Title

The Lock-Down Effects of COVID-19 on the Air Pollution Indices in Iran and Its Neighbors

Authors

Mohammad Fayaz
PhD in Biostatistics, Department of Biostatistics, School of Allied Medical Sciences, Shahid Beheshti University of Medical Sciences, Tehran, Iran. (https://orcid.org/0000-0002-5643-9763), E-mail:Mohammad.Fayaz.89@gmail.com

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.

Method

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 dataset 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 family-wise 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. But Ch4 is statistically significant for all countries except Azerbaijan.

Conclusion

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.[1] 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. [2-5]. On the other hand, one of its positive impacts on the environment is the air pollution reduction in most parts of the World. [6]

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) [6-8] most countries have a lot of lock-down days in this period [6]: Pakistan [9-12], Afghanistan and India [13, 14], Turkmenistan [15] ,Azerbaijan [8] ,Armenia [8], Turkey [16, 17], Iraq [18, 19], Kazakhstan [20], Bahrain [21, 22], Kuwait [23], Oman [8], Qatar [24], Saudi Arabia [25-28], UAE [29-32], Asia [33] and Iran [34-37].

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 NO2 [38, 39], the United States in $PM_{2.5}$ and NO2 [40, 41] and Russia in a meteorological parameter that influence the air pollution indices [42], Japan in NO, NO2, PM2.5, and SPM (Suspended Particulate Matter) [43], Germany in NO2 , $PM_{2.5}$ and PM_{10} [44], the UK in NO*x* about %50 reductions and increase in O3 and SO_2 [45], South Korea in $PM_{2.5}$, PM_{10}, NO2, and CO [46], Canada in NO2, NOX and O3 [47] 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 [48].

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 family-wise error rate in the comparisons [49, 50].

Methods and Materials

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 dataset sources: 1) Daily Statistics for COVID-19 cases and deaths [51] 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 - Table 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 that is available with this research article.(Supplementary 2) [52]

3) Functional Data Analysis: We've noticed from previous steps that there are some outliers in the dataset. On the other hand, the datasets are time-series and we don't 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 [53] (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 [54]. In the last step, we conduct statistical comparisons between functional data in the above step 2 three scenarios. We use an interval-wise 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. [49, 50] We use fda.test in R to do this analysis. [55] The results are presented in the heatmaps with pheatmap R packages. [56]

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 dataset is not very complete. So, 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 (Figure-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. In the grey regions, the dataset 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 (Figure 1 and Supplementary 1 - Figure A.4.1, A.4.2 and A.4.3). According to the Figure 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), 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 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.

Figure 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. But 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.

Figure 3.A indicates that the comparisons between Q2 of three 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 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 don't have any p-values less than 0.05. It indicates that the COVID-19 lock-down effects on the NO2.

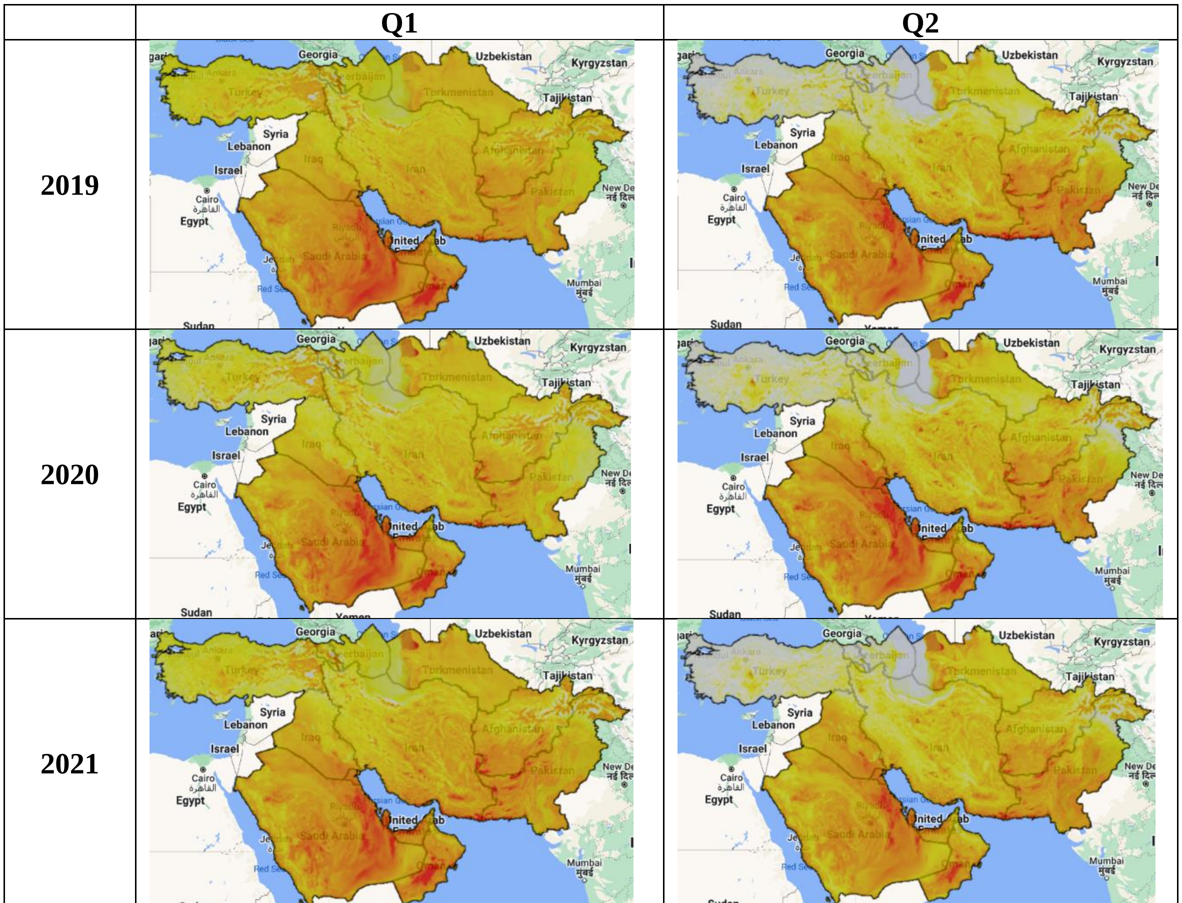
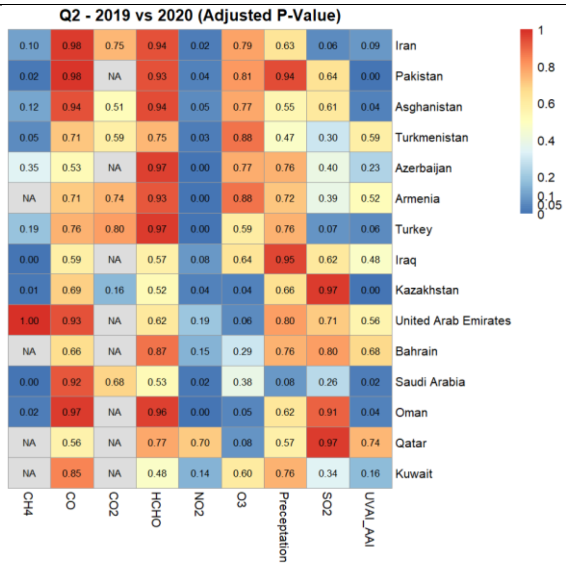
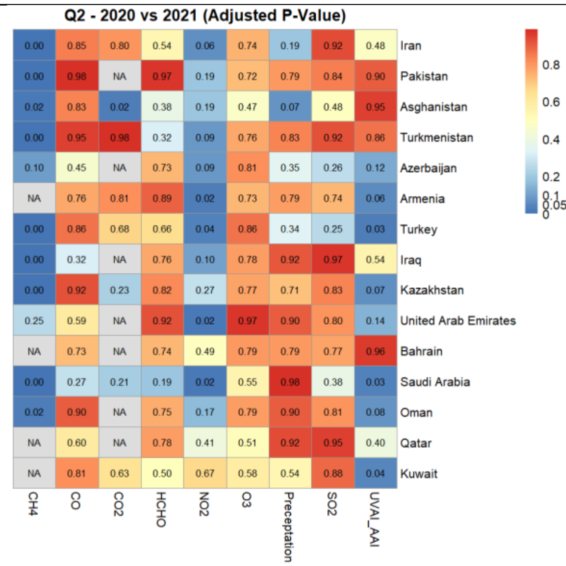


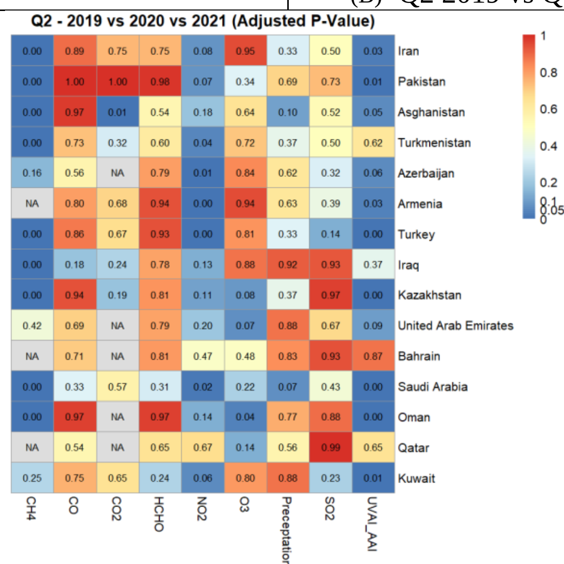
Figure 1 - Spatial Distribution of UVAI_AAI group by year and Q of the year.
(Colors: low to high is from white, yellow, orange and red)



(A) Q2 2019 vs Q2 2020



(B) Q2 2019 vs Q2 2020



(C) Q2 2019 vs Q2 2020 vs Q2 2021

Figure 2 - The Heatmap of IWT P-values for Q2

Conclusion

The WHO Public Health and Social Measures (PHSM) [7] 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 [57]. 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. [1, 58] (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 family-wise error rate [49, 50] and remove the outliers based on the depth function [54]. 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 data (FANOVA) and it is based on the multivariate functional principal component analysis. [59]

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 [60]. And the other limitation is about availability of statistics for COVID-19 in Turkmenistan [61, 62]. 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 [63].

Appendix:

Supplementary 1 – Further Analysis

Supplementary 2 – The Shiny App result.

R codes – The Shiny App R Codes

References

1. Hale, T., et al., *A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker).* Nature human behaviour, 2021. **5**(4): p. 529-538.
2. Chetty, R., et al., *The economic impacts of COVID-19: Evidence from a new public database built using private sector data*. 2020, national Bureau of economic research.
3. Martin, A., et al., *Socio-economic impacts of COVID-19 on household consumption and poverty.* Economics of disasters and climate change, 2020. **4**(3): p. 453-479.
4. Couch, K.A., R.W. Fairlie, and H. Xu, *Early evidence of the impacts of COVID-19 on minority unemployment.* Journal of Public Economics, 2020. **192**: p. 104287.
5. Fuchs-Schündeln, N., et al., *The long-term distributional and welfare effects of Covid-19 school closures.* The Economic Journal, 2022. **132**(645): p. 1647-1683.
6. Venter, Z.S., et al., *COVID-19 lockdowns cause global air pollution declines.* Proceedings of the National Academy of Sciences, 2020. **117**(32): p. 18984-18990.
7. Xing, X., et al., *Predicting the effect of confinement on the COVID-19 spread using machine learning enriched with satellite air pollution observations.* Proceedings of the National Academy of Sciences, 2021. **118**(33).
8. Bonardi, J.-P., et al., *Saving the world from your couch: the heterogeneous medium-run benefits of COVID-19 lockdowns on air pollution.* Environmental Research Letters, 2021. **16**(7): p. 074010.
9. Mehmood, K., et al., *Spatiotemporal variability of COVID-19 pandemic in relation to air pollution, climate and socioeconomic factors in Pakistan.* Chemosphere, 2021. **271**: p. 129584.
10. Mehmood, K., et al., *Investigating connections between COVID-19 pandemic, air pollution and community interventions for Pakistan employing geoinformation technologies.* Chemosphere, 2021. **272**: p. 129809.
11. Khan, Y.A., *The COVID-19 pandemic and its impact on environment: the case of the major cities in Pakistan.* Environmental Science and Pollution Research, 2021. **28**(39): p. 54728-54743.
12. Aslam, B., et al., *A correlation study between weather and atmosphere with COVID-19 pandemic in Islamabad, Pakistan.* Spatial Information Research, 2021. **29**(4): p. 605-613.

13. Mishra, M. and U. Kulshrestha, *A brief review on changes in air pollution scenario over South Asia during COVID-19 lockdown.* Aerosol and Air Quality Research, 2021. **21**(4): p. 200541.
14. Gautam, A.S., et al., *Temporary reduction in air pollution due to anthropogenic activity switch-off during COVID-19 lockdown in northern parts of India.* Environment, Development and Sustainability, 2021. **23**(6): p. 8774-8797.
15. Zhang, Z., et al., *The impact of lockdown on nitrogen dioxide (NO2) over Central Asian countries during the COVID-19 pandemic.* Environmental Science and Pollution Research, 2021: p. 1-9.
16. Ghasempour, F., A. Sekertekin, and S.H. Kutoglu, *Google Earth Engine based spatio-temporal analysis of air pollutants before and during the first wave COVID-19 outbreak over Turkey via remote sensing.* Journal of Cleaner Production, 2021. **319**: p. 128599.
17. Dursun, S., M. Sagdic, and H. Toros, *The impact of COVID-19 measures on air quality in Turkey.* Environmental Forensics, 2022. **23**(1-2): p. 47-59.
18. Hashim, B.M., et al., *On the investigation of COVID-19 lockdown influence on air pollution concentration: regional investigation over eighteen provinces in Iraq.* Environmental Science and Pollution Research, 2021. **28**(36): p. 50344-50362.
19. Hashim, B.M., et al., *Impact of COVID-19 lockdown on NO2, O3, PM2. 5 and PM10 concentrations and assessing air quality changes in Baghdad, Iraq.* Science of the Total Environment, 2021. **754**: p. 141978.
20. Kerimray, A., et al., *Assessing air quality changes in large cities during COVID-19 lockdowns: The impacts of traffic-free urban conditions in Almaty, Kazakhstan.* Science of the Total Environment, 2020. **730**: p. 139179.
21. Benchrif, A., et al., *Air quality during three covid-19 lockdown phases: AQI, PM2. 5 and NO2 assessment in cities with more than 1 million inhabitants.* Sustainable Cities and Society, 2021. **74**: p. 103170.
22. Qaid, A., et al., *Long-term statistical assessment of meteorological indicators and COVID-19 outbreak in hot and arid climate, Bahrain.* Environmental Science and Pollution Research, 2022. **29**(1): p. 1106-1116.
23. Halos, S.H., et al., *Impact of PM2. 5 concentration, weather and population on COVID-19 morbidity and mortality in Baghdad and Kuwait cities.* Modeling Earth Systems and Environment, 2021: p. 1-10.
24. Mahmoud, L., et al., *The improvement in PM2. 5 levels in Education City, Doha, Qatar during the COVID-19 lockdown was limited and transient.* QScience Connect, 2022. **2022**(1): p. 3.
25. Ghanim, A.A., *Analyzing the severity of coronavirus infections in relation to air pollution: evidence-based study from Saudi Arabia.* Environmental science and Pollution Research, 2021: p. 1-11.
26. Habeebullah, T.M., et al., *Modelling the Effect of COVID-19 Lockdown on Air Pollution in Makkah Saudi Arabia with a Supervised Machine Learning Approach.* Toxics, 2022. **10**(5): p. 225.
27. Anil, I. and O. Alagha, *The impact of COVID-19 lockdown on the air quality of Eastern Province, Saudi Arabia.* Air Quality, Atmosphere & Health, 2021. **14**(1): p. 117-128.
28. Morsy, E., T.M. Habeebullah, and A. Othman, *Assessing the air quality of megacities during the COVID-19 pandemic lockdown: a case study from Makkah City, Saudi Arabia.* Arabian Journal of Geosciences, 2021. **14**(7): p. 1-12.
29. Alqasemi, A.S., et al., *Impact of COVID-19 lockdown upon the air quality and surface urban heat island intensity over the United Arab Emirates.* Science of The Total Environment, 2021. **767**: p. 144330.
30. Teixidó, O., et al., *The influence of COVID-19 preventive measures on the air quality in Abu Dhabi (United Arab Emirates).* Air Quality, Atmosphere & Health, 2021. **14**(7): p. 1071-1079.
31. Alalawi, S., et al., *A Review of the Environmental Implications of the COVID-19 Pandemic in the United Arab Emirates.* Environmental Challenges, 2022: p. 100561.

32. Shanableh, A., et al., *COVID-19 Lockdown and the Impact on Mobility, Air Quality, and Utility Consumption: A Case Study from Sharjah, United Arab Emirates.* Sustainability, 2022. **14**(3): p. 1767.
33. Baniasad, M., et al., *COVID-19 in Asia: Transmission factors, re-opening policies, and vaccination simulation.* Environmental research, 2021. **202**: p. 111657.
34. Moazeni, M., et al., *Spatiotemporal analysis of COVID-19, air pollution, climate, and meteorological conditions in a metropolitan region of Iran.* Environmental Science and Pollution Research, 2021: p. 1-14.
35. Broomandi, P., et al., *Impact of COVID-19 event on the air quality in Iran.* Aerosol and Air Quality Research, 2020. **20**(8): p. 1793-1804.
36. Keshtkar, M., et al., *Analysis of changes in air pollution quality and impact of COVID-19 on environmental health in Iran: application of interpolation models and spatial autocorrelation.* Environmental Science and Pollution Research, 2022: p. 1-22.
37. Norouzi, N. and Z. Asadi, *Air pollution impact on the Covid-19 mortality in Iran considering the comorbidity (obesity, diabetes, and hypertension) correlations.* Environmental Research, 2022. **204**: p. 112020.
38. Chen, K., et al., *Air pollution reduction and mortality benefit during the COVID-19 outbreak in China.* The Lancet Planetary Health, 2020. **4**(6): p. e210-e212.
39. He, G., Y. Pan, and T. Tanaka, *The short-term impacts of COVID-19 lockdown on urban air pollution in China.* Nature Sustainability, 2020. **3**(12): p. 1005-1011.
40. Wu, X., et al., *Air pollution and COVID-19 mortality in the United States: Strengths and limitations of an ecological regression analysis.* Science advances, 2020. **6**(45): p. eabd4049.
41. Berman, J.D. and K. Ebisu, *Changes in US air pollution during the COVID-19 pandemic.* Science of the total environment, 2020. **739**: p. 139864.
42. Shankar, K., et al., *Meteorological parameters and COVID-19 spread-Russia a case study*, in *Environmental Resilience and Transformation in Times of COVID-19*. 2021, Elsevier. p. 179-190.
43. Azuma, K., et al., *Impact of climate and ambient air pollution on the epidemic growth during COVID-19 outbreak in Japan.* Environmental research, 2020. **190**: p. 110042.
44. Copat, C., et al., *The role of air pollution (PM and NO2) in COVID-19 spread and lethality: a systematic review.* Environmental research, 2020. **191**: p. 110129.
45. Higham, J., et al., *UK COVID-19 lockdown: 100 days of air pollution reduction?* Air Quality, Atmosphere & Health, 2021. **14**(3): p. 325-332.
46. Ju, M.J., J. Oh, and Y.-H. Choi, *Changes in air pollution levels after COVID-19 outbreak in Korea.* Science of the Total Environment, 2021. **750**: p. 141521.
47. Adams, M.D., *Air pollution in Ontario, Canada during the COVID-19 State of Emergency.* Science of the Total Environment, 2020. **742**: p. 140516.
48. Skirienė, A.F. and Ž. Stasiškienė, *COVID-19 and air pollution: Measuring pandemic impact to air quality in five European countries.* Atmosphere, 2021. **12**(3): p. 290.
49. Pini, A. and S. Vantini, *The interval testing procedure: a general framework for inference in functional data analysis.* Biometrics, 2016. **72**(3): p. 835-845.
50. Pini, A. and S. Vantini, *Interval-wise testing for functional data.* Journal of Nonparametric Statistics, 2017. **29**(2): p. 407-424.
51. Dong, E., H. Du, and L. Gardner, *An interactive web-based dashboard to track COVID-19 in real time.* The Lancet infectious diseases, 2020. **20**(5): p. 533-534.
52. Sievert, C., *Interactive web-based data visualization with R, plotly, and shiny*. 2020: CRC Press.
53. Cuesta-Albertos, J.A. and A. Nieto-Reyes, *The random Tukey depth.* Computational Statistics & Data Analysis, 2008. **52**(11): p. 4979-4988.
54. Febrero-Bande, M. and M.O. de la Fuente, *Statistical computing in functional data analysis: The R package fda. usc.* Journal of statistical Software, 2012. **51**: p. 1-28.
55. Pini, A., S. Vantini, and M.A. Pini, *Package 'fdatest'.* R software environment, 2015.

56. Kolde, R. and M.R. Kolde, *Package 'pheatmap'.* R package, 2015. **1**(7): p. 790.
57. Liu, F., M. Wang, and M. Zheng, *Effects of COVID-19 lockdown on global air quality and health.* Science of the Total Environment, 2021. **755**: p. 142533.
58. Ritchie, H., et al. *Coronavirus Pandemic (COVID-19)*. 2020; Available from: OurWorldInData.org.
59. Acal, C., et al., *Functional ANOVA approaches for detecting changes in air pollution during the COVID-19 pandemic.* Stochastic Environmental Research and Risk Assessment, 2021: p. 1-19.
60. Rosenfeld, D., et al., *Inverse relations between amounts of air pollution and orographic precipitation.* Science, 2007. **315**(5817): p. 1396-1398.
61. Yaylymova, A., *COVID-19 in Turkmenistan: No data, no health rights.* Health and Human Rights, 2020. **22**(2): p. 325.
62. Hashim, H.T., et al., *COVID-19 denial in Turkmenistan veiling the real situation.* Archives of Public Health, 2022. **80**(1): p. 1-4.
63. Mateu, J. and R. Giraldo, *Geostatistical Functional Data Analysis*. 2021: John Wiley & Sons.