Examining Trends in Air Quality Data During The Covid-19 Shutdown

Perfect Skies

Ethan Kadiyala, Mikal de Wit, & Xiomara Mendez
University of California Santa Barbara

UCSB Geography

Introduction

Lockdown measures in response to the COVID-19 pandemic have had profound effects on how society functions. Daily commuter traffic has been substantially reduced during these times, resulting in decreased emissions and improved air quality. These conditions give us a glimpse at what could happen if electric vehicles are more prevalent in the transportation sector or having increased renewable energy generation in the future.

This project studies the decrease in pollution in the atmosphere since quarantine began. It uses the past three years of ozone concentration measurements made by air quality monitoring stations in Los Angeles and the San Francisco Bay Area.

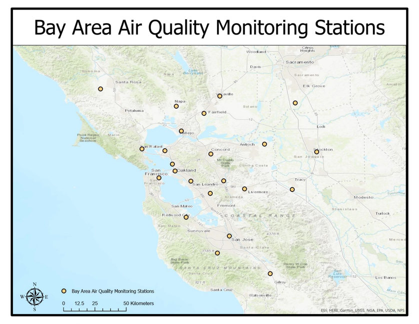
Objectives

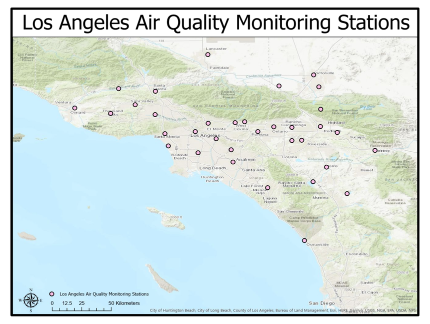
- Determine how quarantine measures have affected air quality in Los Angeles and the San Francisco Bay Area
- Compare tropospheric ozone concentrations over the past three years to concentrations during quarantine
- Use statistical methods to prove whether there has been a significant reduction in ozone since the quarantine measures began

Data and Study Locations

Study Locations

Los Angeles and the San Francisco Bay Area were chosen as our study locations because of their high population density, urbanization, and large amount of commuter traffic. As a result, these locations would more likely show decreased ozone concentrations than rural areas and therefore allow for more meaningful analysis.





Monitoring Stations and Ozone Data

Compounds in vehicle exhaust enter the atmosphere and react with each other to form ozone. Ozone concentrations can then be measured and recorded by air quality monitoring stations. For this project, we used ozone data collected in March and April from 2017-2019 to compare to data measured in March and April of 2020. This data was collected by the U.S. Environmental Protection Agency.

Methodology

Methods were conducted in ArcGIS Pro, Python, and Excel. A significant amount of data cleaning and organizing was required before performing analysis. This primarily involved clipping the data to the extent of each study region in and selecting data from March and April over the four years.

Site averages were calculated in Excel and used in spline interpolations to create baseline and 2020 rasters for each study area. The raster calculator tool was used to find the change in ozone for each study area. Significant regions maps were constructed to identify where statistically significant changes occurred based on a minimum critical value of ozone change (ppm).

Statistical analysis was performed in Python. The three year baseline data was compared to 2020 ozone data through a paired t-test. The t-tests were conducted on both a site-wide scale and on the individual station scale. All tests were one-sided, paired t-tests, alpha = .05 with n-1 degrees of freedom. For each individual station, n = 61.

All code and csv files used in the statistical analysis are available via the Github repository linked in the QR code.

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github.com/ekadiyala/Air-Quality

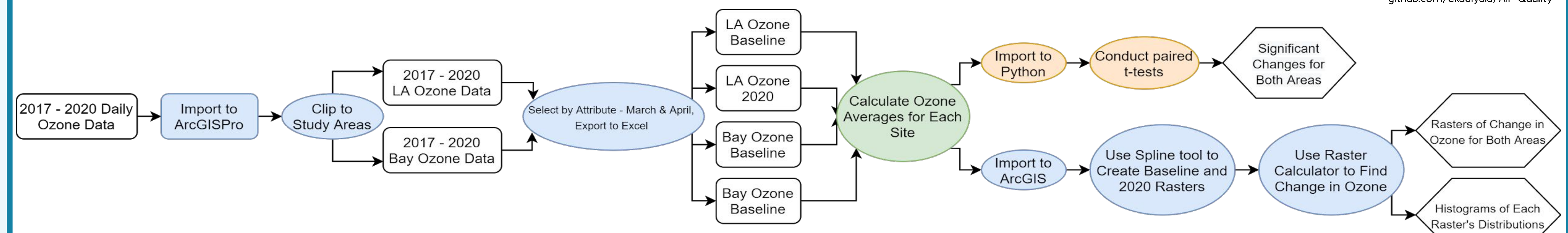


Figure 1: Workflow diagram of the project, conducted in ArcGIS Pro (blue), Python (orange), and Excel (green)

Results

Overall, a mean change of -0.00337 ppm was determined for the Los Angeles Basin, which suggests an increase in air quality due to a decrease in ozone emissions (Figure 4b). A similar but smaller negative trend was observed in the San Francisco Bay Area, resulting in a change of -0.00088 ppm (Figure 4a).

Furthermore, as displayed in the rasters of ozone change, a large portion of cities followed a downward trend in emissions. However, there were a few exceptions to this decline, the largest being the Pomona monitoring station in the Los Angeles study area. This outlier had a large increase in ozone concentration, reflected in Figure 2b.

The paired t-tests proved a significant difference in ozone concentrations seen in March and April of 2020 in comparison to March and April from 2017-2019. This aligns with the stay at home order being issued in California at the beginning of March.

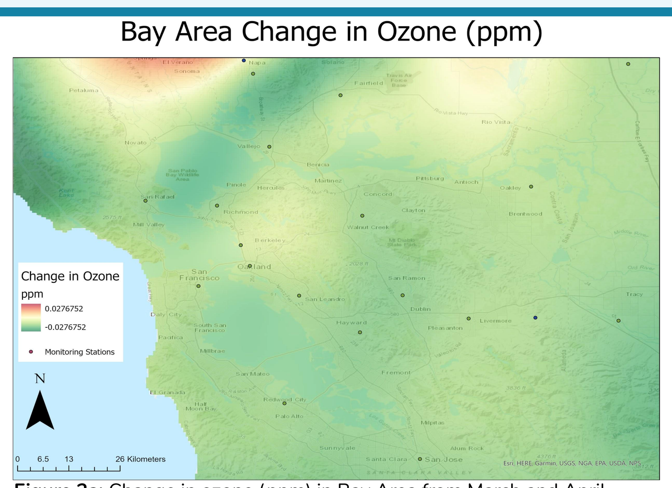


Figure 2a: Change in ozone (ppm) in Bay Area from March and April 2017-2019 baseline to same time span in 2020

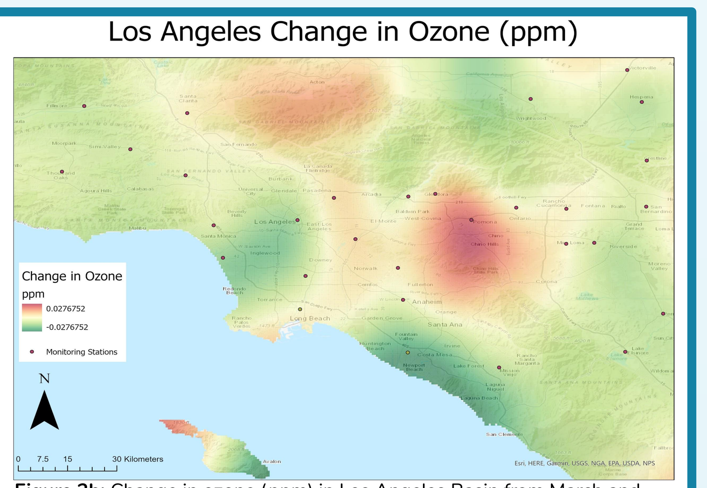


Figure 2b: Change in ozone (ppm) in Los Angeles Basin from March and April 2017-2019 baseline to same time span in 2020

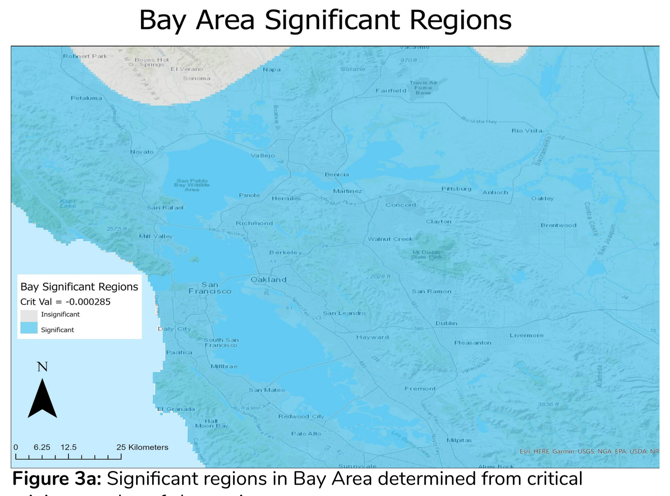


Figure 3a: Significant regions in Bay Area determined from critical minimum value of change in ozone

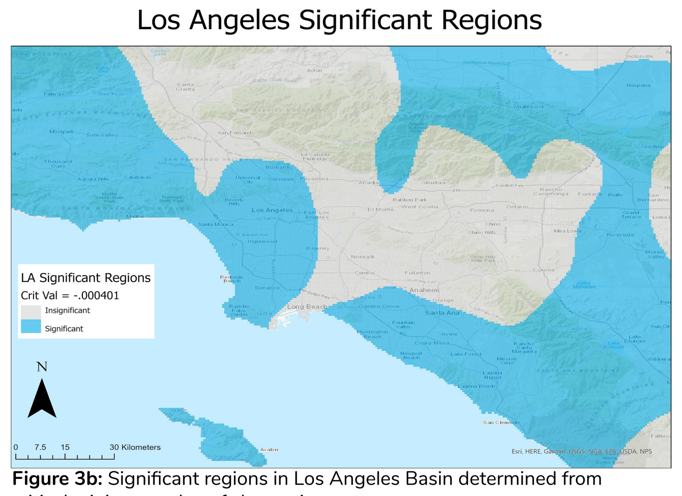
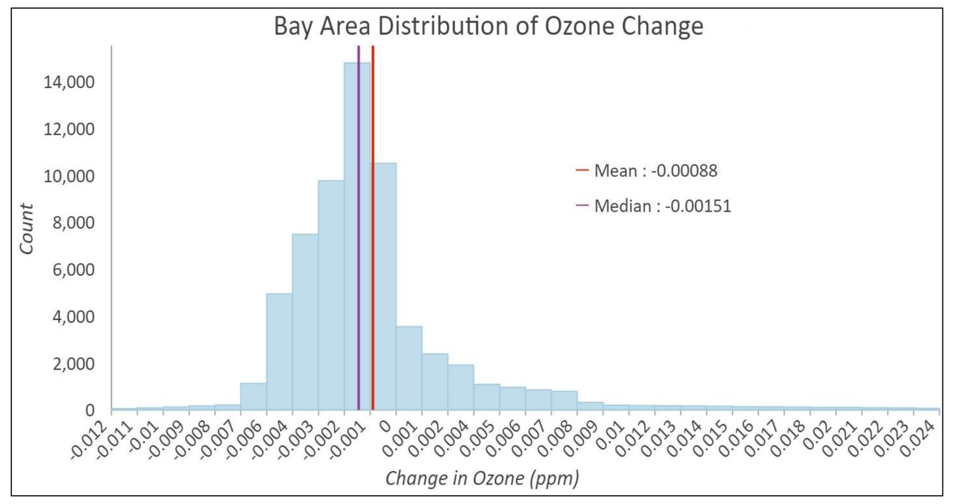
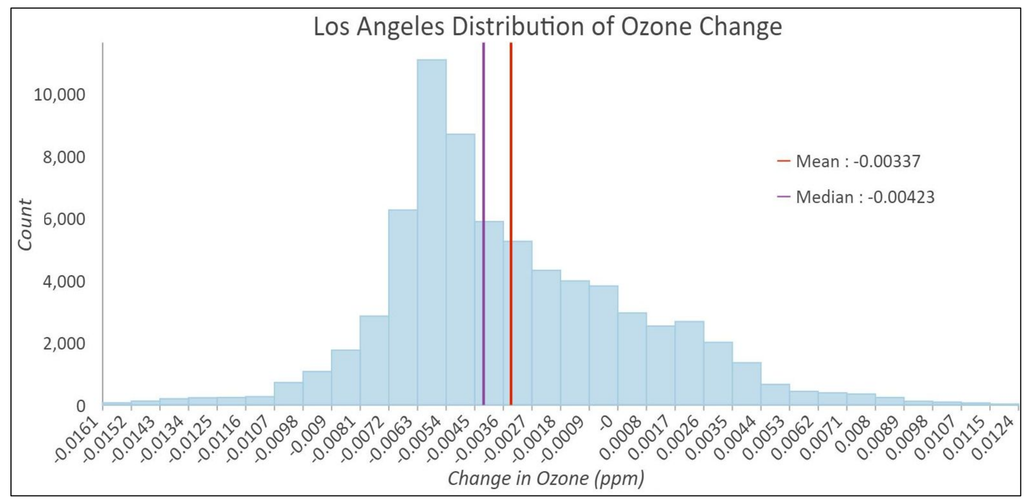


Figure 3b: Significant regions in Los Angeles Basin determined from critical minimum value of change in ozone

Figures 4a & 4b: Distributions of ozone change for each study region. Histograms were created from the difference between the baseline and 2020 spline interpolations. Each distribution displays the count of cells in a given range of ozone changes (ppm). Mean and median values are provided in ppm, representing the mean and median cell values for each raster.





Conclusion

In conclusion, ozone emissions decreased over the span of March and April in 2020 for both our study areas compared to March and April from the previous three years. This change proved to be significant in a site-wide t-test, comparing the average ozone values across both study areas.

On a station to station scale, t-tests proved significant results for each study area. In the Los Angeles Basin, 24 out of 34 stations underwent significant changes. Furthermore, 21 out of 23 stations in the Bay Area experienced significant changes. These trends are captured in the spline interpolations of our study areas (Figures 3a and 3b).

Overall, we can conclude that the stay at home order issued at the beginning of March 2020 led to a decrease in ozone emissions and a subsequent improvement in air quality. This is due to the ensuing decline in traffic, and provides a brief look at what may occur if electric vehicles increased in popularity and use.

Future Directions

Our shortcomings originate from our limited data usage, with only one source of data obtained from the EPA. We recommend using multiple sources in order to cross reference the data and fill in missing values. In addition, we advise attempting a land use regression model in order to obtain more accurate results. Land use regression is considered by experts to be the best method used to model air quality. In the case of our research, we only conducted one type of interpolation due to time constraints and our capabilities.

Furthermore, we recommend exploring the analysis of other pollutants or a combination of multiple in order to provide more information. The decision to focus primarily on ozone was taken after insufficient and inconsistent data was found concerning other pollutants. Although ozone is very indicative of changes in emissions, a study of other gases should also be done in order to supplement the research conducted.

Acknowledgements

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