Present Global CO_2 Emissions

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1 Background

In the 1997 report, we explored the trend and variability in atmospheric CO_2 levels using polynomial and ARIMA models. Our analysis indicated a significant upward trend in CO_2 levels, with an accelerating rate of increase. In this report, we aim to re-evaluate those models and their predictions using the latest data. The central question we are addressing is:

> *Have the previous models accurately predicted current CO_2 levels?*

1.0.1 Null Hypothesis

2 Measurement and Data

2.1 Measuring Atmospheric Carbon

Since our last report, the volcano near the research center has erupted. Therefore the measurements from Dec. 2022 to July 4, 2023 are from the Maunakea Observatories, which are just over 20 miles north of the original observatory. Additionally, there is a note that the last several months worth of data is "preliminary" and therefore could be revised. Furthermore, the provided data consists of weekly averages, and we will need to calculate monthly averages from 1997 to the present in order to compare with the forecast data from the 1997 report.

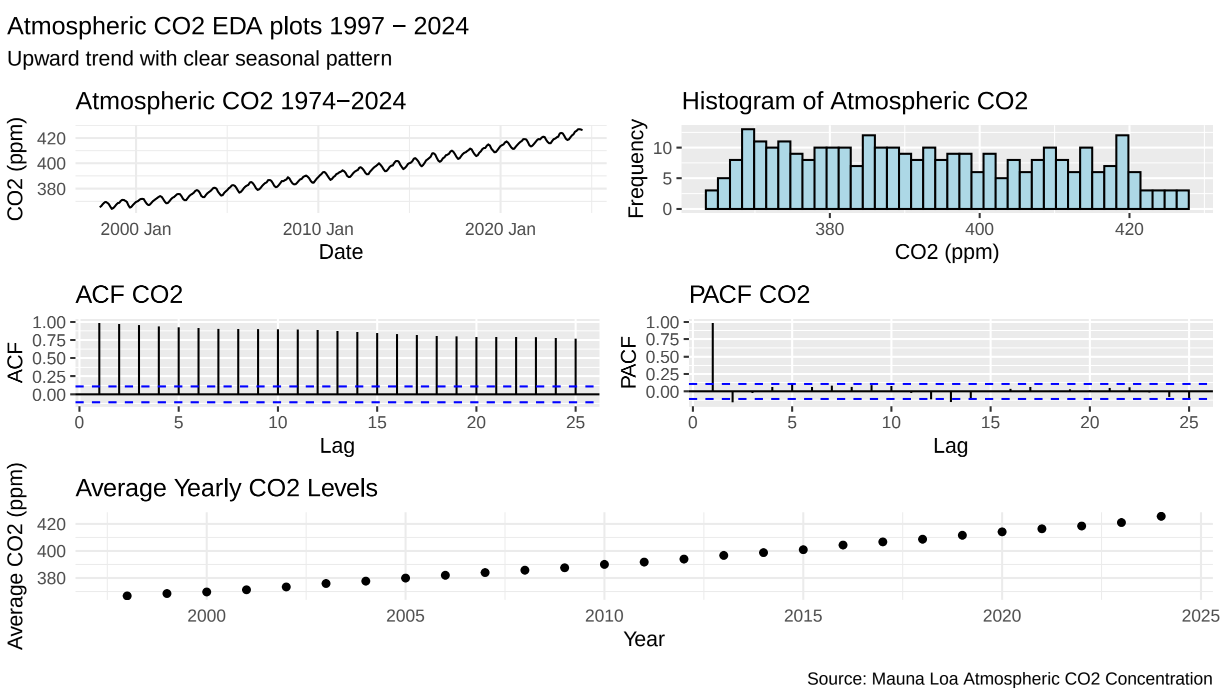


Figure 1: Atmospheric CO2 EDA standard plots

2.2 Historical vs Present Trends in Atmospheric Carbon

We see that the atmospheric CO_2 levels continued to have a strong upward linear trend since 1997, as seen in the bottom plot of average yearly CO_2 as shown in Figure 1. It appears that this linear trend very slightly increased in slope after the year 2000. We also see that the distribution of values is fairly wide from the histogram, with a slight right skew. We also see that the ACF tails off very slowly while the PACF drops off after lag 1. This indicates that there may be some unit roots. As this timeseries is a continuation of our previous time series, we know that this data is also not stationary.

3 Old Models Comparisons

3.1 Linear Model

Our polynomial model looks like it did a pretty good job at predicting CO_2 up to 2024. It is missing the peaks and valleys, but it looks to capture the average yearly increase in CO_2 levels as shown in Figure 2.

3.2 ARIMA Model

In the 1997 report, we used an ARIMA(3,1,0)(2,1,0)[12] model to forecast atmospheric CO_2 levels. Both the ARIMA model forecast and the the realized CO_2 show an upward trend with seasonal pattern. However, the model predicted lower values than the realized values in the long term as shown in Figure 2.

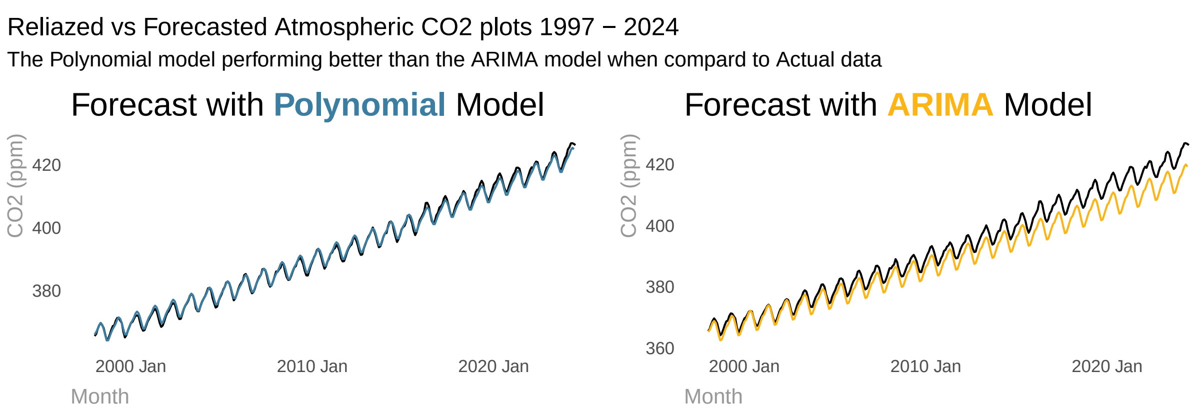


Figure 2: Comparing Realized Atmospheric CO2 Levels with Polynomial and ARIMA Models

3.3 Linear vs ARIMA

In 1997, we predicted that CO_2 levels would reach 420 PPM by March 2025 using our ARIMA model and 2022 May using the Polynomial model. However, Actual CO_2 levels reached 420 PPM by 2022 Apr.

Our ARIMA model with log transformation produces RMSE = 5.463 compared to the Polynomial model with RMSE = 3.48. Based on the descriptive analysis, and the RMSE comparisons, we can conclude that despite the fact that the ARIMA model performed better with the training data the Polynomial model performed better than the ARIMA model in the long term forecast.

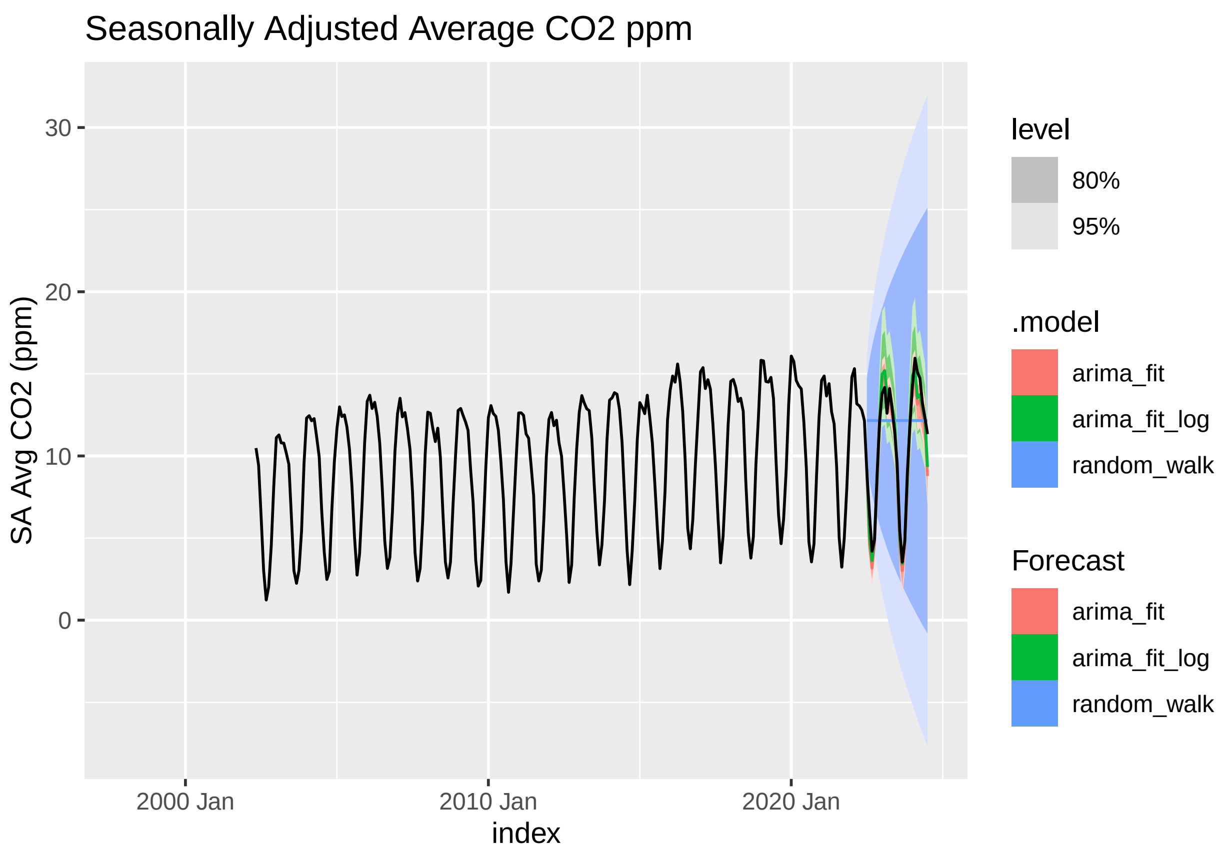
4 New Model

Identically to before, we use the KPSS test to determine whether the SA and the NSA data are stationary. For both series, the first test yields a p value of 0.01, and we reject the null hypothesis, meaning that our data is not stationary. After taking one difference, we see that our p value for both series is 0.1, and we fail to reject the null hypothesis, meaning that the both datasets are stationary after one difference.

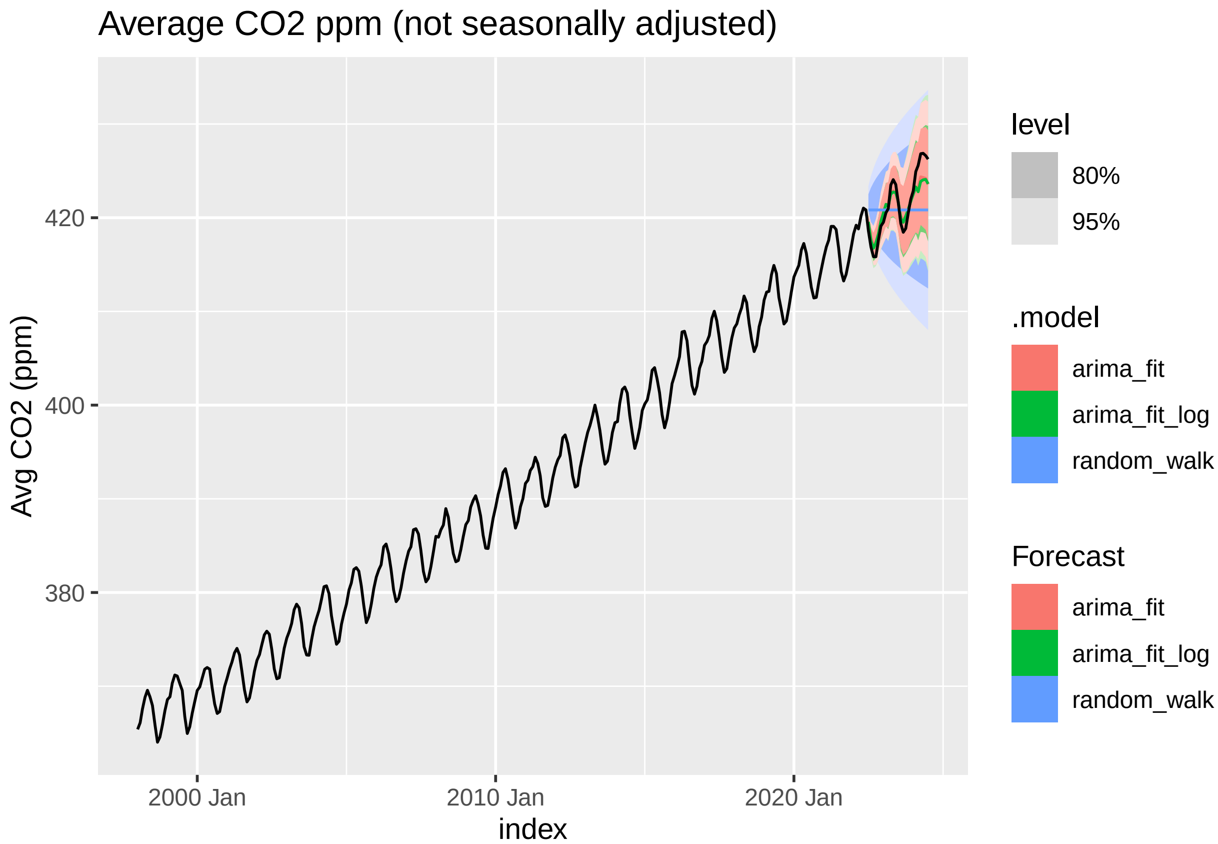
Using the information criteria of AICc, we see that the best SA model was an ARIMA(5,1,0)(1,0,0)[52] with a log transformation. This model has five AR terms and is first differenced. It also has one seasonal AR term with a period of 52 weeks. The best NSA model was an ARIMA(0,1,0)(0,0,1)[52] with a log tranformation. This model is first differenced and has one seasonal MA term where the period is 52 weeks. We selected both of these models because they had the lowest AICc. We will examine the residuals to see if they resemble white noise.

The top performing models for SA and NSA data both has residuals that rejected the null hypothesis of the Ljung-Box test, which indicates that they do not have white noise residuals. Therefore, we selected the models with the second lowest AICc, which have residuals that follow a normal distribution, and appear to be white noise in their ACF plots. Additionally, they both fail to reject the null hypothesis of the Ljung-Box test, indicating that the residuals exhibit no autocorrelation for 10 lags and can be regarded as white noise (SA p-value = 0.23, NSA p-value = 0.48).

The superior model for the SA data is an ARIMA(5,1,0)(1,0,0)[52], which has five AR terms, first differencing, and one seasonal AR term with a period of 52 weeks. The superior model for the NSA data is an ARIMA(1,1,4)(0,0,1)[52], which has one AR term, first differencing, four MA terms, and one seasonal MA term with a period of 52.



Seasonally Adjusted Average CO2 ppm
SA Avg CO2 (ppm)
30
20
10
0
2000 Jan
2010 Jan
2020 Jan
index
level
80%
95%
.model
arima_fit
arima_fit_log
random_walk
Forecast
arima_fit
arima_fit_log
random_walk



- STILL NEED TO DO THE FOLLOWING:*
- Measure and discuss how your models perform in-sample and (psuedo-) out-of-sample,
- Comparing candidate models and explaining your choice.
- Fit a polynomial time-trend model to the seasonally-adjusted series and compare its performance to that of your ARIMA model.

5 Conclusion