Mauna Loa CO2 Time Series Analysis

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2025-03-07

```r
# adding libraries
library(tidyverse)
library(fpp3)
library(ggplot2)
library(dplyr)
library(nortest)
library(tseries)
library(urca)
```

```r
file <- "co2_mm_gl.csv"
climate_data <- read_csv(file, skip = 38)

# filter data to only before 2020
climate_data_clean <- climate_data %>%
    filter(year < 2020)
```

Figure 1

```r
# dividing the data by month
climate_data_ts <- tsibble(month = yearmonth(seq(as.Date("1979-01-01"),
    as.Date("2019-12-01"), by = "1 month")), Time = climate_data_clean$decimal,
    CO2 = climate_data_clean$average, index = month)


Month <- as_factor(month(climate_data_ts$month))

# plot of CO2 over the years
ggplot(climate_data_ts, aes(x = Time, y = CO2)) + geom_line(color = "blue") +
    labs(title = "Figure 1") + labs(title = "Mauna Loa CO2 Concentration Over Time",
    x = "Year", y = "CO2 (ppm)") + theme_minimal()
```

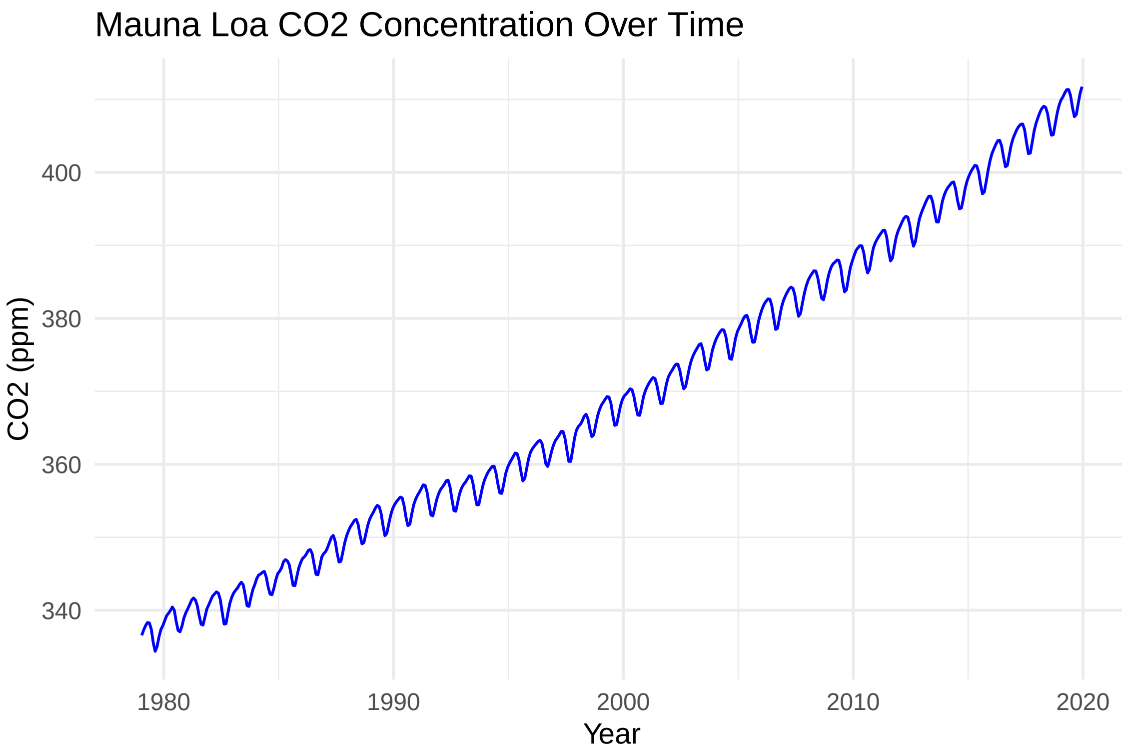


Figure 2

```r
# seasonally adjusted CO2
time_series_components <- climate_data_ts %>%
    model(STL(CO2 ~ season(window = "periodic"))) %>%
    components()

climate_data_ts <- climate_data_ts %>%
    add_column(seasonal = time_series_components$season_year,
        CO2_SA = time_series_components$season_adjust)

autoplot(time_series_components)
```

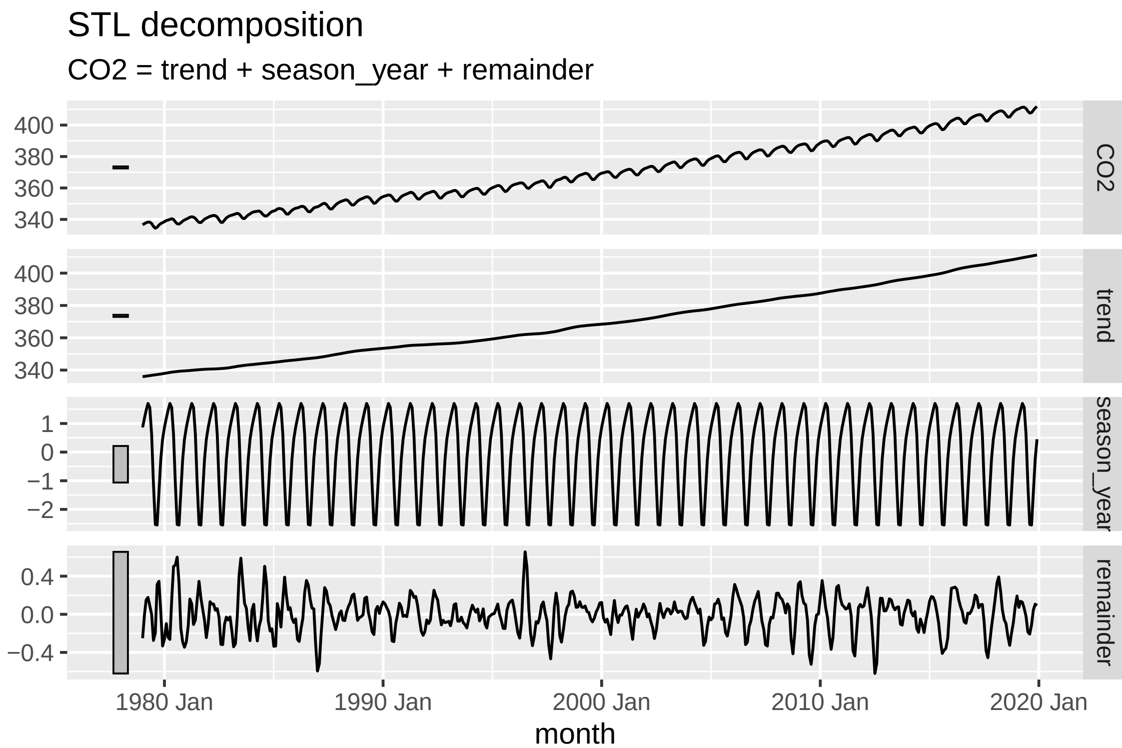
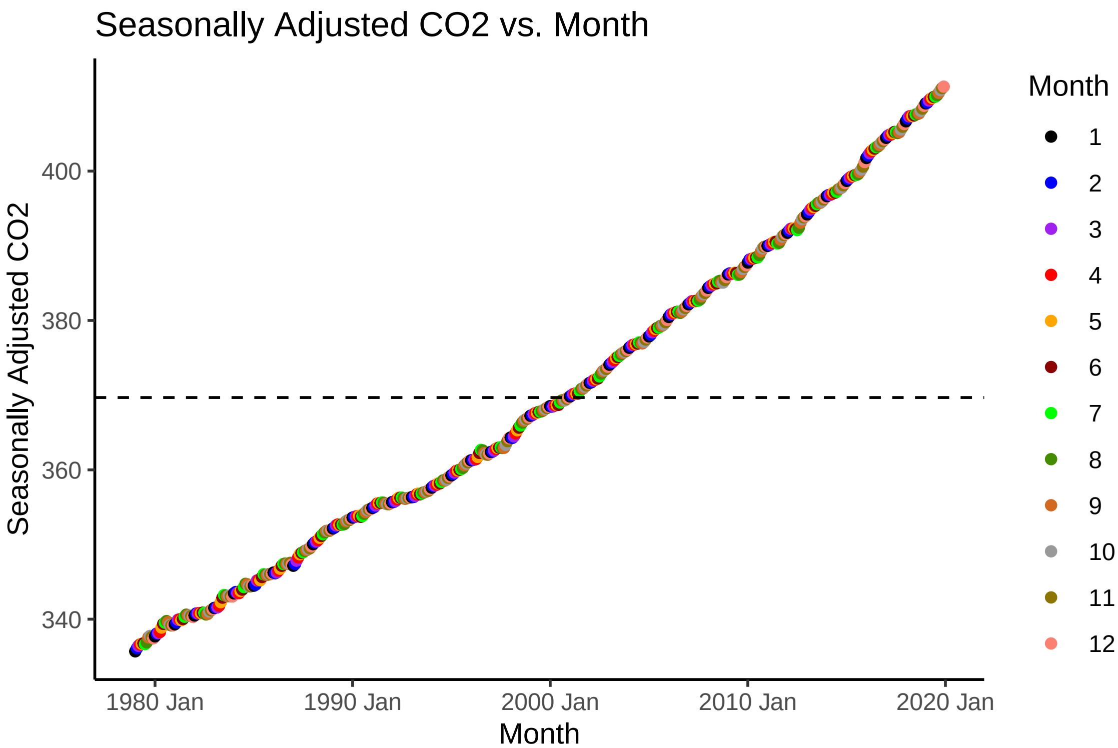


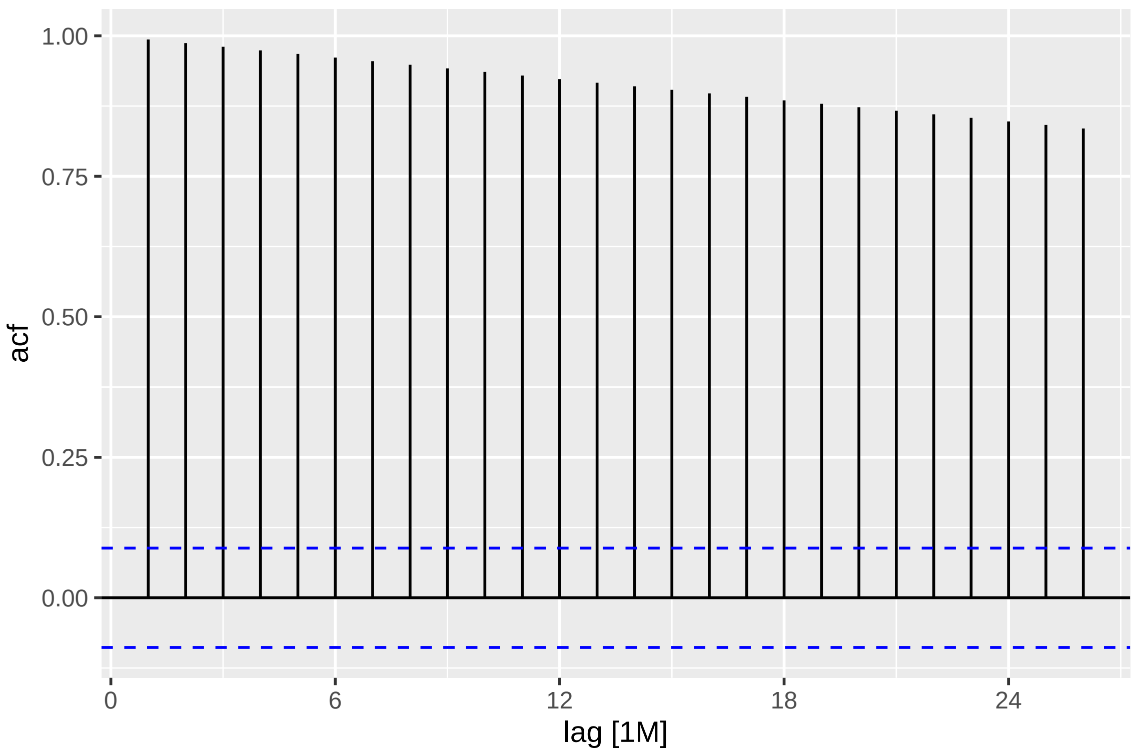
Figure 3

```
# plot of seasonally adjusted CO2 over time

mean_CO2_SA <- mean(climate_data_ts$CO2_SA)
climate_data_ts %>%
    autoplot(CO2_SA) + geom_point(aes(y = CO2_SA, color = Month)) +
    scale_color_manual(values = c("black", "blue", "purple",
        "red", "orange", "darkred", "green", "chartreuse4", "chocolate",
        "gray60", "gold4", "salmon")) + geom_hline(aes(yintercept = mean_CO2_SA),
    lty = 2) + ggtitle("Seasonally Adjusted CO2 vs. Month") +
    xlab("Month") + ylab("Seasonally Adjusted CO2") + theme(panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(), panel.background = element_blank(),
    axis.line = element_line(colour = "black"))
```




```r
# running test to confirm non-stationary data
climate_data_ts %>%
    ACF(CO2_SA) %>%
    autoplot()
```



```r
unitroot_kpss(climate_data_ts$CO2_SA)
```

```
##   kpss_stat kpss_pvalue
##    8.217486    0.010000
```

```r
adf.test(climate_data_ts$CO2_SA)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  climate_data_ts$CO2_SA
## Dickey-Fuller = 0.28767, Lag order = 7, p-value = 0.99
## alternative hypothesis: stationary
```

The time series is clearly non-stationary because the p-value from the KPSS test is 0.01 which is less than 0.05. And the large p-value of ADF test is evidence that the time series is non-stationary.

```r
# Computing first differences
climate_data_ts <- climate_data_ts %>%
    mutate(diff_CO2_SA = difference(CO2_SA))
head(climate_data_ts)
```

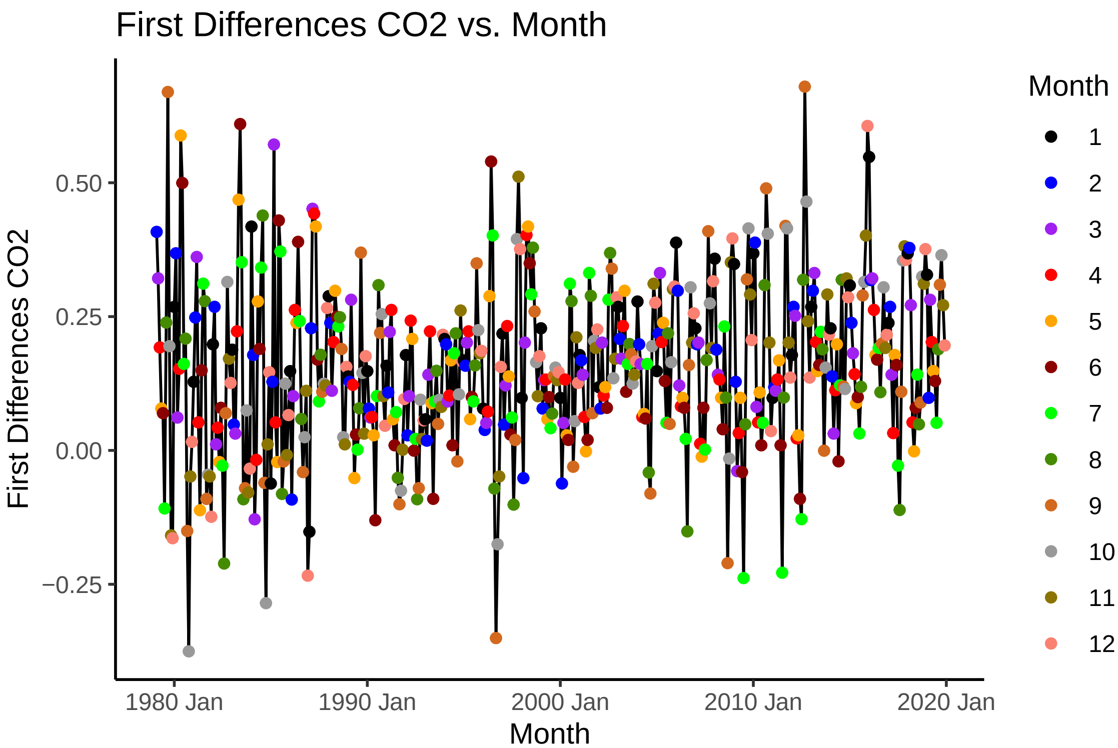
```
## # A tsibble: 6 x 6 [1M]
##      month  Time   CO2 seasonal CO2_SA diff_CO2_SA
##      <mth> <dbl> <dbl>    <dbl>  <dbl>       <dbl>
## 1 1979 Jan 1979.  337.    0.862   336.     NA
## 2 1979 Feb 1979.  337.    1.18    336.      0.408
## 3 1979 Mar 1979.  338.    1.45    336.      0.321
## 4 1979 Apr 1979.  338.    1.70    337.      0.192
## 5 1979 May 1979.  338.    1.56    337.      0.0783
## 6 1979 Jun 1979.  337.    0.612   337.      0.0696
```

```r
tail(climate_data_ts)
```

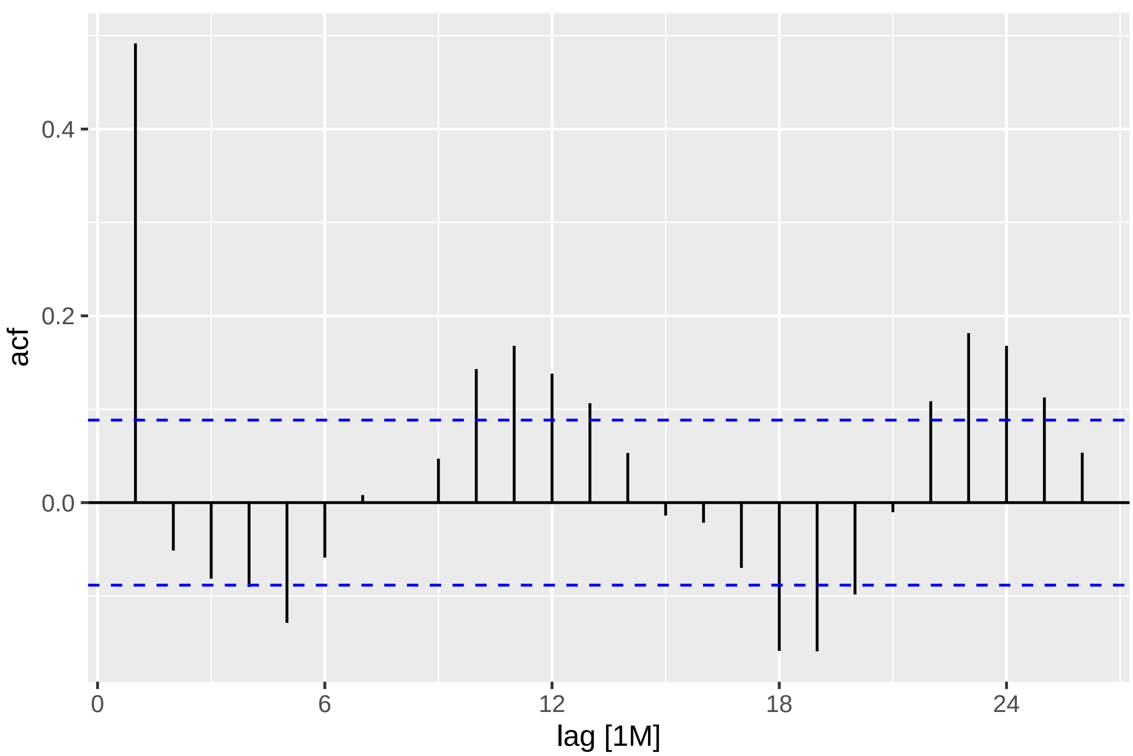
```
## # A tsibble: 6 x 6 [1M]
##      month  Time   CO2 seasonal CO2_SA diff_CO2_SA
##      <mth> <dbl> <dbl>    <dbl>  <dbl>       <dbl>
## 1 2019 Jul 2020.  409.   -1.10    410.      0.0515
## 2 2019 Aug 2020.  408.   -2.53    410.      0.189
## 3 2019 Sep 2020.  408.   -2.55    410.      0.310
## 4 2019 Oct 2020.  409.   -1.40    411.      0.365
## 5 2019 Nov 2020.  411.   -0.244   411.      0.271
## 6 2019 Dec 2020.  412.    0.450   411.      0.196
```

```r
mean_diff_CO2_SA <- mean(climate_data_ts$diff_CO2_SA)

climate_data_ts %>%
    autoplot(diff_CO2_SA) + geom_point(aes(y = diff_CO2_SA, color = Month)) +
    scale_color_manual(values = c("black", "blue", "purple",
        "red", "orange", "darkred", "green", "chartreuse4", "chocolate",
        "gray60", "gold4", "salmon")) + geom_hline(aes(yintercept = mean_diff_CO2_SA),
    lty = 2) + ggtitle("First Differences CO2 vs. Month") + xlab("Month") +
    ylab("First Differences CO2") + theme(panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(), panel.background = element_blank(),
    axis.line = element_line(colour = "black"))
```




```
climate_data_ts %>%
    ACF(diff_CO2_SA) %>%
    autoplot()
```




```
unitroot_kpss(climate_data_ts$diff_CO2_SA)
```

```
##   kpss_stat kpss_pvalue
```

```
##    1.032651    0.010000
```

```r
adf.test(climate_data_ts$diff_CO2_SA[2:492])
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  climate_data_ts$diff_CO2_SA[2:492]
## Dickey-Fuller = -9.6623, Lag order = 7, p-value = 0.01
## alternative hypothesis: stationary
```

(talked to professor - doesn't know why KPSS and ADF test are not showing that it is non-stationary so we are gonna ignore it)

Since the p-value of the ADF test is less than 0.05, there is evidence to reject the null hypothesis in favor of the alternative hypothesis that the time series is stationary.

```r
# choosing ARIMA model

result_dcmp_ARIMA_SNAIVE <- climate_data_ts %>%
    model(decomposition_model(STL(CO2_SA ~ season(window = 21)),
        ARIMA(season_adjust ~ pdq(d = 1, q = 0) + PDQ(0, 0, 0),
            stepwise = FALSE, approximation = FALSE, trace = TRUE),
        SNAIVE(season_year)))
```

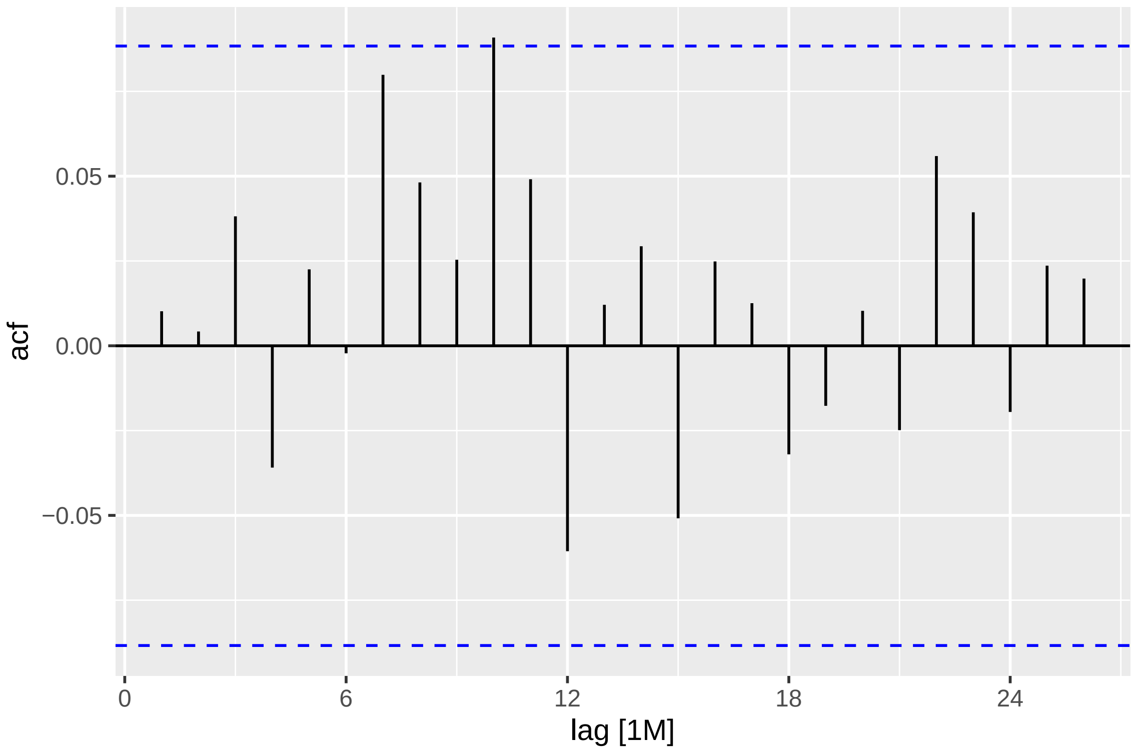
```
## ARIMA(0,1,0)(0,0,0)[12]+c    -536.499114
## ARIMA(1,1,0)(0,0,0)[12]+c    -640.939216
## ARIMA(2,1,0)(0,0,0)[12]+c    -724.035695
## ARIMA(3,1,0)(0,0,0)[12]+c    -752.460659
## ARIMA(4,1,0)(0,0,0)[12]+c    -776.350162
## ARIMA(5,1,0)(0,0,0)[12]+c    -791.415354
## ARIMA(0,1,0)(0,0,0)[12]      -149.198917
## ARIMA(1,1,0)(0,0,0)[12]      -547.537737
## ARIMA(2,1,0)(0,0,0)[12]      -557.487228
## ARIMA(3,1,0)(0,0,0)[12]      -673.684130
## ARIMA(4,1,0)(0,0,0)[12]      -672.644022
## ARIMA(5,1,0)(0,0,0)[12]      -730.930329
```

```r
report(result_dcmp_ARIMA_SNAIVE)
```

```
## Series: CO2_SA
## Model: STL decomposition model
## Combination: season_adjust + season_year
##
## ========================================
##
## Series: season_adjust
## Model: ARIMA(5,1,0) w/ drift
##
## Coefficients:
##          ar1      ar2     ar3      ar4     ar5  constant
##       0.8149  -0.7523  0.5331  -0.3695  0.1851    0.0904
## s.e.  0.0444   0.0552  0.0600   0.0550  0.0443    0.0048
##
## sigma^2 estimated as 0.01169:  log likelihood=402.82
## AIC=-791.65   AICc=-791.42   BIC=-762.27
##
```

```
## Series: season_year
## Model: SNAIVE
##
## sigma^2: 1e-04
```

```r
# Compute autocorrelation function of residuals
result_dcmp_ARIMA_SNAIVE %>%
    augment() %>%
    ACF(.resid) %>%
    autoplot()
```



Explain what time series methods you are using to answer the question and why they are appropriate.

After I talked to the professor, we decided to force the model to take a first difference with a window of 21 to force the output to give a model with first difference instead of the second difference. After running the decomposition model on the seasonally adjusted CO2 values, the ARIMA model with the lowest AICc value of -791.65 is ARIMA(5,1,0) with drift model. The ACF plot of the ARIMA(5,1,0) with drift model displays most spikes are within the blue lines, showing that there is no pattern in the residuals.
