The lock-down effects of COVID-19 on the air pollution indices in Iran and its neighbors

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ORIGINAL ARTICLE

Abstract

Introduction The COVID-19 restrictions have a lot of various peripheral negative and positive effects, like economic shocks and decreasing air pollution, respectively. Many studies showed NO2 reduction in most parts of the world.

Methods Iran and its land and maritime neighbors have about 7.4% of the world population and 6.3% and 5.8% of World COVID-19 cases and deaths, respectively. The air pollution indices of them such as CH4 (Methane), CO_1 (CO), H2O (Water), HCHO (Tropospheric Atmospheric Formaldehyde), NO2 (Nitrogen oxides), O3 (ozone), SO2 (Sulfur Dioxide), UVAI_AAI [UV Aerosol Index (UVAI)/Absorbing Aerosol Index (AAI)] are studied from the First quarter of 2019 to the fourth quarter of 2021 with Copernicus Sentinel 5 Precursor (S5P) satellite data set from Google Earth Engine. The outliers are detected based on the depth functions. We use a two-sample t test, Wilcoxon test, and interval-wise testing for functional data to control the familywise error rate.

Result The adjusted p value comparison between Q2 of 2019 and Q2 of 2020 in NO2 for almost all countries is statistically significant except Iraq, UAE, Bahrain, Qatar, and Kuwait. But, the CO and HCHO are not statistically significant in any country. Although CH4, O3, and UVAI_AAI are statistically significant for some countries. In the Q2 comparison for NO2 between 2020 and 2021, only Iran, Armenia, Turkey, UAE, and Saudi Arabia are statistically significant. However, CH4 is statistically significant for all countries except Azerbaijan.

Conclusions The comparison with and without adjusted p values declares the decreases in some air pollution in these countries.

Keywords COVID-19 · Air quality · NO2 · Aerosol index · Functional data analysis

Introduction

The restrictions have been conducted by governments in many aspects of everyday life such as transportation, education, etc. of citizens of many countries to control and stop the spreading of the COVID-19 pandemic since the first registered affected cases. (Hale et al. 2021) Therefore, the economic indices, income, savings, consumption and poverty have experienced shocks. The unemployment rate has increased. The welfare indices have been affected. These are only some of the negative impacts of lockdown policies, shutdowns, and business interruptions. (Chetty et al. 2020; Martin et al. 2020; Couch et al. 2020; Fuchs-Schündeln et al. 2022). On the other hand, one of its positive impacts on the environment is the air pollution reduction in most parts of the World. (Venter et al. 2020).

The decline and changes of NO2, PM_{2.5} and PM_{10} have been observed in many countries from the first to the mid of Q2 of 2020 (15-May-2020) (Venter et al. 2020; Xing et al. 2021; Bonardi et al. 2021) and most countries and regions have a lot of lock-down days in this period (Venter et al. 2020): Pakistan (Mehmood et al. 2021; Mehmood et al. 2021b; Khan 2021; Aslam et al. 2021), Afghanistan and India (Mishra and Kulshrestha 2021; Gautam et al. 2021), Turkmenistan (Zhang 2021), Azerbaijan (Bonardi et al. 2021), Armenia (Bonardi et al. 2021), Turkey (Ghasempour et al. 2021; Dursun et al. 2022), Iraq (Hashim et al. 2021; Hashim et al. 2021), Kazakhstan (Kerimray et al. 2020), Bahrain (Benchrif et al. 2021; Qaid et al. 2022), Kuwait (Halos et al. 2021), Oman (Bonardi et al. 2021),
Qatar (Mahmoud et al. 2022), Saudi Arabia (Ghanim 2021; Habeebullah et al. 2022; Anil and Alagha 2021; Morsy et al. 2021), UAE (Alqasemi et al. 2021; Teixidó et al. 2021; Alalawi et al. 2022; Shanableh et al. 2022), Asia (Baniasad et al. 2021) and Iran (Moazeni 2021; Broomandi et al. 2020; Keshkhtar 2022; Norouzi and Asadi 2022).

These restrictions have also effect on the air pollution indices in the highest producer of greenhouse gas regions such as China in PM$_{2.5}$ and NO$_2$ (Chen et al. 2020; He et al. 2021), South Korea in PM$_{2.5}$, PM$_{10}$, NO$_2$, and CO (Ju et al. 2020), the United States in PM$_{2.5}$ and NO$_2$ (Wu et al. 2020; Berman and Ebisu 2020) and Russia in a meteorological parameter that influence the air pollution indices (Shankar et al. 2021), Japan in NO, NO$_2$, PM$_{2.5}$, and SPM (Suspended Particulate Matter) (Azuma et al. 2020), Germany in NO$_2$, PM$_{2.5}$ and PM$_{10}$ (Copat et al. 2020), the UK in NOx about %50 reductions and increase in O$_3$ and SO$_2$ (Higham et al. 2021), South Korea in PM$_{2.5}$, PM$_{10}$, NO$_2$, and CO (Ju et al. 2021), Canada in NO$_2$, NOx and O$_3$ (Adams 2020) and five European countries including the United Kingdom, Spain, France, Sweden, and the Northern Italy in NO$_2$, PM$_{2.5}$ and PM$_{10}$ about 20–40% reduced (Skiriena and Stasiškiene 2021).

In this research, we study the air pollution changes with the Google Earth Engine (GEE) and COPERNICUS satellite for Iran and their maritime and land neighbors. In this regard, we provide descriptive statistics, a two sample $t$ test, Wilcoxon test, and a Functional Data Analysis (FDA)-based test that control the familywise error rate in the comparisons (Pini and Vantini 2016, 2017). We also study the pattern of the air pollution indices with the powerful method called Functional Principal Component Analysis (FPCA). There are different algorithms to estimate FPCA and we choose the principal analysis through the conditional expectation (PACE) algorithm. The main reason is its ability to deal with sparse functional observations. (Gajardo et al. 2022; Yao et al. 2005).

Materials and methods

Data gathering and management

In this research, we consider Iran and its neighboring countries. Iran has land borders with Pakistan and Afghanistan in the East, Turkmenistan in North East, Azerbaijan, Armenia, Turkey in the North West, and Iraq in the West. It has also maritime borders around the Caspian Sea in the north with Azerbaijan, Turkmenistan, Russia, and Kazakhstan, and around the Persian Gulf in the south with United Arab Emirates (UAE), Bahrain, Saudi Arabia, Oman, Qatar, Kuwait, and Iraq. We use two data set sources: (1) daily statistics for COVID-19 cases and deaths (Dong et al. 2020) and (2) air quality indices from Google Earth Engine (GEE) as described below.

We query in the GEE all the above countries (the shape files of each country are obtained from ArcGIS online ESRI (https://www.arcgis.com/apps/mapviewer/index.html)) separately from 2018–01-01 to 2022–05-01 (based on the data availability) and we download these air quality indices: (1) CH$_4$ (Averaged Dry Air Mixing Ratio of Methane), (2) CO$_1$ (Vertically integrated CO column density), (3) CO$_2$ (Water vapor column), (4) HCHO (Tropospheric Atmospheric Formaldehyde (HCHO) concentrations), (5) NO$_2$ (Nitrogen oxides), (6) O$_3$ (Ozone Concentrations), (7) SO$_2$ (Sulfur Dioxide), (8) UVAI_AAI (UV Aerosol Index (UVAI)/Absorbing Aerosol Index (AAI)) and it measures the prevalence of aerosols (main types are desert dust, biomass burning and volcanic ash plumes) in the atmosphere from COPERNICUS satellite and a weather condition index (9) Precipitation (Total Precipitation) from ECMWF satellite. The SO$_2$, HCHO, and NO$_2$ numbers product to 10,000 in the analysis. (https://earthengine.google.com/) (Supplementary 1-Tables A.1 and A.2).

We exclude Russia in this analysis, because its neighborhood with Iran proportion to its area is low and extracting a single index from a whole country is not representative of its aerial behavior near borders with Iran.

Statistical analysis

The statistical analysis has three parts: (1) comparing air pollution indices between countries with the parametric method, analysis of variance (ANOVA) and nonparametric method, Kruskal–Wallis Rank Sum test $p$ values and we draw the boxplots of them to see its variability and distributions. We also compare the spatial distribution of NO$_2$, CH4 and UVAI_AAI from GEE.

(2) Comparing air pollution indices group by countries with the parametric method two-sample $t$ test and nonparametric method two-sample Wilcoxon test in three different scenarios:(I) Q1 to Q4 between 2019 and 2020, (II) Q1 to Q4 between 2020 and 2021, and (III) Q1 to Q4 between 2019, 2020, and 2021. The most lock-down days in all countries occurred from mid to the end of Q1 and first to the mid of Q2 of 2020. Therefore, comparing the Q1 and Q2 between 2019, 2020 and 2021 estimate the statistical difference of lock-down effects on the air pollution indices. We also compare Q3 and Q4 of these years for the control group, because the lock-downs or restrictions are not very high in the Q3 and Q4 of 2020 and we assume they are normal days. The result is shown in the shiny app (: https://mohammadfayaz.shinyapps.io/Shiny_Code/) that is available with this research article. (Supplementary 2) (Sievert 2020).

(3) Functional data analysis: we have noticed from previous steps that there are some outliers in the data set. On
the other hand, the data sets are time-series and we do not consider their underlying structure of them and the correlations between points in the previous steps Therefore, first, we convert them to the functional data analysis (FDA), then outlier functional data are omitted. In this regard, we use a statistical method based on the depth of data (Cuesta-Albertos and Nieto-Reyes 2008) (the depth of datum increased if it moved toward the center of the data cloud and it decreased vice versa.) with the fda.usc R packages (Febreiro-Bande and Fuente 2012). In the last step, we conduct statistical comparisons between functional data in the step 2 in three scenarios. We use an intervalwise testing (IWT) procedure for testing FDA with four aims: (1) consider the functional structure of the data, (2) calculate the unadjusted and adjusted P values, (3) A non-parametric permutation tests, and (4) show the significant intervals of the domain. (Pini and Vantini 2016, 2017) We use fda.test in R to do this analysis. (Pini et al. 2015) The results are presented in the heatmaps with pheatmap R packages. (Kolde and Kolde 2015) The weekday pattern of the air pollution indices group by quarter, year and country are calculated with FPCA (PACE algorithm) and fdapace package (Gajardo et al. 2022; Yao et al. 2005). With this algorithm, we can estimate the FPCA in the missing values and sparse observations of functional data situations.

Results

The Iran population is 83,183,741 by the census of 2019 with 7,222,308 and 141,096 COVID-19 cases and deaths since 5/1/2022, respectively. Iran and its neighbors have about 7.4% of the world population and 6.3% and 5.8% of World COVID-19 cases and deaths, respectively. (Supplementary 1—Table A.3).

The daily air pollution time-series indices group by Country showed that (1) all indices are not available for all countries and all-time spans, (2) there are some outliers, and (3) the patterns are not the same. (Supplementary 1—Figure A.1) And the differences between countries are statistically significant for all indices and their variability is different. (Supplementary 1—Table A.4, Figure A.2.1 to A.2.8) The data set is not very complete. Therefore, we aggregate it from daily to quarterly time series to decrease the noise.

The spatial distribution of UVAI_AAI showed some changes including decreases in some points in the Q1 and Q2 of 2020 against 2019 and 2021 (Fig. 1). The same pattern exists for spatial distribution of NO2 and CH4, respectively. (Supplementary 1—Figure A.3.1 and Figure A.3.2). The color range is started from white to yellow, orange and red for low to high values of the indices, respectively. In the grey regions, the data set is not available.

In the next analysis, we test these assumptions (#1: $H_0 : \mu_{Q1,2019} = \mu_{Q1,2020}$, #2: $H_0 : \mu_{Q1,2020} = \mu_{Q1,2021}$, #3: $H_0 : \mu_{Q2,2019} = \mu_{Q2,2020}$, #4: $H_0 : \mu_{Q2,2020} = \mu_{Q2,2021}$, #5: $H_0 : \mu_{Q3,2019} = \mu_{Q3,2020}$, #6: $H_0 : \mu_{Q3,2020} = \mu_{Q3,2021}$, #7: $H_0 : \mu_{Q4,2019} = \mu_{Q4,2020}$, #8: $H_0 : \mu_{Q4,2020} = \mu_{Q4,2021}$, #9: $H_0 : \mu_{Q4,2021} = \mu_{Q4,2022}$, #10: $H_0 : \mu_{Q1,2019} = \mu_{Q1,2020}$, #11: $H_0 : \mu_{Q1,2020} = \mu_{Q1,2021}$, #12: $H_0 : \mu_{Q1,2021} = \mu_{Q1,2022}$). The alternative hypothesis for all of them is that the means are not equal to each other.

The statistical comparisons between years of the air quality indices for all countries are presents in the shiny app and supplementary 2. The result and data show some outliers and some unexpected results for some countries. Therefore, we put this analysis in the supplementary for further analysis.

The result of the final analysis is presented. The outliers are removed using FDA methods and statistical comparisons are done with IWT nonparametric method. The adjusted $p$ values are plotted in the heat map (Fig. 2 and Supplementary 1—Figure A.4.1, A.4.2 and A.4.3). According to the Fig. 1.A, the comparison between Q2 of 2019 and Q2 of 2020 in NO2 for almost all countries are statistically significant except Iraq (0.08), UAE (0.19), Qatar (0.70) and Kuwait (0.14). In the opposite side, the CO and HCHO are not statistically significant in any countries. Although CH4, O3 and UVAI_AAI are statistically significant for some countries.

The Supplementary 1—Figure A.5.1 and Figure A.5.2 showed an example for the outlier detection and IWT comparisons in Iran for two indices in Q2 of 2019 vs 2020, Q2 of 2020 vs 2021 and Q2 of 2019 vs 2020 vs 2021. These methods are done for all indices and all countries, but they are not shown in the supplementary.

Supplementary 1—Fig. 2.A indicates that in comparison between Q2 of 2020 and Q2 of 2021 for NO2, only Iran (0.06), Armenia (0.02), Turkey (0.04), UAE (0.02), and Saudi Arabia (0.02) are statistically significant. However, CH4 is significant for all countries except Azerbaijan (0.10), the others are not available. The CO, CO2 (except in Afghanistan (0.02)), HCHO, O3, and SO2 are not significant in any country.

Supplementary 1—Fig. 3.A indicates that the comparisons between Q2 of 3 years of 2019, 2020, and 2021 are all above 0.05, and the statistically significant pattern exists for almost countries in NO2, CH4, and UVAI_AAI.

With the same methods, the other comparisons for Q1, Q3 and Q4 are available in the figures A.4.1, A.4.2 and A.4.3 in the supplementary 1.

According to the Supplementary 1—Figure A.4.1, the comparison of NO2 in Q2 between 2019 and 2020 have some adjusted $p$ values less than 0.05 and the other Q1, Q3 and Q4 do not have any $p$ values less than 0.05. It indicates that the COVID-19 lock-down effects on the NO2.
The week-day pattern of air pollution indices reveals that (1) the most of the variations in any quarter of 2019, 2020 and 2021 are captured with the first eigenfunctions (FVE > 60%), (2) the eigenfunctions are different from each other yielding different patterns, and (3) the second eigenfunctions are also provide additional information about the remaining variations. All of them are provided in the Supplementary-3.

Conclusions

The WHO Public Health and Social Measures (PHSM) (Xing et al. 2021) or Oxford COVID-19 Government Response Tracker (OxCGRT) including Stringency Index (SI) and Containment and Health Index (CHI) is calculated based on eleven metrics such as testing policy for wear face coverings, closures of public transport and other indices about lock-down in the world. The causal relation between air pollution reduction and these government response indices is well-studied in many countries (Liu et al. 2021). Especially, the mean and standard deviation of CHI for Iran and its neighbors and other countries are 55.40 (SD: 19.70) and 50.37 (SD: 19.97) from 0 to 100, respectively. Therefore, the significant reduction in the NO2 in this analysis can be inferred from these lockdowns. (Hale et al. 2021; Ritchie et al. xxxx) (Supplementary 1: Table A.5 for further analysis.)

We provide three-level analysis from descriptive, simple comparison tests, and functional data analysis-based tests that can control the familywise error rate (Pini and Vantini 2016, 2017) and remove the outliers based on the depth function (Febrezo-Bande and Fuente 2012). The recent studies indicate that NO2, PM10, PM2.5, and benzene in the urban territory of Chieti-Pescara (Central Italy) is changed due to the lock-down with an analysis of variance for functional

Fig. 1 Spatial distribution of UVAI_AAI group by year and Q of the year. (Colors: low to high is from white, yellow, orange and red)
data (FANOVA) and it is based on the multivariate functional principal component analysis. (Acal 2021).

The limitation of this research is that the air pollution indices are not adjusted due to the metrological conditions such as temperature, wind, rain, etc. We also show that Precipitation as an important weather condition is not the same among countries and time (Rosenfeld et al. 2007). In addition, the other limitation is about availability of statistics for COVID-19 in Turkmenistan (Yaylymova 2020; Hashim et al. 2022). Finally, we conclude that the reduction of air pollution indices such as NO₂ is statistically significant with unadjusted and adjusted p values in this research. One of the direction of the future of this research is to develop statistical tests with considering the spatial information (Mateu et al. 2021).

Fig. 2 Heatmap of (functional data analysis method) IWT p values for Q2

(A) Q2 2019 vs Q2 2020

(B) Q2 2019 vs Q2 2020

(C) Q2 2019 vs Q2 2020 vs Q2 2021
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