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

Assignment 5 - Due date 02/28/22

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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. And to do so you will need to fork our repository and link it to your RStudio.

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).

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_A05_Sp22.Rmd"). Submit this pdf using Sakai.

R packages needed for this assignment are listed below. 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(xlsx)
library(forecast)
```

```
## Warning: package 'forecast' was built under R version 4.1.2

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

```
library(tseries)
library(ggplot2)
library(Kendall)
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

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

```
library(tidyverse)  #load this package so yon clean the data frame using pipes
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v tibble  3.1.4     v dplyr   1.0.7
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   2.0.1     v forcats 0.5.1
## v purrr   0.3.4
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x lubridate::as.difftime() masks base::as.difftime()
## x lubridate::date()        masks base::date()
## x dplyr::filter()          masks stats::filter()
## x lubridate::intersect()   masks base::intersect()
## x dplyr::lag()             masks stats::lag()
## x lubridate::setdiff()     masks base::setdiff()
## x lubridate::union()       masks base::union()
```

Decomposing Time Series

Consider the same data you used for A04 from the spreadsheet "Table_10.1_Renewable_Energy_Production_and_Consumptio
The data comes from the US Energy Information and Administration and corresponds to the January 2021 Monthly Energy Review.

```r
#Importing data set - using xlsx package
energy_data <- read.xlsx(file="/Users/emreyurtbay/Documents/Duke/env790/ENV790_TimeSeriesAnalysis_Sp202

#Now let's extract the column names from row 11 only
read_col_names <- read.xlsx(file="/Users/emreyurtbay/Documents/Duke/env790/ENV790_TimeSeriesAnalysis_Sp

colnames(energy_data) <- read_col_names
head(energy_data)
```

```
##        Month Wood Energy Production Biofuels Production
## 1 1973-01-01                129.630       Not Available
## 2 1973-02-01                117.194       Not Available
## 3 1973-03-01                129.763       Not Available
## 4 1973-04-01                125.462       Not Available
## 5 1973-05-01                129.624       Not Available
## 6 1973-06-01                125.435       Not Available
##   Total Biomass Energy Production Total Renewable Energy Production
## 1                         129.787                           403.981
## 2                         117.338                           360.900
## 3                         129.938                           400.161
## 4                         125.636                           380.470
## 5                         129.834                           392.141
## 6                         125.611                           377.232
##   Hydroelectric Power Consumption Geothermal Energy Consumption
## 1                         272.703                         1.491
## 2                         242.199                         1.363
## 3                         268.810                         1.412
## 4                         253.185                         1.649
## 5                         260.770                         1.537
## 6                         249.859                         1.763
##   Solar Energy Consumption Wind Energy Consumption Wood Energy Consumption
## 1            Not Available           Not Available                 129.630
## 2            Not Available           Not Available                 117.194
## 3            Not Available           Not Available                 129.763
## 4            Not Available           Not Available                 125.462
## 5            Not Available           Not Available                 129.624
## 6            Not Available           Not Available                 125.435
##   Waste Energy Consumption Biofuels Consumption
## 1                    0.157        Not Available
```

```
## 2                    0.144       Not Available
## 3                    0.176       Not Available
## 4                    0.174       Not Available
## 5                    0.210       Not Available
## 6                    0.176       Not Available
##   Total Biomass Energy Consumption Total Renewable Energy Consumption
## 1                          129.787                            403.981
## 2                          117.338                            360.900
## 3                          129.938                            400.161
## 4                          125.636                            380.470
## 5                          129.834                            392.141
## 6                          125.611                            377.232
```

```
nobs=nrow(energy_data)
nvar=ncol(energy_data)
```

Q1

For this assignment you will work only with the following columns: Solar Energy Consumption and Wind Energy Consumption. Create a data frame structure with these two time series only and the Date column. Drop the rows with *Not Available* and convert the columns to numeric. You can use filtering to eliminate the initial rows or convert to numeric and then use the drop_na() function. If you are familiar with pipes for data wrangling, try using it!

```
energy_data$`Solar Energy Consumption` <- as.numeric(energy_data$`Solar Energy Consumption`)
```

```
## Warning: NAs introduced by coercion
```

```
energy_data$`Wind Energy Consumption` <- as.numeric(energy_data$`Wind Energy Consumption`)
```

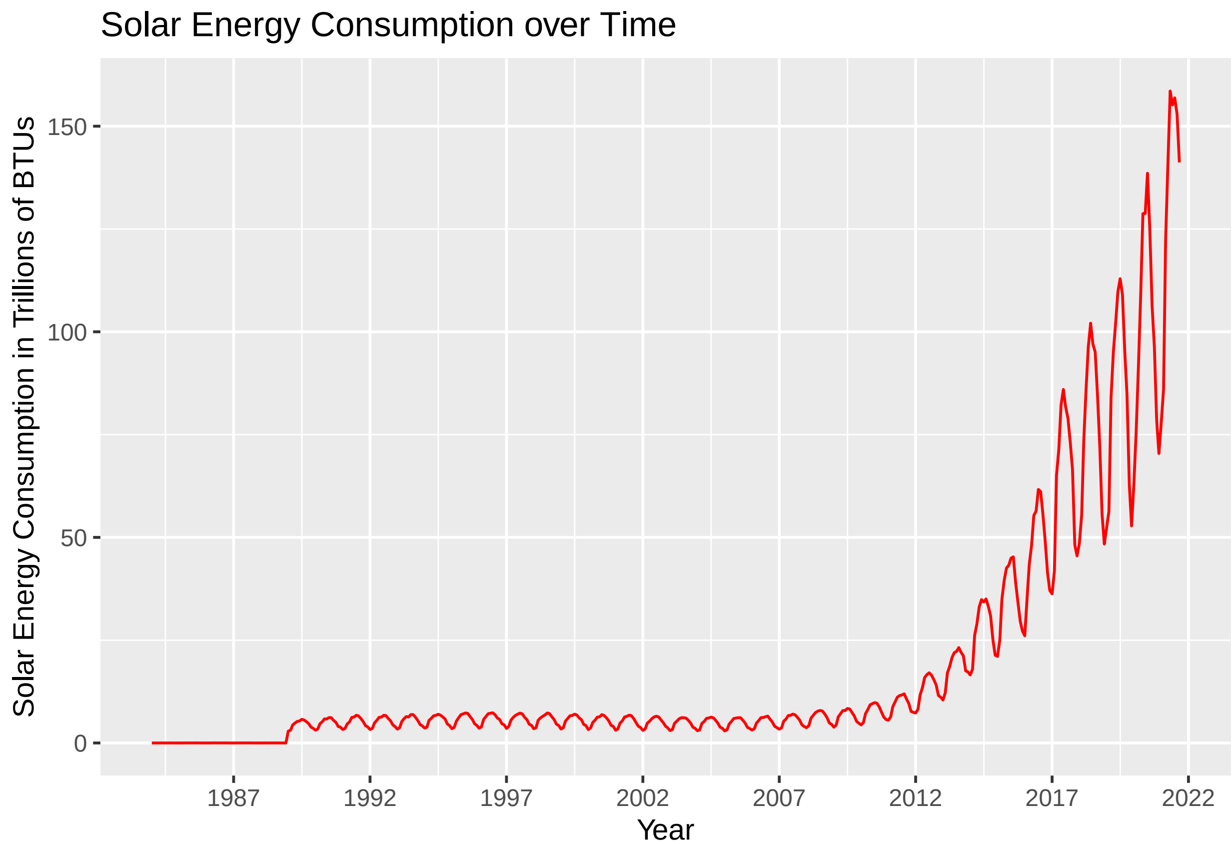
```
## Warning: NAs introduced by coercion
```

```
energy <- energy_data %>%
  select(Month, `Solar Energy Consumption`,
         `Wind Energy Consumption`) %>%
  drop_na()
```

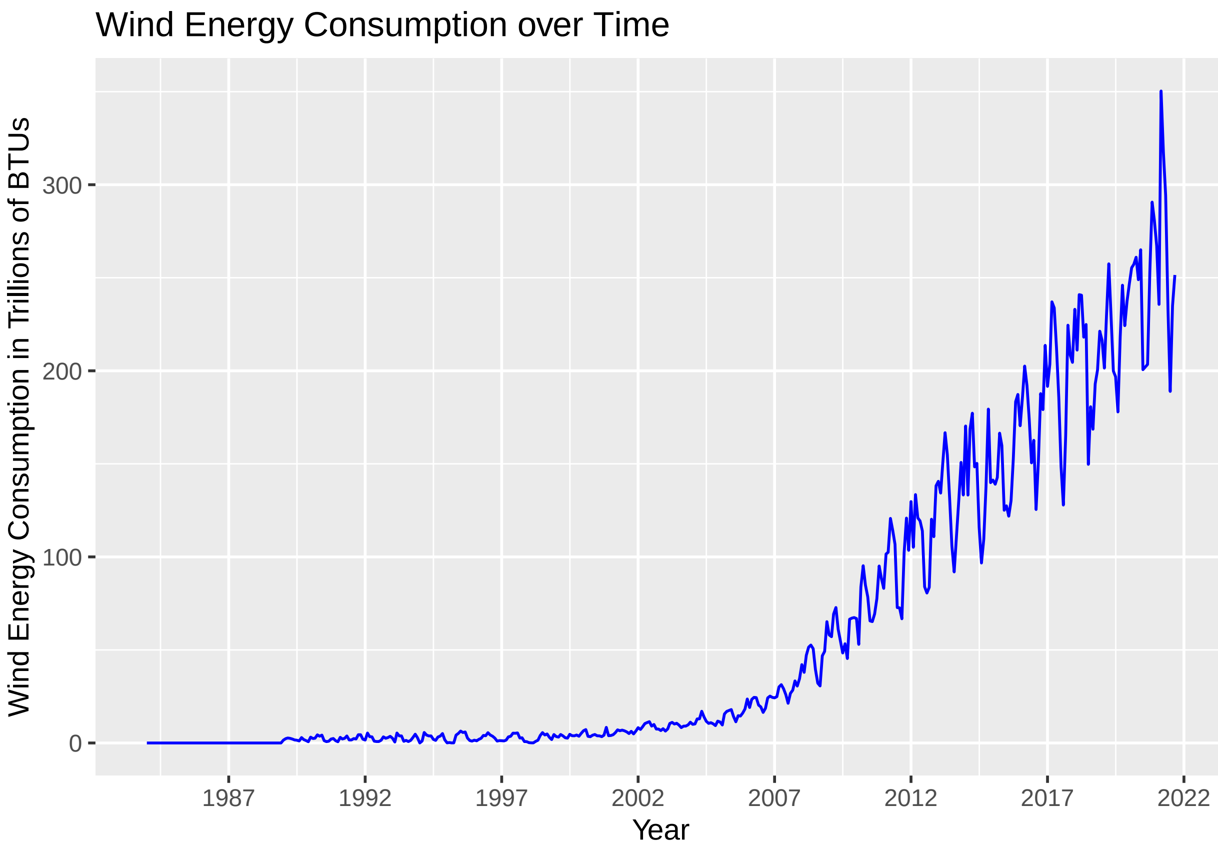
Q2

Plot the Solar and Wind energy consumption over time using ggplot. Plot each series on a separate graph. No need to add legend. Add informative names to the y axis using `ylab()`. Explore the function scale_x_date() on ggplot and see if you can change the x axis to improve your plot. Hint: use *scale_x_date(date_breaks = "5 years", date_labels = "%Y")")*

```
ggplot(energy, aes(Month, `Solar Energy Consumption`)) +
  geom_line(color = "red") +
  scale_x_date(date_breaks = "5 years", date_labels = "%Y") +
  ylab("Solar Energy Consumption in Trillions of BTUs") +
    xlab("Year")+
  ggtitle("Solar Energy Consumption over Time")
```



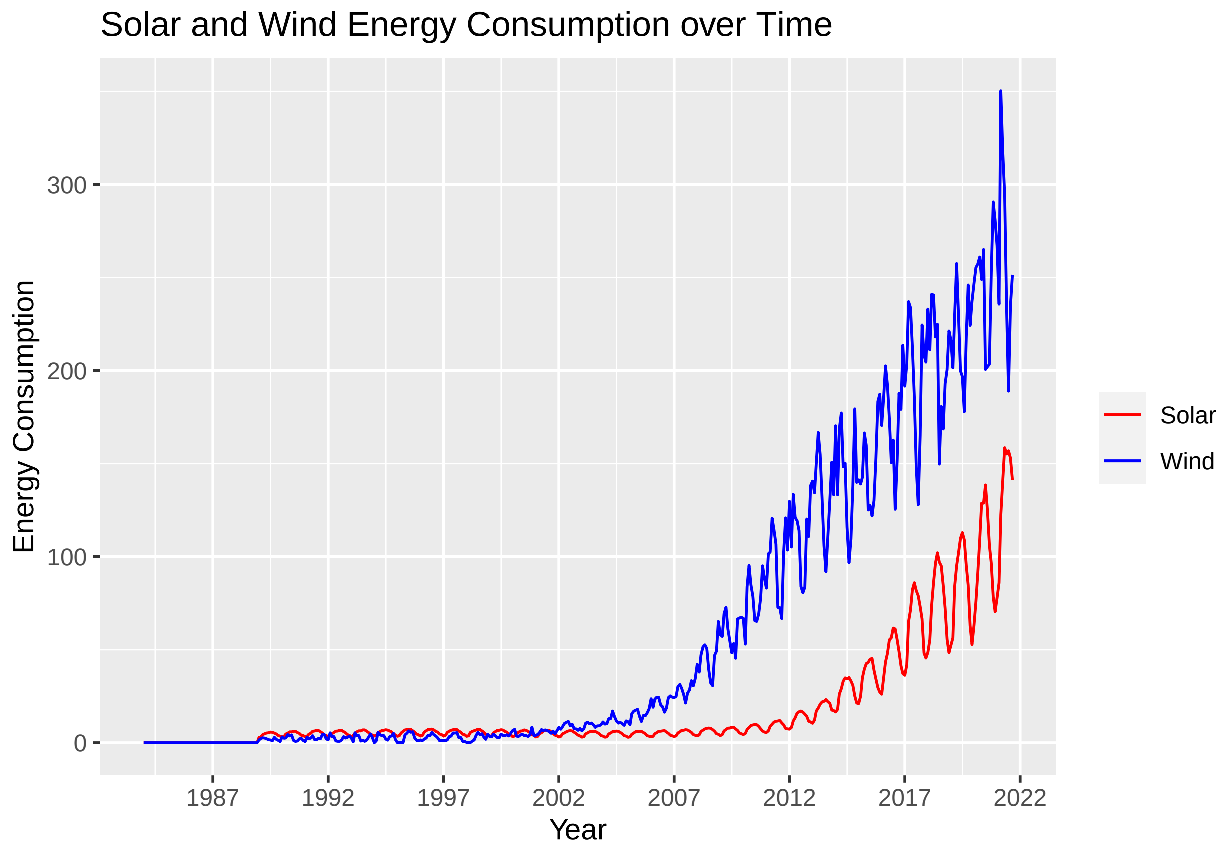

```
ggplot(energy, aes(Month, `Wind Energy Consumption`)) +
  geom_line(color = "blue") +
  scale_x_date(date_breaks = "5 years", date_labels = "%Y") +
  ylab("Wind Energy Consumption in Trillions of BTUs") +
    xlab("Year")+
  ggtitle("Wind Energy Consumption over Time")
```



Q3

Now plot both series in the same graph, also using ggplot(). Look at lines 142-149 of the file `05_Lab_OutliersMissingData_Solution` to learn how to manually add a legend to ggplot. Make the solar energy consumption red and wind energy consumption blue. Add informative name to the y axis using `ylab("Energy Consumption)`. And use function scale_x_date() again to improve x axis.

```
ggplot(energy) +
  geom_line(aes(x = Month, y = `Solar Energy Consumption`, color = "Solar")) +
  geom_line(aes(x = Month, y = `Wind Energy Consumption`, color = "Wind")) +
  scale_color_manual("",
                     breaks = c("Solar", "Wind"),
                     values = c("red", "blue")) +
  ylab("Energy Consumption")+
   xlab("Year")+
  scale_x_date(date_breaks = "5 years", date_labels = "%Y") +
  ggtitle("Solar and Wind Energy Consumption over Time")
```



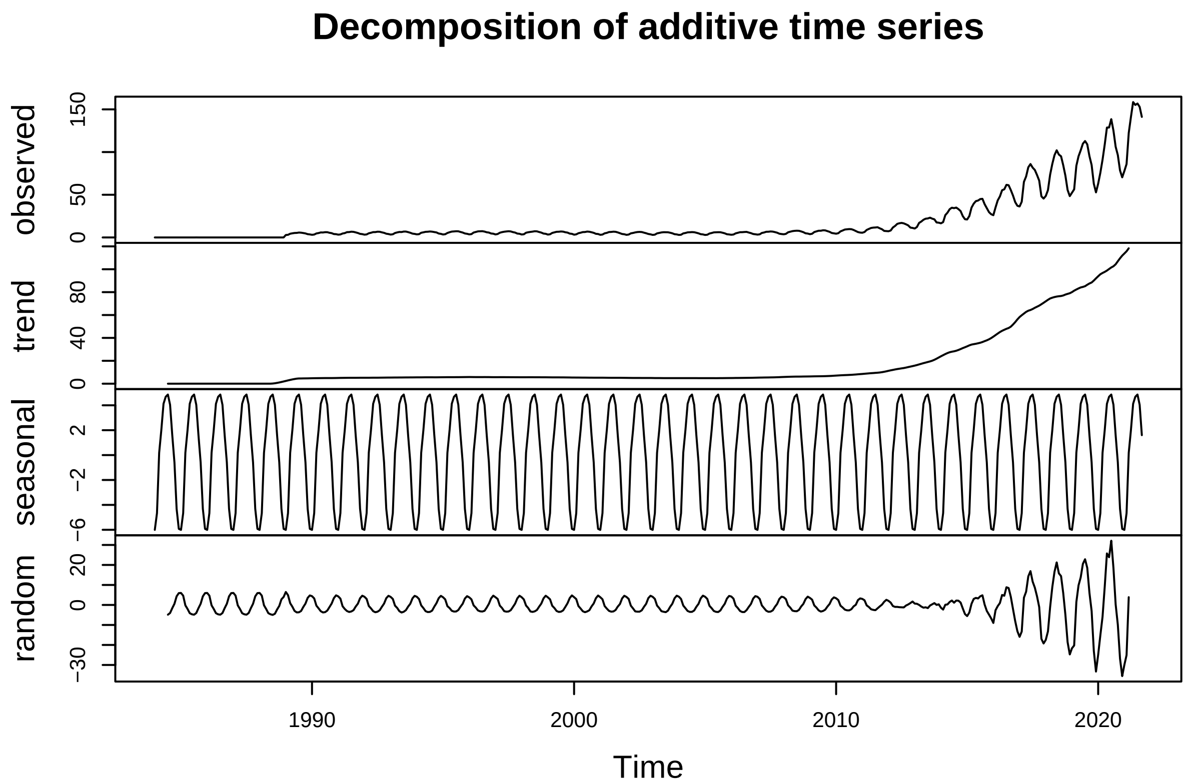
Q3

Transform wind and solar series into a time series object and apply the decompose function on them using the additive option, i.e., `decompose(ts_data, type = "additive")`. What can you say about the trend component? What about the random component? Does the random component look random? Or does it appear to still have some seasonality on it?

```
solar_ts <- ts(energy$`Solar Energy Consumption`,
              frequency = 12, start = c(1984, 1))
wind_ts <- ts(energy$`Wind Energy Consumption`,
              frequency = 12, start = c(1984, 1))
```

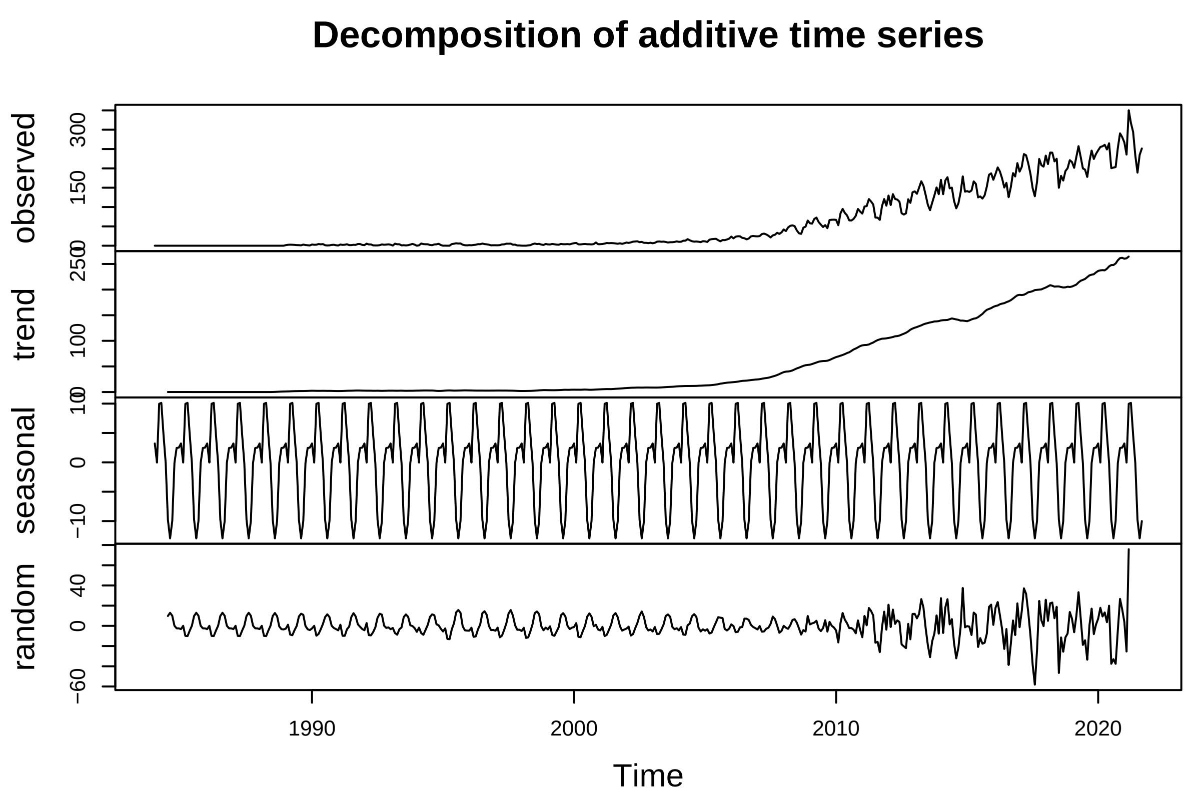
```
solar_decomp <- decompose(solar_ts, type = "additive")
wind_decomp <- decompose(wind_ts, type = "additive")
```

```
plot(solar_decomp)
```



For the solar data, we see very little upward or downward trend until about 2010, when we start to see an upward trend. The random component does not appear to be random - in fact, we seem to see some rather strong seasonality in the random component.

```
plot(wind_decomp)
```



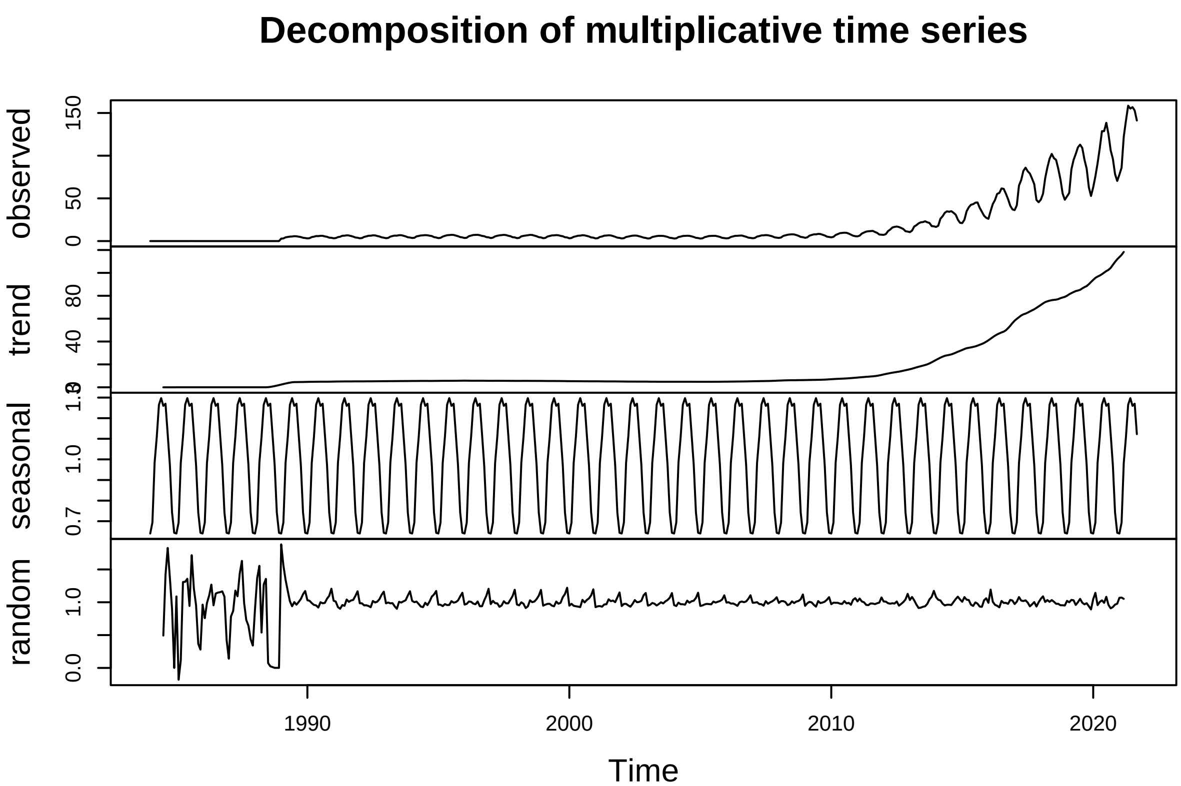
For the wind data, we see very little upward or downward trend until about 2000, when we start to see an upward trend. Again, the random component does not appear to be random - in fact, we seem to see some rather strong seasonality in the random component.

Q4

Use the decompose function again but now change the type of the seasonal component from additive to multiplicative. What happened to the random component this time?

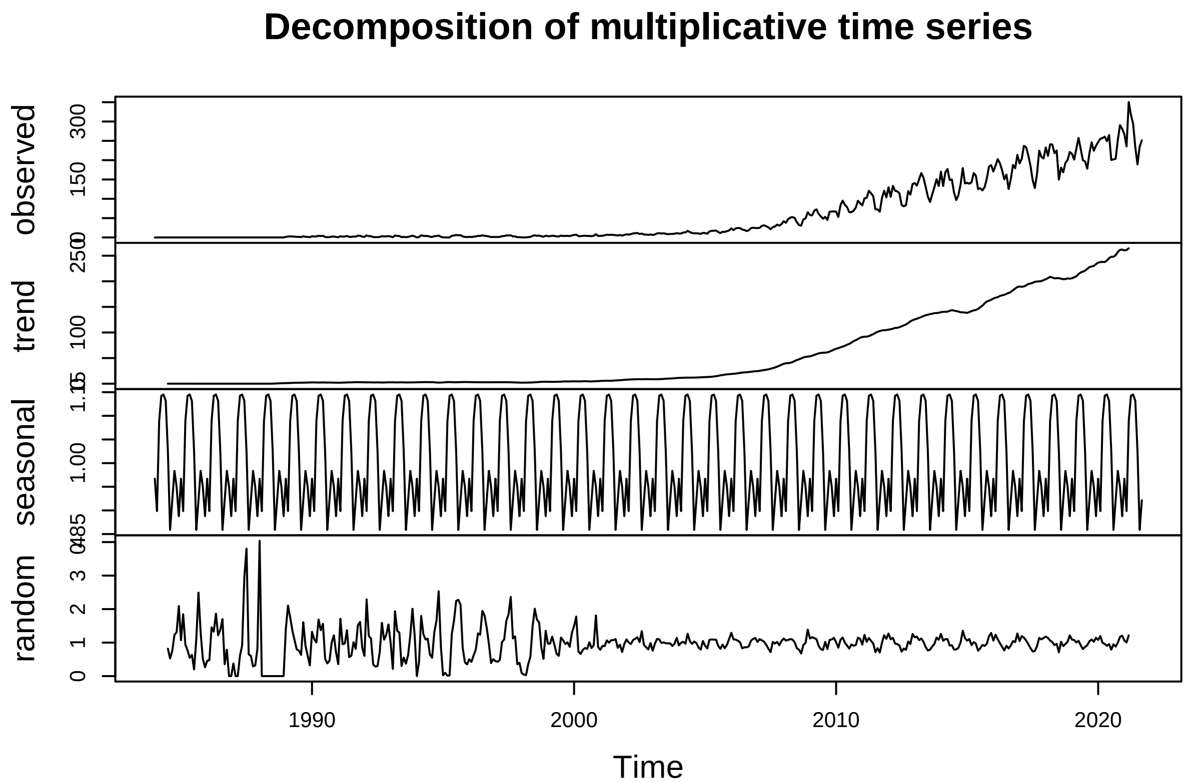
```
solar_decomp_m <- decompose(solar_ts, type = "multiplicative")
wind_decomp_m <- decompose(wind_ts, type = "multiplicative")
```

```
plot(solar_decomp_m)
```



For the solar data, we see more random behavior in the beginning of the random component of the series, and the seasonality is not as smooth as before, but we still see peaks and troughs with some regularity after performing the multiplicative decomposition. The random component looks more random, but not completely random.

```
plot(wind_decomp_m)
```



For the wind data, we see more random behavior in the beginning of the random component of the series, and the seasonality is less regular than before after performing the multiplicative decomposition. Toward the end of the random component series, we see more seasonal looking behavior, with regular peaks and troughs.

In general, the multiplicative model is appropriate if the seasonal fluctuations increase or decrease proportionally with increases and decreases in the level of the series, and this is what we see here, so I think the multiplicative model is more appropriate.

Q5

When fitting a model to this data, do you think you need all the historical data? Think about the data from 90s and early 20s. Are there any information from those years we might need to forecast the next six months of Solar and/or Wind consumption. Explain your response.

> Answer: When trying to predict both series, we should not use all of the historical data. In both plots, we see very different behavior in different parts of the series. For both plots, we see consistently low consumption until about 2002. In 2002, the wind series starts to be trending up, and we see both seasonality and increasing trend until the present. To model the wind data, we shouldn't use data from at least before 2002 to predict past 2022. In about 2012, the solar series starts to be trending up, and we see both seasonality and increasing trend until the present. To model the solar data, we shouldn't use data from before 2012 to predict past 2022.

Q6

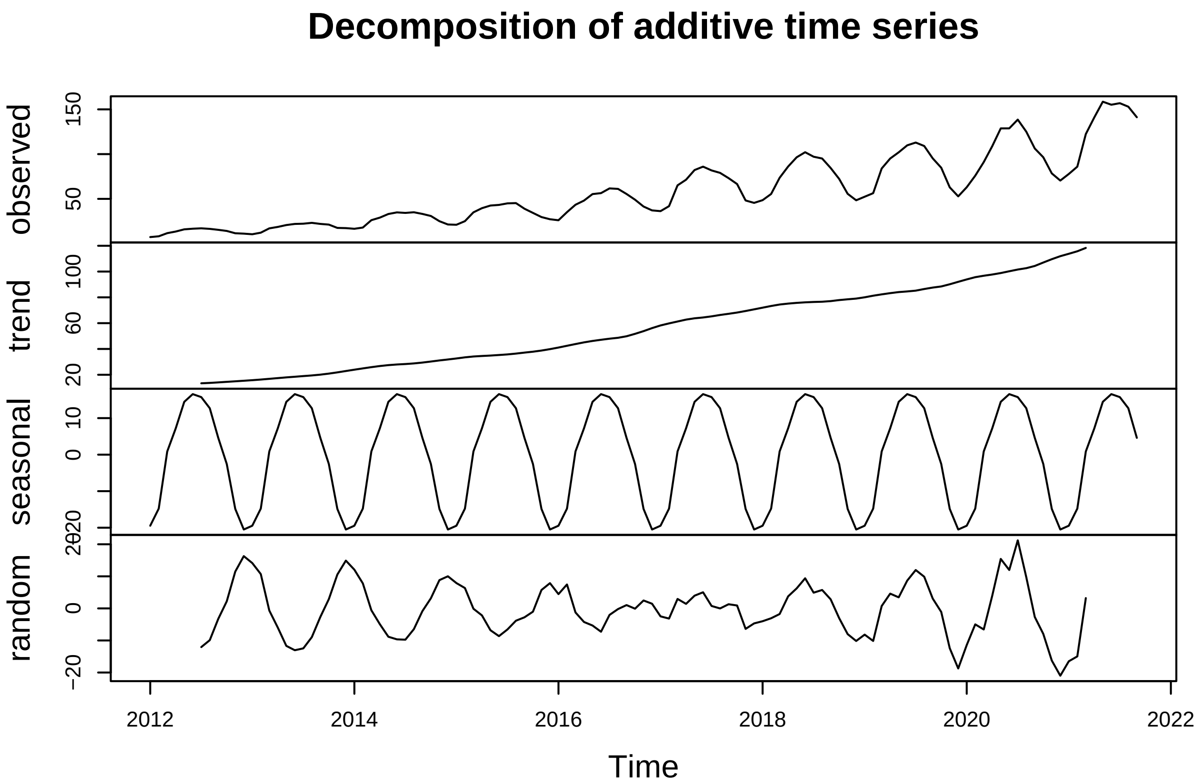
Create a new time series object where historical data starts on January 2012. Hint: use `filter()` function so that you don't need to point to row numbers, .i.e, `filter(xxxx, year(Date) >= 2012 )`. Apply the decompose function `type=additive` to this new time series. Comment the results. Does the random component look random? Think about our discussion in class about trying to remove the seasonal component and the challenge of trend on the seasonal component.

```r
energy2012 <- energy %>%
  filter(year(Month) >= 2012)
```

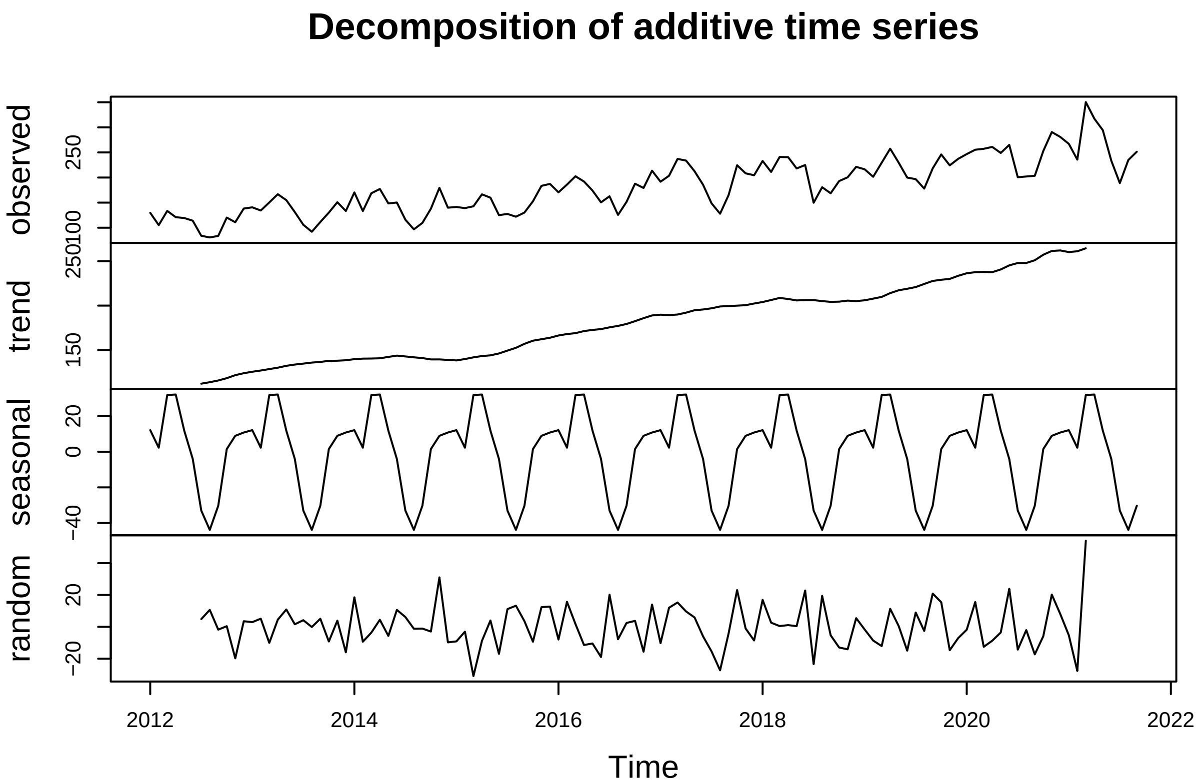
```r
solar_ts_2012 <- ts(energy2012$`Solar Energy Consumption`,
              frequency = 12, start = c(2012, 1))
wind_ts_2012 <- ts(energy2012$`Wind Energy Consumption`,
              frequency = 12, start = c(2012, 1))
```

```r
solar_decomp_2012 <- decompose(solar_ts_2012, type = "additive")
wind_decomp_2012 <- decompose(wind_ts_2012, type = "additive")
```

```r
plot(solar_decomp_2012)
```




```r
plot(wind_decomp_2012)
```



Answer: After the further transformations, we still see some seasonality in the random component of the time series for the solar data. We do not see the same behavior in the wind series - the random component looks more random. We have a challenge again because the seasonal fluctuations for both series increase proportionally with increases in the level of the series, which can make it hard for the additive model to properly decompose the series. Again, I think a muliplicative or log-additive model would be more appropriate here.