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Assessment of the relationship between exposure to air pollutants and COVID-19 pandemic in Tehran city, Iran

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A B S T R A C T

The COVID-19 disease caused by the SARS-CoV-2 virus first identified in December 2019 has resulted in millions of deaths so far around the world. Controlling the spread of the disease requires a good understanding of the factors (e.g., air pollutants) that influence virus transmission and the conditions under which it spreads. This study analyzed the relationships between COVID-19 cases and both short-term (6-month) and long-term (60-month) exposures to eight air pollutants (NO, NO2, NOx, CO, SO2, O3, PM2.5 and PM10) in Tehran city, Iran, by integrating geostatistical interpolation models, regression analysis, and an innovated COVID-19 incidence rate calculation (Q-index) that considered the spatial distributions of both population and air pollution. The results show that the higher COVID-19 incidence rate was significantly associated with the exposure to higher concentrations of CO, NO, and NOx during the short-term period; the higher COVID-19 incidence rate was significantly related to the exposure to higher concentrations of PM2.5 during the long-term period; while COVID-19 incidence rate was not significantly associated with the concentrations of O3, SO2, PM10 and NO2 in either period. This study indicates that exposure to air pollutants can effect an increase in the number of infected people by transmitting the virus through the air or by predisposing people to the disease over time. The Q-index calculation method developed in this study can be also used by other studies to calculate more accurate disease rates that consider the spatial distribution of both population and air pollution.

1. Introduction

The COVID-19 disease caused by the coronavirus 2 (SARS-CoV-2) was first identified in December 2019 in Wuhan, China (Lu et al., 2020; Xu et al., 2020). It quickly spread across China and other countries in the following months, becoming a global public health concern (Chen et al. 2020a, 2020b; Chen and Li 2020; Gilbert et al., 2020; Li et al., 2020; Sohrabi et al., 2020). In general, most people with SARS-CoV-2 have mild symptoms such as fever, dry cough, and sore throat (Huang et al., 2020; Sohrabi et al., 2020). However, some patients have reported severe and even fatal complications such as Acute Respiratory Syndrome (ARDS) (Chen et al., 2020b; Chen and Li 2020; Sohrabi et al., 2020). Clinical studies on COVID-19 have shown that most patients have respiratory and pneumonia problems (Holshue et al., 2020; Zhou et al., 2020). The reported symptoms of COVID-19 are similar to other viral diseases such as MERS and SARS and include symptoms such as cough, fever, and shortness of breath due to respiratory distress. In the worst case, COVID-19 causes kidney failure, pneumonia, and even death (Wang et al., 2020a).

During the ongoing COVID-19 pandemic, in order to control the spread of SARS-CoV-2, it is quite urgent and necessary to gain a better understanding of the critical factors that affect the virus transmission. Many studies have been conducted around the world to analyze the factors. Several preliminary studies have shown that human-to-human contact increases the risk of COVID-19 (Chan et al., 2020; Li et al., 2020; Wang et al., 2020b). In addition, population mobility has a
significant effect on the COVID-19 epidemic (Kraemer et al., 2020). Previous studies have found that environmental factors such as wind speed, humidity, and temperature play a significant role in spreading infectious diseases (Dalziel et al., 2018; Yuan et al., 2006). Experts now believe that excessive levels of air pollution render people more susceptible to the disease. New research has confirmed the associations of COVID-19 with air pollution and ambient temperature (Zhu and Xie, 2020). Furthermore, air pollution is a major problem in countries with severe COVID-19 situation in the early stages of the pandemic, such as China, South Korea, Iran, and Italy, and cities with higher air pollution are at a higher risk (Vetter et al., 2020). Several studies have found that different types of air pollution are associated with an increase in the occurrence of respiratory infections and lung diseases (Ciencewicki and Jaspers, 2007; Cohen et al., 2017; Horne et al., 2018; Liu et al., 2019; Neupane et al., 2010; Schikowski et al., 2005). Findings indicated that exposure to high concentrations of air pollutants increases the risk of SARS-CoV-2 infection due to lower immune system responses (Travaglio et al., 2020). For example, PM$_{2.5}$ particles contain nano-particles that, if inhaled, can cause serious health concerns (Wu et al., 2020). Long-term exposure to air pollution, including PM$_{2.5}$, negatively affects the respiratory and cardiovascular systems and increases the risk of death (Brook et al., 2010; Pope III et al., 2004; Pope III et al., 2019; Namdar-Khojasteh et al., 2021).

However, the results from the previous studies on the relationship between COVID-19 and air pollution have many limitations. First, these studies only focused on the relationship between air pollutants and COVID-19 confirmed cases and not on COVID-19 infection (Zhu et al., 2020). Second, the previous studies worked on the associations of COVID-19 with air pollutants across different cities in a country (Bashir et al., 2020; Travaglio et al., 2020; Wu et al., 2020; Zhu et al., 2020), and factors which affect the COVID-19 infection such as genetic predisposition of the population, following the protocols, climate condition, sensitivity of the pollutants measuring device and so on might not be consistent among different cities, but those studies didn’t consider the inconsistency. In addition, most previous studies focused on short-term exposures to air pollution, but didn’t examine long term and short term at the same time (Travaglio et al., 2020; Wu et al., 2020). Furthermore, the COVID-19 case rates or incidence rates calculated in most of the previous studies were only the number of cases divided by the population in the study area without considering the spatial distributions in population and air pollution across different parts of the study area, so the air pollution exposures of the COVID-19 patients were not very accurate. Thus, in order to get a better understanding of the relationship between air pollution exposure and COVID-19 cases, it is necessary to conduct more studies on the relationship for both long-term and short-term periods using more accurate methods to calculate air pollution exposures of the COVID-19 patients, especially in the developing countries like Iran.

This study aimed to analyze the relationships between COVID-19 cases and both short-term (6-month) and long-term (60-month) exposures to eight air pollutants (NO, NO$_2$, NOx, CO, SO$_2$, O$_3$, PM$_{2.5}$ and PM$_{10}$) in Tehran city, Iran by integrating geostatistical interpolation
models, regression analysis, and an innovated COVID-19 incidence rate calculation, namely, Q-index that considered the spatial distributions of both population and air pollution across the different parts of the study area. The Q-index can reflect a more accurate estimate of air pollution exposure of the COVID-19 patients. To our best knowledge, no previous studies have used the same or similar method to study COVID-19, and very few studies have examined the associations of COVID-19 cases with both long-term and short-term air pollution exposures.

2. Methodology

2.1. Study area

The study was set in the Tehran Metropolitan Area (TMA), covering 676.31 km² and located in the State of Tehran, Iran (Fig. 1). The TMA has a semiarid climate, with only weak seasonal change in weather conditions. The warmer period is from May to September, and the cooler period is from November to February, with the monthly average of 23 °C and 17 °C, respectively. The major urban air pollution sources in TMA are traffic-related emissions and local non-traffic sources, including airports and some local industries located along the Tehran-Karaj highway.

2.2. Data source

In this study, the long-term (past 60 months) from September 2015 to September 2020 and short-term (past 6 months) from March 2020 to September 2020 monitoring data for eight air pollutants (NO, NO₂, NOₓ, CO, SO₂, O₃, PM₂.₅ and PM₁₀) at 25 monitoring stations in the Tehran city were obtained from Tehran’s Environment Organization. The

Table 1

Results of descriptive statistics for the concentrations of air pollutants during the period of 6 months.

| Air Pollutants | S.D | Skewness | Kurtosis | Variance | Mean | Max | Min | Kolmogorov-Smirnov |
|----------------|-----|----------|----------|----------|------|-----|-----|-------------------|
| CO (ppm)       | 0.27| 0.03     | 0.48     | 0.076    | 1.79 | 2.31| 1.26| 0.11              |
| NO (ppb)       | 17.96| 0.09    | -0.33   | 322.82   | 59.5 | 93.68| 29.96| 0.63              |
| SO₂ (ppb)      | 1.93| 0.67    | -0.69   | 3.76     | 5.77 | 9.64| 3.81| 0.63              |
| NO₂ (ppb)      | 3.62| -0.22   | -0.71   | 40.03    | 47.73| 58.21| 36.44| 0.89              |
| NOx (ppb)      | 22.21| 0.04    | -0.76   | 493.40   | 107.02| 145.88| 73.28| 0.81              |
| O₃ (ppb)       | 2.56| -1.57   | 4.56    | 6.56     | 21.94| 26.01| 14.94| 0.32              |
| PM₃.₅ (μg m⁻³)| 6.95| 0.11    | -1.76   | 48.40    | 29.24| 39.90| 21.18| 0.65              |
| PM₁₀ (μg m⁻³)  | 16.31| 0.40    | -1.37   | 266.26   | 75.44| 101.45| 54.67| 0.94              |

Table 2

Comparison of interpolation models.

| Interpolation method | Variables | Statistical parameter (6 month) | Statistical parameter (60 month) |
|----------------------|-----------|---------------------------------|---------------------------------|
|                      |           | RMSE  | R²  | RMSE | R²  |
| IDW                  | CO        | 0.11  | 0.46| 0.02 | 0.55|
|                      | NO        | 18.54| 0.35| 31.22| 0.12|
|                      | SO₂       | 0.59  | 0.66| 0.48 | 0.65|
|                      | NO₂       | 7.78  | 0.51| 5.43 | 0.43|
|                      | NOₓ       | 14.69 | 0.51| 12.76| 0.57|
|                      | O₃        | 1.01  | 0.69| 1.97 | 0.68|
|                      | PM₂.₅     | 5.54  | 0.12| 16.70| 0.008|
|                      | PM₁₀      | 8.24  | 0.32| 17.18| 0.16|
| RBF                  | CO        | 0.82  | 0.16| 0.44 | 0.23|
|                      | NO        | 4.89  | 0.42| 3.67 | 0.55|
|                      | SO₂       | 0.98  | 0.47| 1.12 | 0.43|
|                      | NO₂       | 20.54 | 0.08| 12.33| 0.12|
|                      | NOₓ       | 55.12 | 0.14| 37.55| 0.21|
|                      | O₃        | 4.56  | 0.32| 3.45 | 0.44|
|                      | PM₂.₅     | 3.63  | 0.42| 5.46 | 0.38|
|                      | PM₁₀      | 3.17  | 0.47| 9.12 | 0.25|

Table 3

Results of descriptive statistics for the concentrations of air pollutants during the period of 6 months.

| Air Pollutants | S.D | Skewness | Kurtosis | Variance | Mean | Max | Min | Kolmogorov-Smirnov |
|---------------|-----|----------|----------|----------|------|-----|-----|-------------------|
| CO (ppm)      | 0.23| 0.48     | -0.54    | 0.05     | 1.19 | 1.57| 0.85| 0.32              |
| NO (ppb)      | 9.92| 0.39     | -0.066   | 98.60    | 31.10| 51.91| 16.33| 0.29              |
| SO₂ (ppb)     | 1.06| 0.49     | -1.06    | 1.13     | 4.12 | 5.91| 2.63| 0.98              |
| NO₂ (ppb)     | 3.27| -0.94    | -0.34    | 10.72    | 41.45| 44.83| 34.74| 0.79              |
| NOx (ppb)     | 12.27| -0.07   | -0.61    | 150.71   | 72.47| 94.99| 53.87| 0.49              |
| O₃ (ppb)      | 3.68| -0.84    | 1.27     | 13.59    | 27.30| 34.56| 20.89| 0.99              |
| PM₂.₅ (μg m⁻³)| 4.50| -1.86    | -0.13    | 20.29    | 23.68| 29.02| 17.17| 0.74              |
| PM₁₀ (μg m⁻³) | 12.78| 0.46    | -1.32    | 163.43   | 62.14| 81.67| 46.50| 0.87              |

Table 4

Comparison of interpolation models.

| Interpolation method | Variables | Statistical parameter (6 month) | Statistical parameter (60 month) |
|----------------------|-----------|---------------------------------|---------------------------------|
|                      |           | RMSE  | R²  | RMSE | R²  |
| IDW                  | CO        | 0.11  | 0.46| 0.02 | 0.55|
|                      | NO        | 18.54| 0.35| 31.22| 0.12|
|                      | SO₂       | 0.59  | 0.66| 0.48 | 0.65|
|                      | NO₂       | 7.78  | 0.51| 5.43 | 0.43|
|                      | NOₓ       | 14.69 | 0.51| 12.76| 0.57|
|                      | O₃        | 1.01  | 0.69| 1.97 | 0.68|
|                      | PM₂.₅     | 5.54  | 0.12| 16.70| 0.008|
|                      | PM₁₀      | 8.24  | 0.32| 17.18| 0.16|
| RBF                  | CO        | 0.82  | 0.16| 0.44 | 0.23|
|                      | NO        | 4.89  | 0.42| 3.67 | 0.55|
|                      | SO₂       | 0.98  | 0.47| 1.12 | 0.43|
|                      | NO₂       | 20.54 | 0.08| 12.33| 0.12|
|                      | NOₓ       | 55.12 | 0.14| 37.55| 0.21|
|                      | O₃        | 4.56  | 0.32| 3.45 | 0.44|
|                      | PM₂.₅     | 3.63  | 0.42| 5.46 | 0.38|
|                      | PM₁₀      | 3.17  | 0.47| 9.12 | 0.25|

A. Average of Pollution Concentration.
concentrations of NO, NO\textsubscript{2}, CO, SO\textsubscript{2}, and PM\textsubscript{2.5} were measured at all the 25 stations. O\textsubscript{3} and NO\textsubscript{x} were measured at 22 stations, and PM\textsubscript{10} was measured at 23 stations. The locations of the monitoring stations are shown in Fig. 1. The hourly average concentrations of the air pollutants were collected. COVID-19 data was acquired from the Corona Headquarters in Tehran for 22 districts in Tehran from March 2020 to September 2020. The definitive COVID-19 patients were included in the study, which excludes people who only had disease symptoms. COVID-19 infection was determined by chest computed tomography (CT) at the onset of the disease and then genetic sequences and RT-PCR of respiratory secretions were used to diagnose the virus. The data included the number of people infected with COVID-19, the number of mortality caused from the disease by age group (0–4, 5–14, 15–24, 25–34, 35–65, and more than 85), and the location of those who were infected or died from the disease. The mortality data was not used in this study.

2.3. Instrumentation

Ambient nitric oxide (NO), nitrogen dioxide (NO\textsubscript{2}), and oxides of nitrogen (NO\textsubscript{x}) were measured by Ecotech Serinus 40. Ambient carbon monoxide (CO) and sulfur dioxides (SO\textsubscript{2}) were measured by Ecotech Serinus 30, and Ecotech Serinus 50, respectively. PM\textsubscript{10} and PM\textsubscript{2.5} were measured by BAM 1020–9800 (Rev U).

2.4. Data pre-processing

The hourly average concentrations over the period of 60-month from September 2015 to September 2020 and the period of 6-month from

| Pollutants | P- Value | R\textsuperscript{2} | Period (month) | Pollutants | P- Value | R\textsuperscript{2} | Period (month) |
|------------|----------|----------------|----------------|------------|----------|----------------|----------------|
| NO         | 0.000    | 0.863         | 6              | PM\textsubscript{10} | 0.138    | 0.285         | 6              |
| NO\textsubscript{2} | 0.097    | 0.342         | 60             | PM\textsubscript{2.5} | 0.145    | 0.227         | 6              |
| NO\textsubscript{x} | 0.917    | 0.001         | 60             | CO         | 0.003    | 0.724         | 60             |
| SO\textsubscript{2} | 0.284    | 0.160         | 60             | O\textsubscript{3} | 0.136    | 0.287         | 60             |
|            | 0.387    | 0.108         | 60             |            | 0.845    | 0.005         | 6              |
|            | 0.752    | 0.015         | 60             |            | 0.533    | 0.057         | 60             |

Fig. 1. Correlation between CO concentration for 6 and 60 months with COVID-19.
March 2020 to September 2020 were aggregated to generate the long-term and short-term average, respectively, for each air pollutant at each monitoring station. For long-term and short-term periods, the monthly average was calculated first, and then the annual average was calculated using the monthly average. SPSS V22 statistical software was used to examine the data normality using the Kolmogorov-Smirnov test, to remove outlier data, and to conduct descriptive statistics on the concentrations of the air pollutants. The COVID-19 data were used for analysis without any pre-processing. There were 100,000 COVID-19 patients between March 2020 and September 2020, and 2000 COVID-19 patients were randomized selected from the 100,000 patients and more data analysis was performed on these 2000 patients. The geographical coordinates (based on UTM) of the residence addresses of all patients (2,000) were obtained with Google Earth and were imported to ArcGIS 10.3 software for further analysis (Fig. 2). The population density of each of the 22 districts in Tehran was computed, and the population density map was created using ArcGIS 10.3 software (Fig. 3).

2.5. Air pollutant concentration surface interpolation

We implemented RBF (Radial Basis Function), OK (Ordinary Kriging), and IWD (Inverse Distance Weighting) geostatistical analysis models embedded in Arc GIS 10.3 to estimate the concentration surface of each air pollutant based on its measurements at monitoring stations.

These three models were shown to be very effective for the interpolation of a concentration surface over a large geographical area (Reid et al., 2015). In the process of each geostatistical interpolation model, experimental semivariograms were fitted to a variety of theoretical models, namely spherical, exponential, and Gaussian models and the best models were selected based on the minimum error using the coefficient of determination ($R^2$) and residual sum of squares (RMSE) as indicators (Chiles and Delfiner 2009).

The performance evaluation among RBF, OK, and IWD based on the cross-validation (observed vs modelled concentration) analysis showed the highest $R^2$ value in the RBF and IDW model compared to the OK model. In cross-validation method, one observation point is removed at each step, and that point is estimated using the other points. This is repeated for all observation points so that at the end, there will be an estimate of the number of observation points. This study used the $R^2$ and RMSE as error metrics.

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} [Z(x_i) - \hat{Z}(x_i)]^2}{N}}
\]  

(1)

In Equation (1), $Z(x_i)$ is the observed value, $\hat{Z}(x_i)$ is the estimated value, and $N$ is the number of data.
2.6. Spatial analysis of the relationships between COVID-19 cases and air pollutant concentrations

After preparing the concentration surface maps of the pollutants with the above-mentioned geostatistical methods, the distribution of the number of patients with COVID-19 disease and the population density map were overlaid on the concentration surface maps with Arc GIS 10.3 software. Each pollutant was divided into ten concentration ranges ($I = 1:10$), and the area of each concentration range ($A_i$) was obtained. The number of patients ($p$) in each concentration range per hectare ($N_{\text{COVID-19}}$) was determined by combining the map of the number of patients with COVID-19 and the map of each pollutant as shown in Equation (2).

$$N_{\text{COVID-19}} = \frac{p}{A_i}$$

In the next step, the population-weighted average (per hectare) in each concentration range ($i$) was determined by Equation (2) to consider the effect of the population in each concentration range ($i$) due to the difference in population (people per hectare) in whole 22 districts of Tehran ($j = 1:22$):

$$P_i^{\text{ha}} = \frac{\sum_{j=1}^{22} A_j X_j}{\sum_{j=1}^{22} X_j}$$

In this equation, $A_j$ is the area of each concentration range, $X_j$ is the area population at each concentration range. Finally, the Q index (number of patients per population) for each range of pollutant concentrations was calculated using Equation (4).

$$Q \text{ index} = N_{\text{COVID-19}} / P_{\text{ha}}$$

The Q index was calculated for both long-term and short-term concentrations of each air pollutant. The Q-index was not calculated from air pollutant concentration, but based on the area that was covered by each concentration range, the number of COVID-19 patients and population calculated within each range. It considered the spatial distributions of both population and air pollution across different parts of Tehran. It represents the COVID-19 incidence rate (number of patients per population in 1 ha) associated with a concentration range of each air pollutant.

2.7. Linear regression for Q-index and air pollution concentrations

The association between the dependent variable (the Q-index for a concentration range of an air pollutant) and the independent variable (the concentration range of the air pollutant) was calculated using the linear regression model, which is the accurate and basic tool to evaluate the correlation between variables and relevant responses. The coefficient of determination, $R^2$, and P-value were used in this regression analysis to determine whether or not the mathematical relationship between the dependent and independent variables is statistically significant.

3. Results

3.1. Concentration of the air pollutants

Descriptive statistics were performed on the average concentrations of air pollutants at all monitoring stations for both the long-term and
short-term periods. Table 1 and Table 2 are the results of descriptive statistics for long-term and short-term periods, respectively. The mean concentrations of NO, NO$_2$, and NOx were 59.5, 47.73, and 107.02 ppb, respectively, for the long term. They were 31.10, 41.45, and 72.47 ppb, respectively, for the short-term period (Tables 1 and 2). The majority (>95%) of the long term observed CO and O$_3$ concentrations were below 1.7 ppm (ranging from 1.26 to 2.31 ppm), and 20 ppb (ranging from 14.94 to 26.01 ppb), respectively. The long-term average concentrations of PM$_{10}$, PM$_{2.5}$, and SO$_2$ were 75.44 μg m$^{-3}$, 29.24 μg m$^{-3}$, and 5.77 ppb, respectively (Table 1). The short-term average concentrations of PM$_{10}$ and PM$_{2.5}$ were 62.14 μg m$^{-3}$ (ranging from 46.50 to 81.67 μg m$^{-3}$) and 23.68 μg m$^{-3}$ (ranging from 17.17 to 29.02 μg m$^{-3}$), respectively (Table 2).

Tables 1 and 2 include the results of the Kolmogorov-Smirnov test for determining data normality. The p-values of the Kolmogorov–Smirnov test for NO, NO$_2$, NOx, CO, PM$_{10}$, PM$_{2.5}$, O$_3$ and SO$_2$ pollutants were 0.74, 0.57, 0.63, 1.18, 0.52, 0.73, 0.95 and 0.75 respectively. The results indicated that all pollutant data, both long and short term, are normal. When applying the Kolmogorov-Smirnov test to determine the normality of the data, the variables can be considered normal if the significance level is higher than 0.05.

### 3.2. Performance of interpolation models

Table 3 compares the performance of the two interpolation models (RBF and IDW) that were used to create the concentration surfaces for NO, NO$_2$, NOx, CO, PM$_{10}$, PM$_{2.5}$, O$_3$ and SO$_2$ for both the 60-month and 6-month periods. For both long-term and short-term average concentrations, IDW model had higher R$^2$ values and lower RMSE than RBF model for CO, SO$_2$, NO$_2$, NOx and O$_3$. On the country, RBD model exhibited higher R$^2$ values and lower RMSE than IDW model for PM$_{2.5}$, PM$_{10}$ and NO. Thus, the interpolation results from the IDW model were used to represent the concentration surfaces of CO, SO$_2$, NO$_2$, NOx and O$_3$, while the results from the RBF model were used as the concentration surfaces of PM$_{2.5}$, PM$_{10}$ and NO.

### 3.3. Correlation between air pollutants and COVID-19

The concentration surface maps of air pollutants created using interpolation models for the periods of 6 and 60 months are depicted in Fig. 5. For CO, the concentration of 0.88 ppm had the largest area (19565.74 ha) in the 6-month period, while that of 2.36 ppm occupied the largest area (15886.1 ha) in the 60-month period. For ozone, the concentrations of 26.15 and 21.10 ppb occupied the largest areas, which were 14719.39 and 21096.60 ha, respectively, for the 6-month and 60-month periods. The maximum and minimum areas of each concentration range for other pollutant are showed in Table 4.

Table 5 shows the R$^2$'s of the regression model on the Q index and the concentration of each air pollutant for both 6-month and 60-months periods. The graph of the correlation between the Q index and the concentration of each air pollutant, and the equation of each regression model were included in Fig. 5. As shown from the graphs, all the relationships between Q-index and air pollutant concentration were positive, except O$_3$, which means that higher COVID-19 instance rates were associated with higher concentrations of most air pollutants for both short- and long-term periods in the study area. Based on the R$^2$ and p-value in the regression model of Q-index and the concentration of each air pollutant, in general, pollutant effects can be categorized into three groups. The 1st group is CO, NO, and NOx, which had significant...
relationships with the COVID-19 incidence rate in the short-term (6 months) period with P-value of 0.032, 0.000, and 0.001 respectively. The R² for CO, NO, and NOx were 0.503, 0.863, and 0.789, respectively, for the short-term period, and 0.287, 0.342, and 0.284, respectively, for the long-term period. The 2nd group is PM₂.₅, which had a significant relationship (P-value = 0.003) with the COVID-19 incidence rate only in long-term period, with the R² of 0.724. The third group includes NO₂, SO₂, PM₁₀, and O₃, which didn’t have significant relationships with the COVID-19 incidence rate for either short-term or long-term periods. The deposition of PM₁₀ particles in the air due to long-term deposition is one of the possible causes that this pollutant couldn’t effect the incidence rate in long term. Figs. 4–11 depict the concentration surface map of each air pollutant and the relationship between Q-index and the concentration of each air pollutant for both long-term and short-term periods in TMA.

4. Discussion

We investigated the association between ambient air pollution and COVID-19 confirmed cases using interpolation methods for mapping air pollutants and COVID-19 distribution. The results indicated that the elevated concentrations of pollutants in the long and short term were associated with a rise in the incidence of COVID-19, while the greatest rise occurring at the highest levels of pollutant concentrations. Increased PM₂.₅, CO, NOx, and NO concentrations were strongly correlated to COVID-19 infection cases, while high levels of NO₂, PM₁₀, SO₂, and O₃ pollutants were not linked to the number of confirmed cases or COVID-19 spread. Endogenous NO, and NOx are known to inhibit respiratory syncytial virus (RSV) replication in the lungs, hence inhaled nitrogen oxide may promote RSV replication by lowering endogenous nitrogen oxide synthesis (Hobson and Everard 2008; Travaglio et al., 2020). Although no comparable replicating mechanism for SARS-CoV-2 has been revealed, it’s tempting to suppose that this process could explain the reported link between rising ambient nitrogen NO, and NOx levels and SARS-CoV-2 spread (Travaglio et al., 2020).

In general, the effect of pollutants on the disease’s spread could be related to one of two hypotheses. One is the long-term interaction between pollutant concentrations and the immune system. The results from previous studies showed that there were direct relationships between COVID-19 and air pollutants (Frontera et al., 2020). Inhaled PM₂.₅ or PM₁₀, SO₂, NO₂, CO, and O₃ could cause higher infection rates (Frontera et al., 2020). Levels of PM₂.₅, PM₁₀, CO, NO, and NOx in the environment can influence the spread and intensity of various viruses. People over 60 and those with a history of underlying diseases, such as cardiovascular disease, diabetes, chronic respiratory disease, or cancer, have a higher chance of severe disease and mortality (Travaglio et al., 2020). Long-term exposure to contaminants in the air exacerbates the disease (Wu et al., 2020). Prolonged exposure to pollutants can significantly exacerbate cardiovascular complications, respiratory disease, and asthma (Balmes 2014). Thus, the results from the current study that the long-term concentrations of PM₂.₅ had significant effects on COVID-19 cases support this hypothesis. This study indicates that long-term air pollution exposure is connected to an increased risk of COVID-19 outbreak and could give proof that air pollution plays a role in COVID-19 infection.

The other hypothesis is that viruses spread via airborne transmission.
The impact of air pollutants on the number of SARS-CoV-2 virus infections and deaths caused by airborne transmission of the virus or exacerbation of respiratory diseases, heart disease, etc. due to these pollutants were evidenced by some other studies (Booth et al., 2005; Morawska and Cao 2020; Morawska et al., 2009; Olsen et al., 2003). Because COVID-19 is a respiratory disease and the SARS-CoV-2 virus can live in the aerosol for hours, carrying the virus as a contaminant and spreading COVID-19 is not unusual. The results from this study that COVID-19 incidence rate was significantly associated with the short-term concentrations of CO, NO and NOx confirm this hypothesis.

Previous studies also showed that there is a statistically significant relationship between air pollution and COVID-19 (Cai et al., 2007; Travaglio et al., 2020; Wu et al., 2020; Yongjian et al., 2020). The relationships between COVID-19 cases and the short-term concentrations of CO, NO, and NOx found in this study are consistent with those from a study in China by Zhu et al. (2020). They found that short-term exposure to high concentrations of PM2.5, PM10, CO, NO and O3 was associated with an increased risk of COVID-19 (Yongjian et al., 2020). These findings were consistent with previous studies, indicating that there was a correlation between air pollution and the COVID-19 incidence. Long-term or short-term exposure to higher levels of PM2.5, CO, NO and NOx has been linked to an increased risk of a COVID-19 epidemic. This study confirmed the two hypotheses on the effect of pollutants on the spread of diseases: the long-term interaction between pollutant concentrations and the immune system, and viruses spread via airborne transmission. The positive associations between concentrations of air pollutants and COVID-19 cases

5. Conclusion

This study analyzed the relationships between COVID-19 cases and both short-term (6-month) and long-term (60-month) exposure to eight air pollutants (NO, NO2, NOx, CO, SO2, O3, PM2.5 and PM10) in Tehran city, Iran by integrating geostatistical interpolation models, regression analysis, and an innovated COVID-19 incidence rate calculation, namely, Q-index, that considered the spatial distribution of both population and air pollution.
show that environmentally friendly policy and air pollution regulations focused at reducing air pollution and protection of human health should be promoted in order to restrict the spread of infectious diseases like COVID-19. It is recommended that more extensive research, including long-term cross-country studies that take into account socioeconomic level, age, regional differences, and other factors, be done in the most impacted nations to fight against COVID-19. The Q-index calculation method developed in this study considers the spatial distributions in population and air pollution across the different parts of the study area can provide a more accurate estimate of air pollution exposures, which can be used to study not only COVID-19 in other areas but also other diseases in general.

Authors’ contributions

Davood Namdar khojasteh and Bijan Yeganeh conceived the idea and designed the experiment. Farzaneh Namdar Khojasteh and Ali Maher performed the experiment. Davood Namdar khojasteh analyzed the data. Davood Namdar Khojasteh, Bijan Yeganeh and Jun Tu wrote the manuscript. Davood Namdar Khojasteh and Jun Tu revised the manuscript. All authors read and approved the final draft.

Ethics approval

Not applicable.

Data availability

This study used daily data for air pollutants and COVID-19. The data that support the plots and other findings of this study are available from the corresponding authors upon request.

Code availability

The code to carry out the current analyses is available from the corresponding authors upon request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Fig. 10. Correlation between PM10 concentration for 6 and 60 months with COVID-19.
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