Modeling Earth Systems and Environment
https://doi.org/10.1007/s40808-022-01528-x

ORIGINAL ARTICLE

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

Mohammad Fayaz[1]

Received: 2 July 2022 / Accepted: 6 September 2022

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 CH_4 (Methane), CO_1 (CO), H_2O (Water), HCHO (Tropospheric Atmospheric Formaldehyde), NO_2 (Nitrogen oxides), O_3 (ozone), SO_2 (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 NO_2 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 CH_4, O_3, and UVAI_AAI are statistically significant for some countries. In the Q2 comparison for NO_2 between 2020 and 2021, only Iran, Armenia, Turkey, UAE, and Saudi Arabia are statistically significant. However, Ch_4 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 NO_2, $PM_{2.5}$ 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. 2021a; 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),

✉ Mohammad Fayaz
Mohammad.Fayaz.89@gmail.com

[1] Department of Biostatistics, School of Allied Medical Sciences, Shahid Beheshti University of Medical Sciences, Tehran, Iran

Published online: 19 September 2022

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; Keshtkar 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. 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 NO*x* 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 (Skirienė and Stasiškienė 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) SO2 (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 SO2, 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 (Febrero-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 NO_2 and CH_4, 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: $H_0 : \mu_{Q1\_2019} = \mu_{Q1\_2020} = \mu_{Q1\_2021}$, #4: $H_0 : \mu_{Q2\_2019} = \mu_{Q2\_2020}$, #5: $H_0:\mu_{Q2\_2020} = \mu_{Q2\_2021}$, #6: $H_0 : \mu_{Q2\_2019} = \mu_{Q2\_2020} = \mu_{Q2\_2021}$, #7: $H_0 : \mu_{Q3\_2019} = \mu_{Q3\_2020}$, #8: $H_0:\mu_{Q3\_2020} = \mu_{Q3\_2021}$, #9: $H_0 : \mu_{Q3\_2019} = \mu_{Q3\_2020} = \mu_{Q3\_2021}$, #10: $H_0 : \mu_{Q4\_2019} = \mu_{Q4\_2020}$, #11: $H_0:\mu_{Q4\_2020} = \mu_{Q4\_2021}$, #12: $H_0 : \mu_{Q4\_2019} = \mu_{Q4\_2020} = \mu_{Q4\_2021}$) and 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 NO_2 for almost all countries are statistically significant except Iraq (0.08), UAE (0.19), Bahrain (0.15), Qatar (0.70) and Kuwait (0.14). In the opposite side, the CO and HCHO are not statistically significant in any countries. Although CH_4, O_3 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 NO_2, only Iran (0.06), Armenia (0.02), Turkey (0.04), UAE (0.02), and Saudi Arabia (0.02) are statistically significant. However, CH_4 is significant for all countries except Azerbaijan (0.10), the others are not available. The CO, CO_2 (except in Afghanistan (0.02)), HCHO, O_3, and SO_2 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 NO_2, CH_4, 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 NO_2 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 NO_2.

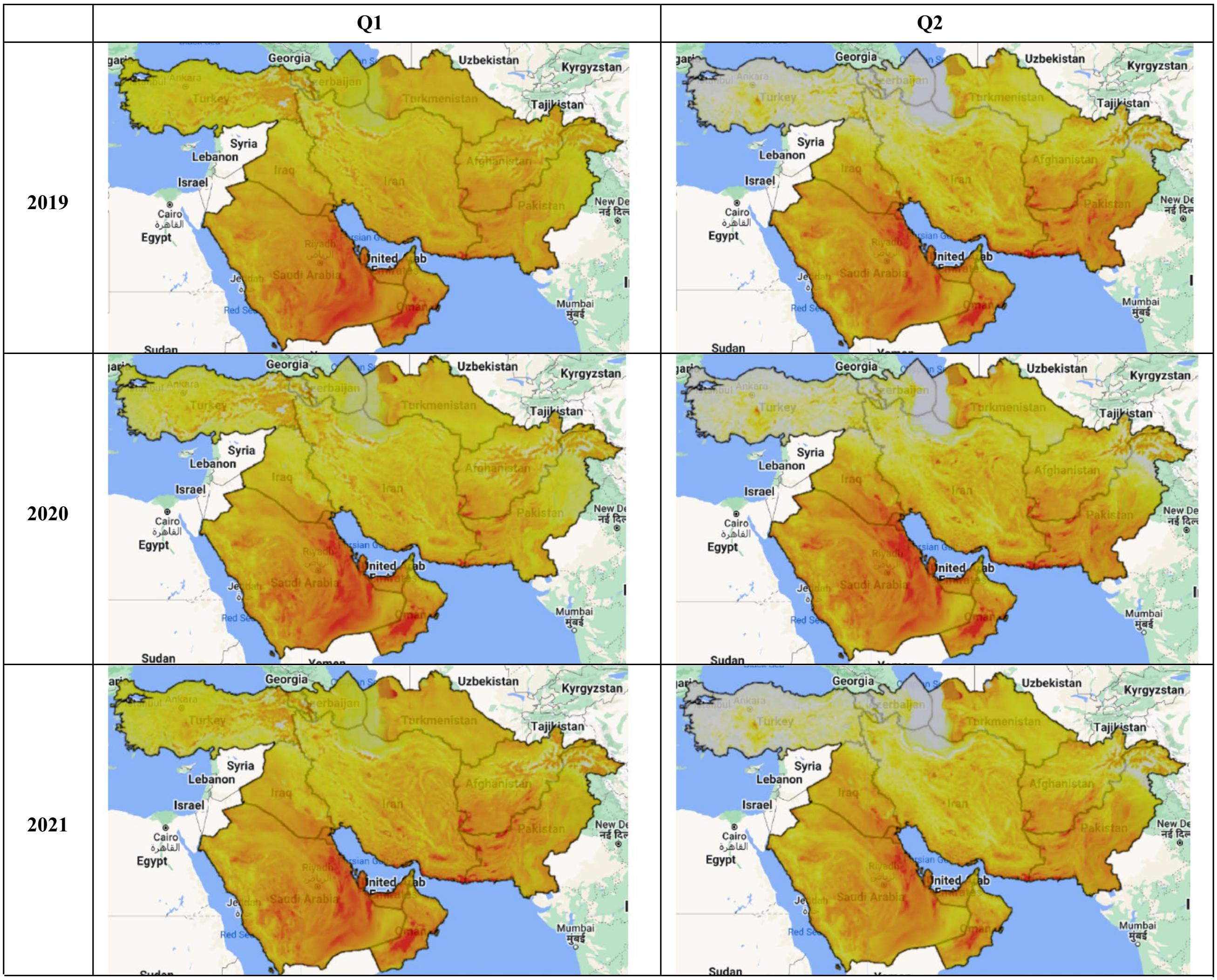


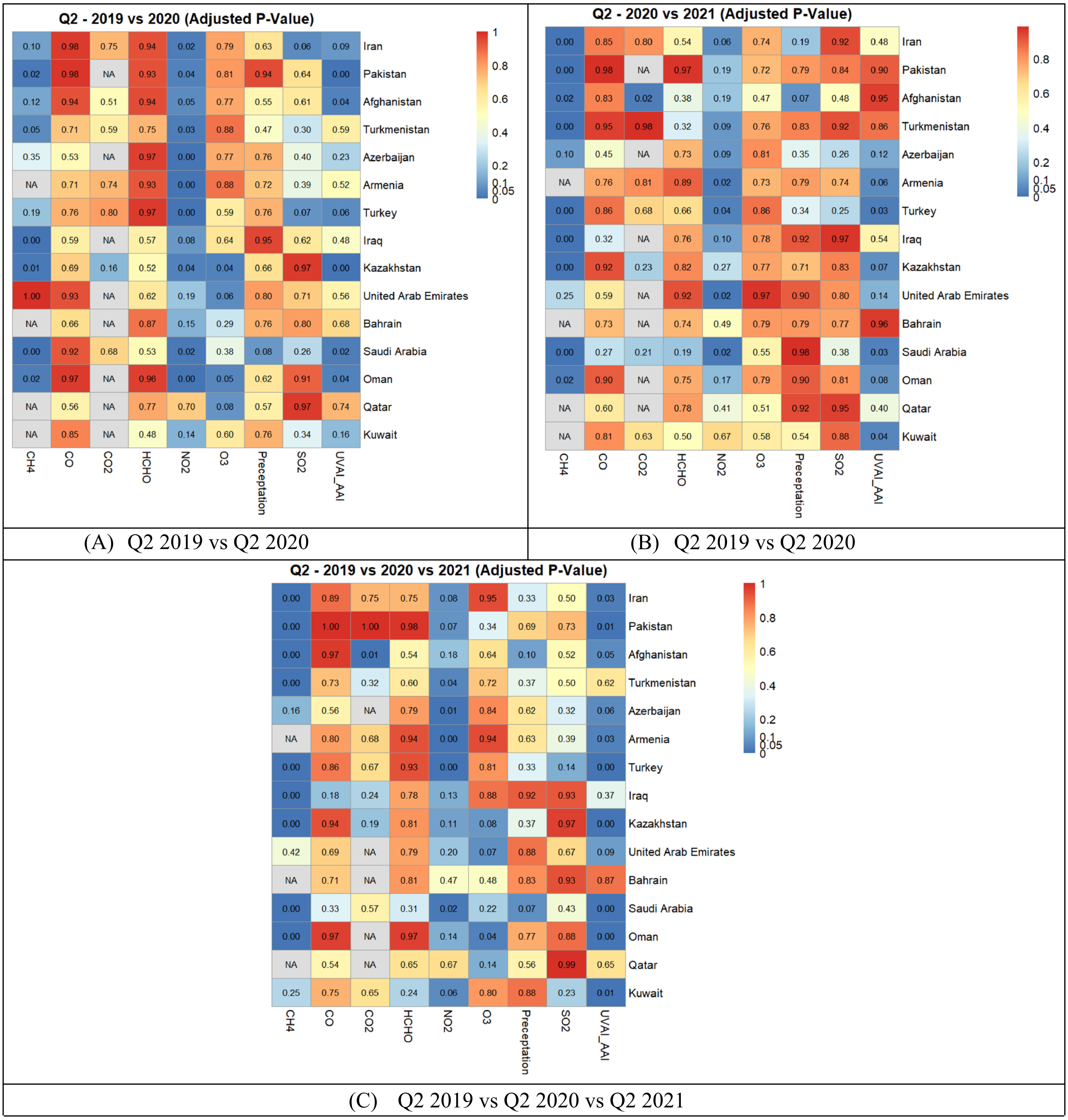
Fig. 1 Spatial distribution of UVAI_AAI group by year and Q of the year. (Colors: low to high is from white, yellow, orange and red)

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 NO_2 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 (Febrero-Bande and Fuente 2012). The recent studies indicate that NO_2, PM_{10}, $PM_{2.5}$, 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



(A) Q2 2019 vs Q2 2020

(B) Q2 2019 vs Q2 2020

(C) Q2 2019 vs Q2 2020 vs Q2 2021

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

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 NO_2 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).

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40808-022-01528-x.

References

Acal C et al (2021) Functional ANOVA approaches for detecting changes in air pollution during the COVID-19 pandemic. Stoch Environ Res Risk Assess 36:1–19

Adams MD (2020) Air pollution in Ontario, Canada during the COVID-19 state of emergency. Sci Total Environ 742:140516

Alalawi S et al (2022) A review of the environmental implications of the COVID-19 pandemic in the United Arab Emirates. Environ Chall 8:100561

Alqasemi AS et al (2021) Impact of COVID-19 lockdown upon the air quality and surface urban heat island intensity over the United Arab Emirates. Sci Total Environ 767:144330

Anil I, Alagha O (2021) The impact of COVID-19 lockdown on the air quality of Eastern Province, Saudi Arabia. Air Qual Atmos Health 14(1):117–128

Aslam B et al (2021) A correlation study between weather and atmosphere with COVID-19 pandemic in Islamabad, Pakistan. Spat Inf Res 29(4):605–613

Azuma K et al (2020) Impact of climate and ambient air pollution on the epidemic growth during COVID-19 outbreak in Japan. Environ Res 190:110042

Baniasad M et al (2021) COVID-19 in Asia: transmission factors, re-opening policies, and vaccination simulation. Environ Res 202:111657

Benchrif A et al (2021) Air quality during three covid-19 lockdown phases: AQI, PM2. 5 and NO_2 assessment in cities with more than 1 million inhabitants. Sustain Cities Soc 74:103170

Berman JD, Ebisu K (2020) Changes in US air pollution during the COVID-19 pandemic. Sci Total Environ 739:139864

Bonardi J-P et al (2021) Saving the world from your couch: the heterogeneous medium-run benefits of COVID-19 lockdowns on air pollution. Environ Res Lett 16(7):074010

Broomandi P et al (2020) Impact of COVID-19 event on the air quality in Iran. Aerosol Air Qual Res 20(8):1793–1804

Chen K et al (2020) Air pollution reduction and mortality benefit during the COVID-19 outbreak in China. Lancet Planet Health 4(6):e210–e212

Chetty R et al (2020) The economic impacts of COVID-19: evidence from a new public database built using private sector data. National Bureau of economic research

Copat C et al (2020) The role of air pollution (PM and NO_2) in COVID-19 spread and lethality: a systematic review. Environ Res 191:110129

Couch KA, Fairlie RW, Xu H (2020) Early evidence of the impacts of COVID-19 on minority unemployment. J Public Econ 192:104287

Cuesta-Albertos JA, Nieto-Reyes A (2008) The random Tukey depth. Comput Stat Data Anal 52(11):4979–4988

Dong E, Du H, Gardner L (2020) An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect Dis 20(5):533–534

Dursun S, Sagdic M, Toros H (2022) The impact of COVID-19 measures on air quality in Turkey. Environ Forensics 23(1–2):47–59

Febrero-Bande M, de Fuente MO (2012) Statistical computing in functional data analysis: the R package fda. usc. J Stat Softw 51:1–28

Fuchs-Schündeln N et al (2022) The long-term distributional and welfare effects of Covid-19 school closures. Econ J 132(645):1647–1683

Gajardo A et al. (2022) Fdapace: functional data analysis and empirical dynamics. URL https://cran.r-project.org/web/packages/fdapace/index.html. R package version 0.5.8 [p 1].

Gautam AS et al (2021) Temporary reduction in air pollution due to anthropogenic activity switch-off during COVID-19 lockdown in northern parts of India. Environ Dev Sustain 23(6):8774–8797

Ghanim AA (2021) Analyzing the severity of coronavirus infections in relation to air pollution: evidence-based study from Saudi Arabia. Environ Sci Pollut Res 29:1–11

Ghasempour F, Sekertekin A, Kutoglu SH (2021) Google earth engine based spatio-temporal analysis of air pollutants before and during the first wave COVID-19 outbreak over Turkey via remote sensing. J Clean Prod 319:128599

Habeebullah TM et al (2022) Modelling the effect of COVID-19 lockdown on air pollution in Makkah Saudi Arabia with a supervised machine learning approach. Toxics 10(5):225

Hale T et al (2021) A global panel database of pandemic policies (Oxford COVID-19 government response tracker). Nat Hum Behav 5(4):529–538

Halos SH et al (2021) Impact of PM2. 5 concentration, weather and population on COVID-19 morbidity and mortality in Baghdad and Kuwait cities. Model Earth Syst Environ 29:1–10

Hashim BM et al (2021a) On the investigation of COVID-19 lockdown influence on air pollution concentration: regional investigation over eighteen provinces in Iraq. Environ Sci Pollut Res 28(36):50344–50362

Hashim BM et al (2021b) Impact of COVID-19 lockdown on NO_2, O_3, PM2. 5 and PM10 concentrations and assessing air quality changes in Baghdad, Iraq. Sci Total Environ 754:141978

Hashim HT et al (2022) COVID-19 denial in Turkmenistan veiling the real situation. Arch Public Health 80(1):1–4

He G, Pan Y, Tanaka T (2020) The short-term impacts of COVID-19 lockdown on urban air pollution in China. Nat Sustain 3(12):1005–1011

Higham J et al (2021) UK COVID-19 lockdown: 100 days of air pollution reduction? Air Qual Atmos Health 14(3):325–332

Ju MJ, Oh J, Choi Y-H (2021) Changes in air pollution levels after COVID-19 outbreak in Korea. Sci Total Environ 750:141521

Kerimray A et al (2020) Assessing air quality changes in large cities during COVID-19 lockdowns: the impacts of traffic-free urban conditions in Almaty, Kazakhstan. Sci Total Environ 730:139179

Keshtkar M et al (2022) Analysis of changes in air pollution quality and impact of COVID-19 on environmental health in Iran: application of interpolation models and spatial autocorrelation. Environ Sci Pollut Res 29:1–22

Khan YA (2021) The COVID-19 pandemic and its impact on environment: the case of the major cities in Pakistan. Environ Sci Pollut Res 28(39):54728–54743

Kolde R, Kolde MR (2015) Package 'pheatmap.' R Packag 1(7):790

Liu F, Wang M, Zheng M (2021) Effects of COVID-19 lockdown on global air quality and health. Sci Total Environ 755:142533

Mahmoud L et al (2022) The improvement in PM2. 5 levels in education city, Doha, Qatar during the COVID-19 lockdown was limited and transient. Qscience Connect 2022(1):3

Martin A et al (2020) Socio-economic impacts of COVID-19 on household consumption and poverty. Econ Dis Clim Chang 4(3):453–479

Mateu J, Giraldo R (2021) Geostatistical functional data analysis. John Wiley & Sons

Mehmood K et al (2021a) Spatiotemporal variability of COVID-19 pandemic in relation to air pollution, climate and socioeconomic factors in Pakistan. Chemosphere 271:129584

Mehmood K et al (2021b) Investigating connections between COVID-19 pandemic, air pollution and community interventions for Pakistan employing geoinformation technologies. Chemosphere 272:129809

Mishra M, Kulshrestha U (2021) A brief review on changes in air pollution scenario over South Asia during COVID-19 lockdown. Aerosol Air Qual Res 21(4):200541

Moazeni M et al (2021) Spatiotemporal analysis of COVID-19, air pollution, climate, and meteorological conditions in a metropolitan region of Iran. Environ Sci Pollut Res 29:1–14

Morsy E, Habeebullah TM, Othman A (2021) Assessing the air quality of megacities during the COVID-19 pandemic lockdown: a case study from Makkah City, Saudi Arabia. Arab J Geosci 14(7):1–12

Norouzi N, Asadi Z (2022) Air pollution impact on the Covid-19 mortality in Iran considering the comorbidity (obesity, diabetes, and hypertension) correlations. Environ Res 204:112020

Pini A, Vantini S (2016) The interval testing procedure: a general framework for inference in functional data analysis. Biometrics 72(3):835–845

Pini A, Vantini S (2017) Interval-wise testing for functional data. J Nonparametric Stat 29(2):407–424

Pini A, Vantini S, Pini MA (2015) Package 'fdatest'. R software environment.

Qaid A et al (2022) Long-term statistical assessment of meteorological indicators and COVID-19 outbreak in hot and arid climate, Bahrain. Environ Sci Pollut Res 29(1):1106–1116

Ritchie H et al. (2020) Coronavirus pandemic (COVID-19); Available from: OurWorldInData.org.

Rosenfeld D et al (2007) Inverse relations between amounts of air pollution and orographic precipitation. Science 315(5817):1396–1398

Shanableh A et al (2022) COVID-19 lockdown and the impact on mobility, air quality, and utility consumption: a case study from Sharjah, United Arab Emirates. Sustainability 14(3):1767

Shankar K et al (2021) Meteorological parameters and COVID-19 spread-Russia a case study. Environmental Resilience and Transformation in Times of COVID-19. Elsevier, pp 179–190

Sievert C (2020) Interactive web-based data visualization with R, plotly, and shiny. CRC Press

Skirienė AF, Stasiškienė Ž (2021) COVID-19 and air pollution: measuring pandemic impact to air quality in five European countries. Atmosphere 12(3):290

Teixidó O et al (2021) The influence of COVID-19 preventive measures on the air quality in Abu Dhabi (United Arab Emirates). Air Qual Atmos Health 14(7):1071–1079

Venter ZS et al (2020) COVID-19 lockdowns cause global air pollution declines. Proc Natl Acad Sci 117(32):18984–18990

Wu X et al (2020) Air pollution and COVID-19 mortality in the United States: strengths and limitations of an ecological regression analysis. Sci Adv 6(45):eabd4049

Xing X et al (2021) Predicting the effect of confinement on the COVID-19 spread using machine learning enriched with satellite air pollution observations. Proc Natl Acad Sci 118(33):18984

Yao F, Müller H-G, Wang J-L (2005) Functional data analysis for sparse longitudinal data. J Am Stat Assoc 100(470):577–590

Yaylymova A (2020) COVID-19 in Turkmenistan: no data, no health rights. Health Hum Rights 22(2):325

Zhang Z et al (2021) The impact of lockdown on nitrogen dioxide (NO_2) over central Asian countries during the COVID-19 pandemic. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-021-17140-y