# ENV 790.30 - Time Series Analysis for Energy Data | Spring 2025

Assignment 3 - Due date 02/04/25

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## 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 file open on your local machine the first thing you will do is rename the file such that it includes your first and last name (e.g., "LuanaLima_TSA_A03_Sp25.Rmd"). Then change "Student Name" on line 4 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. Submit this pdf using Sakai.

## Questions

Consider the same data you used for A2 from the spreadsheet "Table_10.1_Renewable_Energy_Production_and_Consumpti The data comes from the US Energy Information and Administration and corresponds to the December 2024 **Monthly** Energy Review. Once again you will work only with the following columns: Total Renewable Energy Production and Hydroelectric Power Consumption. Create a data frame structure with these two 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)
```

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

```
library(tseries)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

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

```
library(here)
```

```
## here() starts at /home/guest/ENERGY797
```

```
library(Kendall)
library(ggplot2)
library(cowplot)

#load packages to import Excel files
library(readxl)
library(openxlsx)

#import data set
energy_data <-
  read_excel(path = "./Data/Table_10.1_Renewable_Energy_Production_and_Consumption_by_Source.xlsx",
             skip = 12, sheet = 'Monthly Data', col_names = FALSE)
```

```
## New names:
## * `` -> `...1`
## * `` -> `...2`
## * `` -> `...3`
## * `` -> `...4`
## * `` -> `...5`
## * `` -> `...6`
## * `` -> `...7`
## * `` -> `...8`
## * `` -> `...9`
## * `` -> `...10`
## * `` -> `...11`
## * `` -> `...12`
## * `` -> `...13`
## * `` -> `...14`
```

```
#extract column names
read_col_names <-
  read_excel(path="./Data/Table_10.1_Renewable_Energy_Production_and_Consumption_by_Source.xlsx",
             skip = 10,n_max = 1, sheet="Monthly Data",col_names=FALSE)
```

```
## New names:
## * `` -> `...1`
```

```
## * `` -> `...2`
## * `` -> `...3`
## * `` -> `...4`
## * `` -> `...5`
## * `` -> `...6`
## * `` -> `...7`
## * `` -> `...8`
## * `` -> `...9`
## * `` -> `...10`
## * `` -> `...11`
## * `` -> `...12`
## * `` -> `...13`
## * `` -> `...14`
```

```r
#assign column names
colnames(energy_data) <- read_col_names

#select columns
energy_df <- energy_data %>%
  select(5, 6)

#check first few rows
head(energy_df)
```

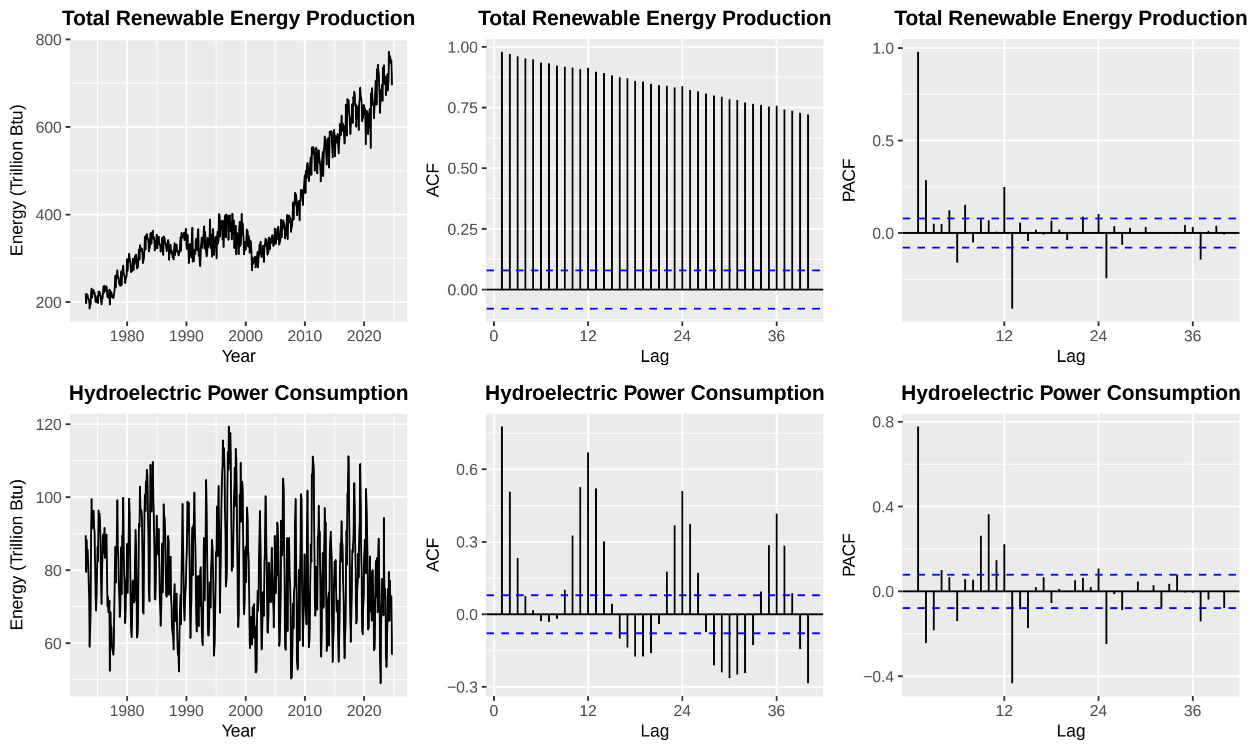
```
## # A tibble: 6 x 2
##   `Total Renewable Energy Production` `Hydroelectric Power Consumption`
##                                 <dbl>                             <dbl>
## 1                                220.                              89.6
## 2                                197.                              79.5
## 3                                219.                              88.3
## 4                                209.                              83.2
## 5                                216.                              85.6
## 6                                208.                              82.1
```

##Trend Component

**Q1**

For each time series, i.e., Renewable Energy Production and Hydroelectric Consumption create three plots: one with time series, one with the ACF and with the PACF. You may use the some code form A2, but I want all the three plots side by side as in a grid. (Hint: use function `plot_grid()` from the `cowplot` package)

```r
#transform data frame to time series object
ts_energy <- ts(energy_df, start = c(1973,1), frequency = 12)

#create lists to store plots for Renewable Energy Production and Hydroelectric Power Consumption
time_series_plots <- list()
acf_plots <- list()
pacf_plots <- list()

#loop through both columns
for (i in 1:2) {
  #time series
  time_series_plots[[i]] <- autoplot(ts_energy[, i]) +
    ggtitle(colnames(ts_energy)[i]) +
    xlab('Year') +
    ylab('Energy (Trillion Btu)') +
    theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 12),
          axis.title.x = element_text(size = 10),
          axis.title.y = element_text(size = 10))

  #ACF
  acf_plots[[i]] <- autoplot(Acf(ts_energy[, i], lag.max = 40, plot = FALSE)) +
    ggtitle(paste(colnames(ts_energy)[i])) +
    theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 12),
          axis.title.x = element_text(size = 10),
          axis.title.y = element_text(size = 10))

  #PACF
  pacf_plots[[i]] <- autoplot(Pacf(ts_energy[, i], lag.max = 40, plot = FALSE)) +
    ggtitle(paste(colnames(ts_energy)[i])) +
    theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 12),
          axis.title.x = element_text(size = 10),
          axis.title.y = element_text(size = 10))
}

#combine all plots in a grid
combined_plots <- plot_grid(
  time_series_plots[[1]], acf_plots[[1]], pacf_plots[[1]],
  time_series_plots[[2]], acf_plots[[2]], pacf_plots[[2]],
  ncol = 3, align = "v"
)

print(combined_plots)
```




## Q2

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

There is an overall rising trend in energy production from renewable energy sources in the last 50 years. However, there is no overall trend for hydroelectric power consumption in the last 50 years - instead, there are fluctuations throughout the time period.

## Q3

Use the *lm()* function to fit a linear trend to the two 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.

```
#create a time vector
nobs <- nrow(ts_energy)
t <- 1:nobs

#initialize lists to store results
linear_models <- list()
coefficients_list <- list()

for (i in 1:2) {
  #fit a linear trend model for each time series
  linear_models[[i]] <- lm(ts_energy[, i] ~ t)

  #print the summary of the regression
```

```r
  print(summary(linear_models[[i]]))

  #store the coefficients
  beta0 <- as.numeric(linear_models[[i]]$coefficients[1])  #intercept
  beta1 <- as.numeric(linear_models[[i]]$coefficients[2])  #slope

  #save the coefficients
  coefficients_list[[colnames(ts_energy)[i]]] <- c(Intercept = beta0, Slope = beta1)
}
```

```
##
## Call:
## lm(formula = ts_energy[, i] ~ t)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -151.11  -37.84   13.53   41.76  149.42
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 176.87293    4.96189   35.65   <2e-16 ***
## t             0.72393    0.01382   52.37   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 61.75 on 619 degrees of freedom
## Multiple R-squared:  0.8159, Adjusted R-squared:  0.8156
## F-statistic:  2743 on 1 and 619 DF,  p-value: < 2.2e-16
##
##
## Call:
## lm(formula = ts_energy[, i] ~ t)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -29.995 -10.422  -0.720   9.161  39.624
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 82.96766    1.12339  73.855  < 2e-16 ***
## t           -0.01098    0.00313  -3.508 0.000485 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.98 on 619 degrees of freedom
## Multiple R-squared:  0.01949,    Adjusted R-squared:  0.01791
## F-statistic:  12.3 on 1 and 619 DF,  p-value: 0.0004848
```

```r
#print the coefficients for both time series
coefficients_list
```

```
## $`Total Renewable Energy Production`
##   Intercept       Slope
```

```
## 176.8729264   0.7239349
##
## $`Hydroelectric Power Consumption`
##   Intercept       Slope
## 82.96766541 -0.01097734
```

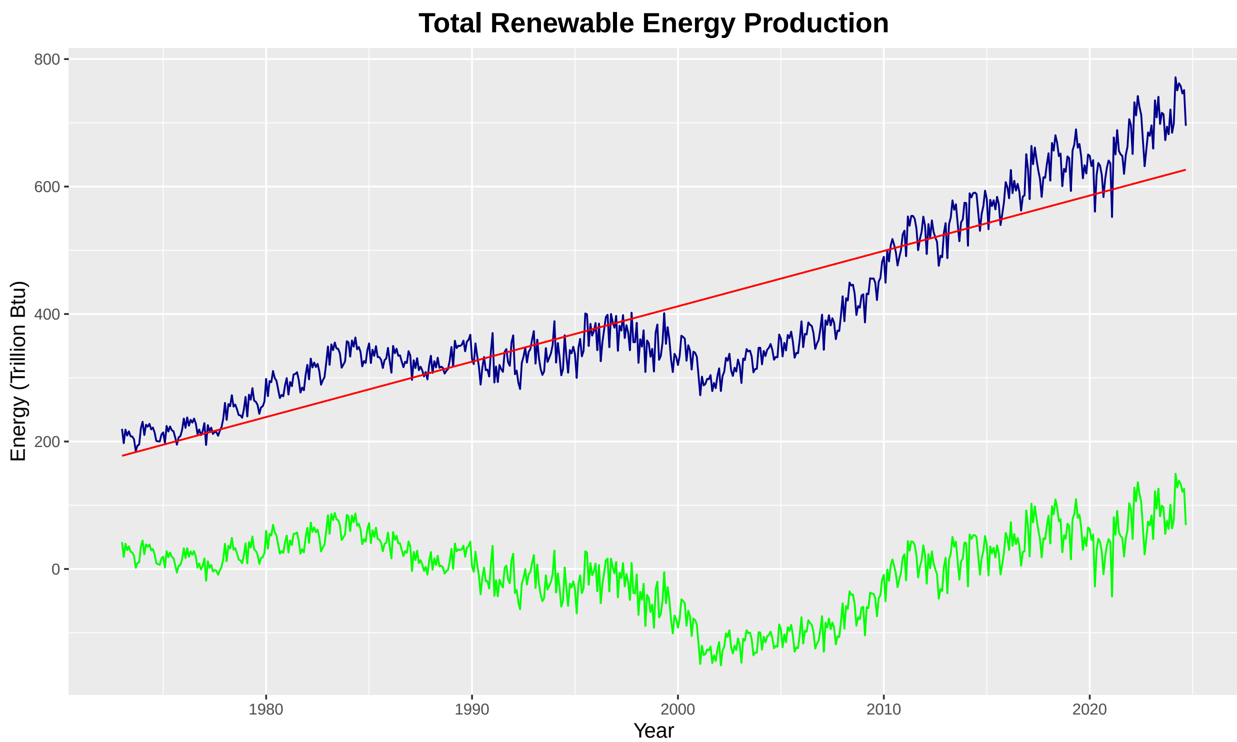
According to the summary of the regression of both time series, in January 1973 (when t = 0), total renewable energy production and hydroelectric power consumption were approximately 177 and 83 trillion Btu (these are the intercept values, beta0), respectively. For each additional month, total renewable energy production increased by approximately 0.72 trillion Btu and hydroelectric consumption decreased by approximately 0.01 trillion Btu. These changes per month are the slopes, or beta1, of each time series.

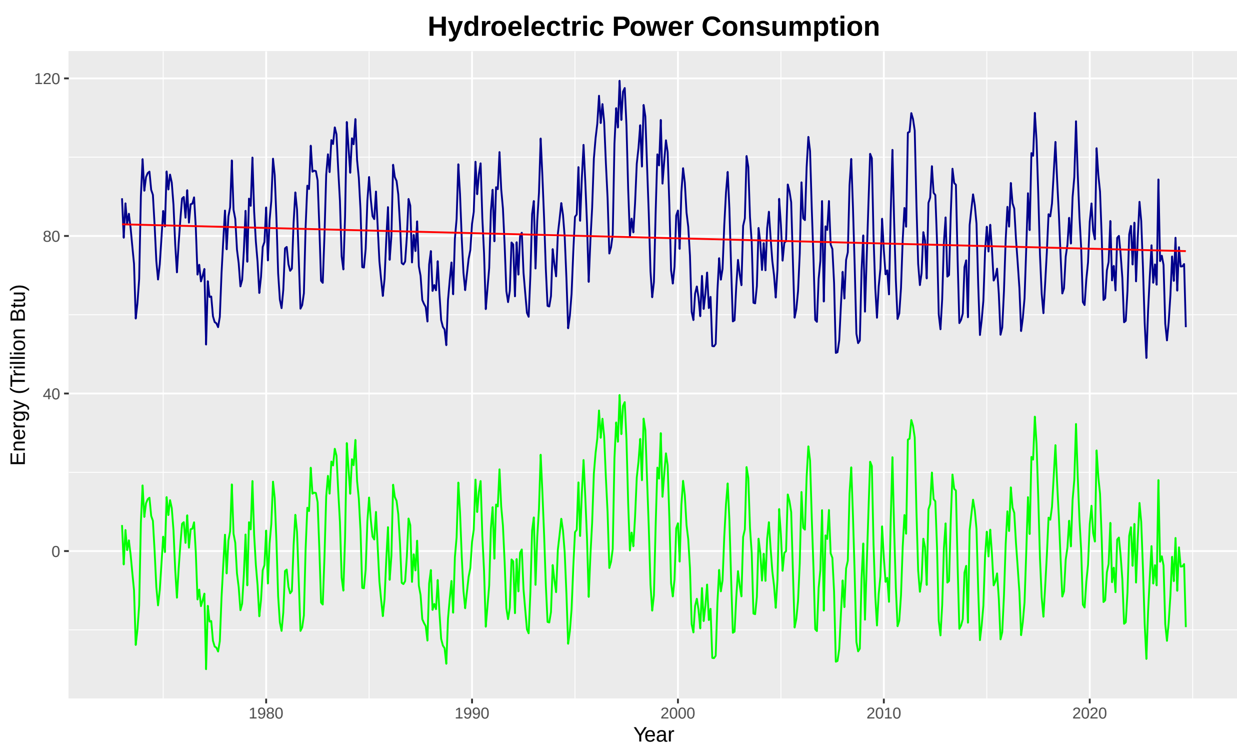
### Q4

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?

```r
#initialize list to store detrended series
ts_detrended_list <- list()

for (i in 1:2) {
  #calculate the linear trend using the regression coefficients (beta0, beta1)
  linear_trend <- coefficients_list[[colnames(ts_energy)[i]]][1] +
    coefficients_list[[colnames(ts_energy)[i]]][2] * t

  #create a time series object for the linear trend
  ts_linear <- ts(linear_trend, start = c(1973, 1), frequency = 12)

  #detrend the time series by subtracting the linear trend from the original series
  detrended_series <- ts_energy[, i] - linear_trend

  #create a time series object for the detrended series
  ts_detrended <- ts(detrended_series, start = c(1973, 1), frequency = 12)

  #store the detrended series for later plotting
  ts_detrended_list[[colnames(ts_energy)[i]]] <- ts_detrended

  #store linear trends
  linear_models[[colnames(ts_energy)[i]]] <- ts_linear
}


#plot the original time series and detrended series for comparison
for (i in 1:2) {
  print(
    autoplot(ts_energy[, i], color = "darkblue") +
      autolayer(ts_detrended_list[[colnames(ts_energy)[i]]], color = "green") +
      autolayer(linear_models[[colnames(ts_energy)[i]]],color="red") +
      ggtitle(paste(colnames(ts_energy)[i])) +
      xlab("Year") +
      ylab("Energy (Trillion Btu)") +
      theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 16),
            axis.title.x = element_text(size = 12),
```

```
            axis.title.y = element_text(size = 12))
  )
}
```



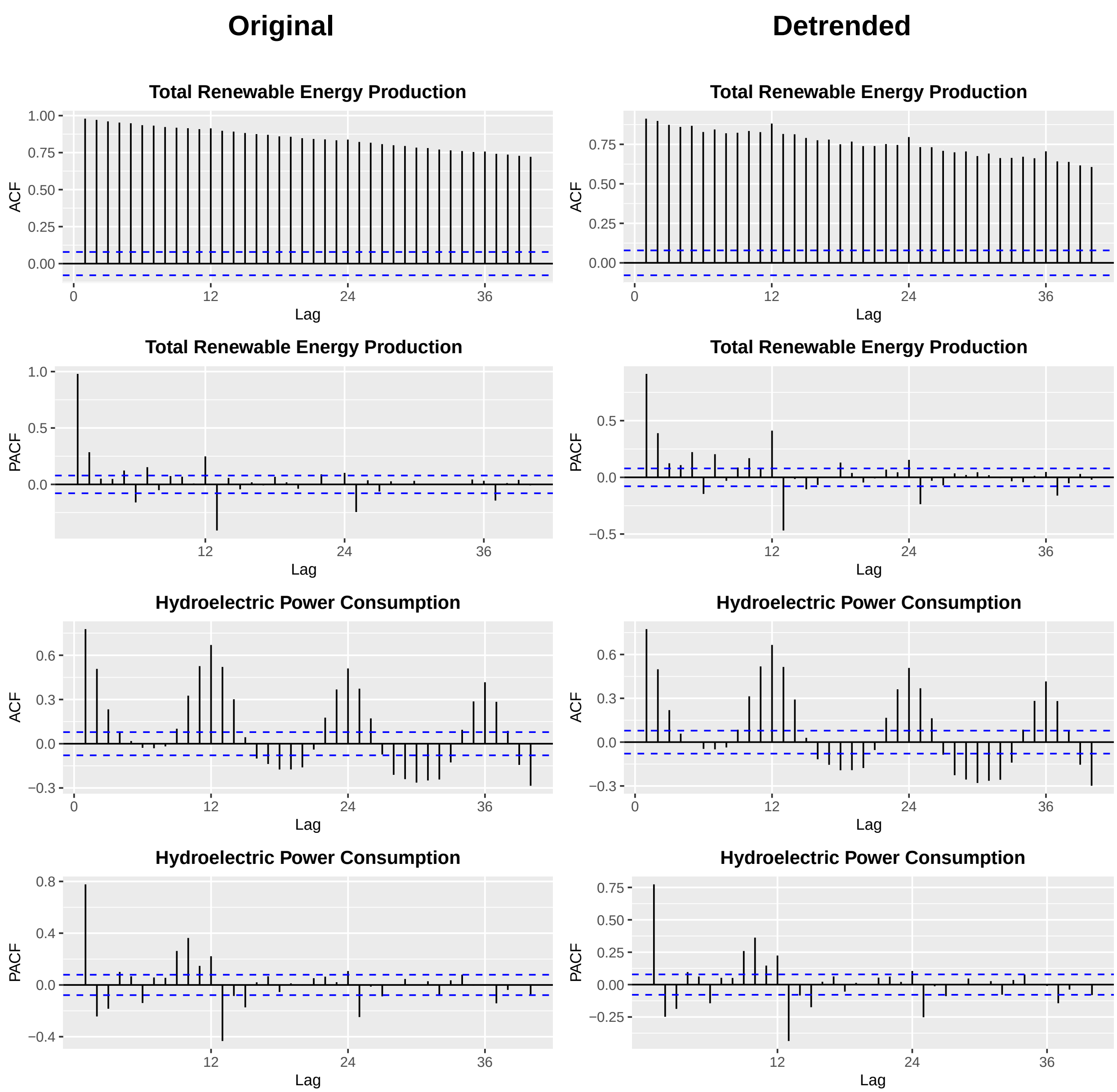
Compared to its time series plot from Q1, the detrended plot for Total Renewable Energy Production appears to have lost its overall increasing trend. In contrast, the fluctuations are still present in the detrended plot for Hydroelectric Power Consumption, when compared to its time series plot from Q1.

## Q5

Plot ACF and PACF for the detrended series and compare with the plots from Q1. You may use plot_grid() again to get them side by side, but not mandatory. Did the plots change? How?

```
#create lists to store detrended ACF and PACF detrended plots
acf_plots_detrended <- list()
pacf_plots_detrended <- list()

for (i in 1:2) {
  #ACF for detrended series
  acf_plots_detrended[[i]] <- autoplot(Acf(ts_detrended_list[[colnames(ts_energy)[i]]],
                                           lag.max = 40, plot = FALSE)) +
    ggtitle(paste(colnames(ts_energy)[i])) +
    theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 12),
          axis.title.x = element_text(size = 10),
          axis.title.y = element_text(size = 10))

  #PACF for detrended series
  pacf_plots_detrended[[i]] <- autoplot(Pacf(ts_detrended_list[[colnames(ts_energy)[i]]],
                                             lag.max = 40, plot = FALSE)) +
    ggtitle(paste(colnames(ts_energy)[i])) +
    theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 12),
          axis.title.x = element_text(size = 10),
          axis.title.y = element_text(size = 10))
}

#combine all plots in a grid: ACF and PACF for original time series and detrended
combined_plots2 <- cowplot::plot_grid(
 plot_grid(
    acf_plots[[1]], acf_plots_detrended[[1]],
    pacf_plots[[1]], pacf_plots_detrended[[1]],
    acf_plots[[2]], acf_plots_detrended[[2]],
    pacf_plots[[2]], pacf_plots_detrended[[2]],
    ncol = 2, align = "v"
  ))

#combine all plots in a grid: ACF and PACF for original time series and detrended
cowplot_titles2 <- cowplot::plot_grid(
  ggdraw() + draw_label("Original", fontface = 'bold', size = 18),
  ggdraw() + draw_label("Detrended", fontface = 'bold', size = 18),
  ncol = 2
)

combined_plots2 <- cowplot::plot_grid(
  cowplot_titles2,
  plot_grid(
    acf_plots[[1]], acf_plots_detrended[[1]],
    pacf_plots[[1]], pacf_plots_detrended[[1]],
```

```
    acf_plots[[2]], acf_plots_detrended[[2]],
    pacf_plots[[2]], pacf_plots_detrended[[2]],
    ncol = 2
  ),
  ncol = 1, rel_heights = c(0.1, 1)
)

print(combined_plots2)
```




After detrending the series for Total Renewable Energy Production and Hydroelectric Power Consumption, it looks like the ACF and PACF plots did not change very much. There are no major visible differences in their plots compared to those from Q1. However, regarding Total Renewable Energy Production, there seems to be a minor spike every 12 months in its detrended ACF plot, suggesting some kind of seasonality present.

## Seasonal Component

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

### Q6

Just by looking at the time series and the acf plots, do the series seem to have a seasonal trend? No need to run any code to answer your question. Just type in you answer below.

According to the time series and the acf plots, only the Hydroelectric Power Consumption series appears to have a seasonal trend due to the fluctuations and peak values lagged at regular intervals.

### Q7

Use function *lm()* to fit a seasonal means model (i.e. using the seasonal dummies) the two time series. Ask R to print the summary of the regression. Interpret the regression output. From the results which series have a seasonal trend? Do the results match you answer to Q6?

```r
#seasonal dummies separately for each time series
dummies_renewable <- seasonaldummy(ts_energy[, 1])
dummies_hydro <- seasonaldummy(ts_energy[, 2])

#fit seasonal models for each time series
seasonal_model_renewable <- lm(ts_energy[, 1] ~ dummies_renewable)
seasonal_model_hydro <- lm(ts_energy[, 2] ~ dummies_hydro)

summary(seasonal_model_renewable)
```

```
##
## Call:
## lm(formula = ts_energy[, 1] ~ dummies_renewable)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -205.65  -91.59  -54.59  117.87  356.19
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)           410.598     20.228  20.299   <2e-16 ***
## dummies_renewableJan    1.973     28.468   0.069    0.945
## dummies_renewableFeb  -34.348     28.468  -1.207    0.228
## dummies_renewableMar    4.721     28.468   0.166    0.868
## dummies_renewableApr   -7.896     28.468  -0.277    0.782
## dummies_renewableMay    7.199     28.468   0.253    0.800
## dummies_renewableJun   -3.394     28.468  -0.119    0.905
## dummies_renewableJul    2.850     28.468   0.100    0.920
## dummies_renewableAug   -4.430     28.468  -0.156    0.876
## dummies_renewableSep  -29.037     28.468  -1.020    0.308
## dummies_renewableOct  -20.205     28.606  -0.706    0.480
## dummies_renewableNov  -20.706     28.606  -0.724    0.469
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 144.5 on 609 degrees of freedom
## Multiple R-squared:  0.008696,   Adjusted R-squared:  -0.009209
## F-statistic: 0.4857 on 11 and 609 DF,  p-value: 0.9126
```

```r
summary(seasonal_model_hydro)
```

```
##
## Call:
## lm(formula = ts_energy[, 2] ~ dummies_hydro)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -31.101  -6.241  -0.444   6.410  32.363
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)        79.981      1.452  55.094  < 2e-16 ***
## dummies_hydroJan    4.941      2.043   2.418 0.015880 *
## dummies_hydroFeb   -2.513      2.043  -1.230 0.219219
## dummies_hydroMar    7.053      2.043   3.452 0.000595 ***
## dummies_hydroApr    5.399      2.043   2.642 0.008441 **
## dummies_hydroMay   13.907      2.043   6.807 2.40e-11 ***
## dummies_hydroJun   10.729      2.043   5.251 2.09e-07 ***
## dummies_hydroJul    4.033      2.043   1.974 0.048845 *
## dummies_hydroAug   -5.399      2.043  -2.643 0.008436 **
## dummies_hydroSep  -16.596      2.043  -8.123 2.54e-15 ***
## dummies_hydroOct  -16.370      2.053  -7.973 7.66e-15 ***
## dummies_hydroNov  -10.805      2.053  -5.263 1.97e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.37 on 609 degrees of freedom
## Multiple R-squared:  0.4695, Adjusted R-squared:  0.4599
## F-statistic:    49 on 11 and 609 DF,  p-value: < 2.2e-16
```

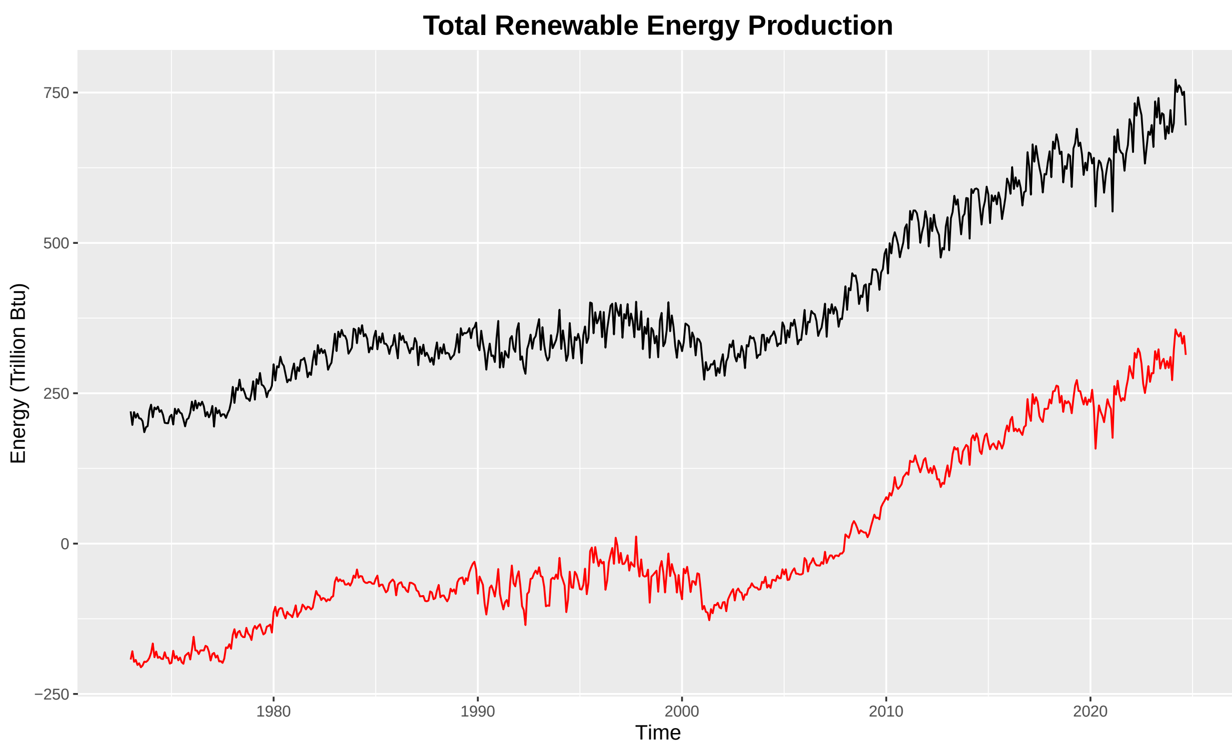
According to the regression output, only the Hydroelectric Power Consumption series seems to have a seasonal trend, because the p-value for this series is less than 0.05. In contrast, the p-value for the Total Renewable Energy Production series is not less than 0.05, so there is no significance for this series. These results match with the answer to Q6.

### Q8

Use the regression coefficients from Q7 to deseason the series. Plot the deseason series and compare with the plots from part Q1. Did anything change?

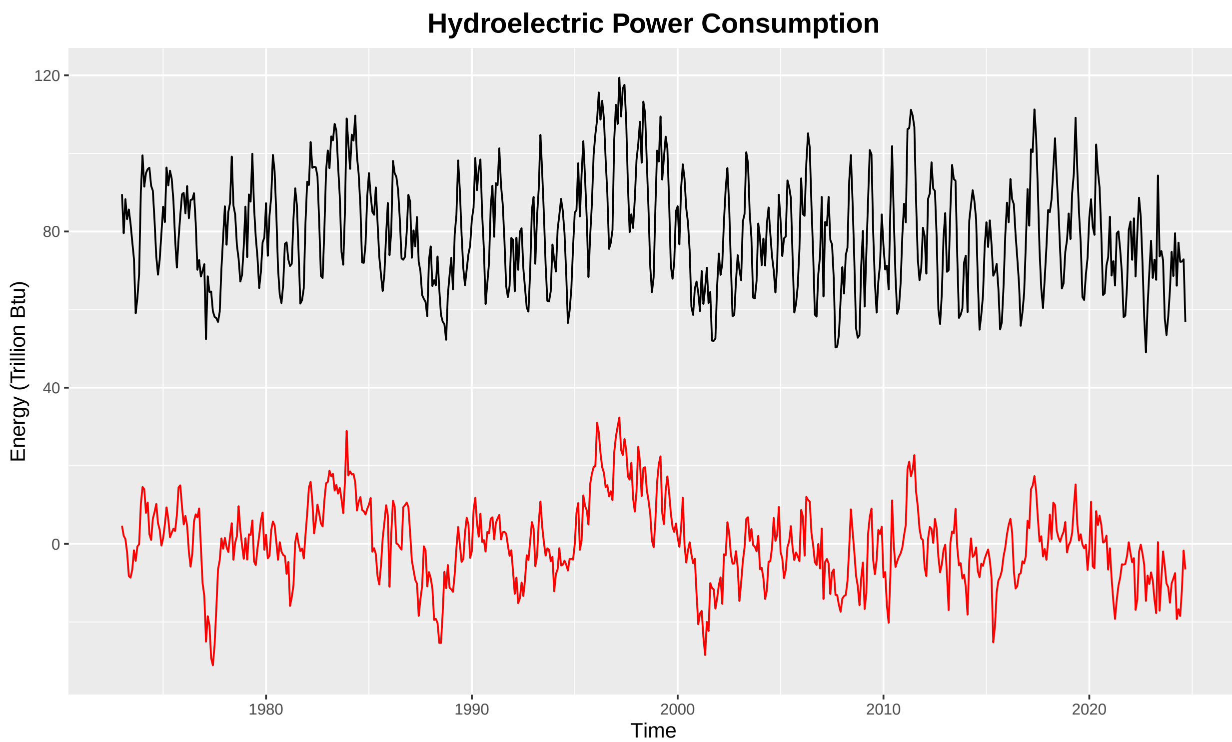
```r
#deseason Total Renewable Energy Production
beta0_seasonal_renew <- seasonal_model_renewable$coefficients[1]
beta1_seasonal_renew <- seasonal_model_renewable$coefficients[2:12]

seas_comp_renew <- array(0,nobs)
for(i in 1:nobs){
  seas_comp_renew[i] <- beta0_seasonal_renew + beta1_seasonal_renew %*% dummies_renewable[i,]
```

```
}

deseason_renew <- ts_energy[,1] - seas_comp_renew

ts_deseason_renew <- ts(deseason_renew, start=start(ts_energy), frequency = 12)

autoplot(ts_energy[,1]) +
  autolayer(ts_deseason_renew,color="red") +
  ggtitle(paste(colnames(ts_energy)[1])) +
  ylab("Energy (Trillion Btu)") +
  theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 16),
        axis.title.x = element_text(size = 12),
        axis.title.y = element_text(size = 12))
```




```
#deseason Hydroelectric Power Consumption
beta0_seasonal_hydro <- seasonal_model_hydro$coefficients[1]
beta1_seasonal_hydro <- seasonal_model_hydro$coefficients[2:12]

seas_comp_hydro <- array(0,nobs)
for(i in 1:nobs){
  seas_comp_hydro[i] <- beta0_seasonal_hydro + beta1_seasonal_hydro %*% dummies_hydro[i,]
}

deseason_hydro <- ts_energy[,2] - seas_comp_hydro

ts_deseason_hydro <- ts(deseason_hydro, start=start(ts_energy), frequency = 12)

autoplot(ts_energy[,2]) +
  autolayer(ts_deseason_hydro,color="red") +
```

```
  ggtitle(paste(colnames(ts_energy)[2])) +
  ylab("Energy (Trillion Btu)") +
  theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 16),
        axis.title.x = element_text(size = 12),
        axis.title.y = element_text(size = 12))
```



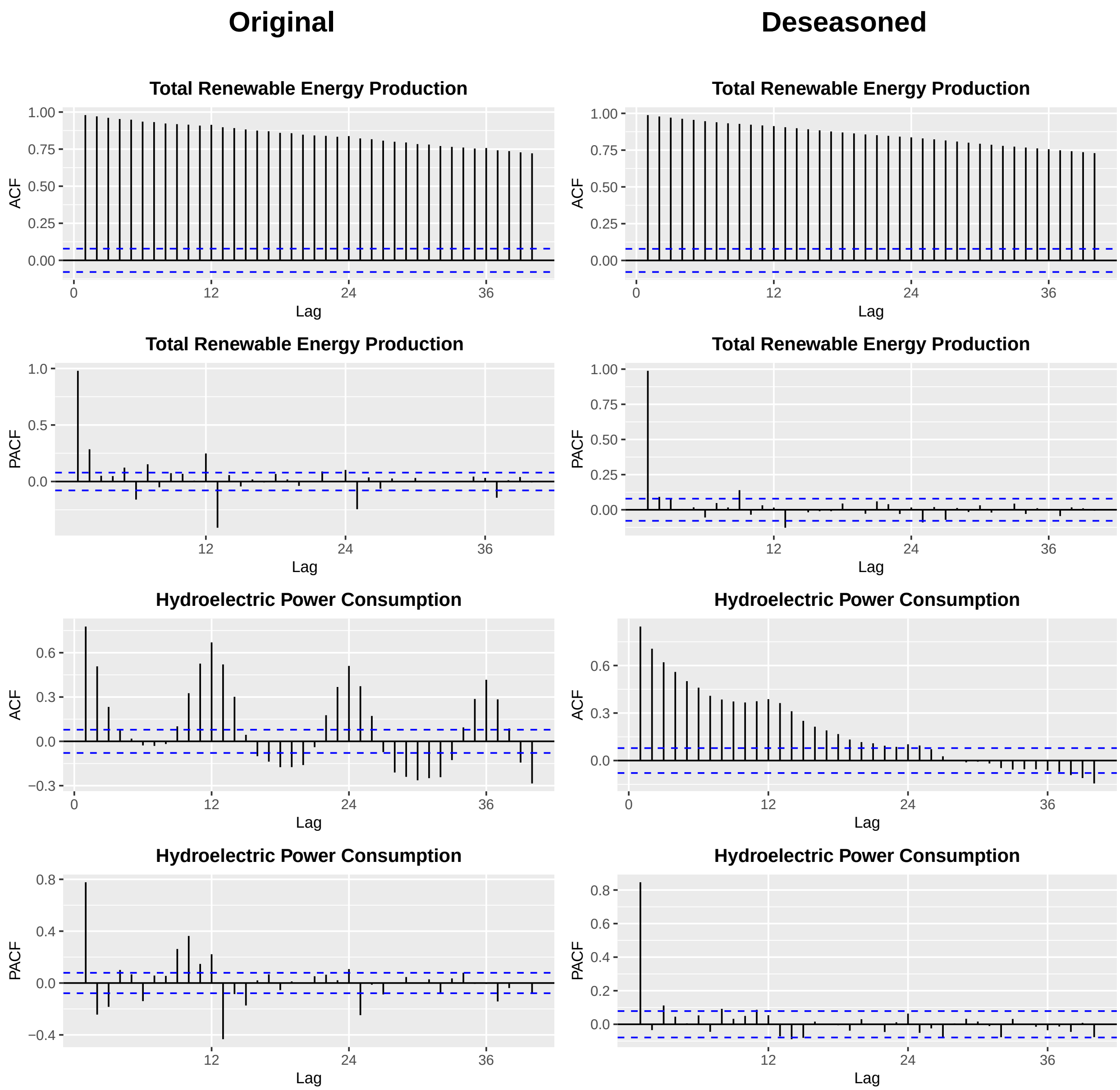

Compared with its plot from Q1, the Total Renewable Energy Production deseasoned series did not change much, which provides more evidence to this series lacking seasonality. On the other hand, when compared with its plot from Q1, the Hydroelectric Power Consumption series has fewer fluctuations in its deseasoned plot, which supports the hypothesis that this series, before being deseasoned, does have a seasonal component.

### Q9

Plot ACF and PACF for the deseason series and compare with the plots from Q1. You may use plot_grid() again to get them side by side, but not mandatory. Did the plots change? How?

```
ts_deseason_list <- list()

ts_deseason_list[[1]] <- ts_deseason_renew
ts_deseason_list[[2]] <- ts_deseason_hydro

acf_plots_deseasoned <- list()
pacf_plots_deseasoned <- list()

for (i in 1:2) {
  #ACF for deseasoned series
  acf_plots_deseasoned[[i]] <- autoplot(Acf(ts_deseason_list[[i]],
                                            lag.max = 40, plot = FALSE)) +
```

```r
    ggtitle(paste(colnames(ts_energy)[i])) +
    theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 12),
          axis.title.x = element_text(size = 10),
          axis.title.y = element_text(size = 10))

  #PACF for deseasoned series
  pacf_plots_deseasoned[[i]] <- autoplot(Pacf(ts_deseason_list[[i]],
                                              lag.max = 40, plot = FALSE)) +
    ggtitle(paste(colnames(ts_energy)[i])) +
    theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 12),
          axis.title.x = element_text(size = 10),
          axis.title.y = element_text(size = 10))
}

#combine all plots in a grid: ACF and PACF for original time series and deseasoned
cowplot_titles3 <- cowplot::plot_grid(
  ggdraw() + draw_label('Original', fontface = 'bold', size = 18),
  ggdraw() + draw_label('Deseasoned', fontface = 'bold', size = 18),
  ncol = 2
)

combined_plots3 <- cowplot::plot_grid(
  cowplot_titles3,
  plot_grid(
    acf_plots[[1]], acf_plots_deseasoned[[1]],
    pacf_plots[[1]], pacf_plots_deseasoned[[1]],
    acf_plots[[2]], acf_plots_deseasoned[[2]],
    pacf_plots[[2]], pacf_plots_deseasoned[[2]],
    ncol = 2
  ),
  ncol = 1, rel_heights = c(0.1, 1)
)

print(combined_plots3)
```




There are no visible changes for the ACF plot of the Total Renewable Energy Production series. The minor spikes at intervals of 12 months seen in its original PACF plot disappeared, however. The fluctuations and spikes (in positive and negative magnitudes) of the original ACF plot of the Hydroelectric Power Consumption series disappeared. Instead, in its deseasoned ACF plot, there is a gradual decline in significance until a sudden minor spike at lag 12, after which the correlation continues to decrease as the lags increase. For this series, the peaks in signifance at regular 12-month intervals disappeared in the deseasoned PACF plot. The very visible and pronounced changes in the deseasoned ACF and PACF plots of this second series suggest, again, that the series is characterized by seasonality.