Assignment 7: Time Series Analysis

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OVERVIEW

This exercise accompanies the lessons in Environmental Data Analytics on time series analysis.

Directions

1. Change "Student Name" on line 3 (above) with your name.
2. Work through the steps, **creating code and output** that fulfill each instruction.
3. Be sure to **answer the questions** in this assignment document.
4. When you have completed the assignment, **Knit** the text and code into a single PDF file.
5. After Knitting, submit the completed exercise (PDF file) to the dropbox in Sakai. Add your last name into the file name (e.g., "Fay_A07_TimeSeries.Rmd") prior to submission.

The completed exercise is due on Monday, March 14 at 7:00 pm.

Set up

1. Set up your session:

- Check your working directory
- Load the tidyverse, lubridate, zoo, and trend packages
- Set your ggplot theme

```
#1
getwd()
```

```
## [1] "C:/Users/cassi/OneDrive - Duke University/Documents/School/Grad School/Spring 2022/Environmental
```

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --
```

```
## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.7
## v tidyr   1.1.4     v stringr 1.4.0
## v readr   2.1.1     v forcats 0.5.1
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
```

```
## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```
library(zoo)
```

```
##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
library(trend)
library(dplyr)

mytheme <- theme_classic(base_size = 14) +
  theme(axis.text = element_text(color = "black"),
        legend.position = "right")
theme_set(mytheme)
```

2. Import the ten datasets from the Ozone_TimeSeries folder in the Raw data folder. These contain ozone concentrations at Garinger High School in North Carolina from 2010-2019 (the EPA air database only allows downloads for one year at a time). Import these either individually or in bulk and then combine them into a single dataframe named `GaringerOzone` of 3589 observation and 20 variables.

```
#2

Ozone2010<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2010_raw.csv", stringsAsFactors =
Ozone2011<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2011_raw.csv", stringsAsFactors =
Ozone2012<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2012_raw.csv", stringsAsFactors =
Ozone2013<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2013_raw.csv", stringsAsFactors =
Ozone2014<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2014_raw.csv", stringsAsFactors =
Ozone2015<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2015_raw.csv", stringsAsFactors =
Ozone2016<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2016_raw.csv", stringsAsFactors =
Ozone2017<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2017_raw.csv", stringsAsFactors =
Ozone2018<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2018_raw.csv", stringsAsFactors =
Ozone2019<-read.csv("./Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2019_raw.csv", stringsAsFactors =

GaringerOzone<-rbind(Ozone2010, Ozone2011, Ozone2012, Ozone2013, Ozone2014, Ozone2015, Ozone2016, Ozone
```

Wrangle

3. Set your date column as a date class.
4. Wrangle your dataset so that it only contains the columns Date, Daily.Max.8.hour.Ozone.Concentration, and DAILY_AQI_VALUE.
5. Notice there are a few days in each year that are missing ozone concentrations. We want to generate a daily dataset, so we will need to fill in any missing days with NA. Create a new data frame that contains a sequence of dates from 2010-01-01 to 2019-12-31 (hint: `as.data.frame(seq())`). Call this new data frame Days. Rename the column name in Days to “Date”.
6. Use a `left_join` to combine the data frames. Specify the correct order of data frames within this function so that the final dimensions are 3652 rows and 3 columns. Call your combined data frame GaringerOzone.

```
# 3
GaringerOzone$Date<-as.Date(GaringerOzone$Date, format = "%m/%d/%Y")
# 4
GaringerOzone.select<-select(GaringerOzone, Date, Daily.Max.8.hour.Ozone.Concentration, DAILY_AQI_VALUE)
```

```
# 5
?seq()
```

```
## starting httpd help server ... done
```

```
Days<-as.data.frame(seq(as.Date("2010-01-01"), as.Date("2019-12-31"), by = "day"))
colnames(Days) <- "Date"
# 6
GaringerOzone<-left_join(Days, GaringerOzone.select, by = ("Date"))
```

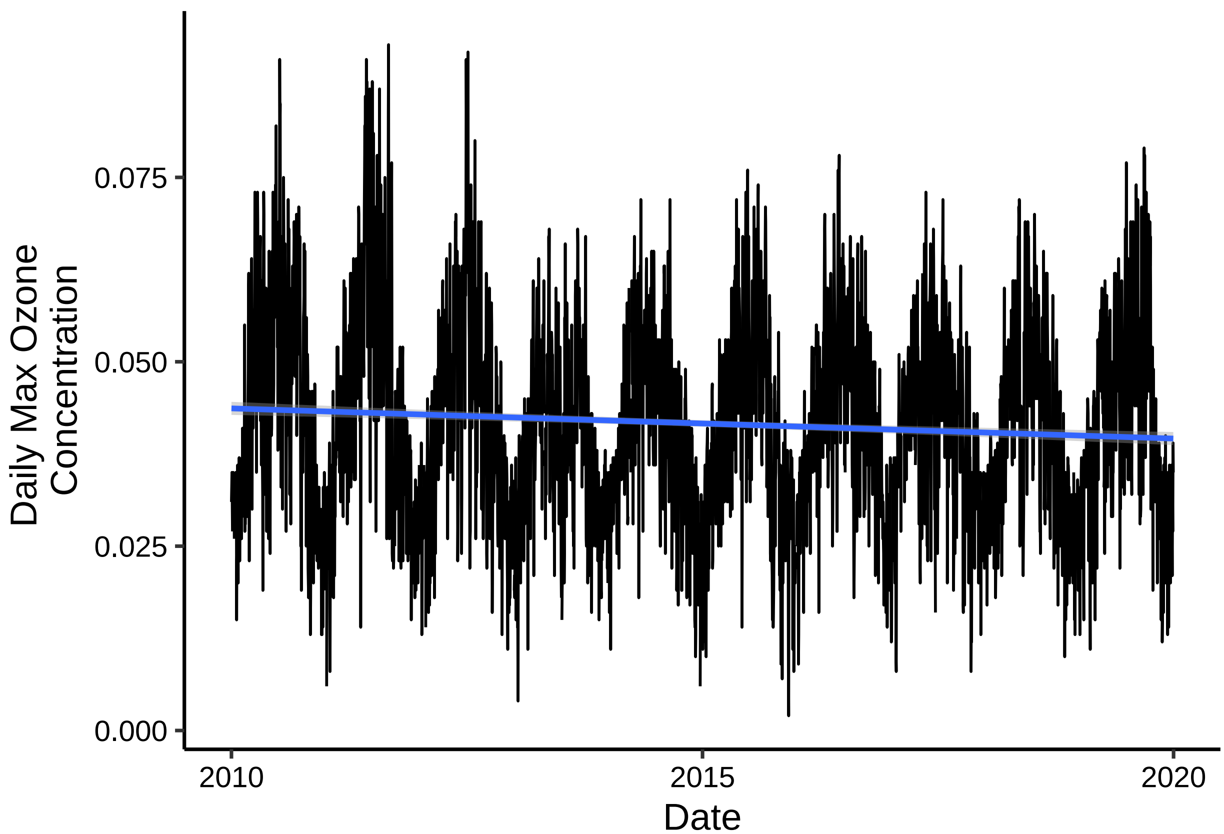
Visualize

7. Create a line plot depicting ozone concentrations over time. In this case, we will plot actual concentrations in ppm, not AQI values. Format your axes accordingly. Add a smoothed line showing any linear trend of your data. Does your plot suggest a trend in ozone concentration over time?

```
#7
ggplot(GaringerOzone, aes(x=Date, y=Daily.Max.8.hour.Ozone.Concentration))+
  geom_line()+
  ylab("Daily Max Ozone \nConcentration")+
  geom_smooth(method = lm)
```

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 63 rows containing non-finite values (stat_smooth).
```



Answer: According to the linear trend fitted to the data, the plot suggests a slightly downward trend over time.

Time Series Analysis

Study question: Have ozone concentrations changed over the 2010s at this station?

8. Use a linear interpolation to fill in missing daily data for ozone concentration. Why didn't we use a piecewise constant or spline interpolation?

```
#8
GaringerOzone.interpolated<-GaringerOzone %>%
  mutate(Max.Ozone = zoo::na.approx(Daily.Max.8.hour.Ozone.Concentration))%>%
  select(Date, DAILY_AQI_VALUE, Max.Ozone)
```

> Answer: Piecewise constant interpolation sets the missing value as the same as that of the nearest data point. We don't want to use piecewise interpolation here because we can see that there is a seasonal trend in the data, values are going up and down, and so missing values are likely to be somewhere in between the previous and the next value. Likewise, we don't want to use spline interpolation because the trend we see is regular. If the trend was changing over time we could use spline to interpolate using a quadratic method, but that is not the best option here.

9. Create a new data frame called `GaringerOzone.monthly` that contains aggregated data: mean ozone concentrations for each month. In your pipe, you will need to first add columns for year and month to form the groupings. In a separate line of code, create a new Date column with each month-year combination being set as the first day of the month (this is for graphing purposes only)

```
#9
GaringerOzone.monthly<-GaringerOzone.interpolated %>%
  mutate(Month = month(Date)) %>%
  mutate(Year = year(Date))
GaringerOzone.monthly$Date<-as.yearmon(paste(GaringerOzone.monthly$Year, GaringerOzone.monthly$Month),
GaringerOzone.monthly<-GaringerOzone.monthly %>%
  group_by(Date) %>%
  summarize(meanOzone = mean(Max.Ozone),
            meanAQI = mean(DAILY_AQI_VALUE))
```

10. Generate two time series objects. Name the first `GaringerOzone.daily.ts` and base it on the dataframe of daily observations. Name the second `GaringerOzone.monthly.ts` and base it on the monthly average ozone values. Be sure that each specifies the correct start and end dates and the frequency of the time series.

```
#10
f_month <- month(first(GaringerOzone.interpolated$Date))
f_month
```

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

```
f_year<-year(first(GaringerOzone.interpolated$Date))
f_year
```

```
## [1] 2010
```

```
GaringerOzone.daily.ts<-ts(GaringerOzone.interpolated$Max.Ozone, start = c(f_month, f_year), frequency =
fmonth <- month(first(GaringerOzone.monthly$Date))
fmonth
```

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

```
fyear<-year(first(GaringerOzone.monthly$Date))
fyear
```

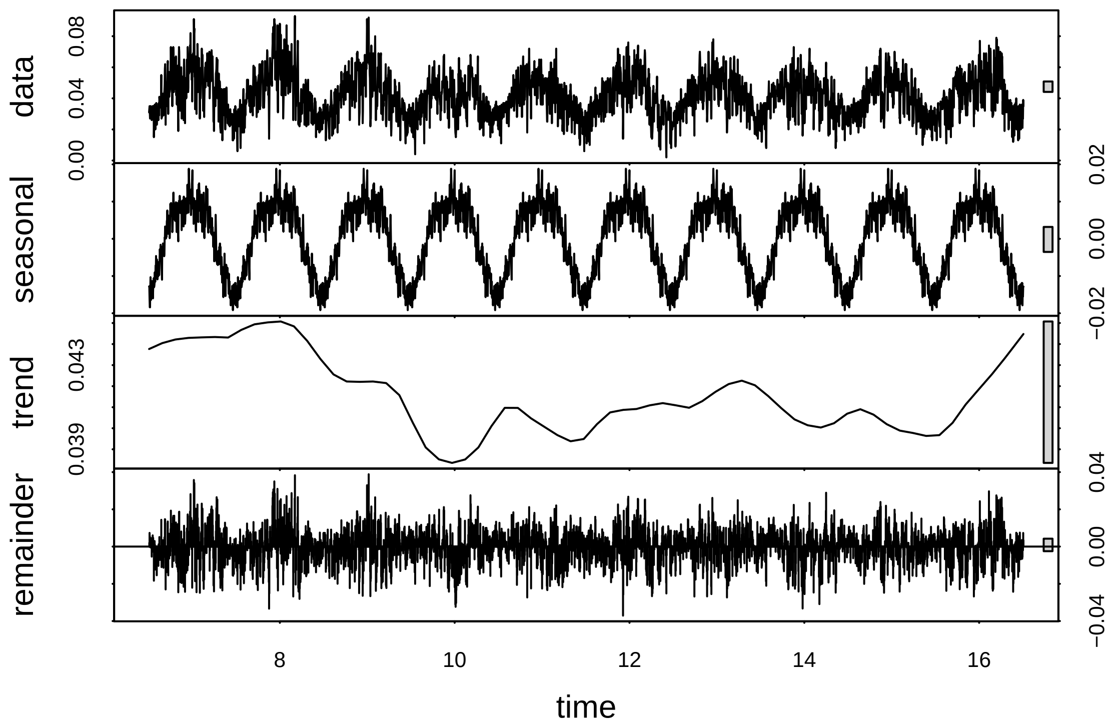
```
## [1] 2010
```

```
GaringerOzone.monthly.ts<-ts(GaringerOzone.monthly$meanOzone, start = c(fmonth, fyear), frequency = 12)
```

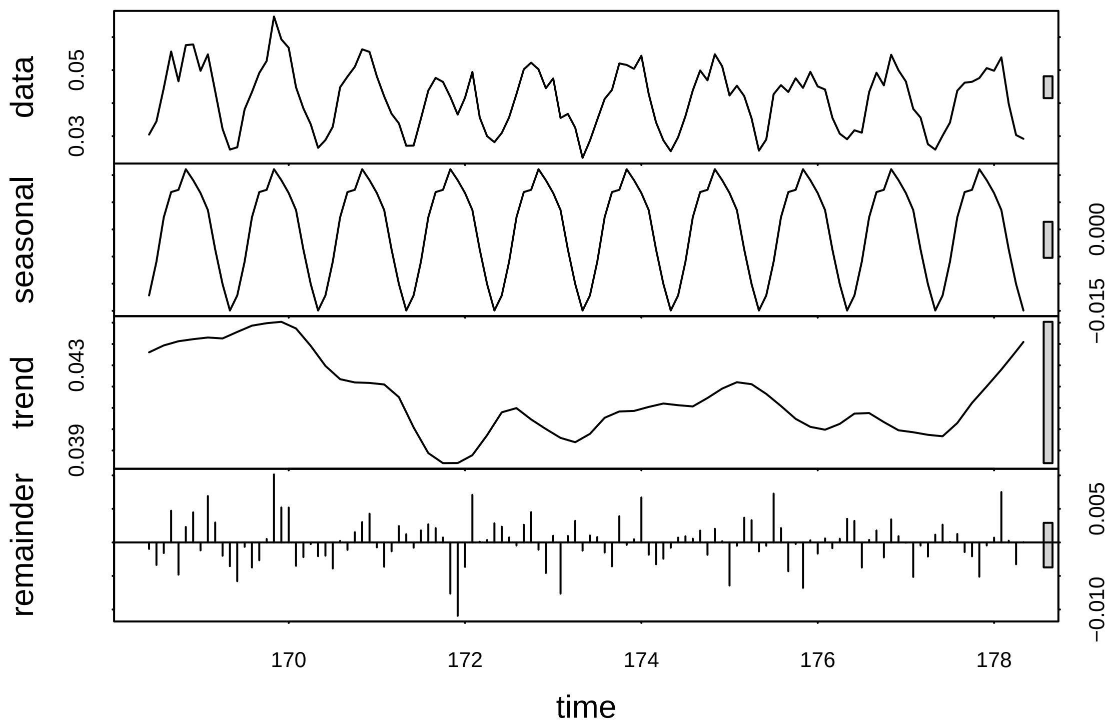
11. Decompose the daily and the monthly time series objects and plot the components using the `plot()` function.

```
#11
GaringerOzone.daily.Decomposed<-stl(GaringerOzone.daily.ts, s.window = "periodic")
GaringerOzone.monthly.Decomposed<-stl(GaringerOzone.monthly.ts, s.window = "periodic")

plot(GaringerOzone.daily.Decomposed)
```




```
plot(GaringerOzone.monthly.Decomposed)
```



12. Run a monotonic trend analysis for the monthly Ozone series. In this case the seasonal Mann-Kendall is most appropriate; why is this?

```
#12
MonthlyOzoneTrend<-Kendall::SeasonalMannKendall(GaringerOzone.monthly.ts)

MonthlyOzoneTrend
```

```
## tau = -0.143, 2-sided pvalue =0.046724
```

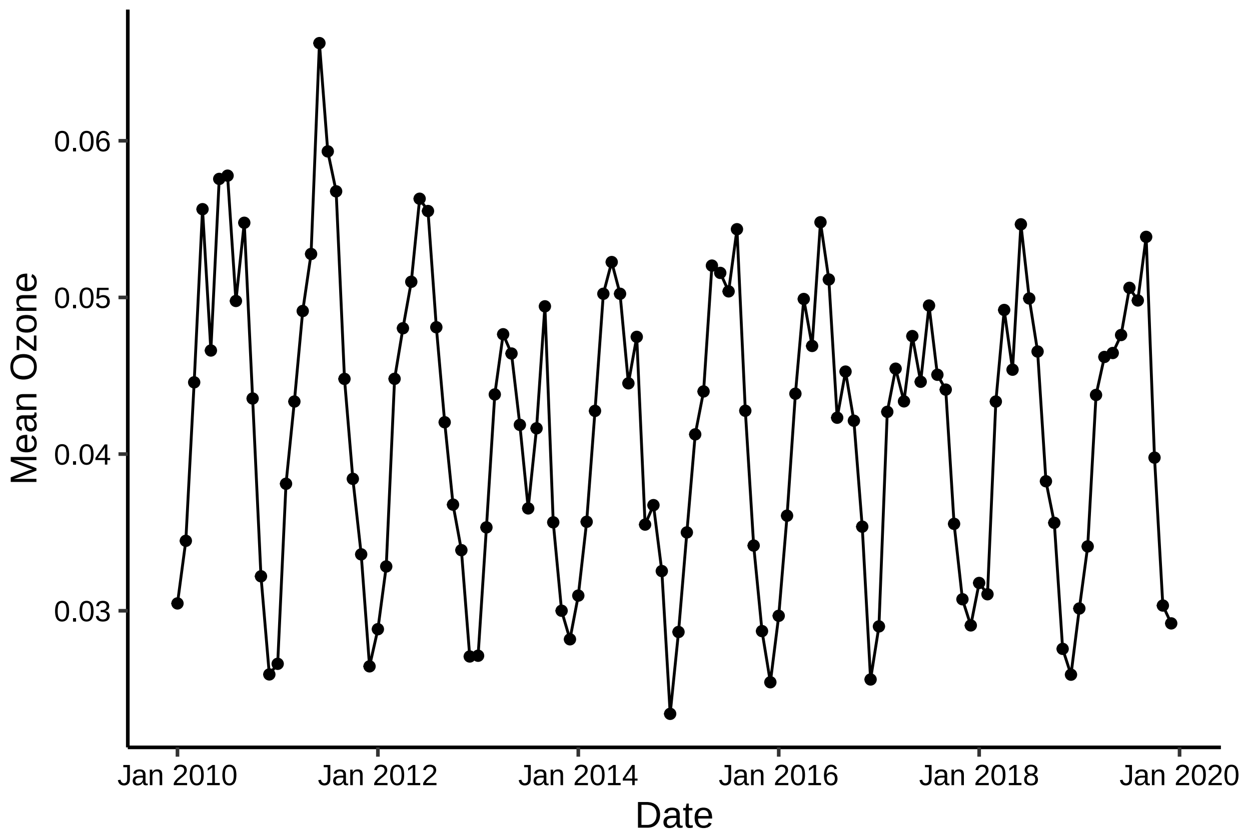
```
summary(MonthlyOzoneTrend)
```

```
## Score =  -77 , Var(Score) = 1499
## denominator =  539.4972
## tau = -0.143, 2-sided pvalue =0.046724
```

Answer: This is the most appropriate trend analysis to perform because it is the only analysis that can be performed on seasonal data.

13. Create a plot depicting mean monthly ozone concentrations over time, with both a geom_point and a geom_line layer. Edit your axis labels accordingly.

```
# 13
ggplot(GaringerOzone.monthly, aes(x=Date, y =meanOzone))+
  geom_point()+
  geom_line()+
  ylab("Mean Ozone")
```



14. To accompany your graph, summarize your results in context of the research question. Include output from the statistical test in parentheses at the end of your sentence. Feel free to use multiple sentences in your interpretation.

    Answer: Yes, according to both the graph and the results of the statistical trend analysis, ozone levels have been decreasing at the study site in the 2010s. The graph shows a slightly declining trend and the trend analysis has a p value <0.5 (p = 0.046724) and a negative tau value (tau = -0.143), indicating that we can reject the null hypothesis of there being no trend and that our data have a declining trend.

15. Subtract the seasonal component from the `GaringerOzone.monthly.ts`. Hint: Look at how we extracted the series components for the EnoDischarge on the lesson Rmd file.

16. Run the Mann Kendall test on the non-seasonal Ozone monthly series. Compare the results with the ones obtained with the Seasonal Mann Kendall on the complete series.

```
#15
GaringerOzoneMonthly.Components<-as.data.frame(GaringerOzone.monthly.Decomposed$time.series[,1:3])
GaringerOzone.Nonseas<-GaringerOzone.monthly.ts - GaringerOzone.monthly.Decomposed$time.series[,1]

#16
GaringerOzoneNonseas.trend <- trend::mk.test(GaringerOzone.Nonseas)
GaringerOzoneNonseas.trend
```

```
##
##  Mann-Kendall trend test
##
## data:  GaringerOzone.Nonseas
```

```
## z = -2.672, n = 120, p-value = 0.00754
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##             S          varS           tau
## -1.179000e+03  1.943657e+05 -1.651376e-01
```

```
summary(GaringerOzoneNonseas.trend)
```

```
##             Length Class  Mode
## data.name   1      -none- character
## p.value     1      -none- numeric
## statistic   1      -none- numeric
## null.value  1      -none- numeric
## parameter   1      -none- numeric
## estimates   3      -none- numeric
## alternative 1      -none- character
## method      1      -none- character
## pvalg       1      -none- numeric
```

Answer: These results are much more significant that those obtained with the seasonal Mann Kendall test (p = 0.00754 compared to p =0.046724), suggesting that when we remove the seasonality the declining trend in the data is more prominent.