# Analysis of Water Supplies and Withdraws' Effects on Water Resources Capacity in Durham, North Carolina

https://github.com/AzuraLiu/Jing_Liu___ENV872_FinalProject.git

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# 1 Rationale and Research Questions

Water is an essential substance for human survival and development. As the world population increases, living standards improve, water trading patterns change, and industry, agriculture, and manufacturing expand, human society's demand for water resources is further expanded (Ercin et al., 2014).

During the last few decades, the scarcity of fresh water is evidently becoming a threat to the sustainable development of human societies due to the steady increase in demand. In addition to these pressures from humans, climate change, including global warming, significant decreases in precipitation in some areas, and increasingly frequent extreme weather events, may reduce water production. These conflicting trends raise further concerns about future water scarcity (Brown et al., 2013). The 2018 edition of the United Nations (UN) World Water Development Report (WWDR) presented concerns about water security that "the capacity of a population to safeguard sustainable access to adequate quantities of water with acceptable quality, is already at risk, and the situation will become worse in the next few decades."

On the global scale, there is enough fresh water on an annual basis to meet the current needs of human society for survival and development (Vörösmarty, et al., 2000). However, there are great variations of water availability and water demands on space and time. that is, the distributions of water resources, population, agriculture, and industry are uneven, leading to existing water scarcity in several specific parts of the world during specific times of the year (Mekonnen et al., 2016). Therefore, the study of long-term water resources capacity for local areas is significant.

The water resources consumed by human society are generally blue water (fresh surface water and groundwater) (Wada et al., 2011). Groundwater supplies drinking water for billions of people and provides nearly half of the water used for agricultural irrigation (Siebert et al., 2010). It has a perennial distribution suitable for providing reliable drinking water and supporting efforts to adapt to extreme natural weather disasters and climate change (Taylor et al., 2013). In other words, the amount of groundwater is more stable in the long term compared to the amount of surface water. Surface water, because of its exposure to the surface, is susceptible to the influence of external substances. Its water volume also fluctuates greatly under natural conditions due to temperature, evaporation, sand content and other factors. And in recent years, influenced by the development of human activities, the aquifers' shrinkage and salt intrusion in coastal areas have been increasing dramatically. (Boretti et al., 2019).

In this study, we focus on the Durham region in North Carolina, and hope to analyze the impact of regional water withdrawal and precipitation on regional water capacity, including surface water and groundwater, through data since complete records are available. ##We perform analysis based on the following sub-questions. ##How is groundwater table related to precipitation? ##How is groundwater table level related to local river discharge? ##How is ground water table level related to local withdraws?

## 2 Dataset Information

In order to better determine trends and the stability of the water resource capacity in Durham, it is important to identify the factors that affect water capacity. We are concerned in this study with the influence of natural factors and human activities, which are precipitation and water withdrawal. Data of precipitation in North Carolina published by National Oceanic and Atmospheric Administration (NOAA) and water resources depletion value related to human activities published by the North Carolina Department of Environmental Quality (NCDEQ) Division of Water Resources are used as the focused factors. Researching and predicting water depletion requires models of certain scale, and these models inevitably rely on a variety of simplifying assumptions. One assumption is that there are no feedbacks between water supply and water demand. Another assumption is that the flow is proportional to the river capacity if both the river width and the riverbed depth remain stable, in another word, the cross-sectional area of individual parts of the river remains constant.

According to the Local Water Supply Planning published annually by the North Carolina Department of Environmental Quality (NCDEQ) Division of Water Resources, the surface water sources of Durham area are mainly Cape Fear Lake, Flat River and Little River, with the Eno River used as a backup source in case of emergency. Among these rivers, Flat River, Little River and Eno River belong to the Neuse River basin, while Cape Fear Lake belongs to the Haw River basin. United States Geological Survey (USGS) provides complete flow data for these rivers. While total discharge and withdrawals are analyzed, we also look for differences in discharge variability and vulnerability to human activities among the rivers. The Local Water Supply Planning also describes the destination of treated sewage in Durham region. According to the report, the treated effluent flows into Ellerbee River and New Hope River, which belong to Neuse River basin and Haw River basin respectively. The design receiving capacity of both rivers is the same, 20 million gallon per day (MGD); the actual receiving capacity is also approximately the same, about 10 MGD, so it can be assumed that the treated effluent is equally distributed to the two rivers. From the report, it is clear that the water withdrawal and discharge points are located in different rivers, even if they are in the same watershed. Therefore, when considering the sources of river recharge, we only considered precipitation recharge without considering the volume of treated wastewater in Durham region.

# 3 Exploratory Analysis

```
#Regular Water Resources
CapeFearRiverDischarge <- readNWISdv(siteNumbers = "02096500",
                                  parameterCd = "00060", # discharge (ft3/s)
                                  startDate = "1990-01-01",
                                  endDate = "2021-12-31")
names(CapeFearRiverDischarge)[4:5] <- c("CapeFear_Discharge", "Approval.Code")
c(min(CapeFearRiverDischarge$Date), max(CapeFearRiverDischarge$Date))
```

```
## [1] "1990-01-01" "2021-12-31"
```

```
#"1990-01-01" "2021-12-31"
CapeFearRiverDischarge_Monthly <- CapeFearRiverDischarge %>%
  mutate(Month = format(Date,"%Y-%m")) %>%
  group_by(Month) %>%
  summarise(Mean_CapeFear_Discharge_Bymonth = mean(CapeFear_Discharge),
            River = paste("Cape Fear River"))

FlatRiverDischarge <- readNWISdv(siteNumbers = "02085500",
                                  parameterCd = "00060", # discharge (ft3/s)
                                  startDate = "1990-01-01",
                                  endDate = "2021-12-31")
names(FlatRiverDischarge)[4:5] <- c("Flat_Discharge", "Approval.Code")
c(min(FlatRiverDischarge$Date), max(FlatRiverDischarge$Date))
```

```
## [1] "1990-01-01" "2021-12-31"
```

```
#"1990-01-01" "2021-12-31"
FlatRiverDischarge_Monthly <- FlatRiverDischarge %>%
  mutate(Month = format(Date,"%Y-%m")) %>%
  group_by(Month) %>%
  summarise(Mean_Flat_Discharge_Bymonth = mean(Flat_Discharge),
            River = paste("Flat River"))

LittleRiverDischarge <- readNWISdv(siteNumbers = "0208524975",
                                  parameterCd = "00060", # discharge (ft3/s)
                                  startDate = "1990-01-01",
                                  endDate = "2021-12-31")
names(LittleRiverDischarge)[4:5] <- c("Little_Discharge", "Approval.Code")
c(min(LittleRiverDischarge$Date), max(LittleRiverDischarge$Date))
```

```
## [1] "1995-10-24" "2021-12-31"
```

```
#"1995-10-24" "2021-12-31"
LittleRiverDischarge_Monthly <- LittleRiverDischarge %>%
  mutate(Month = format(Date,"%Y-%m")) %>%
```

```r
  group_by(Month) %>%
  summarise(Mean_Little_Discharge_Bymonth = mean(Little_Discharge),
            River = paste("Little River"))

#Emergency Water Resources
EnoRiverDischarge <- readNWISdv(siteNumbers = "02085070",
                                  parameterCd = "00060", # discharge (ft3/s)
                                  startDate = "1990-01-01",
                                  endDate = "2021-12-31")
names(EnoRiverDischarge)[4:5] <- c("Discharge", "Approval.Code")
c(min(EnoRiverDischarge$Date), max(EnoRiverDischarge$Date))
```

```
## [1] "1990-01-01" "2021-12-31"
```

```r
#"1990-01-01" "2021-12-31"
EnoRiverDischarge_Monthly <- EnoRiverDischarge %>%
  mutate(Month = format(Date,"%Y-%m")) %>%
  group_by(Month) %>%
  summarise(Mean_Discharge_Bymonth = mean(Discharge),
            River = paste("Eno River"))

#Surrounding Water Resources (Unused)
EllerbeCreekDischarge <- readNWISdv(siteNumbers = "0208675010",
                                  parameterCd = "00060", # discharge (ft3/s)
                                  startDate = "1990-01-01",
                                  endDate = "2021-12-31")
names(EllerbeCreekDischarge)[4:5] <- c("Discharge", "Approval.Code")
c(min(EllerbeCreekDischarge$Date), max(EllerbeCreekDischarge$Date))
```

```
## [1] "2008-08-01" "2021-12-31"
```

```r
#"2008-08-01" "2021-12-31"
EllerbeCreekDischarge_Monthly <- EllerbeCreekDischarge %>%
  mutate(Month = format(Date,"%Y-%m")) %>%
  group_by(Month) %>%
  summarise(Mean_Discharge_Bymonth = mean(Discharge),
            River = paste("Ellerbe Creek"))

SandyCreekDischarge <- readNWISdv(siteNumbers = "0209722970",
                                  parameterCd = "00060", # discharge (ft3/s)
                                  startDate = "1990-01-01",
                                  endDate = "2021-12-31")
names(SandyCreekDischarge)[4:5] <- c("Discharge", "Approval.Code")
c(min(SandyCreekDischarge$Date), max(SandyCreekDischarge$Date))
```

```
## [1] "2008-08-01" "2021-12-31"
```

```r
#"2008-08-01" "2021-12-31"
SandyCreekDischarge_Monthly <- SandyCreekDischarge %>%
  mutate(Month = format(Date,"%Y-%m")) %>%
  group_by(Month) %>%
  summarise(Mean_Discharge_Bymonth = mean(Discharge),
            River = paste("Sandy Creek"))

ThirdForkCreekDischarge <- readNWISdv(siteNumbers = "0209725960",
                                      parameterCd = "00060", # discharge (ft3/s)
                                      startDate = "1990-01-01",
                                      endDate = "2021-12-31")
names(ThirdForkCreekDischarge)[4:5] <- c("Discharge", "Approval.Code")
c(min(ThirdForkCreekDischarge$Date), max(ThirdForkCreekDischarge$Date))
```

```
## [1] "2017-06-16" "2021-12-31"
```

```r
#"2017-06-16" "2021-12-31"
ThirdForkCreekDischarge_Monthly <- ThirdForkCreekDischarge %>%
  mutate(Month = format(Date,"%Y-%m")) %>%
  group_by(Month) %>%
  summarise(Mean_Discharge_Bymonth = mean(Discharge),
            River = paste("Third Fork Creek"))
```

```r
GroundParams <- whatNWISdata(siteNumbers = "355944079013401")
DurhamGroundwater <- readNWISdv(siteNumbers = "355944079013401", #Duke Forest
                                parameterCd = "72019",
                               # /62610/Groundwater level above NGVD 1929 (feet)
                                statCd = "00002",
                                startDate = "2014-01-01",
                                endDate = "2021-12-31")
colnames(DurhamGroundwater) <- c("Agency_Name",
                                "Site_Number",
                                "Date",
                                "Groundwater_Table_feet",
                                "Approval.Code")
summary(DurhamGroundwater)
```

```
##  Agency_Name         Site_Number             Date
##  Length:2911        Length:2911        Min.   :2014-01-01
##  Class :character   Class :character   1st Qu.:2015-12-29
##  Mode  :character   Mode  :character   Median :2017-12-27
##                                        Mean   :2017-12-29
##                                        3rd Qu.:2019-12-27
##                                        Max.   :2021-12-31
##  Groundwater_Table_feet Approval.Code
```

```
##  Min.   :34.12         Length:2911
##  1st Qu.:37.28         Class :character
##  Median :39.15         Mode  :character
##  Mean   :38.76
##  3rd Qu.:40.34
##  Max.   :42.22
```

```
head(DurhamGroundwater)
```

```
##   Agency_Name     Site_Number       Date Groundwater_Table_feet Approval.Code
## 1        USGS 355944079013401 2014-01-01                  42.18             A
## 2        USGS 355944079013401 2014-01-02                  42.07             A
## 3        USGS 355944079013401 2014-01-03                  42.15             A
## 4        USGS 355944079013401 2014-01-04                  42.17             A
## 5        USGS 355944079013401 2014-01-05                  42.08             A
## 6        USGS 355944079013401 2014-01-06                  42.05             A
```

```
DurhamGroundwater_Monthly <- DurhamGroundwater %>%
  mutate(Month = format(Date,"%Y-%m")) %>%
  group_by(Month) %>%
  summarise(Mean_Groundwater_Table_feet = mean(Groundwater_Table_feet))
```

```
#the PSWID of Durham
durham_pswid = '03-32-010'
#years with records
the_years = c(2018:2021)

#Scrap Function
scrape.totalwithdrawal <- function(the_pswid, the_year){
the_website <- read_html(paste0('https://www.ncwater.org/WUDC/app/LWSP/report.php?pwsid=
the_pswid, '&year=', the_year))
water_system_name_tag <- 'div+ table tr:nth-child(1) td:nth-child(2)'
ownership_tag <- 'div+ table tr:nth-child(2) td:nth-child(4)'
avg_daily_use_tag <- '.fancy-table:nth-child(31) th+ td'
water_system_name <- the_website %>% html_nodes(water_system_name_tag) %>% html_text()
ownership <- the_website %>% html_nodes(ownership_tag) %>% html_text()
avg_daily_use <- the_website %>% html_nodes(avg_daily_use_tag) %>% html_text()
df_withdrawals <- data.frame("Year" = rep(the_year,12),
"Month" = rep(1:12),
"Avg_Daily_Use_mgd" = as.numeric(avg_daily_use)) %>%
mutate(Water_System_name = !!water_system_name,
Ownership = !!ownership,
Date = my(paste(Month,"-",Year)))

  print(paste('The Pswid =', the_pswid, ', The Year =', the_year))
  return(df_withdrawals)
```

```
}

total_withdrawal <- map(the_years, scrape.totalwithdrawal, the_pswid = durham_pswid)
```

```
## [1] "The Pswid = 03-32-010 , The Year = 2018"
## [1] "The Pswid = 03-32-010 , The Year = 2019"
## [1] "The Pswid = 03-32-010 , The Year = 2020"
## [1] "The Pswid = 03-32-010 , The Year = 2021"
```

```
total_withdrawal <- bind_rows(total_withdrawal)

total_withdrawal <- read.csv("../Data/Processed/Durham_Withdrawal_Processed.csv")
total_withdrawal$Date <- as_date(total_withdrawal$Date, format = "%m/%d/%y")

total_withdrawal_Monthly <- total_withdrawal %>%
  select(Date, Avg_Daily_Use_mgd) %>%
  mutate(Month = format(Date,"%Y-%m")) %>%
  group_by(Month) %>%
  summarise(Mean_Avg_Daily_Use_mgd = mean(Avg_Daily_Use_mgd))
```

```
#the PSWID of Durham
durham_pswid = '03-32-010'
#years with records
the_years = c(2018:2021)
scrape.withdrawal.distribution <- function(the_pswid, the_year){
  the_website <- read_html(paste0('https://www.ncwater.org/WUDC/app/LWSP/report.php?pwsi
                                  the_pswid, '&year=', the_year))

  water_system_name_tag <- 'div+ table tr:nth-child(1) td:nth-child(2)'
  ownership_tag <- 'div+ table tr:nth-child(2) td:nth-child(4)'
  stream_name_tag <- '.fancy-table:nth-child(35) .left:nth-child(1)'
  avg_daily_use_tag <- '.fancy-table:nth-child(35) .left~ .left+ td'
  the_numberofdaysused_tag <- '.fancy-table:nth-child(35) td:nth-child(4)'

  water_system_name <- the_website %>% html_nodes(water_system_name_tag) %>% html_text()
  ownership <- the_website %>%   html_nodes(ownership_tag) %>%  html_text()
  stream_name <- the_website %>% html_nodes(stream_name_tag) %>% html_text()
  avg_daily_use <- the_website %>% html_nodes(avg_daily_use_tag) %>% html_text()
  the_numberofdaysused <- the_website %>% html_nodes(the_numberofdaysused_tag) %>% html_

  df_withdrawals <- data.frame("Year" = rep(the_year,5),
                               "Stream_Name" = stream_name,
                               "Avg_Daily_Use_mgd" = as.numeric(avg_daily_use),
                               "Number_of_Days_Used" = as.numeric(the_numberofdaysused))
    mutate(Water_System_name = !!water_system_name,
```

```r
        Ownership = !!ownership)

  print(paste('The Pswid =', the_pswid, ', The Year =', the_year))
  return(df_withdrawals)
}
withdrawal_distribution <- map(the_years, scrape.withdrawal.distribution, the_pswid = du
```

```
## [1] "The Pswid = 03-32-010 , The Year = 2018"
## [1] "The Pswid = 03-32-010 , The Year = 2019"
## [1] "The Pswid = 03-32-010 , The Year = 2020"
## [1] "The Pswid = 03-32-010 , The Year = 2021"
```

```r
withdrawal_distribution <- bind_rows(withdrawal_distribution)
```

```r
#Precipitation
PreciParams <- whatNWISdata(siteNumbers = "355852078572045")
DurhamPrecipitaion <- readNWISdv(siteNumbers = "355852078572045",
                                 parameterCd = "00045",
                                 # precipitation (inches)
                                 statCd = "00006",
                                 startDate = "2009-01-01",
                                 endDate = "2021-12-31")
colnames(DurhamPrecipitaion) <- c("Agency_Name",
                                 "Site_Number",
                                 "Date",
                                 "Precipitaion_inches",
                                 "Approval.Code")
summary(DurhamPrecipitaion)
```

```
##  Agency_Name         Site_Number             Date            Precipitaion_inches
##  Length:4614        Length:4614        Min.   :2009-01-01   Min.   :0.0000
##  Class :character   Class :character   1st Qu.:2012-05-18   1st Qu.:0.0000
##  Mode  :character   Mode  :character   Median :2015-08-09   Median :0.0000
##                                        Mean   :2015-07-31   Mean   :0.1383
##                                        3rd Qu.:2018-10-13   3rd Qu.:0.0500
##                                        Max.   :2021-12-31   Max.   :5.5200
##  Approval.Code
##  Length:4614
##  Class :character
##  Mode  :character
##
##
##
```

```r
head(DurhamPrecipitaion)
```

```
##   Agency_Name     Site_Number       Date Precipitaion_inches Approval.Code
## 1        USGS 355852078572045 2009-01-01                0.00             A
## 2        USGS 355852078572045 2009-01-02                0.03             A
## 3        USGS 355852078572045 2009-01-03                0.00             A
## 4        USGS 355852078572045 2009-01-04                0.41             A
## 5        USGS 355852078572045 2009-01-05                0.00             A
## 6        USGS 355852078572045 2009-01-06                0.90             A
```

# 4 Analysis

```
CapeFearRiver_timeseries <- ts(CapeFearRiverDischarge_Monthly$Mean_CapeFear_Discharge_By
                               frequency = 12,start = c(1990, 1, 1), end = c(2021, 12, 1))
CapeFearRiver_Decomposed <- stl(CapeFearRiver_timeseries, s.window = "periodic")
plot(CapeFearRiver_Decomposed)
```

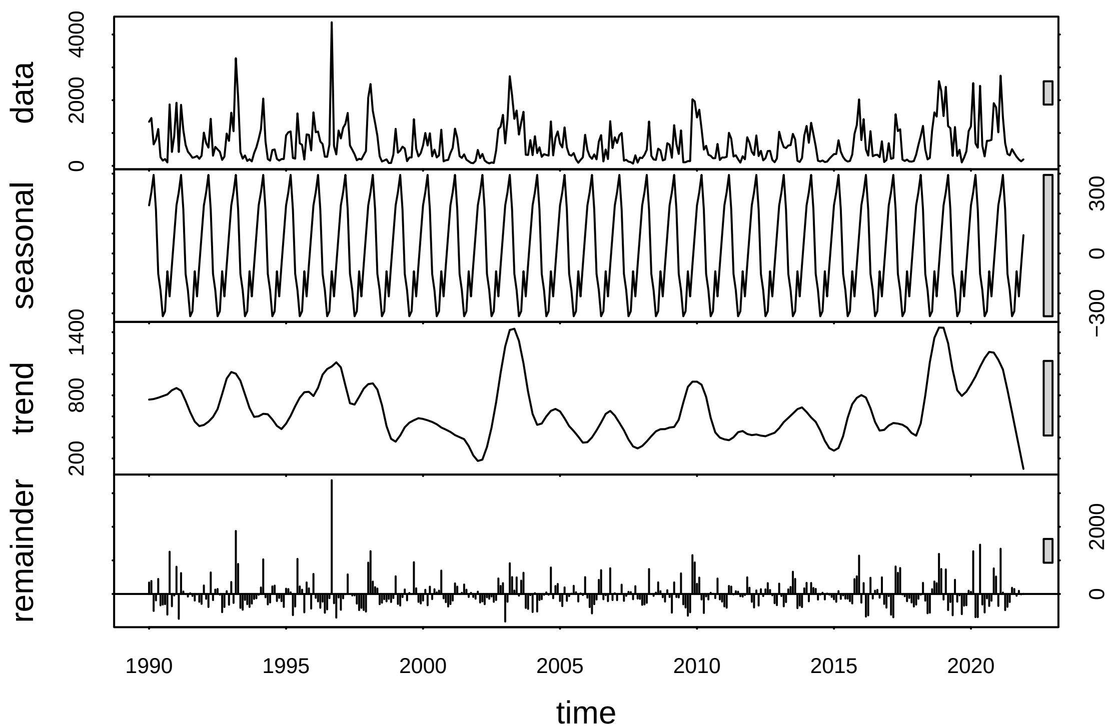


Figure 1: Cap Fear Time Seiries

```
CapeFearRiver_trend <- smk.test(CapeFearRiver_timeseries)
CapeFearRiver_trend
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data:  CapeFearRiver_timeseries
## z = -0.98775, p-value = 0.3233
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##      S   varS
##   -212 45632
```

```r
summary(CapeFearRiver_trend)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: CapeFearRiver_timeseries
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                      S   varS    tau      z Pr(>|z|)
## Season 1:   S = 0  -98 3802.7 -0.198 -1.573  0.11572
## Season 2:   S = 0  -18 3802.7 -0.036 -0.276  0.78279
## Season 3:   S = 0  -72 3802.7 -0.145 -1.151  0.24958
## Season 4:   S = 0  -78 3802.7 -0.157 -1.249  0.21179
## Season 5:   S = 0   32 3802.7  0.065  0.503  0.61517
## Season 6:   S = 0   24 3802.7  0.048  0.373  0.70916
## Season 7:   S = 0  -48 3802.7 -0.097 -0.762  0.44596
## Season 8:   S = 0   24 3802.7  0.048  0.373  0.70916
## Season 9:   S = 0   12 3802.7  0.024  0.178  0.85842
## Season 10:   S = 0  -4 3802.7 -0.008 -0.049  0.96120
## Season 11:   S = 0  -4 3802.7 -0.008 -0.049  0.96120
## Season 12:   S = 0  18 3802.7  0.036  0.276  0.78279
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#p-value is 0.3233, so there is no trend present in Cape Fear River.

FlatRiver_timeseries <- ts(FlatRiverDischarge_Monthly$Mean_Flat_Discharge_Bymonth,
                           frequency = 12,
                           start = c(1990, 1, 1), end = c(2021, 12, 1))
FlatRiver_Decomposed <- stl(FlatRiver_timeseries, s.window = "periodic")
plot(FlatRiver_Decomposed)
```

```r
FlatRiver_trend <- smk.test(FlatRiver_timeseries)
FlatRiver_trend
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data:  FlatRiver_timeseries
## z = 0.84731, p-value = 0.3968
## alternative hypothesis: true S is not equal to 0
## sample estimates:
```

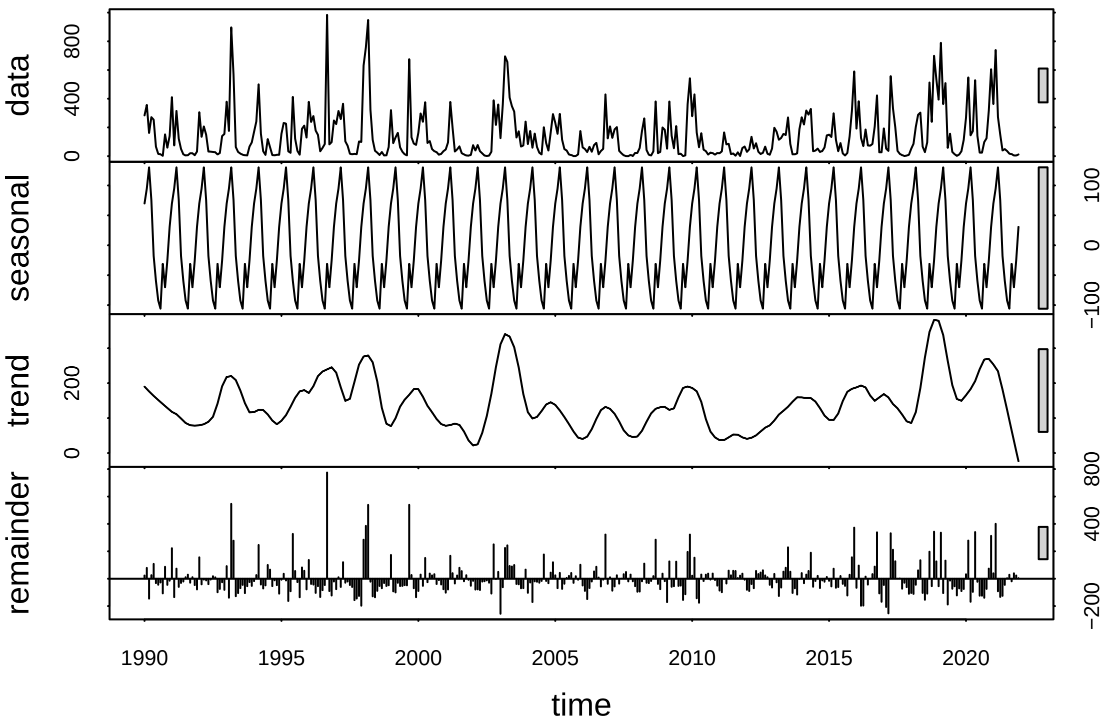


Figure 2: Cap Fear Time Seiries

```
##      S  varS
##    182 45632
```

```
summary(FlatRiver_trend)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: FlatRiver_timeseries
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                      S   varS    tau      z Pr(>|z|)
## Season 1:   S = 0  -76 3802.7 -0.153 -1.216 0.223896
## Season 2:   S = 0    4 3802.7  0.008  0.049 0.961199
## Season 3:   S = 0  -92 3802.7 -0.185 -1.476 0.140025
## Season 4:   S = 0  -18 3802.7 -0.036 -0.276 0.782794
## Season 5:   S = 0  108 3802.7  0.218  1.735 0.082712 .
## Season 6:   S = 0  110 3802.7  0.222  1.768 0.077129 .
## Season 7:   S = 0   38 3802.7  0.077  0.600 0.548500
## Season 8:   S = 0   36 3802.7  0.073  0.568 0.570323
## Season 9:   S = 0   58 3802.7  0.117  0.924 0.355310
## Season 10:   S = 0 -18 3802.7 -0.036 -0.276 0.782794
## Season 11:   S = 0   2 3802.7  0.004  0.016 0.987062
## Season 12:   S = 0  30 3802.7  0.060  0.470 0.638157
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#p-value is 0.3968, so there is no trend present in Flat River.
```

```
LittleRiver_timeseries <-
      ts(LittleRiverDischarge_Monthly$Mean_Little_Discharge_Bymonth,
      frequency = 12,
                           start = c(1990, 1, 1), end = c(2021, 12, 1))
LittleRiver_Decomposed <- stl(LittleRiver_timeseries, s.window = "periodic")
plot(LittleRiver_Decomposed)
```

```
LittleRiver_trend <- smk.test(LittleRiver_timeseries)
LittleRiver_trend
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data:  LittleRiver_timeseries
## z = 0.82859, p-value = 0.4073
```

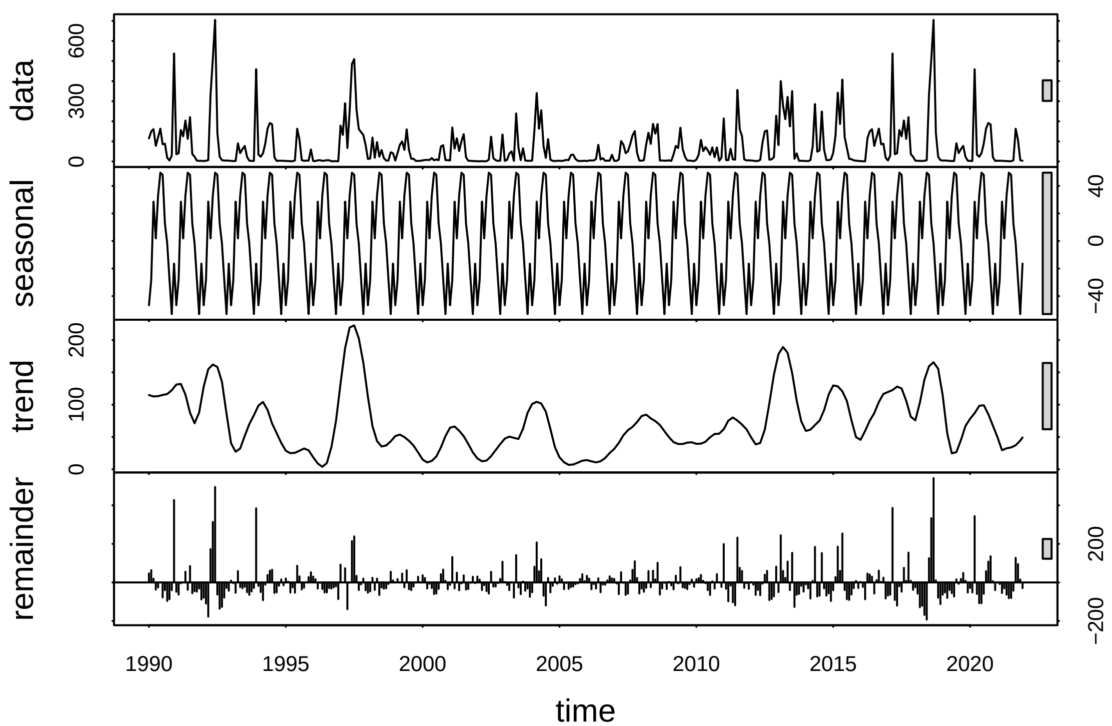


Figure 3: Little River Time Series

```
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##      S  varS
##   178 45632
```

```r
summary(LittleRiver_trend)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: LittleRiver_timeseries
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                        S  varS    tau      z  Pr(>|z|)
## Season 1:   S = 0   -24 3802.7 -0.048 -0.373 0.7091645
## Season 2:   S = 0   -60 3802.7 -0.121 -0.957 0.3386830
## Season 3:   S = 0   -16 3802.7 -0.032 -0.243 0.8078142
## Season 4:   S = 0   -72 3802.7 -0.145 -1.151 0.2495808
## Season 5:   S = 0   -76 3802.7 -0.153 -1.216 0.2238958
## Season 6:   S = 0  -120 3802.7 -0.242 -1.930 0.0536368  .
## Season 7:   S = 0   -18 3802.7 -0.036 -0.276 0.7827941
## Season 8:   S = 0    94 3802.7  0.190  1.508 0.1315212
## Season 9:   S = 0   202 3802.7  0.407  3.260 0.0011161 **
## Season 10:   S = 0  194 3802.7  0.391  3.130 0.0017494 **
## Season 11:   S = 0  126 3802.7  0.254  2.027 0.0426566  *
## Season 12:   S = 0  -52 3802.7 -0.105 -0.827 0.4082149
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#p-value is 0.4073, so there is no trend present in Little River.
#The time-series analysis on Cape Fear Lake, Flat River and Little River
#do not show any obvious trend in long term.
#However, we can tell a great similarity between the trend patterns of
#Cape Fear Lake and Flat River. This raises our concern because
#they do not come from the same basin. Instead, Little River,
#which comes from the same watershed as Flat River,
#shows a more different pattern.
```

```r
#Total Withdrawals
total_withdrawal_timeseries <- ts(total_withdrawal$Avg_Daily_Use_mgd, frequency = 12,
                                  start = c(2006, 1, 1), end = c(2021, 12, 1))
total_withdrawal_Decomposed <- stl(total_withdrawal_timeseries, s.window = "periodic")
plot(total_withdrawal_Decomposed)
```

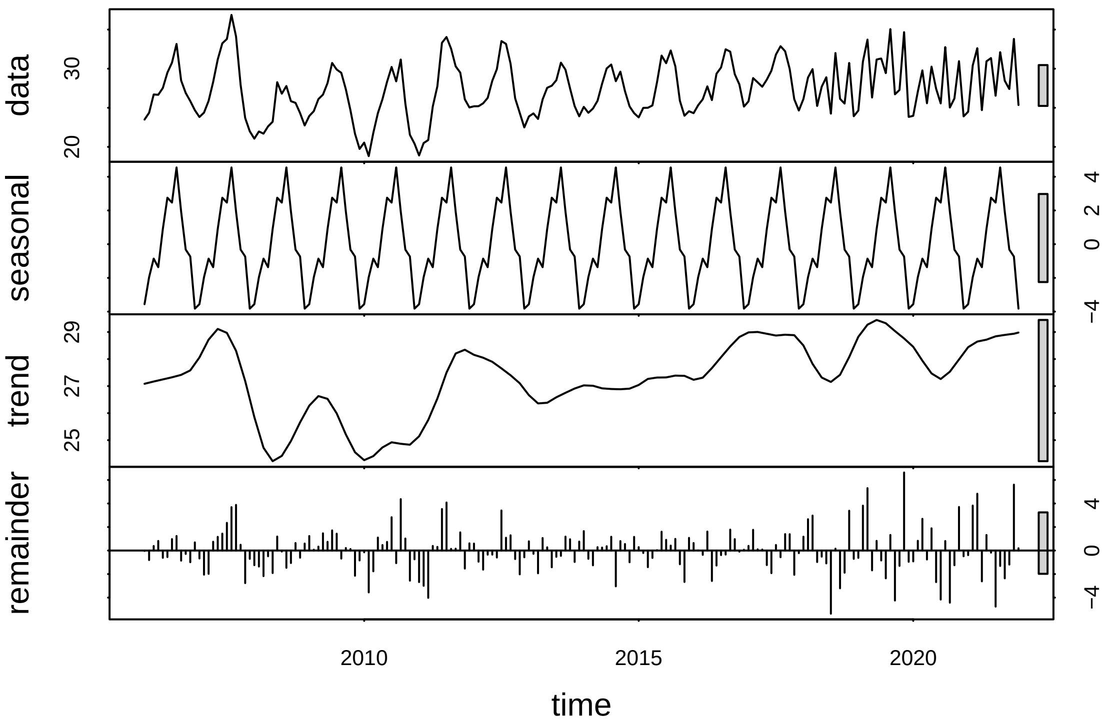


Figure 4: Total Withdraw Time Series

```r
total_withdrawal_trend <- smk.test(total_withdrawal_timeseries)
total_withdrawal_trend
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data:  total_withdrawal_timeseries
## z = 3.5874, p-value = 0.0003339
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##    S varS
##  277 5919
```

```r
summary(total_withdrawal_trend)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: total_withdrawal_timeseries
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                      S  varS    tau      z   Pr(>|z|)
## Season 1:   S = 0   48 493.3  0.400  2.116 0.03433985   *
## Season 2:   S = 0   75 492.3  0.628  3.335 0.00085285 ***
## Season 3:   S = 0   56 493.3  0.467  2.476 0.01327749   *
## Season 4:   S = 0  -12 493.3 -0.100 -0.495 0.62042529
## Season 5:   S = 0   40 493.3  0.333  1.756 0.07910922   .
## Season 6:   S = 0   -6 493.3 -0.050 -0.225 0.82189169
## Season 7:   S = 0  -40 493.3 -0.333 -1.756 0.07910922   .
## Season 8:   S = 0   14 493.3  0.117  0.585 0.55835091
## Season 9:   S = 0  -18 493.3 -0.150 -0.765 0.44404364
## Season 10:   S = 0  14 493.3  0.117  0.585 0.55835091
## Season 11:   S = 0  70 493.3  0.583  3.107 0.00189282  **
## Season 12:   S = 0  36 493.3  0.300  1.576 0.11507465
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#p-value is 0.3775, so there is no trend present in Total Withdrawals.
#The time-series analysis on municipal withdrawals in Durham shows
#an obvious increase since 2010. However, the drop in 2019 and 2021
#needs more data and reports to explain.
```

```r
DurhamGroundwater_timeseries <- ts(DurhamGroundwater$Groundwater_Table_feet, frequency =
                                   start = c(2009, 1, 1), end = c(2021, 12, 1))
DurhamGroundwater_Decomposed <- stl(DurhamGroundwater_timeseries, s.window = "periodic")
plot(DurhamGroundwater_Decomposed)
```

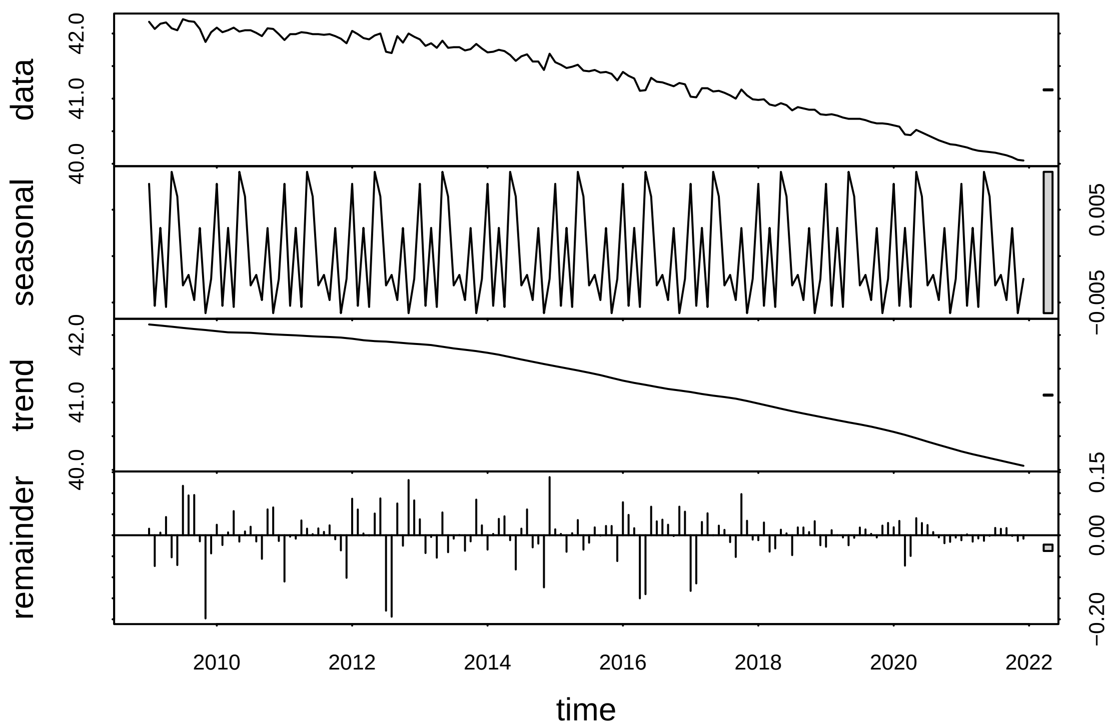


Figure 5: Groundwater Time Series

```r
DurhamGroundwater_trend <- smk.test(DurhamGroundwater_timeseries)
DurhamGroundwater_trend
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data:  DurhamGroundwater_timeseries
## z = -15.964, p-value < 2.2e-16
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##     S varS
## -907 3221
```

```r
summary(DurhamGroundwater_trend)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: DurhamGroundwater_timeseries
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                       S  varS    tau      z   Pr(>|z|)
## Season 1:   S = 0  -74 268.7 -0.949 -4.454 8.4423e-06 ***
## Season 2:   S = 0  -77 267.7 -0.994 -4.645 3.3954e-06 ***
## Season 3:   S = 0  -78 268.7 -1.000 -4.698 2.6313e-06 ***
## Season 4:   S = 0  -76 268.7 -0.974 -4.576 4.7471e-06 ***
## Season 5:   S = 0  -78 268.7 -1.000 -4.698 2.6313e-06 ***
## Season 6:   S = 0  -75 267.7 -0.968 -4.523 6.0945e-06 ***
## Season 7:   S = 0  -76 268.7 -0.974 -4.576 4.7471e-06 ***
## Season 8:   S = 0  -76 268.7 -0.974 -4.576 4.7471e-06 ***
## Season 9:   S = 0  -75 267.7 -0.968 -4.523 6.0945e-06 ***
## Season 10:   S = 0 -76 268.7 -0.974 -4.576 4.7471e-06 ***
## Season 11:   S = 0 -70 268.7 -0.897 -4.210 2.5581e-05 ***
## Season 12:   S = 0 -76 268.7 -0.974 -4.576 4.7471e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#p-value is less than 0.05, so there is no trend present in Total Withdrawals.
#The time-series analysis on groundwater table level in Durham shows a
#significant decrease since 2010.
```

```r
DurhamPrecipitaion_timeseries <- ts(DurhamPrecipitaion$Precipitaion_inches, frequency =
                            start = c(2009, 1, 1), end = c(2021, 12, 1))
DurhamPrecipitaion_Decomposed <- stl(DurhamPrecipitaion_timeseries, s.window = "periodic
plot(DurhamPrecipitaion_Decomposed)
```

```r
DurhamPrecipitaion_trend <- smk.test(DurhamGroundwater_timeseries)
DurhamPrecipitaion_trend
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data:  DurhamGroundwater_timeseries
## z = -15.964, p-value < 2.2e-16
## alternative hypothesis: true S is not equal to 0
## sample estimates:
```

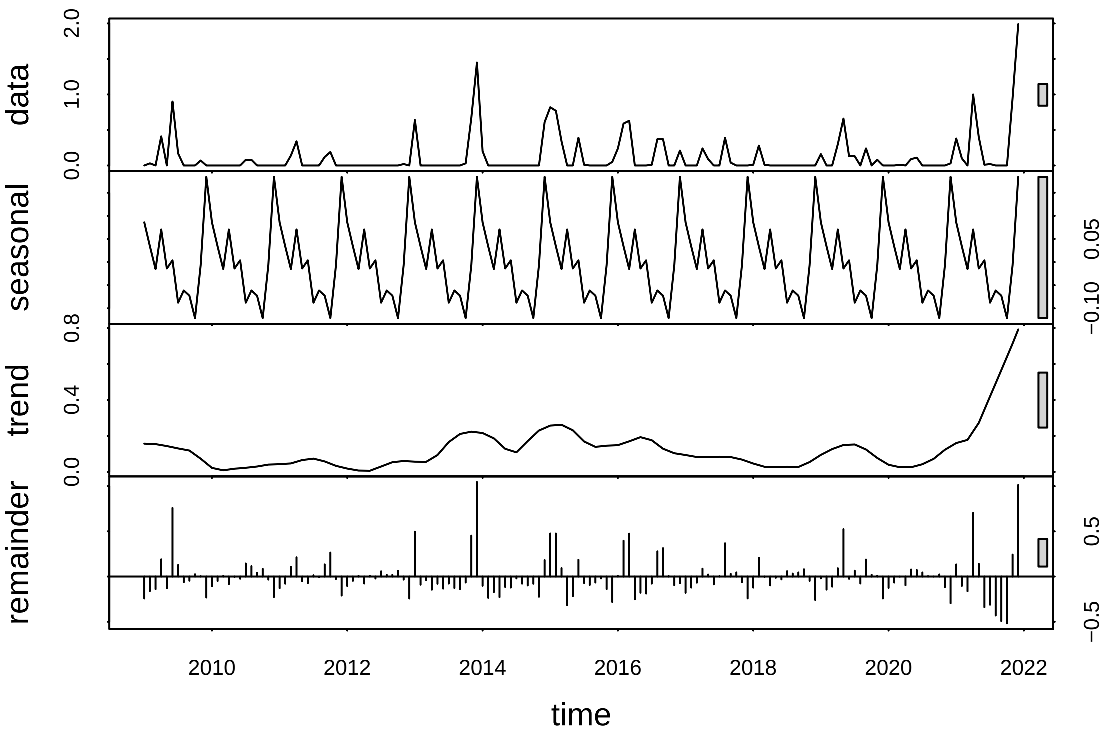


Figure 6: Precipitation Time Series

```
##    S varS
## -907 3221
```

```
summary(DurhamPrecipitaion_trend)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: DurhamGroundwater_timeseries
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                       S  varS    tau      z   Pr(>|z|)
## Season 1:   S = 0  -74 268.7 -0.949 -4.454 8.4423e-06 ***
## Season 2:   S = 0  -77 267.7 -0.994 -4.645 3.3954e-06 ***
## Season 3:   S = 0  -78 268.7 -1.000 -4.698 2.6313e-06 ***
## Season 4:   S = 0  -76 268.7 -0.974 -4.576 4.7471e-06 ***
## Season 5:   S = 0  -78 268.7 -1.000 -4.698 2.6313e-06 ***
## Season 6:   S = 0  -75 267.7 -0.968 -4.523 6.0945e-06 ***
## Season 7:   S = 0  -76 268.7 -0.974 -4.576 4.7471e-06 ***
## Season 8:   S = 0  -76 268.7 -0.974 -4.576 4.7471e-06 ***
## Season 9:   S = 0  -75 267.7 -0.968 -4.523 6.0945e-06 ***
## Season 10:   S = 0 -76 268.7 -0.974 -4.576 4.7471e-06 ***
## Season 11:   S = 0 -70 268.7 -0.897 -4.210 2.5581e-05 ***
## Season 12:   S = 0 -76 268.7 -0.974 -4.576 4.7471e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#The time-series analysis on precipitation in Durham shows a gradual rise
#since 2010 and a dynamic increase in recent years.
```

```
precip <- DurhamPrecipitaion %>%
  select(Date, Precipitaion_inches) %>%
  filter(Date > "2013-12-31")
capefear <- CapeFearRiverDischarge %>%
  select(Date, CapeFear_Discharge) %>%
  filter(Date > "2013-12-31")
flat <- FlatRiverDischarge %>%
  select(Date, Flat_Discharge) %>%
  filter(Date > "2013-12-31")
little <- LittleRiverDischarge %>%
  select(Date, Little_Discharge) %>%
  filter(Date > "2013-12-31")
data1 <- left_join(precip, capefear) %>%
```

```
  left_join(., flat) %>%
  left_join(., little)
```

```
## Joining, by = "Date"
## Joining, by = "Date"
## Joining, by = "Date"
```

```
mod1 <- lm(Precipitaion_inches ~ CapeFear_Discharge + Flat_Discharge +
             Little_Discharge, data = data1)
summary(mod1)
```

```
##
## Call:
## lm(formula = Precipitaion_inches ~ CapeFear_Discharge + Flat_Discharge +
##     Little_Discharge, data = data1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.0634 -0.1224 -0.1047 -0.0677  4.8682
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)         1.041e-01  8.138e-03  12.792  < 2e-16 ***
## CapeFear_Discharge -4.799e-05  8.167e-06  -5.877 4.67e-09 ***
## Flat_Discharge      4.917e-04  4.258e-05  11.547  < 2e-16 ***
## Little_Discharge   -1.576e-04  5.873e-05  -2.683  0.00734 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3848 on 2869 degrees of freedom
##   (12 observations deleted due to missingness)
## Multiple R-squared:  0.1374, Adjusted R-squared:  0.1365
## F-statistic: 152.4 on 3 and 2869 DF,  p-value: < 2.2e-16
```

```
par(mfrow=c(2,2))
plot(mod1)
```

```
totalwit <- total_withdrawal_Monthly %>%
  select(Month, Mean_Avg_Daily_Use_mgd) %>%
  filter(Month > "2013-12")
capefearmonthly <- CapeFearRiverDischarge_Monthly %>%
  select(Month, Mean_CapeFear_Discharge_Bymonth) %>%
  filter(Month > "2013-12") %>%
  mutate(CapeFear_Discharge = Mean_CapeFear_Discharge_Bymonth)
flatmonthly <- FlatRiverDischarge_Monthly %>%
  select(Month, Mean_Flat_Discharge_Bymonth) %>%
```

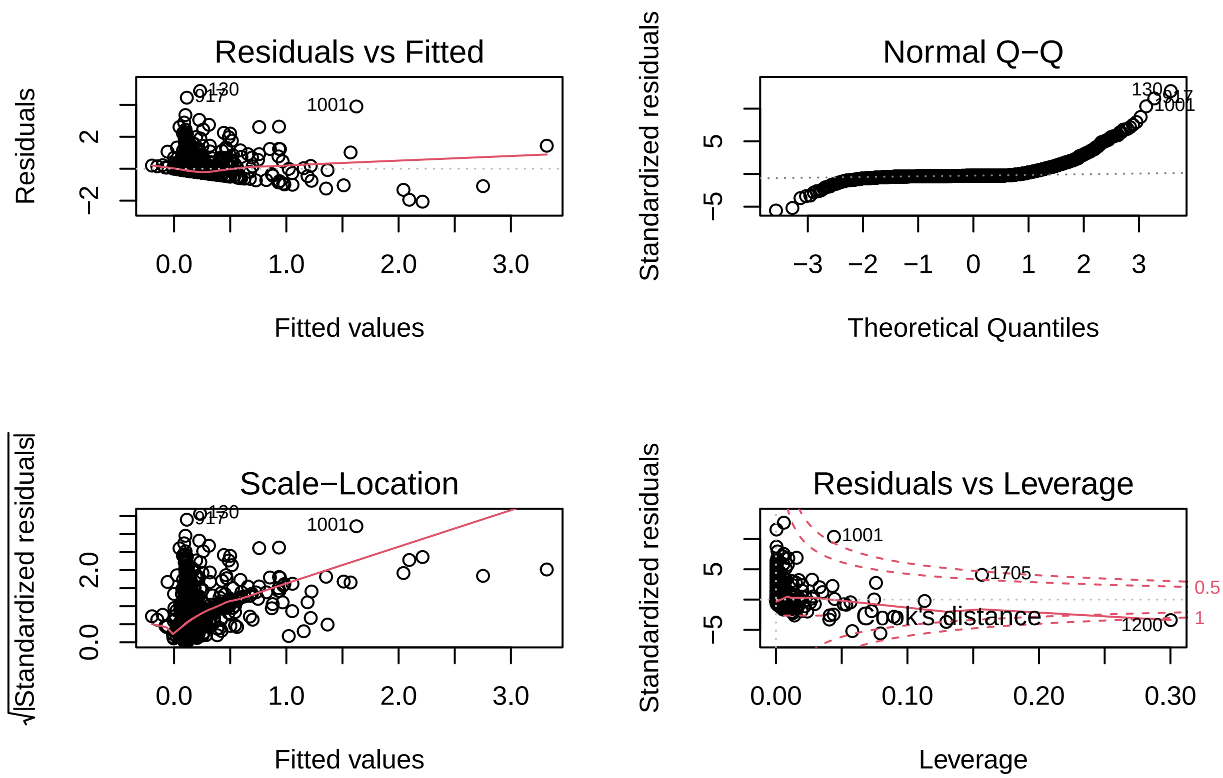


Figure 7: Model 1 Diagnostic Graphs

```r
  filter(Month > "2013-12") %>%
  mutate(Flat_Discharge = Mean_Flat_Discharge_Bymonth)
littlemonthly <- LittleRiverDischarge_Monthly %>%
  select(Month, Mean_Little_Discharge_Bymonth) %>%
  filter(Month > "2013-12") %>%
  mutate(Little_Discharge = Mean_Little_Discharge_Bymonth)
data2 <- left_join(totalwit, capefearmonthly) %>%
  left_join(., flatmonthly) %>%
  left_join(., littlemonthly)
```

```
## Joining, by = "Month"
## Joining, by = "Month"
## Joining, by = "Month"
```

```r
mod2.1 <- lm(Mean_Avg_Daily_Use_mgd ~ CapeFear_Discharge + Flat_Discharge +
               Little_Discharge, data = data2)
summary(mod2.1)
```

```
##
## Call:
## lm(formula = Mean_Avg_Daily_Use_mgd ~ CapeFear_Discharge + Flat_Discharge +
##     Little_Discharge, data = data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.7101 -2.6601 -0.4312  2.3640  6.3019
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        28.525224   0.469178  60.798   <2e-16 ***
## CapeFear_Discharge  0.001259   0.001101   1.144   0.2557
## Flat_Discharge     -0.012179   0.006165  -1.976   0.0512 .
## Little_Discharge    0.010286   0.008614   1.194   0.2355
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.959 on 92 degrees of freedom
## Multiple R-squared:  0.06156,    Adjusted R-squared:  0.03096
## F-statistic: 2.012 on 3 and 92 DF,  p-value: 0.1178
```

```r
mod2.2 <- update(mod2.1, .~. -CapeFear_Discharge)
summary(mod2.2)
```

```
##
## Call:
## lm(formula = Mean_Avg_Daily_Use_mgd ~ Flat_Discharge + Little_Discharge,
```

```
##     data = data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5201 -2.6643 -0.3608  2.1502  6.3973
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)      28.732216   0.433587  66.266   <2e-16 ***
## Flat_Discharge   -0.007467   0.004594  -1.625    0.107
## Little_Discharge  0.008746   0.008522   1.026    0.307
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.964 on 93 degrees of freedom
## Multiple R-squared:  0.04821,    Adjusted R-squared:  0.02774
## F-statistic: 2.355 on 2 and 93 DF,  p-value: 0.1005
```

```
mod2.3 <- update(mod2.2, .~. -Little_Discharge)
summary(mod2.3)
```

```
##
## Call:
## lm(formula = Mean_Avg_Daily_Use_mgd ~ Flat_Discharge, data = data2)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -4.436 -2.550 -0.253  2.222  6.489
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)    28.611617   0.417476  68.535   <2e-16 ***
## Flat_Discharge -0.003045   0.001593  -1.912   0.0589 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.965 on 94 degrees of freedom
## Multiple R-squared:  0.03743,    Adjusted R-squared:  0.02719
## F-statistic: 3.656 on 1 and 94 DF,  p-value: 0.05893
```

```
par(mfrow=c(2,2))
plot(mod2.1)
```

```
precip <- DurhamPrecipitaion %>%
  select(Date, Precipitaion_inches) %>%
  filter(Date > "2013-12-31")
```

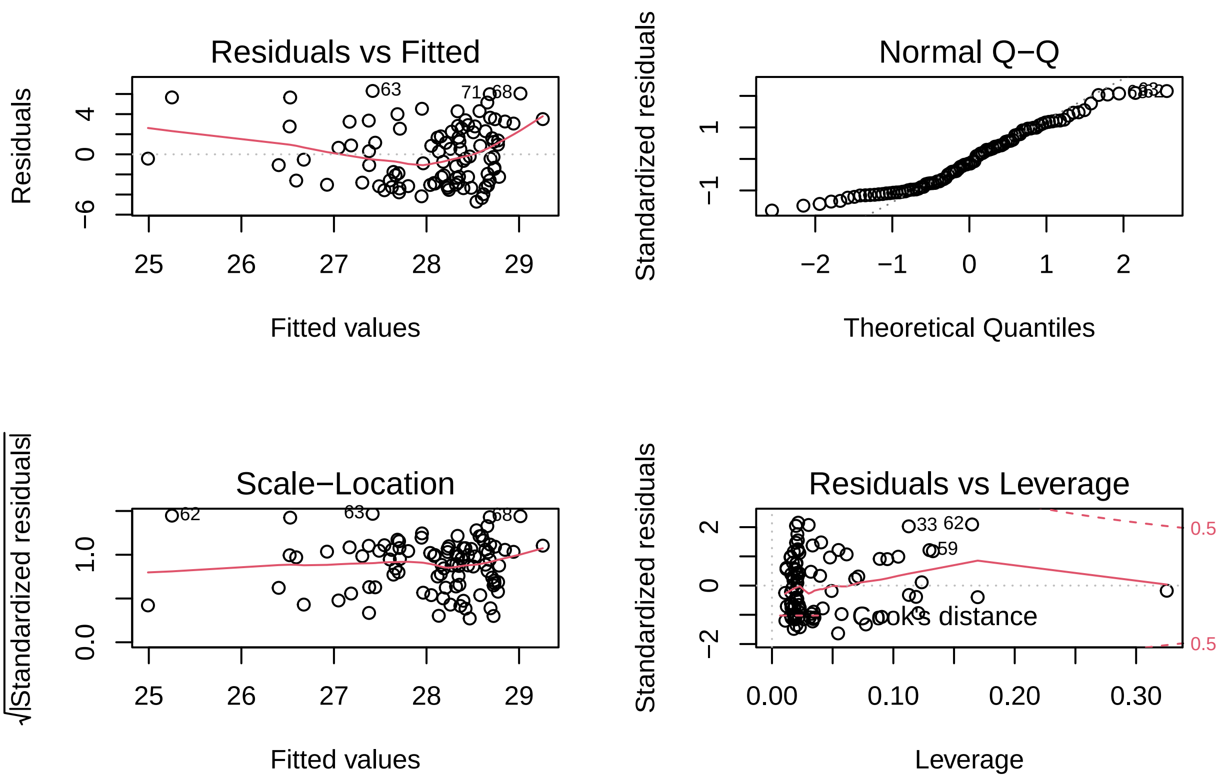


Figure 8: Model 2.1 Diagnostic Graphs

```r
groudw <- DurhamGroundwater %>%
  select(Date, Groundwater_Table_feet) %>%
  filter(Date > "2013-12-31")
data3 <- left_join(groudw, precip)
```

```
## Joining, by = "Date"
```

```r
mod3 <- lm(Groundwater_Table_feet ~ Precipitaion_inches, data = data3)
summary(mod3)
```

```
##
## Call:
## lm(formula = Groundwater_Table_feet ~ Precipitaion_inches, data = data3)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -4.830 -1.490  0.396  1.590  3.480
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         38.74024    0.04274 906.361   <2e-16 ***
## Precipitaion_inches  0.11322    0.09743   1.162    0.245
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.164 on 2872 degrees of freedom
##   (37 observations deleted due to missingness)
## Multiple R-squared:  0.0004699,  Adjusted R-squared:  0.0001219
## F-statistic:  1.35 on 1 and 2872 DF,  p-value: 0.2453
```

```r
par(mfrow=c(2,2))
plot(mod3)
```

```r
totalwit <- total_withdrawal_Monthly %>%
  select(Month, Mean_Avg_Daily_Use_mgd) %>%
  filter(Month > "2013-12")
data4 <- left_join(DurhamGroundwater_Monthly, totalwit)
```

```
## Joining, by = "Month"
```

```r
mod4 <- lm(Mean_Groundwater_Table_feet ~ Mean_Avg_Daily_Use_mgd, data = data4)
summary(mod4)
```

```
##
## Call:
## lm(formula = Mean_Groundwater_Table_feet ~ Mean_Avg_Daily_Use_mgd,
##     data = data4)
```

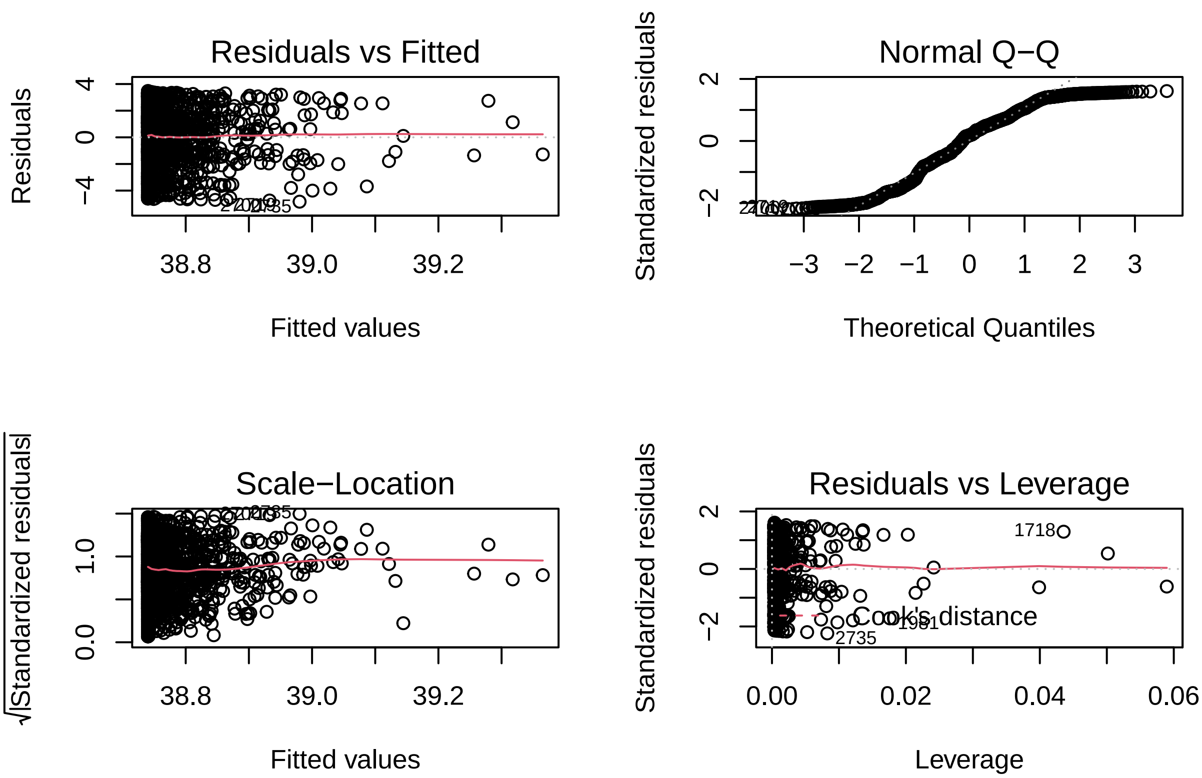


Figure 9: Model 3 Diagnostic Graphs

```
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.7842 -1.7200  0.4354  1.5870  4.1540
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           45.10469    1.99031  22.662  < 2e-16 ***
## Mean_Avg_Daily_Use_mgd -0.22607    0.07053  -3.205  0.00184 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.067 on 94 degrees of freedom
## Multiple R-squared:  0.09854,    Adjusted R-squared:  0.08895
## F-statistic: 10.27 on 1 and 94 DF,  p-value: 0.001843
```

```r
par(mfrow=c(2,2))
plot(mod4)
```

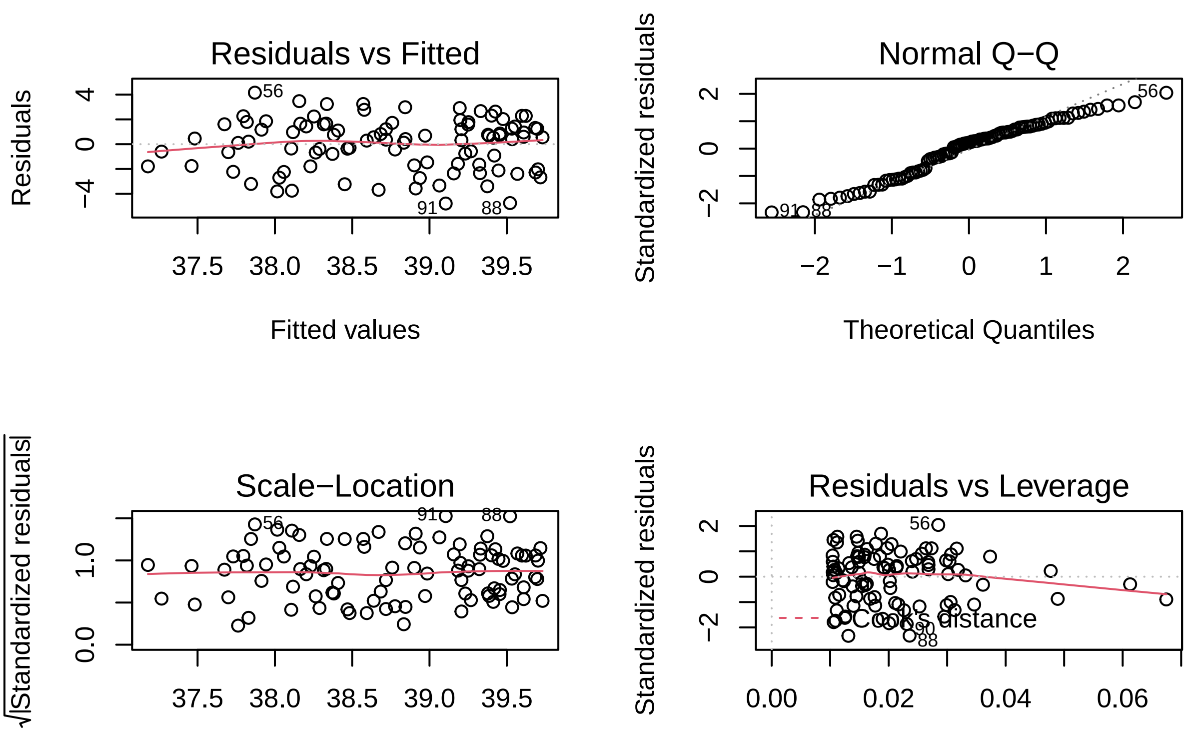


Figure 10: Model 4 Diagnostic Graphs

```
ggplot(data4,aes(x=Mean_Groundwater_Table_feet,y=Mean_Avg_Daily_Use_mgd))+
       geom_point()+
  theme(text = element_text(size = 19))+
  geom_smooth(method = lm) +
  xlab("Average Daily Water Use (million gallon/day)")+ylab("Groundwater table (ft)")
```

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

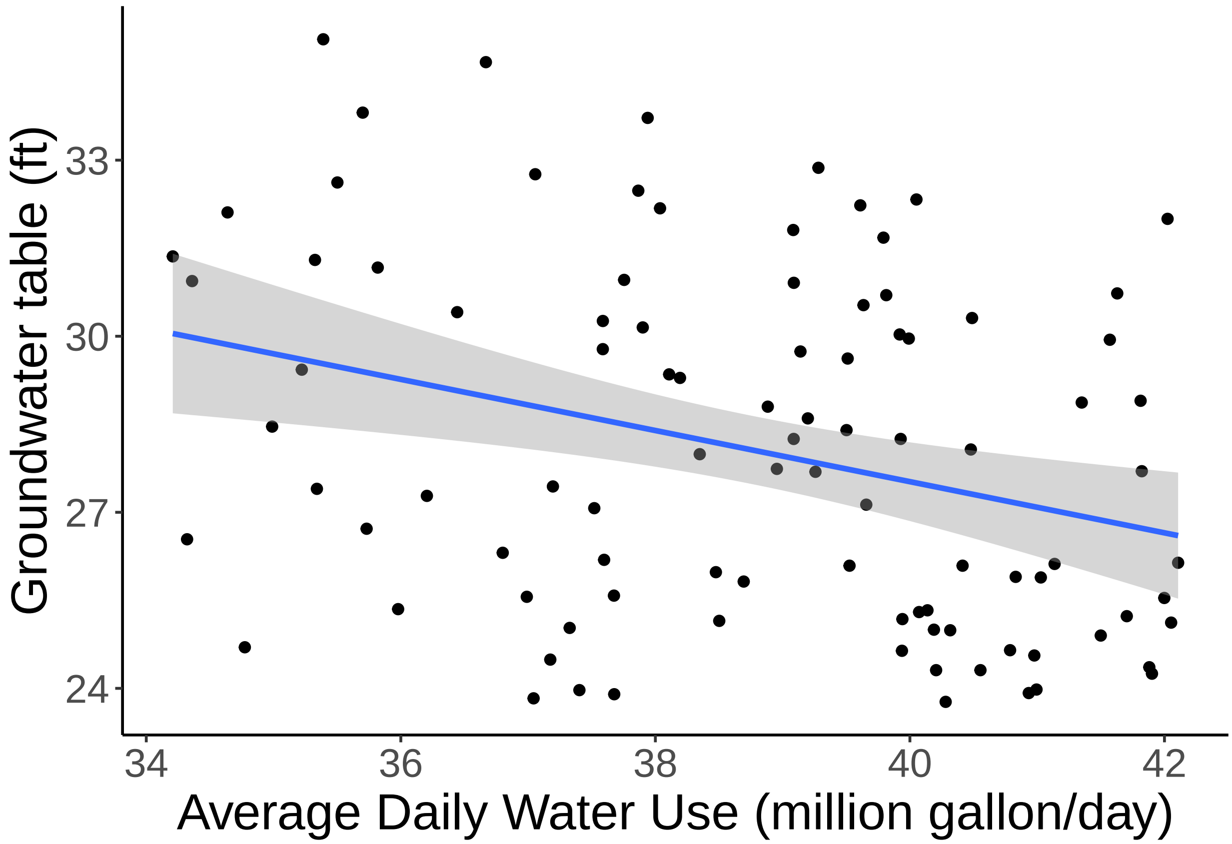


Figure 11: Average Daily Water Use vs. Groundwater Table

```
capefear <- CapeFearRiverDischarge %>%
  select(Date, CapeFear_Discharge) %>%
  filter(Date > "2013-12-31")
flat <- FlatRiverDischarge %>%
  select(Date, Flat_Discharge) %>%
  filter(Date > "2013-12-31")
little <- LittleRiverDischarge %>%
  select(Date, Little_Discharge) %>%
  filter(Date > "2013-12-31")
data5 <- left_join(groudw, capefear) %>%
  left_join(., flat) %>%
```

```r
  left_join(., little)
```

```
## Joining, by = "Date"
## Joining, by = "Date"
## Joining, by = "Date"
```

```r
mod5.1 <- lm(Groundwater_Table_feet ~ CapeFear_Discharge + Flat_Discharge +
               Little_Discharge, data = data5)
summary(mod5.1)
```

```
##
## Call:
## lm(formula = Groundwater_Table_feet ~ CapeFear_Discharge + Flat_Discharge +
##     Little_Discharge, data = data5)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.9713 -1.5423  0.4185  1.5724  3.7801
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)         3.869e+01  4.537e-02 852.837  < 2e-16 ***
## CapeFear_Discharge -5.445e-05  4.564e-05  -1.193  0.23296
## Flat_Discharge      9.599e-04  2.381e-04   4.031 5.69e-05 ***
## Little_Discharge   -9.427e-04  3.285e-04  -2.869  0.00414 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.153 on 2895 degrees of freedom
##   (12 observations deleted due to missingness)
## Multiple R-squared:  0.00795,    Adjusted R-squared:  0.006922
## F-statistic: 7.733 on 3 and 2895 DF,  p-value: 3.828e-05
```

```r
mod5.2 <- update(mod5.1, .~. -CapeFear_Discharge)
summary(mod5.2)
```

```
##
## Call:
## lm(formula = Groundwater_Table_feet ~ Flat_Discharge + Little_Discharge,
##     data = data5)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.9106 -1.5554  0.4229  1.5793  3.7681
##
## Coefficients:
```

```
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)       38.6808326  0.0432155 895.069  < 2e-16 ***
## Flat_Discharge     0.0008109  0.0002017   4.020 5.97e-05 ***
## Little_Discharge -0.0009046  0.0003269  -2.768  0.00568 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.155 on 2901 degrees of freedom
##   (7 observations deleted due to missingness)
## Multiple R-squared:  0.007459,   Adjusted R-squared:  0.006774
## F-statistic:  10.9 on 2 and 2901 DF,  p-value: 1.922e-05
```

```r
par(mfrow=c(2,2))
plot(mod5.2)
```

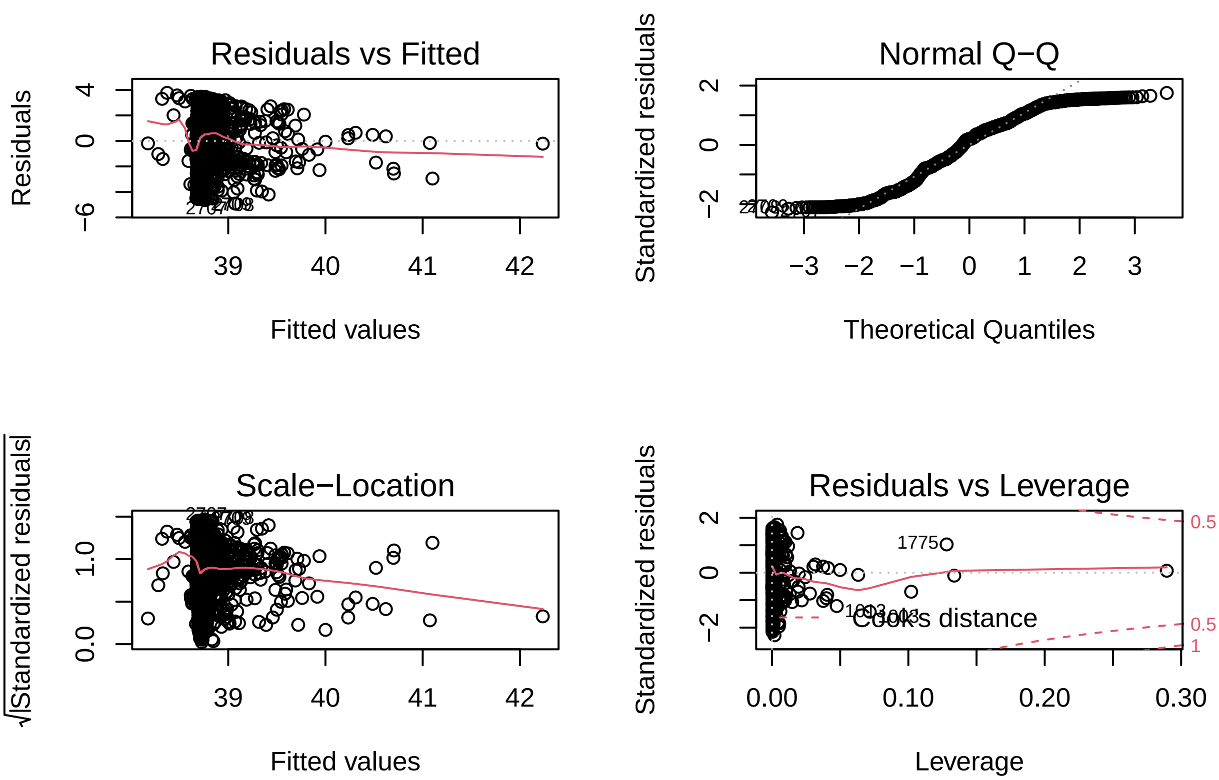


Figure 12: Model 5.2 Diagnostic Graphs

```r
ggplot(data5, aes(Groundwater_Table_feet))+
  theme(text = element_text(size = 20))+
  geom_point(aes(y=Flat_Discharge, color = "Flat River"))+
    geom_point(aes(y=Little_Discharge, color = "Little River"))+
  xlab("Groundwater table/ft")+ylab("River Discharge (sqft/s)")
```

```
## Warning: Removed 2 rows containing missing values (geom_point).
## Warning: Removed 5 rows containing missing values (geom_point).
```

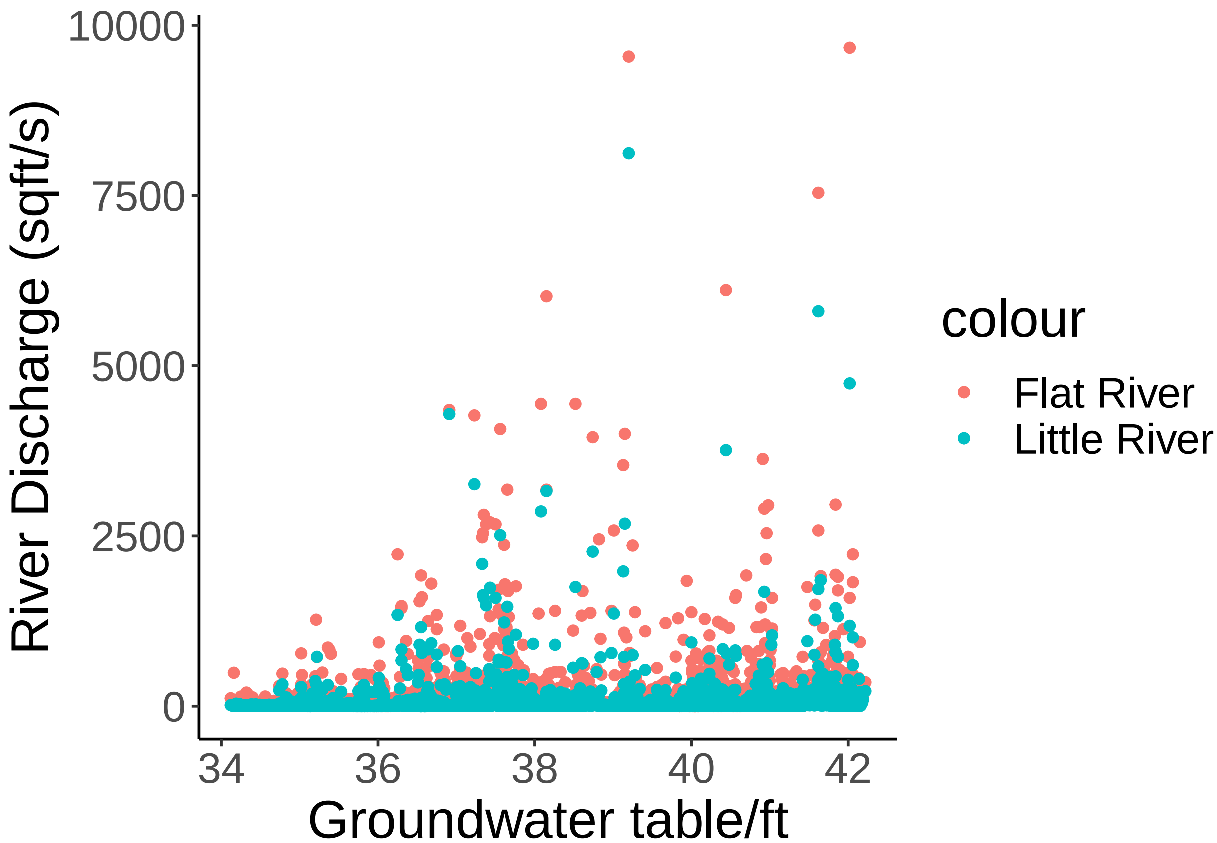


Figure 13: Groundwater table vs. River Discharge

# 5 Summary and Conclusions

The results show that there is no significant correlation between the municipal withdrawals and river discharge. At the same time, there is no significant correlation between the precipitation and groundwater table level. For Cape Fear River, there is a negative correlation with precipitation. For Flat River, there are positive correlations with both precipitation and groundwater table level. For Little River, there are negative correlations with both precipitation and groundwater table level. For the groundwater table level in Durham, there is a negative correlation with municipal withdrawals.

From the time-series analysis, we conclude that the water capacity of the Durham region can remain stable over a certain period of time and provide sufficient water for regional development, human activities. And the analysis proves that the effect of urban water use on river discharge is not significant. It is the natural factors such as precipitation and groundwater table that impact on the river discharge most.

In order to assess the stability of the North Carolina water market and the scope for future development, we analyzed factors that may affect the capacity of surface water resources, including precipitation, water withdrawals. Through time-series analysis and regression analysis, we concluded that the impact of municipal withdrawals on river discharge is not significant, while precipitation and groundwater have a great impact on river flow. The rivers around Durham can maintain a stable amount of water for a certain period of time in the future.

The current analysis is deficient. One possible problem is that we could not obtain the accurate groundwater capacity and groundwater use in North Carolina. Recording changes in groundwater levels greatly reduces the magnitude of changes in groundwater volume. The neglect of this variable may lead to blind optimism about water resource capacity. Therefore, in the future, the accurate data on groundwater is expected to be available to improve this analysis. Another factor that biases the results is that although we do not consider the effect of sewage volume as a factor on river flow because the water withdrawal and discharge points for Durham are located in different rivers, we cannot guarantee that other cities are not discharging sewage to the studied rivers. Similarly, we cannot determine whether the studied river is used as a water source only in Durham. These could have some influence on the experimental results. Therefore, in further studies, we need to identify all withdrawal and discharge points in the studied rivers.

In the more than 60 years since the development of water resources management, the primary goal of water resources development has been to support the economy and to identify ways to increase freshwater supplies to meet anticipated demand (Gleick, 1998).With broadened consideration that includes issues of sustainability and equity, a new debate on water policy has now begun, as reflected by the statements coming from the 1992 Dublin statement, Agenda 21 from Rio, the World Bank, and the Global Water Partnership. The core arguments of the debate are that incorporating sustainability and equity features into water resources planning and policy goals has become a major policy priority, and this requires a high priority to maintain the integrity of water resources and the flora and fauna and human societies that develop around them. This argument is possible because there is already a consensus that economic and environmental constraints on resource development may shape future global groundwater depletion. Not only the volume of physically available water needs to be explored, but also the volume of water that is economically and environmentally exploitable. Then understand how these limitations affect the assessment of when aquifers become unsuitable for human applications (Turner et al., 2019).

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