Assignment 8: 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., "Salk_A06_GLMs_Week1.Rmd") prior to submission.

The completed exercise is due on Tuesday, March 3 at 1:00 pm.

Set up

- 1. Set up your session:
- Check your working directory
- Load the tidyverse, lubridate, zoo, and trend packages
- Set your ggplot theme
- 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). Call these GaringerOzone201*, with the star filled in with the appropriate year in each of ten cases.

```
#Checking working directory and loading packages
getwd()
```

[1] "/Users/clairemullaney/Desktop/ENV 872/Environmental_Data_Analytics_2020"

Wrangle

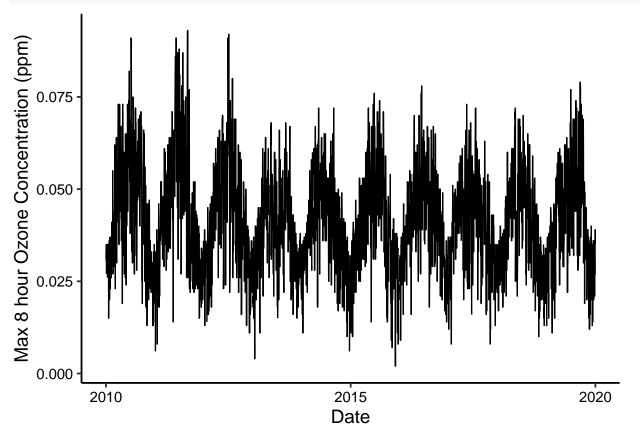
- 2. Combine your ten datasets into one dataset called GaringerOzone. Think about whether you should use a join or a row bind.
- 3. Set your date column as a date class.
- 4. Wrangle your dataset so that it only contains the columns Date, Daily.Max.8.hour.Ozone.Concentration, and DAILY_AQI_VALUE.
- 5. 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.

```
# 2
#Checking column names to decide whether to use join vs. rbind
lapply(Ozone files named, colnames)
#Combining datasets into one; rbind_list was used so the dataframes
#could be bound from the list created above. To use just rbind, the
#code would have looked like this:
#GaringerOzone <- rbind(GaringerOzone2010, GaringerOzone2011,
                             #GaringerOzone2012, GaringerOzone2013,
                             #GaringerOzone2014, GaringerOzone2015,
                             #GaringerOzone2016, GaringerOzone2017,
                             #GaringerOzone2018, GaringerOzone2019)
GaringerOzone <- rbind_list(Ozone_files_named)</pre>
# 3
#Changing date column to date format
GaringerOzone$Date <- as.Date(GaringerOzone$Date,</pre>
                               format = \frac{m}{m}/%d/%Y")
# 4
#Selecting necessary columns
GaringerOzone.wr <- GaringerOzone %>%
  select(Date, Daily.Max.8.hour.Ozone.Concentration, DAILY_AQI_VALUE)
# 5
#Creating a days data frame with a column called "Date"
Days \leftarrow as.data.frame(seq(from = as.Date("2010-01-01"), to =
                             as.Date("2019-12-31"), by = 1))
```

[1] 3652 3

Visualize

7. Create a ggplot depicting ozone concentrations over time. In this case, we will plot actual concentrations in ppm, not AQI values. Format your axes accordingly.



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?

Answer: Piecewise constant interpolation would fill missing data values with measurements taken immediately before or after the absent data points. Because this dataset appears to be highly variable at times, using measurements identical to adjacent data points may not result in accurate estimations. A spline interpolation would use a quadratic or other low-degree polynomial equation to populate missing values. However, non-linear functions are not being used to describe or depict the data currently; existing data points are connected using lines. Approximating data with a spline interpolation would result in data points being connected more smoothly than they would have been had actual observations been present.

- 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)
- 10. Generate a time series called GaringerOzone.monthly.ts, with a monthly frequency that specifies the correct start and end dates.
- 11. Run a time series analysis. In this case the seasonal Mann-Kendall is most appropriate; why is this?

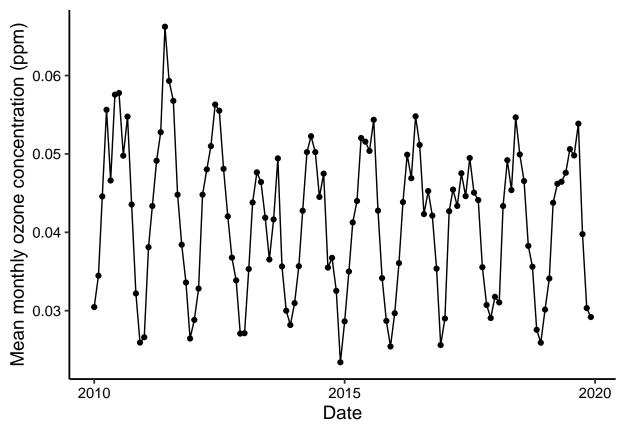
Answer: The graph for Question 7 exhibits clear seasonal trends; increasing and decreasing ozone concentrations occur in cycles over time. The seasonal Mann-Kendall time series analysis is the only test that accounts for seasonality when analyzing monotonic trends. Our data are also non-parametric – they do not come from a population that has a probability distribution with fixed parameters (such as a normal distribution). Additionally, because we are not using daily data and instead found the mean ozone concentration by year and month, temporal autocorrelation is not a large concern. These characteristics of the data eliminate the linear regression, Mann-Kendall, and modified Mann-Kendall tests as possibilities and make the seasonal Mann-Kendall the best option.

- 12. To figure out the slope of the trend, run the function sea.sens.slope on the time series dataset.
- 13. Create a plot depicting mean monthly ozone concentrations over time, with both a geom_point and a geom_line layer. No need to add a line for the seasonal Sen's slope; this is difficult to apply to a graph with time as the x axis. Edit your axis labels accordingly.

```
# 8
#Linear interpolation
GaringerOzone$Daily.Max.8.hour.Ozone.Concentration <-</pre>
  na.approx(GaringerOzone$Daily.Max.8.hour.Ozone.Concentration)
# 9
#Adding Month and Year columns, grouping the df by month/year,
#and summarizing ozone concentrations by month/year
GaringerOzone.monthly <- GaringerOzone %>%
  mutate(Year = year(Date),
         Month = month(Date)) %>%
  group_by(Year, Month) %>%
  summarize(Mean.Ozone.Conc = mean(Daily.Max.8.hour.Ozone.Concentration))
#Adding a new Date column that lists each month/year as a complete
#date including the first day of the month
GaringerOzone.monthly$Date <- seq(from = as.Date("2010-01-01"),</pre>
                                   to = as.Date("2019-12-01"),
                                   by = "month")
# 10
#Creating a time series
```

```
GaringerOzone.monthly.ts <- ts(GaringerOzone.monthly$Mean.Ozone.Conc,</pre>
                              frequency = 12.
                              start = c(2010, 1, 1),
                              end = c(2019, 12, 1)
# 11
#Running a time series analysis (smk)
GaringerOzone.monthly.trend <- smk.test(GaringerOzone.monthly.ts)</pre>
GaringerOzone.monthly.trend
##
## Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: GaringerOzone.monthly.ts
## z = -1.963, p-value = 0.04965
## alternative hypothesis: true S is not equal to O
## sample estimates:
     S varS
##
  -77 1499
summary(GaringerOzone.monthly.trend)
##
## Seasonal Mann-Kendall trend test (Hirsch-Slack test)
## data: GaringerOzone.monthly.ts
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## HO
##
                                         z Pr(>|z|)
                       S varS
                                tau
## Season 1: S = 0 15 125 0.333 1.252 0.21050
## Season 2: S = 0 -1 125 -0.022 0.000 1.00000
## Season 3: S = 0 -4 124 -0.090 -0.269 0.78762
## Season 4: S = 0 -17 125 -0.378 -1.431 0.15241
## Season 5: S = 0 -15 125 -0.333 -1.252 0.21050
## Season 6: S = 0 -17 125 -0.378 -1.431 0.15241
## Season 7: S = 0 -11 125 -0.244 -0.894 0.37109
## Season 8: S = 0 -7 125 -0.156 -0.537 0.59151
## Season 9: S = 0 -5 125 -0.111 -0.358 0.72051
## Season 10: S = 0 -13 125 -0.289 -1.073 0.28313
## Season 11: S = 0 -13 125 -0.289 -1.073 0.28313
## Season 12: S = 0 11 125 0.244 0.894 0.37109
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
sea.sens.slope(GaringerOzone.monthly.ts)
## [1] -0.0002044163
# 13
ggplot(data = GaringerOzone.monthly,
      aes(x = Date, y = Mean.Ozone.Conc)) +
```

```
geom_line() +
geom_point() +
labs(y = "Mean monthly ozone concentration (ppm)")
```



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.

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

Answer: While there were no significant seasonal trends in mean ozone concentration within individual months from 2010 to 2019 at this station, mean ozone concentration significantly decreased overall across the 2010s (S = -77, z = -1.963, p < 0.05). When quantified as a linear regression, this trend has a slope of -0.0002 – that is, mean ozone concentration decreases by about 0.0002 ppm with each passing month.