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Spatial sensitivity analysis of COVID-19 infections concerning the satellite-based four air pollutants levels

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Abstract

The novel coronavirus (COVID-19), first reported in late December 2019, has affected the lives of many people throughout the world. Significant studies have been conducted on this pandemic, some of which have addressed understanding the relationship between different air pollutants and confirmed cases. In this study, the effects of four air pollutants (carbon monoxide, nitrogen dioxide, ozone, and sulfur dioxide) were assessed from February 19 to March 22, 2020 to explore how they can affect COVID-19 contagion in Iran. The mean concentrations of air pollutants were extracted from Sentinel 5P data. The COVID-19 confirmed case densities of two provinces, Semnan and Qom, were more than all other provinces. The effect of pollutants on the confirmed case densities was analyzed using multiple linear regression in order to estimate the impact coefficients for individual provinces. The impact coefficients determine the level of each pollutant's contribution to the density of total confirmed cases. Carbon monoxide, nitrogen dioxide, sulfur dioxide, and ozone had both considerable negative and positive correlations with the density of confirmed COVID-19 cases, although sulfur dioxide was correlated more negatively than positively. In Semnan, a high hot spot province, nitrogen dioxide had the most significant effect on the density of confirmed cases among all pollutants, while the effect of carbon monoxide was greater in Qom. The results indicated that even short-term exposure to higher concentrations of the pollutants could lead to an increased risk of COVID-19 outbreaks, which should be considered in adopting adequate and appropriate control policies to manage the disease.

Keywords Air pollutants · Confirmed cases · Impact coefficient · Iran · Sentinel-5P

Introduction

The newly discovered coronavirus COVID-19 was first observed in Wuhan City, Hubei Province, China in late December 2019 (Ahmadi et al. 2020; Jahangiri et al. 2020; Lu et al. 2020; Xu et al. 2020; Yongjian et al. 2020). The coronavirus spread rapidly in just a few days out of China's boundaries and spread to almost all countries of the world (Chen et al. 2020; Jahangiri et al. 2020; Lu et al. 2020; Ogen 2020; Phan et al. 2020; WHO 2020b; Xu et al. 2020). Data from the World Health Organization (WHO) show that from February 19, 2020 to March 22, 2020, 257,182 new coronavirus cases were identified worldwide, and globally confirmed cases reached almost 333 thousand, with 14,509 deaths (WHO 2020a, c). In the same period, throughout Iran's provinces, 21,638 COVID-19 cases have been confirmed, including 1682 deaths (https://www.behdasht.gov.ir). Symptoms of fever, dry cough, and sore throat have been observed in many infected patients (Huang et al. 2020; Jiang et al. 2020; Ogen 2020; Sohrabi et al. 2020; Yongjian et al. 2020), and in some cases, a severe acute respiratory syndrome was observed which led to death (Chen et al. 2020; Guo et al. 2020; Mehta et al. 2020; Rodriguez-Morales et al. 2020; Sohrabi et al. 2020). Therefore, to determine the role of the most significant factors affecting COVID-19 contagion in urban areas, especially in megacities, multiple studies have been conducted (Bontempi 2020; Chan et al. 2020; Domingo and Rovira 2020; Li et al. 2020; Rastogi et al.

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2020; Wang et al. 2020a). Many factors, including climatic parameters such as temperature and relative humidity (Zhu and Xie 2020), population density (Kraemer et al. 2020), and quality of medical care (Wang et al. 2020b) affect the virus's transmission. To pursue the matter further, the impact of short-term exposure to air pollutants should be particularly considered (Bashir et al. 2020).

Many studies have shown that ambient air pollutants have adverse effects on the human respiratory system, and have reported that chronic respiratory illnesses can also be caused by long-term exposure to major air pollutants (Becker and Soukup 1999; Cai et al. 2007; Chauhan and Johnston 2003; Chen et al. 2007; Ciencewicki and Jaspers 2007; Horne et al. 2018; Mehta et al. 2013; Phosri et al. 2019; Xie et al. 2019; Xu et al. 2016). Carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), and sulfur dioxide (SO_2) are significant harmful ambient air pollutants in many urban regions. The risk of adverse cardiopulmonary events, including death, can be increased by continuous exposure to CO (Chen et al. 2007). High concentrations of NO_2, as a highly reactive gas produced during combustion, cause catastrophic injury to the human lung (Beelen et al. 2008; Chen et al. 2007; Hoek et al. 2013). NO_2 also contributes to the formation of some harmful secondary air pollutants such as O_3 (Khoder 2002). Tropospheric O_3 levels harm public health in areas throughout the world. Many studies have shown that respiratory irritation and decreased lung function from damaged lung tissue, causing pulmonary and heart disease, are caused by short-term exposure to high levels of O_3 (Bell et al. 2004; Filippidou and Koukouliata 2011; Gryparis et al. 2004; Parodi et al. 2005). SO_2 can also lead to respiratory

problems, especially in patients with pulmonary underlying disease (Smith et al. 1977).

COVID-19 can disperse in aerosol form and remain viable for hours in ambient air (Van Doremalen et al. 2020). Hence, a tangible understanding of the impact of ambient air pollutants on the novel coronavirus infection seems necessary. This study aims to assess the relationship between the satellite-based concentrations of four air pollutants and COVID-19 cases in 31 provinces in Iran by combining two databases: the tropospheric concentration of four air pollutants (i.e., CO, NO_2, O_3, and SO_2) and the number of confirmed cases between February 19 to March 22, 2020. As well, the impact coefficients of each pollutant are introduced separately for Iran's provinces, and the most vulnerable provinces are determined. Finally, discussion and concluding remarks are provided.

Materials and methods

Study area

The Islamic Republic of Iran, with over 80 million inhabitants and an area of 1648,195 km^2, is located in western Asia in a transcontinental region, i.e., the Middle East. Iran lies within latitudes 24° and 40°N and longitudes 44° and 64°E. It consists of 31 provinces with a wide range of population densities (Fig. 1). The climate in Iran is classed as between arid and semiarid. Topography, meteorological conditions, and emissions from mobile and stationary sources

Fig. 1 Population densities (ratios of population size to area) in Iran's provinces
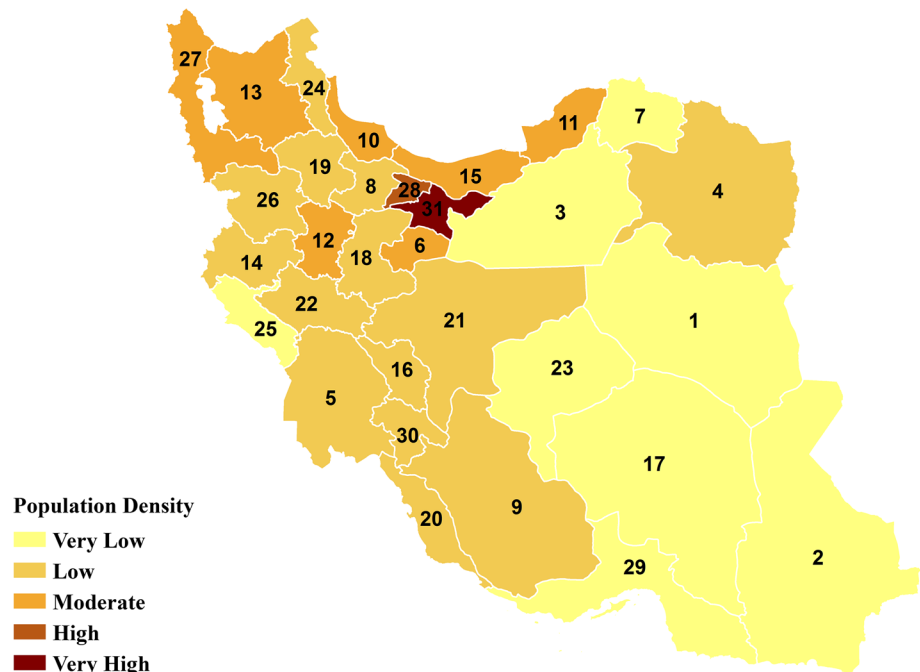
in many megacities in Iran contribute to poor air quality on many days of the year.

Data collection

The daily numbers of coronavirus cases for each province were collected from the official website of the Ministry of Health and Medical Education (https://www.behdasht.gov. ir). The provincial population sizes were obtained from the Statistical Center of Iran (SCI) (https://www.amar.org.ir). It should be noted that the number of cases in each province is only reported from February 19, as the starting point of the outbreak in Iran, to March 22, 2020, as shown in Table 1. The maximum numbers of confirmed cases are in Tehran, Isfahan, and Mazandaran provinces, while the minimum numbers of confirmed cases belong to Bushehr,

Chaharmahal and Bakhtiari, and Kohgiluyeh and Boyer-Ahmad provinces.

Satellite-based data can be used for monitoring air quality and performing health research (Omrani et al. 2020; Putrenko and Pashynska 2017). To obtain the daily tropospheric concentrations of CO, NO_2, O_3, and SO_2 from the surface up to ~ 10 km, satellite data were extracted from the Sentinel-5P Pre-Operations Data Hub (https://s5phu b.copernicus.eu/). The Sentinel-5P, a satellite with a spectral resolution of 0.25–0.55 nm and global daily coverage of 7×7 km^2, is an Earth-observation satellite. It was developed and launched in October 2017 by the European Commission under the "Copernicus" Program. The satellite carries a TROPOspheric Monitoring Instrument (TROPOMI) that provides a 3.5×7 km^2 spatial resolution of the measurements for all trace gases, except for CO, which has a

Table 1 Statistical data from February 19 to March 22, 2020

No.	Province	Total confirmed COVID-19 cases	Population	Average concentration			
				CO (mmol/m^2)	NO$_2$ (μmol/m^2)	O$_3$ (mmol/m^2)	SO$_2$ (mmol/m^2)
1	South Khorasan	178	768,898	0.58	11.66	0.71	0.40
2	Sistan and Balouchestan	134	2,775,014	1.02	13.16	0.59	0.57
3	Semnan	645	702,360	0.88	12.58	0.65	0.53
4	Razavi Khorasan	858	6,434,501	1.12	12.92	0.64	0.66
5	Khuzestan	444	4,710,509	0.79	12.39	0.67	0.48
6	Qom	1178	1,292,283	0.96	13.12	0.61	0.62
7	North Khorasan	165	863,092	0.98	12.78	0.63	0.65
8	Qazvin	669	1,273,761	0.65	11.78	0.72	0.44
9	Fars	505	4,851,274	1.09	13.02	0.61	0.61
10	Gilan	1191	2,530,696	0.79	12.16	0.66	0.48
11	Golestan	391	1,868,619	1.05	13.42	0.64	0.63
12	Hamedan	175	1,758,268	0.96	13.75	0.62	0.63
13	East Azerbaijan	813	3,909,652	1.11	12.62	0.61	0.57
14	Kermanshah	243	1,952,434	1.02	12.91	0.61	0.52
15	Mazandaran	1700	3,283,582	0.84	12.82	0.67	0.55
16	Chaharmahal and Bakhtiari	68	947,763	1.07	12.81	0.60	0.61
17	Kerman	169	3,164,718	1.09	13.64	0.61	0.57
18	Markazi	882	1,429,475	1.10	13.60	0.62	0.64
19	Zanjan	394	1,057,461	1.02	13.42	0.61	0.60
20	Bushehr	55	1,163,400	0.67	11.66	0.68	0.48
21	Isfahan	1979	5,120,850	0.94	12.52	0.64	0.52
22	Lorestan	476	1,760,649	0.92	13.08	0.62	0.60
23	Yazd	725	1,138,533	0.89	12.37	0.63	0.53
24	Ardabil	289	1,270,420	1.09	13.35	0.61	0.57
25	Ilam	183	580,158	1.07	12.84	0.63	0.62
26	Kordestan	238	1,603,011	0.70	11.90	0.69	0.49
27	West Azerbaijan	395	3,265,219	0.94	12.84	0.60	0.61
28	Alborz	1177	2,712,400	1.11	12.39	0.62	0.58
29	Hormozgan	148	1,776,415	0.79	12.34	0.66	0.47
30	Kohgiluyeh and Boyer-Ahmad	73	713,052	0.70	11.57	0.67	0.48
31	Tehran	5098	13,267,637	0.73	11.97	0.67	0.47

7×7 km^2 spatial resolution. In this study, Level 2 geophysical products were collected using "wget," which is a computer program that retrieves content from web servers (https://scihub.copernicus.eu/userguide/BatchScripting).

Daily air pollutant data in a netCDF format were used for both spatial and temporal observations. Since TROPOMI measurements have a varied spatial distribution of grid cells and depend on the viewing zenith angle in every orbit at the moment of observation, each product was resampled for the study area on the regular grid with the same spatial resolution. The dataset was re-projected by latitude/longitude WGS84 using R statistical software (version 3.6.3) (Omrani et al. 2020). Some factors such as cloud cover, saturation, and geometry affect the data quality of individual observations. Therefore, to rectify errors and incomplete retrievals, the data were cleaned using a quality assurance value marked by a 'qa_value' which ranges between 0 (no data) and 1 (full data). Measurements with a 'qa_value' above 0.5 provided by TROPOMI were used, and outliers were eliminated based on Copernicus specifications (Copernicus 2019). For further analysis, spatial assessment of the air pollutant density was done by separately using the monthly raw data for the mean concentrations of each pollutant for all provinces, which was processed by a Python code. Table 1 shows the statistics for the satellite-based mean concentrations of the four air pollutants in each province during the observation period. The mean concentration values for CO, NO$_2$, O$_3$, and SO$_2$ varied between 0.58 and 1.12 mmol/m^2, 11.57 and 13.75 µmol/m^2, 0.59 and 0.72 mmol/m^2, and 0.40 and 0.66 mmol/m^2, respectively.

Multiple linear regression

In this study multiple linear regression (MLR) (İçağa and Sabah 2009; Ng and Awang 2018; Sousa et al. 2007; Ul-Saufie et al. 2012) was used to determine the relationship between daily COVID-19 confirmed cases density (CCD) and the average concentrations of the four criteria air pollutants (i.e., CO, NO$_2$, O$_3$, and SO$_2$). CCD is obtained by dividing the number of total confirmed cases by the population size. The basic model using the least square method was defined as follows:

$$N_{CCD} = aC_{CO} + bC_{NO_2} + cC_{O_3} + dC_{SO_2} \quad (1)$$

where N_{CCD} indicates the normalized CCD, , b, c, and d are the impact coefficients of CO, NO$_2$, O$_3$, and SO$_2$, respectively. C_{CO}, C_{NO2}, C_{O3}, and C_{SO2} indicate the daily normalized average concentrations of CO, NO$_2$, O$_3$, and SO$_2$, respectively. The normalized values were obtained by dividing the difference between the daily and the average values by the standard deviations of their daily values.

The above four air pollutants collectively covered 83,624 grid cells over Iran. The impact coefficients determine the contribution level of each pollutant to the occurrence of COVID-19 infections. These coefficients vary between −1 and 1 to, respectively, indicate relative decreasing and increasing effects.

Results and discussion

Results

Descriptive analysis

The spatial distribution of CCD is shown in Fig. 2. Mapping the CCD over Iran revealed major COVID-19 'hotspots' in Semnan and Qom (which include nearly 9% of all confirmed cases). Aside from these two provinces, nine other provinces located close to the center of Iran had high CCDs and collectively included 64% of all cases. In contrast, five southern provinces, particularly Bushehr and Sistan and Balouchestan, had the lowest CCDs due to their lower case numbers and populations.

The provincial mean concentrations of CO, NO$_2$, O$_3$, and SO$_2$ and the corresponding CCDs are shown in Fig. 3. The mean CO concentrations in 13 provinces which collectively included more than 63% of all cases were over 1 mmol/m^2. The mean NO$_2$ concentrations were higher than 13 µmol/m^2 for 10 provinces which collectively included 58% of all cases. The average O$_3$ concentrations in 11 provinces which collectively included 20% of total cases were more than 0.65 mmol/m^2, and 12 provinces with average SO$_2$ concentrations over 0.6 mmol/m^2 encompassed 55% of confirmed cases. It should be noted that Semnan and Qom had both high CCDs and high concentrations of the four pollutants. Moreover, three provinces which collectively included 4% of total confirmed cases had mean CO concentrations lower than 0.7 mmol/m^2. Six provinces had average NO$_2$ concentrations lower than 12 µmol/m^2 and collectively included 5% of all confirmed cases. The mean O$_3$ concentrations were less than 0.6 mmol/m^2 for two provinces that together encompassed only 3% of all confirmed cases. There were also two provinces with average SO$_2$ concentrations lower than 0.45 mmol/m^2 that included only one percent of total confirmed cases.

Air pollutant impact coefficients

The spatial distribution of the four impact coefficients a, b, c, and d, corresponding to CO, NO$_2$, O$_3$, and SO$_2$, respectively, are shown in Fig. 4. The results show that the impact

Fig. 2 Confirmed COVID-19 Case Densities (CCD) from February 19 to March 22, 2020
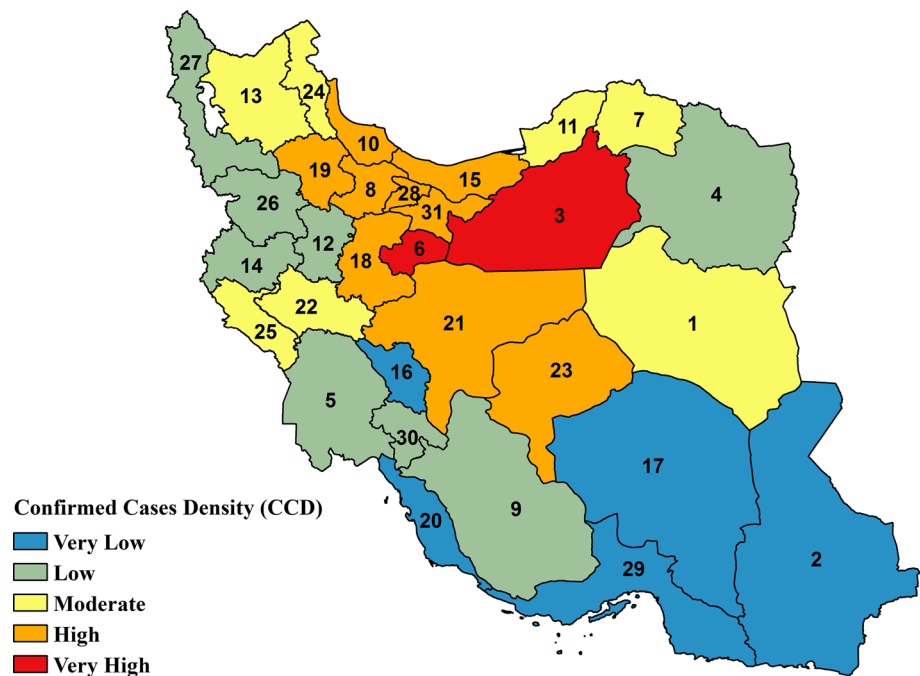
coefficients *a*, *b*, *c*, and *d* varied between −0.4 and 0.6, −0.3 and 0.8, −0.5 and 0.6, and −0.6 and 0.8, respectively. There were five provinces with *a* coefficients higher than 0.4, with Tehran having the largest value, and nine provinces with *a* coefficients smaller than −0.2, with South Khorasan having the lowest. The impact coefficient *b* was larger than 0.4 for seven provinces and smaller than 0 for nine provinces, with Golestan having the highest and North Khorasan having the lowest. The impact coefficient *c* was over 0.4 for four provinces and less than −0.25 for five provinces, of which Kohgiluyeh and Boyer-Ahmad had the highest and Markazi the lowest. The impact coefficient *d* was larger than 0.4 for four provinces, of which Chaharmahal and Bakhtiari had the highest, and smaller than −0.2 for four provinces, of which Golestan had the lowest. Also, the provinces with the highest *a*, *b*, *c*, and *d* coefficients had over 31%, 13%, 3%, and 3% of all confirmed cases, respectively. Conversely, the provinces with the lowest *a*, *b*, *c*, and *d* coefficients had over 22%, 37%, 33%, and 9% of total confirmed cases, respectively.
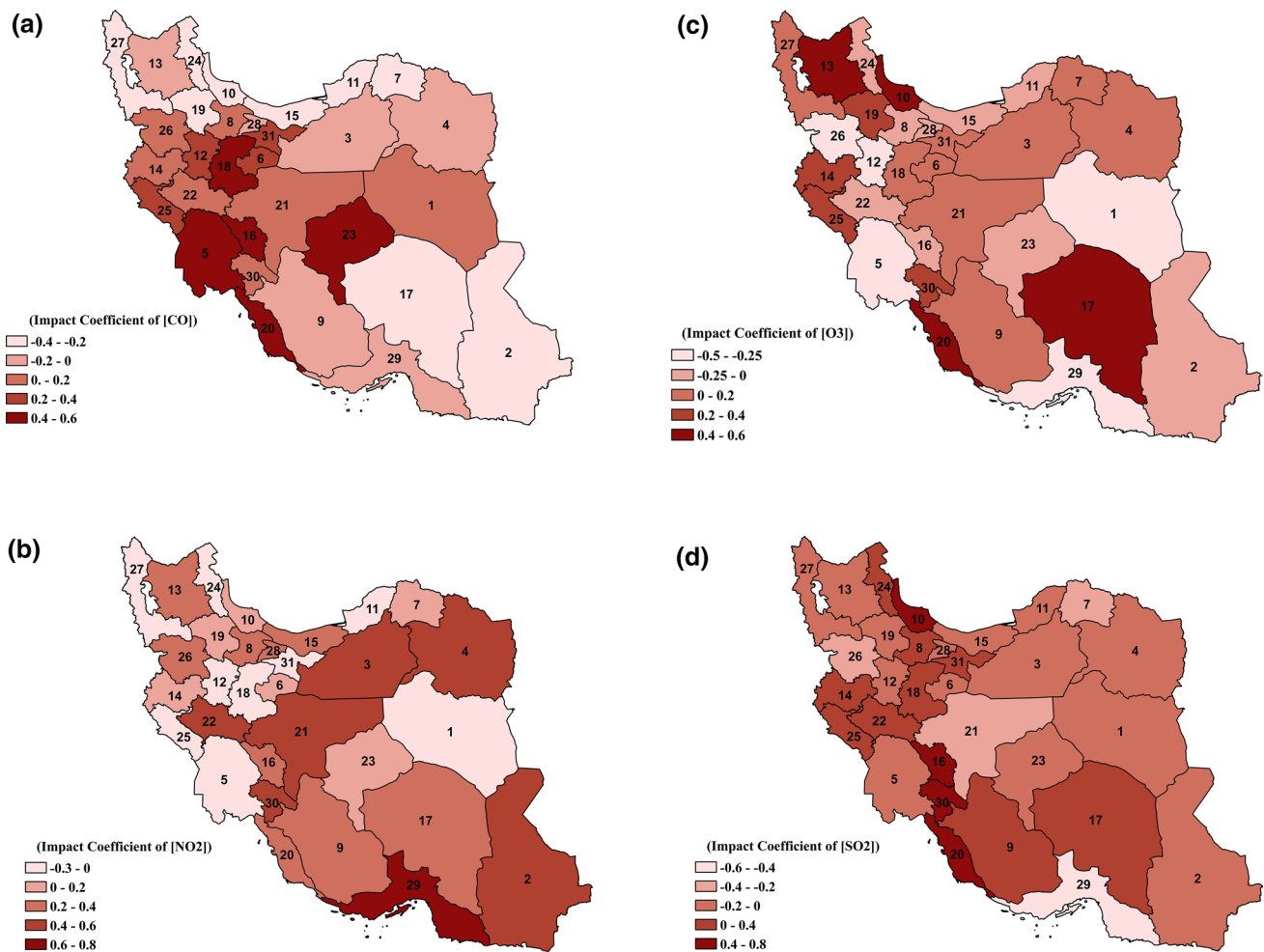
Sensitivity analysis

In order to perform a provincial sensitivity analysis and to figure out the different effects of the impact coefficients on each province, the influences of each impact coefficient on the density of confirmed COVID-19 cases along with the CCDs are shown in Fig. 5. Each province had different impact coefficients during the study period. Accordingly, the absolute (regardless of positive or negative sign) value of the impact coefficient *a* was higher than other coefficients in 10 provinces which included 51% of all confirmed cases. The

absolute values of the impact coefficient *b* outnumbered the other three coefficients in 10 provinces which collectively included 32% of total confirmed cases, while the impact coefficient *c* had the highest absolute value among the other coefficients in eight provinces that collectively encompassed 15% of all confirmed cases. Among the four impact coefficients, the absolute value of coefficient *d* was highest in merely three provinces that collectively included 2% of confirmed cases. However, in comparison with the other coefficients, the absolute value of impact coefficient *a* was lowest in only five provinces that collectively had 11% of all cases. The absolute value of impact coefficient *b* was lower than all other coefficients in seven provinces which collectively had 14% of total cases. The impact coefficient *c* had the lowest value compared with the other coefficients in 12 provinces which collectively had 41% of all confirmed cases. The absolute value of coefficient *d* was lowest in seven provinces which collectively had 34% of total confirmed cases compared with the other impact coefficients. Therefore, the overall trend of the four impact coefficients was such that the absolute values of the coefficients *a*, *b* and *d*, and *c* were significant in many provinces, respectively. It should be noted that the impact coefficients had negative or positive associations in various provinces. Positive values imply relative increasing effect, while negative values indicate a relative decreasing impact on the density of COVID-19 confirmed cases. Among all provinces, the impact coefficients *a*, *b*, *c*, and *d* had a positive correlation in 16, 22, 17, and 13 provinces, respectively.

The value of impact coefficient *a* outnumbered the other coefficients' values, regardless of positive or negative

Fig. 3 Average provincial air pollutant concentrations vs. CCDs from February 19 to March 22, 2020

Fig. 4 Impact coefficients for: **a** CO, **b** NO$_2$, **c** O$_3$, and **d** SO$_2$ during February 19 to March 22, 2020

influences, in Qom, Yazd, and Markazi as the three regions with high CCDs. Exceptionally, in Semnan, which had the highest CCD, the value of impact coefficient *b* was larger than that of *a*.

Discussion

The results of the investigation into the COVID-19 outbreak in Iran's provinces show that provinces such as Semnan, Qom, Yazd, and Markazi had the highest CCDs and means that such provinces are affected more than others by the novel coronavirus considering their population sizes. Based on the results, it seems that restricting movement and following health instructions should be considered more in these provinces. In addition, provinces located mostly in the center and northern center of Iran with significant population densities had relatively high CCDs. Among these provinces, Tehran, with the largest population, is reckoned to have a potential for COVID-19 infection that may lead to a critical situation unless strict health

regulations are put in place. Given that pollutant levels have a prominent role in the virus outbreak, emissions reductions might be a useful approach to control the infection in these provinces. Therefore, some decisions such as setting low-emission zones to reduce daily commutes, prohibiting heavy-duty vehicles entry to high-risk regions, and limiting the work hours of power plants and refineries should be taken. The results reveal that air pollutant levels were influential in the period of the disease outbreak. The mean concentration of CO was high in 13 out of 31 provinces implying that there are more cases in areas with higher concentrations of CO, and a similar trend for NO$_2$ can be observed. Unlike CO and NO$_2$, O$_3$ had a somewhat different trend. Given the results, southern provinces that had lower CCDs were exposed to higher concentrations of O$_3$ during the study period, even though it should be mentioned that the COVID-19 outbreak was assessed in the winter when surface ozone was more likely to have been destroyed by nitrogen oxides. Similar to CO and NO$_2$, mean SO$_2$ concentrations were significant in provinces. This shows that high-risk provinces were subjected to more SO$_2$ pollution. It can be concluded

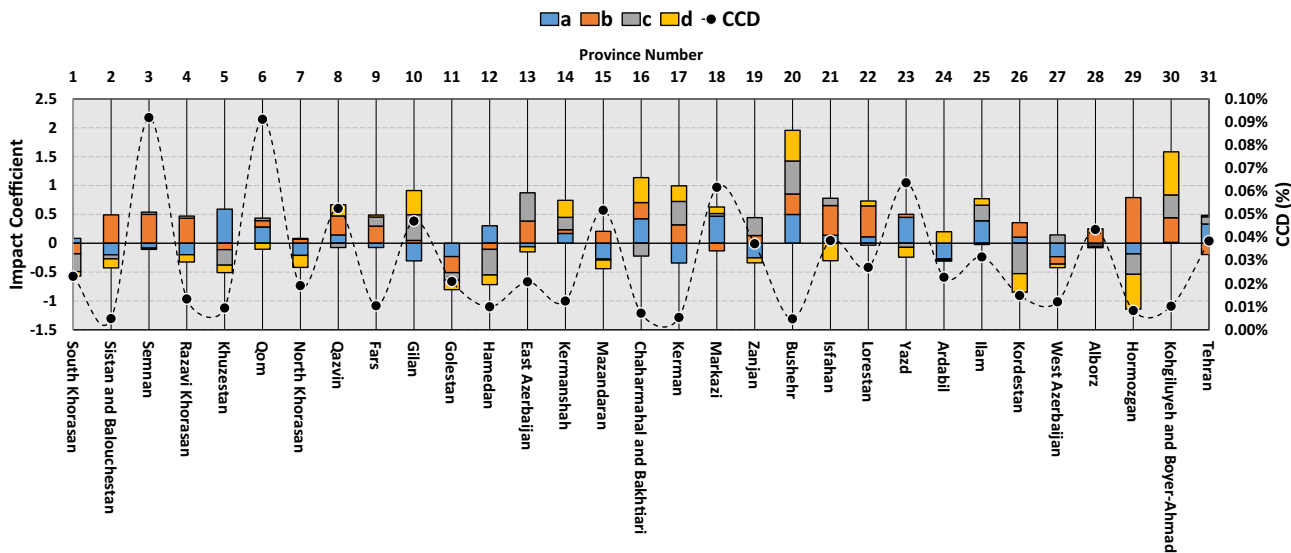| Name	COVID19	CO (mmol/m2)	NO2 (umol/m2)	O3 (mmol/m2)	SO2 (mmol/m2)	a	b	c	d	Population (1395)	ratio
South Khorasan	178	0.843402092	12.81957261	0.671459546	0.549459018	0.0845	-0.1837	-0.3087	-0.0775	7,68,898	0.02%
Sistan and Balouchestan	134	0.645141308	11.77535592	0.717159546	0.442017496	-0.2007	0.4914	-0.0693	-0.1579	27,75,014	0.00%
Semnan	645	1.097999089	13.59752796	0.616532863	0.640306855	-0.0844	0.4996	0.0394	-0.0225	7,02,360	0.09%
Razavi Khorasan	858	1.048686493	13.42272477	0.636702392	0.626960257	-0.1995	0.4336	0.0361	-0.1252	64,34,501	0.01%
Khuzestan	444	0.785950683	12.15551636	0.660160157	0.477222366	0.5907	-0.112	-0.2676	-0.1293	47,10,509	0.01%
Qom	1178	0.957029256	13.75052754	0.620171498	0.631176544	0.2813	0.1107	0.0422	-0.1035	12,92,283	0.09%
North Khorasan	165	1.120581691	12.92176778	0.637573284	0.664523162	-0.2105	0.0887	0.014	-0.2075	8,63,092	0.02%
Qazvin	669	1.09056845	13.35201472	0.605078735	0.56944606	0.1433	0.3303	-0.0743	0.1927	12,73,761	0.05%
Fars	505	0.671292001	11.66325148	0.676217623	0.48099684	-0.0744	0.2967	0.1577	0.0339	48,51,274	0.01%
Gilan	1191	1.109683487	12.391188	0.61566364	0.575348046	-0.3063	0.0495	0.4454	0.4172	25,30,696	0.05%
Golestan	391	0.984404898	12.78381184	0.627988216	0.651587258	-0.2309	-0.2775	-0.1314	-0.1651	18,68,619	0.02%
Hamedan	175	0.962793925	13.11628715	0.612551579	0.621046402	0.3027	-0.1064	-0.4441	-0.1655	17,58,268	0.01%
East Azerbaijan	813	1.113174014	12.62494096	0.610213228	0.56971877	-0.061	0.3848	0.4883	-0.0886	39,09,652	0.02%
Kermanshah	243	0.94319709	12.83915003	0.600575608	0.609763905	0.1684	0.0657	0.2141	0.2956	19,52,434	0.01%
Mazandaran	1700	1.090357712	13.01744898	0.61144979	0.610938863	-0.27	0.2055	-0.0203	-0.1497	32,83,582	0.05%
Chaharmahal and Bakhtiari	68	0.790850095	12.34272767	0.664824093	0.471659259	0.4248	0.2795	-0.222	0.4321	9,47,763	0.01%
Kerman	169	0.703246993	11.89882523	0.692521124	0.487571036	-0.3435	0.3191	0.4052	0.27	31,64,718	0.01%
Markazi	882	0.922441002	13.0806028	0.617578739	0.603949521	0.4683	-0.1325	0.046	0.1128	14,29,475	0.06%
Zanjan	394	1.022052695	12.90989478	0.605605444	0.52416552	-0.2537	0.1336	0.3094	-0.0858	10,57,461	0.04%
Bushehr	55	0.702966908	11.57375873	0.669806257	0.482325303	0.4983	0.3539	0.5714	0.532	11,63,400	0.00%
Isfahan	1979	0.878685838	12.57824595	0.651183039	0.525140976	0.1385	0.5144	0.1252	-0.303	51,20,850	0.04%
Lorestan	476	0.940045675	12.5181571	0.637914153	0.521362933	0.111	0.5355	-0.034	0.0843	17,60,649	0.03%
Yazd	725	0.788756297	12.38867593	0.669713761	0.47945652	0.4476	0.0543	-0.0718	-0.1702	11,38,533	0.06%
Ardabil	289	1.06675629	12.83981804	0.633380318	0.619927817	-0.2704	-0.0228	-0.0163	0.1985	12,70,420	0.02%
Ilam	183	0.887977917	12.36909472	0.63044621	0.530846337	0.388	-0.0222	-0.2702	0.1131	5,80,158	0.03%
Kordestan	238	1.018274875	13.16269609	0.592591684	0.565174686	0.1051	0.2514	-0.5262	-0.322	16,03,011	0.01%
West Azerbaijan	395	1.065620214	12.81350731	0.595760178	0.607825725	-0.2333	-0.1289	0.1431	-0.0603	32,65,219	0.01%
Alborz	1177	1.085294268	13.64410584	0.6128543	0.570429494	-0.0121	0.251	-0.0428	-0.023	27,12,400	0.04%
Hormozgan	148	0.584560843	11.66172061	0.705628048	0.403799802	-0.186	0.7899	-0.3525	-0.6034	17,76,415	0.01%
Kohgiluyeh and Boyer-Ahma	73	0.733424037	11.97335508	0.668265416	0.472128018	0.0149	0.4267	0.395	0.7462	7,13,052	0.01%
Tehran	5098	1.021066264	13.42103658	0.613583216	0.603947327	0.3337	-0.1965	0.1248	0.0256	1,32,67,637	0.04%

Fig. 5 Provincial impact coefficients

that provinces with larger CCDs, such as Semnan and Qom, had higher mean concentrations of almost all the pollutants.

In this study, significant negative and positive linear correlations have been found between the impact coefficients *a*, *b*, *d*, and *c* and confirmed COVID-19 cases. However, the impact coefficient *d* was correlated more negatively than positively with the density of confirmed cases among the provinces. These findings provide evidence that the air pollutants CO, NO_2, and O_3 unlike SO_2, mostly had relatively increasing rather than decreasing effects, even though all of them could be important contributing factors in COVID-19 infections.

Although almost all the air pollutants could be risk factors for the respiratory system, results demonstrated that impact coefficient *d* had more decreasing effects on COVID-19 cases. Thus, to figure out the effect of SO_2 precisely and comprehensively, additional research should be done. Based on the study results, in order to control COVID-19 infections, reducing emissions of CO, NO_2, and O_3 could be effective, especially in provinces that have experienced larger COVID-19 outbreaks. Meanwhile, further research is needed to understand the effect

of SO_2 on infections and to illuminate its correlation with confirmed COVID-19 cases.

The current study has several constraints. First of all, only the association between air pollutants and the density of COVID-19 cases was considered, and the results did not address the effects of air pollutants on the disease transmission rate. Second, no distinction was considered for the gender or ages of confirmed cases, nor was the presence of background diseases taken into account. Also, various features of pollutant emission sources were not considered in the data used. Furthermore, the results of this study are mainly focused on Iran, and subsequent studies are required to generalize the conclusions.

Conclusion

The COVID-19 pandemic has affected many countries throughout the world, including both developed and developing countries, since late December 2019. Iran has varied provincial population densities and many highly air-polluted

megacities that have different infection rates. Therefore, understanding the effects of major air pollutants on the spread of the virus is vital. Tehran, Isfahan, and Mazandaran provinces had the most COVID-19 confirmed cases, while Bushehr, Chaharmahal and Bakhtiari, and Kohgiluyeh and Boyer-Ahmad provinces had the least confirmed cases.

The COVID-19 CCDs showed that Semnan and Qom were affected by the virus more than other provinces. Nine central provinces had high CCDs, and collectively had 64% of all confirmed cases, while several southern provinces such as Bushehr and Sistan and Balouchestan had the lowest CCDs.

The Sentinel-5P data showed that the largest values of the mean concentrations of CO, NO_2, O_3, and SO_2 were measured in provinces, which had 63%, 58%, 20%, and 55% of all COVID-19 cases. This shows that short-term exposure to larger concentrations of these pollutants could be an important factor leading to an increase in the risk of COVID-19 infection.

Based on the results of modeling, there is a considerable statistical relationship between air pollutants and COVID-19 infection. The provinces with the largest values for the impact coefficients a, b, c, and d held over 31%, 13%, 3%, and 3% of all confirmed COVID-19 cases, while the provinces with the lowest coefficients for a, b, c, and d comprised over 22%, 37%, 33%, and 9% of total confirmed cases. The provincial sensitivity analysis demonstrated that the influences of each impact coefficient on the density of confirmed COVID-19 cases were different. Among all provinces, the impact coefficients a, b, c, and d had positive correlations, i.e., an increasing effect, in 16, 22, 17, and 13 provinces, respectively. The value of impact coefficient a was larger than that of the other coefficients in Qom, Yazd, and Markazi, which had high CCD values. This means that CO had the most significant effect on the density of confirmed cases. In Semnan, as a top hot spot province, the effect of NO_2 was greater than that of CO.

Since there is not yet any scientific reason which explains why SO_2 had a decreasing effect on the density of confirmed virus cases, conducting more studies to shed light on the underlying mechanisms seems to be necessary.

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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