Air Pollution Amidst the COVID-19 Pandemic Shelter-in-Place Orders

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ABSTRACT

Shelter in place orders during the COVID-19 pandemic in 2020 instructed citizens to stay indoors and only go out for essential necessities. This implies that more people will be off the roads and staying at home and therefore potentially decreasing pollutants from vehicles. However, with the uncertainty that people were actually obeying the orders put in place, this poses the question of: do shelter in place precautions during the COVID-19 pandemic have an effect on air quality in major cities in the United States? In order to answer this question, I used $PM_{2.5}$ datasets from the EPA from 8 different cities across the United States. With those 8 datasets I was able to assess trends in the data and see if the shelter in place orders for COVID-19 had any influence on $PM_{2.5}$ measurements. The overwhelming majority of the findings indicate that the pandemic's shelter in place orders decreased the $PM_{2.5}$ measurements, especially during the beginning months of the pandemic. My findings also indicate that annual trends due to seasonality were not affected by shelter in place orders, only emphasized in the beginning of the pandemic. In conclusion, shelter in place orders did seem to have an effect on air quality more so during the beginning of the pandemic than the later months of 2020.

KEYWORDS

Air quality, Pm2.5, COVID-19, pandemic, EPA, virus

INTRODUCTION

The spread of a virus is slow when travel restriction and shelter-in-place orders are put in place during a pandemic. When the Ebola virus was actively spreading at high rates in 2014-2016, travel precautions were also implemented to slow the spread of the virus. Monitoring the movement of people in West Africa helped control the spread of Ebola (Cohen Et. al 2016). Understanding how viruses have been controlled in the past is essential for the success of stopping COVID-19 (Cohen Et. Al 2016). Rima J. Isaifan, a public health analyst, researches how death rates due to air quality have been affected since the lockdown worldwide and explores whether the lockdown has saved more lives than it has killed. Her findings suggest that more lives were saved by the lockdown due to preventing poor ambient air quality than by infection of COVID-19. This means that the people who would die from bad air quality previously were less likely to die than those infected by the virus (Isaifan 2020). Although, this study may seem to prove that shelter-in-place may not be effective as a means to stop the virus, but by preventing deaths due to poor ambient air quality lead to an overall decrease in total global deaths. It also has been proven that death rates of individuals between the ages of 50-65 years old have decreased 82% when sheltering in place as well as consciously wearing a mask (Zhang Et. al 2020). However, there are also effects on the environment that need to be considered when dealing with a pandemic.

Countries in different parts of the world have already seen the effects that the shelter-in-place orders can have on air quality. In the Sao Paulo state in Brazil, two researchers, Nakada and Urban, study how COVID-19 precautionary measures have possibly affected the air quality in different parts of the state. Their findings indicate significant decreases in nitric oxide, nitrogen dioxide, ozone, and carbon monoxide concentrations in different parts of the state (Nakada & Urban 2020). Within the first two weeks of the lockdown in Barcelona, a decrease in air pollutants occurred. The individual pollutants varied in quantities and overall there was a downward trend in air pollutants in the urban areas. However, they saw a 50% increase in ozone. The study shows the exact decreases in air pollutants and discusses some possible assumptions on why they differ (Tobias Et al. 2020). In the city of Auckland, New Zealand, traffic flows were reduced by 60-80% when the lockdown was put in place. This city is known to produce its own pollutants due to its isolated location, so it is a good “control” experiment in a sense. Ozone concentrations increased while other pollutants decreased (Patel Et al. 2020). Similarly, in 44 cities across China, where heavy travel restrictions were put in place as soon as the virus was discovered, a strong association was seen between these travel restrictions and the air quality (Bao, R. and A. Zhang. 2020). Similar findings of COVID-19 precautions affecting air quality have flood journals worldwide.

These similar findings can also be seen in other parts of the world. In Ajmer, Rajasthan, India, they also observed approximately a 50% decrease in $PM_{2.5}$ pollutants after travel restrictions were put in place (Gulabchandani and Sehti 2020). 20-70% reductions in common pollutants was seen in Istanbul, Turkey (Şahin 2020). In Ecuador, major metropolitan areas experienced significant reductions (over 30%) in air pollutants (Zalakeviciute Et al. 2020). During the executive lockdown in California, from March 19 to May 7, the entire state saw a 30+% decrease in nitrogen dioxide, carbon monoxide, and $PM_{2.5}$ (Qian Et al. 2020). With all this information about how different places around the world have had air quality affected due to different restrictions and orders, it is important to remember why these findings are so important. In order to stop viruses and end pandemics, we must consciously choose the best methods for the least amounts of human deaths. It is also important to take into account how the environment is affected by these kinds of major events. By seeing how these shelter in place orders have affected the air quality in several places, it would not be surprising to have more mandated orders in the future with the sole purpose of slowing the effects of climate change.

The central research question for this thesis is: do shelter in place precautions during the COVID-19 pandemic have an effect on air quality in major cities in the United States? The next sub questions and hypotheses will help direct the research. I answer the following sub questions in order to answer my central research question: (1)How are air pollution levels affected by the shelter-in-place orders in major cities around the United States? (2) Did shelter-in-place orders change air quality outside normal inter-annual or seasonal variation? (3) Over the course of the COVID-19 pandemic, is there any sort of greater shift of air quality in cities compared to other cities? I hypothesize that (1) the air quality in those various locations will have lowered since the beginning of shelter-in-place orders due to the decrease in vehicle traffic on the roads. (2) The air quality in these locations will change outside the normal seasonal variation of the air quality due to varying levels of traffic throughout shelter-in-place orders. Finally, (3) there will be a shift in air quality throughout shelter-in-place orders due to varying amounts of traffic.

METHODS

Study sites

There are eight total study sites for my research. Each study site is an Environmental Protection Agency monitored site that collected air quality data (Table 1). The study site locations were chosen as optimal study sites for conducting air quality research during the COVID-19 pandemic shelter-in-place orders.

Table 1. Summary of study sites, location, and land use type. Study sites were chosen from the EPA.

City, State	Site Number	Latitude, Longitude	Urban/Rural
San Francisco, CA	60750005	37.765946, -122.39904	Urban
Los Angeles, CA	60371103	34.06659, -118.22688	Urban
Seattle, WA	530330030	47.597222, -122.31972	Urban
Miami, FL	120861016	25.794222, -80.215556	Urban
Chicago, IL	171971011	41.2215371, -88.190967	Rural
San Diego, CA	60730001	32.842318, -116.76829	Rural
Boston, MA	250092006	42.4746421, -70.9708155859215	Urban
Dallas, TX	482570005	32.564968, -96.317687	Rural

Data Collection

The data for this study is collected from the United States Environmental Protection Agency (EPA) which collects air quality index (AQI) data, in various measurements and pollutants, from thousands of sites across the United States. I use the particulate matter 2.5 ($PM_{2.5}$) measurements to represent air pollution. I chose to use $PM_{2.45}$ because of its danger to public health and high suspension time in the air compared to other pollutants. $PM_{2.5}$ pollutants are 100x smaller than the circumference of human hair, which makes $PM_{2.5}$ pollutants suspended for much longer compared to larger pollutants. Also due to their small size, $PM_{2.5}$ pollutants are able to travel much further than larger pollutants into human lungs and the rest of the respiratory tract. Some sources of these $PM_{2.5}$ molecules are vehicle exhausts, forest fires, burning or heating oils, or natural gases.

Through the EPA's public website, *Outdoor Air Quality Data*, I downloaded the $PM_{2.5}$ data from the past 6 years for each of the 8 study sites for a total of 40 separate data sets. To determine trends that rise from COVID-19, I used the trends from the past 6 years (2015-2020) as the control for my experiment. By looking at the past 6 years of data in comparison to 2020 data, I determined seasonal characteristics of $PM_{2.5}$, how wildfires affect $PM_{2.5}$ measurements, and if COVID-19 shelter-in-place orders had a prominent role affecting $PM_{2.5}$ measurements. I then cleaned all the data, deleting unnecessary columns, and renaming columns. I will be using the *gg.plot* and *stats* packages within R to do my analysis.

Analysis

To determine if COVID-19 altered $PM_{2.5}$ in major United States cities, I used R Studio (R 2014) to analyze my datasets. First, to visualize the data, I made a graph for each year at each site. These graphs were used to visualize the datasets and expose the outliers in the datasets. Active wildfires and residual smoke in proximity to site areas could end up affecting the $PM_{2.5}$ measurements. These are considered outliers and are mentioned in the results section. Then, I was able to begin the in-depth analysis of the datasets.

Confidence Intervals of Monthly Means

I used 95% confidence intervals of 2015-2019 monthly means to determine if the months between the different years varied enough compared to the 2020 shelter-in-place data.

City Comparison through ANOVA

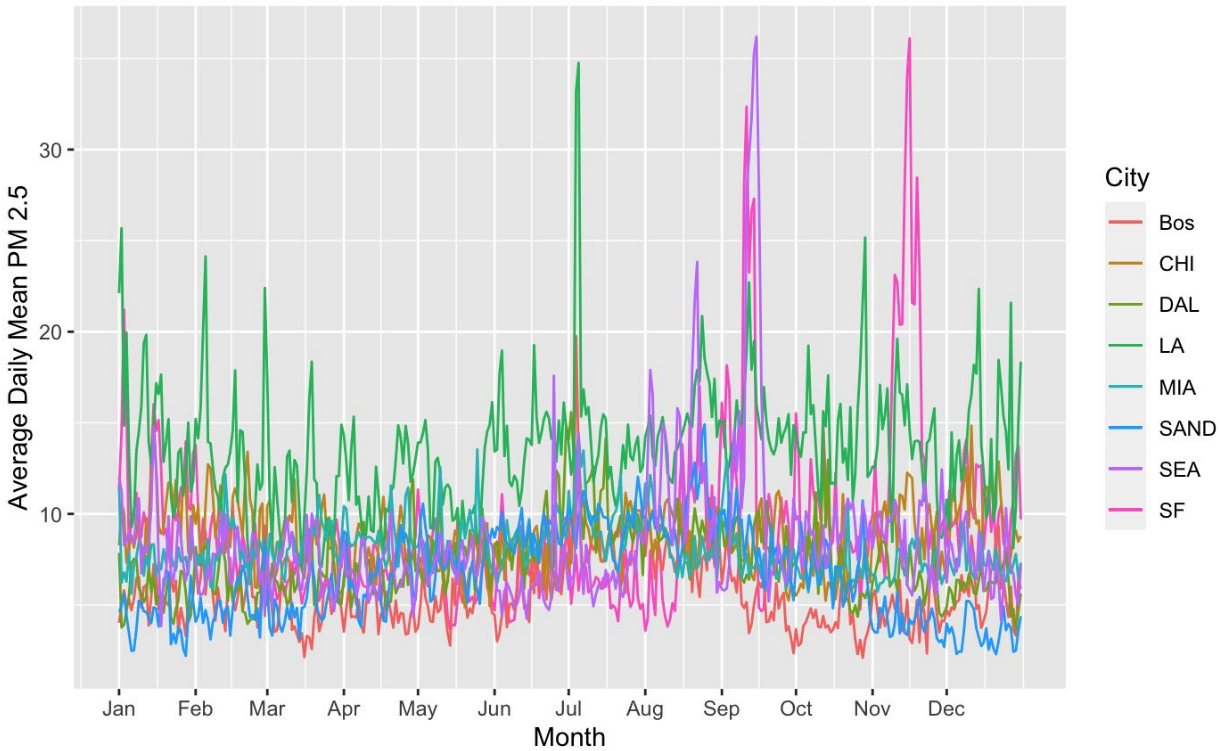
In order to measure variance between daily means in the data, I used analysis of variance (ANOVA) to determine any differences seen between the different cities before and after the 2020 shelter-in-place orders. ANOVA analysis assesses if there is a difference in daily means between 2015 and 2020. I used ANOVA to test for variation in shelter-in-place influences.

RESULTS

Interannual and Seasonal AQI Variability

Some cities, Los Angeles, San Francisco, and Chicago, experienced higher $PM_{2.5}$ data values in the beginning and end of the year. Boston, Dallas, and San Diego experienced higher $PM_{2.5}$ measurements during the middle of the year, or the summer months (May, June, July, and August). Seattle experienced averaging $PM_{2.5}$ measurements during the end part of the summer (August and September). No matter the cities, spring/summer and fall/winter months had contrasting data. This is shown below in the figure of the averaging data across the 6 years of data for each of the cities (Figure A.).

Figure A. All cities average $PM_{2.5}$ measurements throughout a year.



Months towards the end of the summer and beginning of fall contain $PM_{2.5}$measurements taken during the time of active wildfires, especially in California, which due to a mass of toxic air particles, are expected to raise the $PM_{2.5}$ measurements higher than usual.

Across all cities, no cities had their lowest average $PM_{2.5}$ readings in 2020. In the table below, cities average $PM_{2.5}$ measurements are listed. Bolded text indicates the highest average $PM_{2.5}$ reading over the past 6 year, and italicized text indicates the lowest readings (Table 2).

Table 2. Annual Average $PM_{2.5}$ readings from 2015-2020.

Annual Means	2015	2016	2017	2018	2019	2020
Dallas, TX	7.489174	7.331302	7.830523	7.355043	*6.670474*	**7.850877**
Boston, MA	6.209636	5.06302	*4.750652*	6.4	**6.547354**	5.515642
Miami, FL	8.152972	8.324364	8.417301	**8.582878**	*7.601316*	7.696401
Chicago, IL	**10.01895**	8.42475	*7.859249*	8.43595	8.736261	8.274785
Seattle, WA	9.296369	7.708805	8.089086	9.415775	*7.375978*	**9.459202**
San Francisco, CA	*7.57591*	7.583333	9.680168	**11.67649**	7.667409	10.58784
Los Angeles, CA	14.50263	13.32729	13.68516	14.21036	*11.71174*	**14.23584**
San Diego, CA	6.163222	7.243503	7.138643	**7.566185**	*5.240286*	6.503064

Shelter in Place Effects on AQI Values

In Dallas, the lowest measurement was 0.3 $PM_{2.5}$ in December of 2020. The highest value was in October of 2020 with a measurement of 48.7 $PM_{2.5}$. Both the highest and the lowest $PM_{2.5}$ measurements for Dallas took place in 2020.

In Boston, the lowest measurement was -2.9 $PM_{2.5}$in June of 2017. The highest value was in July of 2015 at 29.5 $PM_{2.5}$.

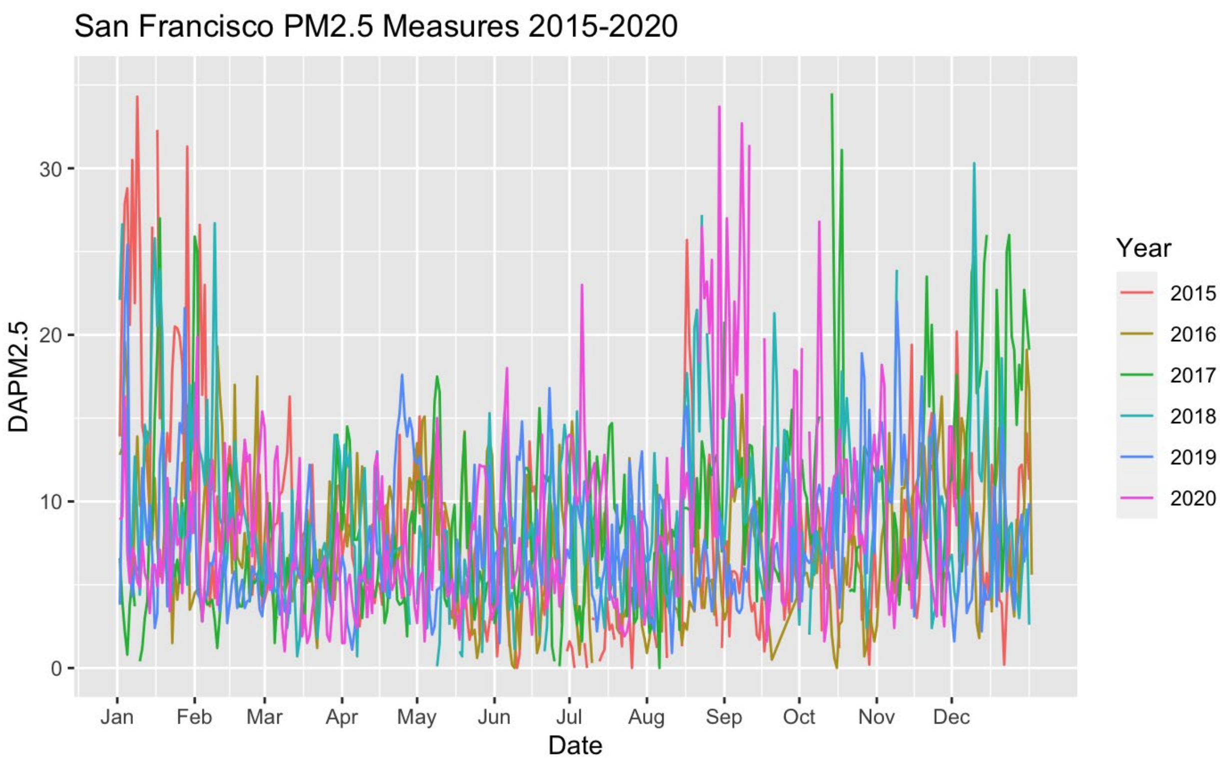
In Miami, the lowest measurement took place in June of 2017 as wells with a measurement of 0 $PM_{2.5}$. The highest measurement was in July of 2018 with 29.6 $PM_{2.5}$.

In Chicago, the lowest measurement taken was -0.7 $PM_{2.5}$ in February of 2016. The highest measurement was in July of 2020 with 40.9. It is important to emphasize here that the highest reading was during the months of quarantine in Chicago.

In Seattle, the lowest reading was 0.9 $PM_{2.5}$ and took place on multiple days including: January of 2019, January of 2020, March of 2020, and June of 2020. The highest value was in September of 2020 with a measurement of 179.

In San Francisco, the lowest measured value was -3.5 $PM_{2.5}$ in August of 2015. The highest recorded value for San Francisco was in November of 2020 at 177.4 $PM_{2.5}$. The highest value for San Francisco, similarly to Chicago and Seattle, took place in 2020. San Francisco also had the highest and lowest values of $PM_{2.5}$ compared to all of the other cities across all years studied.

Figure J. $PM_{2.5}$ measurements in San Francisco from 2015 to 2020.



In Los Angeles, the lowest measurement was taken in May of 2015 with a value of 0 PM 2.5. The highest recorded value was 175 in July of 2020.

Lastly in San Diego, the lowest value was -1.2 $PM_{2.5}$ in December of 2016. The highest measurement was taken in August of 2018 with a measurement of 29.7 $PM_{2.5}$.

In conclusion to the last findings, the highest values of $PM_{2.5}$ over the 6 years in this study ended up being recorded in 2020 for Dallas, Chicago, Seattle, San Francisco, and Los Angeles. The lowest values of $PM_{2.5}$ over the course of the 6 years ended up being in 2020 for Dallas, Miami, and Seattle.

Overall, no matter the city, a general decrease in $PM_{2.5}$ was experienced at the beginning of the pandemic compared to data from previous years. However, as the pandemic went on, the AQI values steadily went back to their mean values of previous years.

Using ANOVA, I was able to find the F values below (Table 3). The larger the F value is, the more variation between the $PM_{2.5}$ measurements. San Francisco and Chicago's sites had $PM_{2.5}$ measurements with the most variation throughout the 6 years.

Table 3. F values of each city found using ANOVA.

ANOVA	F Value
Dallas, TX	0.189
Boston, MA	2.123
Miami, FL	9.312
Chicago, IL	19.64
Seattle, WA	0.009
San Francisco, CA	13.04
Los Angeles, CA	4.958
San Diego, CA	5.501

City Based Comparison on Shelter in Place Effects on AQI

As previously mentioned, Dallas' lowest and highest $PM_{2.5}$ values occurred during the time when shelter in place protocols were in place (Figure K).

Boston's lowest $PM_{2.5}$ values occurred in September and November in 2020 with measurements of -0.2 $PM_{2.5}$. Boston's highest measurement during shelter in place orders was in December of 2020, towards the end of the orders (Figure L).

Miami's lowest $PM_{2.5}$ value during shelter in place orders was 0 $PM_{2.5}$ in November. Miami experienced its highest $PM_{2.5}$ measurement during January with a measurement of 25.7 $PM_{2.5}$ (Figure M).

Chicago's lowest $PM_{2.5}$ value during shelter in place orders was 2.1 $PM_{2.5}$ in December. Chicago experienced its highest $PM_{2.5}$ measurement during July with a measurement of 40.9 $PM_{2.5}$ (Figure N).

Seattle's lowest $PM_{2.5}$ value during shelter in place orders was 0.9 $PM_{2.5}$ in January, March, and June. Seattle experienced its highest $PM_{2.5}$ measurement during September with a measurement of 179 $PM_{2.5}$ (Figure O).

San Francisco's lowest $PM_{2.5}$value during shelter in place orders was1 $PM_{2.5}$ in March, at the beginning of the pandemic. San Francisco experienced its highest $PM_{2.5}$ measurement during September with a measurement of 147.3 $PM_{2.5}$ (Figure J).

Los Angeles's lowest $PM_{2.5}$ value during shelter in place orders was 1.3 $PM_{2.5}$ in March. Los Angeles experienced its highest $PM_{2.5}$ measurement during July with a measurement of 175 $PM_{2.5}$ (Figure Q).

San Diego's lowest $PM_{2.5}$ value during shelter in place orders was -1.1 $PM_{2.5}$ in December. San Diego experienced its highest $PM_{2.5}$ measurement during October with a measurement of 22.9 $PM_{2.5}$(Figure R).

95% Confidence Intervals

In the confidence intervals made for each city over each year, their findings are stated in the table below (Table 4). The confidence intervals indicate that 95% of the data is to lie between those two numbers indicated. The smaller the confidence interval, the more closely the rest of the data should be to that range of data.

Table 4. 95% confidence intervals of daily mean $PM_{2.5}$ measurements from 2015-2020.

Confidence Intervals	2015	2016	2017	2018	2019	2020
Dallas, TX	7.074294, 7.904053	6.990307, 7.672297	7.442751, 8.218295	6.968429 ,7.741657	6.352272 , 6.988675	7.326291, 8.375463
Boston, MA	5.827313, 6.591959	4.773936, 5.352104	4.388246, 5.113058	5.917421, 6.882579	6.193307, 6.901400	5.188013, 5.843272
Miami, FL	7.907421, 8.398522	8.145382, 8.503346	8.142335, 8.692267	8.287053, 8.878704	7.334456, 7.868176	7.371990, 8.020812
Chicago, IL	9.620934, 10.416972	8.099002, 8.750498	7.456771, 8.261726	7.970657, 8.901244	8.299138, 9.173383	7.831432, 8.718138
Seattle, WA	8.818032, 9.774705	7.339256, 8.078354	7.309160, 8.869011	8.383354, 10.448195	7.012961, 7.738995	7.204854 ,11.713550
San Francisco , CA	6.925676, 8.226145	7.156096, 8.010571	8.883731, 10.476604	9.834087, 13.518888	7.260592, 8.074227	8.965803, 12.209881
Los Angeles, CA	13.89771, 15.10756	12.86301, 13.79158	13.20897, 14.16134	13.69206 ,14.72866	11.32653, 12.09695	13.43512, 15.03656
San Diego, CA	5.773844, 6.552600	6.790848, 7.696158	6.779846, 7.497440	7.121005, 8.011365	4.922469, 5.558103	6.067266, 6.938862

DISCUSSION

The discussion below includes many of the findings from my study, as well as what they mean or imply for my research and others. The overwhelming majority of the findings indicate that the pandemic's shelter in place orders decreased the $PM_{2.5}$ measurements, especially visible during the beginning months of the pandemic. There is also reason to believe that rural sites revealed lower $PM_{2.5}$ measurements than any other city, including during the shelter in place orders. Annual trends did not seem to be affected during the beginning of the shelter in place orders, only emphasized. Lastly, some cities, more than others, demonstrated stronger decreases in $PM_{2.5}$ measurements.

City based findings

San Diego, Chicago, and Dallas were all indicated to be rural sites. This meant that the data would most likely look a bit different than other cities in the study. All of these cities ended up having lower daily average means than any of the other urban city sites. In a study done in Bangladesh, they also found that cities more rural in the area ended having slightly lower readings in their concentrations of NO2, SO2, CO, and O3 (Islam Et al. 2021). They also found however that their NO2 readings highly correlated with the number of regional COVID-19 cases, something that I did not use as a variable in my own research. Their findings however, do agree with my findings of decreased values of pollutants in more rural areas. This shows that rural and urban areas are seeing contrasting measures of $PM_{2.5}$.

Another interesting finding was that 3 cities, Dallas, Seattle, and Los Angeles all had data which pointed to an increase in the annual mean $PM_{2.5}$ measurements during the year of 2020. This could indicate something else contributing to an increase in the data during shelter in place orders. I can hypothesize that they experienced the highest annual means of $PM_{2.5}$ because of the rise of global greenhouse gases which has been growing exponentially for decades (Hansen and Sato 2004). While other years did not have their mean annual highest $PM_{2.5}$ reading in 2020, 6 of the 8 cities (Boston and Chicago excluded) saw increases in their annual $PM_{2.5}$ measurements from 2019 to 2020. This would also support the research of Hansen and Sato. While overall rising $PM_{2.5}$ measurements does not support my hypothesis of decreasing $PM_{2.5}$ measurements, the more narrowed findings of at the beginning of the pandemic and the end of 2020 do support my hypothesis.

Annual trends and Shelter in place trends

In terms of annual trends and covid-19 shelter in place orders, the data tended to follow the annual trends. This can imply that annual trends may be more impactful on $PM_{2.5}$ measurements than the shelter in place orders. This would make sense seeing that annual trends of $PM_{2.5}$ and other pollutants have been taking place over many years which has established the trends I was able to see over the short period of only 6 years. In a study done in Northern China, researchers found that short-term control measures and meteorological factors mainly affected air quality data (Xian Et al. 2021). Their research also looked at annual trends and if those would be influenced. The researchers decided to separate the factors one by one and found no impact of the air quality data from the annual trends. This perfectly aligns with my findings that annual trends are not truly affected by shelter in place orders, nor are they affected by them. In a similar study done in Mexico

City's metropolitan area, the researchers minimize the variable of annual trends and seasonality in order to not have it impact their findings of air quality during lockdowns (Hernandez-Paniagua Et al. 2021). Both studies show that the annual trends do not have a significant impact on the possible trends on shelter in place orders which agrees with my findings. While trends of decreasing $PM_{2.5}$ were very prominent in the beginning of the pandemic and shelter in place orders, there was usually some sort of decrease during those months in other years which points to these annual trends in the data.

Shelter in place trends

Two cities, Seattle and San Diego, had more visible decreases in their $PM_{2.5}$ measurements during the 2020 pandemic, especially in the beginning of the shelter in place orders, compared to the other cities (Figures O and R). A reason for why San Diego could have had this more explicit decrease is because of its location outside of the downtown area and in a canyon which has a possibly better chance to distribute the $PM_{2.5}$ measurements with better circulation of the air. However, a downtown site, like Seattle's, indicates the opposite. Therefore, I must conclude that individual sites' $PM_{2.5}$measurements are influenced by the region that they are located as well as the circulation and placement of the actual site itself (on a hill, in a canyon, next to a highway, etc). In a study done in mainland China, the researchers found that temperatures, wind speed, and air pressure are all inversely correlated to the spread of COVID-19 (Lin Et al.2021). While this study discusses the relationship between COVID-19 and meteorological factors, it does describe this relationship which I mention between location and air quality during the time of shelter in place orders. This is important to mention because it describes how location can spread the virus as well as impact air quality. The reason for why many places did see a decrease in $PM_{2.5}$ at the beginning of the pandemic and not as much towards the end of the year could suggest relaxed caution and shelter in place orders.

I suspect that there are two main reasons cities saw increases in annual mean $PM_{2.5}$ measurements during the COVID-19 pandemic. The first reason could be due to cities in close proximity to wildfires which contributed an outlier to the data for the 2020 year during the COVID-19 pandemic. The second reason could be that people were using public transportation less and driving their own personal vehicles instead. The reason that people would switch to their own vehicles during the pandemic is to avoid contact with people with the COVID-19 virus. However, in a study done in India, their findings point to a decrease in the pollutants from their studies (Verma and Kamyotra 2021). They tie this finding to the fact that transportation, different industries, and commercial activities were shut down because of the COVID-19 pandemic.

Limitations

In terms of limitations, it is important to address the negative $PM_{2.5}$ measurements from the datasets collected from the EPA. Negative $PM_{2.5}$ measurements are usually taken when equipment being used is not calibrated correctly, not functioning properly, or simply not being used properly. The EPA has thousands of these sites all across the country so I can understand maintenance and proper usage of their equipment to be difficult at times. In a research gate discussion forum, many scientists were discussing how to make the datasets better and understanding how these negative values ended up in the dataset. Hovorka states that there are two options for when your dataset turns out with negative values: either discard the data set or make negative values other values (Hovorka 2014). They also state however that working with a dataset with more than 10% of the data needing to be manipulated is not acceptable.

After some quick calculations, I was able to find out that negative values make up roughly 2% of my data, therefore if I did decide to do these manipulations it would be acceptable. However, the numbers being as small off from 0 made it unnecessary to do so because their impacts on the accuracy of the findings in this study were negligible. However, if I were to go back and redo a part of my study, this would be it. Manipulating the data to be more accurately representing the $PM_{2.5}$ measurements would definitely help with the study's both credibility and accuracy.

Future directions

Some lingering questions I have about my research include whether or not my findings would be the same for other pollutants measured in these sites. If so, do some of those pollutants have contrasting outcomes from the shelter in place orders? It would be interesting to also look at how other past viruses have affected air quality as well as how future ones might. If another one happens in the next 50 years with multiple of the same generations living through multiple virus outbreaks, would the data end up looking any different?

Conclusions

My findings indicate that there was a decrease in $PM_{2.5}$ measurements during the beginning of the shelter in place order in 2020. These findings can also indicate that people were taking the pandemic slightly more seriously in the beginning compared to later in the course of the virus. Overall, these decreases in $PM_{2.5}$ measurements are important for the world, which faces a large impact from the accumulation of greenhouse gases in the atmosphere. This accumulation ends up warming the earth and melting the ice caps. If shelter in place orders were able to bring down those measurements, maybe a few extra days in the year spent indoors and off the roads could be beneficial to the health of the environment.

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APPENDIX

Table 1. Summary of study sites, location, and land use type. Study sites were chosen from the EPA.

City, State	Site Number	Latitude, Longitude	Urban/Rural
San Francisco, CA	60750005	37.765946, -122.39904	Urban
Los Angeles, CA	60371103	34.06659, -118.22688	Urban
Seattle, WA	530330030	47.597222, -122.31972	Urban
Miami, FL	120861016	25.794222, -80.215556	Urban
Chicago, IL	171971011	41.2215371, -88.190967	Rural
San Diego, CA	60730001	32.842318, -116.76829	Rural
Boston, MA	250092006	42.4746421, -70.9708155859215	Urban
Dallas, TX	482570005	32.564968, -96.317687	Rural

Table 2. Annual Average $PM_{2.5}$ readings from 2015-2020.

Annual Means	2015	2016	2017	2018	2019	2020
Dallas, TX	7.489174	7.331302	7.830523	7.355043	*6.670474*	**7.850877**
Boston, MA	6.209636	5.06302	*4.750652*	6.4	**6.547354**	5.515642
Miami, FL	8.152972	8.324364	8.417301	**8.582878**	*7.601316*	7.696401
Chicago, IL	**10.01895**	8.42475	*7.859249*	8.43595	8.736261	8.274785
Seattle, WA	9.296369	7.708805	8.089086	9.415775	*7.375978*	**9.459202**
San Francisco, CA	*7.57591*	7.583333	9.680168	**11.67649**	7.667409	10.58784
Los Angeles, CA	14.50263	13.32729	13.68516	14.21036	*11.71174*	**14.23584**
San Diego, CA	6.163222	7.243503	7.138643	**7.566185**	*5.240286*	6.503064

Table 3. F values of each city found using ANOVA.

ANOVA	F Value
Dallas, TX	0.189
Boston, MA	2.123
Miami, FL	9.312
Chicago, IL	19.64
Seattle, WA	0.009
San Francisco, CA	13.04
Los Angeles, CA	4.958
San Diego, CA	5.501

Table 4. 95% confidence intervals of daily mean $PM_{2.5}$ measurements from 2015-2020.

Confidence Intervals	2015	2016	2017	2018	2019	2020
Dallas, TX	7.074294, 7.904053	6.990307, 7.672297	7.442751, 8.218295	6.968429 ,7.741657	6.352272 , 6.988675	7.326291, 8.375463
Boston, MA	5.827313, 6.591959	4.773936, 5.352104	4.388246, 5.113058	5.917421, 6.882579	6.193307, 6.901400	5.188013, 5.843272
Miami, FL	7.907421, 8.398522	8.145382, 8.503346	8.142335, 8.692267	8.287053, 8.878704	7.334456, 7.868176	7.371990, 8.020812
Chicago, IL	9.620934, 10.416972	8.099002, 8.750498	7.456771, 8.261726	7.970657, 8.901244	8.299138, 9.173383	7.831432, 8.718138
Seattle, WA	8.818032, 9.774705	7.339256, 8.078354	7.309160, 8.869011	8.383354, 10.448195	7.012961, 7.738995	7.204854 ,11.713550
San Francisco , CA	6.925676, 8.226145	7.156096, 8.010571	8.883731, 10.476604	9.834087, 13.518888	7.260592, 8.074227	8.965803, 12.209881
Los Angeles, CA	13.89771, 15.10756	12.86301, 13.79158	13.20897, 14.16134	13.69206 ,14.72866	11.32653, 12.09695	13.43512, 15.03656
San Diego, CA	5.773844, 6.552600	6.790848, 7.696158	6.779846, 7.497440	7.121005, 8.011365	4.922469, 5.558103	6.067266, 6.938862

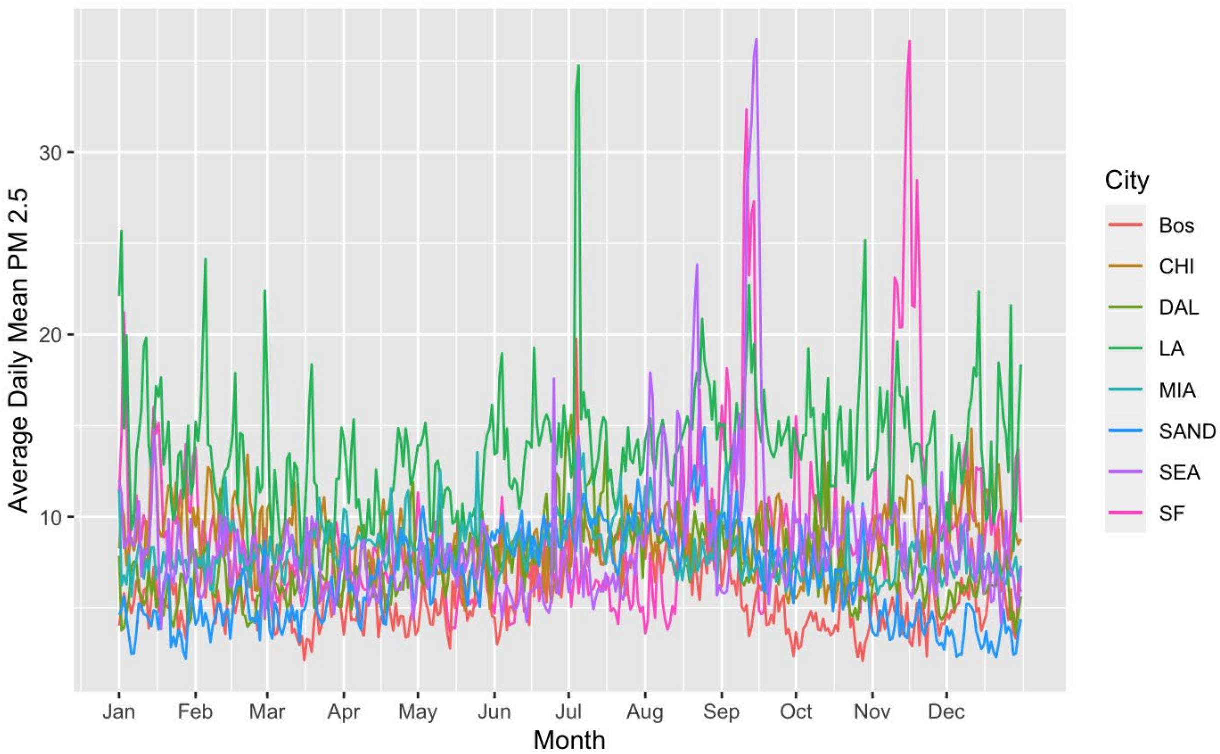

Figure A. All cities average $PM_{2.5}$ measurements throughout a year.

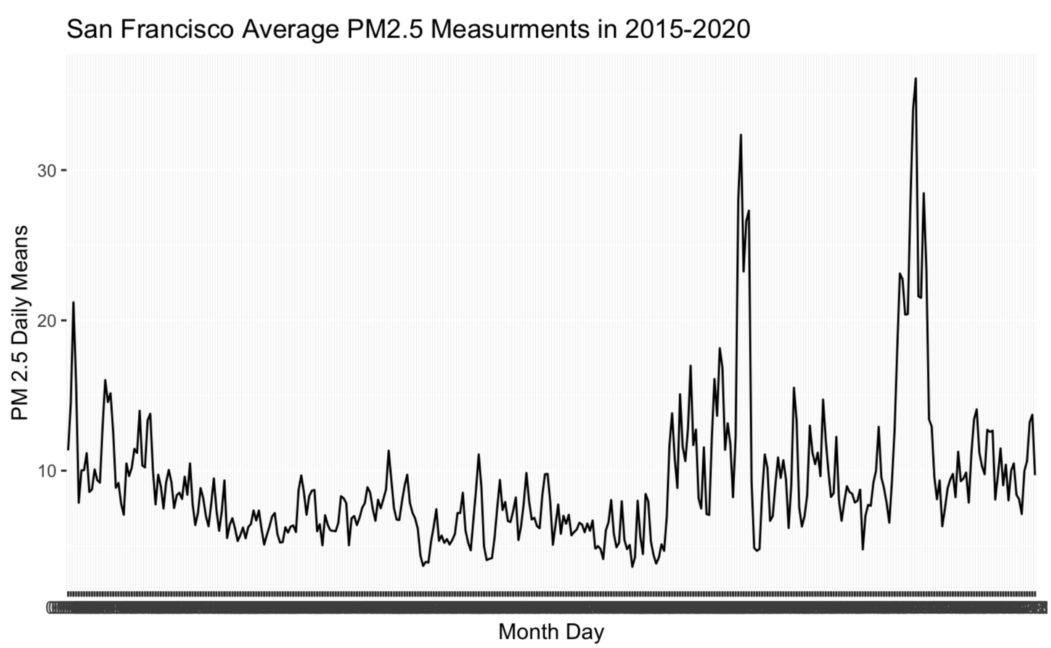

Figure B. San Francisco average $PM_{2.5}$ Measurements from 2015-2020.

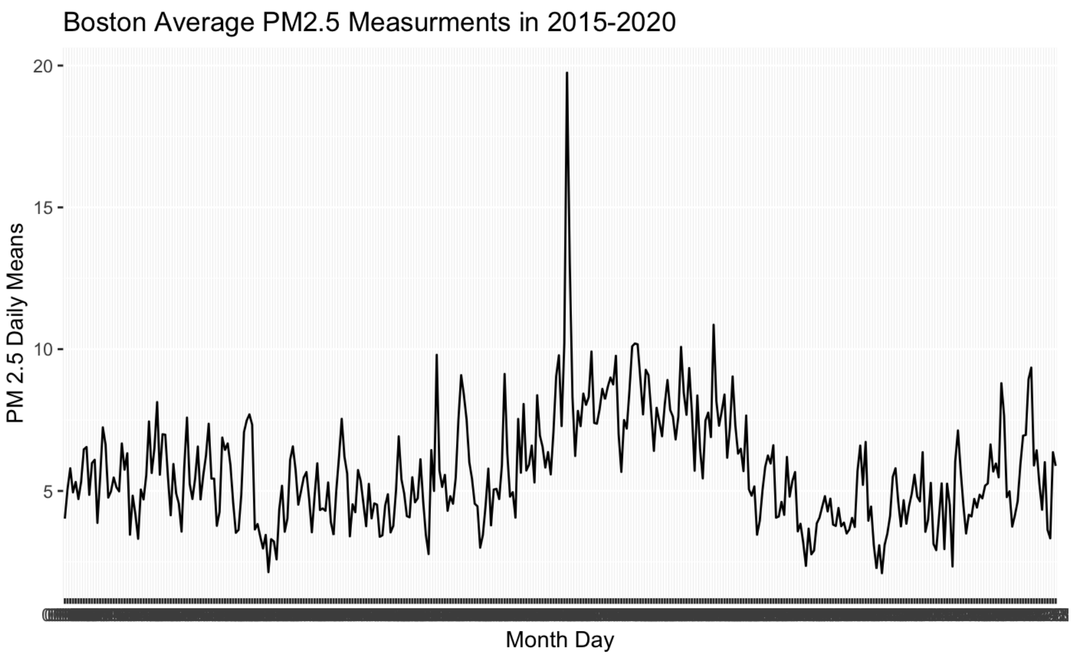

Figure C. Boston average $PM_{2.5}$ Measurements from 2015-2020.

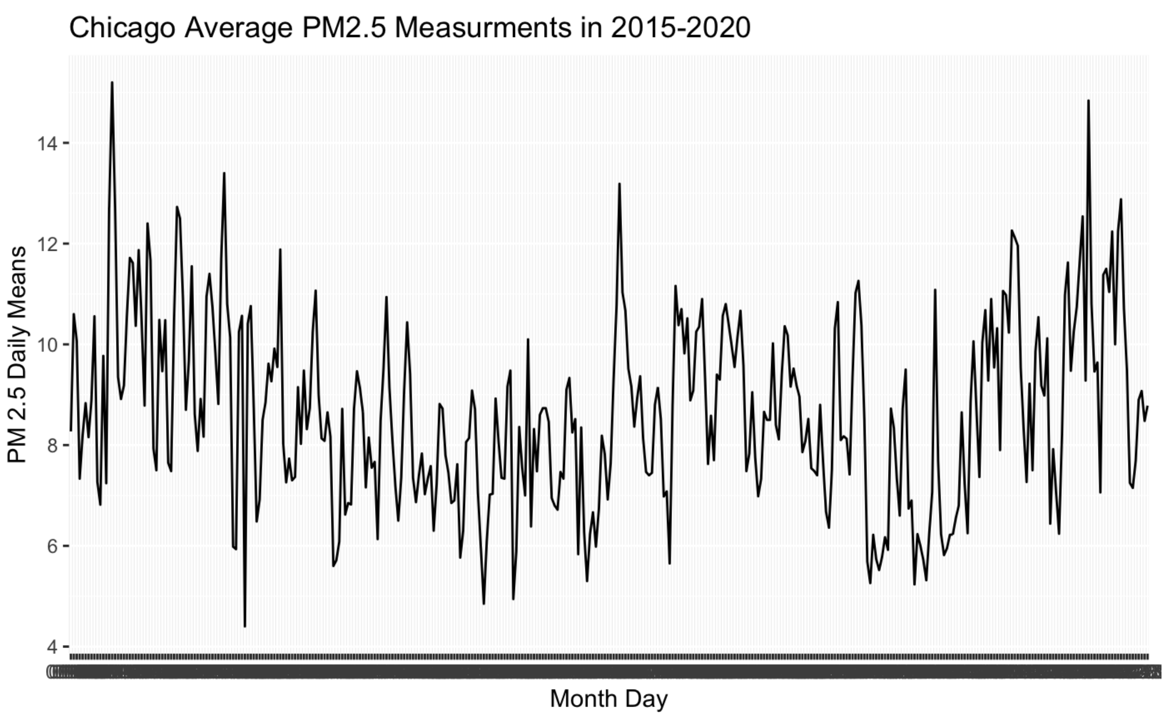

Figure D. Chicago average $PM_{2.5}$ Measurements from 2015-2020.

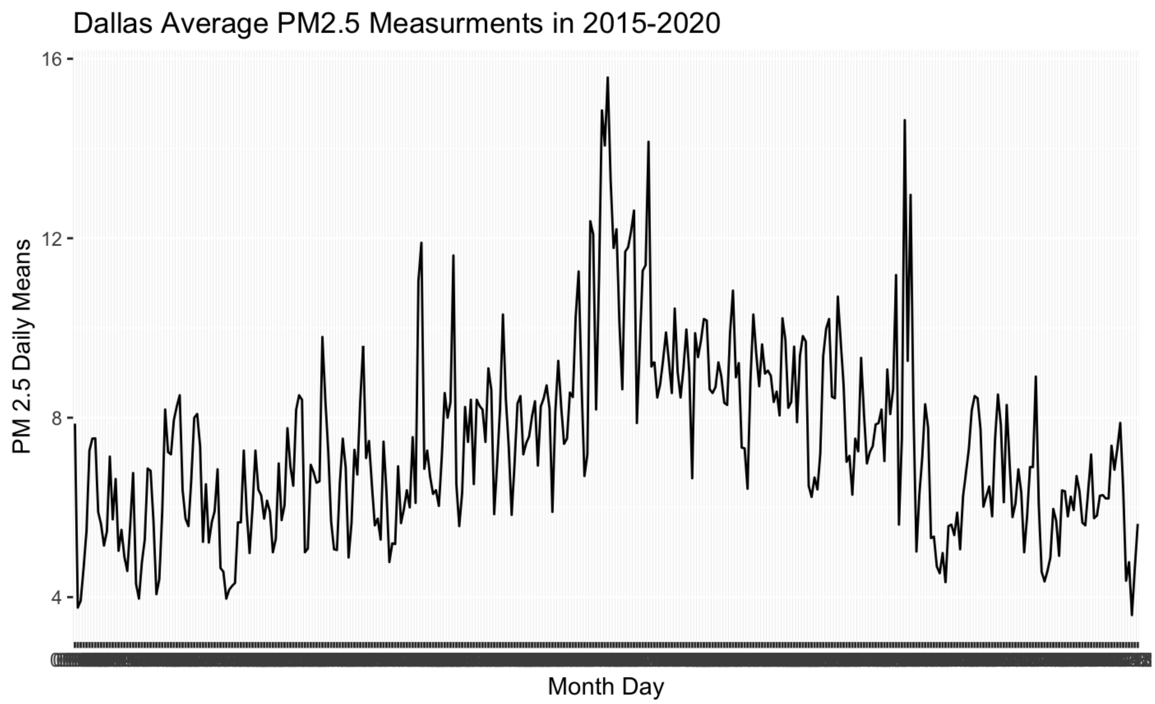

Figure E. Dallas average $PM_{2.5}$ Measurements from 2015-2020.

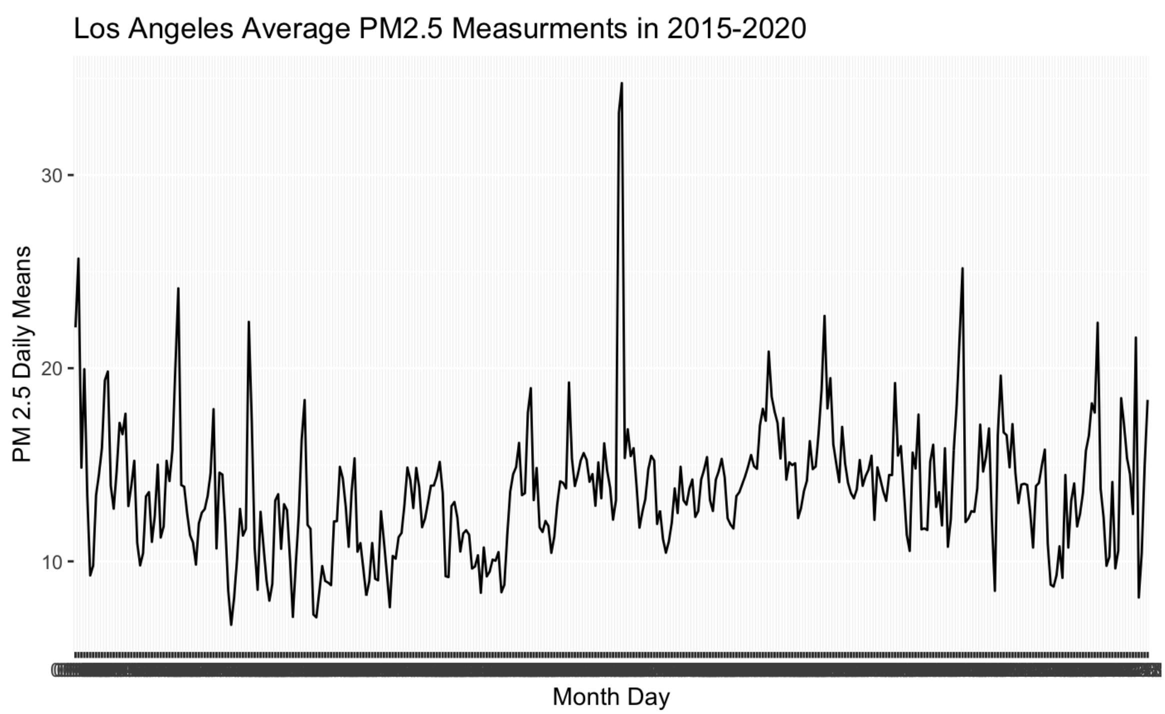

Figure F. Los Angeles average $PM_{2.5}$ *Measurements from 2015-2020.*

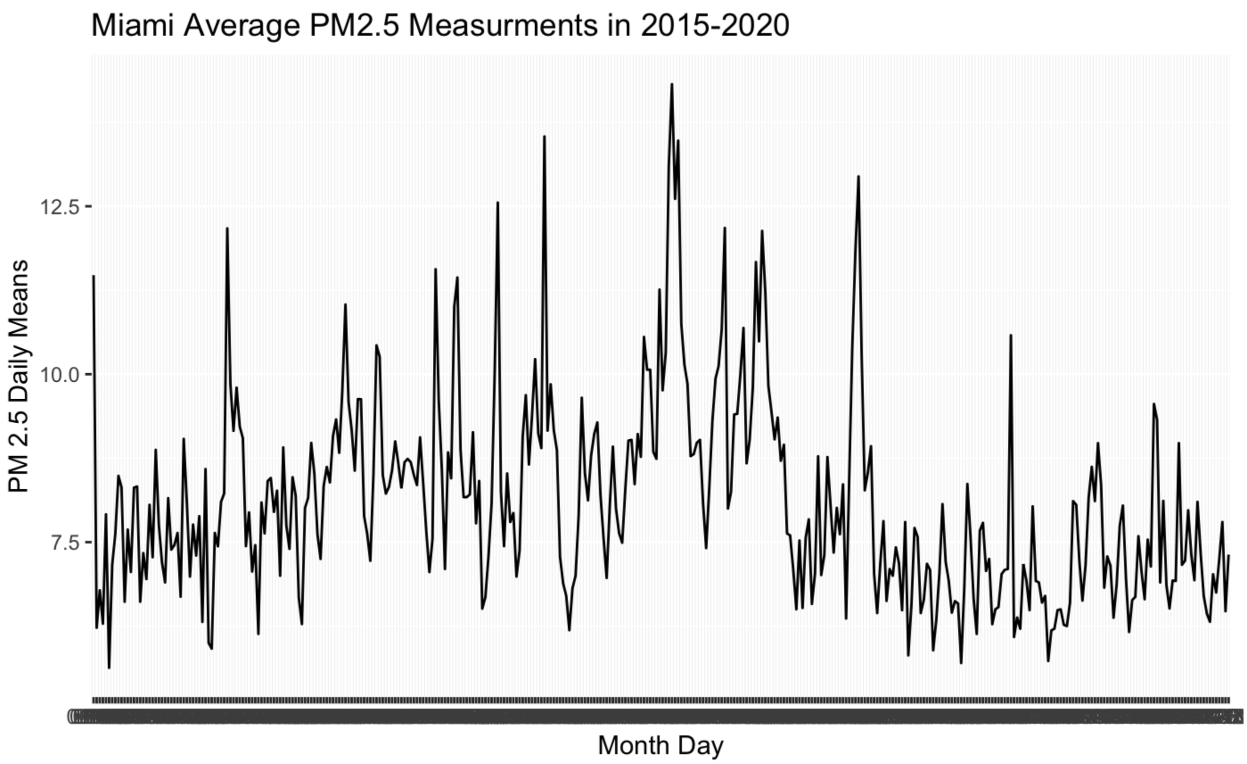

Figure G. Miami average $PM_{2.5}$ *Measurements from 2015-2020.*

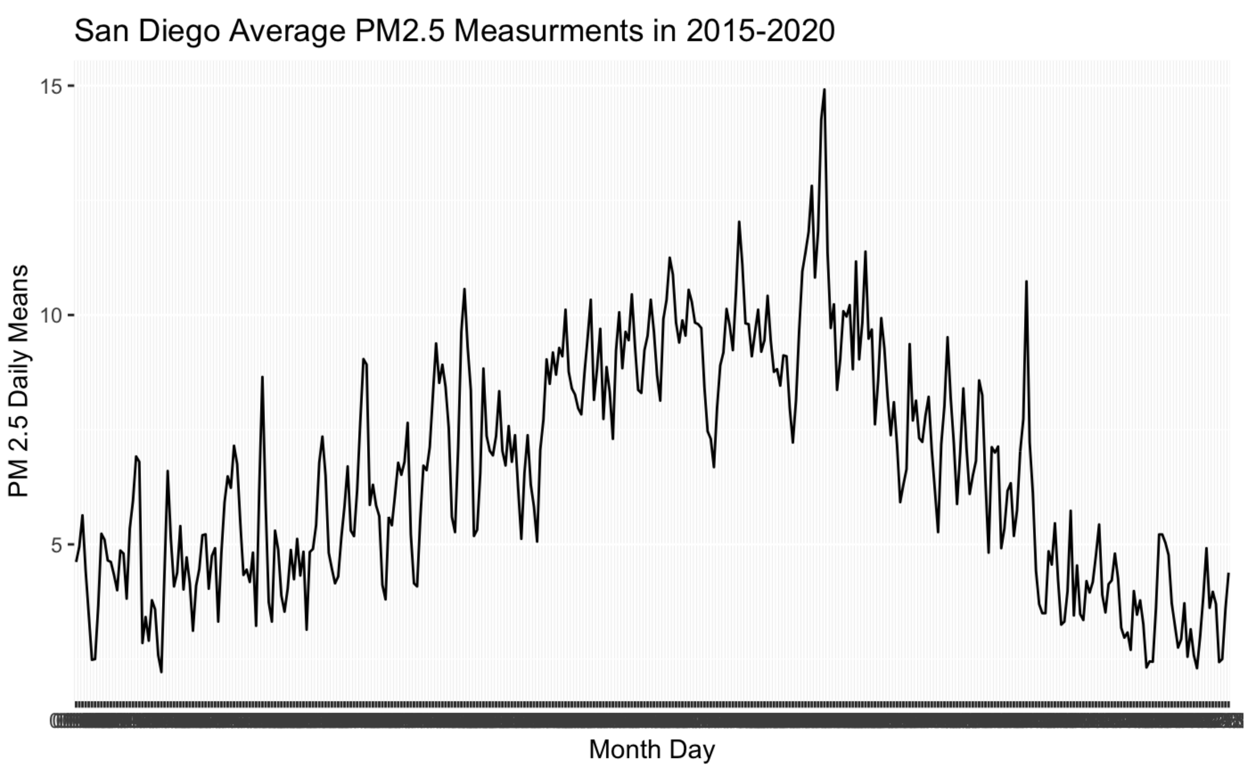

Figure H. San Diego average $PM_{2.5}$ Measurements from 2015-2020.

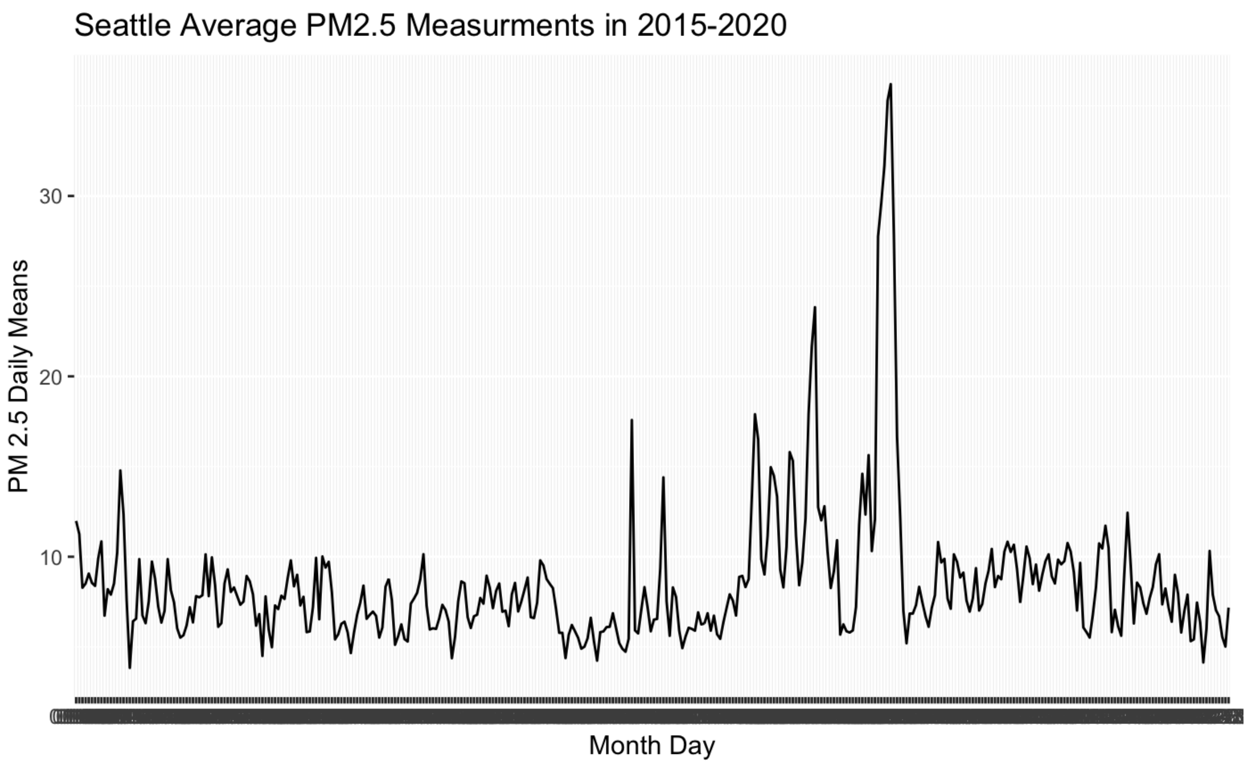

Figure I. Los Angeles average $PM_{2.5}$ Measurements from 2015-2020.

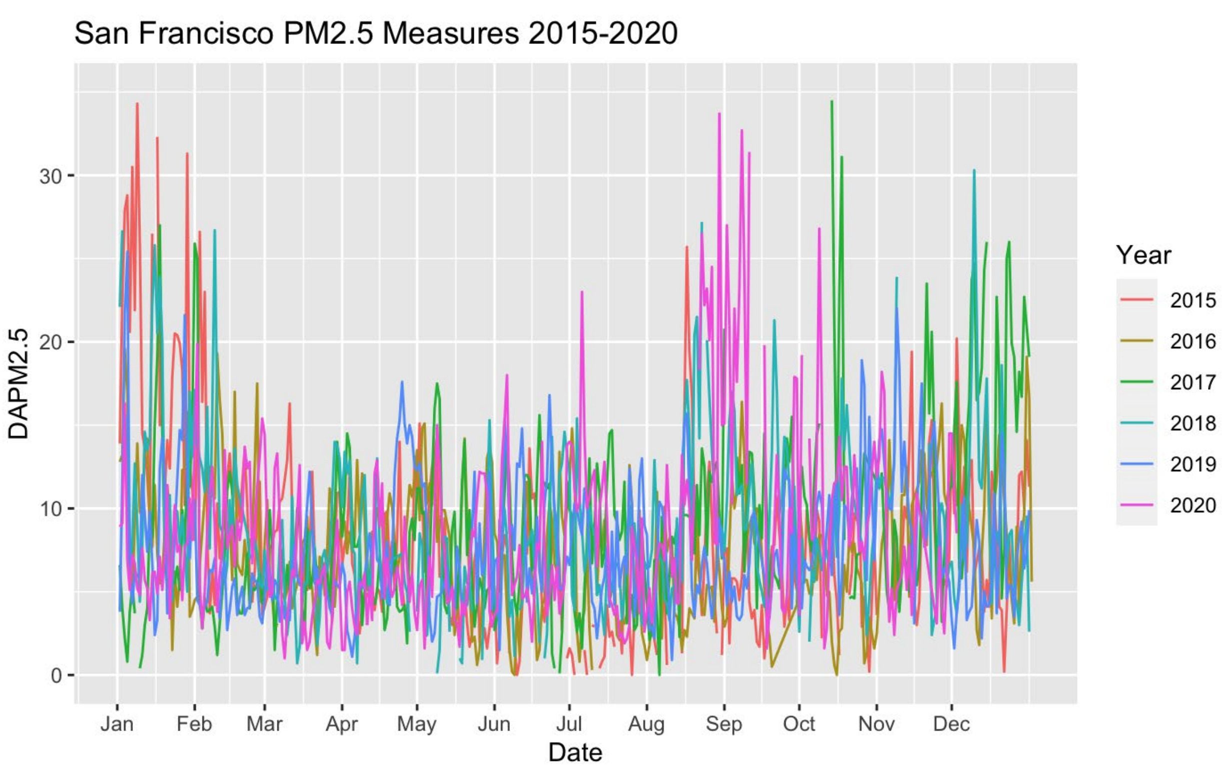

Figure J. $PM_{2.5}$ measurements in San Francisco from 2015 to 2020.

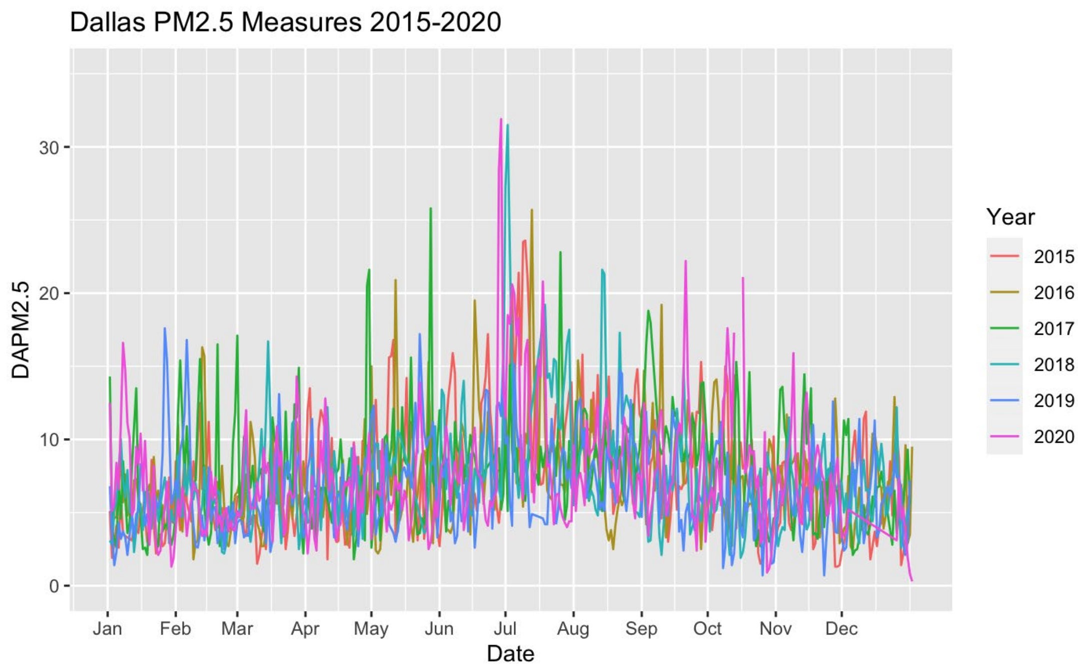

Figure K. Dallas Daily $PM_{2.5}$ Measurements during 2015 to 2020.

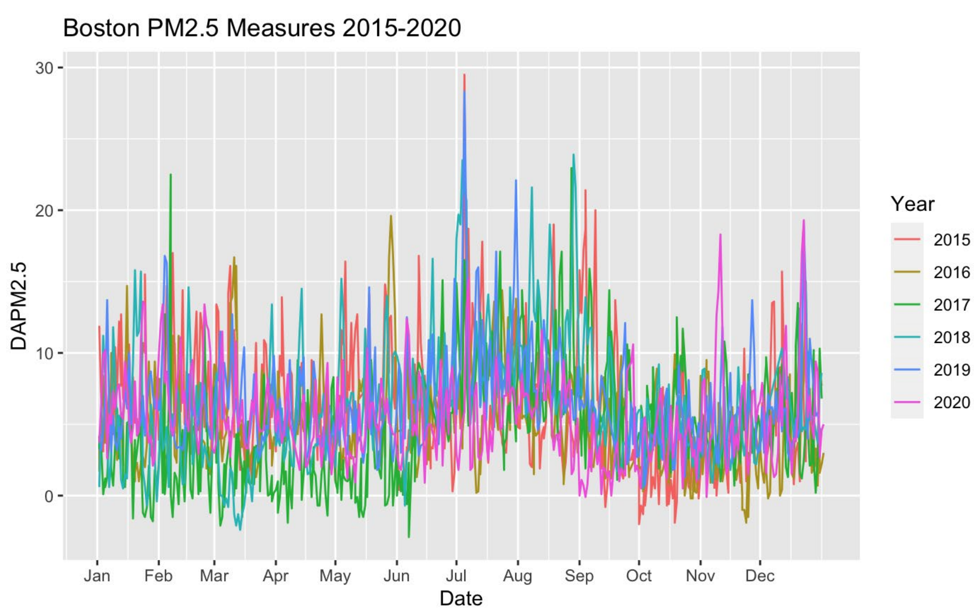

Figure L. Boston Daily $PM_{2.5}$ Measurements during 2015 to 2020.

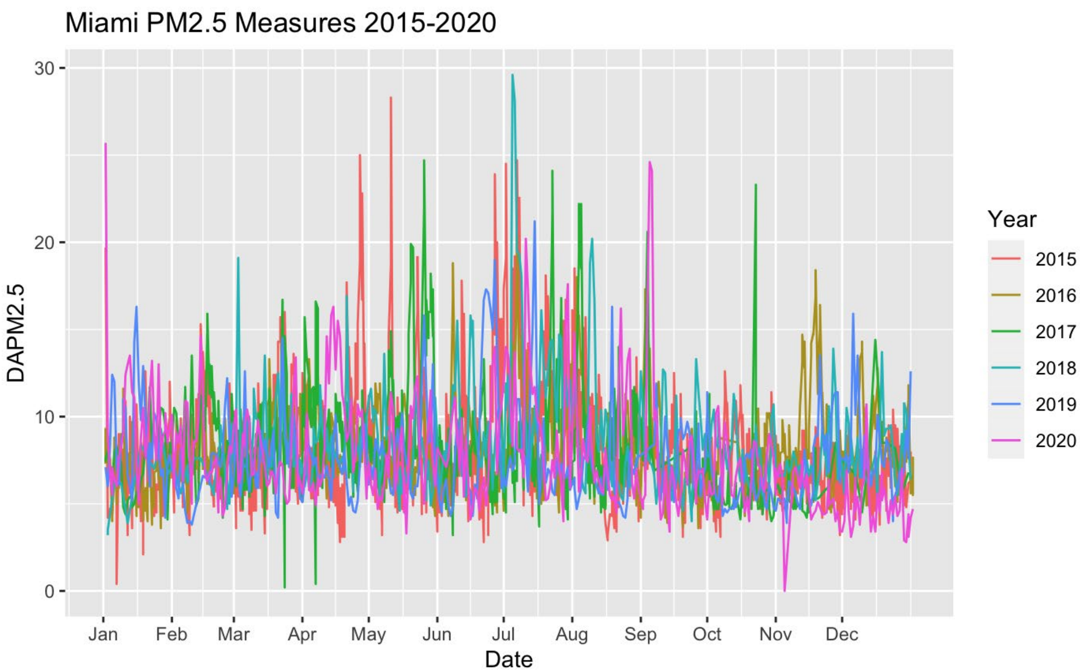

Figure M. Miami's daily average $PM_{2.5}$ measurements from 2015 to 2020.

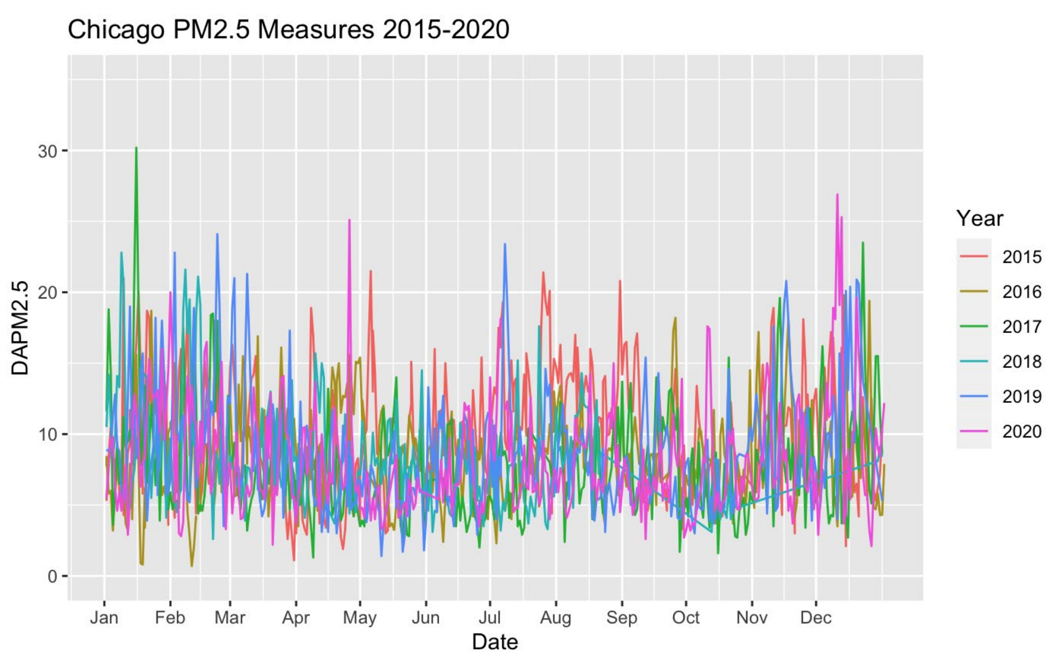

Figure N. Chicago's daily average $PM_{2.5}$ measurements from 2015 to 2020.

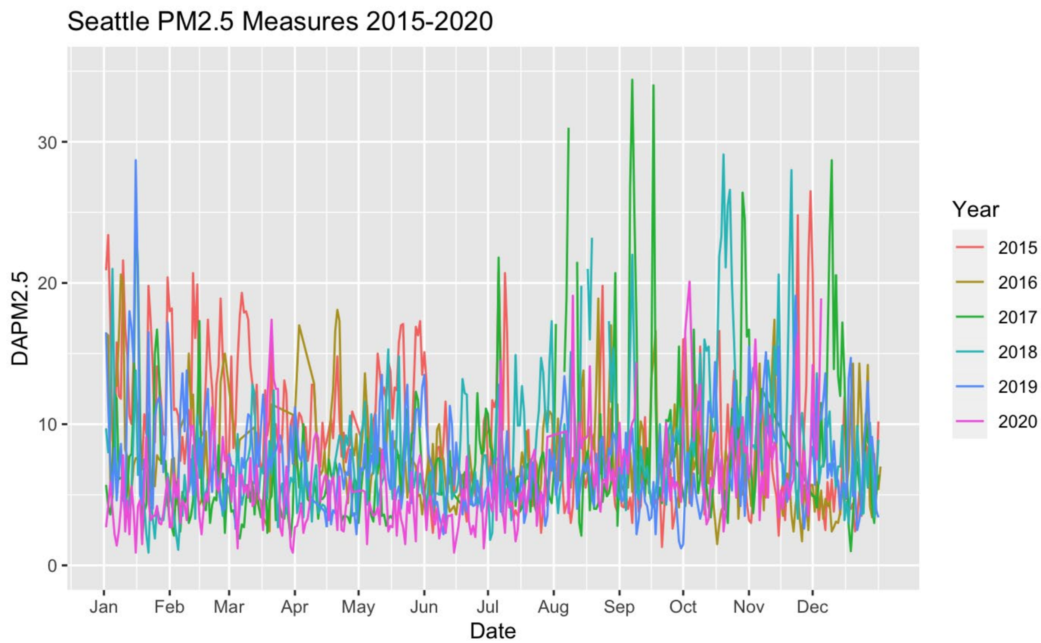

Figure O. Seattle's daily average $PM_{2.5}$ measurements from 2015 to 2020.

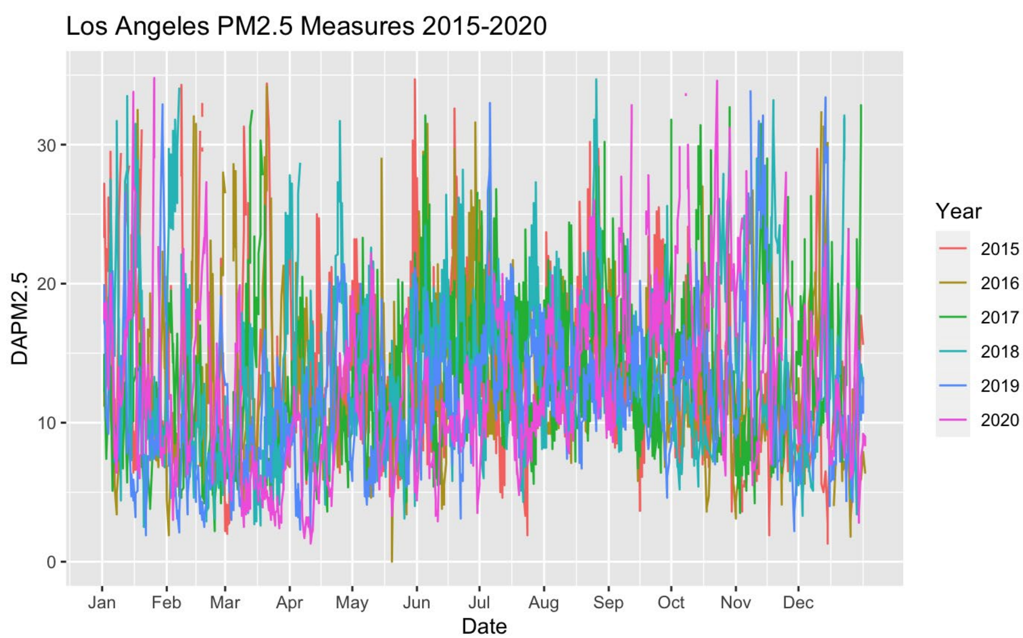

Figure Q. Los Angeles' daily average $PM_{2.5}$ measurements from 2015 to 2020.

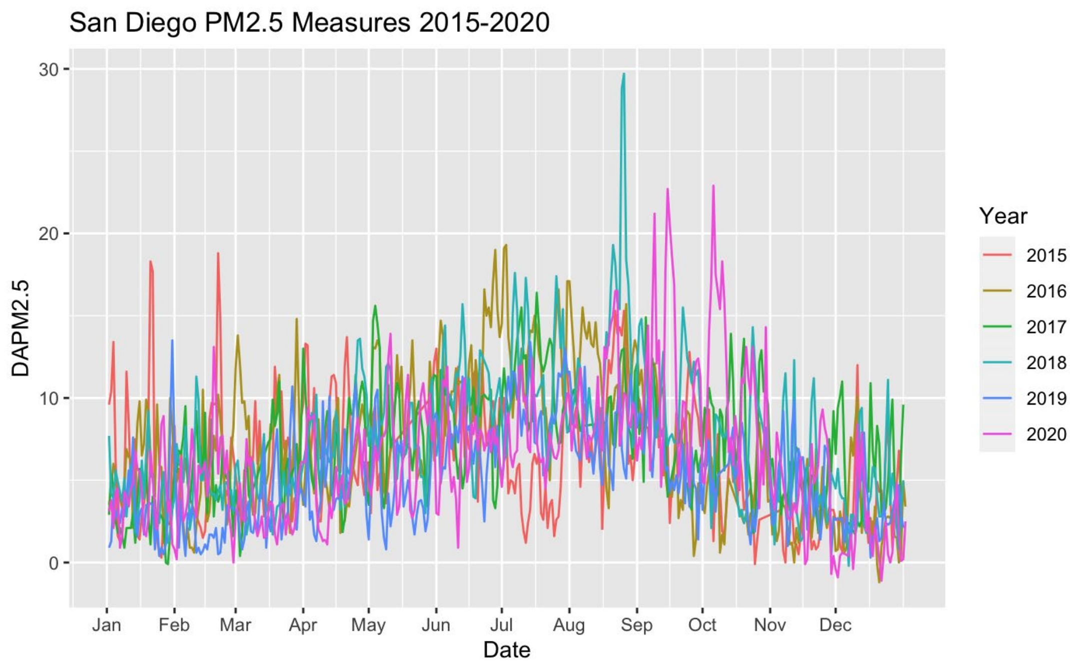

Figure R. San Diego's daily average $PM_{2.5}$ measurements from 2015 to 2020.