

Assignment 8: Time Series Analysis

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OVERVIEW

This exercise accompanies the lessons in Environmental Data Analytics (ENV872L) on time series analysis.

Directions

1. Change “Student Name” on line 3 (above) with your name.
2. Use the lesson as a guide. It contains code that can be modified to complete the assignment.
3. Work through the steps, **creating code and output** that fulfill each instruction.
4. Be sure to **answer the questions** in this assignment document. Space for your answers is provided in this document and is indicated by the “>” character. If you need a second paragraph be sure to start the first line with “>”. You should notice that the answer is highlighted in green by RStudio.
5. When you have completed the assignment, **Knit** the text and code into a single PDF file. You will need to have the correct software installed to do this (see Software Installation Guide) Press the **Knit** button in the RStudio scripting panel. This will save the PDF output in your Assignments folder.
6. After Knitting, please submit the completed exercise (PDF file) to the dropbox in Sakai. Please add your last name into the file name (e.g., “Salk_A08_TimeSeries.pdf”) prior to submission.

The completed exercise is due on Tuesday, 19 March, 2019 before class begins.

Brainstorm a project topic

1. Spend 15 minutes brainstorming ideas for a project topic, and look for a dataset if you are choosing your own rather than using a class dataset. Remember your topic choices are due by the end of March, and you should post your choice ASAP to the forum on Sakai.

Question: Did you do this?

ANSWER: I have an idea but haven't posted my choice yet.

Set up your session

2. Set up your session. Upload the EPA air quality raw dataset for PM2.5 in 2018, and the processed NTL-LTER dataset for nutrients in Peter and Paul lakes. Build a ggplot theme and set it as your default theme. Make sure date variables are set to a date format.

```
#packages
getwd()

## [1] "C:/Users/Xin Zhang/Desktop/EDA"

library(tidyverse)
library(lubridate)
library(nlme)
library(lsmeans)
library(multcompView)
library(trend)

#load datasets
PM2.5 <- read.csv("./Data/Raw/EPAair_PM25_NC2018_Raw.csv")
PeterPaul.nutrients <- read.csv("./Data/Processed/NTL-LTER_Lake_Nutrients_PeterPaul_Processed.csv")
```

```
# Set date to date format
PM2.5$Date<- as.Date(PM2.5$Date, format = "%m/%d/%y")
PeterPaul.nutrients$sampldate <- as.Date(PeterPaul.nutrients$sampldate,
                                         format = "%Y-%m-%d")

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

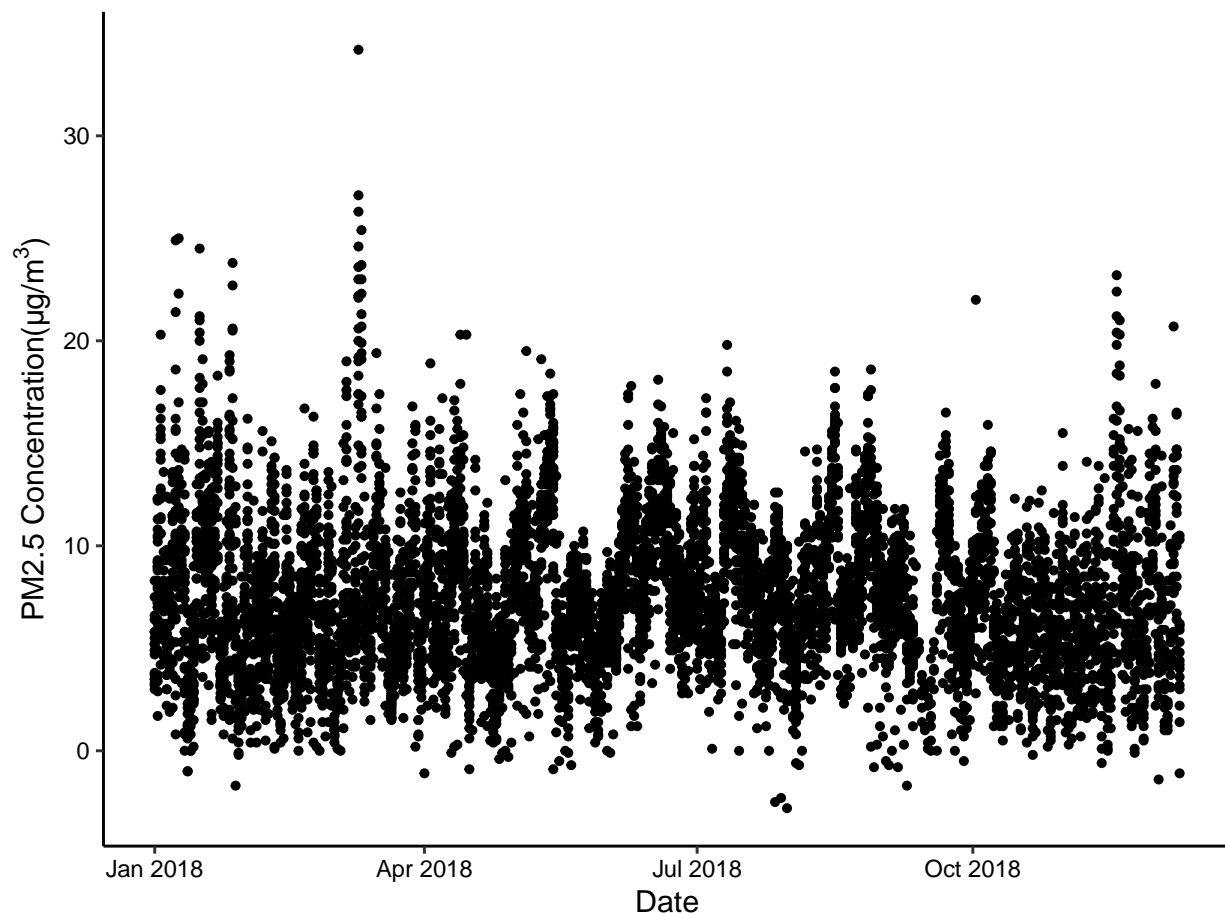
Run a hierarchical (mixed-effects) model

Research question: Do PM2.5 concentrations have a significant trend in 2018?

3. Run a repeated measures ANOVA, with PM2.5 concentrations as the response, Date as a fixed effect, and Site.Name as a random effect. This will allow us to extrapolate PM2.5 concentrations across North Carolina.

3a. Illustrate PM2.5 concentrations by date. Do not split aesthetics by site.

```
ggplot(PM2.5, aes(x = Date, y = Daily.Mean.PM2.5.Concentration))+
  geom_point()+
  ylab(expression(paste("PM2.5 Concentration(\u003BCg/m\"^3,\""))))
```



```
PM2.5Test1 <- lme(data = PM2.5,
                  Daily.Mean.PM2.5.Concentration ~ Date, random = ~1|Site.Name)
summary(PM2.5Test1)
```

```
## Linear mixed-effects model fit by REML
## Data: PM2.5
##      AIC      BIC    logLik
## 40602.76 40630.51 -20297.38
##
## Random effects:
## Formula: ~1 | Site.Name
##      (Intercept) Residual
## StdDev:      1.841425 3.457061
##
## Fixed effects: Daily.Mean.PM2.5.Concentration ~ Date
##              Value Std.Error   DF   t-value p-value
## (Intercept) 20.141836  7.382570 7586  2.728296  0.0064
## Date        -0.000742  0.000417 7586 -1.779991  0.0751
## Correlation:
##      (Intr)
## Date -0.999
##
## Standardized Within-Group Residuals:
##      Min      Q1      Med      Q3      Max
## -3.4251256 -0.6846871 -0.1385351  0.5919707  7.9199389
##
## Number of Observations: 7611
## Number of Groups: 24
```

3b. Insert the following line of code into your R chunk. This will eliminate duplicate measurements on single dates for each site. `PM2.5 = PM2.5[order(PM2.5[, 'Date'], -PM2.5[, 'Site.ID']),]` `PM2.5 = PM2.5[!duplicated(PM2.5$Date),]`

3c. Determine the temporal autocorrelation in your model.

3d. Run a mixed effects model.

```
#eliminate duplicate measurements
PM2.5 = PM2.5[order(PM2.5[, 'Date'], -PM2.5[, 'Site.ID']),]
PM2.5 = PM2.5[!duplicated(PM2.5$Date),]
#temporal autocorrelation
PM2.5Test.auto <- lme(data = PM2.5,
                      Daily.Mean.PM2.5.Concentration ~ Date, random = ~1|Site.Name)
PM2.5Test.auto
```

```
## Linear mixed-effects model fit by REML
## Data: PM2.5
## Log-restricted-likelihood: -928.6076
## Fixed: Daily.Mean.PM2.5.Concentration ~ Date
## (Intercept)      Date
## 90.465022634 -0.004727976
##
## Random effects:
## Formula: ~1 | Site.Name
##      (Intercept) Residual
## StdDev:      1.650184 3.559209
```

```
##
## Number of Observations: 343
## Number of Groups: 3
```

```
ACF(PM2.5Test.auto)
```

```
##      lag      ACF
## 1      0 1.000000000
## 2      1 0.513829909
## 3      2 0.194512680
## 4      3 0.117925187
## 5      4 0.126462863
## 6      5 0.100699787
## 7      6 0.058215891
## 8      7 -0.053090104
## 9      8 0.017671857
## 10     9 0.012177847
## 11    10 -0.003699721
## 12    11 -0.020305291
## 13    12 -0.044621086
## 14    13 -0.055602646
## 15    14 -0.065787345
## 16    15 -0.123987593
## 17    16 -0.055414056
## 18    17 0.002911218
## 19    18 0.025133456
## 20    19 -0.015306468
## 21    20 -0.143472007
## 22    21 -0.155495492
## 23    22 -0.060369985
## 24    23 0.003954231
## 25    24 0.042295682
## 26    25 0.001320007
```

```
PM2.5Test.mixed <- lme(data = PM2.5,
  Daily.Mean.PM2.5.Concentration ~ Date,
  random = ~1|Site.Name,
  #specify autocorrelation structure of order 1
  correlation = corAR1(form = ~ Date|Site.Name, value = 0.514),
  #define method as restricted maximum likelihood
  method = "REML")
summary(PM2.5Test.mixed)
```

```
## Linear mixed-effects model fit by REML
## Data: PM2.5
##      AIC      BIC    logLik
## 1756.622 1775.781 -873.311
##
## Random effects:
## Formula: ~1 | Site.Name
##      (Intercept) Residual
## StdDev: 0.001028133 3.597269
##
## Correlation Structure: ARMA(1,0)
## Formula: ~Date | Site.Name
```

```
## Parameter estimate(s):
##      Phi1
## 0.5384349
## Fixed effects: Daily.Mean.PM2.5.Concentration ~ Date
##              Value Std.Error   DF   t-value p-value
## (Intercept) 83.14801  60.63585 339   1.371268  0.1712
## Date       -0.00426   0.00342 339  -1.244145  0.2143
## Correlation:
##      (Intr)
## Date -1
##
## Standardized Within-Group Residuals:
##      Min      Q1      Med      Q3      Max
## -2.3220745 -0.6187194 -0.1116751  0.6164257  3.4192603
##
## Number of Observations: 343
## Number of Groups: 3
```

Is there a significant increasing or decreasing trend in PM2.5 concentrations in 2018?

ANSWER: No, there is not a significant decreasing trend in PM2.5 concentration in 2018 (hierarchical (mixed-effects) model, $t=-1.244$, $p=0.2143$)

3e. Run a fixed effects model with Date as the only explanatory variable. Then test whether the mixed effects model is a better fit than the fixed effect model.

```
PM2.5Test.fixed <- gls(data = PM2.5,
                       Daily.Mean.PM2.5.Concentration ~ Date,
                       method = "REML")
summary(PM2.5Test.fixed)
```

```
## Generalized least squares fit by REML
## Model: Daily.Mean.PM2.5.Concentration ~ Date
## Data: PM2.5
##      AIC      BIC    logLik
## 1865.202 1876.698 -929.6011
##
## Coefficients:
##              Value Std.Error   t-value p-value
## (Intercept) 98.57796  34.60285  2.848840  0.0047
## Date       -0.00513   0.00195 -2.624999  0.0091
##
## Correlation:
##      (Intr)
## Date -1
##
## Standardized residuals:
##      Min      Q1      Med      Q3      Max
## -2.3531000 -0.6348100 -0.1153454  0.6383004  3.4063068
##
## Residual standard error: 3.584321
## Degrees of freedom: 343 total; 341 residual
```

```
anova(PM2.5Test.mixed, PM2.5Test.fixed)
```

```
##              Model df      AIC      BIC    logLik    Test  L.Ratio
## PM2.5Test.mixed    1   5 1756.622 1775.781 -873.3110
```

```
## PM2.5Test.fixed      2  3 1865.202 1876.698 -929.6011 1 vs 2 112.5802
##                      p-value
## PM2.5Test.mixed
## PM2.5Test.fixed    <.0001
```

Which model is better?

ANSWER: The mixed-effects model is better ($p < 0.0001$, $AIC = 1756.622 < 1865.202$).

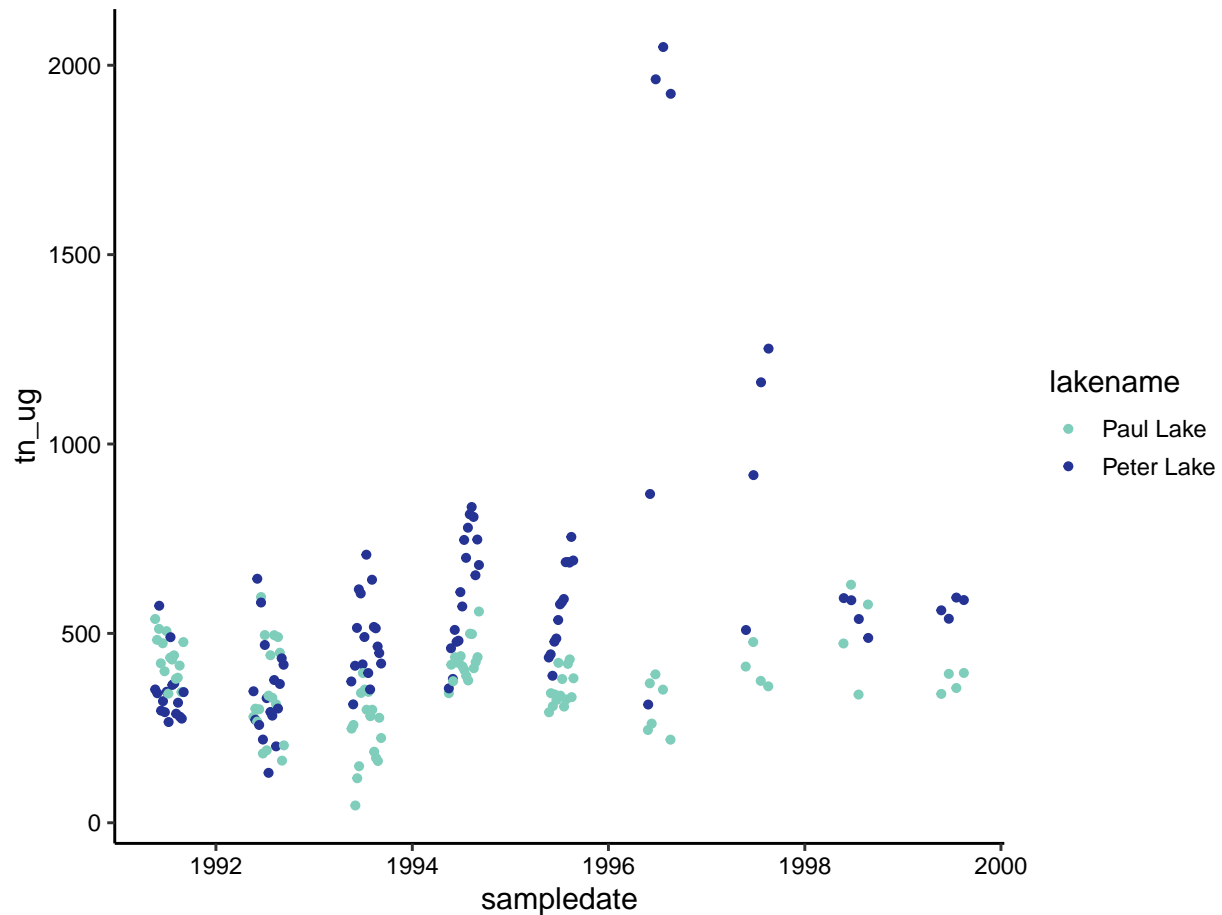
Run a Mann-Kendall test

Research question: Is there a trend in total N surface concentrations in Peter and Paul lakes?

4. Duplicate the Mann-Kendall test we ran for total P in class, this time with total N for both lakes. Make sure to run a test for changepoints in the datasets (and run a second one if a second change point is likely).

```
# Wrangle our dataset
PeterPaul.nutrients.surface <-
  PeterPaul.nutrients %>%
  select(-lakeid, -depth_id, -comments) %>%
  filter(depth == 0) %>%
  filter(!is.na(tn_ug))

#ggplot Data Overview
ggplot(PeterPaul.nutrients.surface, aes(x = sampleddate, y = tn_ug, color = lakename)) +
  geom_point() +
  scale_color_manual(values = c("#7fcdbb", "#253494"))
```



```
# Split dataset by lake
Peter.nutrients.surface <- filter(PeterPaul.nutrients.surface, lakename == "Peter Lake")
Paul.nutrients.surface <- filter(PeterPaul.nutrients.surface, lakename == "Paul Lake")

#PeterLake
# Run a Mann-Kendall test
mk.test(Peter.nutrients.surface$tn_ug)

##
## Mann-Kendall trend test
##
## data: Peter.nutrients.surface$tn_ug
## z = 7.2927, n = 98, p-value = 3.039e-13
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##      S      varS      tau
## 2.377000e+03 1.061503e+05 5.001052e-01

# Test for change point
pettitt.test(Peter.nutrients.surface$tn_ug)

##
## Pettitt's test for single change-point detection
##
## data: Peter.nutrients.surface$tn_ug
```

```

## U* = 1884, p-value = 3.744e-10
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                                     36

# Run separate Mann-Kendall for each change point
mk.test(Peter.nutrients.surface$tn_ug[1:35])

##
## Mann-Kendall trend test
##
## data: Peter.nutrients.surface$tn_ug[1:35]
## z = -0.22722, n = 35, p-value = 0.8203
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##          S          varS          tau
## -17.00000000 4958.33333333 -0.02857143

mk.test(Peter.nutrients.surface$tn_ug[36:98])

##
## Mann-Kendall trend test
##
## data: Peter.nutrients.surface$tn_ug[36:98]
## z = 3.1909, n = 63, p-value = 0.001418
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##          S          varS          tau
## 5.390000e+02 2.842700e+04 2.759857e-01

# Is there a second change point?
pettitt.test(Peter.nutrients.surface$tn_ug[36:98])

##
## Pettitt's test for single change-point detection
##
## data: Peter.nutrients.surface$tn_ug[36:98]
## U* = 560, p-value = 0.001213
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                                     21

# Run another Mann-Kendall for the second change point
mk.test(Peter.nutrients.surface$tn_ug[36:56])

##
## Mann-Kendall trend test
##
## data: Peter.nutrients.surface$tn_ug[36:56]
## z = -1.0569, n = 21, p-value = 0.2906
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##          S          varS          tau
## -36.00000000 1096.6666667 -0.1714286

```



```
mk.test(Peter.nutrients.surface$tn_ug[57:98])

##
## Mann-Kendall trend test
##
## data: Peter.nutrients.surface$tn_ug[57:98]
## z = 0.15172, n = 42, p-value = 0.8794
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##          S          varS          tau
## 15.0000000 8514.3333333 0.0174216
```

```
#PaulLake
# Run a Mann-Kendall test
mk.test(Paul.nutrients.surface$tn_ug)
```

```
##
## Mann-Kendall trend test
##
## data: Paul.nutrients.surface$tn_ug
## z = -0.35068, n = 99, p-value = 0.7258
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##          S          varS          tau
## -1.170000e+02 1.094170e+05 -2.411874e-02
```

```
# Test for change point
pettitt.test(Paul.nutrients.surface$tn_ug)
```

```
##
## Pettitt's test for single change-point detection
##
## data: Paul.nutrients.surface$tn_ug
## U* = 704, p-value = 0.09624
## alternative hypothesis: two.sided
## sample estimates:
## probable change point at time K
##                                16
```

```
#No changing point for PualLake
```

What are the results of this test?

ANSWER: For Peter lake, there is a trend over time according to the Mann-Kendall test ($p < 0.0001$), $Z = 7.29$, which indicates a positive trend over time. There are two changing points: 36 (around 1993/5/30) and 57 (around 1994/6/25). For Paul lake, there is not a trend over time according to the Mann-Kendall test ($p = 0.7258$).

5. Generate a graph that illustrates the TN concentrations over time, coloring by lake and adding vertical line(s) representing changepoint(s).

```
ggplot(PeterPaul.nutrients.surface, aes(x = sampleddate, y = tn_ug, color = lakename)) +
  geom_point() +
  labs(x = "Date", y = "Total Nitrogen (mg/L)", color = "Lake") +
  geom_vline(xintercept = as.Date("1993/5/30"), color = "#253494", lty = 2) +
  geom_vline(xintercept = as.Date("1994/6/25"), color = "#253494", lty = 2) +
  scale_color_manual(values = c("#7fcdbb", "#253494"))
```

