Assignment 8: Time Series Analysis

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OVERVIEW

This exercise accompanies the lessons in Water 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, check your PDF against the key and then submit your assignment completion survey at https://forms.gle/dKEutwXiFewkSTwN9

Having trouble? See the assignment's answer key if you need a hint. Please try to complete the assignment without the key as much as possible - this is where the learning happens!

Target due date: 2022-03-29

Setup

1. Verify your working directory is set to the R project file. Load the tidyverse, lubridate, trend, forecast, and dataRetrieval packages. Set your ggplot theme (can be theme_classic or something else).

```
# 1. Check directory, load packages, set theme
getwd()
```

```
## [1] "/Users/lydiecostes/Documents/Duke/WaterDataAnalytics/Water_Data_Analytics_2022/Assignments"
```

```
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(trend)
library(forecast)
```

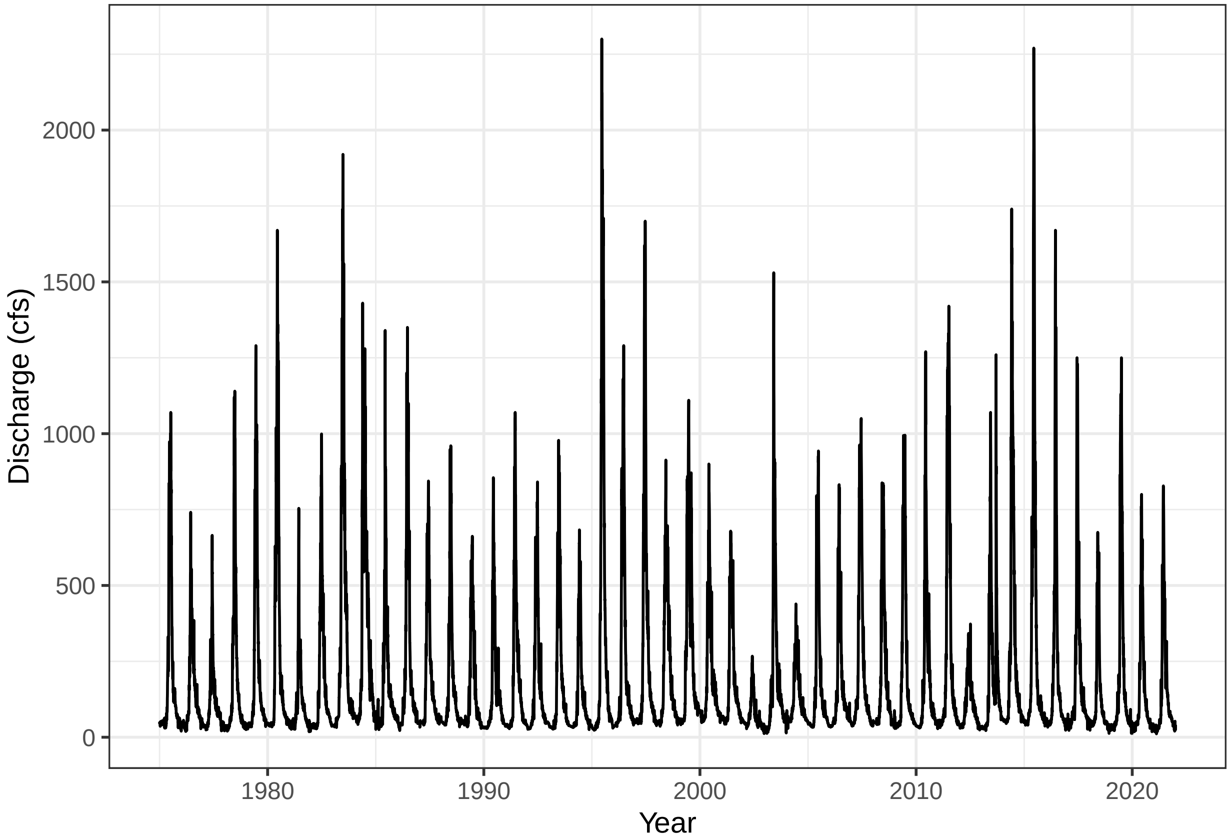
```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
library(dataRetrieval)

theme_set(theme_bw())
```

Data Import and Processing

2. Import discharge data (parameter 00060) from Clear Creek, Colorado (site 06719505) from the start of 1975 through the end of 2021.
3. Graph Clear Creek discharge over time.
4. Create a new data frame with the sum of monthly discharge in acre-feet per month.

```
# 2. Import discharge data
ClearCreek <- readNWISdv(siteNumbers = "06719505",
                         parameterCd = "00060",
                         startDate = "1975-01-01",
                         endDate = "2021-12-31")
names(ClearCreek)[4:5] <- c("Discharge", "Approval.Code")

# 3. Graph discharge over time
ggplot(ClearCreek, aes(x = Date, y = Discharge)) +
  geom_line() +
  labs(x = "Year", y = "Discharge (cfs)")
```



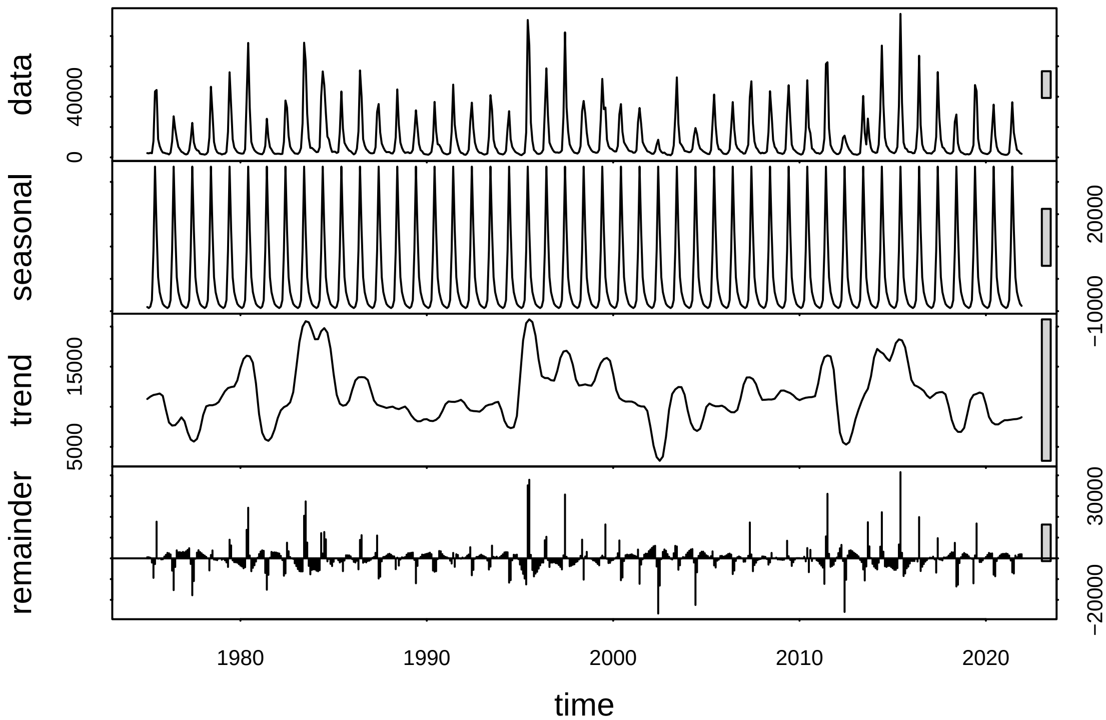

```r
# 4. Sum monthly discharge
ClearCreek_mo <- ClearCreek %>%
  mutate(Month = month(Date),
         Year = year(Date)) %>%
  group_by(Year, Month) %>%
  summarise(Discharge_acftmo = sum(Discharge)*1.98347)
```

```
## `summarise()` has grouped output by 'Year'. You can override using the `.groups` argument.
```

Time Series Decomposition

5. Create a time series of discharge from the monthly data frame. Make sure to add start and end dates like we did in class.
6. Decompose the time series using the `stl` function.
7. Visualize the decomposed time series.

```r
# 5. Create time series
Clear_ts <- ts(ClearCreek_mo$Discharge_acftmo, frequency = 12,
                          start = c(1975, 01, 1), end = c(2021, 12, 1))

# 6. Decompose time series
Clear_decomposed <- stl(Clear_ts, s.window = "periodic")

# 7. Plot the decomposed time series
plot(Clear_decomposed)
```



8. How do the seasonal and trend components of the decomposition compare to the Neuse River discharge dataset?

   Seasonal: The seasonal component of the Clear Creek shows a more clean drop off of discharge in between peaks, perhaps suggesting the influence of snowmelt. Also, the seasonal component is larger for Clear Creek.

   Trend: Both trend lines are pretty variable over time.

Trend Analysis

Research question: Has there been a monotonic trend in discharge in Clear Creek over the period of study?

9. Run a Seasonal Mann-Kendall test on the monthly discharge data. Inspect the overall trend and the monthly trends.

```r
# 9. Mean-Kendall test
Clear_trend <- smk.test(Clear_ts)
Clear_trend
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data:  Clear_ts
## z = -0.23296, p-value = 0.8158
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##      S   varS
##    -89 142689
```

```r
summary(Clear_trend)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: Clear_ts
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                          S  varS    tau      z Pr(>|z|)
## Season 1:   S = 0   -26 11890 -0.024 -0.229 0.818658
## Season 2:   S = 0   -57 11891 -0.053 -0.514 0.607570
## Season 3:   S = 0   159 11891  0.147  1.449 0.147357
## Season 4:   S = 0   181 11891  0.167  1.651 0.098804 .
## Season 5:   S = 0   135 11891  0.125  1.229 0.219132
## Season 6:   S = 0    45 11891  0.042  0.403 0.686580
## Season 7:   S = 0  -117 11891 -0.108 -1.064 0.287432
## Season 8:   S = 0  -124 11890 -0.115 -1.128 0.259314
## Season 9:   S = 0  -169 11891 -0.156 -1.541 0.123405
## Season 10:   S = 0    4 11890  0.004  0.028 0.978051
## Season 11:   S = 0  -49 11891 -0.045 -0.440 0.659805
## Season 12:   S = 0  -71 11891 -0.066 -0.642 0.520918
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

10. Is there an overall monotonic trend in discharge over time? Are there monthly trends over time? If so, are they positive or negative?

    There is not an overall monotronic trend (z = -0.233, p = 0.816), nor are there any significant monthly trends over time.

Forecasting

Research question: can we predict discharge in Clear Creek moving into the future?

11. Run the auto.arima function on the Clear Creek time series to search for the best fit. Create an object that defines the best fit model.
12. Make a prediction into the future and plot the future predictions.

```r
# 11. Search for best fit
auto.arima(Clear_ts, trace = TRUE)
```

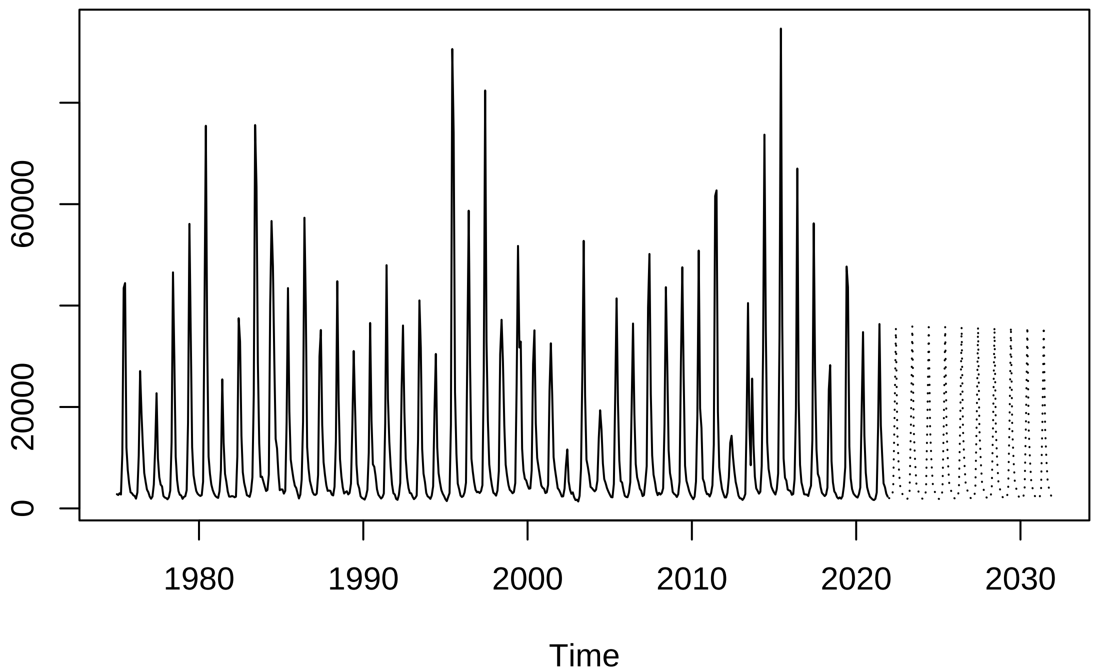
```
##
##  Fitting models using approximations to speed things up...
##
##  ARIMA(2,0,2)(1,1,1)[12] with drift         : Inf
##  ARIMA(0,0,0)(0,1,0)[12] with drift         : 11531.74
##  ARIMA(1,0,0)(1,1,0)[12] with drift         : 11207.99
##  ARIMA(0,0,1)(0,1,1)[12] with drift         : 11098.86
```

```
##  ARIMA(0,0,0)(0,1,0)[12]                    : 11529.75
##  ARIMA(0,0,1)(0,1,0)[12] with drift         : 11360.07
##  ARIMA(0,0,1)(1,1,1)[12] with drift         : Inf
##  ARIMA(0,0,1)(0,1,2)[12] with drift         : 11097.52
##  ARIMA(0,0,1)(1,1,2)[12] with drift         : Inf
##  ARIMA(0,0,0)(0,1,2)[12] with drift         : Inf
##  ARIMA(1,0,1)(0,1,2)[12] with drift         : 11090.53
##  ARIMA(1,0,1)(0,1,1)[12] with drift         : 11091.09
##  ARIMA(1,0,1)(1,1,2)[12] with drift         : Inf
##  ARIMA(1,0,1)(1,1,1)[12] with drift         : Inf
##  ARIMA(1,0,0)(0,1,2)[12] with drift         : 11106.28
##  ARIMA(2,0,1)(0,1,2)[12] with drift         : 11093.22
##  ARIMA(1,0,2)(0,1,2)[12] with drift         : 11092.11
##  ARIMA(0,0,2)(0,1,2)[12] with drift         : 11090.91
##  ARIMA(2,0,0)(0,1,2)[12] with drift         : 11095.42
##  ARIMA(2,0,2)(0,1,2)[12] with drift         : Inf
##  ARIMA(1,0,1)(0,1,2)[12]                    : 11088.51
##  ARIMA(1,0,1)(0,1,1)[12]                    : 11089.08
##  ARIMA(1,0,1)(1,1,2)[12]                    : Inf
##  ARIMA(1,0,1)(1,1,1)[12]                    : Inf
##  ARIMA(0,0,1)(0,1,2)[12]                    : 11095.52
##  ARIMA(1,0,0)(0,1,2)[12]                    : 11104.26
##  ARIMA(2,0,1)(0,1,2)[12]                    : 11091.2
##  ARIMA(1,0,2)(0,1,2)[12]                    : 11090.08
##  ARIMA(0,0,0)(0,1,2)[12]                    : Inf
##  ARIMA(0,0,2)(0,1,2)[12]                    : 11088.9
##  ARIMA(2,0,0)(0,1,2)[12]                    : 11093.41
##  ARIMA(2,0,2)(0,1,2)[12]                    : Inf
##
##  Now re-fitting the best model(s) without approximations...
##
##  ARIMA(1,0,1)(0,1,2)[12]                    : Inf
##  ARIMA(0,0,2)(0,1,2)[12]                    : Inf
##  ARIMA(1,0,1)(0,1,1)[12]                    : Inf
##  ARIMA(1,0,2)(0,1,2)[12]                    : Inf
##  ARIMA(1,0,1)(0,1,2)[12] with drift         : Inf
##  ARIMA(0,0,2)(0,1,2)[12] with drift         : Inf
##  ARIMA(1,0,1)(0,1,1)[12] with drift         : Inf
##  ARIMA(2,0,1)(0,1,2)[12]                    : Inf
##  ARIMA(1,0,2)(0,1,2)[12] with drift         : Inf
##  ARIMA(2,0,1)(0,1,2)[12] with drift         : Inf
##  ARIMA(2,0,0)(0,1,2)[12]                    : Inf
##  ARIMA(2,0,0)(0,1,2)[12] with drift         : Inf
##  ARIMA(0,0,1)(0,1,2)[12]                    : Inf
##  ARIMA(0,0,1)(0,1,2)[12] with drift         : Inf
##  ARIMA(0,0,1)(0,1,1)[12] with drift         : Inf
##  ARIMA(1,0,0)(0,1,2)[12]                    : Inf
##  ARIMA(1,0,0)(0,1,2)[12] with drift         : Inf
##  ARIMA(1,0,0)(1,1,0)[12] with drift         : 11430.06
##
##  Best model: ARIMA(1,0,0)(1,1,0)[12] with drift
```

```
## Series: Clear_ts
## ARIMA(1,0,0)(1,1,0)[12] with drift
```

```
##
## Coefficients:
##          ar1     sar1    drift
##       0.5288  -0.5061  -3.9277
## s.e.  0.0361   0.0363  37.7171
##
## sigma^2 = 56658295:  log likelihood = -5710.99
## AIC=11429.99   AICc=11430.06   BIC=11447.24
```

```
best_fit <- arima(Clear_ts, c(1,0,0),seasonal = list(order = c(1,1,0), period = 12))

# 12. Plot future predictions
Clearprediction <- predict(best_fit, n.ahead = 10*12)
ts.plot(Clear_ts, Clearprediction$pred, lty = c(1, 3))
```



13. How did the forecasting for Clear Creek compare to the Neuse River?

    The forecasting for Clear Creek includes seasonality whereas the Neuse River prediction quickly tapered to a constant amount of discharge.