Climate Data Visualization -

Atmospheric CO_2 Concentration / Temperature / Precipitation

Wolfgang Vollmer

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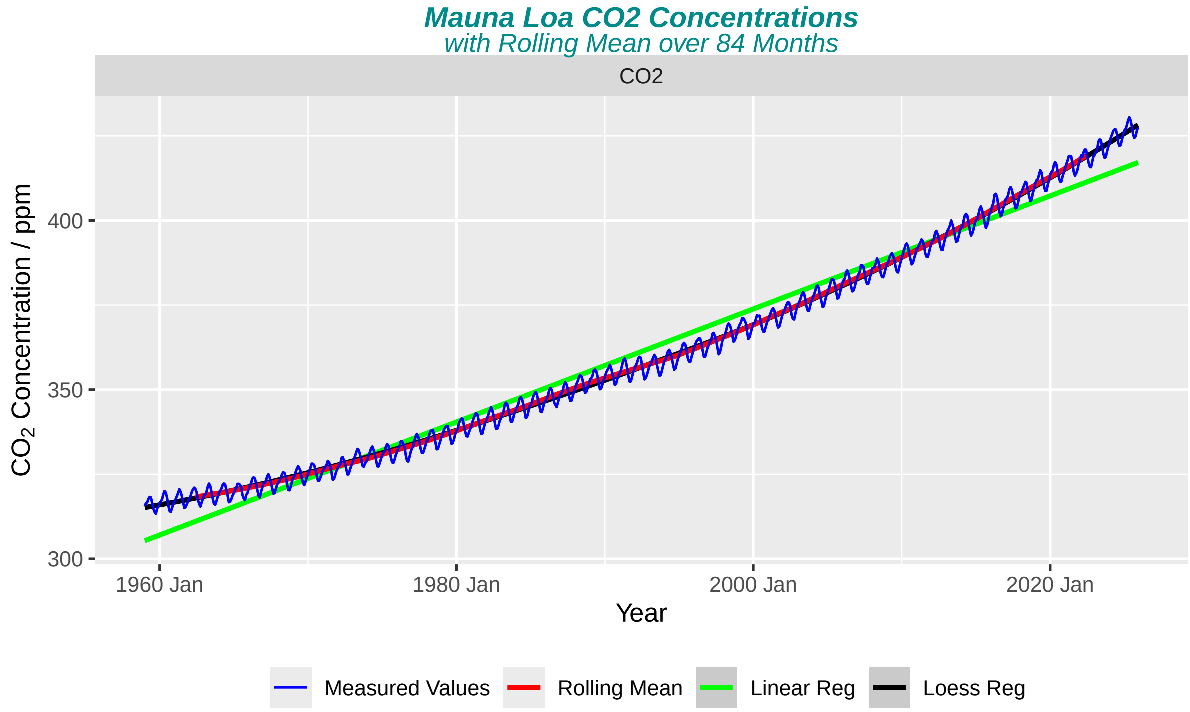
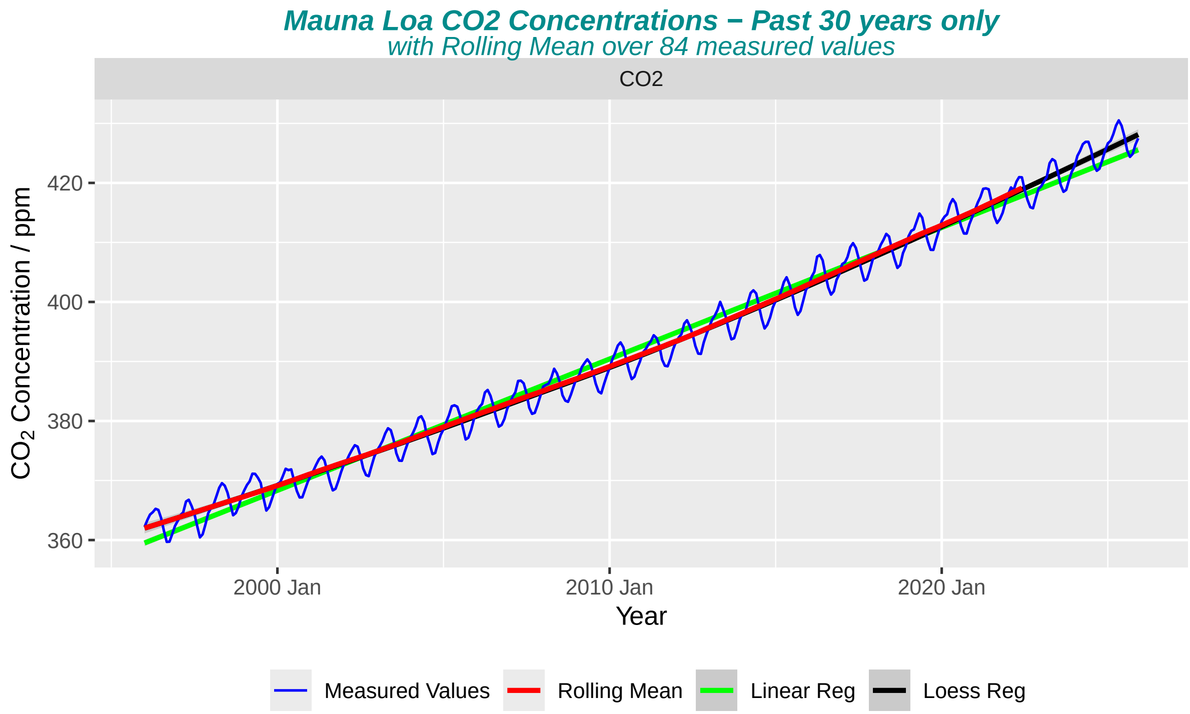
Contents

1 Mauna Loa - Visualization of CO2 Data 1959 - 2025

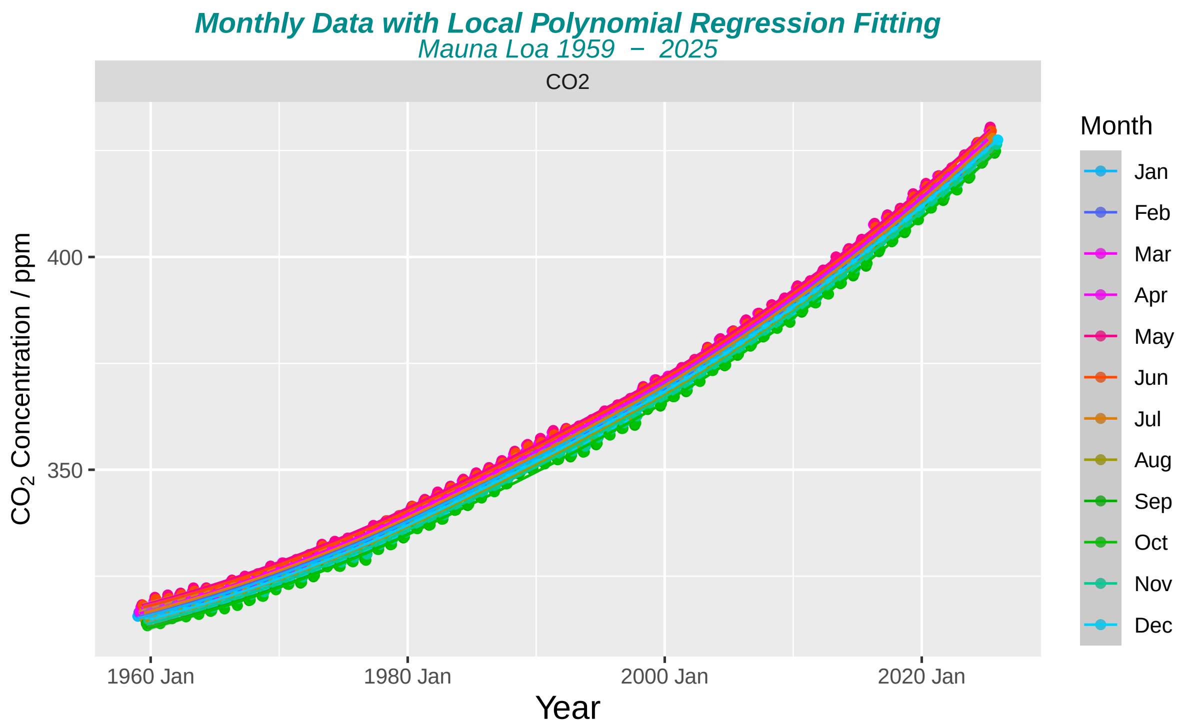
1.1 Monthly Time Plots with Rolling Mean





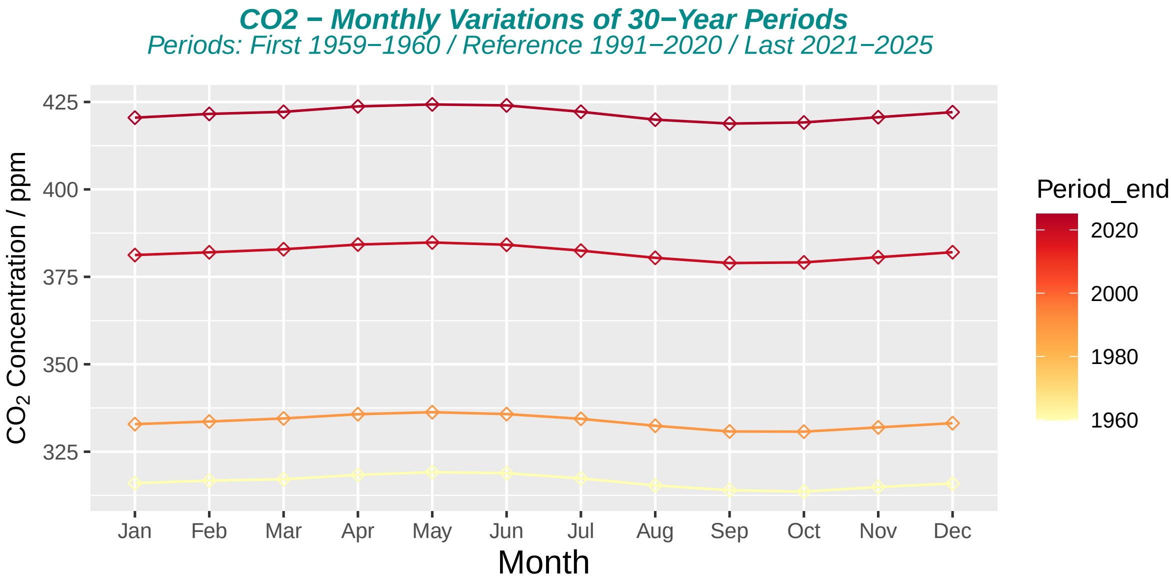
1.2 Annual seasonal plots with monthly breakdown

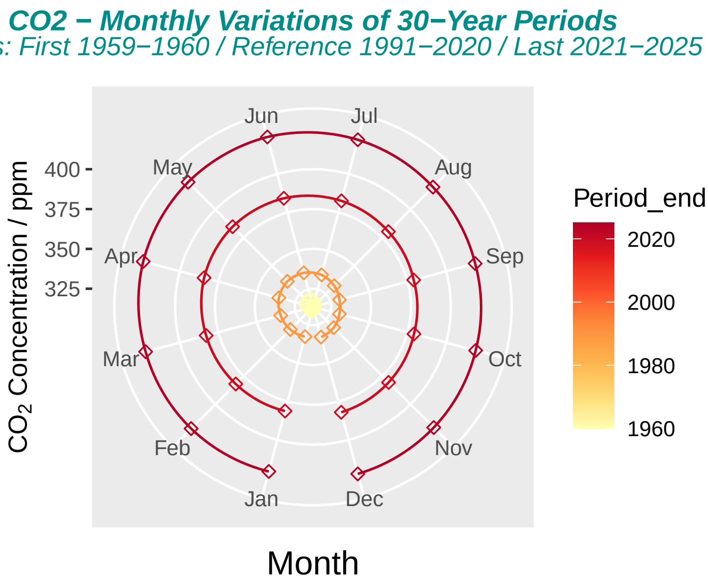
The seasonal charts show the monthly seasonal patterns, where available.



Monthly Data with Local Polynomial Regression Fitting
Mauna Loa 1959 − 2025
CO2
CO_2 Concentration / ppm
400
350
1960 Jan
1980 Jan
2000 Jan
2020 Jan
Year
Month
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

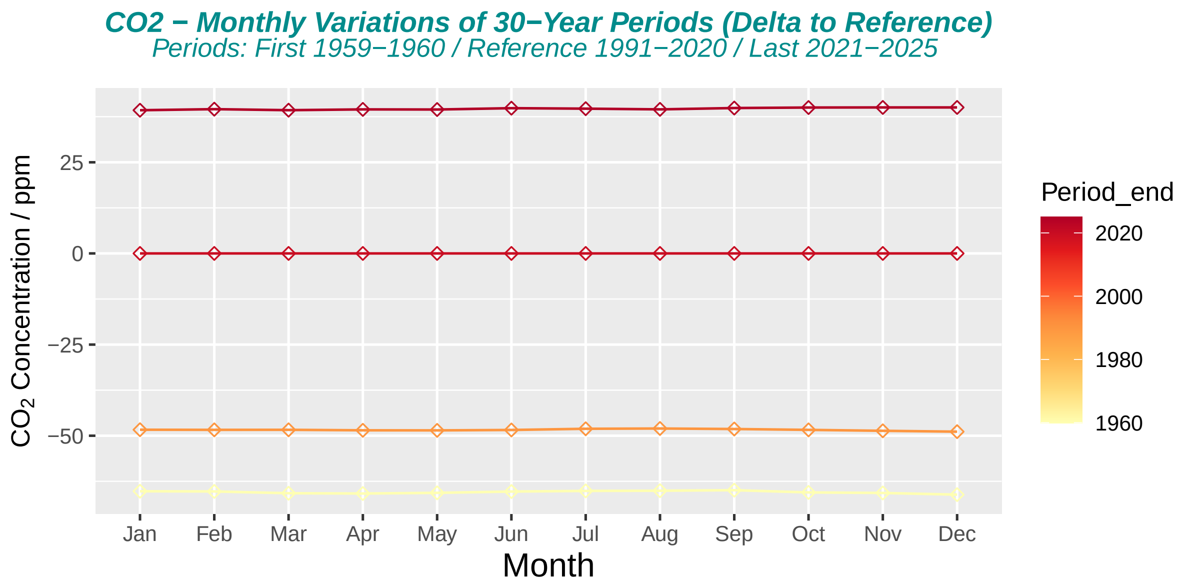
1.2.1 30-year period plots with monthly breakdown - Cartesian and Polar Coordinates

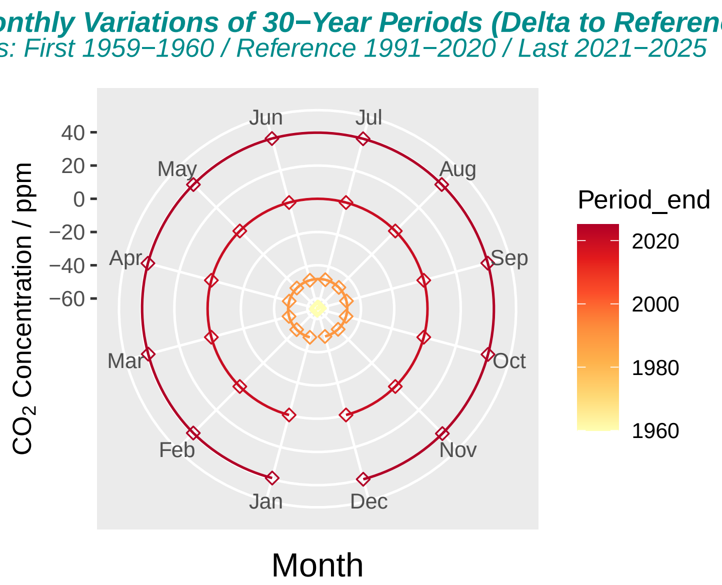


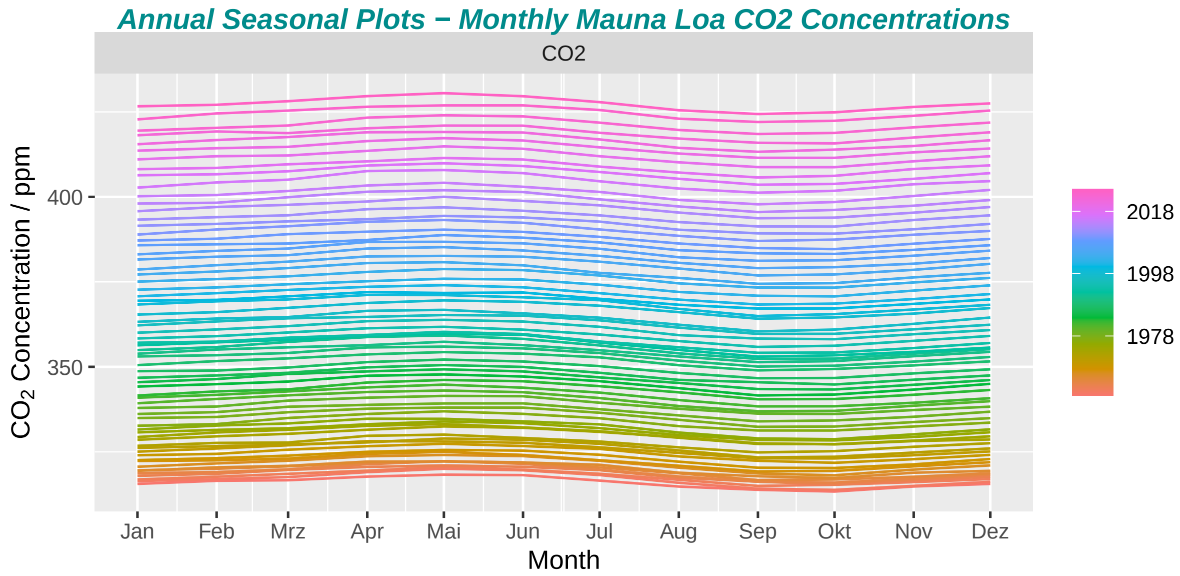


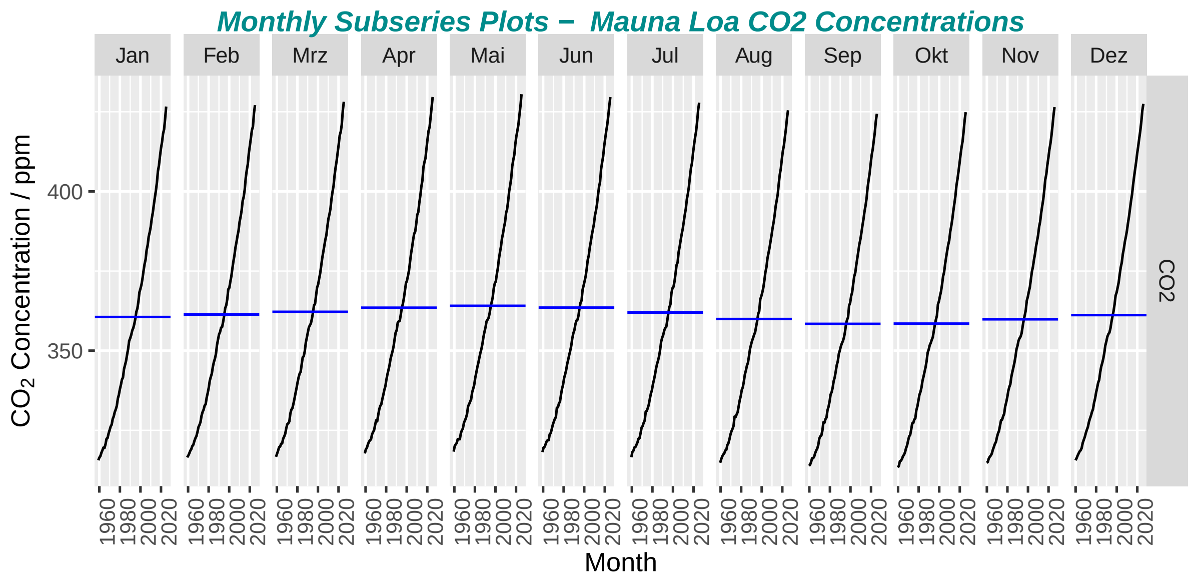

```
#>
#> _
```

1.2.2 Plot Monthly Delta to Reference Period - Cartesian and Polar Coordinates





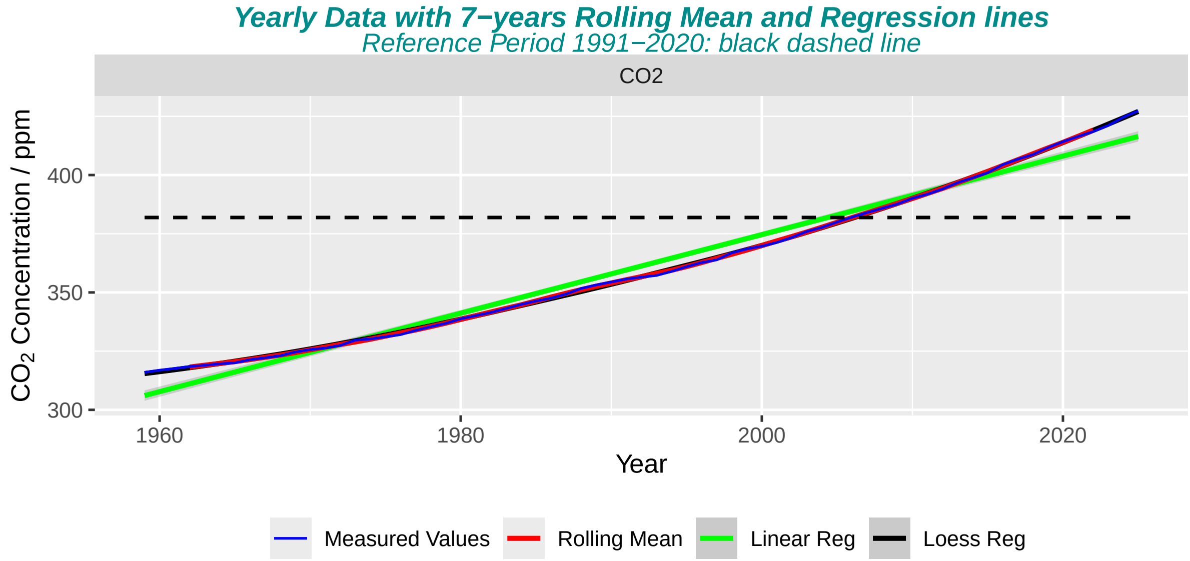




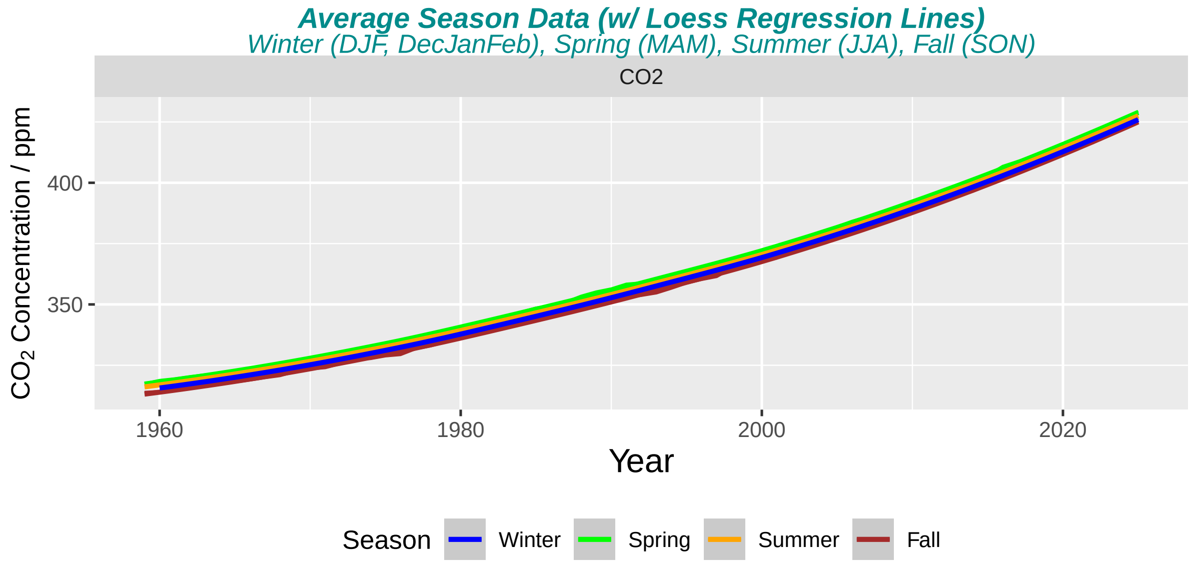
The blue horizontal lines within the seasonal subseries plot indicate the means for each month.

1.3 Annual Mauna Loa CO2 Concentrations

1.3.1 Annual Time Plot of CO2



1.3.2 Annual Seasonal Plot of CO2



2 Trend and Seasonal Analysis

2.1 Time Series Decomposition - Trend and Seasonal Components

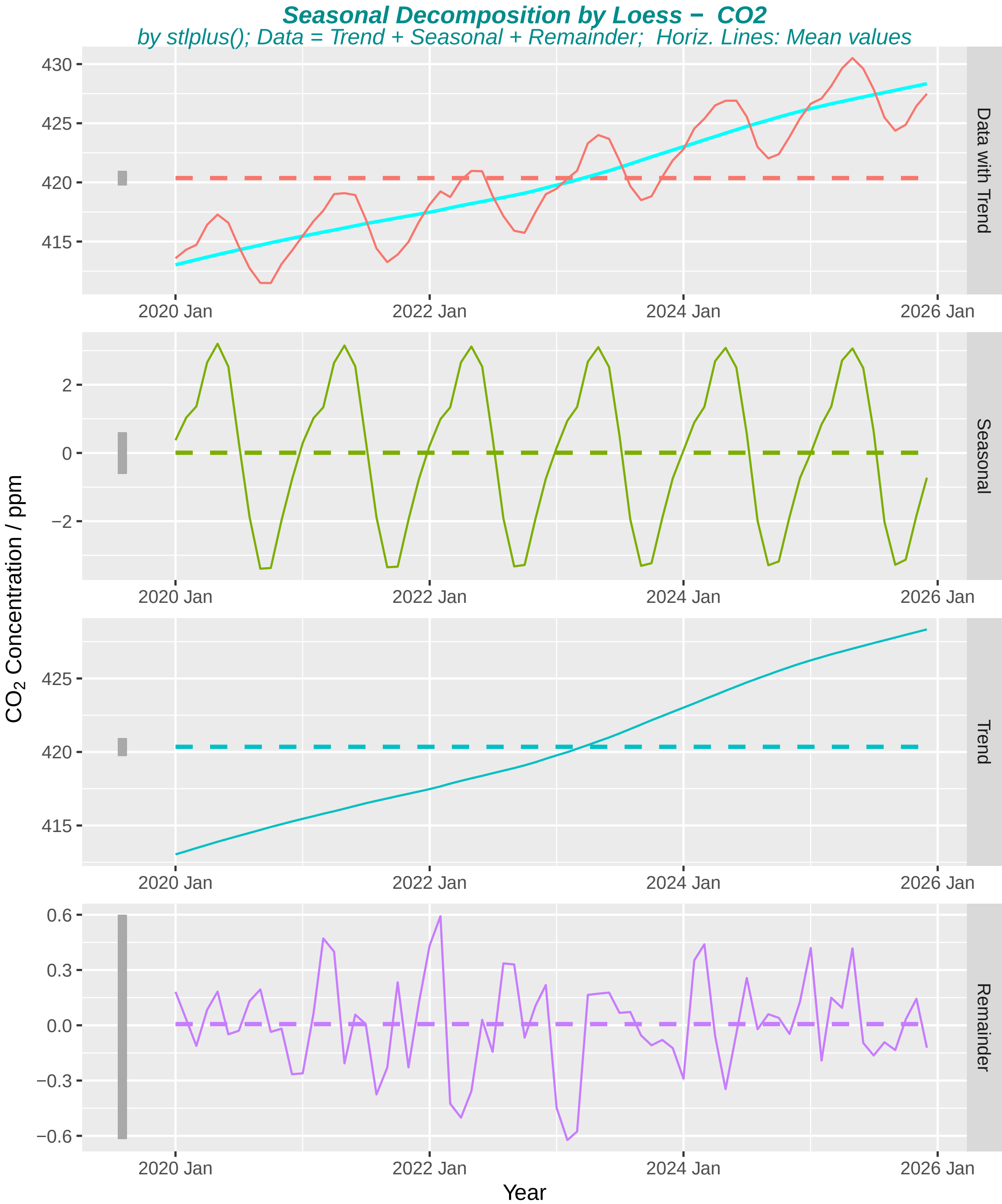
An *additive model* would be used when the variations around the trend do not vary with the level of the time series whereas a *multiplicative model* would be appropriate if the trend is proportional to the level of the time series.

Time series using an

- additive model: $y_t = T_t + C_t + S_t + \epsilon_t$
- multiplicative model: $y_t = T_t * C_t * S_t * \epsilon_t$

Trend / Cycle / Seasonal / Noise component
Cyclical components is often grouped into the Trend component

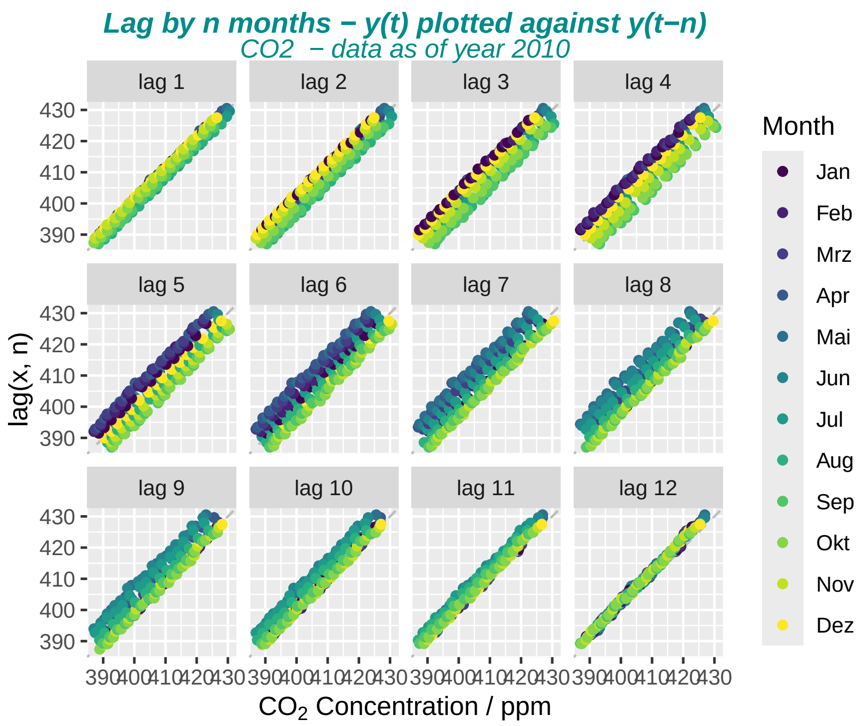
For *Seasonal decomposition of time series by Loess (stlplus)* uses in general an additive error model, it only provides facilities for additive decompositions. It is possible to obtain a multiplicative decomposition by first taking logs of the data.



2.2 Periodicities - Season Frequency

2.2.1 Lag Plot - Differences

Lagged scatterplots, where the horizontal axis shows lagged $(k = 1, .., 12)$ values of the time series. Each graph shows y_t plotted against y_{t-k} for different values of k. For seasonal data the relationship is strongly positive at a lag $k = 12$, reflecting the strong seasonality of the data. The strongly negative relationship is evident in the case oflag $k = 6$.



Lag by n months − y(t) plotted against y(t−n)
CO2 − data as of year 2010
lag 1
lag 2
lag 3
lag 4
lag 5
lag 6
lag 7
lag 8
lag 9
lag 10
lag 11
lag 12
430
420
410
400
390
lag(x, n)
390
400
410
420
430
CO2 Concentration / ppm
Month
Jan
Feb
Mrz
Apr
Mai
Jun
Jul
Aug
Sep
Okt
Nov
Dez

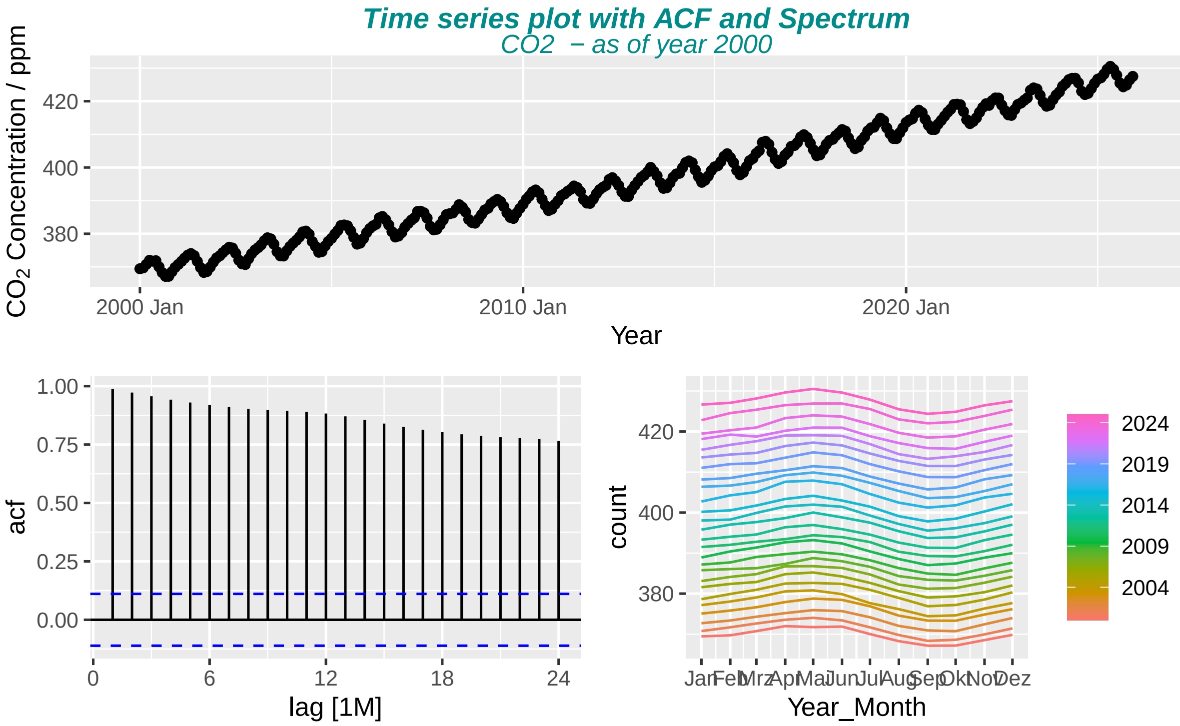
2.2.2 Periodogram - Spectral Density Estimation of a Time Series

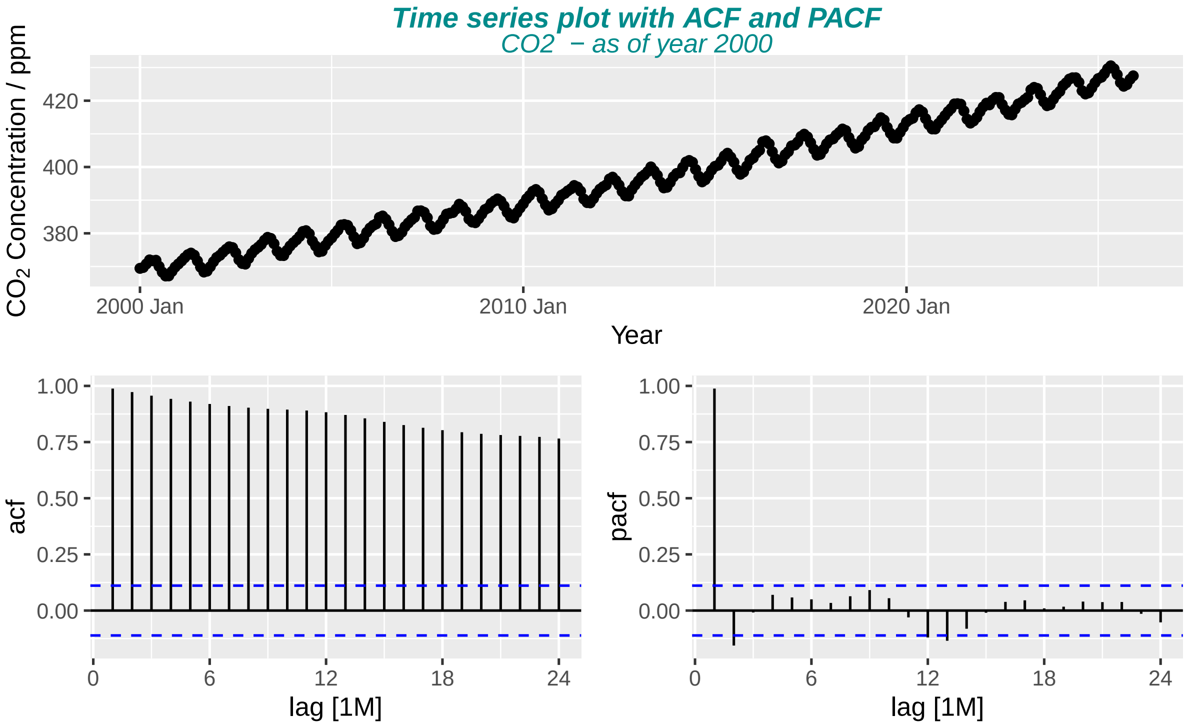
The spectral density characterizes the frequency content of the signal. One purpose of estimating the spectral density is to detect any periodicities in the data, by observing peaks at the frequencies corresponding to these periodicities.

At frequency $\lambda = 1/12$ there is a significant peak => This pattern repeats every full frequency = every 12 months / every year

The remaining peaks are random and therefore cannot be assigned significantly.

Note: The blue dashed lines in the (P)ACF plots ((Partial) Autocorrelation Function) indicate white noise series limits. In that case 95% of the spikes lie within the dashed lines.





3 Forecasting - Estimate/Train the model

3.1 Forecasting with ETS and ARIMA model

Exponen**T**ial **S**moothing (**ETS**) and **A**uto**R**egressive **I**ntegrated **M**oving **A**verage Forecasting Models **ARIMA** models are the two most widely used approaches to time series forecasting, and provide complementary approaches to the problem.

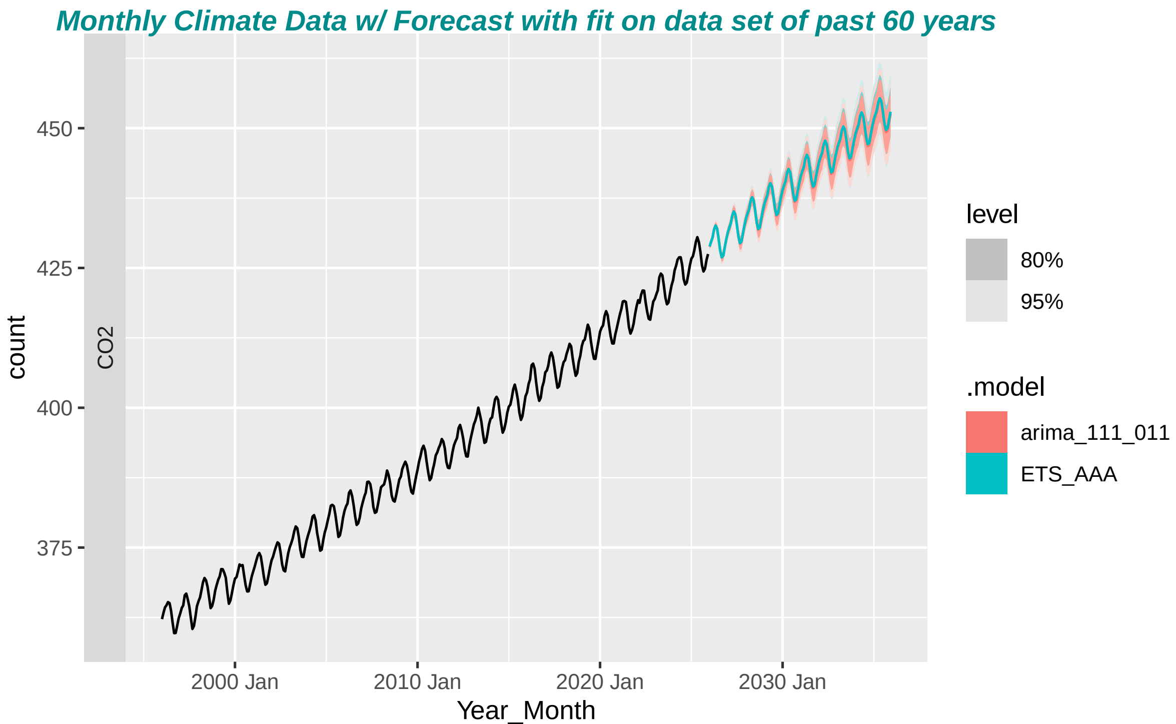
Forecasts produced using **ETS** methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older.

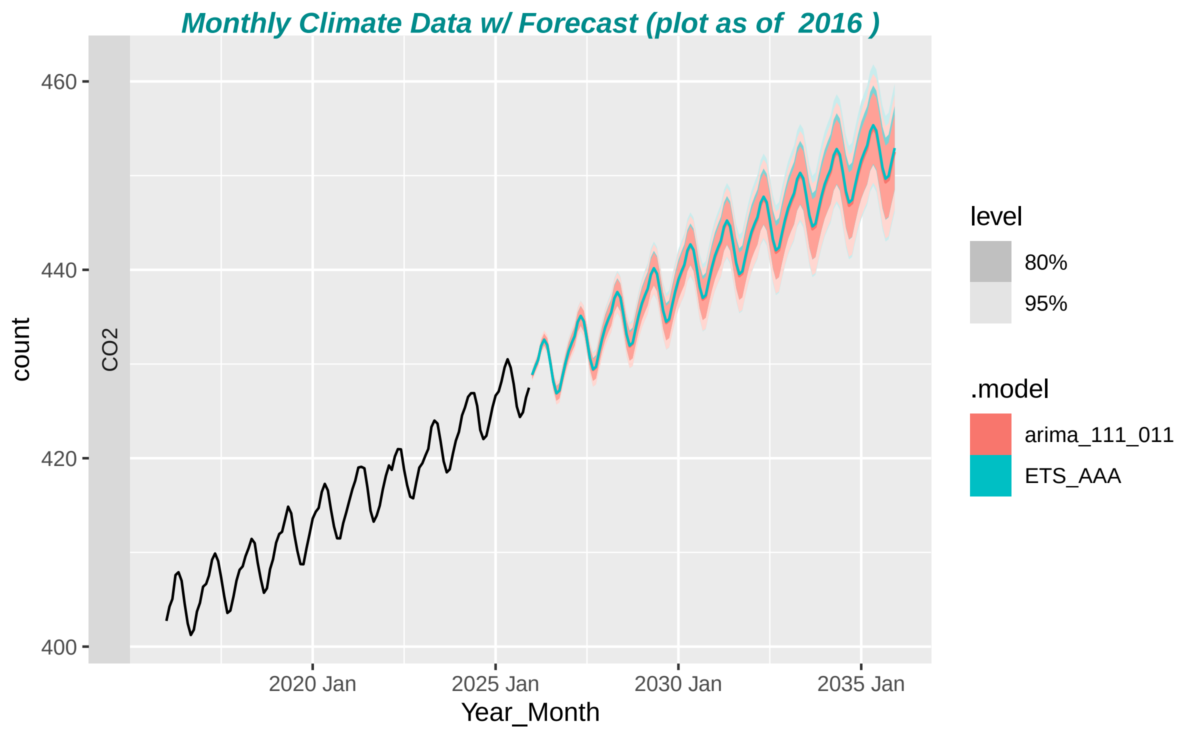
Here a $ETS(A, A|A)$ **model** with additive ("A") *Error term*, *Trend term* and *Seasonal term* was chosen.

While exponential smoothing models are based on a description of the trend and seasonality in the data, **ARIMA** models aim to describe the autocorrelations in the data.

Here a $ARIMA(111)(011)_{12}$ **model** with autoregressive, differencing, and moving average terms of (111) in the ordinary and 011 in the seasonal term with a seasonal period 12 (12 months/year)

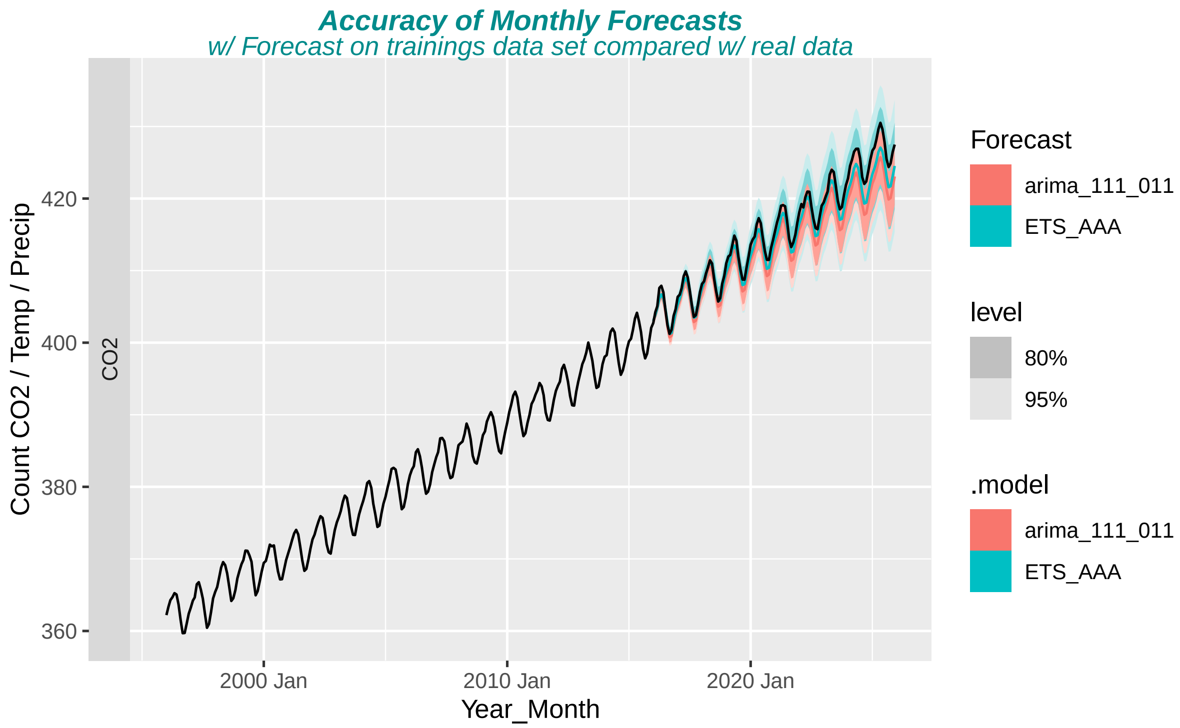
```
#> # A mable: 1 x 4
#> # Key:     City, Measure [1]
#>   City      Measure      ETS_AAA                 arima_111_011
#>   <chr>     <fct>        <model>                       <model>
#> 1 Mauna Loa CO2     <ETS(A,A,A)> <ARIMA(1,1,1)(0,1,1)[12]>
```




Monthly Climate Data w/ Forecast (plot as of 2016)
count
CO2
460
440
420
400
2020 Jan
2025 Jan
2030 Jan
2035 Jan
Year_Month
level
80%
95%
.model
arima_111_011
ETS_AAA

3.2 Forecast Accuracy Evaluation

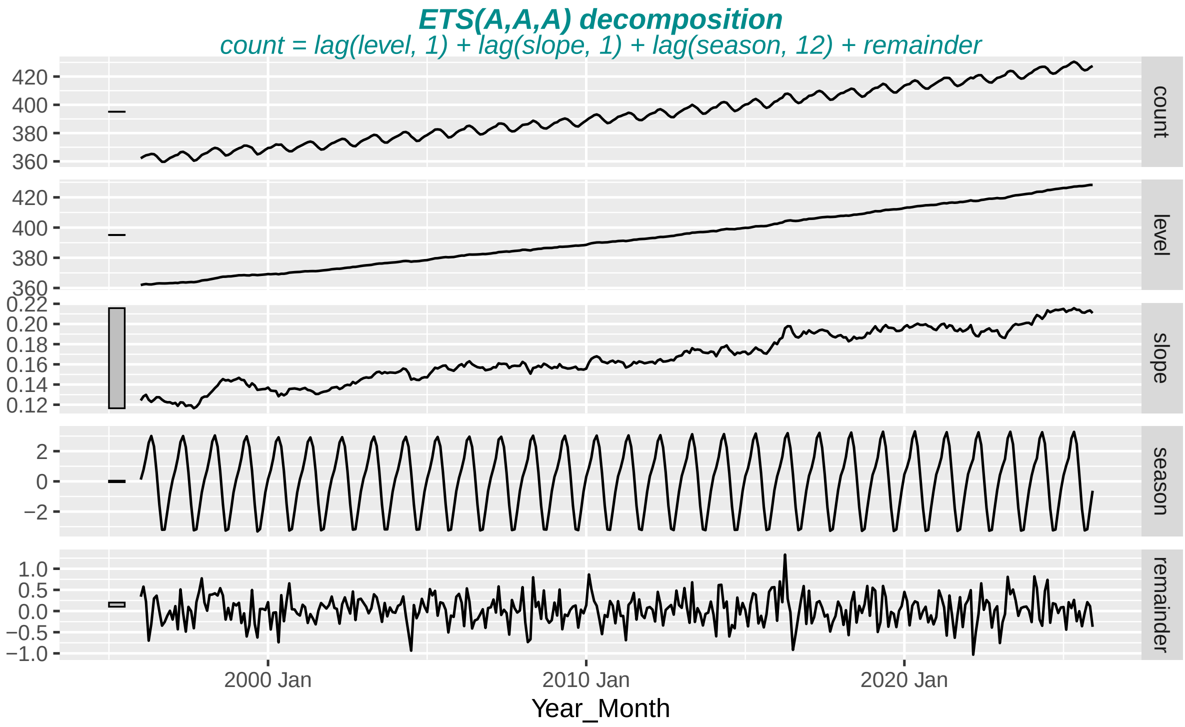
- Forecast Accuracy Evaluation w/ training data "data_train" & test data "data_test"
  - "data" : complete dataset includes the forecasted (future) data range on top of data_train
  - "data_train" = "data" - forecast_range ("data_test")
    - data used to train the model (~80% of "data)
  - "data_test" = "data" - "data_train"
    - ~ 20% of "data"
  - e.g. for last_year = 2025:
    - data_train is selected from 1966 - 2015
    - data_test is selected from 2016 - 2025



3.2.1 components(fit_ets) - plot of the decomposition of the fitted ETS model

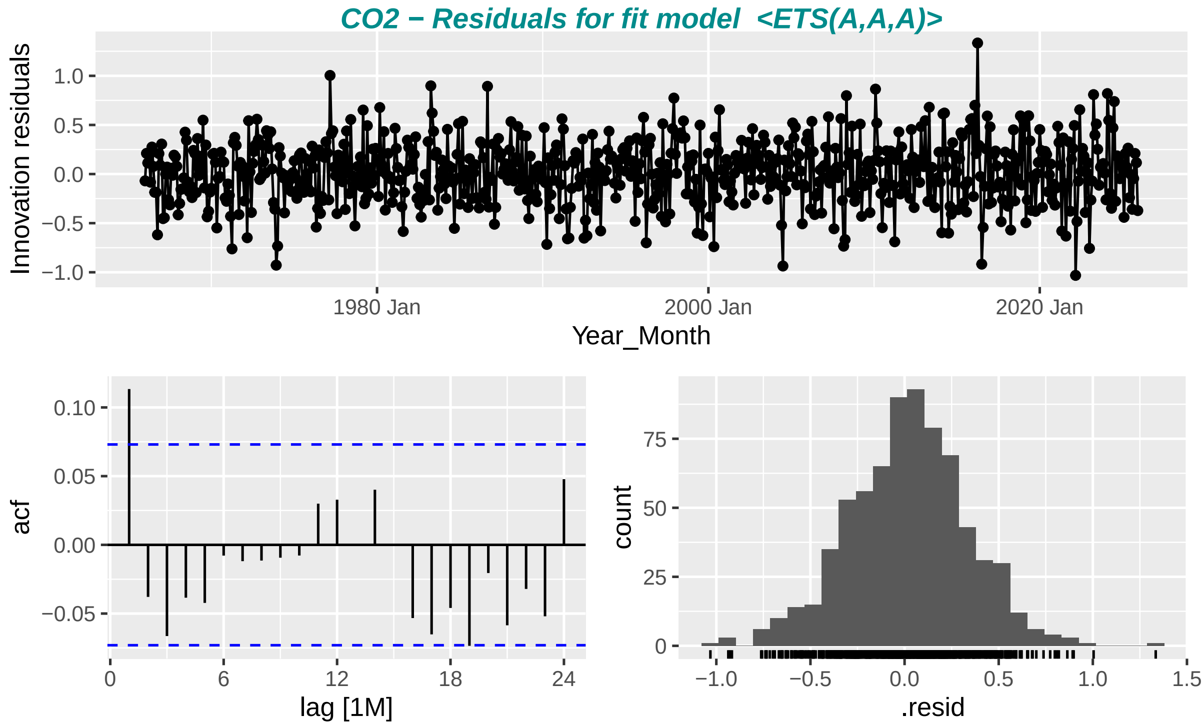
- Note: compare Time series decomposition, for ETS model is valid:
  - count = lag(level, 1) + lag(slope, 1) + lag(season, 12) + remainder

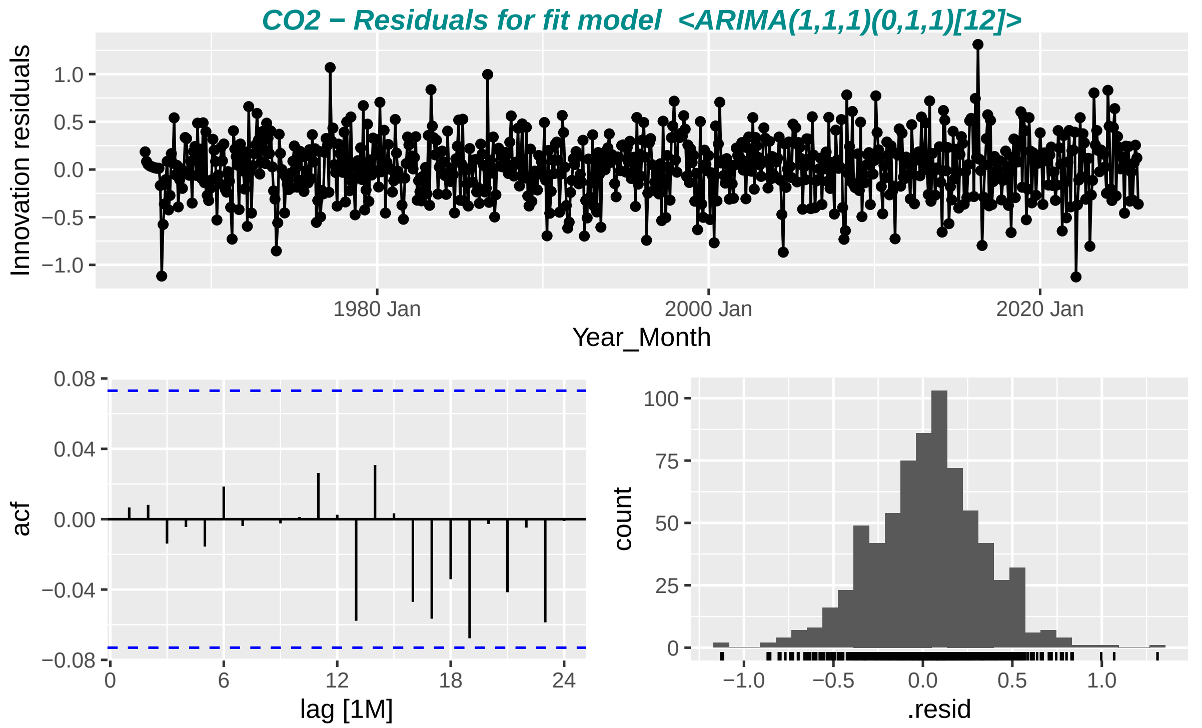
```
#> [1] "CO2"
```



3.2.2 gg_tsresiduals(fit) - plot of innovation residuals, acf and histogram

- gg_tsresiduals(fit) (Ch 7.3 Evaluating the regression model)
  - TS of innovation residuals, acf plot, histogram of residuals | PACF (plot_type='partial')
  - innovation residuals should have constant variance ("homoscedasticity")
  - histogram of the innovation residuals: should be normally distributed





4 Forecast Tables

4.1 Yearly mean values of past time periods

Table 1: Mean values for the given time periods; Units: Temperature (degree C), Precipitation (mm/Month), CO2 (ppm)

Period_Time	CO2
1959-1960	316.4
1961-1990	333.5
1991-2020	381.9
2021-2025	421.6

4.2 Yearly mean forecast values for the next 25 years

Table 2: Mean Yearly ARIMA and ETS Forecast values (next 25 years); Units: Temperature (degree C), Precipitation (mm/Month), CO2 (ppm)

City	Measure	Year	ETS_AAA	arima_111_011
Mauna Loa	CO2	2026	429.73	429.73
Mauna Loa	CO2	2030	439.85	439.70
Mauna Loa	CO2	2035	452.50	452.15
Mauna Loa	CO2	2040	465.15	464.60
Mauna Loa	CO2	2045	477.80	477.05
Mauna Loa	CO2	2050	490.45	489.50

Table 3: Forecast increase/decrease over the next 25 years; Units: Temperature (degree C), Precipitation (mm/Month), CO2 (ppm)

Measure	Year.x	Year.y	ETS.x	ARIMA.x	ETS.y	ARIMA.y	Delta_ETS	Delta_ARIMA
CO2	2026	2050	429.73	429.73	490.45	489.5	60.72	59.77

Table 4: Forecast increase/decrease over the next 25 years; Units: Temperature (degree C), Precipitation (mm/Month), CO2 (ppm)

Measure	Month	Year.x	Year.y	Mean.x_ETS	Mean.x_ARIMA	Mean.y_ETS	Mean.y_ARIMA	Delta_ETS	Delta_ARIMA
CO2	Jan	2026	2050	428.86	428.79	489.58	488.58	60.72	59.79
CO2	Feb	2026	2050	429.73	429.70	490.45	489.48	60.72	59.77
CO2	Mar	2026	2050	430.43	430.43	491.15	490.19	60.72	59.77
CO2	Apr	2026	2050	431.93	431.93	492.65	491.69	60.72	59.77
CO2	May	2026	2050	432.59	432.61	493.31	492.38	60.72	59.76
CO2	Jun	2026	2050	432.00	432.08	492.72	491.84	60.72	59.76
CO2	Jul	2026	2050	430.17	430.28	490.89	490.04	60.72	59.76
CO2	Aug	2026	2050	428.10	428.14	488.82	487.91	60.72	59.76
CO2	Sep	2026	2050	426.90	426.87	487.62	486.63	60.72	59.76
CO2	Oct	2026	2050	427.19	427.14	487.91	486.91	60.72	59.76
CO2	Nov	2026	2050	428.75	428.70	489.47	488.47	60.72	59.76
CO2	Dec	2026	2050	430.16	430.11	490.88	489.87	60.72	59.76

5 Backup

5.1 Mauna Loa - Average Yearly and Seasonal Data

Table 5: Annual paste(CO[2], " Concentration / ppm") (first and last 10 years)

City	Measure	Year	Winter_avg	Spring_avg	Summer_avg	Fall_avg	Year_avg
Mauna Loa	CO2	1959	NA	317.6	316.5	314.0	316.0
Mauna Loa	CO2	1960	316.3	318.9	317.9	314.3	316.9
Mauna Loa	CO2	1961	316.9	319.5	318.4	315.5	317.6
Mauna Loa	CO2	1962	317.8	320.4	319.2	316.1	318.5
Mauna Loa	CO2	1963	318.5	321.2	319.7	316.4	319.0
Mauna Loa	CO2	1964	319.3	321.6	320.3	317.1	319.6
Mauna Loa	CO2	1965	319.5	321.7	320.6	318.0	320.0
Mauna Loa	CO2	1966	320.5	323.4	322.2	318.8	321.4
Mauna Loa	CO2	1967	322.0	324.1	322.5	319.8	322.2
Mauna Loa	CO2	1968	322.6	324.8	323.9	320.6	323.0
Mauna Loa	CO2	2016	403.0	406.9	404.7	402.2	404.4
Mauna Loa	CO2	2017	405.9	408.9	407.2	404.2	406.8
Mauna Loa	CO2	2018	407.9	410.5	409.0	406.7	408.7
Mauna Loa	CO2	2019	410.8	413.5	412.1	409.3	411.6
Mauna Loa	CO2	2020	413.3	416.1	414.6	412.0	414.2
Mauna Loa	CO2	2021	415.5	418.6	416.8	414.0	416.4
Mauna Loa	CO2	2022	418.0	420.0	419.0	416.4	418.5
Mauna Loa	CO2	2023	419.6	422.8	421.7	419.3	421.1
Mauna Loa	CO2	2024	423.1	426.3	425.2	422.8	424.6
Mauna Loa	CO2	2025	426.4	429.4	427.7	425.2	427.3

Table 6: Monthly Means over all Years (CO2 Concentration / ppm)

City	Month	CO2
Mauna Loa	Jan	360.6
Mauna Loa	Feb	361.4
Mauna Loa	Mar	362.2
Mauna Loa	Apr	363.5
Mauna Loa	May	364.1
Mauna Loa	Jun	363.5
Mauna Loa	Jul	362.0
Mauna Loa	Aug	359.9
Mauna Loa	Sep	358.4
Mauna Loa	Oct	358.5
Mauna Loa	Nov	359.8
Mauna Loa	Dec	361.2

5.2 Mauna Loa - Head and tail of data

```
#> # A tsibble: 6 x 5 [1M]
#> # Key:       City, Measure [1]
#> # Groups:    City, Measure [1]
#>   City      Measure Year_Month Period_Time count
#>   <chr>     <fct>        <mth> <chr>       <dbl>
#> 1 Mauna Loa CO2       1959 Jan 1959-1960    316.
#> 2 Mauna Loa CO2       1959 Feb 1959-1960    316.
#> 3 Mauna Loa CO2       1959 Mrz 1959-1960    317.
```

```
#> 4 Mauna Loa CO2        2025 Okt 2021-2025    425.
#> 5 Mauna Loa CO2        2025 Nov 2021-2025    426.
#> 6 Mauna Loa CO2        2025 Dez 2021-2025    427.
```

5.3 Data Sources

5.3.1 Temperatures and Precipitation

- Basel / Davos: **Federal Office of Meteorology and Climatology MeteoSwiss**
  - https://www.meteoswiss.admin.ch/home/climate/swiss-climate-in-detail/homogeneous-data-series-since-1864.html
- Cottbus/ Giessen/ Hohenpeissenberg/ Mannheim/ Potsdam: **DWD Archiv Monats- und Tageswerte**
  - https://www.dwd.de/DE/leistungen/klimadatendeutschland/klarchivtagmonat.html
  - *Monatswerte historisch und aktuell*
  - File: produkt_klima_monat_xy.txt
    - column MO_TT (Temperature; Monatsmittel der Lufttemperatur in 2m Höhe in °C and MO_RR (Precipitation; Monatssumme der Niederschlagshoehe in mm))
- England **Met Office - National Meteorological Service for the UK**
  - https://www.metoffice.gov.uk/hadobs/hadcet/data/download.html
  - Monthly_HadCET_mean.txt, 1659 to date

5.3.2 CO2 Concentrations

- **National Oceanic & Atmospheric Administration - Earth System Research Laboratory**
  - *NOAA ESRL* https://www.esrl.noaa.gov/gmd/ccgg/trends/global.html
  - Data file: ***Mauna Loa CO2*** monthly mean data
  - https://www.esrl.noaa.gov/gmd/ccgg/trends/data.html

5.4 R code

- Source code (maybe not yet the latest version) and output files are stored on GitHub repository https://github.com/WoVollmer/R-TimesSeriesAnalysis/tree/master/Climate
- Partially based on *c't Magazin* articles by *Andreas Krause*:
  - #3/2014 p.188 http://www.ct.de/1403188 & #6/2014 p.180 http://www.ct.de/1406180
- *Forecasting: Principles and Practice (3rd ed)* https://otexts.com/fpp3
  - Rob J Hyndman and George Athanasopoulos; Monash University, Australia