from the California Air Resources Board's Air Quality and Meteorological Information System. COVID-19-related hospitalizations and fatalities were obtained from EMR inpatient and mortality records. Correlations among freeway, non-freeway and total near-roadway air pollution as well as among regional PM$_{2.5}$ and NO$_2$ across shorter- and longer-term periods were assessed using Pearson correlation coefficients. | While statistically significant drops were seen in CO and NO$_2$ levels at most of the sites, such drop was seen in few sites in the case of PM$_{2.5}$ and O$_3$ levels during lockdown period. These studies call the need for investigating the sources for local O$_3$ and PM$_{2.5}$ formation so that the contribution of local versus transboundary sources towards O$_3$ and PM$_{2.5}$ could be assessed. | [63] |
| Ontario, Canada | CO, NO$_x$, PM$_{2.5}$, and O$_3$ levels | Air quality data and pollutant concentrations pre- and post-lockdown were obtained from the Ministry of Environment, Conservation and Parks. The Wilcoxon Mann-Whitney randomi-zation test was used to measure to measure spatio-temporal differences in PM$_{2.5}$ and other pollutant levels. | Higher temperatures were found not to reduce transmission of COVID-19. | [64] |
| Alberta, British Columbia, Ontario and Quebec, Canada | Meteorological parameters and COVID-19 incidence | Daily data on temperature, precipitation, and wind gust speed were obtained from Environment and Climate Change Canada. COVID-19 case data was obtained from the Ontario Ministry of Health and local public health agencies. | While statistically significant drops were seen in CO and NO$_2$ levels at most of the sites, such drop was seen in few sites in the case of PM$_{2.5}$ and O$_3$ levels during lockdown period. These studies call the need for investigating the sources for local O$_3$ and PM$_{2.5}$ formation so that the contribution of local versus transboundary sources towards O$_3$ and PM$_{2.5}$ could be assessed. | [65] |
| Northern Egypt | PM$_{10}$, PM$_{2.5}$, and NO$_2$ levels | PM samples were collected onto 47 mm Teflon filters for gravimetric analysis. NO$_2$ was monitored using a NO$_2$/NO/NO$_x$ monitor. The association between COVID-19 and climate parameters (temperature, wind speed, relative humidity, and air quality) was assessed by using Kendall and Spearman rank correlation tests. | A significant correlation was found between air quality and COVID-19. However, during the lockdown period the air quality improved and a reduction in COVID-19 was noted. | [66] |
| Iran | Meteorological parameters and COVID-19 spread | Meteorological data was obtained from the Weather Spark Online Web Service. COVID-19 data was obtained from the WHO. The Partial correlation coefficient and Sobol-Jansen methods were used for analyzing the effect and correlation of variables with the COVID-19 | Low values of wind speed, humidity, and solar radiation were found to be associated with a high rate of COVID-19 infection. Population density and movement within the provinces were found to be conducive for COVID-19 spread. | [67] |
| Study area*+ | Pollutants/environmental parameters studied                                                                 | Methods employed                                                                                           | Important findings                                                                                                                                                                                                 | Reference |
|-------------|----------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| Tehran, Mashhad, and Tabriz, Iran | Air pollutant concentrations and number of COVID-19 cases and deaths                                          | spreading rate. Air pollutant data were obtained from the Ministry of Environment. Data on COVID-19 cases and deaths were obtained from the Ministry of Health and Medical Education. A generalized additive model (GAM) was used to model the associations up to lag-day 7 (for mortality) and 14 (for morbidity). | Exposure to PM$_{2.5}$, NO$_2$, and O$_3$ showed significant associations with COVID-19 cases but not necessarily mortality.                                                                 | [68]      |
| Khuzestan, Iran | PM$_{10}$ from dust storms and COVID-19 infection rate                                                        | Episodic events of dust storms and PM$_{10}$ data were obtained from the National Air Quality Information System. Data on number of COVID-19 cases and deaths were obtained from the Ministry of Health database. Random Forest Analysis was used to evaluate the importance of parameters such as aerosol optical depth, temperature, pressure, humidity, and wind speed on the daily increase of COVID-19 infection. | The Middle East Dust incursion monitored by aerosol optical depth showed a statistically significant correlation with COVID-19 cases in some cities indicating the plausible role played by PM$_{10}$ in the spread of virus. | [69]      |
| Fifteen (15) provinces in Turkey | Concentrations of PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$, O$_3$ and COVID cases                                | Data on air quality parameters were obtained from the Air Quality Open Data Platform. Meteorological data were obtained from the Ministry of Agriculture and Forestry. Data on COVID cases were obtained from the Ministry of Health. Spearman’s rank correlation test was used to determine the relationship between air pollutants, meteorological parameters and COVID cases. | PM$_{2.5}$ showed a strong correlation with COVID cases in some areas while in others PM$_{10}$ showed a strong correlation. Among meteorological parameters, temperature, windspeed and rainfall showed a positive correlation with COVID cases. | [70]      |
| Riyadh, Jeddah and Makkah, Saudi Arabia | Meteorological parameters, air pollutants and COVID cases                                                | The meteorological and air pollution data were obtained from the General Authority of Meteorology and Environmental Protection and the Saudi National Oceanic and Atmospheric Administration. Data on COVID cases were obtained from the Ministry of Health. Negative binominal regression and Poisson regression models were used to analyze the relationship between the number of COVID-19 cases and the meteorological and air quality parameters | A significantly positive association was noted between short-term exposure to high concentrations of PM$_{10}$, NO$_2$, and O$_3$ with COVID-19 cases. | [71]      |
| Bahrain | Meteorological factors, PM$_{2.5}$ and COVID-19 cases                                                          | Data for meteorological parameters were obtained from the Ministry of Environment. Data on total COVID-19 cases, deaths, and active cases were obtained from the John Hopkins coronavirus database. Kendall and Spearman rank correlation coefficients on quantile regression were used to analyze the relationship between related variables. | Temperature, humidity, solar radiation, windspeed, and PM$_{2.5}$ showed a significant association with COVID-19 cases. | [72]      |
| Twenty (20) countries in Europe, North America, and Asia | Meteorological factors, COVID-19 cases, recovery and deaths                                              | Data for meteorological parameters were obtained from NASA. COVID-19 health outcome data were obtained from John Hopkins COVID-19 real-time data. Data normalization technique was used to correct negative data inputs. Data was also controlled for cross-section dependence (correlation among countries). Appropriate methods were used to check for potential heterogeneity and to avoid spurious statistical interpretations. | High temperature and high relative humidity were found to reduce the viability, stability, survival and transmission of COVID-19. On the other hand, low temperature, wind speed, dew/frost point, precipitation, and solar radiation pressure were found to prolong the activation and infectivity of the virus. | [73]      |
| Thirty-nine (39) countries | Coal combustion, nitrous oxide (N$_2$O) emissions, traffic emissions and COVID-19 cases                      | Data for pollutants mentioned in the left column were obtained from the World Bank database. COVID-19 data was obtained from the “Worldometer”, an open access real time data project developed by volunteer experts. The Markov two-stage switching regimes method was adopted to find the relationship between the smog factors and COVID-19 cases. The variance decomposition analysis method was used to forecast relationships between the stated variables. | N$_2$O emissions, coal combustion, and traffic emissions were found to significantly increase COVID-19 cases. | [74]      |
| One hundred and sixty-six (166) countries (excluding China) | Meteorological parameters, new cases and deaths of COVID-19                                             | Meteorological data were obtained from the National Oceanic and Atmospheric Administration (NOAA) Center. A log-linear GAM was used to analyze the associations between temperature and relative humidity and daily new cases and daily new deaths of COVID-19. The variables were controlled to adjust for regional variation, including wind speed, median age of the population, and country | Temperature increase was found to be associated with decrease in deaths due to COVID-19. Temperature along with humidity may partially suppress COVID-19 transmission. | [75]      |
previously established associations between geography, exposures to air pollution, extreme heat, and adverse health outcomes. PM has been shown to be a causative agent in several, environmentally-induced diseases including asthma, chronic obstructive pulmonary disease (COPD), pulmonary hypertension, arterial hypertension, arrhythmia, myocarditis, other cardiovascular- and cardiometabolic diseases [1]. Place of residence also has been found to have a direct bearing on climate and air pollution exposures and indirect impact on health. A correlation between geographical variation in long-term exposure to PM$_{2.5}$ concentrations and people with comorbidities (diabetes, hypertension, obesity and smoking status) was reported in Mexico City [98]. People who lived near the sea in Italy had relatively low hospitalization rates during the COVID pandemic, suggesting that altitude may play a role in the transmission of COVID-19 [30]. While some other criteria air pollutants have shown a positive correlation with COVID incidence, others have not. A significant negative effect of PM$_{10}$ concentration and mortalities four to ten days after the COVID-19 pandemic were hit hard by COVID-19 [99].

Long-term PM$_{2.5}$ exposure has been associated with increased disease burden and is likely to exacerbate COVID-19 and associated morbidities and mortality. A positive relationship between long-term PM$_{2.5}$ exposure and COVID-19 cases, hospital admissions and deaths has been reported by Mehmood et al., [100] and Cole et al. [32], in India, Pakistan, and Iraq. A strong association between PM$_{2.5}$ and PM$_{10}$ and COVID-19 case fatality rates (CFR) was found in 49 Chinese cities, including Wuhan, the epicenter of the COVID quake [92]. Yao et al. [93] found that over 45 days, for every 10 $\mu$g/m$^3$ increase in PM$_{2.5}$ and PM$_{10}$ concentrations, COVID-19 CFR increased by 0.24% and 0.26%, respectively.

A cross-sectional study conducted in the United States found a correlation between long-term exposure to PM$_{2.5}$ and the COVID-19 mortality rates [94]. Annual daily data of hourly concentrations of air pollutants showed significant associations with daily, PCR-confirmed cases and deaths in three major Iranian cities [68]. A 10-year, retrospective study among COVID-19 patients, of exposure to PM prior to the emergence of pandemic revealed a 14% higher rate of hospitalization [101]. A recent study in California showed that traffic-related air pollution was associated with an increased risk of COVID-19 incidence, severity, and mortality in a multiethnic cohort of patients [63]. Other studies have pointed to the relationship between COVID-19 and air pollutants, including exposure to wildfires and [102] and smoking [103,104]. On the other hand, studies conducted in Italy observed no uniform association between air pollutant concentrations and COVID-19 incidence during the early stages of the pandemic. Logarithmic transformation of data using a universal mixed model likewise revealed increased COVID-19 incidence associated with PM$_{10}$, PM$_{2.5}$ and O$_3$ concentrations. The authors attributed the high COVID incidence to high air pollutant levels, coupled with low temperature and low wind speed [29]. Short-term exposure to COVID-19 and proliferation of cases in Germany highlighted a significant effect of PM$_{10}$ concentration and mortalities four to ten days after the onset of symptoms [105].

While some other criteria air pollutants have shown a positive correlation with COVID incidence, others have not. A significant negative

Table 1

| Study area** | Pollutants/environmental parameters studied | Methods employed | Important findings | Reference |
|-------------|-----------------------------------------------|------------------|-------------------|-----------|
| Two hundred and ten (210) countries | Meteorological parameters, PM$_{2.5}$, PM$_{10}$, O$_3$, NO$_2$, SO$_2$, CO, COVID-19 cases and deaths | The daily meteorological data and air pollution indicators were obtained from the open access platforms such as “Our World In Data”, a project of the Global Change Data Lab, Wales, England and “Wunderground”, an entity of The Weather Company, an IBM business enterprise. The COVID-19 data was obtained from the “World In Data” and “Worldometer”, another open access real time data project developed by volunteer experts. Spearman correlation and generalized additive model were used to determine the association between meteorological data and air pollution indicators with COVID-19 average growth rate of daily cases and deaths. Statistical analyses were conducted using R software. | Decline in air quality contributed to a greater number of daily COVID-19 cases and deaths | [76] |
| Global | Meteorological variables, COVID-19 infections and mortality | Weather data were extracted from the NOAA database, COVID infection and death rates were obtained from World Health Organization reports. | A 1 °F increase in daily temperature resulted in a reduction in the number of COVID cases by 6.4 per day. Also, a positive correlation was noted between precipitation and COVID-19 transmission. An average increase of 1 in. rainfall/day, showed an increase of 56.01 COVID-19 cases/day. Higher average temperatures an showed an inverse association with COVID-19 mortality rates. | [77] |
| Thirty-seven (37) OECD (Organization for Economic Co-operation and Development) countries, the fifty (50) states and District of Columbia in the USA | Ambient temperature and COVID-19 mortality | Data on meteorological parameters and COVID-19 cases and deaths were obtained from publicly available sources. Data were adjusted for other conditions such as humidity, and precipitation, air pollution, measures of social distancing, measures of population density, economic and health indices. The SAS software program was used to analyze the relationship between temperature and deaths due to COVID-19. | Globally, the PM$_{2.5}$ concentrations showed a reduction during the quarantine Bogotá (Colombia) and Delhi (India) showed a significant reduction amounting to 57% and 40% respectively. During lockdown, capital cities in Europe had a better air quality index followed by America, Asia and Africa. | [78] |
| Fifty (50) most polluted capital cities of the world | PM$_{2.5}$ levels | Data from the World Air Quality Index, an online platform was used pertaining to PM$_{2.5}$ levels in each capital before- and during quarantine. Population and weather data were obtained from respective countries. | | [79] |

* If no region is specified in any country, it indicates that a nationwide study was performed.
* If the study area covers less than 10 cities/states/provinces etc., specific names for those were listed by name.
association of daily confirmed COVID-19 cases in Bangkok metropolitan region was found with CO, NO2, SO2, O3, PM2.5, and PM10 concentrations [87]. Achebak et al. [21] reported a strong reduction in NO2 levels was associated with a significant decrease in COVID-19 related deaths, but a rise in O3 levels was found to cause a small increase in deaths. Meanwhile, no correlations were found between COVID-19 incidence and concentrations of PM2.5 and ozone in a study conducted in nine counties of NY state [58]. Therefore, trade-offs between different pollutants should be taken into consideration while assessing the impact of environmental exposures on COVID-19 incidence.

Spatial variability in climatic and air pollution exposures also has been shown to exacerbate existing health issues and initiate the emergence of new ones. Strong associations between climatic and air pollution exposures and severe health issues have been observed more frequently for those living in urban than rural areas [106,107]. In addition to stationary sources, episodic air pollution events caused by local, regional, or transboundary emissions of air pollutants have been found to be influenced by meteorological factors [108].

Other studies have reported that COVID lockdown measures have led to improved air and water qualities, ozone layer, and reduction in greenhouse gas emissions; a global survey conducted in 184 countries and 105 cities revealed that the changes were only transient [109]. Statistical data compiled by the NASA Earth Observatory, the European Space Agency and the Global Carbon Project revealed improved air quality during COVID-19 lockdown. Significant declines in concentrations of pollutants such as O3, NO2, CO and PM2.5 during periods of COVID-induced lockdown and travel restriction were reported by Al-Abadleh et al., [64], and Park et al., [110]. However, objective evidence was lacking that lockdown led to a decline in energy consumption leading to a decline in global CO2 concentrations. Differences in findings between COVID-19 incidence and meteorological parameters and air pollutants have been attributed to different measurement approaches (collection of data from monitoring stations), modeling strategies, accuracy of COVID-19 mortality data (provincial/county, state-, and national levels, detailed in Table 1), the inherent errors associated with measurements and the spatial variability exhibited by some pollutants such as NO2 causing bias in the exposure-response associations [21].

### 3.2. Role of climate change in COVID-19 spread

Climate change contributes to rising temperatures and amounts of carbon dioxide in the atmosphere and has been linked to increased pollen production, increased duration of pollen seasons, and increased allergenicity of pollen. In addition, climate change has been found to alter indoor air quality by changing the availability and distribution of plant- and fungal-derived allergens that contribute to allergic rhinitis, asthma, and other chronic respiratory diseases [111]. Respiratory defense mechanisms have been altered in recent years resulting in worsening of asthma in susceptible subjects [112]. As a result, socially vulnerable populations have been found to experience disproportionately greater health burden due to the interplay of climate change and other factors across the natural, built, social and policy environments [113–115].

In recent years, climate change has been found to facilitate waves of Chikungunya, Dengue, West Nile Fever, and other diseases caused by viruses, yet not much attention has been paid to this pathogenic property until the emergence of COVID-19 [116]. COVID-19 is exclusively zoonotic in origin, and climate change is one of the anthropogenic drivers of zoonotic disease emergence and spread. Climate change contributes to public health crises both individually and by synergizing with wildlife-human interface and land use [117,118]. Since respiratory syndrome viruses previously have demonstrated poor survival in hot, humid and warm climates, the WHO warned that the COVID pandemic could affect countries in the tropical belt that record scorching temperatures [119].

Using molecular phylogenetic analysis, Bajaj and Arya [120] studied the SARS-CoV-2 evolution and its relationship to abiotic factors (humidity, precipitation, radiation, temperature, and wind speed). These studies pointed out two genetically distinct variant groups G1 and G2 on the basis of four mutations. While the G1 group was prevalent in temperate
region (warm and moist climate), the G2 group enjoyed distribution in cold climate of higher latitudes and the tropical region (hot climate). These studies revealed that the G1 group was evolved into G2 by undergoing significant mutations in some genes (C241T in leader sequence, F924 in ORF1a, P214L in ORF1b, and D614G in S gene) thus emphasizing the role of natural selection on evolution of virus to thrive in different climatic regimes.

Climate change also has been shown to affect COVID spread through modulation of particle concentrations that serve as carriers [121]. Rohrer et al. [122] previously compared mean daily PM$_{2.5}$ concentrations, prevalence, virulence of COVID-19 and deaths in Tenerife (Canary Island), London, Canton of Ticino (Switzerland) and Greater Paris region (France). They found that peaks of PM$_{2.5}$ contributed to COVID-19 prevalence during thermal inversion of boundary layer of atmosphere characterized by cool and moist conditions in Ticino, Paris and London and during Saharan dust intrusions (desertic dust storms serving as carriers of coronavirus viruses) in Canary Islands. Extreme climate fluctuations also have been shown to cause mass migration of populations on a global scale. Climate change was identified as having forced relocation of 48 million socially disadvantaged people across 59 countries [123]. Such a situation continuing during the pandemic contributed to overcrowded urban dwellings, which, in turn may have facilitated the rapid spread of SARS-CoV-2 [124]. In addition to contributing to overcrowded residential dwellings, climate change-induced, COVID-19 spread has lead to overwhelmed healthcare facilities [125]. Additionally, diffusion of COVID-19 through human interaction associated with internal trade has been implicated in the spread of the virus [126].

3.3. Role of comorbid conditions in COVID-19 spread

Exposure to PM constitutes an important co-risk factor for COVID-19. COVID-19 primarily affects lung tissues through inhalation of bioaerosols delivered via PM. Once it enters the lung and causes injury to the alveolar endothelium [127], and enters the bloodstream and reach other organs. Sustained exposure to air pollutants provides a conducive environment in the body for COVID-19 to trigger an inflammatory storm in infected individuals. The effects of exposures to multiple environmental and social stressors have been found to increase allostatic load [128] which, in turn, is a risk factor for contracting COVID-19.

It has been reported that elevated PM$_{2.5}$ levels influence the progression of COVID-19 through chronic inflammation and immune dysregulation [129,130]. Prolonged exposure to PM has been reported to induce a significant increase in angiotensin converting enzyme (ACE2), which targets the nuclear factor erythroid 2-related factor 2 (Nrf2 pathway, contributing to a proinflammatory response and increase the probability of severe effects of COVID infection [131]. A single nucleotide polymorphism, rs2285666, has been identified as a potential risk factor for people with hypertension, type 2 diabetes, and coronary artery disease, making them predisposed to COVID-19 infections [132].

Individuals with pre-existing cardiovascular disease run a greater risk of mortality from exposure to PM, including myocardial- [133], microvascular [134] malfunction, atrial fibrillation [135], pulmonary embolism and cardiac failure [136]. Pre-existing respiratory system diseases such as asthma, chronic obstructive pulmonary disease [137,138] and pneumonia [139] also have been found to aggravate COVID-19 infections. Recent studies reported that people with gastrointestinal disorders also are at increased risk of complications due to COVID-19 [140]. Additionally, some of the drugs used to treat COVID-19 have been found to have adverse effects on the cardiac system [141,142].

Symptoms related to central and peripheral nervous systems impairments have been reported among COVID-19 patients [143]. Reyes and Medina [144] hypothesized that environmental pollutant exposure, especially PM$_{2.5}$, exacerbates the neurologic symptoms in COVID-19 cases through neuroinflammatory mechanisms. They postulated that prior exposure to PM$_{2.5}$ primes the central nervous system (CNS) creating a hyperinflammatory state in the CNS when SARS-CoV-2 infection occurs. The resulting hyperinflammation can lead to neuronal death, tissue damage, breakdown of blood-brain barrier etc. [145]. People with pre-existing neurological problems are not only at greater risk of COVID-19, but are more likely to manifest neuropsychiatric symptoms, cerebrovascular issues such as ischemic stroke, intracerebral hemorrhage, unspecified encephalopathy, dementia-like syndrome, suicidal ideation, behavior etc. [146].

Environmental dust containing PM also has been found to interact with the respiratory and gastrointestinal systems (gut-lung axis) in a disease state that together contribute to comorbidity from COVID-19 [147]. PM enters the esophagus after mucociliary clearance to reach the intestine via the stomach, thereby causing inflammation [148]. Once COVID-19 reaches the intestine, it uses transmembrane protease serine 2 receptors (TMPRSS2 and TMRPSS4) to enter small intestinal epithelial cells causing enterocyte dysfunction and increasing the intestinal permeability [149]. Serum samples from hospitalized patients with severe COVID-19 infection showed higher levels of plasma zonulin, which is implicated in increased intestinal permeability [150].

Smokers and patients with smoke-associated cancers also have been reported to be at a greater risk from COVID-19 infection because of the interaction of Coronavirus with ACE2 and TMRPSS2 receptors that are overexpressed in smokers and people who had upper respiratory tract cancers [151]. It is highly likely that smoking aggravates the health issues of people, who are at a greater risk from cardio-vascular and -metabolic diseases [152]. Scoping [153] and systematic [154] reviews of literature conducted to examine the relationship between smoking and COVID-19 revealed that current smoking habits and record of previous smoking significantly increased COVID-19 severity and mortality in infected individuals. In support of these reviews was a published report on a retrospective study of 14,260 patients (some were either active or former smokers while the others non-smokers) admitted to Spanish hospitals. A greater incidence of intensive care unit admissions, mortality in hospitals and readmission within a month in smoking versus non-smoking patients was revealed [155].

Factors which contribute to obesity, including limited social interactions, sedentary life-style, and eating less nutritious food [156,157] are comorbidities for coronavirus spread [158] due to the association of obesity with inflammation and lung damage [159]. The forced lockdown, extended period of quarantine, lack of opportunities to travel and socialize with friends also have been identified as social determinants affecting adverse COVID outcomes [160,161].

3.4. Health disparities in COVID-19 outcomes

Racial and ethnic minorities have experienced increased risk for contracting COVID 19, levels of hospitalizations, serious outcomes, and deaths since the beginning of the pandemic [162]. A number of studies have reported a greater risk of COVID-19 in African Americans and Latinos compared to other racial and ethnic groups [163–165]. Socially vulnerable populations in the United States, including racial and ethnic minorities, gender and sexual minorities, people experiencing homelessness, and migrant farm workers have been found to be at greater risk of contracting COVID-19 and its effects. Farmworkers are at particularly high risk for COVID 19 due to experiencing numerous social determinants, including environmental exposures, documentation status, lack of authorization to work in the United States, language barriers, and access barriers to receiving federal aid, legal assistance, and healthcare [166,167].

A survey conducted on COVID-19 outcomes (case and mortality rates) for racial/ethnic minorities in 3108 US counties during pandemic early-second- and third phases (in 2020) revealed disproportionately high rates of COVID-19 cases and mortality among African Americans [168]. These associations were reversed in the third phase when non-Latino Whites were at higher risk. Resultant time-varying associations were found to be consistent across climate regions and could not be explained by socioeconomic factors [169]. These studies revealed that COVID-19 racial/ethnic disparities have shifted over the course of the pandemic suggesting that social, cultural, political, and other influences may play a role.
Environmental, occupational, and social hazards not only contribute to increased risk for COVID, they also exacerbate risk for severity of infection and contribute to racial/ethnic health disparities. Other environmental factors that have been associated with disparities in contracting COVID-19 include access to healthy food and healthcare, living in high density housing (without opportunities for social distancing), and working in essential service sectors, such as food services, healthcare and transportation [170]. Additionally, a culturally insensitive healthcare system coupled with the history of racial injustices, and mistrust about participation in vaccine trials have been identified as barriers to increasing the spread of herd immunity [171].

Systemic factors as well as short term natural disaster both have contributed to the increased risk of COVID experienced by communities of color [172] and have contributed to the disproportionate rate of COVID 19 mortality experienced by African-Americans, Latinos and Indigenous populations [173]. Segregated housing practices resulting in minority communities living in close proximity to hazardous waste storage sites, disposal facilities, coal-fired power plants, and former industrial sites [174–175] were identified as risk factors for COVID and for experiencing adverse outcomes experienced by racial and ethnic minorities. Chronic and disproportionate exposure of urban communities of color to poor air quality emanating from coal-fired power plants, industrial emissions, and combustion-related activities generated inequities in COVID-19 comorbidities, such as CVD [1,2]. Previous studies by Juarez et al., [1], Valdez et al., [2], and Tessum et al. [176] found that air pollutants, especially PM2.5, is positively associated with increased risk of cardiovascular and cardiometabolic incidence and mortality among people of color in general and African-Americans in particular. In addition, natural disasters such as wildfires in California and the seasonal freeze in Texas have had a direct effect on COVID-19’s spread by forcing a disproportionate number of people of color to stay in crowded emergency shelters where there were limited opportunities for social distancing [177]. The crowded conditions in jails and prisons that disproportionately impact African Americans and Hispanic/Latinx populations may have greatly contributed to COVID deaths among incarcerated populations [178].

Susceptibility to some health conditions place people of color at risk of COVID complications. African-American, Latino and Latino children have been found to be more likely to develop a hyperinflammatory condition called multisystem inflammatory syndrome (MIS-C) that manifests soon after SARS-CoV-2 infection [179]. In addition, African Americans who are afflicted with systemic lupus erythematosus and lupus nephritis [180,181] are at greater risk for COVID complications than Whites. To study how the COVID-19 pandemic affects racial and ethnic minorities, the COVID-19 Global Rheumatology Alliance and COVID-19 Sickle Cell Registry were established. These initiatives are expected to enhance education and awareness within minority communities by establishing proactive partnerships with community organizations and community-based social networks [182]. Aside from COVID-19 patients already suffering from pre-existing health issues, and health issues as a consequence of SARS-CoV-2 infection, social determinants of health also contribute to COVID-19-related health issues. County level analyses of COVID-19 exposure risk in California revealed Latinos more often live in high-exposure-risk households experiencing worst COVID health outcomes [183].

3.5. Further steps

Modeling global climate and land use offer opportunities to help understand the spread of infectious diseases including COVID-19 [117]. Comprehensive monitoring of weather-related events such as thermal inversions that contribute to haze or fog, desert borne-dust storms, and emissions of PM2.5 from combustion sources such as vehicles and industries, are important tools to predicting and limiting future waves of COVID-19 and its variants [117]. Understanding the interactions among COVID-19, meteorological factors, PM2.5 and other pollutants, and preexisting health issues are key emerging topics for mitigating COVID risk.

The Health Opportunity Index (HOI) is a new multivariate tool that has potential for increasing understanding at the local level of the interplay of complex social determinants of health (SDH), health risks, and outcomes at small spatial resolutions. The HOI provides opportunities to assess access and capacity of health systems by identifying those areas where provider-topopulation ratio is low and can be predicted to be further exacerbated and strained during a pandemic such as COVID-19. Retrospective application of HOI to COVID data shows strong relationships with census tracts that were most disproportionately impacted and provides a novel tool for local agencies to predict those areas that are most likely to be seriously impacted by future COVID-19 surges. The HOI utilizes principal component analysis, a data-reduction technique, to determine the impact of SDH on optimal health at the census track level. Ogijika et al. [184] demonstrated the utility of this 13-variable tool by deriving a composite metric of health (HOI score) to identify vulnerable communities in the three largest counties in Ohio: Franklin (Columbus), Cuyahoga (Cleveland), and Hamilton (Cincinnati). HOI was used to successfully identify census tracts that were at increased risk for disparate COVID-19 health outcomes. HOI composite score and subcomponent scores provided measures of SDH useful for identifying vulnerable communities and guide COVID mitigation/intervention practices.

This systematic review detailed how the interrelationships between COVID-19, air pollution, and chronic diseases are intertwined and have contributed to increased COVID-19 risk, severe outcomes and disparities experienced by racial and ethnic minorities. Primary and community healthcare systems can play a major role in coordinating population-based health services and public health interventions and are particularly key players in responding to a pandemic such as COVID which has unfolded with rolling surges across the country at a local level [185].

Availability of data and materials

All data were based on previously published articles and information from governmental agencies that are available in the public domain.

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CRediT authorship contribution statement

Paul D. Juarez, Aramandla Ramesh: Conceptualization, Review of literature. Aramandla Ramesh, Paul D. Juarez, Darryl B. Hood, Mounika P. Aramandla: Critical Analysis. Aramandla Ramesh, Paul D. Juarez, Donald J. Alcendor, Darryl B. Hood, Mounika P. Aramandla, Robert O. Valdez, Mohammad Al-Hamdhan, Michael A. Langston, Patricia Matthews-Juarez, Amruta Nori-Sarma, Mohammad Tabatabai, Wansoo Im, Charles P. Mouton: Final Draft Preparation, Review, and Editing. Paul D. Juarez: Project Administration. Paul D. Juarez, Patricia Matthews-Juarez, Mohammad Tabatabai: Funding Acquisition.

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Declaration of Competing Interest

The authors declare no conflicts of interest.

References

[1] P.D. Juarez, M. Tabatabai, R.B. Valdez, D.B. Hood, W. Im, C. Mouton, C. Coden, M.Z. Al-Hamdan, F. Matthews-Juarez, M.G. Lichtenfels, D. Sarpogin, A. Ramesh, M.A. Langston, G.L. Rogers, C.A. Phillips, J.F. Reichard, M.M. Donneyong, W. Blot, The effects of social, personal, and behavioral risk factors and PM2.5 on cardiovascular disease and PM2.5 in a cohort of community health center patients, Int. J. Environ. Res. Public Health 17 (2020) 2077.

[2] R.B. Valdez, M.Z. Al-Hamdan, M. Tabatabai, D.B. Hood, W. Im, D. Wilus, A. Ramesh, A. Nori-Sarma, M.M. Donneyong, M.A. Langston, C.P. Mouton, P.D. Juarez, Association of Cardiovascular disease and long-term exposure to fine particulate matter (PM2.5) in the Southeastern United States, Atmosphere 12 (2021) 947.

[3] M.Z. Al-Hamdan, W. Crosson, A. Limaye, D. Braun, D. Rickman, M. Estes, J. Langston, G.L. Rogers, C.A. Phillips, J.F. Reichard, M.M. Donneyong, and W. Blot, The authors declare no conflicts of interest, J. Air Waste Manage. Assoc. 59 (2009) 865–881.

[4] M.Z. Al-Hamdan, W.L. Crosson, S.A. Economou, M.G. Estes Jr., S.M. Estes, S.N. Hembree, S.T. Kott, D.P. Packett, D.L. Quattrochi, D.L. Rickman, G.M. Wade, L.A. McClure, Environmental public health applications using remotely sensed data, Geocarto Int. 29 (2014) 85–98.

[5] A.Z. Al-Hamdan, R.N. Alhasbaireh, M.Z. Al-Hamdan, W.L. Crosson, The association of remotely-sensed outdoor fine particulate matter with cancer incidence of respiratory system in USA, J. Environ. Sci. Health A. Tox. Hazard. Subst. Environ. Eng. 52 (2017) 547–554.

[6] A.Z. Al-Hamdan, P.P. Preetha, M.Z. Al-Hamdan, W.L. Crosson, R.N. Alhasbaireh, Reconciling the linkage between cardiovascular disease morbidity and long-term exposures to outdoor environmental factors in the USA using remotely-sensed data, J. Environ. Sci. Health A. Tox. Hazard. Subst. Environ. Eng. 53 (2018) 809–818.

[7] J. Wang, G. Du, COVID-19 may transmit through aerosol, J. Med. Med. 189 (2020) 766.

[8] S. Ogen, Assessing nitrogen dioxide (NO2) levels as a contributing factor to coronavirus (COVID-19) mortality, Sci. Total Environ. 726 (2020), 138605.

[9] E.S. Coker, L. Cavalli, E. Fachiz, G. Guastella, E. Lippo, M.L. Parisi, N. Pantanozzo, M. Rizzati, A. Varacca, A. Sverdlov, S. Vergalli, The effects of air pollution on COVID-19 related mortality in Northern Italy, Environ. Resour. Econ. (Dordr) 76 (2020) 610–614.

[10] G. Perone, The determinants of COVID-19 case fatality rate (CFR) in the Italian regions and provinces: an analysis of environmental, demographic, and healthcare factors, Sci. Total Environ. 755 (Pt 1) (2021), 142523.

[11] S. Yari, H. Mohammadi, The effect of ambient air pollution on severity of COVID19: hospitalization and death, Asian Pac Environ Cancer 3 (2020) 15–16.

[12] X. Wu, R.C. Nethery, B.M. Sabath, D. Braun, F. Dominici, Exposure to air pollution and COVID-19 mortality in the United States: A nationwide cross-sectional study, medRxiv (2021), 21735–1742.

[13] R. Khiawat, T. Singh, A. Binwal, V. Singh, S. Mor, S. Impact of COVID-19 lockdown on ambient air quality in megacities of India and implication for air pollution control strategies, Environ. Sci. Pollut. Res. 28 (2021) 21621–21632.

[14] M.M. Sahoo, Significance among air pollutants, meteorological factors, and COVID-19 infections: probable evidences in India, Environ. Sci. Pollut. Res. 28 (2021) 40474–40495.

[15] Y.A. Khan, The COVID-19 pandemic and its impact on environment: the case of the major cities in Pakistan, Environ. Sci. Pollut. Res. 28 (2021) 54728–54743.

[16] M.S. Hassan, M.A.H. Buihuay, F. Tareq, M. Bodrud-Doza, S.M. Tanu, K.A. Rabbani, Relationship between COVID-19 infection rates and air pollution, geo-meteorological, and social parameters, Environ. Monit. Assess. 193 (2021) 29.

[17] A.Z. Al-Hamdan, M. Islam, M. Shamshur, M. Shamsuzzaman, M. Shabnur, M. Bodrud-Doza, M.M. Rahman, M.A. Mannan, S. Haq, Are meteorological factors enhancing COVID-19 transmission in Bangladesh? Novel findings from a compound Poison general linearized error modeling approach, Environ. Sci. Pollut. Res. 28 (2021) 11245–11258.

[18] M. Nagash, D.G. Sharma, M. Sethi, D. Sethi, M. Al-Hamdan, M. Al-Hamdan, M.M. Rahman, COVID-19 cases, deaths, and meteorological factors in South Asia, Environ. Sci. Pollut. Res. 28 (2021) 28518–28534.

[19] R.K. Pani, N.H. Lin, S. Ravindra Babu, Association of COVID-19 pandemic with meteorological parameters over Singapore, Sci. Total Environ. 740 (2020), 140112.

[20] S. Pongpichai, T. Chetiyarakomkul, W. Maansanitwong, Relationship between COVID-19-infected number and PM2.5 level in ambient air of Bangkok, Thailand, Aerosol. Sci. Eng. 5 (2021) 393–392.

[21] R. Tosepu, J. Gunawan, D.S. Effendy, O.A.I. Ahmad, H. Lestari, P. Asan, Correlation between weather and Covid-19 pandemic in Jakarta, Indonesia, Sci. Total Environ. 725 (2021), 138436.

[22] T.P.M. Nguyen, T.H. Nguyen, T.H. Nguyen, T.V. Vu, H.L. Pham, Impact of Covid-19 partial lockdown on PM2.5, SO2, NO2, O3, and trace elements in PM2.5 in Hanoi, Vietnam, Environ. Sci. Pollut. Res. 29 (2021) 41875–41885.

[23] C. Huang, T. Wang, T. Niu, M. Li, H. Liu, C. Ma, Study on the variation of air pollutant concentration and its formation mechanism during the COVID-19 period in Wuhan, Atmos. Chem. Phys. 251 (2021), 118276.

[24] C.K. Hou, Y.F. Qin, G. Wang, Q.L. Liu, Y.X. Yang, H. Wang, Impact of a long-term air pollution exposure on the case fatality rate of COVID-19 patients-A multi-city study, J. Epidemiol. 31 (2021), 11258.

[25] J. Xie, Y. Zhu, Association between ambient temperature and COVID-19 incidence in 122 cities from China, Sci. Total Environ. 724 (2020), 138301.

[26] Y. Ma, S. Pei, J. Shaman, R. Dubrow, K. Chen, Role of meteorological factors in the transmission of SARS-CoV-2 in the United States, Nat. Commun. 12 (2021) 3602.

[27] Y. Jiang, X.J. Wu, Y.J. Guan, Effect of ambient air pollution and meteorological variables on COVID-19 incidence, Infect. Control Hosp. Epidemiol. 41 (2021) 1011–1015.

[28] A. Al-Rousan, H. Al-Najjar, The correlation between the spread of COVID-19 infections and weather variables in 13 provinces and the government mitigation plans, Eur. Rev. Med. Pharmacol. Sci. 24 (2020) 4565–4571.
K. Anser, D.I. Godil, M.A. Khan, A.A. Nassani, K. Zaman, M.M.Q. Abro, The impact of meteorological indicators and COVID-19 outbreak in hot and arid climate, Bahrain, Int. J. Tuberc. Lung Dis. 11 (2007) 938–943.

E. Goumzouzou, M.E. Falagas, Exposure to and control of respiratory tract infections, Int. J. Tuberc. Lung Dis. 11 (2007) 938–943.

W. Yang, S. Elankumaran, L.C. Mart, Concentrations and size distribution of airborne infectious A viruses measured at a health centre, a day-care centre and on aeroplanes, JR Soc Interface. (2011) 1176–1184.

C. Alonso, P.C. Raynor, P.R. Davies, M. Torremorell, Concentration, size distribution, and infectivity of airborne particles carrying swine viruses, PLoS One 10 (2015), e0135675.

Y.W. Choi, A. Tuel, E.A.B. Eltahir, On the environmental determinants of COVID-19 seasonality, Geohalth 5 (2021) (e2021GHO00413).

S. Sangham, S. Thongpib, P. Voongkrua, Investigation of air pollution and meteorological factors on the spread of COVID-19 in the Bangkok metropolitan region and air quality during the outbreak, Environ. Res. 197 (2021), 111104.

M. Sahin, Impact of weather on COVID-19 pandemic in Turkey, Sci. Total Environ. 728 (2020), 138851.

F. Sera, B. Armstrong, S. Abbott, S. Meunin, K.O. Reilly, R. van Bornies, R. Schneider, D. Royé, M. Hashizume, M. Pascual, A. Tobías, A.M. Vicedo-Cabrera, CMID COVID Working Group, A. Gasparini, R. Lowe, MCC Collaborative Research Network, A cross-sectional analysis of the role of meteorological factors and PM2.5 Covid-19 transmission in 49 cities across 26 countries, Nat. Commun. 12 (2021) 5968.

P. Meecenas, R.T.D.R.M. A, Bastos, C.R.V. Villanino, D. Normando, Effects of temperature and humidity on the spread of COVID-19: A systematic review, PLoS One 15 (2020), e0238339.

H. Qi, S. Xiao, R. Shi, M.P. Ward, Y. Chen, W. Tu, Q. Su, W. Wang, X. Wang, Z. Zhang, COVID-19 transmission in Mainland China is associated with temperature and humidity: a time-series analysis, Sci. Total Environ. 728 (2020), 138778.

G.L. Nichols, E.L. Gillhampton, A. MacGregor, S. Vardoulakis, S. Hajat, C.E. Saran, K. Amanawka, R. Palkay, Coronavirus seasonality, respiratory infections and weather, BMC Infect. Dis. 21 (2021) 1101.

Y. Yao, J. Pan, W. Wang, Z. Liu, H. Kan, Y. Qiu, X. Meng, W. Wang, Association of particulate matter pollution and case fatality rate of COVID-19 in 49 Chinese cities, Sci. Total Environ. 741 (2020), 140396.

X. Xu, W. Zhang, Y. Yin, D. Yong, D. Jiang, L. Yu, W. Yin, Environmental implications of reduced electricity consumption in Wuhan during COVID-19 outbreak: a brief study, Environ. Technol. Innov. 23 (2021), 101578.

R.K. Singh, M. Drews, M. De la Sen, P.K. Srivastava, B.H. Triasongko, M. Kumar, M.K. Pandey, A. Anand, S.S. Singh, A.K. Pandey, M. Dobriyal, M. Rani, P. Kumar, Highlighting the compound risk of COVID-19 and environmental pollutants using geospatial tools, Sci. Total Environ. 779 (2021), 145271.

P.S. Chen, F.T. Tsai, C.K. Lin, C.Y. Yang, C.C. Chan, C.Y. Young, C.H. Lee, Ambient influenza and avian influenza virus during dust storm days and background days, Environ. Health Per. 118 (2021) 1211–1216.

Q. Li, F. Fu, J.H. Miao, X.O. Shang, Haze is a risk factor contributing to the rapid spread of respiratory syncytial virus in children, Environ. Sci. Polit. Int. 23 (2016) 20178–20185.

A. López-Feldman, D. Heres, F. Marquez-Padilla, Air pollution exposure and COVID-19: A look at mortality in Mexico City using individual-level data, Sci. Total Environ. 756 (2021), 143929.

S. Comunian, D. Donghi, M. Palintini, Pollution and air pollution and Covid-19: The role of particulate matter in the spread and increase of Covid-19’s morbidity and mortality, Int. J. Environ. Res. Public Health 17 (2020) 11659.

K. Mehmood, M.M. Sahifalab Aibr, M. Ishq, E. Haider, H.M.H. Shoukat, Can PM (2.5) pollution worsen the death rate due to COVID-19 in India and Pakistan? Sci. Total Environ. 779 (2021), 145271.

A. Mendy, X. Wu, J.L. Keller, C.S. Fassler, S. Apewokin, T.B. Mersha, C. Xie, S.M. Martin, B. Murray, B. Jessiman, B.A.S. Wilton, A. Kopp, R.T. Burnett, Living near major megacities, air quality and climate, Atmos. Environ. 126 (2016) 235.

C. Alonso, P.C. Raynor, P.R. Davies, M. Torremorell, Concentration, size distribution, and infectivity of airborne particles carrying swine viruses, PLoS One 10 (2015), e0135675.
roads and the incidence of dementia, Parkinson’s disease, and multiple sclerosis: a population-based cohort study. Lancet 369 (2007) 1273–1279.

[107] S. Shin, R.T. Barnett, J.C. Kwong, P. Hystad, A. van Donkelaar, J.R. Brook, R. Copes, K. Tu, M.S. Goldberg, P.J. Villeneuve, R.V. Martin, B.J. Murray, A.S. Wilson, A. Kopp, H. Chen, Effects of ambient air pollution on incident Parkinson’s disease in Ontario, 2001 to 2013: a population-based cohort study. Int. J. Epidemiol. 47 (2018) 2038–2048.

[108] L. Morawska, T. Zhu, N. Liu, M. Amoore Torkmahalleh, M. de Fatima Andrade, B. Wang, H. Chen, Y.L. Chan, B.G. Oliver, Is there an association between the level of polycyclic aromatic hydrocarbons in road dust and the incidence of dementia, Parkinson’s disease, and multiple sclerosis: a population-based cohort study. Int. J. Epidemiol. 47 (2018) 2038–2048.

[109] L. Iqulizui-Gracias, A.G. Mathioudakis, S. Bartel, S.J.H. Vijereberg, E. Fuertes, P. Comberiati, Y.S. Cai, F.V. Tomazic, D. Zambito, V. Calcan, B. Hoffman, The need for clean air: The way air pollution and climate change affect allergic rhinitis and asthma. Allergy 75 (2020) 2170–2184.

[110] J.A. Poole, C.S. Barnes, J.G. Demain, J.A. Bernstein, M.A. Padukudju, W.J. Sheehan, G.G. Fogelberg, J. Wedner, R. Codina, E. Levent, J.R. Cohn, S. Kagen, J.M. Portnoy, A.E. Nel. Impact of weather and climate change with indoor and outdoor air quality in asthma: a Work Group Report of the AAAAI Environmental Exposure and Respiratory Health Committee. J. Allergy Clin. Immunol. 143 (2019) 1702–1710.

[111] A.P. Mananag, C.K. Uejio, S. Saha, P.J. Schramm, G.D. Martinucci, C.L. Brown, J.H. Lober, Assessing vulnerability to heat waves in Canada: a guide for health departments, in: C. Evans (Ed.), Climate Change and Public Health: Federal Preparedness Efforts, Nova Science Publishers; Hauppauge, NY, USA, 2016, pp. 71–93.

[112] M.A. Benevolenska, L. Deligné, The impact of climate change and natural disasters on vulnerable populations: A systematic review of literature, J. Hum. Behav. Soc. Environ. 29 (2019) 266–281.

[113] J. Seguin, Human Health in a Changing Climate: A Canadian Assessment of Vulnerabilities and Adaptive Capacity, Health Canada, Ottawa, ON, Canada, 2008 (494pp).

[114] J.C. Semenza, S. Par, Climate change and infectious disease in Europe: impact, projection and adaptation, Lancet Reg Health Eur. 9 (2020), 100230.

[115] R. Roberts, A. Dobson, O. Restif, K. Wells, Challenges in modelling the dynamics of infectious diseases at the wildlife-human interface, Epidemics 37 (2021), 100523.

[116] A.P. Mananag, C.K. Uejio, S. Saha, P.J. Schramm, G.D. Martinucci, C.L. Brown, J.H. Lober, Assessing vulnerability to heat waves in Canada: a guide for health departments, in: C. Evans (Ed.), Climate Change and Public Health: Federal Preparedness Efforts, Nova Science Publishers; Hauppauge, NY, USA, 2016, pp. 71–93.

[117] C. Iqulizui-Gracias, A.G. Mathioudakis, S. Bartel, S.J.H. Vijereberg, E. Fuertes, P. Comberiati, Y.S. Cai, F.V. Tomazic, D. Zambito, V. Calcan, B. Hoffman, The need for clean air: The way air pollution and climate change affect allergic rhinitis and asthma. Allergy 75 (2020) 2170–2184.

[118] J.A. Poole, C.S. Barnes, J.G. Demain, J.A. Bernstein, M.A. Padukudju, W.J. Sheehan, G.G. Fogelberg, J. Wedner, R. Codina, E. Levent, J.R. Cohn, S. Kagen, J.M. Portnoy, A.E. Nel. Impact of weather and climate change with indoor and outdoor air quality in asthma: a Work Group Report of the AAAAI Environmental Exposure and Respiratory Health Committee. J. Allergy Clin. Immunol. 143 (2019) 1702–1710.

[119] A.P. Mananag, C.K. Uejio, S. Saha, P.J. Schramm, G.D. Martinucci, C.L. Brown, J.H. Lober, Assessing vulnerability to heat waves in Canada: a guide for health departments, in: C. Evans (Ed.), Climate Change and Public Health: Federal Preparedness Efforts, Nova Science Publishers; Hauppauge, NY, USA, 2016, pp. 71–93.

[120] M.A. Benevolenska, L. Deligné, The impact of climate change and natural disasters on vulnerable populations: A systematic review of literature, J. Hum. Behav. Soc. Environ. 29 (2019) 266–281.

[121] J. Seguin, Human Health in a Changing Climate: A Canadian Assessment of Vulnerabilities and Adaptive Capacity, Health Canada, Ottawa, ON, Canada, 2008 (494pp).

[122] J.C. Semenza, S. Par, Climate change and infectious disease in Europe: impact, projection and adaptation, Lancet Reg Health Eur. 9 (2020), 100230.

[123] R. Roberts, A. Dobson, O. Restif, K. Wells, Challenges in modelling the dynamics of infectious diseases at the wildlife-human interface, Epidemics 37 (2021), 100523.

[124] A.P. Mananag, C.K. Uejio, S. Saha, P.J. Schramm, G.D. Martinucci, C.L. Brown, J.H. Lober, Assessing vulnerability to heat waves in Canada: a guide for health departments, in: C. Evans (Ed.), Climate Change and Public Health: Federal Preparedness Efforts, Nova Science Publishers; Hauppauge, NY, USA, 2016, pp. 71–93.

[125] C. Iqulizui-Gracias, A.G. Mathioudakis, S. Bartel, S.J.H. Vijereberg, E. Fuertes, P. Comberiati, Y.S. Cai, F.V. Tomazic, D. Zambito, V. Calcan, B. Hoffman, The need for clean air: The way air pollution and climate change affect allergic rhinitis and asthma. Allergy 75 (2020) 2170–2184.

[126] J.A. Poole, C.S. Barnes, J.G. Demain, J.A. Bernstein, M.A. Padukudju, W.J. Sheehan, G.G. Fogelberg, J. Wedner, R. Codina, E. Levent, J.R. Cohn, S. Kagen, J.M. Portnoy, A.E. Nel. Impact of weather and climate change with indoor and outdoor air quality in asthma: a Work Group Report of the AAAAI Environmental Exposure and Respiratory Health Committee. J. Allergy Clin. Immunol. 143 (2019) 1702–1710.

[127] A.P. Mananag, C.K. Uejio, S. Saha, P.J. Schramm, G.D. Martinucci, C.L. Brown, J.H. Lober, Assessing vulnerability to heat waves in Canada: a guide for health departments, in: C. Evans (Ed.), Climate Change and Public Health: Federal Preparedness Efforts, Nova Science Publishers; Hauppauge, NY, USA, 2016, pp. 71–93.

[128] M.A. Benevolenska, L. Deligné, The impact of climate change and natural disasters on vulnerable populations: A systematic review of literature, J. Hum. Behav. Soc. Environ. 29 (2019) 266–281.

[129] J. Seguin, Human Health in a Changing Climate: A Canadian Assessment of Vulnerabilities and Adaptive Capacity, Health Canada, Ottawa, ON, Canada, 2008 (494pp).

[130] J.C. Semenza, S. Par, Climate change and infectious disease in Europe: impact, projection and adaptation, Lancet Reg Health Eur. 9 (2020), 100230.

[131] R. Roberts, A. Dobson, O. Restif, K. Wells, Challenges in modelling the dynamics of infectious diseases at the wildlife-human interface, Epidemics 37 (2021), 100523.
D.J. Alcendor, Targeting COVID vaccine hesitancy in rural communities in Tennessee: A systematic review and meta-analysis, J. Med. Virol. 93 (2021) 1045–1056.

S.J. Islam, A. Nayak, Y. Hu, A. Mehta, K. Dieppa, Z. Almuwaqqat, Y.A. Ko, S.A. Patel, A. P.M. Ryan, N.M. Caplice, Is adipose tissue a reservoir for viral spread, immune activations in the US, J. Clin. Med. 9 (2020) 2442.

S. Siddiqui, M. Jakaria, Lockdown leading obesity and its possible impacts on the second wave of COVID-19 pandemic, Nat. Rev. Rheumatol. 17 (2021) 125–126.

M.B. Reitsma, A.L. Claypool, J. Vargo, P.B. Shete, R. McCorvie, W.H. Wheeler, D.A. E. Sirotich, J.S. Hausmann, Removing barriers and disparities in health: lessons from the COVID-19 crisis. BMJ Glob. Health 6 (2021), e106272.

K. Lima, C.R. Phillips, J. Williams, J. Peterson, C.H. Feldman, R. Ramsey-Goldman, Factors associated with participation in rheumatic disease-related research among underrepresented populations: a qualitative systematic review, Arthritis Care Res. (2022) 1481–1489.

E. Sirotich, J.S. Hausmann, Removing barriers and disparities in health: lessons from the COVID-19 pandemic, Nat. Rev. Rheumatol. 17 (2021) 125–126.

M.B. Reitsma, A.L. Claypool, J. Vargo, P.B. Shete, R. McCorvie, W.H. Wheeler, D.A. E. Sirotich, J.S. Hausmann, Removing barriers and disparities in health: lessons from the COVID-19 crisis. BMJ Glob. Health 6 (2021), e106272.