2017, 2018 Ozone in North Carolina

https://github.com/xqy1012/ENV872project

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Abstract

Experimental overview. This section should be no longer than 250 words.

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1 Research Question and Rationale

According to American Lung Association, the 2018 "State of the Air" report reveals that unhealthful levels of pollution put the citizens at risk. Compare to 2017 repost, North Carolina Ozone Pollution worsened in 2018 compare to 2017 because there are more unhealthy days of high ozone in 2018's year report, especially in some cities. The report indicated that more work needs to be done to protect the health of residents from harms of ozone pollution. However, the EPA website showed that in Charlotte, NC, the number of days reaching unhealthy for sensitive groups for ozone pollution has been continue decreasing to 2017. There is no analysis report for ozone pollution in 2018 from EPA yet. Therefore, the interest for this project is to verify the accuracy of the news report by American Lung Association and analyze the ozone pollution in 2017 and 2018 in North Carolina.

It is important to study ozone because human ozone exposure may result in adverse health effects including reduced lung function, respiratory symptoms, asthma, and other premature mortality from respiratory causes. For the nature, ozone damages vegetation, decreasing crop yields, and even may alter ecosystem structure. Ozone is also a greenhouse gas that contribute to global warming.

There will be three main research questions for the report: 1. Does year 2018 has a worsened ozone pollution than 2017? 2. Are there any trend /fluctuation of ozone pollution among different months within a year? Is it true in this data that ozone level is higher when it is hot, dry and sunny in the summer? Does the trend similar in year 2017 and year 2018? 3. Does Ozone pollution level related to population size/ household income/ population density of a county? I will use the raw data that downloaded from EPA our door air quality dataset for 2017 and 2018, combining with demographic data obtained from United States Census Bureau website.

2 Dataset Information

3 Exploratory Data Analysis and Wrangling

First, display the data summary to get information of the data on: the dimension of data, how many different counties/ Ozone monitoring sites are there in North Carolina, where does the county located (e.g. Raleigh, Charlotte, etc.), which columns of the raw data are useful in this report analysis, filter the useful column and save as new files. Also check the format of concentration, AQI, and date, check on if these value needs reformat to numeric or dates. Combine the 2017, 2018 data together and save in another file.

```
dim(EPA_Ozone_2017.data)
```

```
## [1] 10219    20
```

```
colnames(EPA_Ozone_2017.data)
```

```
##  [1] "Date"
##  [2] "Source"
##  [3] "Site.ID"
##  [4] "POC"
##  [5] "Daily.Max.8.hour.Ozone.Concentration"
##  [6] "UNITS"
##  [7] "DAILY_AQI_VALUE"
##  [8] "Site.Name"
##  [9] "DAILY_OBS_COUNT"
## [10] "PERCENT_COMPLETE"
## [11] "AQS_PARAMETER_CODE"
## [12] "AQS_PARAMETER_DESC"
## [13] "CBSA_CODE"
## [14] "CBSA_NAME"
## [15] "STATE_CODE"
## [16] "STATE"
## [17] "COUNTY_CODE"
## [18] "COUNTY"
## [19] "SITE_LATITUDE"
## [20] "SITE_LONGITUDE"
```

```
summary(EPA_Ozone_2017.data$Site.Name)
```

```
##
##                                                                       206
##                                                                  Beaufort
##                                                                       338
##                                                               Bent Creek
##                                                                       240
##                                                             Bethany sch.
##                                                                       240
```

```
##                                                          Blackstone
##                                                                 355
##                                                         Bryson City
##                                                                 223
##                                                          Bushy Fork
##                                                                 241
##                                                              Butner
##                                                                 243
##                                                              Candor
##                                                                 325
##                                                        Castle Hayne
##                                                                 239
##                                                        Cherry Grove
##                                                                 232
##                                                     Clemmons Middle
##                                                                 240
##                                                             Coweeta
##                                                                 344
##                                                           Cranberry
##                                                                 307
##                                                              Crouse
##                                                                 237
##                                                       Durham Armory
##                                                                 245
##                                                  Frying Pan Mountain
##                                                                 229
##                                                 Garinger High School
##                                                                 358
##                                                       Hattie Avenue
##                                                                 242
##                                                    Honeycutt School
##                                                                 219
##                                                   Jamesville School
##                                                                 244
##                                                         Joanna Bald
##                                                                 227
##                                                             Leggett
##                                                                 236
##                                                       Lenoir (city)
##                                                                 239
##                                              Lenoir Co. Comm. Coll.
##                                                                 244
##                                                      Linville Falls
##                                                                 234
##                                                   Mendenhall School
```

```
##                                                            239
##                                              Millbrook School
##                                                            339
##                                                 Monroe School
##                                                            236
##                                                  Mt. Mitchell
##                                                            199
## OZONE MONITOR ON SW SIDE OF TOWER/MET EQUIPMENT 10FT ABOVE TOWER
##                                                            199
##                                             Pitt Agri. Center
##                                                            245
##                                                 Purchase Knob
##                                                            234
##                                                      Rockwell
##                                                            354
##                                        Taylorsville Liledoun
##                                                            234
##                                                   Union Cross
##                                                            243
##                                           University Meadows
##                                                            243
##                                                          Wade
##                                                            245
##                                           Waynesville School
##                                                            237
##                                             West Johnston Co.
##                                                            245
```

```r
summary(EPA_Ozone_2017.data$COUNTY)
```

```
##   Alexander       Avery    Buncombe    Caldwell   Carteret     Caswell
##         234         541         240         239        338         232
##  Cumberland      Durham   Edgecombe    Forsyth      Graham   Granville
##         464         245         236         725        227         243
##    Guilford     Haywood     Jackson   Johnston        Lee      Lenoir
##         239         700         199         245        355         244
##     Lincoln       Macon      Martin Mecklenburg  Montgomery New Hanover
##         237         344         244         601        325         239
##      Person        Pitt  Rockingham      Rowan       Swain       Union
##         241         245         240         354        429         236
##        Wake      Yancey
##         339         199
```

```r
class(EPA_Ozone_2017.data$Daily.Max.8.hour.Ozone.Concentration)
```

```
## [1] "numeric"
```

```r
class(EPA_Ozone_2017.data$DAILY_AQI_VALUE)
```

```
## [1] "integer"
```

```r
class(EPA_Ozone_2017.data$Date)
```

```
## [1] "factor"
```

```r
#Wranggling
EPA_Ozone_2017.data$Date <-as.Date(EPA_Ozone_2017.data$Date, format = "%m/%d/%y")
EPA_Ozone_2018.data$Date <-as.Date(EPA_Ozone_2018.data$Date, format = "%m/%d/%y")

EPA_Ozone_2017.data.Processed <- EPA_Ozone_2017.data %>%
  select(Date, Daily.Max.8.hour.Ozone.Concentration,
         UNITS,DAILY_AQI_VALUE,Site.Name,COUNTY,SITE_LATITUDE, SITE_LONGITUDE) %>%
    mutate(year = year(Date)) %>%
  mutate(month = month(Date)) %>%
  mutate(day = day(Date))

EPA_Ozone_2018.data.Processed <- EPA_Ozone_2018.data %>%
  select(Date, Daily.Max.8.hour.Ozone.Concentration,
         UNITS,DAILY_AQI_VALUE,Site.Name,COUNTY,SITE_LATITUDE, SITE_LONGITUDE) %>%
    mutate(year = year(Date)) %>%
  mutate(month = month(Date)) %>%
  mutate(day = day(Date))

write.csv(EPA_Ozone_2017.data.Processed, row.names = F,
          file = "../Processed data/EPA_Ozone_2017.data.Processed.csv")
write.csv(EPA_Ozone_2018.data.Processed, row.names = F,
          file = "../Processed data/EPA_Ozone_2018.data.Processed.csv")

EPA_totalOzone.data <- rbind(EPA_Ozone_2017.data.Processed,
                             EPA_Ozone_2018.data.Processed)
EPA_totalOzone.data$Date <-as.Date(EPA_totalOzone.data$Date, format = "%m/%d/%y")
EPA_totalOzone.data.processed <- EPA_totalOzone.data %>%
  mutate(year = year(Date)) %>%
  mutate(month = month(Date)) %>%
  mutate(day = day(Date))

write.csv(EPA_totalOzone.data, row.names = F,
          file = "../Processed data/EPA_totalOzone.data.processed.csv")

#group by year/ sites
OzoneSummary_ByYearSites <-
  EPA_totalOzone.data.processed %>%
  group_by(year, COUNTY) %>%
```

```
  na.omit() %>%
  summarise(MeanOzoneAQI = mean(DAILY_AQI_VALUE),
            MeanOzoneConc =  mean(Daily.Max.8.hour.Ozone.Concentration),
            Units = 'ppm',
            minOzoneAQI = min(DAILY_AQI_VALUE),
            maxOzoneAQI = max(DAILY_AQI_VALUE))

write.csv(OzoneSummary_ByYearSites, row.names = F,
          file = "../Processed data/OzoneSummary_ByYearSites.csv")
```

The summary table include the information of ozone mean, min, max AQI, and mean concentration grouped by year and counties.

Table 1: Summary of Ozone AQI/Concentration in year 2017 and 2018 by counties

year	COUNTY	MeanOzoneAQI	MeanOzoneConc	Units	minOzoneAQI	maxOzoneAQI
2017	Alexander	40.19231	0.0426239	ppm	14	93
2017	Avery	39.42884	0.0419316	ppm	16	93
2017	Buncombe	38.90833	0.0414750	ppm	12	84
2017	Caldwell	42.23431	0.0442427	ppm	15	90
2017	Carteret	35.25148	0.0379497	ppm	13	64
2017	Caswell	38.68103	0.0414009	ppm	13	71
2017	Cumberland	40.98922	0.0432220	ppm	10	100
2017	Durham	40.04898	0.0423306	ppm	6	100
2017	Edgecombe	38.77966	0.0413347	ppm	11	80
2017	Forsyth	44.03034	0.0456745	ppm	15	100
2017	Graham	41.14978	0.0436432	ppm	12	87
2017	Granville	42.16872	0.0441893	ppm	19	93
2017	Guilford	44.06276	0.0454812	ppm	16	112
2017	Haywood	42.37714	0.0448114	ppm	13	84
2017	Jackson	45.34171	0.0467889	ppm	16	100
2017	Johnston	38.42449	0.0408857	ppm	11	93
2017	Lee	37.66479	0.0402225	ppm	8	97
2017	Lenoir	38.97541	0.0412254	ppm	11	90
2017	Lincoln	41.55696	0.0437764	ppm	14	93
2017	Macon	33.51744	0.0359070	ppm	8	74
2017	Martin	37.67213	0.0402910	ppm	16	74
2017	Mecklenburg	41.10815	0.0425757	ppm	7	115
2017	Montgomery	36.59077	0.0392338	ppm	10	71
2017	New Hanover	35.50628	0.0380837	ppm	5	67
2017	Person	40.46888	0.0429793	ppm	12	74
2017	Pitt	39.38776	0.0417469	ppm	16	87
2017	Rockingham	41.43750	0.0436375	ppm	15	84
2017	Rowan	37.71469	0.0400876	ppm	11	80
2017	Swain	35.13054	0.0378228	ppm	8	71
2017	Union	42.52119	0.0441441	ppm	15	115
2017	Wake	37.95870	0.0399204	ppm	7	100
2017	Yancey	45.37688	0.0472161	ppm	18	93
2018	Alexander	38.74737	0.0405193	ppm	16	100
2018	Avery	38.35237	0.0404780	ppm	0	87
2018	Buncombe	37.46786	0.0395464	ppm	12	93
2018	Caldwell	39.22300	0.0409233	ppm	10	93
2018	Carteret	37.96861	0.0404081	ppm	17	77
2018	Caswell	39.30980	0.0409216	ppm	10	97

year	COUNTY	MeanOzoneAQI	MeanOzoneConc	Units	minOzoneAQI	maxOzoneAQI
2018	Cumberland	41.69593	0.0433640	ppm	17	100
2018	Durham	38.05155	0.0400241	ppm	9	100
2018	Edgecombe	38.57708	0.0406680	ppm	15	84
2018	Forsyth	43.70955	0.0446578	ppm	12	101
2018	Graham	42.35599	0.0440162	ppm	19	97
2018	Granville	40.03833	0.0416585	ppm	10	93
2018	Guilford	43.80989	0.0444867	ppm	13	105
2018	Haywood	41.40159	0.0432514	ppm	0	105
2018	Johnston	37.75839	0.0397114	ppm	15	90
2018	Lee	39.83256	0.0420884	ppm	17	77
2018	Lenoir	39.94902	0.0419373	ppm	16	108
2018	Lincoln	39.78113	0.0417849	ppm	13	90
2018	Macon	32.52647	0.0346029	ppm	12	93
2018	Martin	38.86192	0.0409707	ppm	6	80
2018	Mecklenburg	40.81804	0.0415633	ppm	13	108
2018	Montgomery	34.46291	0.0369110	ppm	0	71
2018	New Hanover	37.72199	0.0398423	ppm	16	77
2018	Person	38.85091	0.0408655	ppm	10	97
2018	Pitt	39.36585	0.0413031	ppm	16	87
2018	Rockingham	38.50904	0.0404187	ppm	10	90
2018	Rowan	36.34277	0.0389057	ppm	14	74
2018	Swain	36.08725	0.0383870	ppm	5	80
2018	Union	42.85433	0.0435591	ppm	16	122
2018	Wake	38.01183	0.0398136	ppm	6	90
2018	Yancey	42.90076	0.0447786	ppm	4	84

Then for exploratory graphs, normality is visualized first by QQ norm plots in Figure 1.The sample size is larger than 5,000, so Kolmogorov-Smirnov test is applied together to test normality for ozone daily AQI value. The result shows that both original data and log-transformed data are not normally distributed.

Correlation between AQI and Ozone 8-hour concentration is also test with spearman correlation and plotted in Figure 2. In the raw data, there are both AQI and Ozone 8-hour max concentrations, the reason for correlation test is to make sure if using AQI is appropriate to represent Ozone pollution level. The correlation figure shows that there is a correlation coefficient of 1.00 between these two variables, so only AQI will be used in later analysis.

Figure 3 displays a monthly boxplot for year 2017 and 2018, February and September have higher ozone AQI in 2017, it is hard to identify other obvious differences only from this figure.

Figure 4 shows a LOESS trend in 2017 and 2018, it provide a first impression on the potential seasonal trend before conducting statistical analysis in the next section.

Figure 5 shows the density function and correlation among Mean Ozone AQI by county, income, population, and population density. There is a correlation of 0.64 between population density and income. But I will still conduct a mixed effect generalized linear model with the data.

There is also a map generated to show different location of the counties, how they distributed in NC.

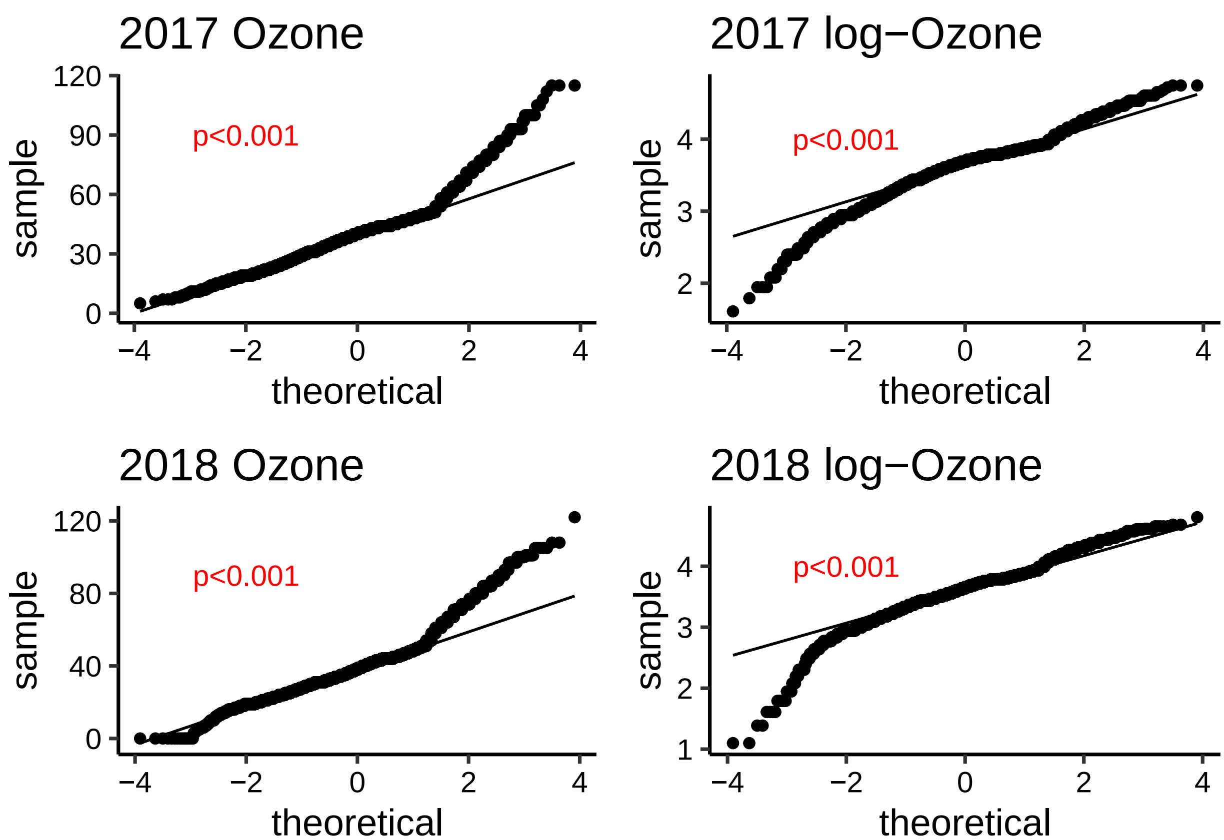


Figure 1: QQ plots for 2017 and 2018 with/without log transform

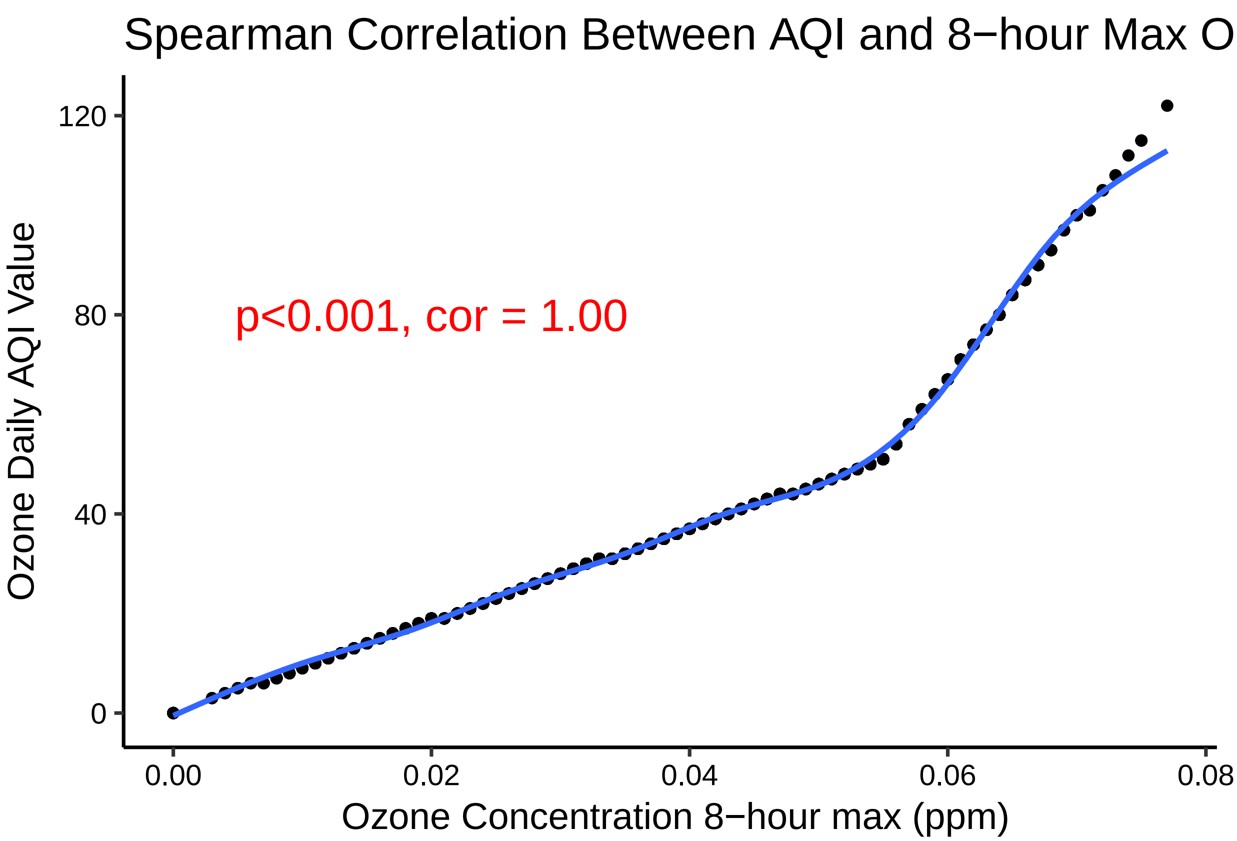


Figure 2: Correlation Between AQI and 8-hour Max Ozone Concentration

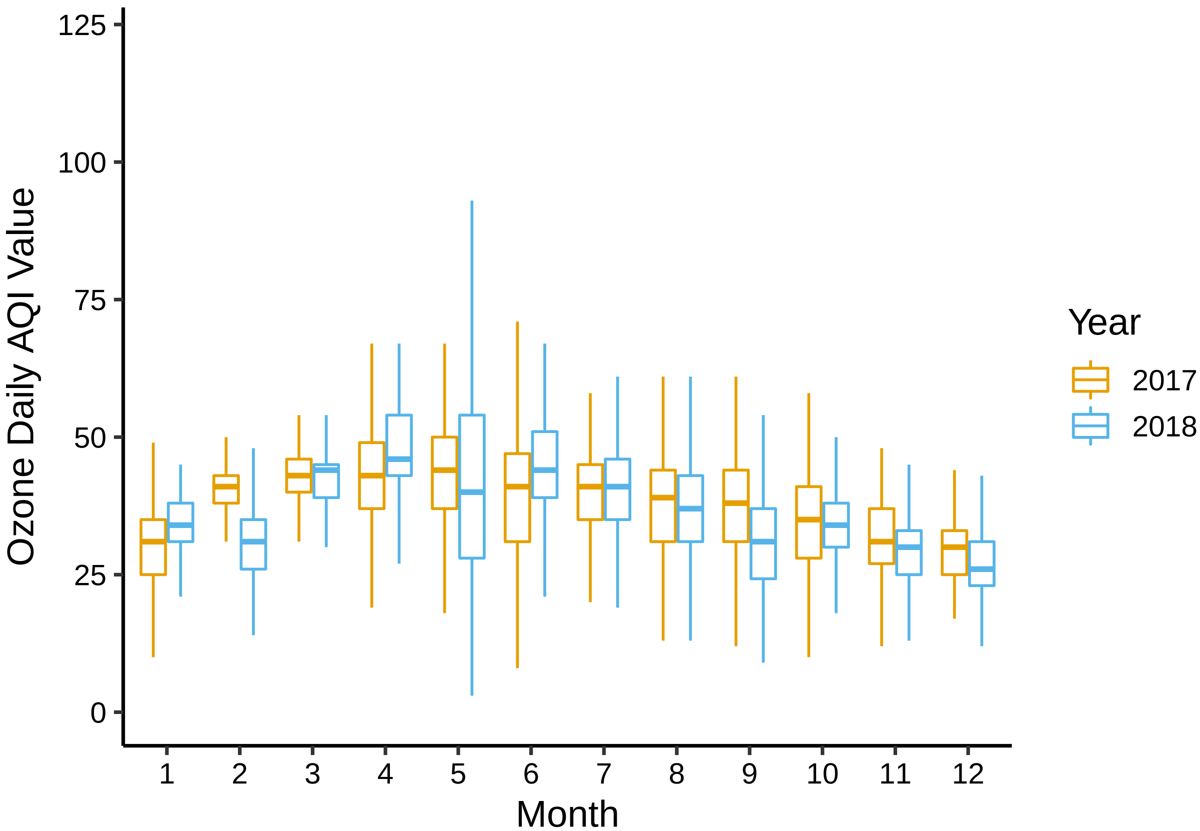


Figure 3: Monthly Box Plot of 2017 and 2018 Ozone AQI

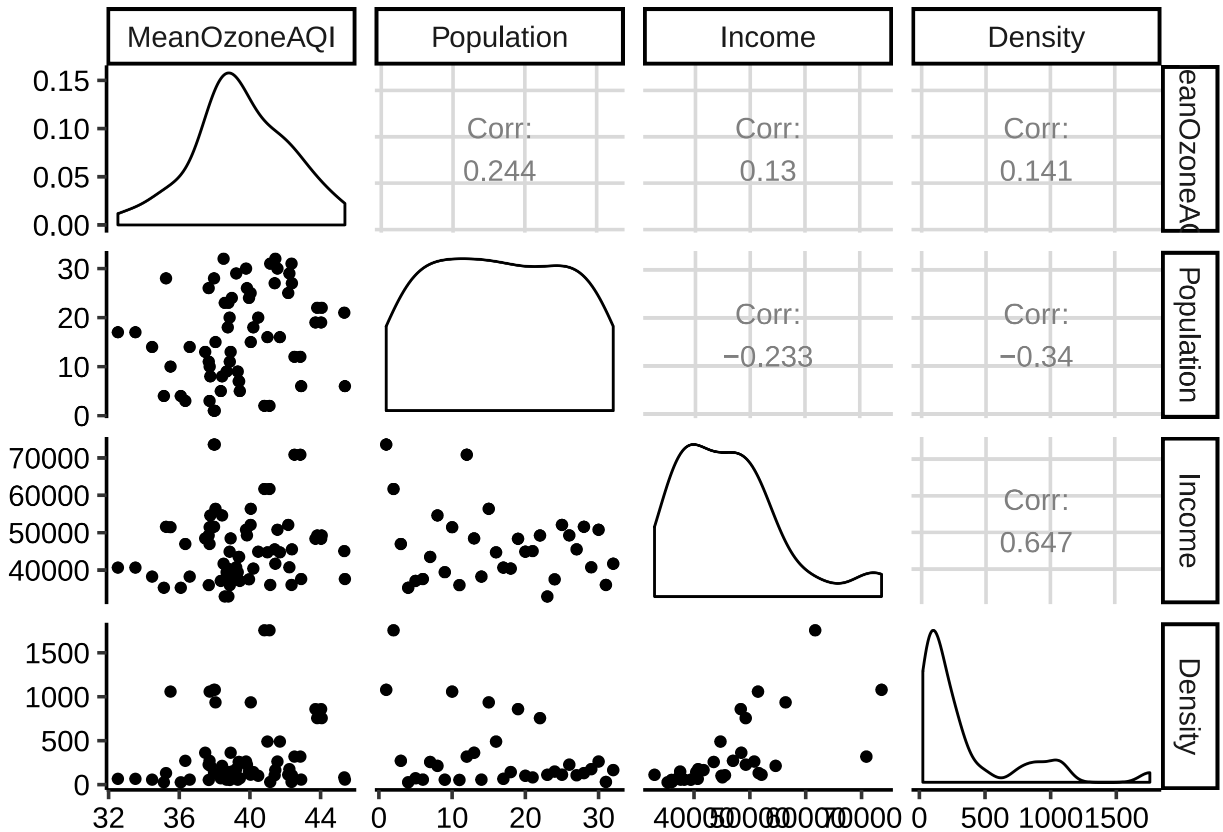


Figure 4: Density Function and correlation among variables for GLM

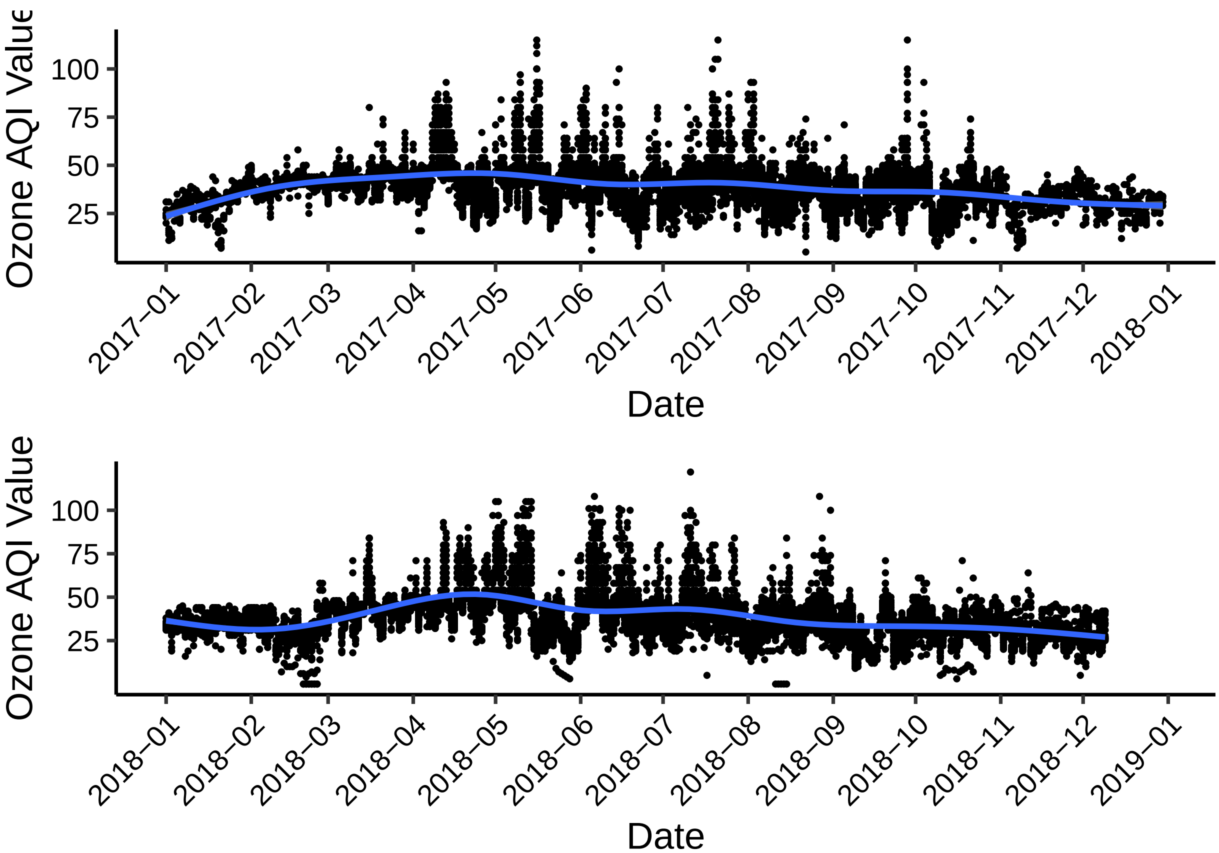


Figure 5: 2017 and 2018 ozone AQI change through out year

4 Analysis

4.1 4.1

First analysis is the Wilcoxon test to test if ozone AQI in 2017 is lower than 2018. Wilcoxon test is conducted since the data are non-parametric data, which means not normally distributed. T-test or ANOVA test cannot be used here. Both the difference for yearly mean and monthly difference are tested. One interesting finding before conducting the test is that the 2017 AQI mean is actually higher than the 2018 AQI, so the null hypothesis is adjusted as follow:

H0: 2017 and 2018 mean ozone AQI are identical.

Ha: 2017 has a higher mean ozone AQI than 2018.

From the result and the visualization figures we see that, the 2017 has a significantly lower mean AQI than 2018 (p-value <0.001). Among the 12 months, February (p-value <0.001), May (p-value <0.001), August (p-value <0.001), September (p-value <0.001), October (p-value = 0.04), November (p-value <0.001), December (p-value <0.001) also have higher mean ozone AQI than 2018.

While in January, April, June, the p-value is 1, and the mean of AQI in 2018 in these month are higher than 2017.

```
#ANOVA Test Assumption
#Previous tested for normality not met
ks.test(EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE,pnorm)
```

```
## Warning in ks.test(EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE, pnorm):
## ties should not be present for the Kolmogorov-Smirnov test

##
##  One-sample Kolmogorov-Smirnov test
##
## data:  EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE
## D = 1, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

```
ks.test(log(EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE),pnorm)
```

```
## Warning in ks.test(log(EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE),
## pnorm): ties should not be present for the Kolmogorov-Smirnov test

##
##  One-sample Kolmogorov-Smirnov test
##
## data:  log(EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE)
## D = 0.99173, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

```r
ks.test(EPA_Ozone_2018.data.Processed$DAILY_AQI_VALUE,pnorm)
```

```
## Warning in ks.test(EPA_Ozone_2018.data.Processed$DAILY_AQI_VALUE, pnorm):
## ties should not be present for the Kolmogorov-Smirnov test

##
##  One-sample Kolmogorov-Smirnov test
##
## data:  EPA_Ozone_2018.data.Processed$DAILY_AQI_VALUE
## D = 0.99821, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

```r
ks.test(log(EPA_Ozone_2018.data.Processed$DAILY_AQI_VALUE),pnorm)
```

```
## Warning in ks.test(log(EPA_Ozone_2018.data.Processed$DAILY_AQI_VALUE),
## pnorm): ties should not be present for the Kolmogorov-Smirnov test

##
##  One-sample Kolmogorov-Smirnov test
##
## data:  log(EPA_Ozone_2018.data.Processed$DAILY_AQI_VALUE)
## D = 0.98881, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

```r
#test for homogenecity of variance met
class(EPA_totalOzone.data.processed$year)
```

```
## [1] "numeric"
```

```r
EPA_totalOzone.data.processed$year <- as.factor(EPA_totalOzone.data.processed$year)

sd(EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE)/
  sd(EPA_Ozone_2018.data.Processed$DAILY_AQI_VALUE)
```

```
## [1] 0.87895
```

```r
# bartlett.test(EPA_totalOzone.data.processed$DAILY_AQI_VALUE~
# EPA_totalOzone.data.processed$year, EPA_totalOzone.data.processed)

#T-test Assumption not met, data is not normally distributed.
#So I will conduct Mann-Whitney-Wilcoxon Test.

mean(EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE)
```

```
## [1] 39.86897
```

```r
mean(EPA_Ozone_2018.data.Processed$DAILY_AQI_VALUE)
```

```
## [1] 39.45543
```

```r
wilcox.test(EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE,
            EPA_Ozone_2018.data.Processed$DAILY_AQI_VALUE, alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  EPA_Ozone_2017.data.Processed$DAILY_AQI_VALUE and EPA_Ozone_2018.data.Processe
## W = 58178000, p-value = 9.077e-13
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_1_2017$DAILY_AQI_VALUE,month_1_2018$DAILY_AQI_VALUE,
            alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_1_2017$DAILY_AQI_VALUE and month_1_2018$DAILY_AQI_VALUE
## W = 30854, p-value = 1
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_2_2017$DAILY_AQI_VALUE,month_2_2018$DAILY_AQI_VALUE,
            alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_2_2017$DAILY_AQI_VALUE and month_2_2018$DAILY_AQI_VALUE
## W = 114220, p-value < 2.2e-16
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_3_2017$DAILY_AQI_VALUE,month_3_2018$DAILY_AQI_VALUE,
            alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_3_2017$DAILY_AQI_VALUE and month_3_2018$DAILY_AQI_VALUE
## W = 725790, p-value = 0.0865
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_4_2017$DAILY_AQI_VALUE,month_4_2018$DAILY_AQI_VALUE,
            alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_4_2017$DAILY_AQI_VALUE and month_4_2018$DAILY_AQI_VALUE
```

```
## W = 486820, p-value = 1
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_5_2017$DAILY_AQI_VALUE,month_5_2018$DAILY_AQI_VALUE,
            alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_5_2017$DAILY_AQI_VALUE and month_5_2018$DAILY_AQI_VALUE
## W = 794380, p-value = 1.553e-07
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_6_2017$DAILY_AQI_VALUE,month_6_2018$DAILY_AQI_VALUE,
            alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_6_2017$DAILY_AQI_VALUE and month_6_2018$DAILY_AQI_VALUE
## W = 503450, p-value = 1
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_7_2017$DAILY_AQI_VALUE,month_7_2018$DAILY_AQI_VALUE,
            alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_7_2017$DAILY_AQI_VALUE and month_7_2018$DAILY_AQI_VALUE
## W = 689380, p-value = 0.6059
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_8_2017$DAILY_AQI_VALUE,month_8_2018$DAILY_AQI_VALUE,
            alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_8_2017$DAILY_AQI_VALUE and month_8_2018$DAILY_AQI_VALUE
## W = 767460, p-value = 7.514e-07
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_9_2017$DAILY_AQI_VALUE,month_9_2018$DAILY_AQI_VALUE,
            alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
```

```
##
## data:  month_9_2017$DAILY_AQI_VALUE and month_9_2018$DAILY_AQI_VALUE
## W = 618390, p-value < 2.2e-16
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_10_2017$DAILY_AQI_VALUE,
            month_10_2018$DAILY_AQI_VALUE, alternative = "greater")
```

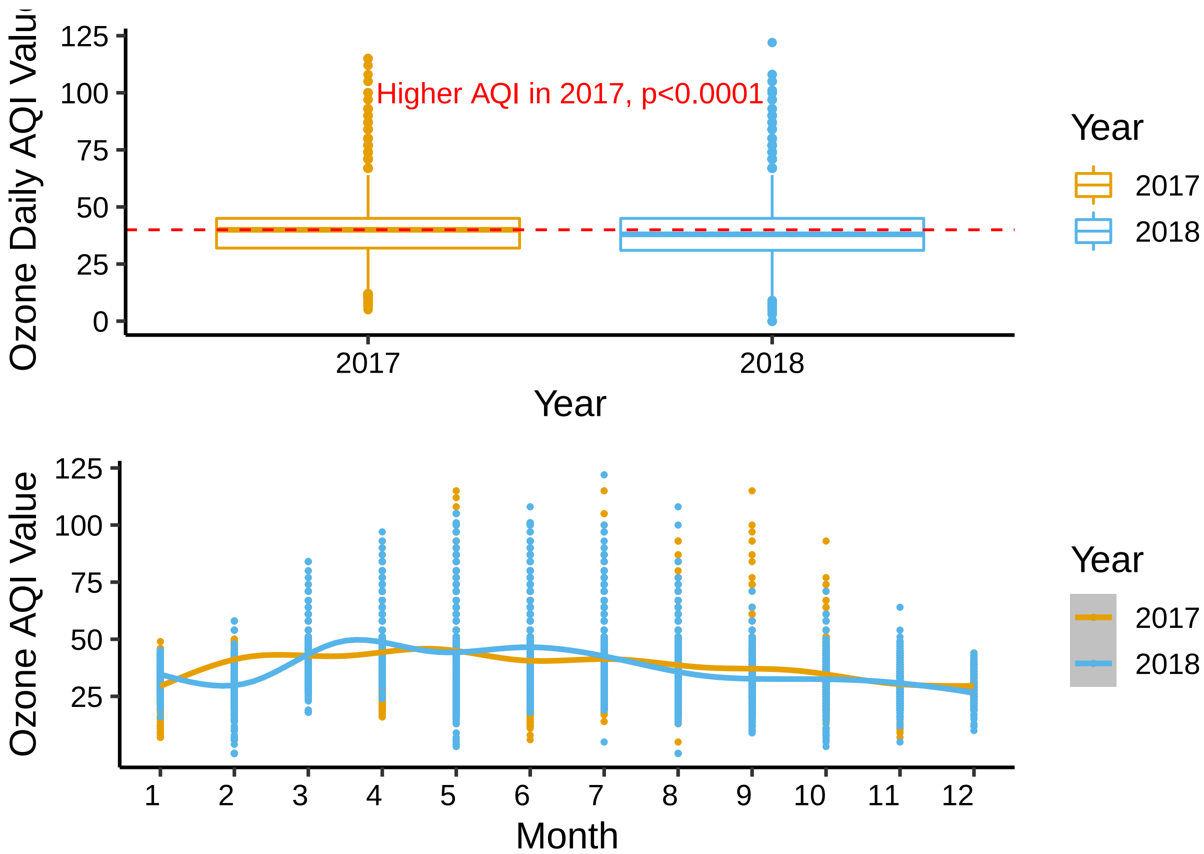
```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_10_2017$DAILY_AQI_VALUE and month_10_2018$DAILY_AQI_VALUE
## W = 607880, p-value = 0.03632
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_11_2017$DAILY_AQI_VALUE,
            month_11_2018$DAILY_AQI_VALUE, alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_11_2017$DAILY_AQI_VALUE and month_11_2018$DAILY_AQI_VALUE
## W = 89283, p-value = 0.0003441
## alternative hypothesis: true location shift is greater than 0
```

```r
wilcox.test(month_12_2017$DAILY_AQI_VALUE,
            month_12_2018$DAILY_AQI_VALUE, alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  month_12_2017$DAILY_AQI_VALUE and month_12_2018$DAILY_AQI_VALUE
## W = 25216, p-value = 0.0003636
## alternative hypothesis: true location shift is greater than 0
```


Ozone Daily AQI Valu
125
100
75
50
25
0
Higher AQI in 2017, p<0.0001
2017
2018
Year
Year
2017
2018
Ozone AQI Value
125
100
75
50
25
1
2
3
4
5
6
7
8
9
10
11
12
Month
Year
2017
2018

4.2 4.2

The second main analysis employs the Mann-kenndal test to determine whether there is a monotonic trend combining with Pettitt's test which find the shift point in the central tendency of time series. Weather is especially favorable for ozone formation when it is hot, dry and sunny. The two tests help to understand how ozone pollution level fluctuated through a yearly time period in 2017 and 2018.

H0: There is no monotonic trend in the ozone AQI in 2017 (2018).

Ha: There is a trend exist. In 2017, two significant change points are detected, one is on August 6th ($p < 0.001$), another is on October 7th ($p<0.001$). There is a significant positive trend from start of the year to August 6th ($z = 4.65$, $p < 0.001$), and a significant negative general trend from August 6th to the end of year ($z = -4.24$, $p <0.001$). There is also a suggestive slight positive trend from August 6th to October 7th ($z = 1.80$, $p = 0.07$), and a non-significant negative trend after October 7th ($z =-1.16$, $p = 0.24$).

In 2018, there are three significant change points are detected, on July 29th ($p < 0.001$), on September 9th ($p<0.001$), and on October 7th ($p = 0.002$). There is a significant positive trend from start of the year to July 29th ($z = 5.66$, $p < 0.001$), and a significant negative general trend from July 29th to the end of year ($z = -3.85$, $p <0.001$). There is also a non-significant positive trend from July 29th to September 9th ($z = 1.36$, $p = 0.17$), a significant positive trend from September 9th to October 7th ($p = 0.007$), a significant negative trend after October 7th ($z =- 2.28$, $p = 0.02$).

Both the result and the figure show that the trends of ozone level fluctuate are similar in 2017 and 2018. There are change points in summer/ fall in both years and the change point is on the exact same date on October 7th. And there are positive trends in first half of year (from winter to summer) and negative trends in the later part of year (from summer/fall to the following winter in end of year).

```r
#Mann-Kendall test for trend of Ozone in both 2017 and 2018.
#group_by date
Ozonebydate_2017 <- EPA_Ozone_2017.data.Processed %>%
   group_by(Date) %>%
  summarise(MeanOzoneAQI = mean(DAILY_AQI_VALUE))

Ozonebydate_2018 <- EPA_Ozone_2018.data.Processed %>%
   group_by(Date) %>%
  summarise(MeanOzoneAQI = mean(DAILY_AQI_VALUE))
#Non-normal data 2017:

#Test for Change point
pettitt.test(Ozonebydate_2017$MeanOzoneAQI)
```

```
##
```

```
##  Pettitt's test for single change-point detection
##
## data:  Ozonebydate_2017$MeanOzoneAQI
## U* = 14903, p-value = 2.158e-12
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                              218
```

```r
# 218: 2017-08-06

# Run seperate Mann-Kendall for each change point: possitive trend
  mk.test(Ozonebydate_2017$MeanOzoneAQI[1:218])
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2017$MeanOzoneAQI[1:218]
## z = 4.6491, n = 218, p-value = 3.334e-06
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##            S         varS          tau
## 5.006000e+03 1.158979e+06 2.117105e-01
```

```r
  #negative trend
mk.test(Ozonebydate_2017$MeanOzoneAQI[218:364])
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2017$MeanOzoneAQI[218:364]
## z = -4.2373, n = 147, p-value = 2.262e-05
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##             S          varS           tau
## -2.531000e+03  3.564963e+05 -2.359687e-01
```

```r
#Another Change point at 280 : 2017-10-07
pettitt.test(Ozonebydate_2017$MeanOzoneAQI[218:364])
```

```
##
##  Pettitt's test for single change-point detection
##
## data:  Ozonebydate_2017$MeanOzoneAQI[218:364]
## U* = 2666, p-value = 3.236e-06
## alternative hypothesis: two.sided
## sample estimates:
```

```
## probable change point at time K
##                              62
```

```
mk.test(Ozonebydate_2017$MeanOzoneAQI[218:280]) #no significant trend
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2017$MeanOzoneAQI[218:280]
## z = 1.8031, n = 63, p-value = 0.07138
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##          S       varS        tau
## 3.0500e+02 2.8427e+04 1.5617e-01
```

```
mk.test(Ozonebydate_2017$MeanOzoneAQI[281:364]) #no significant trend
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2017$MeanOzoneAQI[281:364]
## z = -1.1551, n = 84, p-value = 0.248
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##             S           varS           tau
## -3.000000e+02  6.699933e+04 -8.615744e-02
```

```
#anythird change point?
pettitt.test(Ozonebydate_2017$MeanOzoneAQI[281:364]) #not significant
```

```
##
##  Pettitt's test for single change-point detection
##
## data:  Ozonebydate_2017$MeanOzoneAQI[281:364]
## U* = 566, p-value = 0.08113
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                              59
```

```
#Non-normal data 2018:

#Test for Change point
pettitt.test(Ozonebydate_2018$MeanOzoneAQI)
```

```
##
##  Pettitt's test for single change-point detection
##
```

```
## data:  Ozonebydate_2018$MeanOzoneAQI
## U* = 14869, p-value = 1.165e-14
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                              210
```

```r
# 210: 2018-07-29

# Run seperate Mann-Kendall for each change point: possitive trend
  mk.test(Ozonebydate_2018$MeanOzoneAQI[1:210])
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2018$MeanOzoneAQI[1:210]
## z = 5.6612, n = 210, p-value = 1.503e-08
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##            S         varS          tau
## 5.764000e+03 1.036289e+06 2.626746e-01
```

```r
  #negative trend
mk.test(Ozonebydate_2018$MeanOzoneAQI[210:343])
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2018$MeanOzoneAQI[210:343]
## z = -3.8546, n = 134, p-value = 0.0001159
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##             S          varS           tau
## -2.005000e+03  2.702983e+05 -2.250281e-01
```

```r
#Another Change point at 252 : 2017-09-09
pettitt.test(Ozonebydate_2018$MeanOzoneAQI[210:343])
```

```
##
##  Pettitt's test for single change-point detection
##
## data:  Ozonebydate_2018$MeanOzoneAQI[210:343]
## U* = 1957, p-value = 0.0001528
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                               42
```

```r
mk.test(Ozonebydate_2018$MeanOzoneAQI[210:252]) #no significant trend
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2018$MeanOzoneAQI[210:252]
## z = 1.3605, n = 43, p-value = 0.1737
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##           S        varS         tau
##  131.000000 9130.333333    0.145072
```

```r
mk.test(Ozonebydate_2018$MeanOzoneAQI[252:343]) #no significant trend
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2018$MeanOzoneAQI[252:343]
## z = -0.74202, n = 92, p-value = 0.4581
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##             S           varS            tau
## -2.210000e+02  8.790500e+04 -5.280134e-02
```

```r
#anythird change point?
pettitt.test(Ozonebydate_2017$MeanOzoneAQI[252:343]) #At 280, 2018-10-07
```

```
##
##  Pettitt's test for single change-point detection
##
## data:  Ozonebydate_2017$MeanOzoneAQI[252:343]
## U* = 938, p-value = 0.002446
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                               28
```

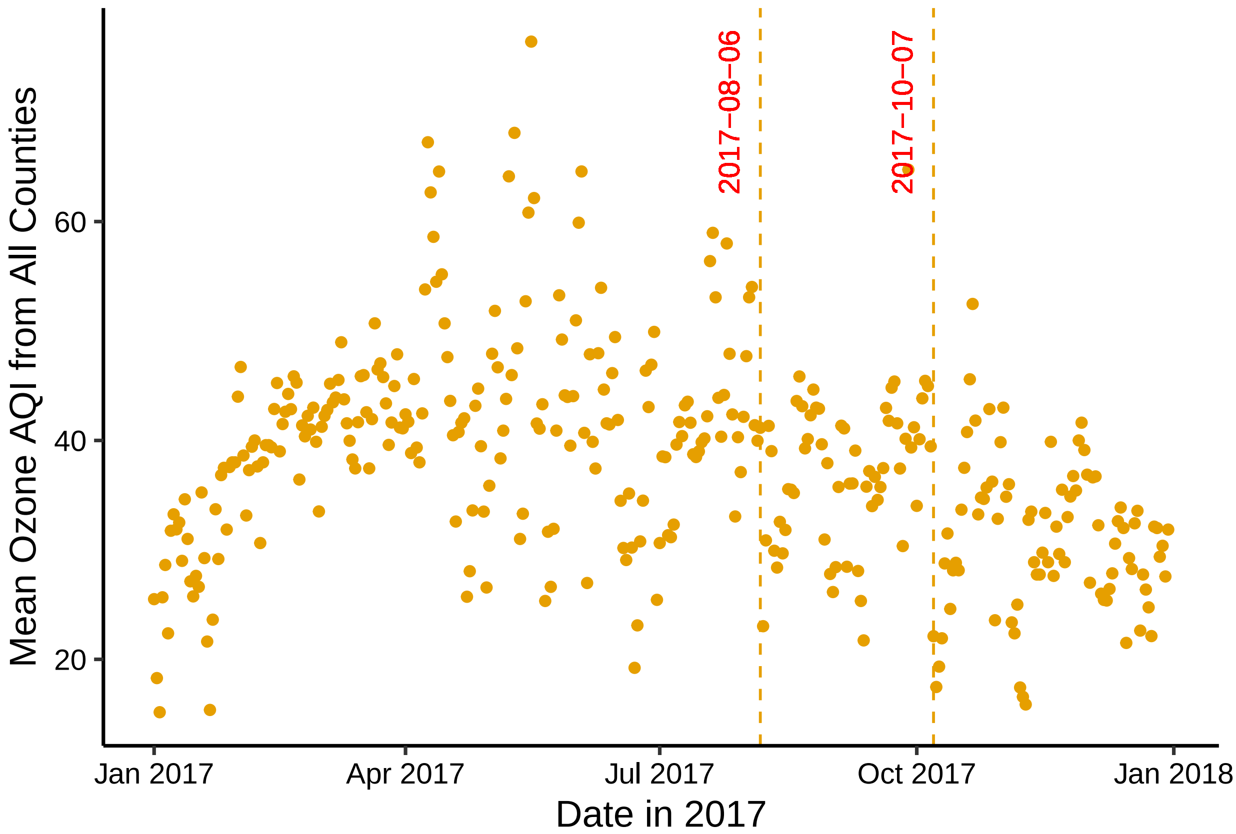
```r
mk.test(Ozonebydate_2018$MeanOzoneAQI[252:280])
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2018$MeanOzoneAQI[252:280]
## z = 2.6824, n = 29, p-value = 0.00731
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##            S         varS          tau
```

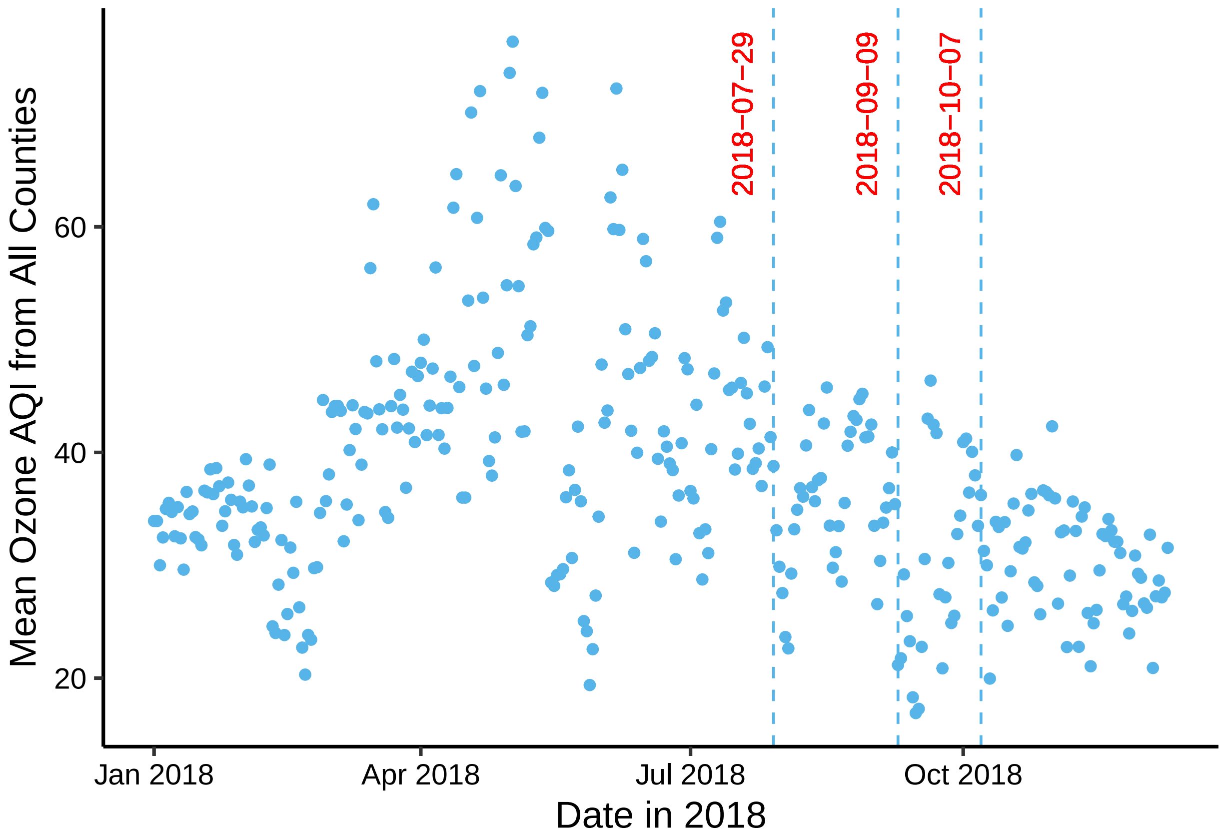
```
##  144.0000000 2842.0000000    0.3546798
```

```r
mk.test(Ozonebydate_2018$MeanOzoneAQI[280:343])
```

```
##
##  Mann-Kendall trend test
##
## data:  Ozonebydate_2018$MeanOzoneAQI[280:343]
## z = -2.2827, n = 64, p-value = 0.02245
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##             S          varS           tau
##  -395.0000000 29791.0000000    -0.1959812
```



Mean Ozone AQI from All Counties
20
40
60
2017–08–06
2017–10–07
Jan 2017
Apr 2017
Jul 2017
Oct 2017
Jan 2018
Date in 2017


Mean Ozone AQI from All Counties
60
40
20
2018−07−29
2018−09−09
2018−10−07
Jan 2018
Apr 2018
Jul 2018
Oct 2018
Date in 2018

4.3 4.3

The third analysis is the generalized linear model to test whether population, density, or income is correlated with Ozone AQI level. Random effect for county is included in the model.

H0: There is no significant correlation for all the variables, all the coefficients are zero.

Ha: At least one variable is significant.

After testing the data, I found out that only the mean AQI value (p-value = 0.73) passed the Shapiro-Wilk normality test. Other variables are not normally distributed. The initial model established included all the variables, and then based on the AIC score, best fit model is selected which is MeanOzoneAQI   Population (P = 0.07). Due to a small sample size, a p value of 0.07 is considered to be suggestive significant. The diagnostic residual plot shows that the residuals are evenly distributed above and below the center, so there is no skew problem.

From the result, our final model is: Mean Ozone AQI = 38.35 + 0.08 x Population. The intercept is 38.35, which means that when population is 0, there will be a mean AQI Ozone value of 38.35. And every single person increase in population will result in a 0.08 increase in the mean Ozone AQI.

```r
#Generalized linear model.
LG <- read.csv("../Processed data/OzoneSummary1.csv")
library(lme4)
```

```
## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following object is masked from 'package:tidyr':
##
##     expand
```

```r
#Density =(population/square mile)
#normaility -test : not normal
shapiro.test(FLG$Population)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  FLG$Population
## W = 0.95153, p-value = 0.01467
```

```r
shapiro.test(FLG$Income)
```

```
##
##  Shapiro-Wilk normality test
```

```
##
## data:  FLG$Income
## W = 0.90107, p-value = 9.929e-05
```

```r
shapiro.test(FLG$Density)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  FLG$Density
## W = 0.71204, p-value = 8.183e-10
```

```r
#Normal
shapiro.test(FLG$MeanOzoneAQI)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  FLG$MeanOzoneAQI
## W = 0.98676, p-value = 0.7344
```

```r
#Counties as a mixed effect
MLG <- LG %>%
  select(MeanOzoneAQI, Population, Income, Density,COUNTY)
MLG$Population <-  as.numeric(FLG$Population)
MLG$Income <-  as.numeric(FLG$Income)
MLG$Density <-  as.numeric(FLG$Density)

glm1 <- lmer(data = MLG, MeanOzoneAQI ~Population + Income + Density+(1|COUNTY) )
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```r
glm2 <-lmer(data = MLG, MeanOzoneAQI ~Population + (1|COUNTY))
summary(glm1)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: MeanOzoneAQI ~ Population + Income + Density + (1 | COUNTY)
##    Data: MLG
##
## REML criterion at convergence: 298
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.54194 -0.57372  0.07852  0.56102  1.59841
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
```

```
##  COUNTY   (Intercept) 6.483    2.546
##  Residual             1.223    1.106
## Number of obs: 63, groups:  COUNTY, 32
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept) 3.639e+01  2.955e+00  12.314
## Population  9.986e-02  5.431e-02   1.839
## Income      2.487e-05  6.501e-05   0.382
## Density     1.251e-03  1.609e-03   0.778
##
## Correlation of Fixed Effects:
##            (Intr) Popltn Income
## Population -0.366
## Income     -0.913  0.016
## Density     0.374  0.259 -0.620
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```r
AIC(glm1)
```

```
## [1] 310.0305
```

```r
summary(glm2)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: MeanOzoneAQI ~ Population + (1 | COUNTY)
##    Data: MLG
##
## REML criterion at convergence: 270.9
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.53118 -0.64085  0.06108  0.52879  1.53735
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  COUNTY   (Intercept) 6.447    2.539
##  Residual             1.222    1.105
## Number of obs: 63, groups:  COUNTY, 32
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept) 38.35664    0.96173  39.883
## Population   0.07543    0.05088   1.483
##
```

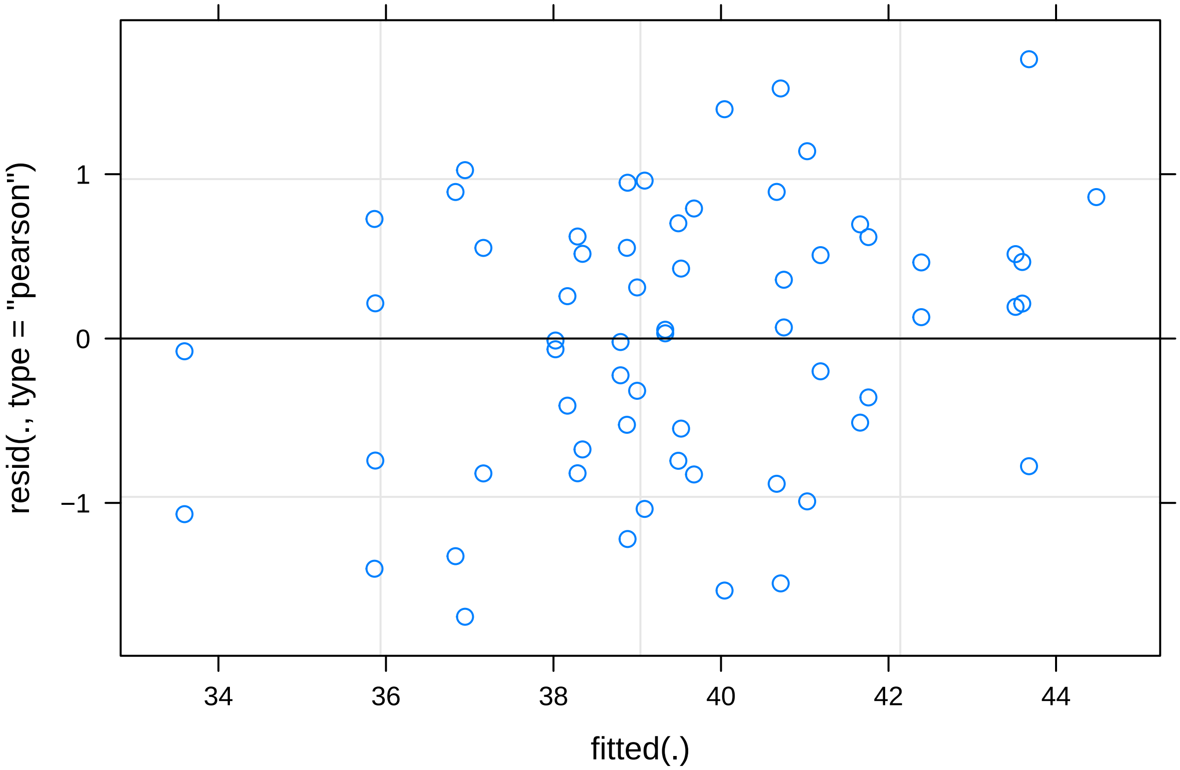


Figure 6: Residual Plot

```
## Correlation of Fixed Effects:
##            (Intr)
## Population -0.872
```

```
AIC(glm2)
```

```
## [1] 278.8938
```

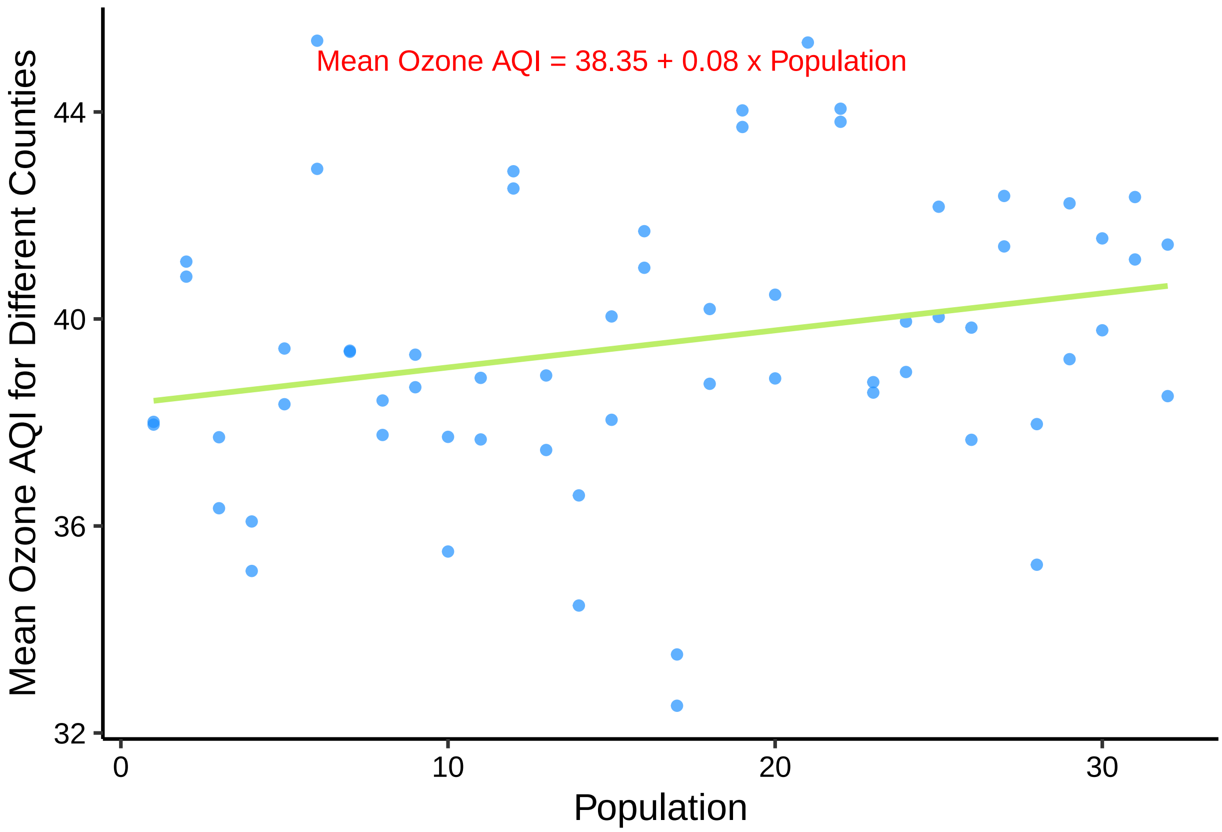


Figure 7: Relationship Between Ozone AQI and Population

5 Summary and Conclusions

Based on the analysis above, we can conclude that:

1. 2018 does not have a worsened ozone pollution compare to 2017. And moreover, in February, May, August, September, October, November, December, there was a higher ozone concentration in most months in 2017 than 2018. Therefore, it is not accurate for American Lung Association to report a worsened ozone pollution in 2018. The implication we obtain from this is that, to become scientists, we should have critical thoughts on the news we see every day and confirm/deny the truth by ourselves will be interesting.

2. There are trends patterns for Ozone AQI level within a yearly period both in 2017 and 2018. The patterns are similar in these two years where there are positive trends in first half of year (from winter to summer) and negative trends in the later part of year (from summer/fall to the following winter in end of year). This result is consistent with the fact that weather may affect the ozone formation, and ozone pollution tends to be higher when it is hot, dry and sunny without much wind.

3. Population size affects Ozone AQI level, population density or income does not affect Ozone AQI level. In our data, the association between Ozone AQI and population size is: Mean Ozone AQI = 38.35 + 0.08 x Population Therefore, in a city/community with a larger population size, the ozone pollution may be worse than a low population area. People who live in a large and sunny city should pay more attention to their ozone pollution.