Ozone in Los Angeles County 1980-2018

https://github.com/lhr12

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Abstract

This project explores the temporal and spatial trends of tropospheric ozone in Los Angeles County from 1980 to 2018. Through the use of non-parametric statistical analyses, it was determined that ozone levels had decreased over time between 1980 and 2011, but had increased slightly after 2011 until 2018. There was found to be a significant difference in ozone levels between each season and each month of measurements. Finally, it was determined that ozone levels varied significantly between the sites over the time period. The Clean Air Act was amended in 1990 is likely the reason for the decline in tropospheric ozone after that year. However, the increasing population in a car-dependent city as well as economic growth following the 2008 Great Recession are likely the cause for the increase in ozone levels after 2011. Additionally, the higher levels of ozone found inland are likely due to daytime sea-breezes blowing smog away from the coast and trapping it within the surrounding mountain range. Climate change poses the risk of increasing ozone levels through higher average temperatures. Increasing the proportion of electric and hybrid vehicles on the road will likely help to decrease ozone levels in the future and mitigate the impacts of climate change.

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1 Research Question and Rationale

Ozone (O_3) in the troposphere is a main component of photochemical smog, which is air pollution associated with chemical reactions driven by sunlight (Sillman, 2003). Ozone can have health impacts on human respiratory systems, as well as negatively affecting forests and agricultural crops (Sillman, 2003). High ozone events are exacerbated by sunshine, high temperatures, light winds, and conditions that suppress vertical atmospheric mixing (Sillman, 2003). Smog is also associated with high levels of automobile emissions containing hydrocarbons and nitrogen oxides (Haagen-Smit, 1952). Therefore, because it experiences high temperatures, plentifly sunshine, low atmospheric mixing, and is predominantly transversed by car, smog has become infamous in the city of Los Angeles (Sillman, 2003; Haagen-Smit, 1952).

I want to determine through statistical analysis if ozone levels in Los Angeles County have changed temporally and spatially across the county. I am using daily ozone data collected at various Los Angeles County locations between the years of 1980 and 2018. This data will provide me the date, location, and AQI value for each day between January 1, 1980 through December 31, 2018. The AQI is an index used to represent ozone levels in the atmosphere.

2 Dataset Information

The data were collected from the EPA's outdoor air quality data website using the Download Daily Data tool. The data were downloaded individually by year, leading to a total of 39 data sets. Each data set contained the date, the source of the data, the daily 8-hour ozone concentration, the daily AQI value, the site name, and the longitude and latitude of each site, as well as other columns that are of slightly less importance to the study. Table 1 shows a summary of the raw data structure using the 1980 dataset as an example.

Table 1: 1980 Raw Data Table

Date	Source	Ozone Concentration	Units	AQI	Site	Latitude	Longitude
1980-01-01	AQS	0.045	ppm	146	Azusa	34.1365	-117.9239
1980-01-02	AQS	0.036	ppm	137	Azusa	34.1365	-117.9239
1980-01-03	AQS	0.025	ppm	72	Azusa	34.1365	-117.9239
1980-01-04	AQS	0.022	ppm	45	Azusa	34.1365	-117.9239
1980-01-05	AQS	0.027	ppm	90	Azusa	34.1365	-117.9239

3 Exploratory Data Analysis and Wrangling

To first explore my data, I looked at a summary of the AQI values for 1980, 1990, 2000, 2010, and 2018 to get an idea of how the minimum, median, mean, and maximum values of ozone levels have changed over time by decade throughout the entire county.

```
summary(O3_1980$DAILY_AQI_VALUE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00   39.00   93.00   90.84  144.00  170.00
```

```
summary(O3_1990$DAILY_AQI_VALUE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00   23.00   37.00   61.55   84.00  276.00
```

```
summary(O3_2000$DAILY_AQI_VALUE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     0.0    19.0    32.0    39.5    45.0   243.0
```

```
summary(O3_2010$DAILY_AQI_VALUE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     0.0    29.0    36.0    41.9    45.0   200.0
```

```
summary(O3_2018$DAILY_AQI_VALUE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     0.0    33.0    41.0    47.7    50.0   201.0
```

To wrangle my data, I made summary tables for each of the 39 years of data by summarizing the AQI values and grouping by month. I made sure that all of the dates were classified as dates. Then, I used rbind to combine all of my summary tables from each year into one large data set. Below is an example of the wrangling process for the year 1980, which was repeated for each year through 2018. I corrected the column names to make my data analysis easier and filtered the full data set to only combine the 9 sites with the most complete data for all of the years. Additionally, I created a master data set of all of the non-summarized years of ozone data and wrangled it in a similar manner to only include the 9 sites.

```
O3_1980$Date <- as.Date(O3_1980$Date, format = "%m/%d/%Y")

O3_1980_summary_month <- O3_1980 %>%
  mutate(Year = year(O3_1980$Date)) %>%
  mutate(Month = month(O3_1980$Date)) %>%
  filter(DAILY_AQI_VALUE != ".") %>%
  filter(Site.Name != "") %>%
  group_by(as.character(Site.Name), Month, Year) %>%
  summarise(MeanAQI = mean(as.numeric(DAILY_AQI_VALUE)))
```

```r
O3_total_month <- rbind(
  O3_1980_summary_month,O3_1981_summary_month,O3_1982_summary_month,
  O3_1983_summary_month,O3_1984_summary_month,O3_1985_summary_month,
  O3_1986_summary_month,O3_1987_summary_month,O3_1988_summary_month,
  O3_1989_summary_month,O3_1990_summary_month,O3_1991_summary_month,
  O3_1992_summary_month,O3_1993_summary_month,O3_1994_summary_month,
  O3_1995_summary_month,O3_1996_summary_month,O3_1997_summary_month,
  O3_1998_summary_month,O3_1999_summary_month,O3_2000_summary_month,
  O3_2001_summary_month,O3_2002_summary_month,O3_2003_summary_month,
  O3_2004_summary_month,O3_2005_summary_month,O3_2006_summary_month,
  O3_2007_summary_month,O3_2008_summary_month,O3_2009_summary_month,
  O3_2010_summary_month,O3_2011_summary_month,O3_2012_summary_month,
  O3_2013_summary_month,O3_2014_summary_month,O3_2015_summary_month,
  O3_2016_summary_month,O3_2017_summary_month,O3_2018_summary_month)

colnames(O3_total_month) <- c("Site.Name","Month", "Year", "MeanAQI")

O3_total_month_processed <-  O3_total_month %>%
  filter(Site.Name != "") %>%
  filter(Site.Name != "Hawthorne") %>%
  filter(Site.Name != "Compton") %>%
  filter(Site.Name != "Lancaster-Division Street") %>%
  filter(Site.Name != "Long Beach (Hudson)") %>%
  filter(Site.Name != "Lancaster-N. Beech St.") %>%
  filter(Site.Name != "Lancaster-Ponderosa St.") %>%
  filter(Site.Name != "Lancaster-Division Street") %>%
  filter(Site.Name != "LAX Hastings") %>%
  filter(Site.Name != "Lynwood") %>%
  filter(Site.Name != "Pico Rivera #2") %>%
  filter(Site.Name != "Santa Clarita") %>%
  filter(Site.Name != "SITE IS LOCATED ONE HALF MILE EAST OF THE I-57/I-60 INTERCHANGE")
  filter(Site.Name != "SB25 trailer at Hollenbeck School") %>%
  filter(Site.Name != "Santa Clarita-Honby St.") %>%
  filter(Site.Name != "Wilmington-N. Mahar Ave") %>%
  filter(Site.Name != "Palmdale-East Ave S") %>%
  filter(Site.Name != "Lebec") %>%
  filter(Site.Name != "West Los Angeles-Robertson Blvd")

O3_alldata <- rbind(O3_1980,O3_1981,O3_1982,O3_1983,O3_1984,O3_1985,
                    O3_1986,O3_1987,O3_1988,O3_1989,O3_1990,O3_1991,
                    O3_1992,O3_1993,O3_1994,O3_1995,O3_1996,O3_1997,
                    O3_1998,O3_1999,O3_2000,O3_2001,O3_2002,O3_2003,
                    O3_2004,O3_2005,O3_2006,O3_2007,O3_2008,O3_2009,
                    O3_2010,O3_2011,O3_2012,O3_2013,O3_2014,O3_2015,
```

```
                  O3_2016,O3_2017,O3_2018)


O3_alldata_processed <- O3_alldata %>%
  filter(DAILY_AQI_VALUE != ".") %>%
  filter(Site.Name != "") %>%
  filter(Site.Name != "Hawthorne") %>%
  filter(Site.Name != "Compton") %>%
  filter(Site.Name != "Lancaster-Division Street") %>%
  filter(Site.Name != "Long Beach (Hudson)") %>%
  filter(Site.Name != "Lancaster-N. Beech St.") %>%
  filter(Site.Name != "Lancaster-Ponderosa St.") %>%
  filter(Site.Name != "Lancaster-Division Street") %>%
  filter(Site.Name != "LAX Hastings") %>%
  filter(Site.Name != "Lynwood") %>%
  filter(Site.Name != "Pico Rivera #2") %>%
  filter(Site.Name != "Santa Clarita") %>%
  filter(Site.Name != "SITE IS LOCATED ONE HALF MILE EAST OF THE I-57/I-60 INTERCHANGE")
  filter(Site.Name != "SB25 trailer at Hollenbeck School") %>%
  filter(Site.Name != "Santa Clarita-Honby St.") %>%
  filter(Site.Name != "Wilmington-N. Mahar Ave") %>%
  filter(Site.Name != "Palmdale-East Ave S") %>%
  filter(Site.Name != "Lebec") %>%
  filter(Site.Name != "West Los Angeles-Robertson Blvd")
```

To explore my data visually, I first wanted to see how the monthly AQI values were distributed. Figure 1 shows a histogram of the AQI monthly averages, and it was apparent that the data was not normally distributed. To confirm this, Figure 2 is a Q-Q plot of the Monthly AQI means, which shows that the points did not follow the Q-Q line very well, giving me further evidence that the data was not normally distributed. This indicated to me that I would need to perform non-paramentric statistical tests on my data. Finally, Figure 3 is a box plot of all of the monthly AQI averages separated by site showing how ozone differed by location.

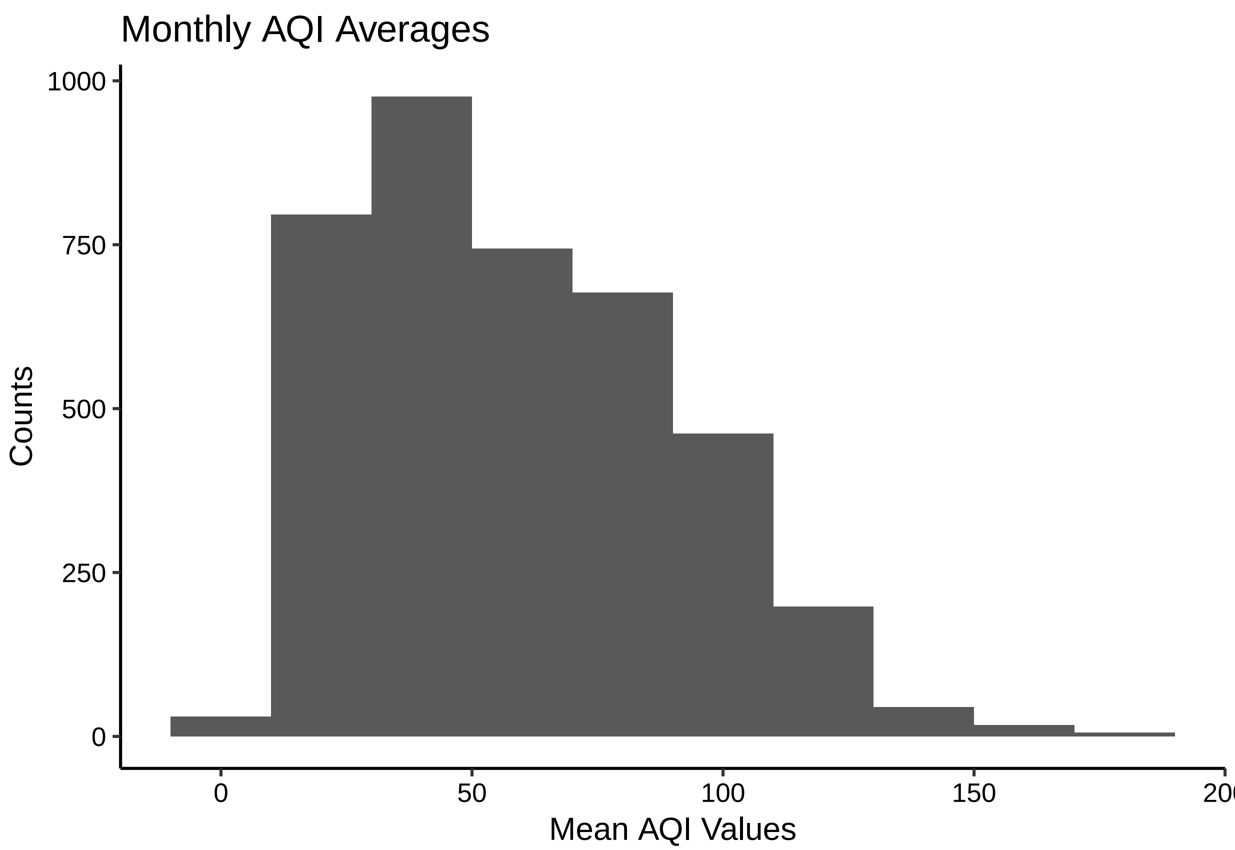

Figure 1: Histogram of monthly AQI averages for all sites 1980-2018

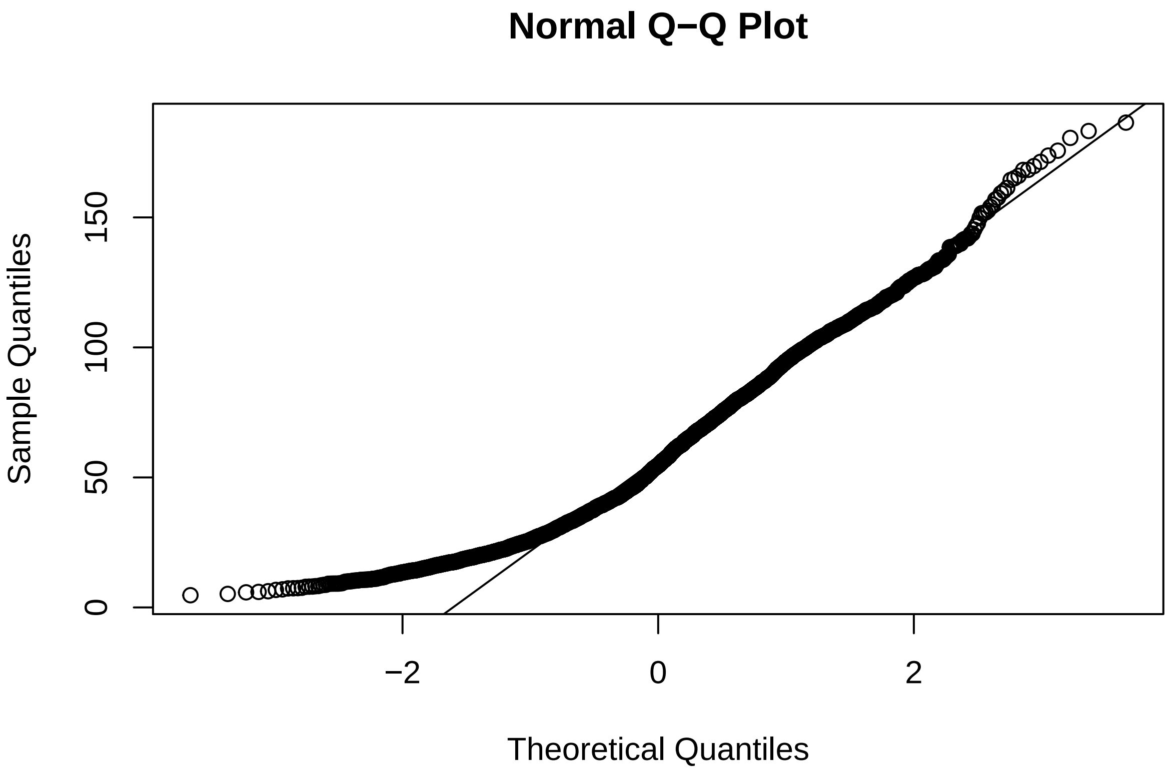

Figure 2: Q-Q plot of monthly AQI averages for all sites 1980-2018

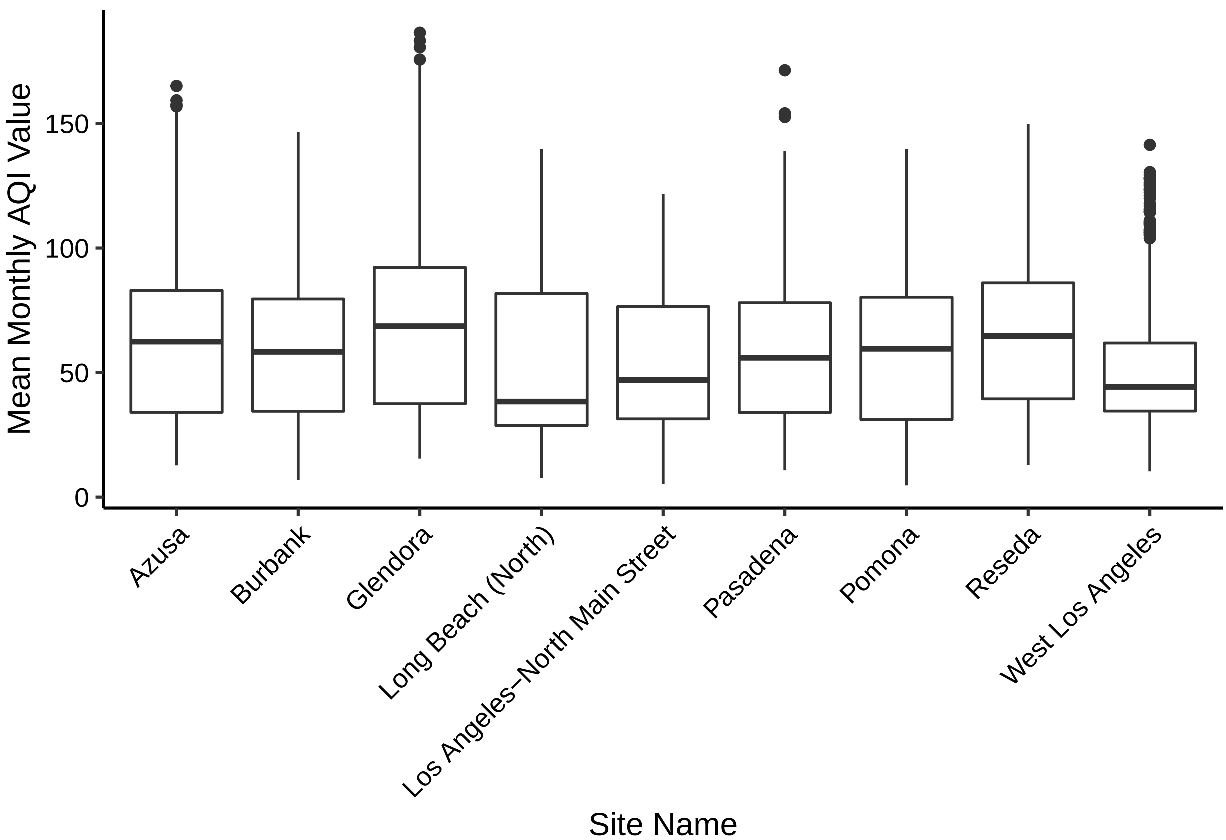

Figure 3: Boxplot of monthly AQI averages for each site 1980-2018

4 Analysis

I ran a series of Mann-Kendall and Pettitt tests to find where the statistically significant breakpoints were in the monthly summary data. First, the Mann-Kendall test on the entire data set showed that there was a significant negative trend for all of the years of ozone data ($z = -27.304$, $n = 3951$, p-value $< 2.2e-16$). Next, the Pettitt test on the entire data set showed that there was a break point at the year 1995 ($U = 2454000$, p-value $< 2.2e-16$). Mann-Kendall tests on the data before and after the break point showed a significant negative trend between 1980 and 1995 ($z = -5.1171$, $n = 1499$, p-value $= 3.102e-07$) and significant positive trend from 1995 to 2018 ($z = 7.2036$, $n = 2452$, p-value $= 5.863e-13$). A second Pettitt test showed another break point in 2011 ($U = 227390$, p-value $= 1.462e-09$). The Mann-Kendall tests showed there was not a significant trend from 1995 to 2011 ($z = 1.8849$, $n = 1790$, p-value $= 0.05945$) and a significant positive trend from 2011 to 2018 ($z = 2.9277$, $n = 662$, p-value $= 0.003415$). A third Pettitt test showed one more break point at 2016 ($U = 18004$, p-value $= 0.002478$). The Mann-Kendall tests showed there was a significant positive trend from 2011 to 2016 ($z = 2.618$, $n = 486$, p-value $= 0.008846$), and no significant trend between 2016 and 2019 ($z = -0.83549$, $n = 176$, p-value $= 0.4034$). A final Pettitt test was run on the remaining section to ensure there were no more statistically significant break points in the data remaining ($U^* = 1387$, p-value $= 0.2436$).

```r
mk.test(O3_total_month_processed$MeanAQI)
```

```
##
##  Mann-Kendall trend test
##
## data:  O3_total_month_processed$MeanAQI
## z = -27.304, n = 3951, p-value < 2.2e-16
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##             S          varS           tau
## -2.260713e+06  6.855566e+09 -2.897297e-01
```

```r
pettitt.test(O3_total_month_processed$MeanAQI) #change point at 1500
```

```
##
##  Pettitt's test for single change-point detection
##
## data:  O3_total_month_processed$MeanAQI
## U* = 2454000, p-value < 2.2e-16
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                             1500
```

```r
mk.test(O3_total_month_processed$MeanAQI[1:1499])
```

```
##
##  Mann-Kendall trend test
##
## data:  O3_total_month_processed$MeanAQI[1:1499]
## z = -5.1171, n = 1499, p-value = 3.102e-07
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##             S          varS           tau
## -9.904400e+04  3.746245e+08 -8.822030e-02
```

```
mk.test(O3_total_month_processed$MeanAQI[1500:3951])
```

```
##
##  Mann-Kendall trend test
##
## data:  O3_total_month_processed$MeanAQI[1500:3951]
## z = 7.2036, n = 2452, p-value = 5.863e-13
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##            S         varS          tau
## 2.916390e+05 1.639020e+09 9.706037e-02
```

```
pettitt.test(O3_total_month_processed$MeanAQI[1500:3951]) #change point at 1790 +1500
```

```
##
##  Pettitt's test for single change-point detection
##
## data:  O3_total_month_processed$MeanAQI[1500:3951]
## U* = 227390, p-value = 1.462e-09
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                              1790
```

```
mk.test(O3_total_month_processed$MeanAQI[1500:3289])
```

```
##
##  Mann-Kendall trend test
##
## data:  O3_total_month_processed$MeanAQI[1500:3289]
## z = 1.8849, n = 1790, p-value = 0.05945
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##            S         varS          tau
## 4.760300e+04 6.377932e+08 2.973262e-02
```

```r
mk.test(O3_total_month_processed$MeanAQI[3290:3951])
```

```
##
##  Mann-Kendall trend test
##
## data:  O3_total_month_processed$MeanAQI[3290:3951]
## z = 2.9277, n = 662, p-value = 0.003415
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##            S         varS          tau
## 1.664200e+04 3.230810e+07 7.606989e-02
```

```r
pettitt.test(O3_total_month_processed$MeanAQI[3290:3951]) #change point at 3290+ 243
```

```
##
##  Pettitt's test for single change-point detection
##
## data:  O3_total_month_processed$MeanAQI[3290:3951]
## U* = 18004, p-value = 0.002478
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                               243
```

```r
mk.test(O3_total_month_processed$MeanAQI[3290:3775])
```

```
##
##  Mann-Kendall trend test
##
## data:  O3_total_month_processed$MeanAQI[3290:3775]
## z = 2.618, n = 486, p-value = 0.008846
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##            S         varS          tau
## 9.365000e+03 1.279379e+07 7.946947e-02
```

```r
mk.test(O3_total_month_processed$MeanAQI[3776:3951])
```

```
##
##  Mann-Kendall trend test
##
## data:  O3_total_month_processed$MeanAQI[3776:3951]
## z = -0.83549, n = 176, p-value = 0.4034
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##             S          varS           tau
## -6.540000e+02  6.108627e+05 -4.247305e-02
```

```r
pettitt.test(O3_total_month_processed$MeanAQI[3776:3951]) #change point not significant
```

```
##
##  Pettitt's test for single change-point detection
##
## data:  O3_total_month_processed$MeanAQI[3776:3951]
## U* = 1387, p-value = 0.2436
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                             114
```

I then Ran a Seasonal Mann-Kendall test on the entire data set to determine if there was any statistically significant differences between subsets of each year. First, I ran a seasonal test with a frequency of 4, representing the 3 months of each annual season. The results showed a statistically significant difference between all four seasons ($p<0.01$). Next, I ran a seasonal test with a frequency of 12, representing all 12 months out of the year. The results showed a statistically significant difference between each of the 12 months out of the year ($p<0.01$).

```r
O3_alldata_processed$DAILY_AQI_VALUE <- as.numeric(O3_alldata_processed$DAILY_AQI_VALUE)
O3_alldata_processed_timeseries_season <- ts(O3_alldata_processed$DAILY_AQI_VALUE,
                                start = c(1980, 1) ,frequency = 4)

O3_alldata_season_smk <- smk.test(O3_alldata_processed_timeseries_season)
summary(O3_alldata_season_smk)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: O3_alldata_processed_timeseries_season
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                            S         varS    tau      z   Pr(>|z|)
## Season 1:   S = 0 -11299544 2.772015e+12 -0.027 -6.787 1.1467e-11 ***
## Season 2:   S = 0 -11753598 2.772032e+12 -0.028 -7.059 1.6715e-12 ***
## Season 3:   S = 0 -11894469 2.772026e+12 -0.028 -7.144 9.0600e-13 ***
## Season 4:   S = 0 -10999066 2.772012e+12 -0.026 -6.606 3.9405e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
O3_alldata_processed_timeseries_month <- ts(O3_alldata_processed$DAILY_AQI_VALUE,
                                start = c(1980, 1) ,frequency = 12)
```

```r
O3_alldata_month_smk <- smk.test(O3_alldata_processed_timeseries_month)
summary(O3_alldata_month_smk)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: O3_alldata_processed_timeseries_month
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                             S        varS    tau      z   Pr(>|z|)
## Season 1:   S = 0  -1431794 102687255634 -0.030 -4.468 7.8921e-06 ***
## Season 2:   S = 0  -1417358 102687481705 -0.030 -4.423 9.7323e-06 ***
## Season 3:   S = 0  -1518742 102688379095 -0.032 -4.739 2.1436e-06 ***
## Season 4:   S = 0  -1316975 102686618118 -0.028 -4.110 3.9601e-05 ***
## Season 5:   S = 0  -1012104 102688613953 -0.021 -3.158 0.00158652  **
## Season 6:   S = 0  -1201587 102688467008 -0.026 -3.750 0.00017706 ***
## Season 7:   S = 0  -1306967 102687768801 -0.028 -4.079 4.5319e-05 ***
## Season 8:   S = 0  -1150782 102689041525 -0.024 -3.591 0.00032925 ***
## Season 9:   S = 0  -1320892 102656313482 -0.028 -4.123 3.7457e-05 ***
## Season 10:   S = 0 -1298046 102658010792 -0.028 -4.051 5.0936e-05 ***
## Season 11:   S = 0 -1135191 102657128173 -0.024 -3.543 0.00039557 ***
## Season 12:   S = 0 -1197109 102655990485 -0.025 -3.736 0.00018675 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Finally, since the data was not normally distributed, I ran a Kruskal-Wallis test to determine if there was a significant difference in Ozone concentration between each site. The results of the test showed that there is a significant difference between the monthly averaged AQI values for each site between 1980 and 2018 (Kruskal-Wallis chi-squared = 102.21, df = 8, p-value $< 2.2e$-16).

```r
O3_total_month_processed$Site.Name <- as.factor(O3_total_month_processed$Site.Name)
kruskal.test(O3_total_month_processed$MeanAQI, O3_total_month_processed$Site.Name)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  O3_total_month_processed$MeanAQI and O3_total_month_processed$Site.Name
## Kruskal-Wallis chi-squared = 102.21, df = 8, p-value < 2.2e-16
```

Figure 4 shows the summarized monthly AQI values by year. The green portion of the graph indicates “Good” levels of trophospheric ozone, the yellow portion “Moderate” levels, the orange portion “Unhealthy for sensitive groups”, and the red portion “Unhealthy”. The blue

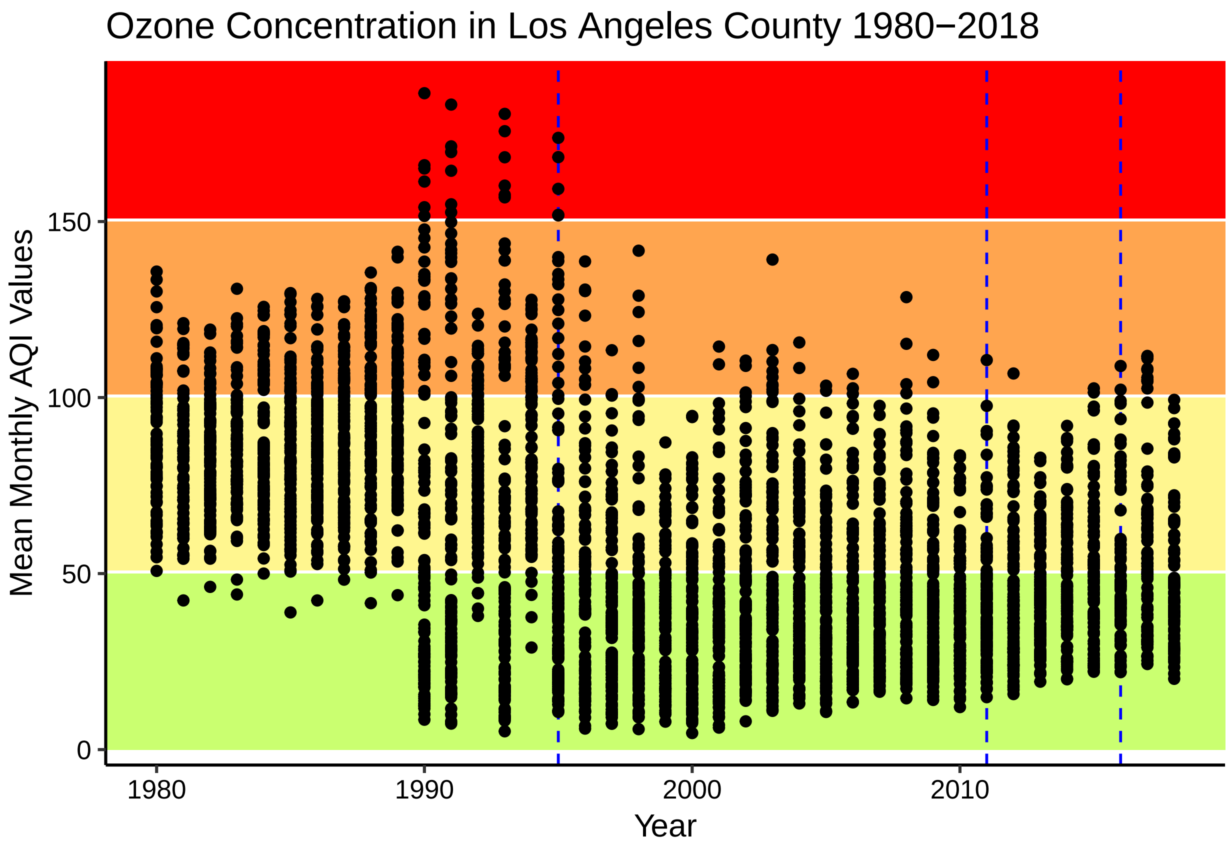

Figure 4: Monthly AQI averages from 1980 to 2018 with break points

dashed lines indicate the break points determined by the Pettitt tests.

Figure 5 shows the summarized monthly AQI values by year and colored by month. As noted by Sillman, it is expected that the highest ozone levels will be in the hottest months, and the lowest ozone levels will be in the cooler months. This is clearly seen after 1990 with the blue-green colors having higher ozone levels each year, and the yellow and purple colors having lower ozone levels each year. Between 1980 and 1990, there is not as clear of a distinction between the months and levels of ozone.

Figures 6-10 show the total daily AQI values for each site in the years 1980, 1990, 2000, 2010, and 2018. From 1980 to 2000, it is easy to see that ozone is decreasing for each site over time. It seems that for some of the sites between 2000 and 2010 the ozone levels seem to have more concentrated AQI values at lower levels with some extreme events as outliers, but the mean AQI values remain fairly constant. Locations more inland like Reseda, Azusa, Burbank, Glendora, and Pasadena have higher AQI values than sites closer to the coast such as West Los Angeles and Los Angeles-North Main Street.

```
## Warning: Removed 17 rows containing non-finite values (stat_boxplot).
```

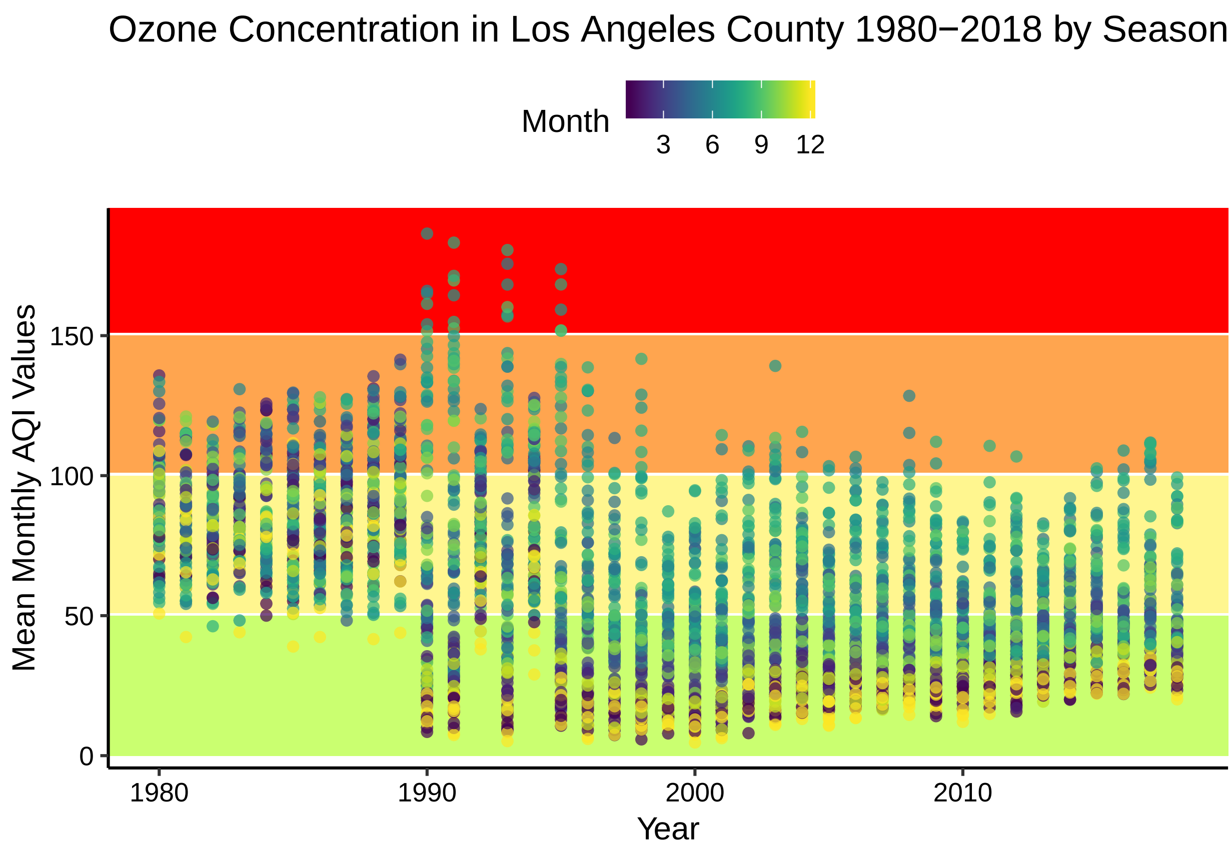

Figure 5: Monthly AQI averages from 1980 to 2018 by season

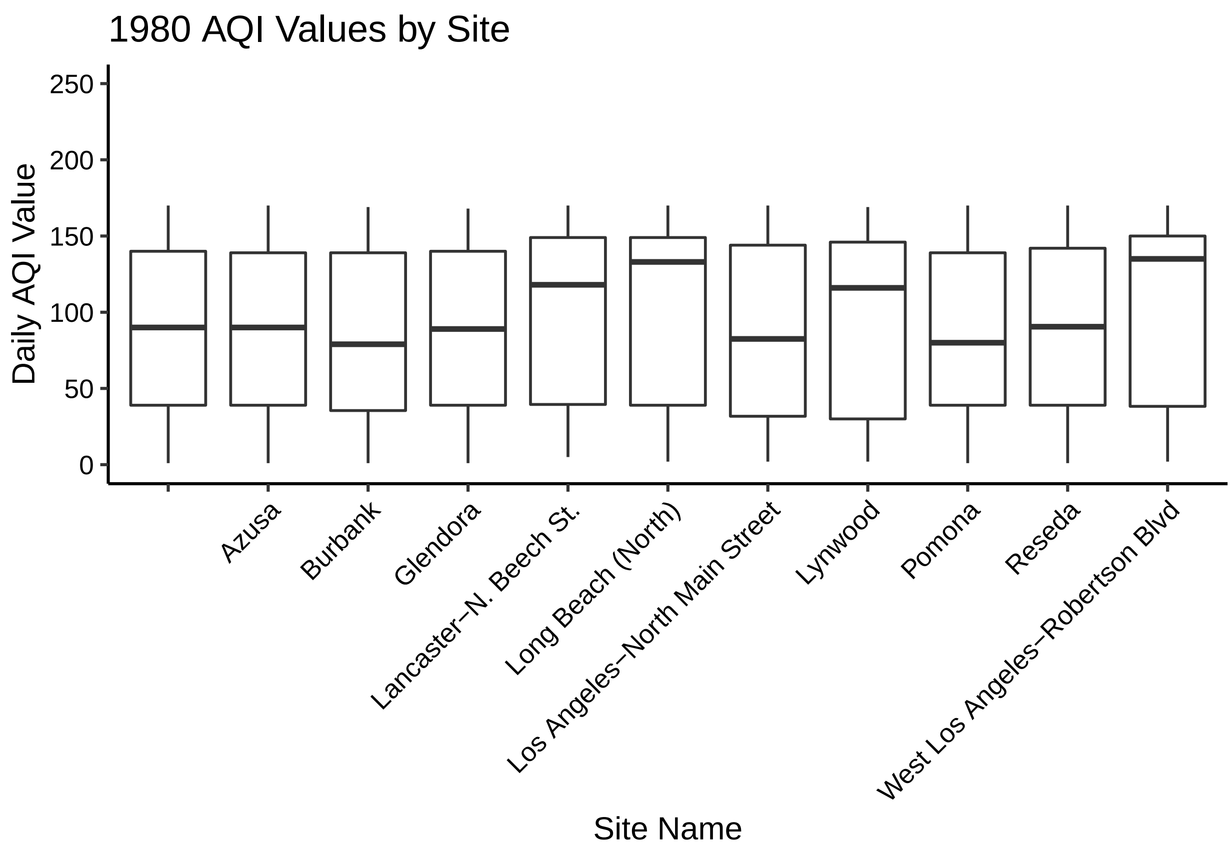

Figure 6: Boxplot of 1980 AQI values by site

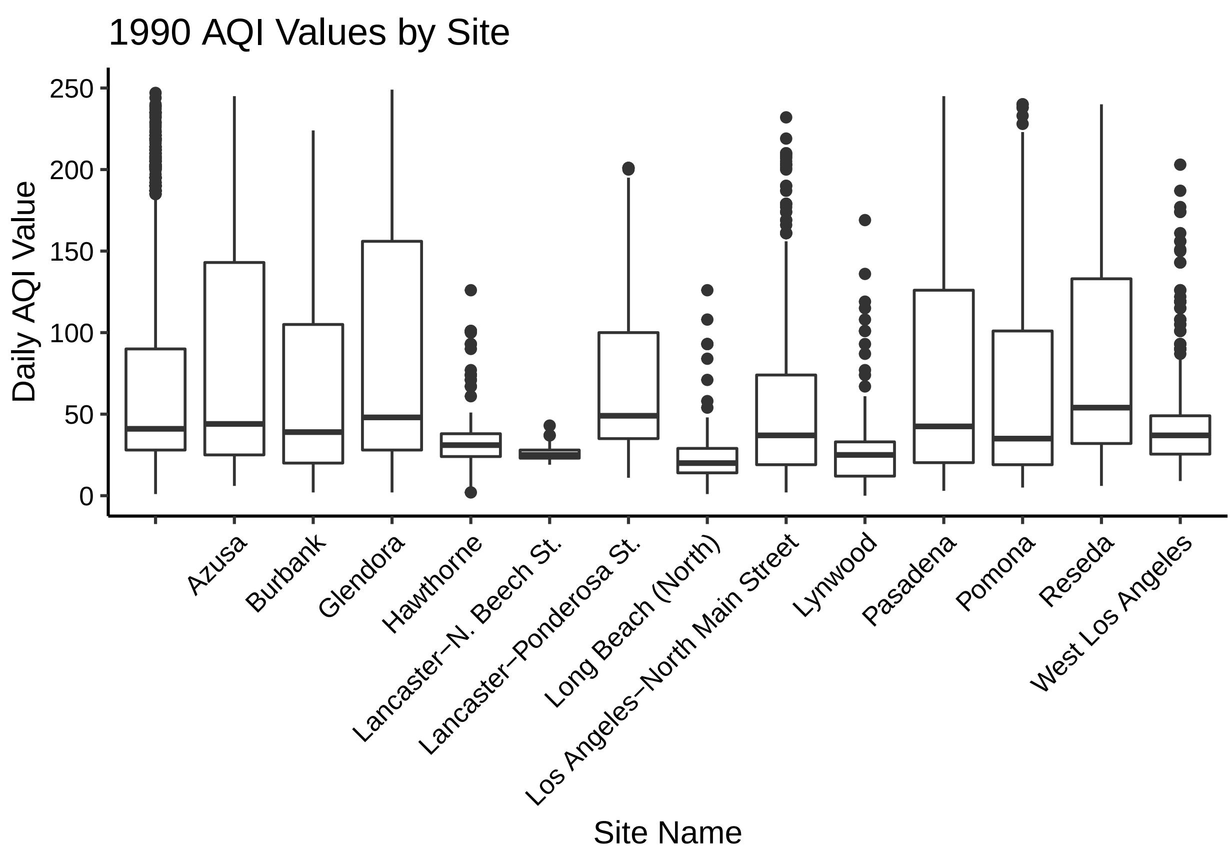

Figure 7: Boxplot of 1990 AQI values by site

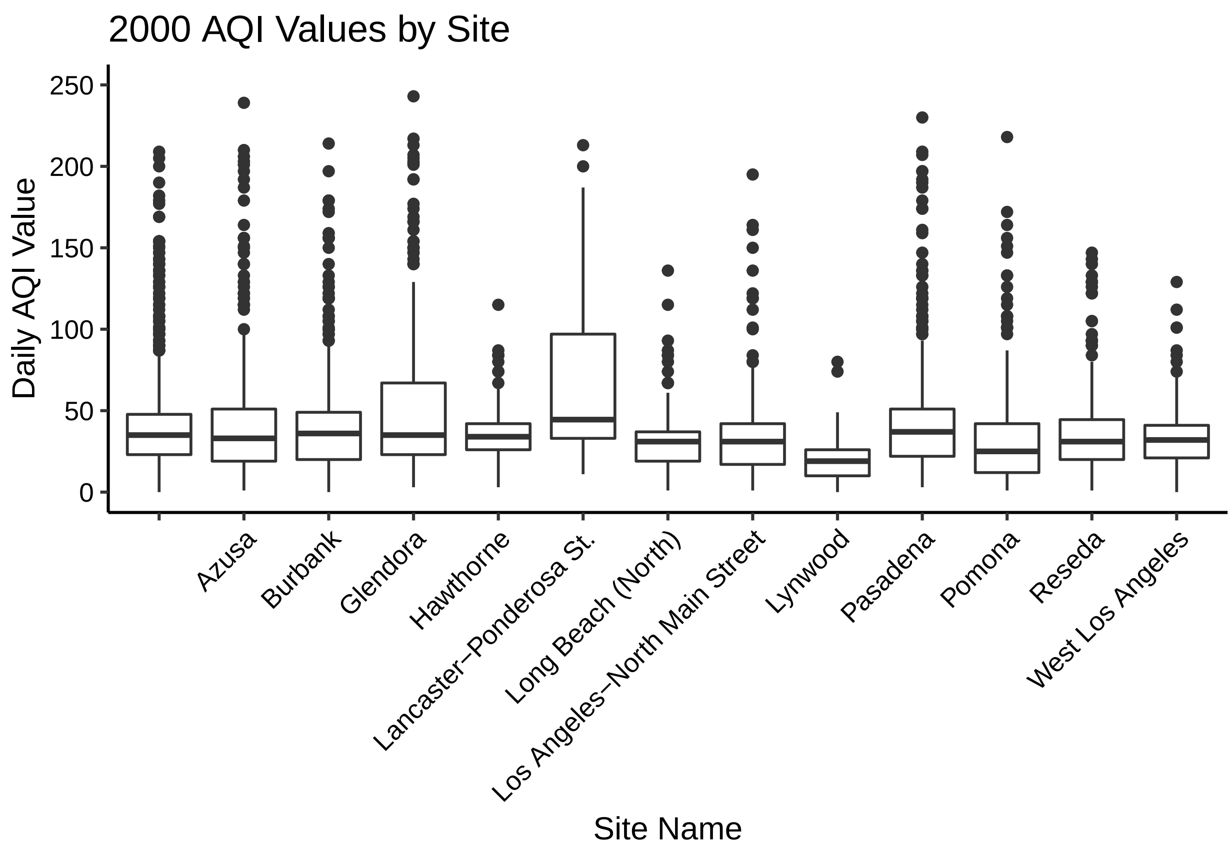

Figure 8: Boxplot of 2000 AQI values by site

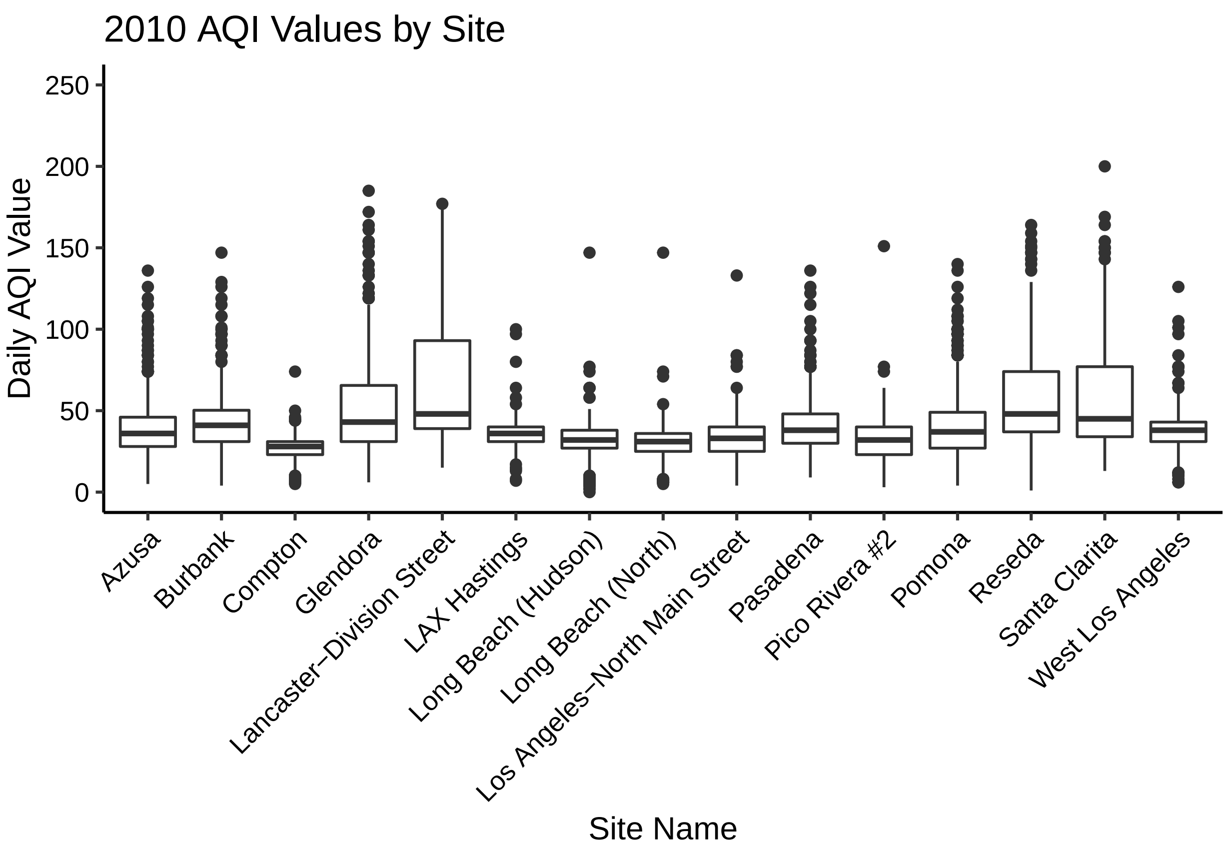

Figure 9: Boxplot of 2010 AQI values by site

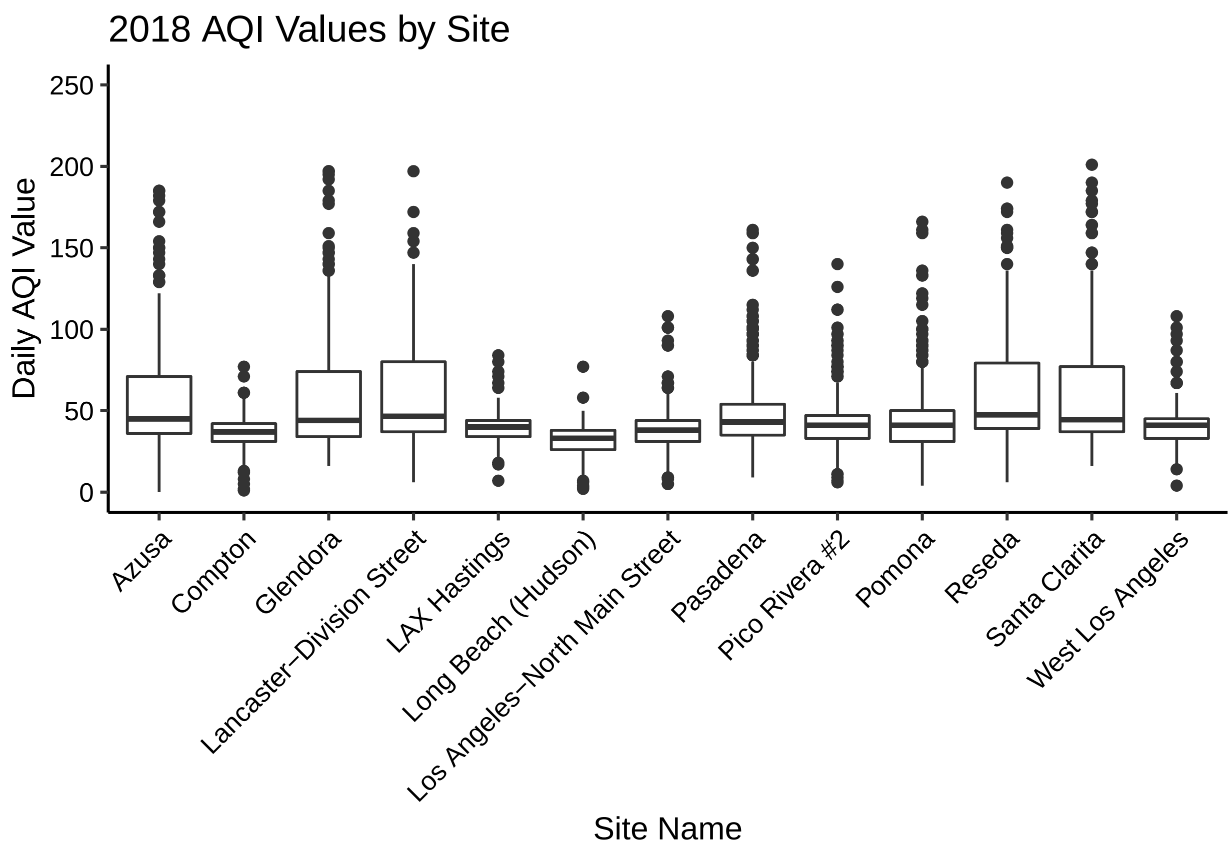

Figure 10: Boxplot of 2018 AQI values by site

5 Summary and Conclusions

This analysis shows that average ozone levels as well as the intensity of extreme ozone events have decreased overall in Los Angeles County between 1980 and 2018. The implementation of more stringent ozone regulations by way of lowering the NAAQS levels for tropospheric ozone and higher standards for automobile emissions put in place in 1990 as an amendment to the Clean Air Act are likely the reason for this trend (EPA, 2017). However, it also showed that there have been some increasing average ozone levels since 2011. This may be due to population growth in a city whose transportation is dominated by personal automobiles as well as an increase in economic growth and emissions following the Great Recession of 2008 (Peters et al., 2012). This, combined with rising average annual temperatures as a result of climate change, would likely result in higher levels of ozone throughout the more recent years. Because vehicle emissions are such a large contributor to tropospheric ozone and photochemical smog, increasing the proportion of electric and hybrid vehicles owned and driven by Los Angeles County residents could reduce this effect in the coming decades in order to mitigate the impacts of climate change.

Additionally, there were found to be higher levels of ozone at inland measurement sites compared to those closer to the coast. This could be attributed to the unique geographic composition of Los Angeles County. The daytime sea breeze blows smog away from the coast, where it is then trapped by the surrounding mountain formations, leading to higher levels of ozone around the inner edges of Los Angeles during the day (Lu & Turco, 1996). There were some irregularities in the data between 1980 and 1990, as seen by the lack of seasonality of the graphed data points and the dramatic shift in the range of AQI values. This could potentially be due to a change in collection methodology around 1990, allowing for more accurate ozone measurements to be taken, but more research into that anomaly is required.

6 Sources

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