Global CO_2 Emissions in 2023 and beyond

By *

I. Introduction

In follow-up to our 1997 report we continue investigating the trend of rising CO_2 levels and whether or not it is likely caused by a larger trend or stochastic effects.

II. Mona Loa CO_2 Data

NASA provides daily measurement of $[CO_2]$ that we download for our analysis.

In April of 2019 the Mauna Loa laboratory updated their equipment to measure CO_2 with a new technique called Cavity Ring-Down Spectroscopy (CRDS) in contrast to the prior infrared absorption technique. As such, all data from April 2019 onwards will contain measurements using the new method. Additionally, due to eruptions at the Mauna Loa site in 2022, data from December 2022 onwards are from a site at the Maunakea laboratory.

A. Recent Trends in Atmospheric Carbon

Conduct the same EDA on this data. Describe how the Keeling Curve evolved from 1997 to the present, noting where the series seems to be following similar trends to the series that you "evaluated in 1997" and where the series seems to be following different trends. This EDA can use the same, or very similar tools and views as you provided in your 1997 report.

Atmospheric carbon is plotted in Figure 1, and shows relentless increase in atmospheric CO_2 concentration even at the remote Hawaiian island.

III. Models and Forecasts

In this section we will evaluate performance of historic models and generate new models based on the most recent data.

A. 1997 Models vs realized data

Figure 1 demonstrates the recent trends in $[CO_2]$ along with the models fitted on the data prior to 1997. It is clear that ever accelerating trend continues, with

* : , .

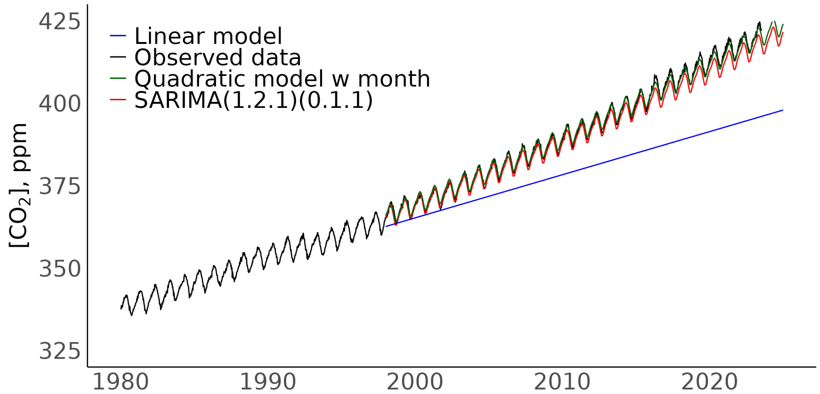


Figure 1. : Recent trend in $[CO_2]$ and models trained on pre-1997 data

no noticeable slow down or even reduced acceleration. Clearly, accuracy of predictions from the linear model does not justify even electricity spent on fitting this model. The trend is accelerating and linear model grossly underestimates the real concentration. Remarkably, simple quadratic model augmented with months as categories is extremely accurate, capturing both accelerating trend and seasonal variability 25 years into the future! Our best ARIMA model underestimates real observations only slightly and its performance is still unexpetedly good for predictions that far out. Worth noticing that both seasonal models perform extremely well up until approximately 2016, when the real trend seemed to have had an additional boost. At then time ARIMA model started falling behind at an increased rate. That might be a statistical fluke, or might indicate the change in the CO_2 emissions.

B. Performance of 1997 linear and ARIMA models

It appears that the first time $[CO_2]$ exceeded 420ppm was in Feb 2023 and the last time it was that low was in Mar 2023. It is unlikely it will return to this value any time soon. That correlates surprisingly well with out 25 year-old prediction that it will reach this threshold on 2023-04-01. As predicted, we are still far away from crossing 500 ppm threshold.

In this case, an RMSE of 1.9 means that our model, on average, makes an error of about 1.9ppm in its predictions.

We use Mincer-Zarnowitz regression to quantify predictive power of our model. To avoid extrapolation too far from the data, we shift both predicted

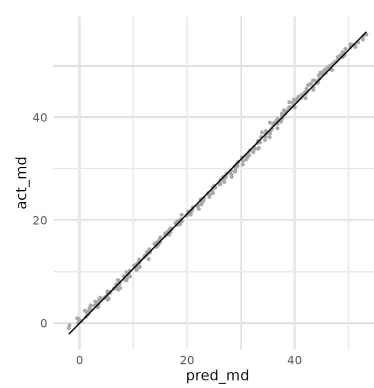


Figure 2. : Mincer-Zarnowitz regression for 1997 ARIMA model

and actual data by 365 ppm. Intercept of this regression is 0 and slope is 1.062. Given how close these parameters are to 0 and 1, we conclude that our ARIMA model has high predictive power. However, t-test rejects hypothesis that they are equal to 0 and 1 with p-values of 0.61479298 and $5.13297408 \times 10^{-79}$ respectively. This is likely due to the high number of data points, that makes small deviations highly significant.

C. *Best models on present data*

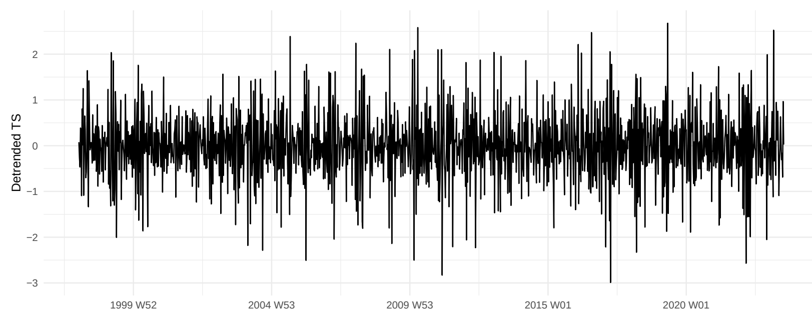


Figure 3. : De-seasoned/-trended series for CO_2 concentration

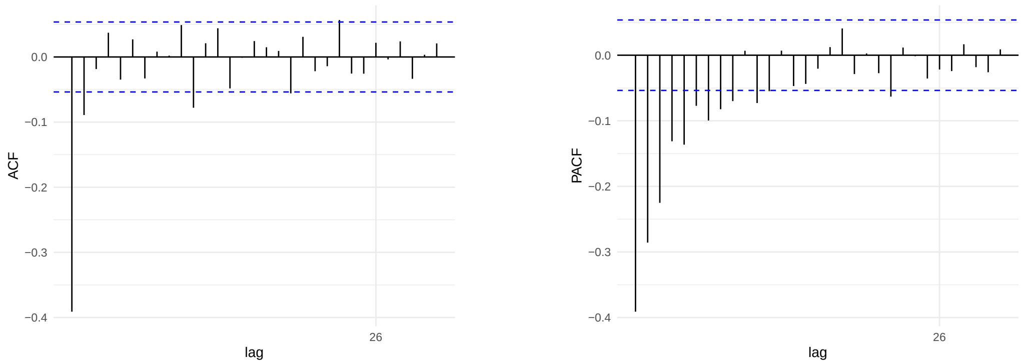
In this section we will compare perfromance of various models in terms of their predictive power. For that we will save a small portion of our data, the most recent 2 years, as a test set. We will use the rest of the data (train set) to generate the models.

```
split.point <- "2021-06-01"

# Create a training set
co2_train <- co2_diff %>% filter((week > yearweek("1998-01-01")) &
  (week < yearweek("2021-06-01")))

# Cretae a test set
co2_test <- co2_diff %>% filter(week >= yearweek(split.point))
```

We first focus on seasonally adjusted train data. Grid search of the model space, similar to what we performed in 1997, yields ARIMA(0.1.2) as the most suitable model with the lowest BIC. Using this model as a baseline, we shift to non-seasonally adjusted data and compensate by adding a seasonal component



(a) Recent trend in CO_2 concentration

(b) Recent trend in CO_2 concentration

Figure 4. : Diagnostic plots for de-trended series

to our models. The search restricted to PDQ parameter variations shows that SARIMA(1.1.2)(0.1.1)[52] has the lowest BIC of 1682.8. Figure 5a shows that ACF plot for this model residuals hardly has significant values, a good indication of the in-sample performance. Building up on our experience from 1997, we also fitted a double-differencing model SARIMA(1.2.2)(0.1.1) that we expect to have better long-term performance. This model has increased BIC of 1743.1 and demonstrates virtually the same pattern in residual ACF plot (Figure 5b). We believe that short-term increased accuracy might not be relevant and simpler model would be better because of reduced prediction uncertainty. However, for longer-term predictions the additional non-linearity of double-differencing will be beneficial.

Fitting ARIMA models to raw train data with no seasonal adjustments yields inferior models. Grid search of the model space, restricted to pdq parameters only, yields ARIMA(2.1.3) as the most suitable model with the lowest BIC. However, its BIC 2011.9 is significantly higher than that of SARIMA models (1682.8 for SARIMA (1.1.2)(0.1.1)) and ACF plot of its residuals (Figure 6) has more significant peaks. It is not clear what advantage ARIMA would have over SARIMA in this context.

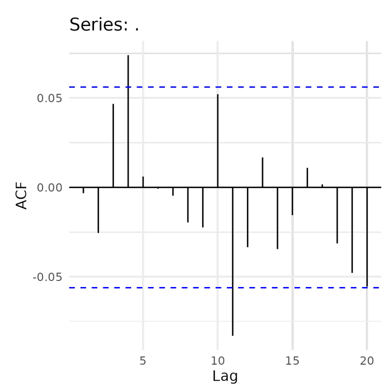
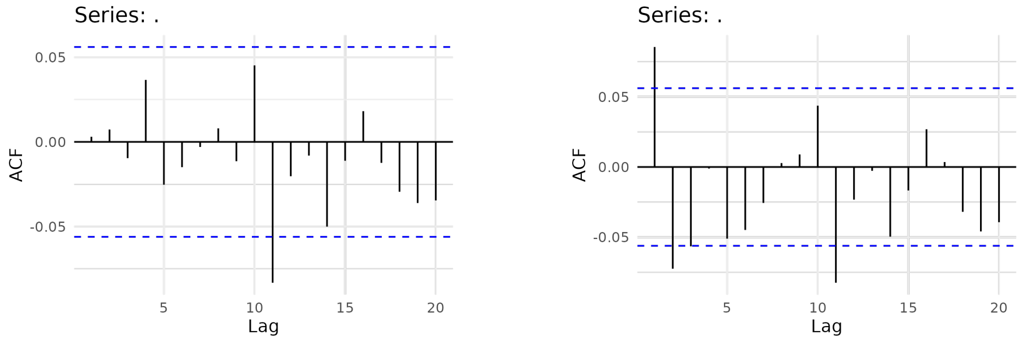


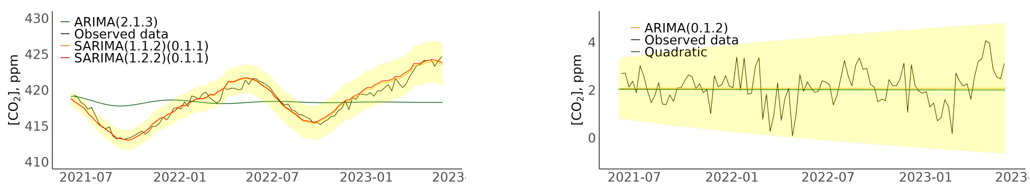
Figure 6. : ACF plot for residuals of ARIMA(2.1.3) model

Predictive performance of the three models discussed above is illustrated by



(a) SARIMA(1.1.2)(0.1.1)[52] (b) SARIMA(1.2.2)(0.1.1)[52]

Figure 5. : ACF plots for SARIMA model residuals



(a) Models on raw data (b) Models on de-seasoned data

Figure 7. : Predictive performance of the fitted models

Figure 7a. Both SARIMA models closely match observed data. Confidence interval of SARIMA(1.1.2)(0.1.1) shown in yellow, contains test data throughout whole region. ARIMA model, lacking seasonal component, fails almost immediately. Fitting quadratic model to de-seasoned data demonstrates very good performance, as does ARIMA model (Figure 7b).

D. *Forecasts: How bad could it get?*

Based on the SARIMA(1.2.2)(0.1.1) model that we deem more suitable for long-term forecasting, we can attempt to predict some important milestones. For the year 2122 we expect $[CO_2]$ to be 656 ppm with 95% CI from 453 ppm to 860 ppm. Our previous model was successful at predicting data 25 years out, and the overall trend remains the same for the past 60 years, so we are cautiously optimistic about

Table 1—: $[CO_2]$ thresholds crossing

ppm	As early as	Expected	Last time
420	2022-01-25	2022-03-29	2023-04-04
500	2044-03-08	2056-02-15	NA

quality of this prediction. There is so far no sign of slowing down of the trend, so sigmoidal inflection will not happen any time soon. Table 1 summarizes when 420 ppm and 500 ppm thresholds might be crossed. Fast-increasing uncertainty in predictions, typical for SARIMA models, limits our ability to make meaningful predictions about distant future. For instance, despite fast growing trend, the model can not exclude possibility that atmospheric CO_2 will never exceed 500 ppm thresholds.

IV. Conclusions

What to conclude is unclear.