

# Comparing Global $CO_2$ Emission Models from 1997 and Today

Carolyn Dunlap, Ayda Nayeb Nazar, Qian Qiao, Hector Rincon

## Abstract

In 1997, our team analyzed  $CO_2$  concentration average monthly trends from 1959 to 1997. Our work culminated in a report that discussed multiple linear and ARIMA models of these concentration data and attempted to forecast  $CO_2$  trends into the future, as far out as 2100. Given that we now have 25 more years of data, and at a highly weekly resolution, this report aims to revisit and evaluate our 1997 models. Using weekly average  $CO_2$  concentration levels taking from the Mauna Loa observatory, we also analyze our data to fit new models and generate updated forecasts for potential  $CO_2$  concentrations as far out as 100 years into the future.

## Introduction

In this report, we are continuing to evaluate atmospheric  $CO_2$  trends (commonly referred to as the Keeling Curve), generating models and forecasts to help understand how we might expect atmospheric  $CO_2$  levels to change in the future. Specifically, we are re-evaluating our best performing linear and ARIMA models from our 1997 report on  $CO_2$  concentrations, using more recently generating weekly average  $CO_2$  data up through the end of 2022. This report continues to use the  $CO_2$  concentration data collected by the Mauna Loa observatory, with the key exception that we have weekly average  $CO_2$  concentration data, compared to the monthly average concentration data used in 1997. Depending on the purposes of our analyses, we will either keep the weekly granularity or regenerate monthly averages as necessary. In addition to evaluating our 1997 models and forecasts, we will also use more recent data to generate new models and forecasts for  $CO_2$  concentrations.

## Measurement and Data

The data that we are using from this report was accessed via the United States' National Oceanic and Atmospheric Administration website, where they house continually updated weekly  $CO_2$  concentration data collected from the Mauna Loa observatory. This data was collected in a similar manner to the data in 1997 with a few key exceptions.

The first key exception is that in 2019, the observatory installed a new  $CO_2$  analyzer that measures  $CO_2$  concentration (defined as the number of  $CO_2$  molecules out of a random million atmospheric molecules, or parts per million (ppm)) via cavity-ring down spectroscopy versus the previously used infrared absorption. We are presuming that this change in analysis technique does not dramatically alter the concentration of  $CO_2$ . Another exception is that this dataset has a gap in December 1975: for the purposes of these analyses, we decided to fill all gaps using the previous  $CO_2$  concentration gathered (e.g. we decided to use the  $CO_2$  concentration taken on November 11, 1975 as the  $CO_2$  values for all of the missing December 1975 datapoints).

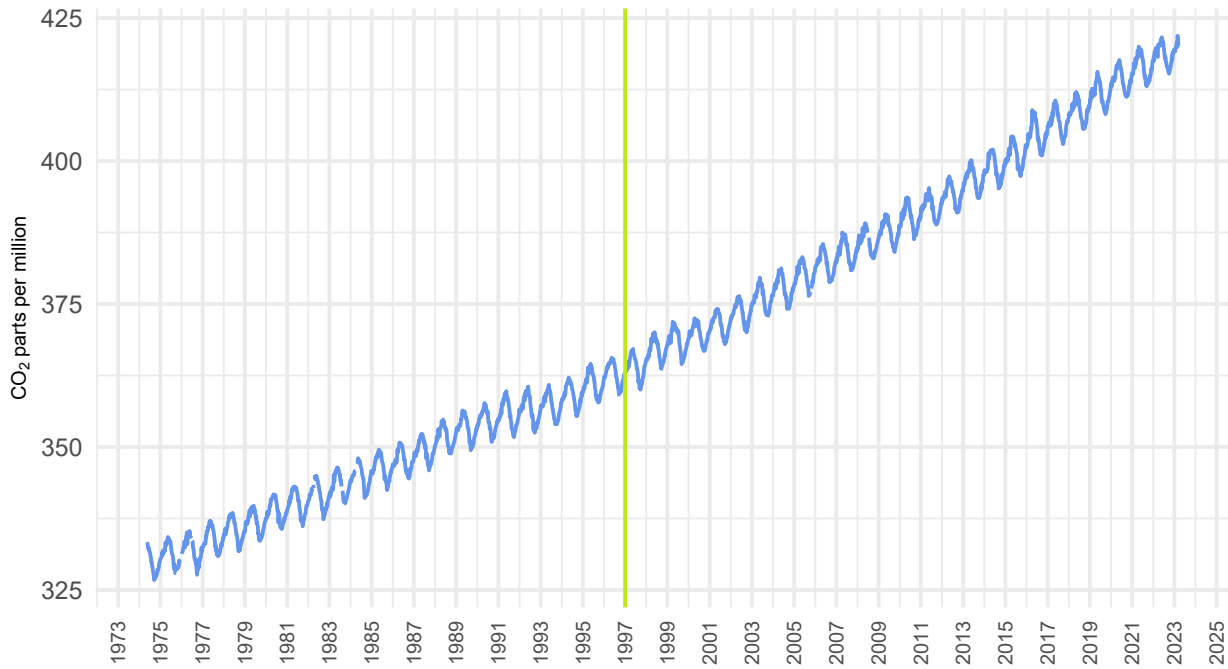
A final note about this data set is that in November 29, 2022 Mauna Loa erupted and thus all subsequent data points were collected at the Maunakea observatories, approximately 21 miles north of the Mauna Loa observatory. For ease and data consistency, we have decided to only use data through the end of 2022 in our models and forecasts (up to but not including the recent Maunakea observations).

## Historical Trends in Atmospheric Carbon

To begin, we conducted the same analysis on this dataset as was done in 1997, beginning with a map of the time series data, shown below in Figure 1, with a vertical red line at 1997 to reflect what new data we have compared to the previous report.

Figure 1: Weekly Mean  $\text{CO}_2$  at Mauna Loa 1974-2023

A continuation of the Keeling Curve (red line denotes 1997)



From this time series, we observe a steady continuation of the Keeling curve, with a continual increase in  $\text{CO}_2$  concentration (ppm) as well as a notable seasonal component. The curve of the overall increasing  $\text{CO}_2$  concentration, compared to data prior to 1997, does appear to be increasing at a slightly higher rate than what was previously observed.

To more carefully compare the distribution and autocorrelation aspects of this times series, we conducted further analysis, as shown below in Figure 2.

Figure 2a

Histogram of Weekly Mean  $\text{CO}_2$

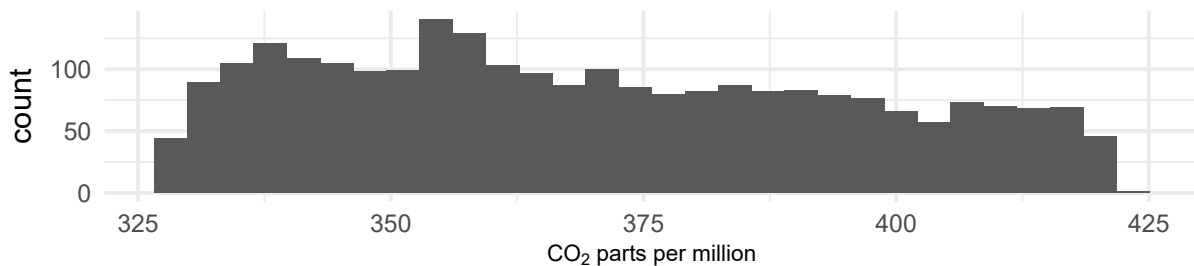


Figure 2b

ACF of Weekly Mean  $\text{CO}_2$

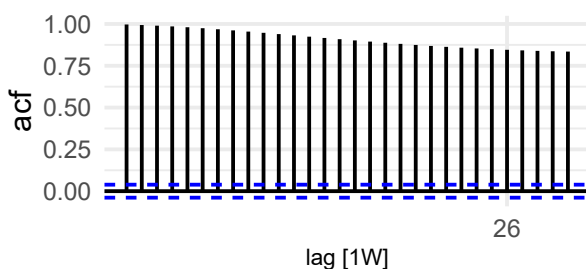


Figure 2c

PACF of Weekly Mean  $\text{CO}_2$

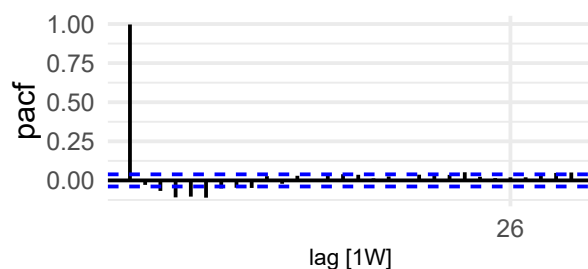


Figure 2 reveals that the present dataset recapitulates the behavior observed in the 1997 dataset. Similar to what was seen in 1997, there is a strong autocorrelation in  $CO_2$  concentration with very mild decay, maintaining its strong correlation even after a lag of 30 weeks (Fig 2b). The partial autocorrelation, PACF plot, reveals a first correlation of almost 1 and some cyclical correlations that may correspond to the seasonality of the data (Fig 2c). Taken together, this analysis suggests that there is a seasonal and potentially autoregressive component to the data.

## Models and Forecasts

Through our exploratory data analysis, we found that our weekly data from 1974-2022 appears to behave very similarly to the data that was analyzed in 1997. Stemming from this analysis, we move to specifically evaluating the best linear and ARIMA model from the 1997 report against this newer dataset.

### Comparing 1997 Linear Models

To begin, we compared the best linear model from the 1997 report. In that report, we assessed four different models and determined that the quadratic model with a seasonal adjustment component most accurately described the data up to 1997. To compare this model, we forecasted this model 25 years in the future to encompass 2023, and graphed it against our current dataset, shown below in Figure 3.

**Figure 3: Quadratic model forecast vs realised values 1997-2022**

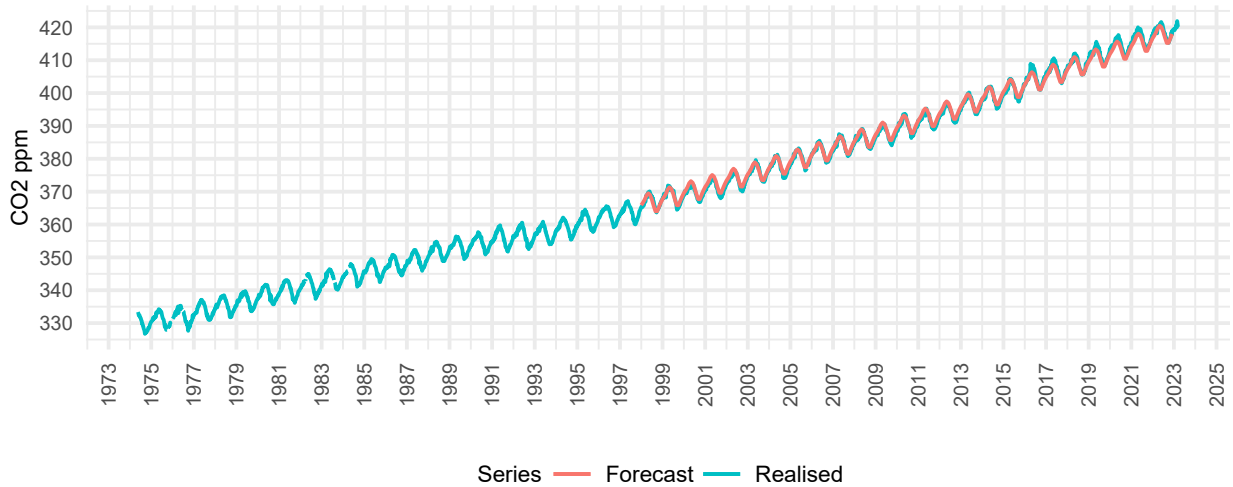
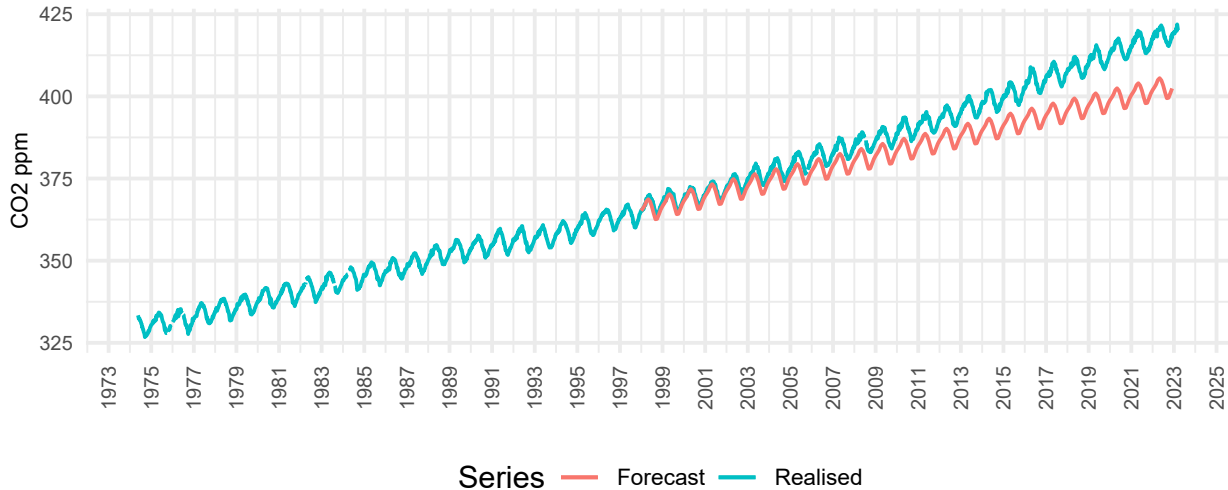


Figure 3 reveals that the quadratic with seasonality model forecast fairly accurately predicts the actual data from 1997-2022. Up until about 2016, the 1997 model does seem to routinely over-predict the trough  $CO_2$  values per year and after 2016, the 1997 quadratic with seasonality model routinely under-predicts the peak  $CO_2$  values per year. This suggests that while the quadratic model fits the data fairly closely, a model that combines several localized trends might better capture the data than a single overarching model.

### Comparing 1997 ARIMA Models

In addition to the linear model, the 1997 report also fit an ARIMA model to the Keeling Curve  $CO_2$  data. We therefore wanted to additionally evaluate how well that ARIMA model,  $ARIMA(0,1,3)(0,1,1)[12]$ , recapitulated the realized  $CO_2$  concentrations from 1997-2022 (Figure 4 below).

**Figure 4: ARIMA model forecast vs realised values 1997-2022**



As evident from Figure 4, the 1997 ARIMA model poorly predicted the  $CO_2$  concentrations from 1997-2022, especially compared to the quadratic with seasonality model also developed in 1997. From visual inspection, the 1997 ARIMA model predicted a linearly increasing Keeling Curve, rather than the quadratic process demonstrated in the previous model. Because the  $CO_2$  concentration trends does appear to increase more each year post 1997, following a quadratic pattern more than a linear pattern, the ARIMA model consistently and more drastically underpredicted  $CO_2$  concentrations at all points throughout the year post 1997.

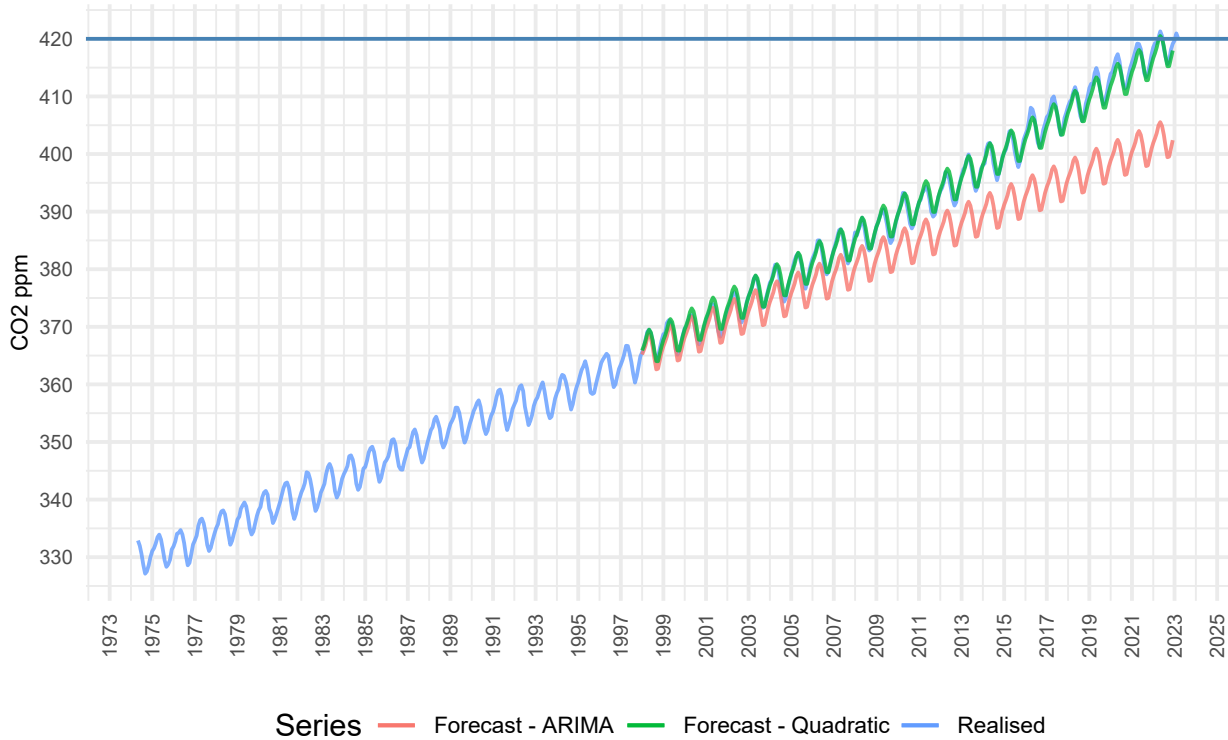
### Evaluation of 1997 forecasts

To more formally compare the 1997 models, we evaluate the specific accuracy of several forecasts generated in the 1997 report to assess how closely they matched the current realized data. In 1997, we predicted the first and final times  $CO_2$  concentration levels would reach 420 ppm and 500 ppm. We also evaluated predicted  $CO_2$  concentrations in the year 2100. As of the date of writing this report (published March 2023), we have not yet crossed the 500 ppm threshold nor have data on  $CO_2$  in the year 2100, however we have already reached 420 ppm.

In the 1997 report, 420 ppm predictions were generated using the  $ARIMA(0,1,3)(0,1,1)[12]$  model only, because at the time that model was assessed to best recapitulate the data. In the 1997 report,  $CO_2$  concentrations was predicted to first cross the 420 ppm threshold in April 2032, however, the current data reveals that we actually first crossed the 420 ppm threshold in May 2021 according to the weekly data and April 2022 when the current data is aggregated monthly, a full 10-11 years prior to the 1997 ARIMA model estimate. As discussed above, the 1997 ARIMA model severely underestimated the growth rate of the Keeling Curve past 1997. In contrast and as can be shown below in Figure 5 (the blue horizontal line corresponds to the 420 ppm threshold), the quadratic model with seasonality developed in the 1997 report predicted a May 2022 estimate for monthly mean  $CO_2$  concentration, which compared to the ARIMA model is a much more accurate forecast.

**Figure 5**

ARIMA model forecast, quadratic model forecast, and realised values 1997-2022



To more rigorously compare the accuracy of the two models, we assessed numerous accuracy measures for each 1997 model against the aggregated monthly average data used in this report, comparing forecasted accuracy from 1997-2022. The results are summarized in Table 1 (below) and reveal that across each metric (mean error (ME), root mean squared error (RMSE), mean absolute error (MAE), mean percentage error (MPE), mean absolute percentage error (MAPE), mean absolute scaled error (MASE), root mean squared scaled error (RMSSE), and autocorrelation errors at lag 1 (ACF1)), the 1997 quadratic with seasonality model outperformed the 1997 ARIMA model.

Table 1: 1997 Model Forecasting Accuracy 1997-2022

.model	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE	ACF1
arima013011	6.974	8.496	6.97	1.737	1.737	4.727	5.382	0.985
TSLM(value ~ trend() + I(trend()^2) + season())	0.006	0.919	0.72	-0.003	0.183	0.488	0.582	0.837

## Training New Models Based on Present Data

### ARIMA Models

Since we have conducted a thorough analysis of the models developed in the 1997 report, we now wanted to devise updated models on this more granular and recent  $CO_2$  concentration data. In order to do this, we seasonally adjusted the weekly data, and split both the seasonally adjusted (SA) and non-seasonally adjusted (NSA) data into training and test sets. Because we are working with time series data, our test sets were comprised of the most recent 2 years of weekly  $CO_2$  concentrations (2020-2022). We fitted both SA and NSA training data sets to ARIMA models. Before fitting ARIMA models, we took the first difference of the data to remove the increasing trend and evaluated whether or not the weekly data was stationary post differencing (since stationarity is an assumption of ARIMA models).

##

```
## Phillips-Perron Unit Root Test
##
## data: train.diff.sa$diff[-1]
## Dickey-Fuller = -108, Truncation lag parameter = 8, p-value = 0.01
##
## Augmented Dickey-Fuller Test
##
## data: train.diff.sa$diff[-1]
## Dickey-Fuller = -19, Lag order = 13, p-value = 0.01
## alternative hypothesis: stationary
```

As shown above, using both the Phillips-Perron Unit Root Test and Augmented Dickey-Fuller Test we reject the null hypothesis that the first difference of the SA weekly  $CO_2$  concentration data is non-stationary.

```
##
## Phillips-Perron Unit Root Test
##
## data: train.diff.nsa$diff[-1]
## Dickey-Fuller = -53, Truncation lag parameter = 8, p-value = 0.01
##
## Augmented Dickey-Fuller Test
##
## data: train.diff.nsa$diff[-1]
## Dickey-Fuller = -16, Lag order = 13, p-value = 0.01
## alternative hypothesis: stationary
```

Similarly, using both the Phillips-Perron Unit Root Test and Augmented Dickey-Fuller Test we also reject the null hypothesis that the first difference of the NSA weekly  $CO_2$  concentration data is non-stationary. We therefore call the first difference of both datasets stationary processes and can proceed to fit ARIMA models.

For the NSA data, both the BIC and AIC criteria fit the same ARIMA model ARIMA(1,0,1)(1,1,0)[52] (AIC = 3524, BIC=3553) from all permutations of ARIMA models with up to 10 autoregressive processes, 2 unit roots differences, 10 moving average processes, and the equivalent in seasonality components. We used similar techniques to fit the SA data, and found that the same ARIMA model, ARIMA(0,1,3)(2,0,0)[52], had the lowest AIC (AIC = 1711) and BIC (BIC = 1751) for the SA data (model shown below).

For each of these models, we evaluated the model accuracy against the training (in-sample) and test (out-sample) data sets.

### Evaluating accuracy

To evaluate the ARIMA models, we first assessed each model (the best model via AIC or BIC for either the NSA or SA data sets) accuracy against the training data provided, which is described in Table 2 below.

Table 2: Evaluating ARIMA model accuracy for present data (Training Data)

model	IC	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE	ACF1
ARIMA(1,0,1)(1,1,0)[52] (NSA data)	AIC	0.008	0.501	0.382	0.002	0.104	0.208	0.249	0.127
ARIMA(0,1,3)(2,0,0)[52] (SA data)	AIC	-0.001	0.342	0.259	-0.001	0.070	0.141	0.170	0.000
ARIMA(1,0,1)(1,1,0)[52] (NSA data)	BIC	0.008	0.501	0.382	0.002	0.104	0.208	0.249	0.127
ARIMA(0,1,3)(2,0,0)[52] (SA data)	BIC	-0.001	0.342	0.259	-0.001	0.070	0.141	0.170	0.000

To evaluate our chosen ARIMA models further, we used each model (for NSA and SA data respectively) to forecast 2 years in the future (2021 and 2022) and compared the accuracy of each model against our test data sets (both for

NSA and SA data). These results are described in Table 3.

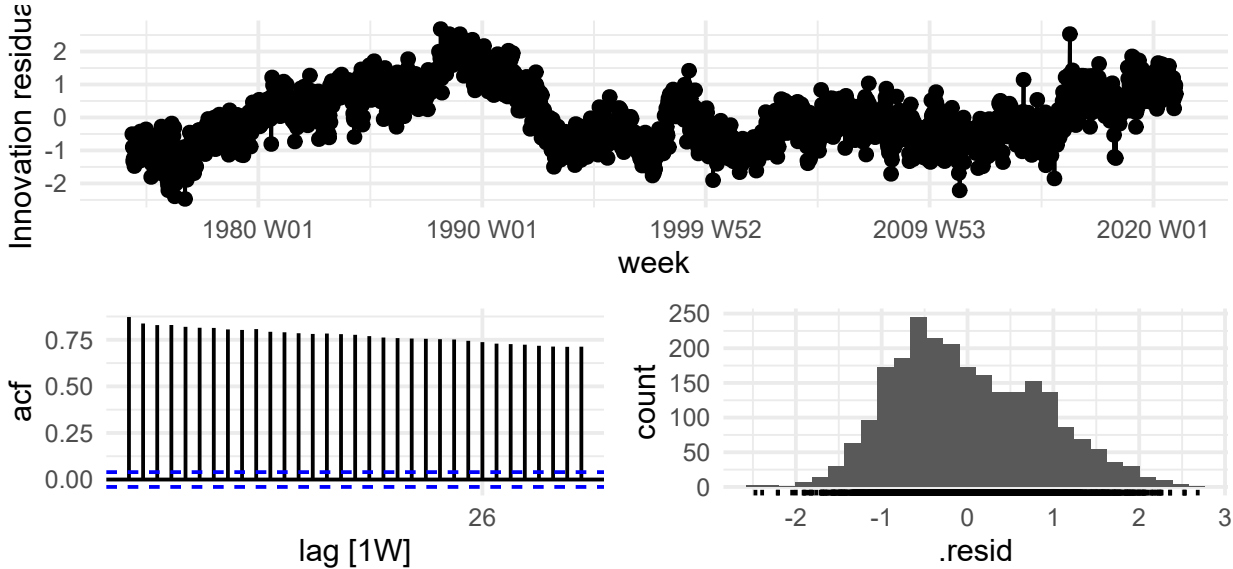
Table 3: Present ARIMA Model Forecasting Accuracy 2021,2022

data	.model	ME	RMSE	MAE	MPE	MAPE	ACF1
Non-seasonally adjusted	auto	0.277	0.608	0.507	0.066	0.121	0.252
Seasonally adjusted	auto	0.858	1.015	0.885	0.205	0.212	0.439

## Polynomial Model

Because in 1997, we observed that the quadratic model outperformed the ARIMA model, we also wanted to look at the forecasting accuracy of a polynomial model on the seasonally adjusted weekly  $CO_2$  concentration data and compare that to our ARIMA forecasts. We fit a quadratic model on the seasonally adjusted data, and show the model outputs and residuals below.

```
## Series: season_adjust
## Model: TSLM
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.471  -0.644  -0.126   0.634   2.682
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.31e+02  5.19e-02  6376  <2e-16 ***
## trend()      2.23e-02  9.84e-05   226  <2e-16 ***
## I(trend()^2) 4.95e-06  3.91e-08   127  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.852 on 2431 degrees of freedom
## Multiple R-squared:  0.999,    Adjusted R-squared:  0.999
## F-statistic: 9.83e+05 on 2 and 2431 DF, p-value: <2e-16
```



Based on plotting the residuals, we do see a normal distribution of residuals but still have high autocorrelation, suggesting that the residuals from the polynomial model is not a white noise process and we are still not encapsulating some trends with the polynomial model on the seasonally adjusted data alone. We also saw this in 1997, which is what led us to choose an ARIMA model for forecasting then as well.

## Evaluating Accuracy

To evaluate the accuracy of forecasting, we compared the accuracy of the polynomial model and the ARIMA model for seasonally adjusted data against our 2020-2022 test dataset, as shown in Table 4 below.

Table 4: Polynomial model accuracy 2021, 2022

.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE	ACF1
TSLM(season_ adjust ~ trend() + I(trend()^2))	Test	0.68	0.853	0.723	0.163	0.173	NaN	NaN	0.432

Based on Table 4, we do see that our ARIMA model outperforms our polynomial model, which gives us confidence to move forward with future predictions using the ARIMA model with this current dataset.

## How Bad Could It Get?

Table 5: Predictions on crossing the 420 and 500 CO2 ppm

target	week	.mean	ci.80.lower	ci.80.upper	ci.95.lower	ci.95.upper
420	2022 W13	421	419	422	419	422
420	2025 W40	421	418	423	417	424
500	2065 W09	500	492	508	488	512
500	2068 W35	500	492	508	488	513

As we can see from the table, the model predicts that the 420 mark will be first crossed in W13 of 2022 (in mean value) (corresponding to the end of March 2022), and left behind by week 40 of 2025, roughly the end of September 2025. For the 500 values, we get a predicted achieving of this value circa week 9 of 2065 (roughly end of Feb. 2065) and for the last time on W35 of 2068 (roughly end of Aug. 2068).

We now show predictions for the year 2122, along with their corresponding 80% and 95% confidence intervals:

Table 6: Predictions for the year 2122

week	.mean	ci.80.lower	ci.80.upper	ci.95.lower	ci.95.upper
2122 W02	605	593	616	587	623
2122 W03	605	593	617	587	623
2122 W04	605	593	616	587	623
2122 W05	604	592	616	586	622
2122 W06	604	592	616	586	622
2122 W07	604	592	615	586	621
2122 W08	603	592	615	585	621
2122 W09	603	591	614	585	620
2122 W10	602	591	614	584	620
2122 W11	601	590	613	584	619
2122 W12	601	589	612	583	618
2122 W13	601	589	612	583	618
2122 W14	600	589	612	583	618
2122 W15	600	588	611	582	618
2122 W16	600	588	611	582	617
2122 W17	599	587	611	581	617
2122 W18	599	587	610	581	617
2122 W19	599	587	610	581	617
2122 W20	598	587	610	581	616
2122 W21	598	587	610	581	616



week	.mean	ci.80.lower	ci.80.upper	ci.95.lower	ci.95.upper
2122 W22	599	587	610	581	616
2122 W23	599	587	610	581	616
2122 W24	599	587	611	581	617
2122 W25	599	587	611	581	617
2122 W26	599	588	611	582	617
2122 W27	600	589	612	582	618
2122 W28	600	588	612	582	618
2122 W29	601	589	613	583	619
2122 W30	601	590	613	583	619
2122 W31	601	589	613	583	619
2122 W32	602	590	613	584	619
2122 W33	602	590	614	584	620
2122 W34	603	591	614	585	620
2122 W35	603	591	614	585	621
2122 W36	603	591	614	585	620
2122 W37	604	592	615	586	621
2122 W38	604	592	615	586	621
2122 W39	604	592	616	586	622
2122 W40	604	593	616	586	622
2122 W41	604	592	615	586	621
2122 W42	604	592	615	586	622
2122 W43	604	592	615	586	622
2122 W44	604	592	616	586	622
2122 W45	604	592	616	586	622
2122 W46	605	593	616	587	622
2122 W47	605	593	617	587	623
2122 W48	606	594	617	588	624
2122 W49	606	594	617	588	624
2122 W50	606	594	617	588	623
2122 W51	606	595	618	589	624
2122 W52	606	595	618	589	624
2122 W53	607	595	618	589	625

## Conclusions

This updated analysis of the Keeling Curve data has provided valuable insights into the dynamics of atmospheric carbon dioxide concentrations.

Having analyzed and adjusted our previous model for data for the past 20+ years, some concerning results are evident. First,  $CO_2$  concentration (as we have used in this analysis) is increasing at an even greater pace than we had originally predicted. Even after we adjust our model, we see that the model under-performs as related to the most current data. This provides us with evidence that more sophisticated model specifications are necessary to adequately capture the increase in  $CO_2$ , especially in the past 10 years.

Furthermore, the findings of this analysis highlights the importance of continued monitoring of  $CO_2$  concentrations and the need for effective policies and strategies to mitigate the impacts of climate change. The Keeling Curve has become an iconic symbol of the global climate crisis, and the updated version analyzed in this report reinforces the urgency of taking action to reduce greenhouse gas emissions and limit global warming.