# ENV 790.30 - Time Series Analysis for Energy Data | Spring 2022

Assignment 3 - Due date 02/08/22

Yu Hai

## Directions

You should open the .rmd file corresponding to this assignment on RStudio. The file is available on our class repository on Github.

Once you have the project open the first thing you will do is change "Student Name" on line 3 with your name. Then you will start working through the assignment by **creating code and output** that answer each question. Be sure to use this assignment document. Your report should contain the answer to each question and any plots/tables you obtained (when applicable).

Please keep this R code chunk options for the report. It is easier for us to grade when we can see code and output together. And the tidy.opts will make sure that line breaks on your code chunks are automatically added for better visualization.

When you have completed the assignment, **Knit** the text and code into a single PDF file. Rename the pdf file such that it includes your first and last name (e.g., "LuanaLima_TSA_A03_Sp22.Rmd"). Submit this pdf using Sakai.

## Questions

Consider the same data you used for A2 from the spreadsheet "Table_10.1_Renewable_Energy_Production_and_Consumpt
The data comes from the US Energy Information and Administration and corresponds to the January 2022 **Monthly** Energy Review. Once again you will work only with the following columns: Total Biomass Energy Production, Total Renewable Energy Production, Hydroelectric Power Consumption. Create a data frame structure with these three time series only.

R packages needed for this assignment:"forecast","tseries", and "Kendall". Install these packages, if you haven't done yet. Do not forget to load them before running your script, since they are NOT default packages.\

```
#Load/install required package here
library(forecast)
```

```
## Warning:   'forecast' R 4.1.2
```

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

```
library(tseries)
```

```
## Warning:   'tseries' R 4.1.2
```

```
library(Kendall)
```

```
## Warning:   'Kendall' R 4.1.2
```

```
library(lubridate)
```

```
##
##    'lubridate'
```

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

```
library(ggplot2)
```

```
library(readxl)
```

```
## Warning:   'readxl' R 4.1.2
```

```
raw_RE_data<-read_excel(path="./Data/Table_10.1_Renewable_Energy_Production_and_Consumption_by_Source.xl
raw_RE_data
```

```
## # A tibble: 586 x 14
##    Month               `Wood Energy Prod~ `Biofuels Product~ `Total Biomass Ene~
##    <dttm>              <chr>              <chr>              <chr>
##  1 NA                  (Trillion Btu)     (Trillion Btu)     (Trillion Btu)
##  2 1973-01-01 00:00:00 129.63             Not Available      129.787
##  3 1973-02-01 00:00:00 117.194            Not Available      117.338
##  4 1973-03-01 00:00:00 129.763            Not Available      129.938
##  5 1973-04-01 00:00:00 125.462            Not Available      125.636
##  6 1973-05-01 00:00:00 129.624            Not Available      129.834
##  7 1973-06-01 00:00:00 125.435            Not Available      125.611
##  8 1973-07-01 00:00:00 129.616            Not Available      129.787
##  9 1973-08-01 00:00:00 129.734            Not Available      129.918
## 10 1973-09-01 00:00:00 125.603            Not Available      125.782
## # ... with 576 more rows, and 10 more variables:
## #   Total Renewable Energy Production <chr>,
## #   Hydroelectric Power Consumption <chr>, Geothermal Energy Consumption <chr>,
## #   Solar Energy Consumption <chr>, Wind Energy Consumption <chr>,
## #   Wood Energy Consumption <chr>, Waste Energy Consumption <chr>,
## #   Biofuels Consumption <chr>, Total Biomass Energy Consumption <chr>,
## #   Total Renewable Energy Consumption <chr>
```

##Trend Component

### Q1

Create a plot window that has one row and three columns. And then for each object on your data frame, fill the plot window with time series plot, ACF and PACF. You may use the some code form A2, but I want all three plots on the same window this time. (Hint: use par() function)

```
sub_RE_data <- raw_RE_data[-c(1),4:6]
head(sub_RE_data)
```

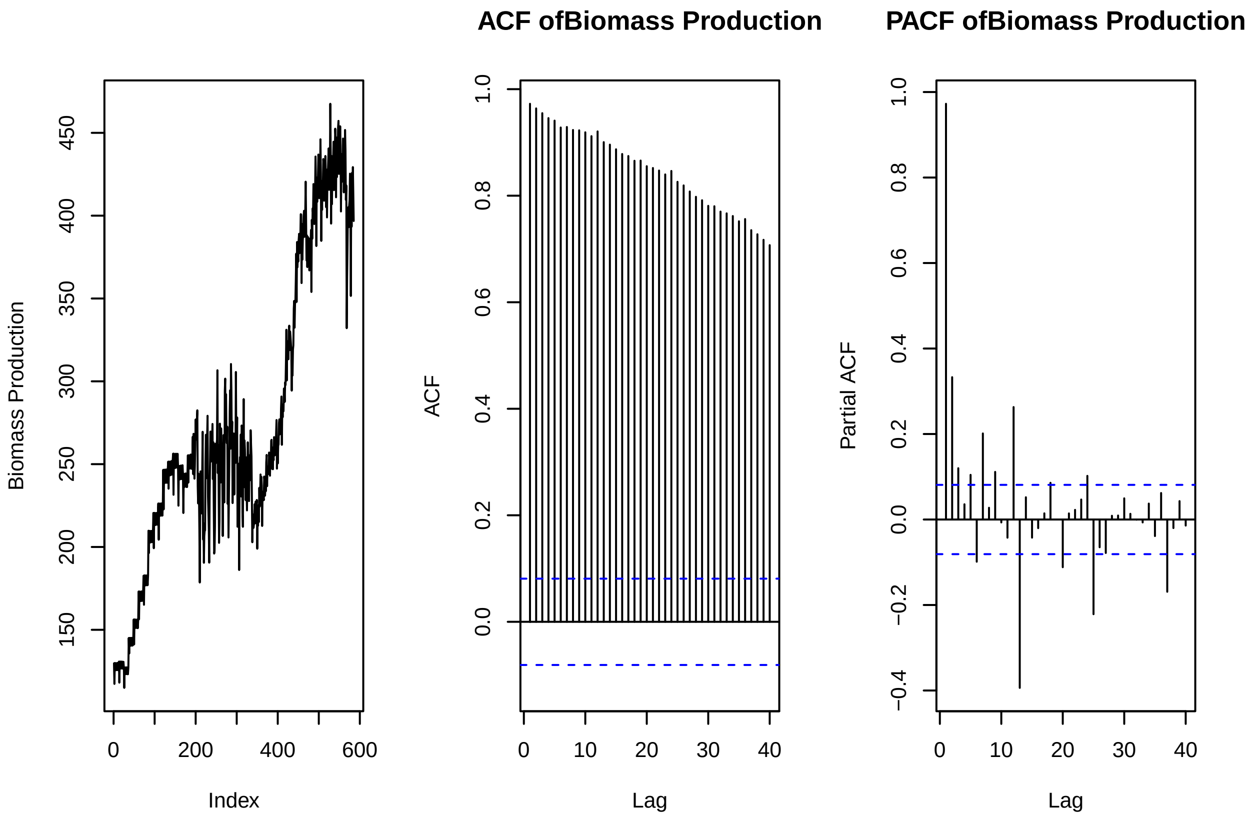
```
## # A tibble: 6 x 3
##   `Total Biomass Energy Production` `Total Renewable Ener~ `Hydroelectric Power~
##   <chr>                             <chr>                  <chr>
## 1 129.787                           403.981                272.703
## 2 117.338                           360.9                  242.199
## 3 129.938                           400.161                268.81
## 4 125.636                           380.47                 253.185
## 5 129.834                           392.141                260.77
## 6 125.611                           377.232                249.859
```

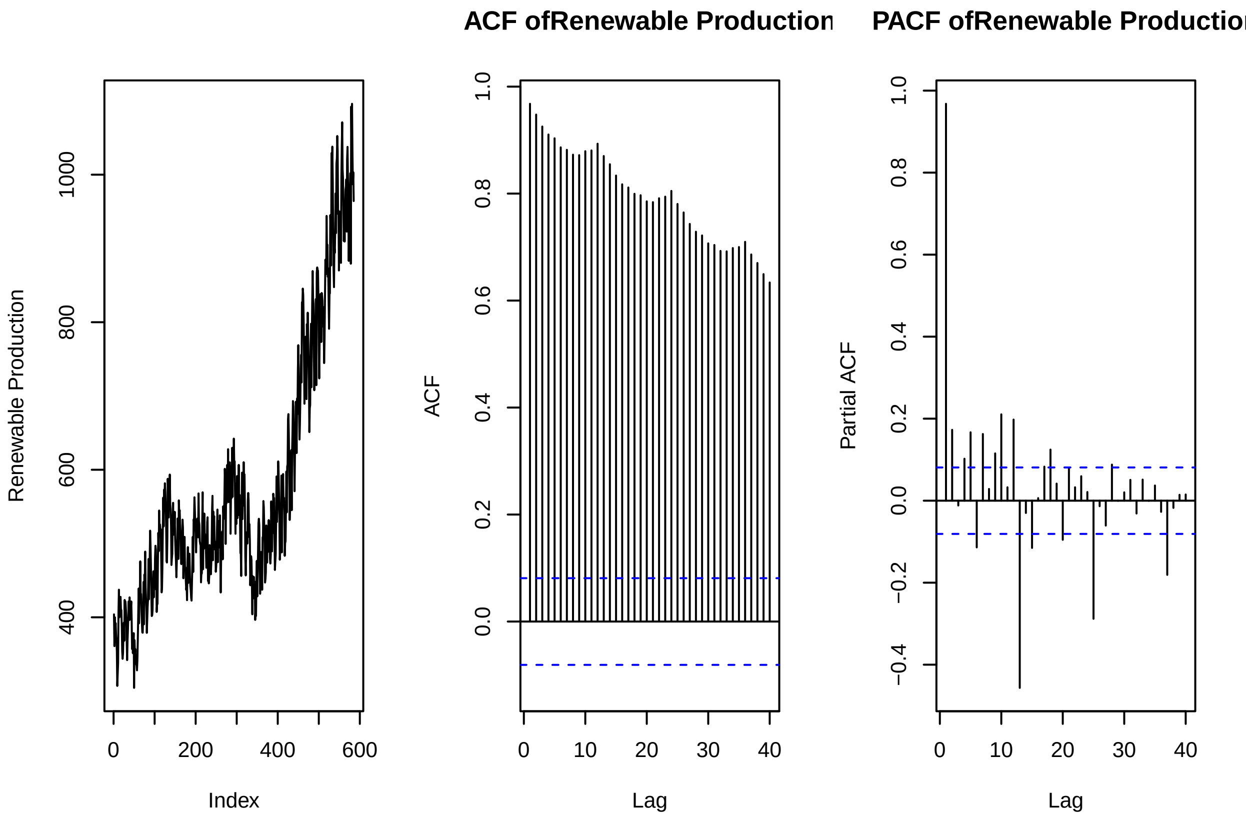
```
RE_data <- cbind(raw_RE_data[-c(1),1],sub_RE_data[,])
RE_data$`Total Biomass Energy Production`<- as.numeric(RE_data$`Total Biomass Energy
↪ Production`)
RE_data$`Total Renewable Energy Production`<- as.numeric(RE_data$`Total Renewable Energy
↪ Production`)
RE_data$`Hydroelectric Power Consumption`<- as.numeric(RE_data$`Hydroelectric Power
↪ Consumption`)
head(RE_data)
```

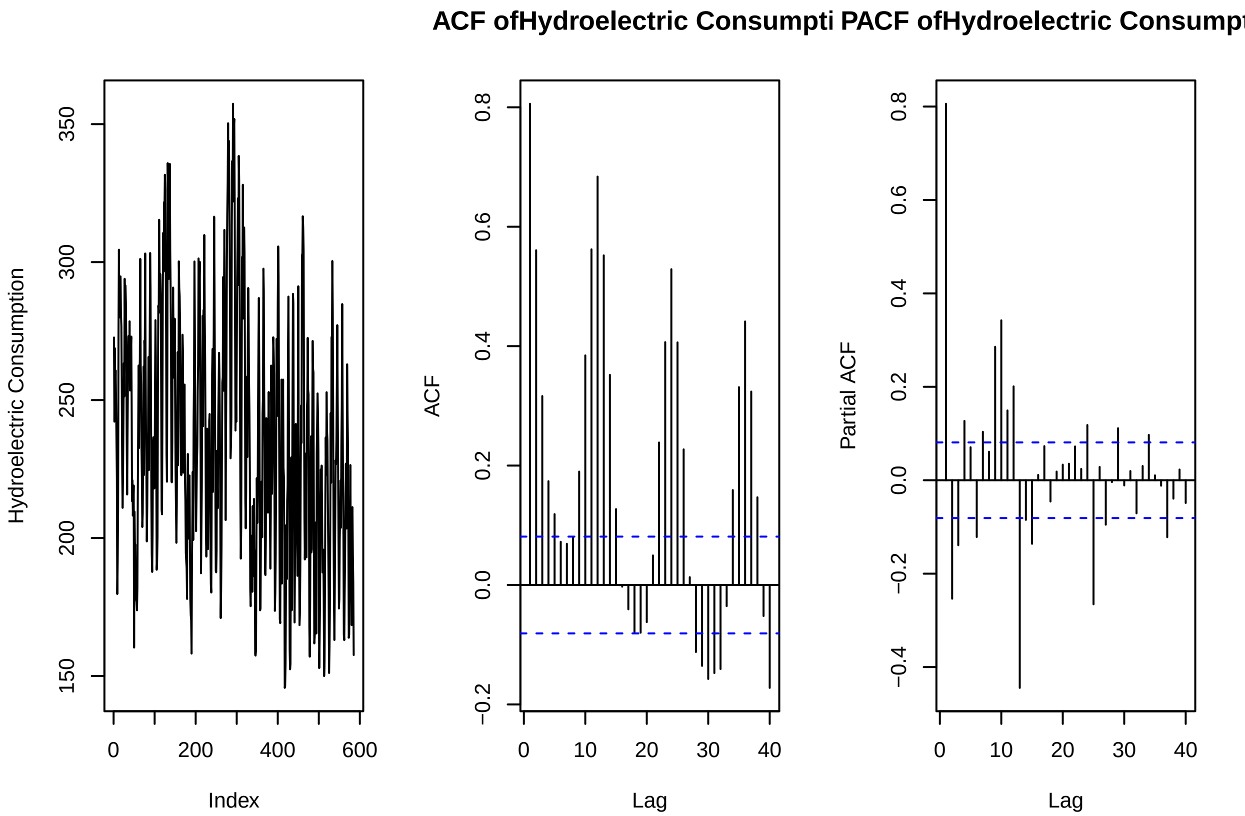
```
##        Month Total Biomass Energy Production Total Renewable Energy Production
## 1 1973-01-01                         129.787                           403.981
## 2 1973-02-01                         117.338                           360.900
## 3 1973-03-01                         129.938                           400.161
## 4 1973-04-01                         125.636                           380.470
## 5 1973-05-01                         129.834                           392.141
## 6 1973-06-01                         125.611                           377.232
##   Hydroelectric Power Consumption
## 1                         272.703
## 2                         242.199
## 3                         268.810
## 4                         253.185
## 5                         260.770
## 6                         249.859
```

```
colnames<-c("Biomass Production","Renewable Production","Hydroelectric Consumption")
```

```
par(mfrow=c(1,3))
for(i in 2:4){
  plot(RE_data[,i],type="l",ylab=colnames[i-1])
  Acf(RE_data[,i],lag.max=40,main=paste("ACF of",colnames[i-1],sep=""))
  Pacf(RE_data[,i],lag.max=40,main=paste("PACF of",colnames[i-1],sep=""))
}
```


ACF ofBiomass Production
PACF ofBiomass Production
Biomass Production
Index
ACF
Lag
Partial ACF
Lag


ACF ofRenewable Production
PACF ofRenewable Productio
Renewable Production
Index
ACF
Lag
Partial ACF
Lag




### Q2

From the plot in Q1, do the series Total Biomass Energy Production, Total Renewable Energy Production, Hydroelectric Power Consumption appear to have a trend? If yes, what kind of trend?

Biomass and renewable production show a linear, increasing trend, while the hydroelectric power consumption shows a linear, decreasing trend. All three series seems to have seasonality as there is consistent fluctuation pattern between observations within each year.

### Q3

Use the *lm()* function to fit a linear trend to the three time series. Ask R to print the summary of the regression. Interpret the regression output, i.e., slope and intercept. Save the regression coefficients for further analysis.

```
ts_RE_data <- ts(RE_data[,2:4], start=c(1973, 1), end=c(2021, 09), frequency=12)
head(ts_RE_data)
```

```
##          Total Biomass Energy Production Total Renewable Energy Production
## Jan 1973                         129.787                           403.981
## Feb 1973                         117.338                           360.900
## Mar 1973                         129.938                           400.161
## Apr 1973                         125.636                           380.470
## May 1973                         129.834                           392.141
```

```
## Jun 1973                         125.611                            377.232
##          Hydroelectric Power Consumption
## Jan 1973                         272.703
## Feb 1973                         242.199
## Mar 1973                         268.810
## Apr 1973                         253.185
## May 1973                         260.770
## Jun 1973                         249.859
```

```
#nhydro <- ncol(RE_data)-2
nobs <- nrow(RE_data)
t <- c(1:nobs)
lm1=lm(RE_data[,2]~t)
lm2=lm(RE_data[,3]~t)
lm3=lm(RE_data[,4]~t)

print("Results of Biomass Time Series")
```

```
## [1] "Results of Biomass Time Series"
```

```
print(summary(lm1))
```

```
##
## Call:
## lm(formula = RE_data[, 2] ~ t)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -101.892  -24.306    4.932   33.103   82.292
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.348e+02  3.282e+00   41.07   <2e-16 ***
## t           4.744e-01  9.705e-03   48.88   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.64 on 583 degrees of freedom
## Multiple R-squared:  0.8039, Adjusted R-squared:  0.8035
## F-statistic:  2389 on 1 and 583 DF,  p-value: < 2.2e-16
```

For total biomass energy production, the p-value of the linear regression is less than 0.05, so there is a significant trend in biomass energy production overtime. The value of the intercept indicates that the initial biomass energy production at time t=0 (January 1973) is 134.8 trillion Btu, and after each month, it is expected that the total biomass production will increase by 0.4744 trillion Btu.

```
print("Results of Renewable Time Series")
```

```
## [1] "Results of Renewable Time Series"
```

```r
print(summary(lm2))
```

```
##
## Call:
## lm(formula = RE_data[, 3] ~ t)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -230.488  -57.869    5.595   62.090  261.349
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 323.18243    8.02555   40.27   <2e-16 ***
## t             0.88051    0.02373   37.10   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 96.93 on 583 degrees of freedom
## Multiple R-squared:  0.7025, Adjusted R-squared:  0.702
## F-statistic:  1377 on 1 and 583 DF,  p-value: < 2.2e-16
```

For total renewable energy production, the p-value of the linear regression is less than 0.05, so there is a significant trend in renewable energy production overtime. The value of the intercept indicates the initial renewable energy production at time t=0 (January 1973), that the biomass production is 323 trillion Btu, and after each month, it is expected that the total renewable energy production will increase by 0.88 trillion Btu.

```r
print("Results of Hydroelectric Time Series")
```

```
## [1] "Results of Hydroelectric Time Series"
```

```r
print(summary(lm3))
```

```
##
## Call:
## lm(formula = RE_data[, 4] ~ t)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -94.892 -31.300  -2.414  27.876 121.263
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 259.18303    3.47464  74.593  < 2e-16 ***
## t            -0.07924    0.01027  -7.712 5.36e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 41.97 on 583 degrees of freedom
## Multiple R-squared:  0.09258,    Adjusted R-squared:  0.09103
## F-statistic: 59.48 on 1 and 583 DF,  p-value: 5.364e-14
```

For total hydroelectric power consumption, the p-value of the linear regression is less than 0.05, so there is a significant trend in the consumption overtime. The value of the intercept indicates the initial consumption at time t=0 (January 1973) is 259.18 trillion Btu, and after each month, it is expected that the consumption will decrease by 0.079 trillion Btu.

### Q4

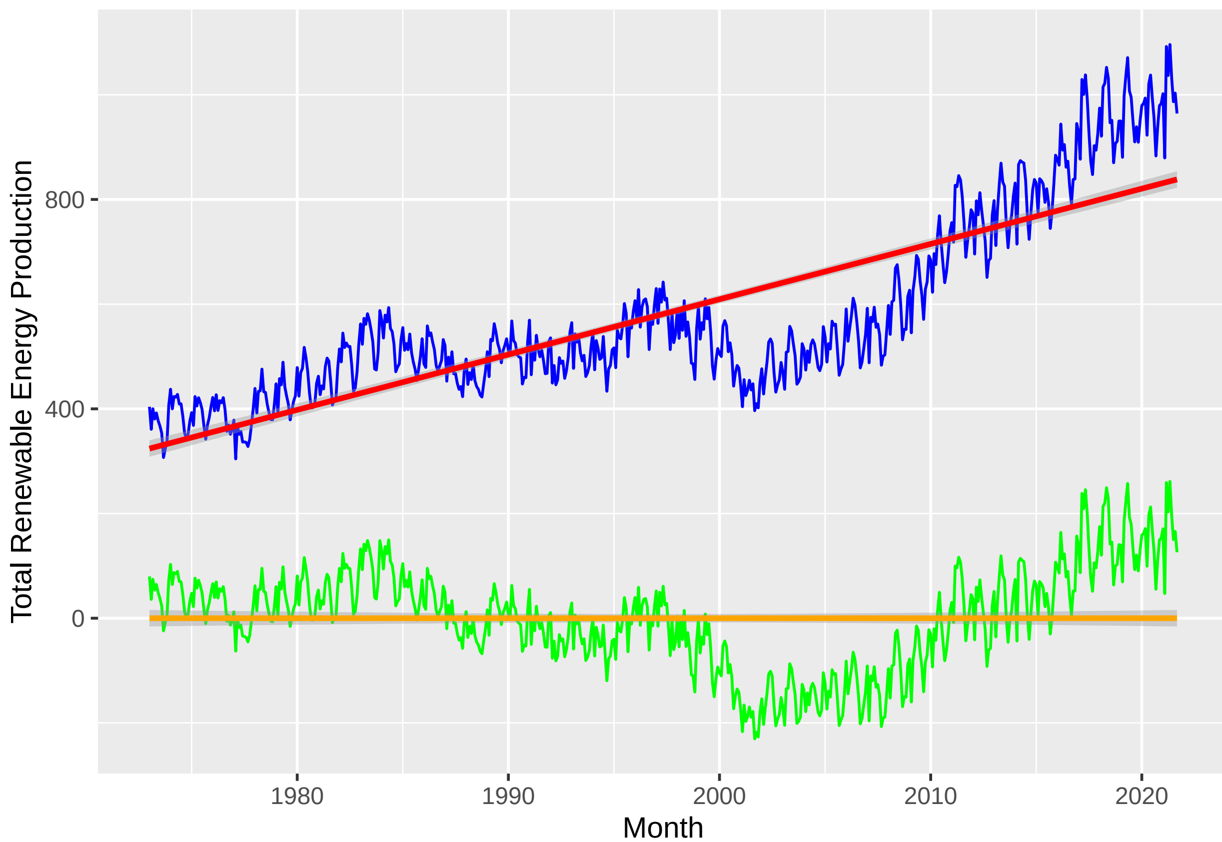
Use the regression coefficients from Q3 to detrend the series. Plot the detrended series and compare with the plots from Q1. What happened? Did anything change?

```
#Biomass
beta0_bio=as.numeric(lm1$coefficients[1])
beta1_bio=as.numeric(lm1$coefficients[2])

detrend_bio <- RE_data[,2]-(beta0_bio+beta1_bio*t)
 ggplot(RE_data, aes(x=Month, y=RE_data[,2])) +
            geom_line(color="blue") +
            ylab("Total Biomass Energy Production") +
            geom_smooth(color="red",method="lm") +
            geom_line(aes(y=detrend_bio), col="green")+
            geom_smooth(aes(y=detrend_bio),color="orange",method="lm")
```

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

```
#renewable
beta0_renew=as.numeric(lm2$coefficients[1])
beta1_renew=as.numeric(lm2$coefficients[2])

detrend_renew <- RE_data[,3]-(beta0_renew+beta1_renew*t)
 ggplot(RE_data, aes(x=Month, y=RE_data[,3])) +
            geom_line(color="blue") +
            ylab("Total Renewable Energy Production") +
            geom_smooth(color="red",method="lm") +
            geom_line(aes(y=detrend_renew), col="green")+
            geom_smooth(aes(y=detrend_renew),color="orange",method="lm")
```

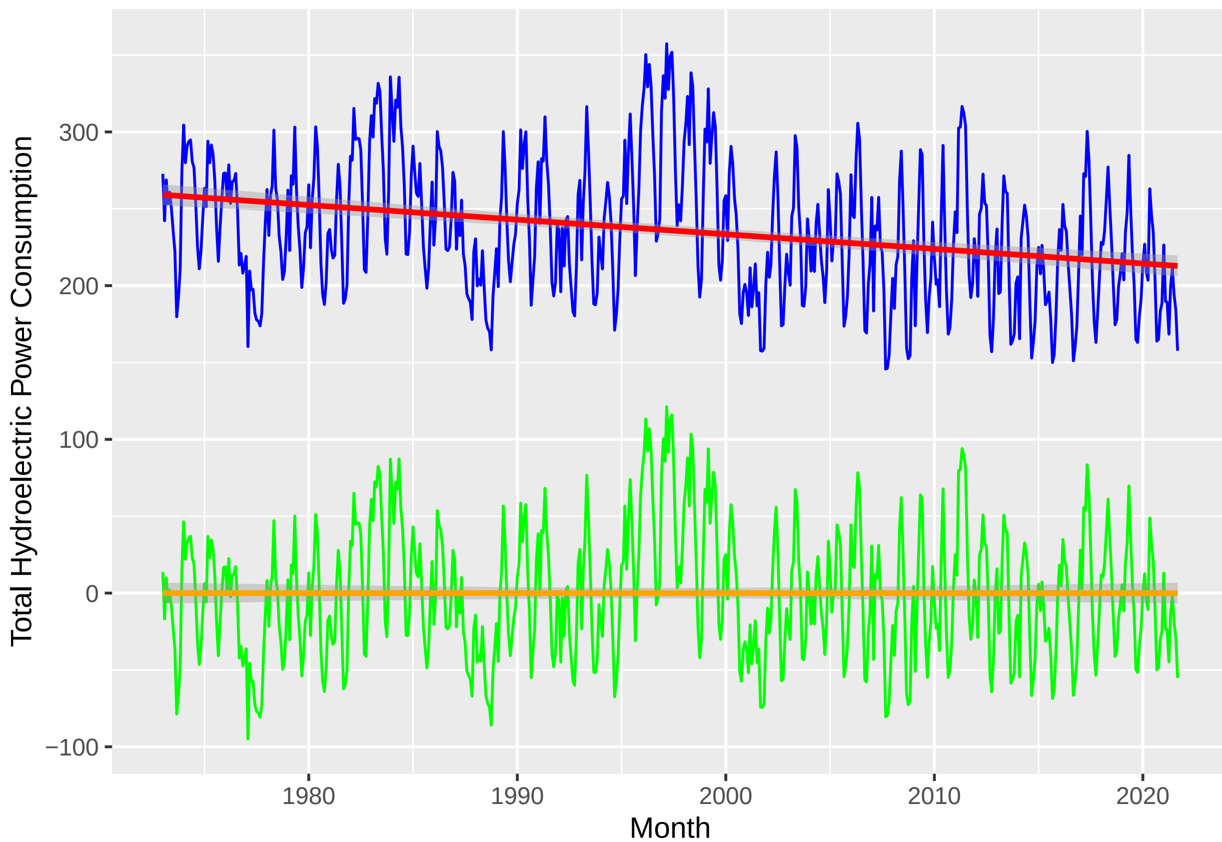
```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```




```
#hydro
beta0_hydro=as.numeric(lm3$coefficients[1])
beta1_hydro=as.numeric(lm3$coefficients[2])

detrend_hydro <- RE_data[,4]-(beta0_hydro+beta1_hydro*t)
 ggplot(RE_data, aes(x=Month, y=RE_data[,4])) +
            geom_line(color="blue") +
            ylab("Total Hydroelectric Power Consumption") +
            geom_smooth(color="red",method="lm") +
```

```
          geom_line(aes(y=detrend_hydro), col="green")+
          geom_smooth(aes(y=detrend_hydro),color="orange",method="lm")
```

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

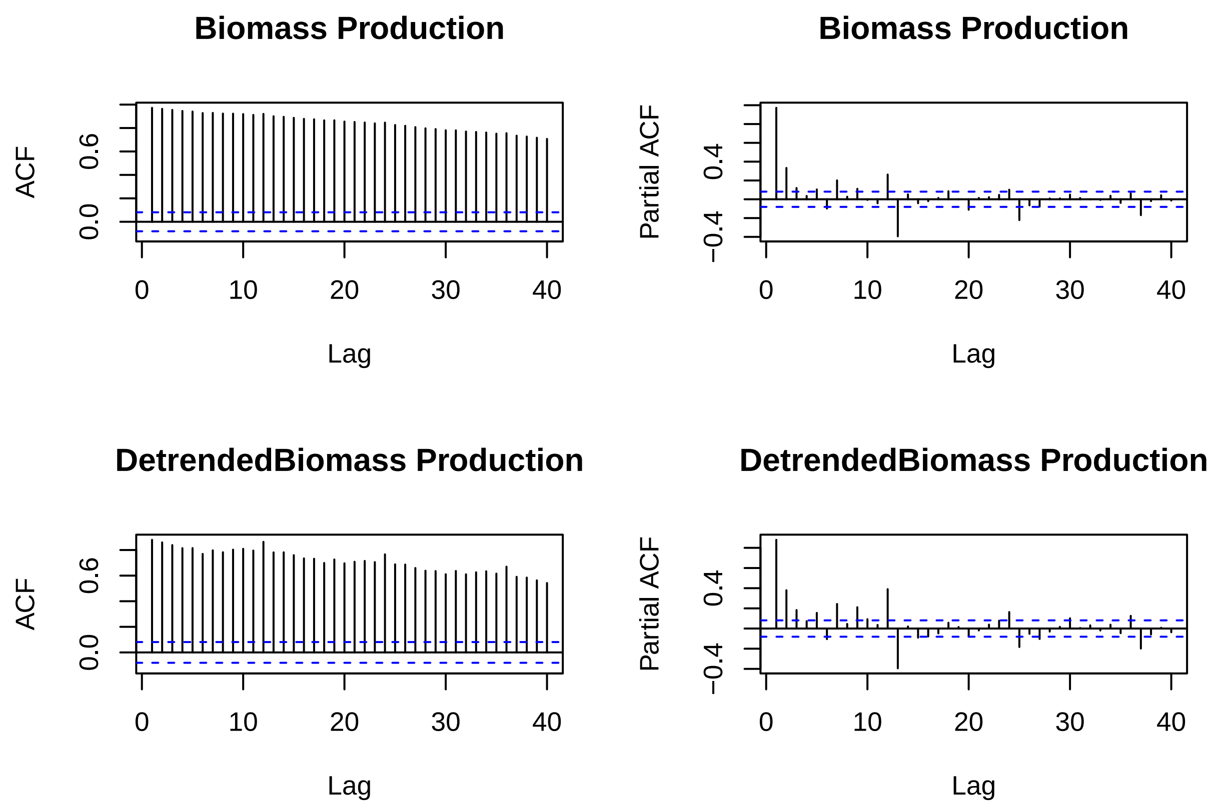



The linear trend after detrending become horizontal, so both beta 1 and beta 0 becomes 0. The detrending process removed the effects of trend from the original data but keep other components (e.g. seasonality and clynicality) the same, so the detrending process allows those components to be identified.

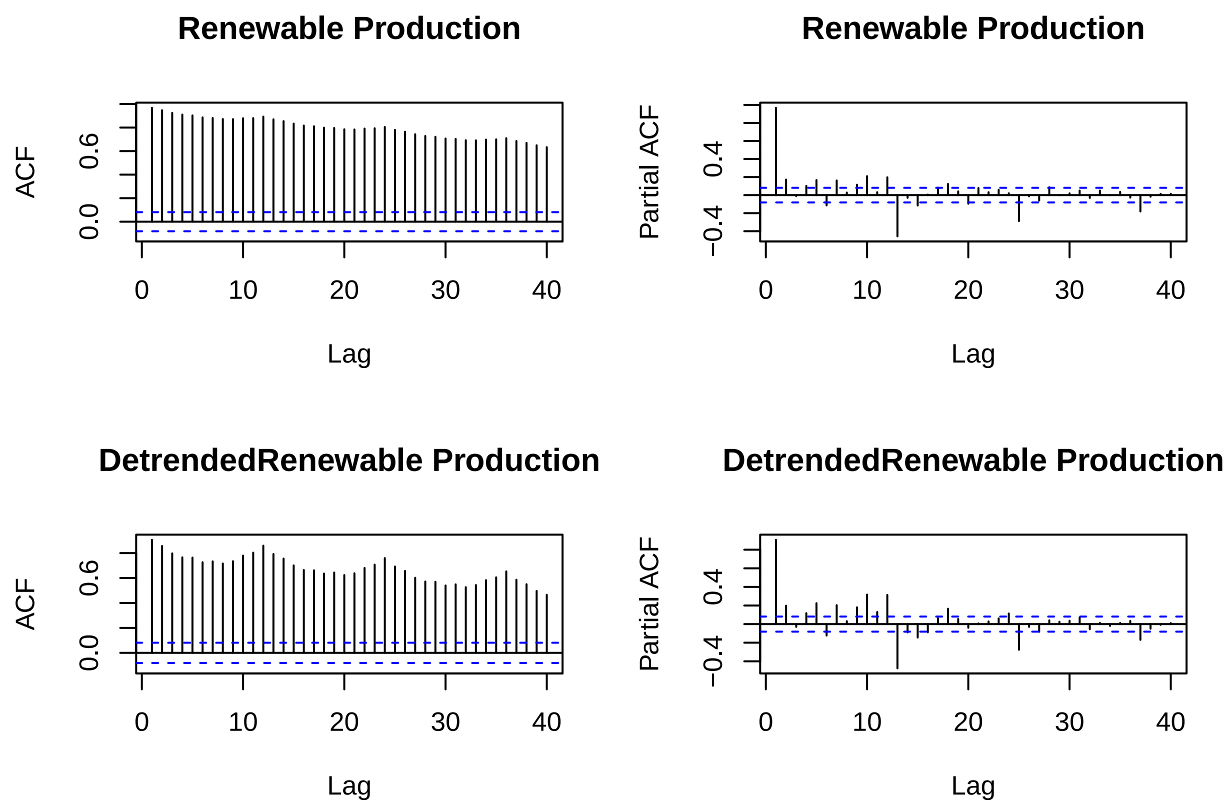
**Q5**

Plot ACF and PACF for the detrended series and compare with the plots from Q1. Did the plots change? How?

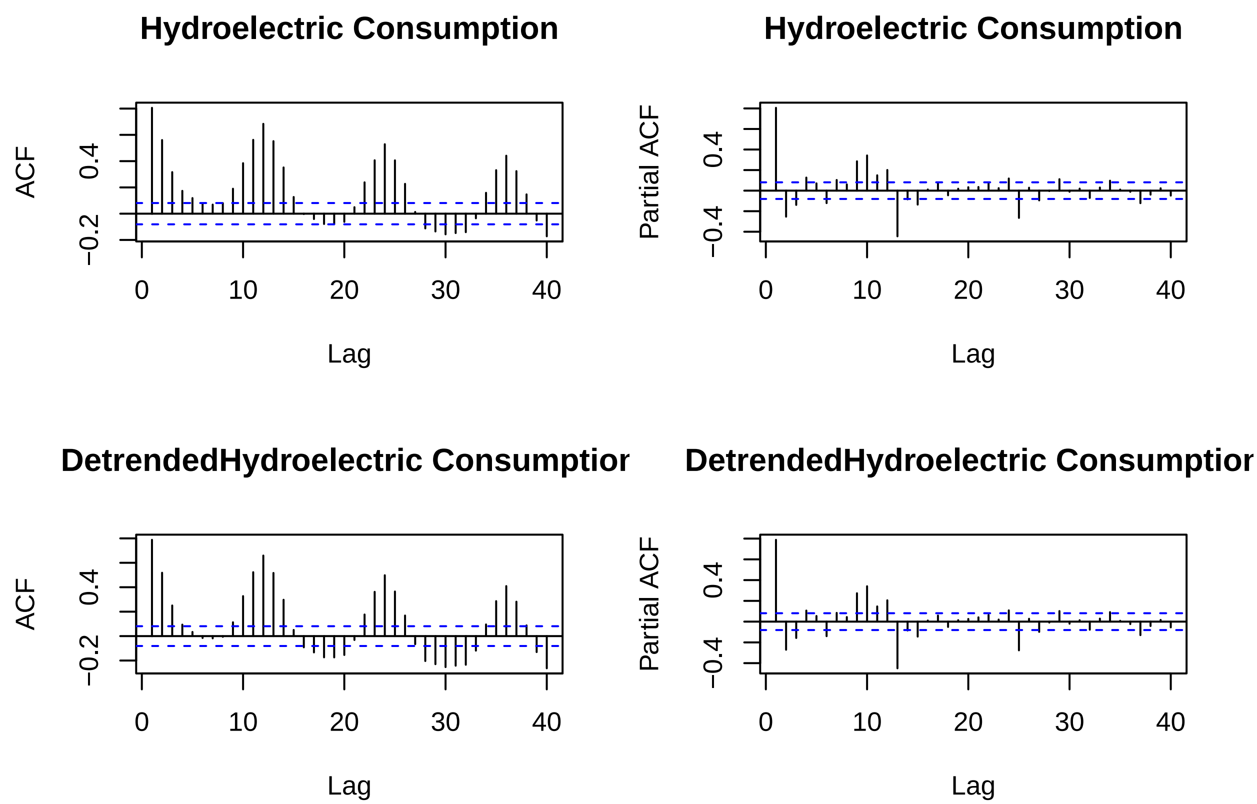
```
#biomass
par(mfrow=c(2,2))
  Acf(RE_data[,2],lag.max=40,main=colnames[1])
  Pacf(RE_data[,2],lag.max=40,main=colnames[1])
  Acf(detrend_bio,lag.max=40,main=paste("Detrended",colnames[1],sep="") )
  Pacf(detrend_bio,lag.max=40,main=paste("Detrended",colnames[1],sep="") )
```




```
#renewable
par(mfrow=c(2,2))
  Acf(RE_data[,3],lag.max=40,main=colnames[2])
  Pacf(RE_data[,3],lag.max=40,main=colnames[2])
  Acf(detrend_renew,lag.max=40,main=paste("Detrended",colnames[2],sep="") )
  Pacf(detrend_renew,lag.max=40,main=paste("Detrended",colnames[2],sep="") )
```




```
#hydro
par(mfrow=c(2,2))
  Acf(RE_data[,4],lag.max=40,main=colnames[3])
  Pacf(RE_data[,4],lag.max=40,main=colnames[3])
  Acf(detrend_hydro,lag.max=40,main=paste("Detrended",colnames[3],sep="") )
  Pacf(detrend_hydro,lag.max=40,main=paste("Detrended",colnames[3],sep="") )
```




In ACF plots of all three variables, there are greater fluctuation as ACF is decaying (i.e. the seasonality becomes more obvious), the changes in PACF plots are relatively small.

## Seasonal Component

Set aside the detrended series and consider the original series again from Q1 to answer Q6 to Q8.

### Q6

Do the series seem to have a seasonal trend? Which serie/series? Use function *lm()* to fit a seasonal means model (i.e. using the seasonal dummies) to this/these time series. Ask R to print the summary of the regression. Interpret the regression output. Save the regression coefficients for further analysis.

```
#Biomass
dummies_bio <- seasonaldummy(ts_RE_data[,1])
seas_means_model_bio=lm(RE_data[,(2)]~dummies_bio)
summary(seas_means_model_bio)
```

```
##
## Call:
## lm(formula = RE_data[, (2)] ~ dummies_bio)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -156.96  -51.40  -22.15   60.65  183.31
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)     284.241     12.962  21.928   <2e-16 ***
## dummies_bioJan   -1.498     18.238  -0.082   0.9346
## dummies_bioFeb  -30.582     18.238  -1.677   0.0941 .
## dummies_bioMar   -8.873     18.238  -0.486   0.6268
## dummies_bioApr  -21.009     18.238  -1.152   0.2498
## dummies_bioMay  -14.065     18.238  -0.771   0.4409
## dummies_bioJun  -19.601     18.238  -1.075   0.2829
## dummies_bioJul   -3.499     18.238  -0.192   0.8479
## dummies_bioAug   -0.252     18.238  -0.014   0.9890
## dummies_bioSep  -12.518     18.238  -0.686   0.4928
## dummies_bioOct   -3.629     18.331  -0.198   0.8432
## dummies_bioNov   -9.592     18.331  -0.523   0.6010
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 89.81 on 573 degrees of freedom
## Multiple R-squared:  0.01056,    Adjusted R-squared:  -0.008439
## F-statistic: 0.5557 on 11 and 573 DF,  p-value: 0.8647
```

```
beta_int_bio=seas_means_model_bio$coefficients[1]
beta_coeff_bio=seas_means_model_bio$coefficients[2:12]
```

```
#Renewable
dummies_renew <- seasonaldummy(ts_RE_data[,2])
seas_means_model_renew=lm(RE_data[,(3)]~dummies_renew)
summary(seas_means_model_renew)
```

```
##
## Call:
## lm(formula = RE_data[, (3)] ~ dummies_renew)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -272.95 -111.55  -59.35   65.68  480.41
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       589.971     25.464  23.169   <2e-16 ***
## dummies_renewJan   11.793     35.828   0.329   0.7422
## dummies_renewFeb  -40.992     35.828  -1.144   0.2530
## dummies_renewMar   21.892     35.828   0.611   0.5414
## dummies_renewApr    8.908     35.828   0.249   0.8037
## dummies_renewMay   37.500     35.828   1.047   0.2957
## dummies_renewJun   19.465     35.828   0.543   0.5871
## dummies_renewJul    8.115     35.828   0.227   0.8209
## dummies_renewAug  -18.359     35.828  -0.512   0.6086
## dummies_renewSep  -62.115     35.828  -1.734   0.0835 .
## dummies_renewOct  -51.377     36.012  -1.427   0.1542
## dummies_renewNov  -41.789     36.012  -1.160   0.2464
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 176.4 on 573 degrees of freedom
## Multiple R-squared:  0.03139,    Adjusted R-squared:  0.0128
## F-statistic: 1.688 on 11 and 573 DF,  p-value: 0.07235
```

```
beta_int_renew=seas_means_model_renew$coefficients[1]
beta_coeff_renew=seas_means_model_renew$coefficients[2:12]
```

```
#Hydroelectric
dummies_hydro <- seasonaldummy(ts_RE_data[,3])
seas_means_model_hydro=lm(RE_data[,(4)]~dummies_hydro)
summary(seas_means_model_hydro)
```

```
##
## Call:
## lm(formula = RE_data[, (4)] ~ dummies_hydro)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -90.253 -23.017  -3.042  21.487  99.478
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       237.841      4.892  48.616  < 2e-16 ***
## dummies_hydroJan   13.558      6.883   1.970  0.04936 *
## dummies_hydroFeb   -8.090      6.883  -1.175  0.24037
## dummies_hydroMar   20.067      6.883   2.915  0.00369 **
## dummies_hydroApr   16.619      6.883   2.414  0.01607 *
## dummies_hydroMay   39.961      6.883   5.805 1.06e-08 ***
## dummies_hydroJun   31.315      6.883   4.549 6.57e-06 ***
## dummies_hydroJul   10.511      6.883   1.527  0.12732
## dummies_hydroAug  -17.853      6.883  -2.594  0.00974 **
## dummies_hydroSep  -49.852      6.883  -7.242 1.43e-12 ***
## dummies_hydroOct  -48.086      6.919  -6.950 9.96e-12 ***
## dummies_hydroNov  -32.187      6.919  -4.652 4.08e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 33.89 on 573 degrees of freedom
## Multiple R-squared:  0.4182, Adjusted R-squared:  0.4071
## F-statistic: 37.45 on 11 and 573 DF,  p-value: < 2.2e-16
```

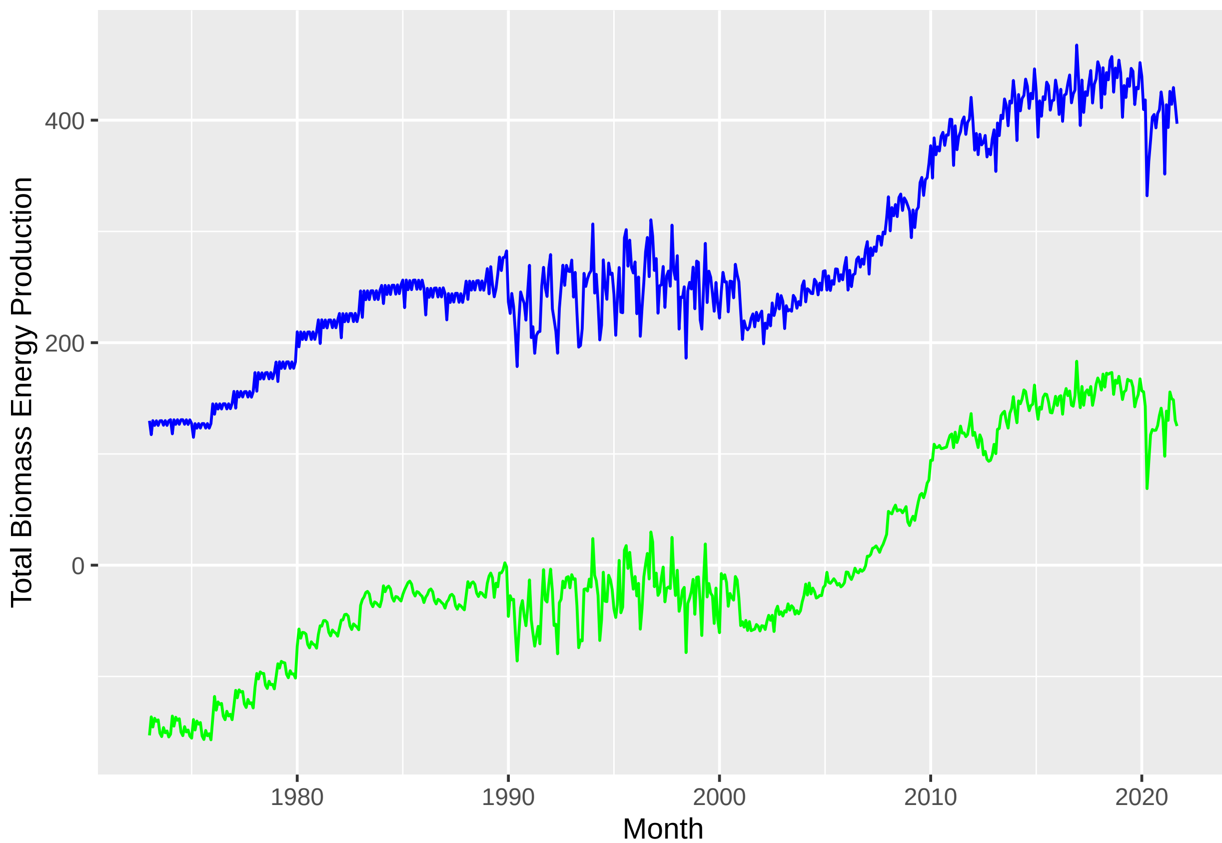
```
beta_int_hydro=seas_means_model_hydro$coefficients[1]
beta_coeff_hydro=seas_means_model_hydro$coefficients[2:12]
```

The seasonal mean models show that there is a significant seasonality for hydroelectric power consumption ($p<0.05$), while there isn't a significant seasonality for biomass energy production ($p=0.86$) or for renewable energy production ($p=0.07$).

**Q7**

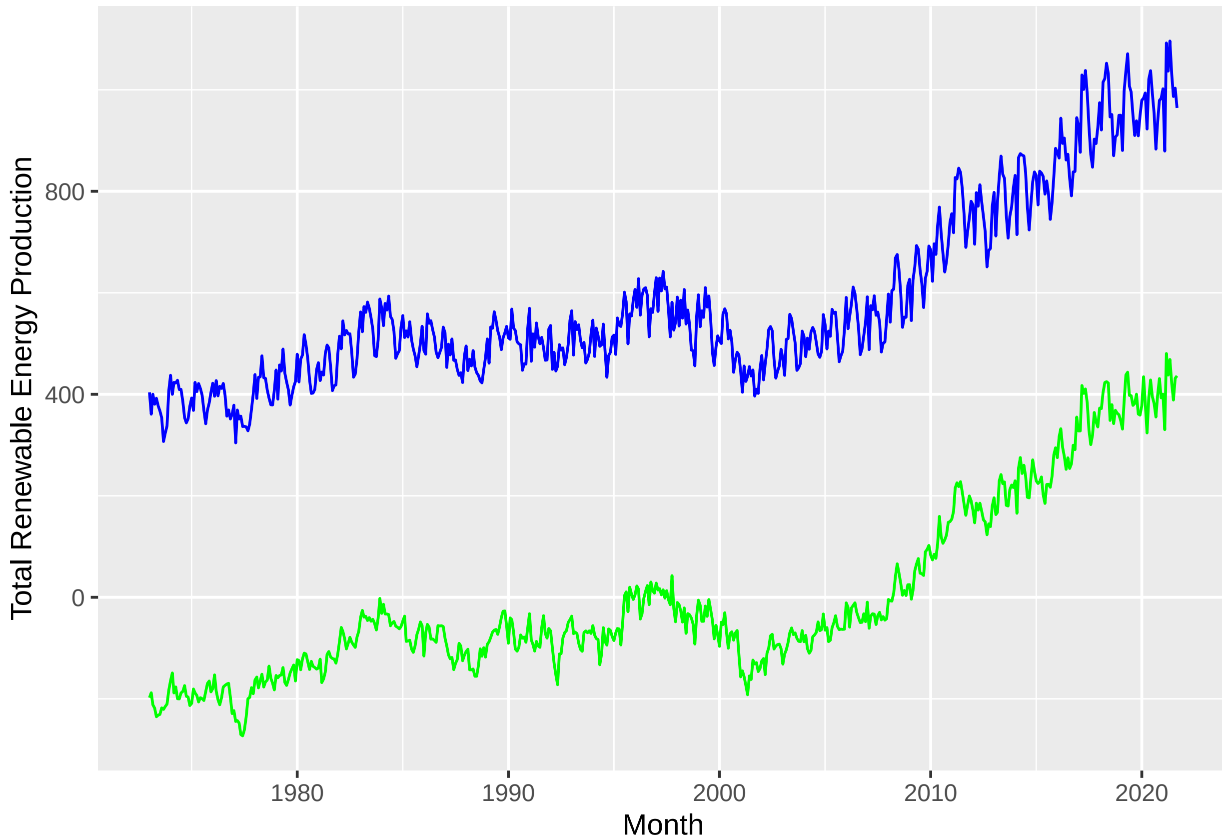
Use the regression coefficients from Q6 to deseason the series. Plot the deseason series and compare with the plots from part Q1. Did anything change?

```
#Biomass deseason
RE_seas_comp_bio=array(0,nobs)
for(i in 1:nobs){
  RE_seas_comp_bio[i]=(beta_int_bio+beta_coeff_bio%*%dummies_bio[i,])
}
deseason_RE_data_bio <- RE_data[,2]-RE_seas_comp_bio
ggplot(RE_data, aes(x=Month, y=RE_data[,2])) +
            geom_line(color="blue") +
            ylab(colnames(RE_data)[2]) +
            geom_line(aes(y=deseason_RE_data_bio), col="green")
```

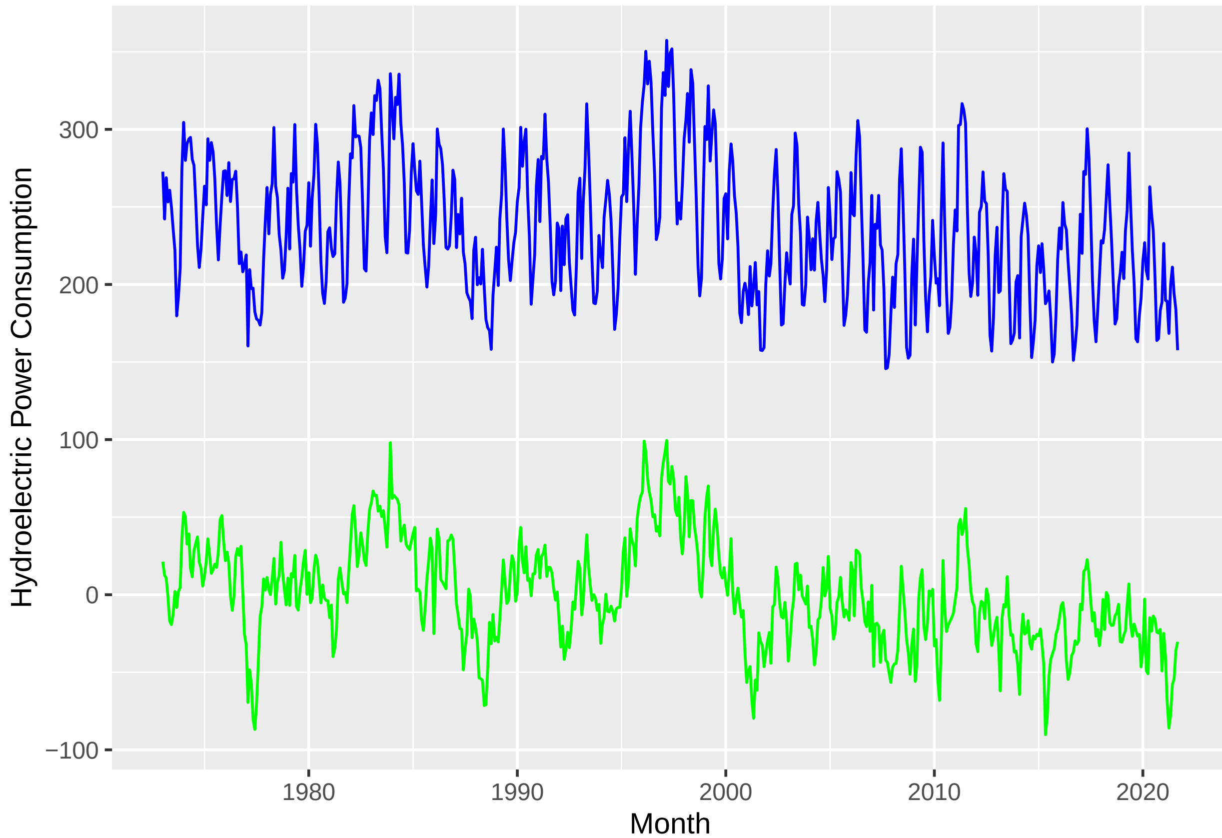



```
#Renewable
RE_seas_comp_renew=array(0,nobs)
for(i in 1:nobs){
  RE_seas_comp_renew[i]=(beta_int_renew+beta_coeff_renew%*%dummies_renew[i,])
}
deseason_RE_data_renew <- RE_data[,3]-RE_seas_comp_renew

ggplot(RE_data, aes(x=Month, y=RE_data[,3])) +
            geom_line(color="blue") +
```

```
            ylab(colnames(RE_data)[3]) +
            geom_line(aes(y=deseason_RE_data_renew), col="green")
```




```
#Hydro
RE_seas_comp_hydro=array(0,nobs)
for(i in 1:nobs){
  RE_seas_comp_hydro[i]=(beta_int_hydro+beta_coeff_hydro%*%dummies_hydro[i,])
}
deseason_RE_data_hydro <- RE_data[,4]-RE_seas_comp_hydro
ggplot(RE_data, aes(x=Month, y=RE_data[,4])) +
            geom_line(color="blue") +
            ylab(colnames(RE_data)[4]) +
            geom_line(aes(y=deseason_RE_data_hydro), col="green")
```

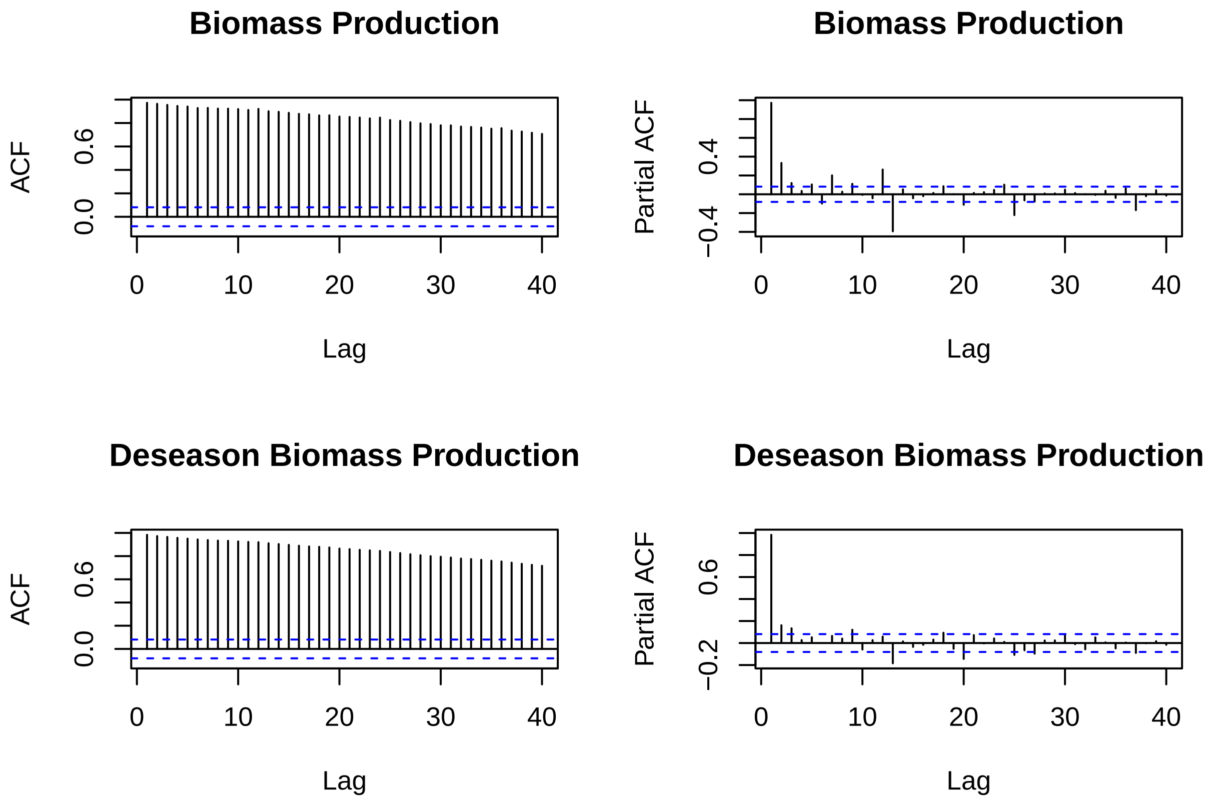



There are changes in all three variables: there are less variations between observations that within one year in the deseason series. As the variation caused by seasonality is removed, and the long-term trend is more obvious.

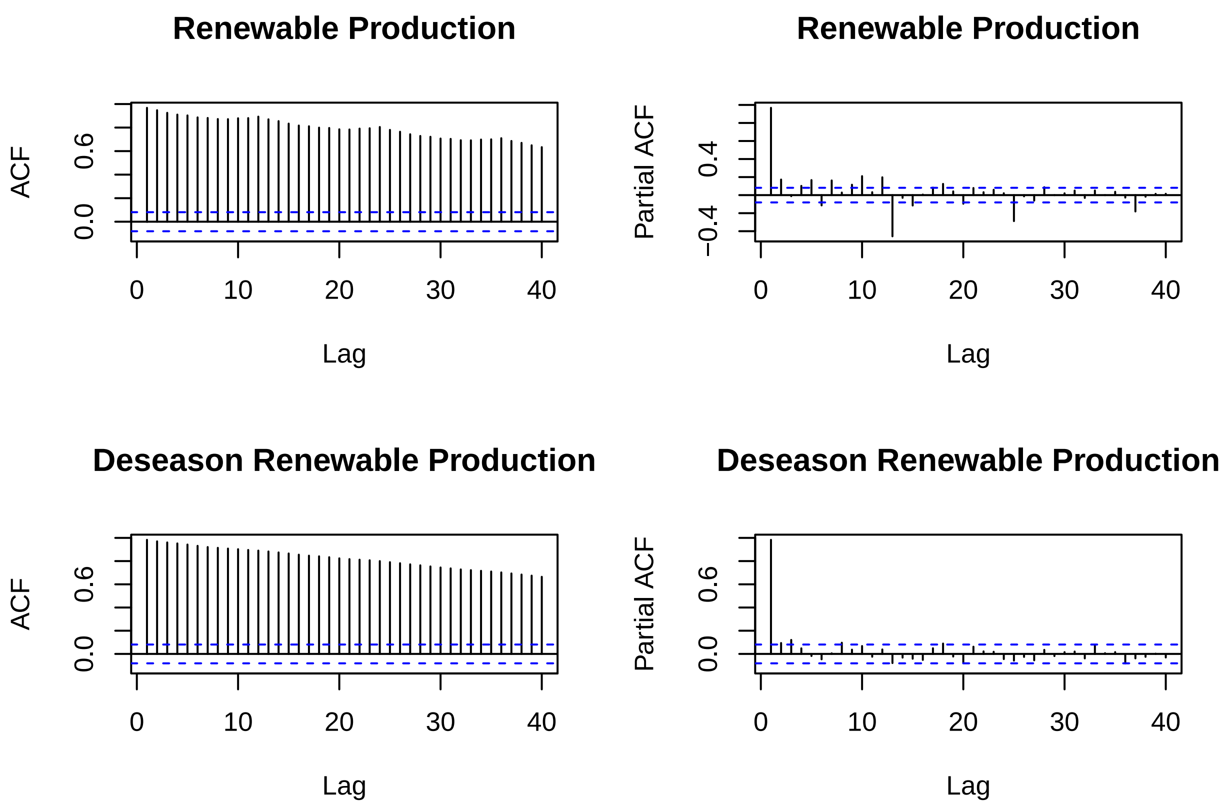
### Q8

Plot ACF and PACF for the deseason series and compare with the plots from Q1. Did the plots change? How?

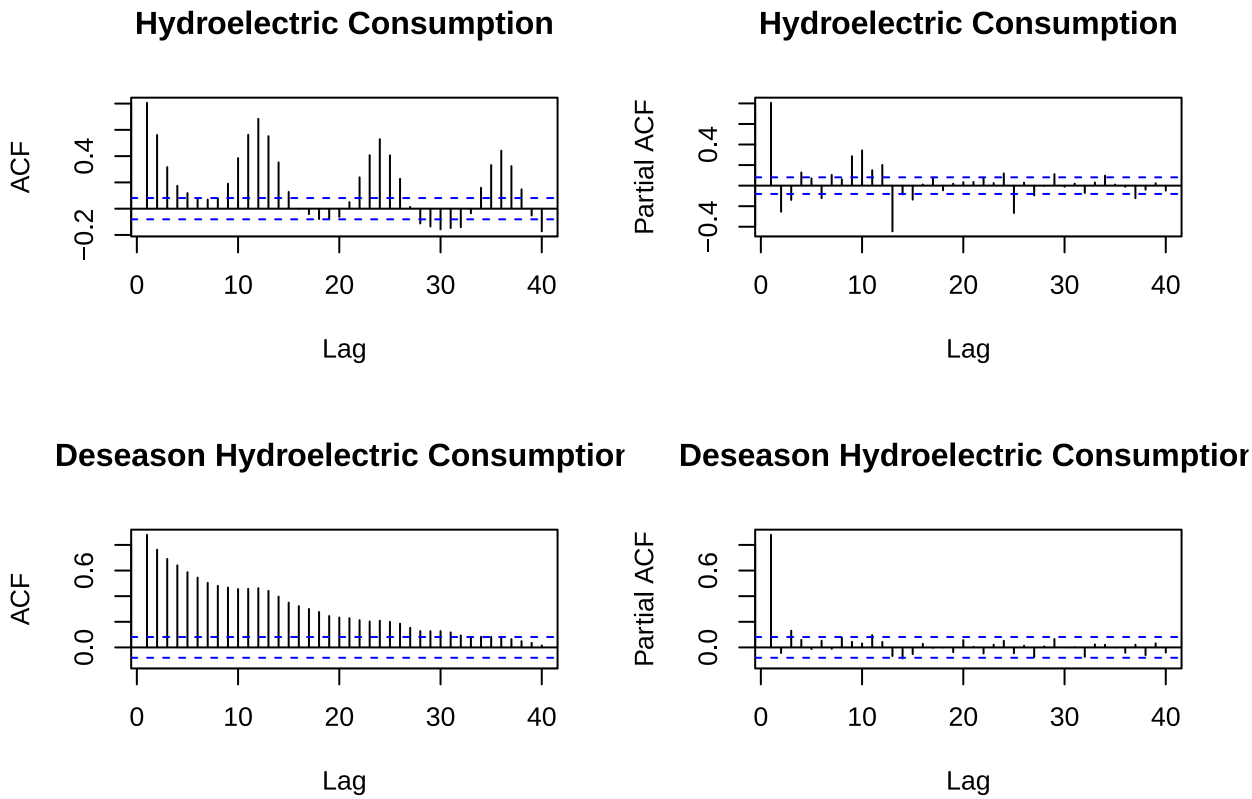
```
deseason_RE_data<-c(deseason_RE_data_bio,deseason_RE_data_renew,deseason_RE_data_hydro)
#biomass
par(mfrow=c(2,2))
  Acf(RE_data[,2],lag.max=40,main=colnames[1])
  Pacf(RE_data[,2],lag.max=40,main=colnames[1])
  Acf(deseason_RE_data_bio,lag.max=40,main=paste("Deseason ",colnames[1],sep=""))
  Pacf(deseason_RE_data_bio,lag.max=40,main=paste("Deseason ",colnames[1],sep=""))
```




```
#renewable
par(mfrow=c(2,2))
  Acf(RE_data[,3],lag.max=40,main=colnames[2])
  Pacf(RE_data[,3],lag.max=40,main=colnames[2])
  Acf(deseason_RE_data_renew,lag.max=40,main=paste("Deseason ",colnames[2],sep=""))
  Pacf(deseason_RE_data_renew,lag.max=40,main=paste("Deseason ",colnames[2],sep=""))
```




```
#hydroelectric
par(mfrow=c(2,2))
  Acf(RE_data[,4],lag.max=40,main=colnames[3])
  Pacf(RE_data[,4],lag.max=40,main=colnames[3])
  Acf(deseason_RE_data_hydro,lag.max=40,main=paste("Deseason ",colnames[3],sep=""))
  Pacf(deseason_RE_data_hydro,lag.max=40,main=paste("Deseason ",colnames[3],sep=""))
```




For biomass and renewable energy production, the seasonal mean models indicate that there is no significant seasonality, but from deseason ACF plots, we can still observe less fluctuation as ACF is decaying. For hydroelectric power consumption ACF plot, all ACF becomes positive, the ACF decays faster, and the seasonal pattern disappears. In PACF for all three variables, the significant PACF with the original data between the observations at lag=0 and at lag=12, 24, and 36 become weaker, especially for renewable production and hydroelectric consumption, those PACF values recede into the insignificant range (indicated by blue dash lines).