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Does urban particulate matter hinder COVID-19 transmission rate?

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Abstract

The COVID-19 pandemic has had a significant impact on global health, with millions of people affected by the disease. Recent studies have shown that environmental factors such as air quality, temperature, and humidity can impact the survival and transmission of the virus, leading to differences in the rate of spread and severity of the disease in different regions. In this global cross-sectional study, we analyzed the relationship between environmental factors and the transmission and survival of the virus in 167 cities distributed all over the world. We used a dataset containing daily COVID-19 data for 167 cities from 01/05/2020 to 01/01/2022, along with variables related to atmospheric and environmental conditions. We found an expected positive relationship between increases in atmospheric NO_2 concentration and increases in the infective rate of COVID-19. We also found an unexpected negative relationship between PM10 and COVID-19 spread, which was stronger in unpolluted cities, and indicating a likely stronger and faster deactivation of the viruses by the absorption to the larger than to the smaller particles, to PM10 more than to PM2.5. Although a complete analysis would require taking into account the restrictions in the city and the immunization status of the population, and the variance of COVID-19 spread explained by PM10 was small, only up to approx. 2%, these results contribute to a better understanding of the impact of particles on the spread of COVID-19 and other respiratory viral diseases thus informing public health policies and interventions aimed at mitigating the impact of these pandemics.

Keywords Urban atmospheric particulate matter · PM10 · PM2.5 · COVID-19 · Transmission rate · NO_2 · Respiratory viral diseases · Public health

Introduction

The COVID-19 pandemic has had a significant impact on global health, with millions of people affected by the disease. While the initial focus was on identifying the virus and developing effective treatments and vaccines, it is now clear that multiple environmental and social factors play a critical role in the transmission and spread of the disease, leading to differences in the rate of spread and severity of the disease in different cities and regions. Ahmed et al. (2021) found that higher population density is associated with the quick spreading of COVID-19, while GDP (PPP) and PM2.5 are linked with fewer cases. Lim et al. (2021) found that the duration of sunshine and ozone level positively correlate with COVID-19 cases in two regions of the Republic of Korea. Suvvari et al. (2021) reviewed studies related to the environmental effect on COVID-19 and found that atmospheric temperature, ventilation, climate change, and humidity have been studied to understand the effect of these factors on COVID-19 spread. Karim et al. (2022) observed that meteorological factors may show a substantial role in the spread of COVID-19.

Multiple environmental and social factors play a critical role in the transmission and spread of diseases. Research suggests that higher temperatures and humidity levels may reduce the stability of the SARS-CoV-2 virus, potentially leading to decreased transmission rates (He et al. 2021; Morris et al. 2021). Conversely, colder and drier conditions

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may enhance the virus's viability and promote its spread (Landier et al. 2021). The impact of temperature and humidity on COVID-19 prevalence can vary across different cities due to variations in weather conditions. Air pollution, including particulate matter (PM2.5 and PM10) and toxic gases, can weaken the respiratory system, making individuals more susceptible to respiratory infections like COVID-19 (Bianconi et al., 2020; Lee et al. 2021). Cities with higher levels of air pollution may experience increased COVID-19 prevalence and severity. The concentration of pollutants in the air can vary significantly between cities due to variations in industrial activities, traffic, and geographical factors (Querol et al. 2008). While significant progress has been made in understanding the potential associations between air pollution, especially nitrogen dioxide (NO2), and particulate matter, and the prevalence and severity of COVID-19 (Zang et al. 2022), there are still several unknowns that require further exploration.

NO_2, a common air pollutant, has gained attention due to its potential influence on respiratory health and viral infections (Chauhan et al. 2003). NO_2 is primarily released from combustion processes, including vehicle emissions, industrial activities, and power generation (Cuevas et al. 2014). High levels of NO_2 have long been associated with adverse respiratory health effects, including increased susceptibility to respiratory infections and exacerbation of respiratory conditions (Huangfu and Atkinson 2020). Prolonged exposure to NO_2 can cause airway inflammation, oxidative stress, and compromise lung function, making individuals more vulnerable to respiratory viruses, including SARS-CoV-2, the virus responsible for COVID-19 (Baldasano 2020). NO_2 exposure has been shown to disrupt immune system function, particularly the innate immune response, which plays a crucial role in early defense against viral infections. Exposure to NO_2 may impair the immune system's ability to mount an effective defense against SARS-CoV-2, potentially leading to increased transmission rates (Di Ciaula et al. 2022). Furthermore, the COVID-19 pandemic has led to widespread lockdowns and reduced economic activities, resulting in significant reductions in air pollution levels, including NO_2. Studies have shown that decreased NO_2 levels during lockdown periods are associated with improved air quality (Saha et al. 2022). Cleaner air may thus indirectly reduce the transmission of respiratory infections, including COVID-19, by improving respiratory health and reducing the susceptibility of individuals to viral infections at the same time, indicating better lockdown accomplishment (Ravindra et al. 2022).

Some research has suggested that elevated levels of PM2.5 and PM10 may also contribute to higher COVID-19 prevalence, severity, and mortality rates (Meo et al. 2021). The interaction between air pollution and the virus could potentially exacerbate respiratory symptoms, impair immune responses, and increase susceptibility to respiratory infections. Both PM2.5 and PM10 have been associated with inflammation, oxidative stress, and compromised lung function (Leikauf et al. 2020; Thangavel et al. 2022). These effects could make individuals more vulnerable to SARS-CoV-2. The smaller size of PM2.5 particles allows them to penetrate deeper than PM10 into the respiratory system, potentially reaching the lungs' sensitive regions and causing more severe respiratory impacts (Marshall, 2013). This characteristic may contribute to a greater association between PM2.5 and COVID-19 severity compared to PM10 (Bourdrel et al. 2021). Further investigations are needed to elucidate the precise mechanisms, establish causality, and identify the specific threshold levels and durations of exposure. Additionally, as in the case of NO_2, we could expect a positive correlation between both PM2.5 and PM10 with the transmission rate when the concentration of these particles increases, and there is no effective lockdown. However, particulate matter, specifically PM10 and PM2.5, could also adsorb and inactivate viruses, including SARS-CoV-2 (Wathore et al. 2020). While it is known that certain surfaces can facilitate viral attachment and persistence, the specific interactions between particulate matter and viruses, and their impact on viral inactivation, are still not well understood.

Particulate matter, including PM10 and PM2.5, can act as surfaces for viral particles to attach to (Wathore et al. 2020). The surface properties of these particles, such as their composition and charge, may influence viral adsorption. However, the extent to which particulate matter serves as a viable surface for viral attachment and subsequent inactivation is still uncertain. Some studies suggest that viruses can remain viable on surfaces, including particulate matter, for varying periods, and the conditions required for viral inactivation are complex and can depend on multiple factors. Environmental conditions such as temperature, humidity, and exposure to UV radiation may affect the viability and persistence of viruses on particulate matter surfaces (Kampf et al. 2020).

The inactivation of viruses on particulate matter surfaces might occur due to several factors, including physical processes (e.g., desiccation, degradation), chemical reactions, or interactions with other substances present on the particles (Fernández-Raga et al., 2021; Guo et al. 2021). Furthermore, the time that these particles remain suspended in the air and can be inhaled also plays a key role in the transmission rate. If a particle adsorbs several viruses and falls to the soil, it diminishes the risk of inhaling these viruses. As each individual PM10 particle has more surface area and possibilities of adsorbing viruses and less time of permanence in the air, we can hypothesize that these larger particles may

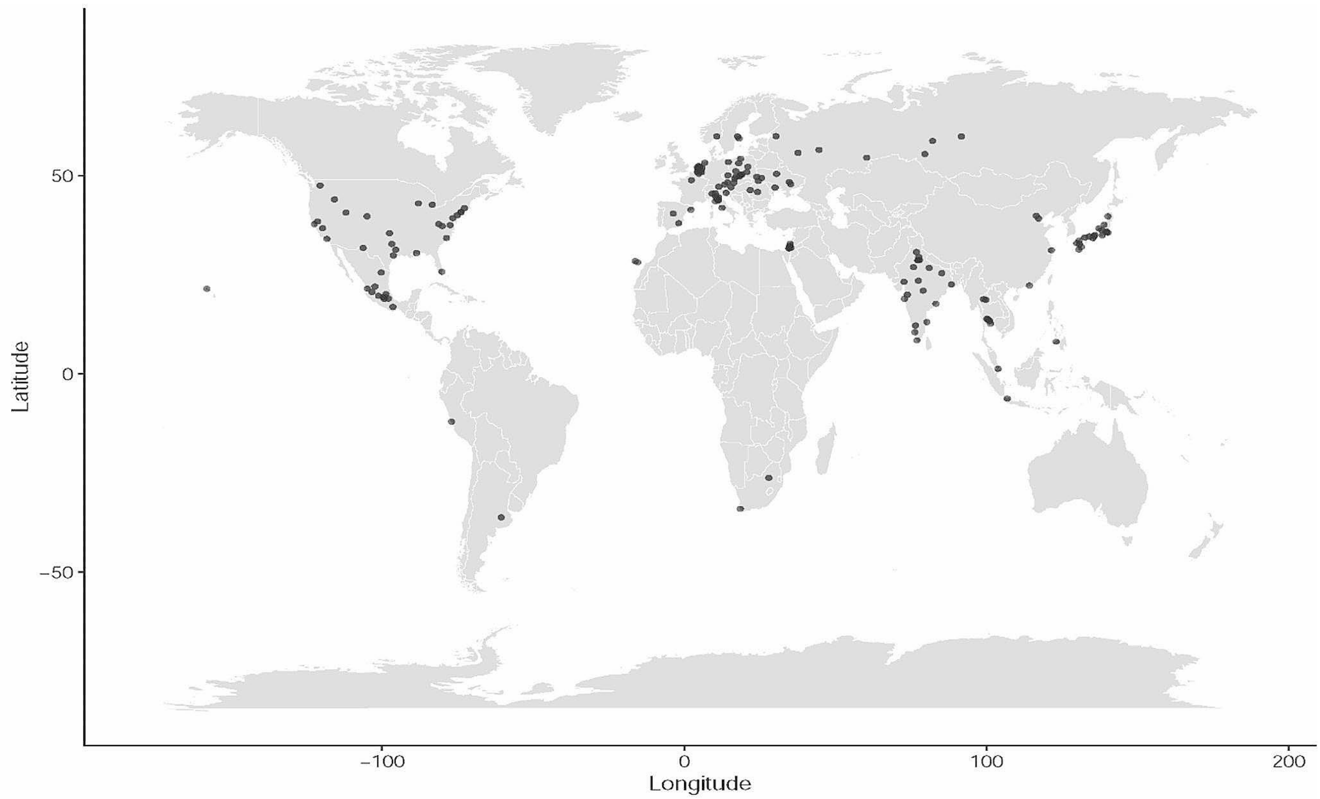

Fig. 1 Map of the studied cities

reduce the possibilities of virus transmission even more than PM2.5.

Overall, while there is ongoing research exploring the potential interactions between particulate matter and viruses, including SARS-CoV-2, the ability of PM10 and PM2.5 to adsorb and inactivate viruses is not yet firmly established. It is important to continue studying this topic to gain a more comprehensive understanding of the dynamics between particulate matter and viral inactivation, which can inform public health strategies for mitigating viral spread and transmission. In this study, we aimed to analyse which was the relationship of urban environmental factors listed in the next Materials and methods section including temperature, humidity and air pollution with COVID-19 transmission rates in 167 cities distributed all over the world with the main objective of assessing whether the air pollutants, NO_2 and particulate matter, increase or decrease COVID-19 transmission rate.

Materials and methods

Data

We conducted a global cross-sectional study using city-level data (Table 1, Fig. 1). We gathered a database containing covid data for 167 cities around the world. The dataset contained the daily data of covid for 2 years, from 01/05/2020 to 01/01/2022.

The database contains the following variables:

- Date: daily data from 01/05/2020 to 01/01/2022.
- Country: 27 different countries.
- City: 167 different cities.
- Location key: Unique identifier code for each city, 167 different locations key.
- Latitude: Latitude of the city.
- Longitude: Longitude of the city.
- Density: Population density of the city.
- T0_Covidcases: Cases of covid notified the current day.
- T0_Deaths: Deaths of covid notified the current day.
- T0_Covidcum: Cumulative cases of covid.
- T0_Deathscum: Cumulative deaths of covid.
- Rt: Transmission rate, Cumulative covid case count for the last 7 days/(Cumulative covid case count for the last

Table 1 List of cities analysed in this study. Their location and country are also depicted

Country	City	Latitude	Longitude
AR	Buenos Aires Province	-36.157	-60.570
AT	Graz	47.071	15.439
AT	Innsbruck-Stadt	47.200	11.400
AT	Linz	48.300	14.283
AT	Salzburg	47.767	13.364
AT	Vienna	48.208	16.373
BE	Antwerp	51.217	4.417
BE	Brussels	50.850	4.350
BE	Namur	50.467	4.850
CN	Beijing	39.904	116.408
CN	Shanghai	31.167	121.467
CN	Tianjin	39.147	117.206
CZ	Brno-City District	49.191	16.612
CZ	Olomouc Region	49.717	17.100
CZ	Ostrava-City District	49.800	18.217
CZ	Prague	50.083	14.417
ES	Barcelona	41.383	2.177
ES	Comunidad de Madrid	40.425	-3.691
ES	Las Palmas de Gran Canaria	28.127	-15.431
ES	Region de Murcia	38.000	-1.833
ES	Santa Cruz de Tenerife	28.467	-16.250
FR	Paris	48.857	2.351
HK	Hong Kong	22.278	114.159
ID	Jakarta	-6.215	106.845
IL	Ashdod	31.798	34.650
IL	Ashkelon	31.666	34.566
IL	Haifa	32.800	34.983
IL	Jerusalem	31.783	35.217
IL	Netanya	32.333	34.860
IL	Petah Tikva	32.083	34.883
IL	Tel Aviv	32.080	34.780
IN	Bhopal	23.500	77.417
IN	Chandigarh	30.735	76.791
IN	Chennai	13.084	80.270
IN	Delhi	28.667	77.217
IN	Gandhinagar	23.217	72.683
IN	Ghaziabad	28.667	77.433
IN	Hapur	28.731	77.776
IN	Jaipur	26.926	75.824
IN	Kolkata	22.573	88.364
IN	Lucknow	26.750	81.000
IN	Mumbai	18.960	72.820
IN	Muzaffarnagar	29.450	77.583
IN	Mysuru	12.210	76.490
IN	Nagpur	21.000	79.000
IN	Nashik	19.994	73.797
IN	Patna	25.417	85.167
IN	Thiruvananthapuram	8.480	76.940
IN	Thrissur	10.520	76.220
IN	Visakhapatnam	17.688	83.219
IT	Bologna	44.494	11.343
IT	Brescia	45.539	10.219
IT	Firenze	43.771	11.254
IT	Livorno	43.550	10.317
IT	Milano	45.464	9.190

Table 1 (continued)

Country	City	Latitude	Longitude
IT	Modena	44.180	10.648
IT	Parma	44.795	10.331
IT	Prato	43.881	11.097
IT	Roma	41.893	12.483
IT	Trieste	45.636	13.804
JP	Akita	39.719	140.103
JP	Chiba	35.605	140.123
JP	Fukuoka	33.600	130.583
JP	Hiroshima	34.396	132.460
JP	Kagoshima	31.400	130.517
JP	Kumamoto	32.717	130.667
JP	Kyoto	35.022	135.756
JP	Miyazaki	32.017	131.350
JP	Nagano	36.250	138.100
JP	Nagasaki	32.967	129.800
JP	Niigata	37.617	138.867
JP	Okayama	34.662	133.935
JP	Osaka	34.686	135.520
JP	Saitama	35.950	139.550
JP	Shizuoka	34.916	138.316
JP	Tokyo	35.690	139.692
JP	Toyama	36.717	137.150
JP	Wakayama	34.226	135.168
MX	Aguascalientes	22.022	-102.356
MX	Cuernavaca	18.924	-99.222
MX	Guadalajara	20.667	-103.333
MX	Mexico City	19.419	-99.146
MX	Monterrey	25.577	-100.284
MX	Morelia	19.703	-101.192
MX	Oaxaca	16.898	-96.414
MX	Pachuca	20.123	-98.736
MX	Puebla	19.004	-97.888
MX	Tepic	21.512	-104.892
MX	Toluca	19.328	-99.660
NL	Amsterdam	52.383	4.900
NL	Breda	51.589	4.776
NL	Dordrecht	51.796	4.678
NL	Eindhoven	51.434	5.484
NL	Groningen	53.258	6.738
NL	Haarlem	52.380	4.641
NL	Maastricht	50.867	5.683
NL	Nijmegen	51.848	5.863
NL	Rotterdam	51.923	4.479
NL	The Hague	52.080	4.310
NL	Utrecht	52.103	5.179
NO	Oslo	59.911	10.753
PE	Lima Region	-12.043	-77.028
PH	Zamboanga del Norte	8.133	123.000
PL	Bydgoszcz	53.117	18.000
PL	Gda?Ñsk County	54.267	18.633
PL	Katowice	50.250	19.000
PL	Kielce	50.873	20.632
PL	Rybnik	50.083	18.500
PL	Szczecin	53.425	14.555

Table 1 (continued)

Country	City	Latitude	Longitude
PL	Warsaw	52.230	21.011
PL	Wroc?Çaw County	51.117	17.033
PL	Zabrze	50.300	18.783
RO	Arad	46.360	21.800
RO	Sibiu	45.870	24.230
RU	Chelyabinsk Oblast	54.533	60.333
RU	Krasnoyarsk Krai	59.883	91.667
RU	Moscow	55.756	37.618
RU	Nizhny Novgorod Oblast	56.483	44.533
RU	Novosibirsk Oblast	55.450	79.550
RU	Saint Petersburg	59.950	30.317
RU	Tomsk Oblast	58.750	82.133
SE	Stockholm	59.333	18.167
SE	Uppsala	59.858	17.650
SG	Singapore	1.300	103.800
TH	Bangkok	13.750	100.517
TH	Chiang Mai	18.837	98.971
TH	Chonburi	13.362	100.983
TH	Lampang	18.696	99.726
TH	Nakhon Pathom	13.916	100.116
TH	Rayong	12.676	101.278
TH	Samut Prakan	13.599	100.597
UA	Dnipropetrovsk	48.390	34.710
UA	Ivano-Frankivsk	48.658	24.505
UA	Kiev	50.450	30.524
UA	Lviv	49.718	23.950
UA	Odessa	47.000	30.000
UA	Ternopil	49.393	25.560
UA	Zaporizhzhya	47.833	35.167
US	Austin County	29.880	-96.280
US	Baltimore	39.286	-76.615
US	Boise County	44.010	-115.740
US	Bronx County	40.847	-73.873
US	Columbus County	34.260	-78.670
US	Dallas County	32.770	-96.780
US	Denver County	39.739	-104.985
US	El Paso County	31.770	-106.240
US	Fresno County	36.750	-119.650
US	Hartford County	41.810	-72.730
US	Honolulu County	21.467	-157.967
US	Houston County	31.320	-95.430
US	Jackson County	30.460	-88.620
US	Los Angeles County	34.050	-118.250
US	Miami-Dade County	25.774	-80.194
US	Milwaukee County	43.000	-87.967
US	Oakland County	42.660	-83.380
US	Oklahoma County	35.480	-97.530
US	Philadelphia County	40.010	-75.130
US	Queens County	40.704	-73.918
US	Raleigh County	37.780	-81.260
US	Richmond	37.533	-77.467
US	Sacramento County	38.450	-121.350
US	Salem	37.287	-80.056
US	Salt Lake County	40.670	-111.930

Table 1 (continued)

Country	City	Latitude	Longitude
US	San Francisco County	37.778	-122.443
US	Washington	47.500	-120.500
ZA	City of Cape Town Metropolitan Municipality	-34.000	18.500
ZA	City of Johannesburg Metropolitan Municipality	-26.177	27.964

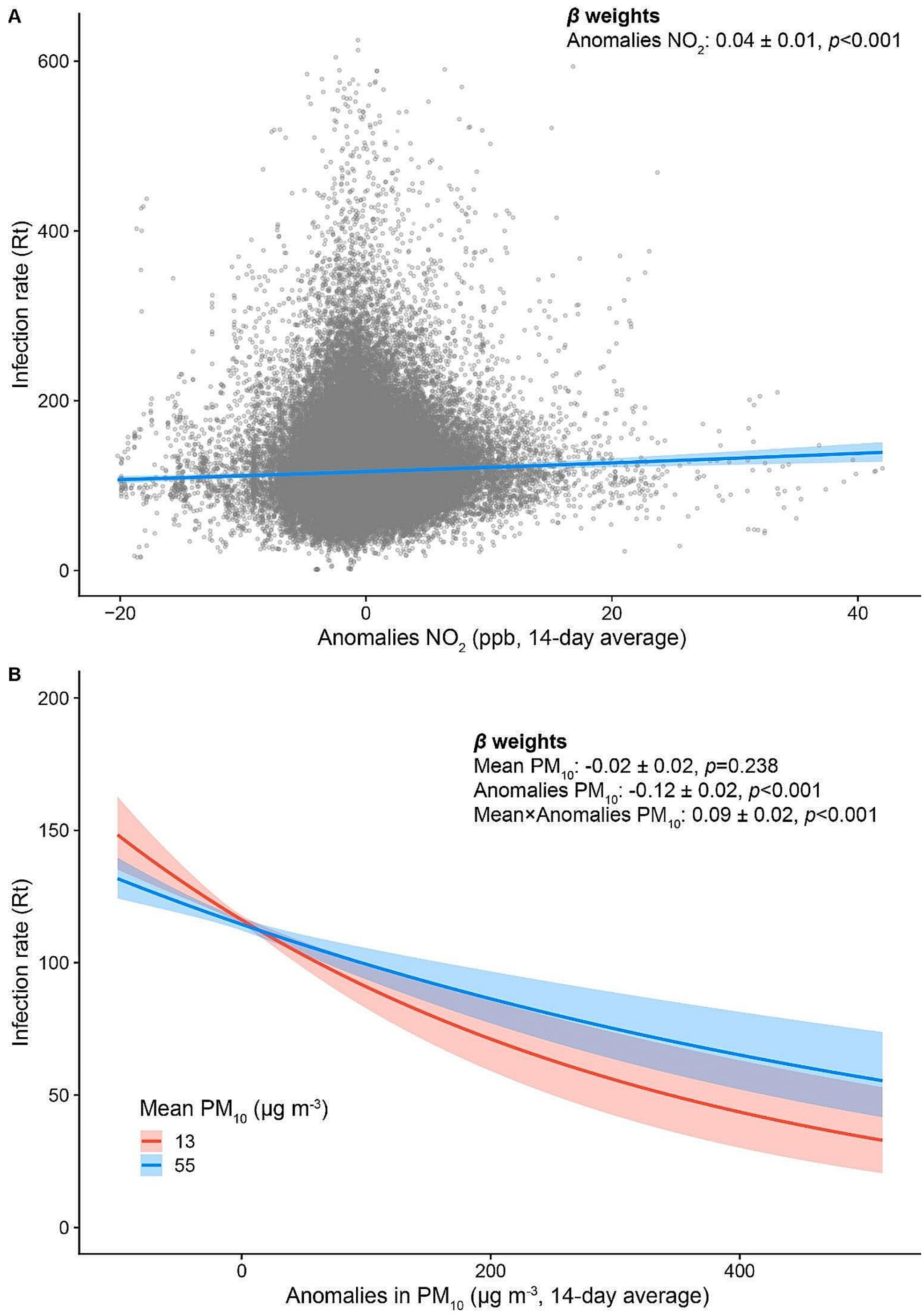

Fig. 2 Effects of anomalies in atmospheric concentrations of NO2 (**panel A**) and PM10 (**panel B**) on COVID-19 infection rates. Anomalies represent 14-day averages, and infection rate was multiplied by a factor of 100. Panel A also show the partial residuals of the relationship

14 days - Cumulative covid case count for the last 7 days).
- T1_CovidIncrease: Rate of increase of covid cases compared to yesterday's covid cases.
- T7_CovidIncrease: Rate of increase of covid cases compared to the number of cases 7 days ago.
- T14_CovidIncrease: Rate of increase of covid cases compared to the number of cases 14 days ago.
- PM10: Atmospheric particulate matter with a diameter less than 10 µm and more than 2.5 µm in EU EPA standard units.
- Humidity: Concentration of humidity in %.
- O_3: Measurement of the concentration of O_3 in EU EPA standard units.
- Wind Measurement of wind speed in km/h.
- PM25: Measurement of the atmospheric particulate matter with a diameter less than 2.5 µm in EU EPA standard units.
- NO2: Measurement of the concentration of NO_2 in EU EPA standard units.
- Pressure: Measurement of the pressure in hPa.
- Temp: Measurement of the temperature in ºC.
- Precipitation: Measurement of the precipitation in mm.
- CO: Measurement of the concentration of CO in EU EPA standard units.

For the variables PM10, Humidity, O_3, Wind_speed, PM2.5, NO_2, Pressure, Temp, Precipitation and C0 we had 6 measures:

- T0_var is the median value of the variable measured during the current day.
- T1_var is the average of the median variable measure of the current day and the previous day.
- T3_var is the average of the median measurement of the variable of the current day and 3 previous days.
- T7_var is the average of the median measurement of the variable of the current day and 7 previous days.
- T14_var is the average of the median variable measurement of the current day and 14 previous days.
- T30_var is the average of the median variable measurement of the current day and 30 previous days.

The covid data was extracted from JHU CSSE COVID-19 Data (https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data#daily-reports-csse_covid_19_daily_reports) and the variables of environmental and atmospheric conditions were extracted from World's Air Pollution website (https://waqi.info/#/c/2.6/0/2z).

Initially we had a total of 112,929 records in a database from 01/01/2020 to 01/01/2022.

We then selected a final database after considering several consistency and integrity checks:

- Data only from 1/05/2020 on since this was the date when data started to be collected in a more rigorous way.
- Eliminate those locations that had data recorded less than 200 days.
- Eliminate records with more than 50 missing values per row in pollution or climate variables.
- Delete extreme weather data, transmission and increase rates.
- Delete records that have negative daily covid cases.

Once we had taken into account these considerations, we did multiple imputation of the data using an EM (Expectation-maximization) algorithm in two steps:

- Expectation step (step E): In this expectation step, using the observed available data from the dataset, we tried to estimate the missing data values.
- Maximization step (step M): We used the now complete data prepared in the expectation step to update the parameters.

The final database had 69,200 records, 38.72% less than the initial number of records.

Statistical methods

We employed linear mixed-effects models to explore the association between environmental variables and the transmission rate (Rt) of COVID-19, while considering potential sources of error associated with different countries and cities (i.e., nested random factors, city within country). A total of seven models with increasing complexity were fitted to assess the significance of the predictors on the response variable (i.e., the natural logarithm of Rt multiplied by 100). The simplest models tested the effects of the average of median city air concentrations of NO_2, PM2.5 and PM10 and their respective interactions with their anomalies (i.e., deviations from their mean; models M1, M2 and M3). We then fitted two models (M4 and M5) combining the effects of NO_2 and PM2.5, and NO_2 and PM10 while also including their respective interaction with their anomalies. Finally, we fitted two more models (M5 and M6) resembling M4 and M6 but also including air concentrations O_3, air humidity and temperature and their respective anomalies. These predictors encompassed the average of median city air concentrations of PM2.5, PM10, O_3, NO_2, humidity, and temperature, as well as their anomalies (deviations from the mean) in the 14 days preceding the current Rt observations. Interactions between the averages and anomalies of the same variables (e.g., PM2.5 × anomaly PM2.5) were fitted to examine whether the anomalies exhibited distinct effects on Rt depending on the average values of the corresponding variable.

Notably, all models were repeated using PM10 instead of PM2.5, consistently showing lower Bayesian Information Criterion (BIC) values when utilizing PM10. To fit these models, the "lme" function from the "nlme" package in R (Pinehiro et al. 2018) was employed. A temporal correlation structure of order one (AR1) was implemented by specifying the argument "correlation = corAR1()". This temporal autocorrelation structure allowed for observations at time t to be affected by previous observations (time t-1). Maximum likelihood estimation was used for model fitting. The BIC was computed using the "BIC" function to identify the best-performing model among the nine candidate models. Response curves were generated using the "visreg" package in R (6. Breheny et al. 2017). All statistical analyses were conducted using R statistical software version 4.1.1 (R Core Team 2021).

Results and discussion

Our study found a positive relationship of **the transmission rate of COVID-19** with **NO_2concentration.** This finding is consistent with previous research that has shown NO_2 to be an agent that directly damages the respiratory system, especially in vulnerable populations such as children (Ghanbari Ghozikali et al. 2016; Pfeffer et al. 2019; Bahrami Asl 2018; Chen et al. 2019; Kowalskaet al. 2020; To et al. 2020). Additionally, exposure to NO_2 has long been associated with an increased likelihood of contracting viral infections (Zhu et al. 2020). But more than that, NO_2 is significantly related to human activity and mobility, so to higher probability of COVID-19 spread due to increased human contact. The direct effect of NO_2 causing injury to human health can facilitate the expansion and damage caused by COVID-19, while infected people with stronger COVID infections can be a more powerful source of contamination to others, increasing the probability of transmission.

Importantly, these results also show the effective role of lockdown during the COVID outbreak (Wang and Penuelas 2021; Xing et al. 2021). Recent studies have shown that lockdowns in 2019 and 2020 established to fight COVID-19 reduced atmospheric NO_2 concentrations in 65 studied cities around the world Cooper et al. 2022). They also confirm the initial observations that linked ambient concentrations of NO_2 to the spread of the COVID-19 pandemic across Europe, China, and the United States (Zhu et al. 2020; Bashir et al. 2020; Fattorini and Regoli 2020; Jiang et al. 2020; Li et al. 2020; Ogen 2020; Zoren et al. 2022a), and differ from the very few that like those of Zoran et al. (2020a); Bashir et al. (2020) report either no association or a negative one between NO_2 and daily death counts. In China, Zhu et al. (2020), observed that a 10-µg/m^3 increase in NO_2 is associated with a 6.94% (95% CI: 2.38–11.51) increase in the daily counts of COVID-19 confirmed cases in 120 cities. These findings are consistent with those of Jiang et al. (2020) and Li et al. (2020), who used the same method described for PM. Jiang et al. (2020) found a significant positive association between NO_2 and COVID-19 in Wuhan and XiaoGan (Wuhan RR = 1.056, CI:1.053–1.059; XiaoGan RR = 1.115, CI = 1.095–1.136), but not in Li et al. (2020) found a significant linear correlation in Wuhan ($R^2 = 0.329$, $p < 0.001$) and XiaoGan ($R^2 = 0.158$, $p < 0.05$). Taking into account this scientific evidence, it can be stated that exposure to NO_2 not only harms human health and increases the risk of respiratory diseases, but it is also an indicator of human activity driving to human connectivity that triggers the spread of COVID-19.

Surprisingly, our findings reveal a negative correlation between PM10 levels and the spread of COVID (Fig. 2). This negative correlation is even more pronounced in less polluted cities. Unlike the relationships observed with NO_2, these results are not consistent with previous reports and the expected effects of lockdown, which would decrease both transmission and pollution linked to human activity. Although there are a few studies that have not found evidence linking PM10 particles to the spread of COVID-19 (Bontempi 2020), most studies have reported a significant association between ambient concentrations of PM10 and the COVID-19 pandemic in the most affected countries, including China, Italy, and the United States (Zhu et al. 2020; Bashir et al. 2020; Coccia 2020; Fattorini and Regoli 2023; Yao et al. 2020; Zoran et al. 2020b). For example, Wannaz et al. (2021) studied the relationships between the presence of PM2.5 and PM10 particles in the low atmosphere and the spread of COVID-19 in the city of Arequipa, Peru. They observed a significant correlation between day concentrations of PM10 particles and the number of new COVID-19 cases registered in the next 18 days, particularly after 15–18 days. The authors hypothesized that the COVID-19 virus might circulate attached to coarse particle PM10, acting as a vector of infection. However, the study also observed that the decrease in PM10 was mainly observed on Sundays, coinciding with a radical drop in human activity, mobility, and direct transmission facilities. Thus, it cannot be ruled out that the positive relationship between PM10 and COVID-19 spread they found could simply be also an indicator of increased human activity as it is the case for NO_2. Moreover, some studies have observed that in general PM directly induces inflammation in lung cells and thus can increase the susceptibility and severity of the COVID-10 in humans (Comunian et al. 2020).

Instead, our finding of a negative relationship might indicate a lower suspension time of PM10 particles in the air than that of viral particles. In fact, the SARS-CoV-2 virus, responsible for COVID-19, has a diameter of approximately 60–140 nm whereas the diameter of PM10 particles ranges from 2.5 to 10 micrometers. The adsorption of viral particles would favour a lower permanence of the virus in the air. The contrary pattern, i.e. the possibility that PM particles might promote a longer permanence of viral particles in the atmosphere has been hypothesized to explain reported positive relationships (Anugerah et al. 2021). Meo et al. (2021), analyzing a global database reporting data from December 2019 to September 30, 2021, concluded that there is a possible causal link between increasing particulate matter PM2.5 and PM10 in the atmosphere and increasing incidence and mortality of COVID-19. However, several studies have observed that the suspension time of PM particles in the air, prior deposition, and the possibility of resuspension strongly depend on several variables, such as climate, human activities, sources of emission, and the particle material (Kauhaniemi et al. 2011; Kupainen et al. 2016; Tohidi et al. 2022; Zhang et al. 2022).

Several studies that have observed direct relationships between proxies indicating more human mobility and human contacts with PM concentrations in the lower atmosphere by comparing lockdown versus non-lockdown periods and/or under different levels of human/traffic/industrial activity (Setti et al. 2020; Tung et al. 2021; Choi and Kim 2022; Gorrochategui et al. 2022; Pala et al. 2022). Nonetheless, these relationships are not very clear or significant because the source of PM particles is not only the urban (traffic, industrial) origin. Other factors related to climate, such as wind, precipitation, or atmospheric pressure can also play a role that can distort the direct relationships between lockdown and PM concentrations (Bera et al. 2022; Gilardi et al. 2022). Furthermore, little information is available about the virus's suspension capacity by itself and its absorption to particles of PM10, which may increase or decrease the mean time of air suspension of COVID-19 virus. It is not clear whether the COVID virus remains suspended in the air longer by itself or when attached to a PM10 particle, although it seems that when attached, it is able to travel greater distances, as observed in road dust (Alex et al., 2023). There is indirect evidence suggesting that high concentrations of air pollutants, associated with low wind speeds, may promote a longer permanence of viral particles in the polluted air of cities (Coccia, 2020). However, it is not clear either, and it would be essential to know if the attachment/absorption of viral particles on PM10 deactivates the virulence of the virus and how this depends on environmental conditions such as sunlight or temperature levels, and the specific material of each PM10 (coal, organic matter, silicates, clays, lime, etc.). Our results could be due to the viral particle adsorption on PM reducing COVID infectivity by mechanisms related to molecular alterations that limit the virus' ability to interact with human cells and penetrate them (Woodby et al. 2021). Furthermore, sunlight and photochemical reactions on PM with absorbed virus could trigger heating and/or deactivate the virus's virulence capacity, as hypothesized by some authors (Edge and Truscott 2021). The viability and virulence of COVID-19 virus stuck on the particulate surface are not yet confirmed (Srivastava 2021) and surely depend on the particle material. Thus, although the structural/compositional changes of virus capsid when absorbed on a PM10 particle and their impacts on virus virulence level remain to be fully understood, our results are compatible with a reduced infectivity of COVID-19 by viral absorption on PM10.

In this regard, certain studies have observed that SARS-CoV-2 virus absorbed on PM10 particles from different fuels combustion deactivates the virus, thus reducing transmission. However, this positive effect is counterbalanced by the negative impact of these particles on host oxidative stress and immunity (de la Fuente et al. 2022). Effectively, PM10 pollution can have more health effects by itself: lowering the body's immune system and making people more susceptible to infection, resulting in a potential increase in the spread rate. But on the other side, PM10 pollution can also decrease the rate of spread of infections, possibly due to behavioral changes in response to air pollution levels. When pollution is high, and thus the presence of PM10 is also high, the protective measures such as reducing outdoor activities are higher, reducing the spread rate. Conversely, when pollution is low, people may leave protective measures, increasing outdoor activities and taking more contact with PM10 particles.

We can conclude that most studies, including the present one, demonstrate non-neutral interactions between PM2.5 and primarily PM10 particles and the spread of viruses, particularly in areas with high population density and significant pollution levels. The effects of PM particles on COVID spread can vary depending on the chemical composition of the particles and the specific environmental and climatic conditions of the location. These factors determine the duration of particle persistence in the atmosphere and the likelihood of resuspension as well as deactivation potential. It is important to consider these local conditions when assessing the positive or negative impacts of PM particles on the transmission of viruses like COVID-19. Although a complete analysis would require taking into account the restrictions in the city and the immunization status of the population, and although our models explain small part of the variance, up to approximately 2%, these results will contribute to a better understanding of the environmental factors that impact the spread of COVID-19 thus informing public health policies and interventions aimed at mitigating the impact of these pandemics, particularly in regions that are vulnerable to the effects of environmental factors.

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