Global CO_2 Emissions in 2023 and beyond

By *

I. Introduction

In this introduction, you can assume that your reader will have just read your 1997 report.

II. Mona Loa CO_2 Data

We first download data Create a data pipeline that starts by reading from the appropriate URL, and ends by saving an object called `co2_present` that is a suitable time series object.

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 **??**, and shows relentless increase in atmospheric CO_2 concentration even at the remote Hawaiian island.

III. Models and Forecasts

While these plots might be compelling, it is often challenging to learn the exact nature of a time serires process from only these overview, "time vs. outcome" style of plots. In this section, we present evaluate two classes models to assess which time series model is most appropriate to use.

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 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

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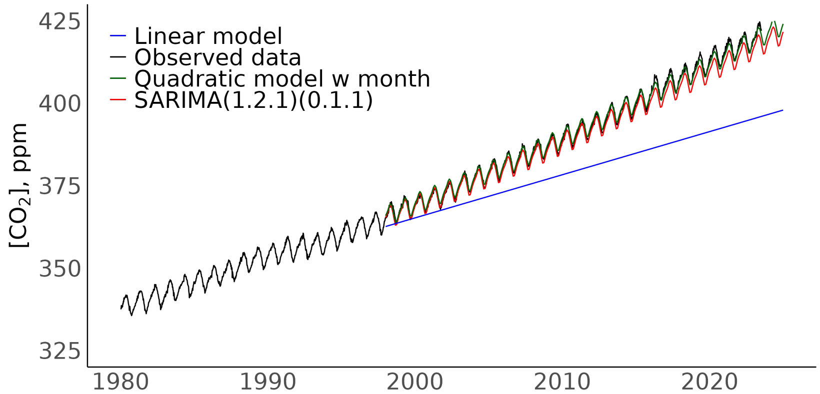


Figure 1. : Recent trend in CO_2 concentration

Note: CO_2 concentration from 1974 onward continues to exhibit ever accelerating growth, with strong seasonal oscillations. These patterns points to the need of de-seasoning and de-trending before further analysis.

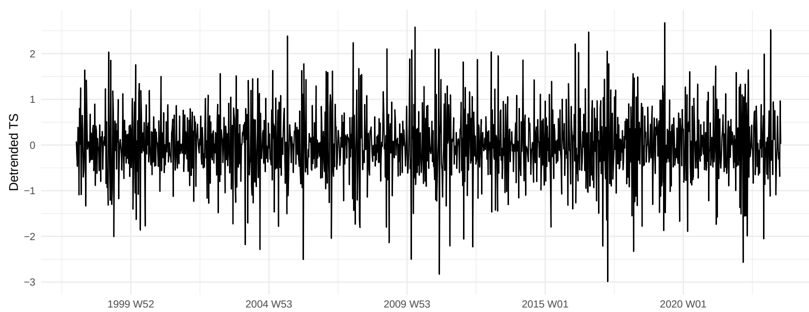
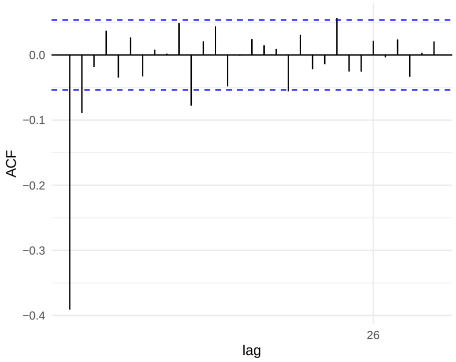
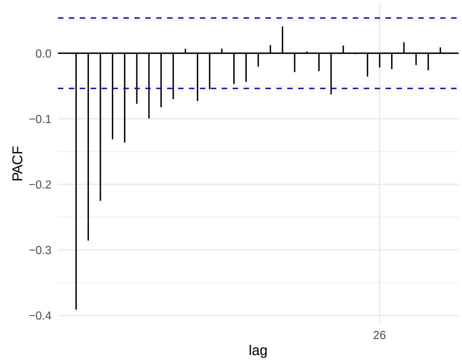


Figure 2. : De-seasoned/-trended series for CO_2 concentration

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.



(a) Recent trend in CO_2 concentration



(b) Recent trend in CO_2 concentration

Figure 3. : Diagnostic plots for de-trended series

B. *Performance of 1997 linear and ARIMA models*

In 1997 you made predictions about the first time that CO2 would cross 420 ppm. How close were your models to the truth?

After reflecting on your performance on this threshold-prediction task, continue to use the weekly data to generate a month-average series from 1997 to the present, and compare the overall forecasting performance of your models from Parts 2a and 3b over the entire period. (You should conduct formal tests for this task.)

C. *Best models on present data*

Seasonally adjust the weekly NOAA data, and split both seasonally-adjusted (SA) and non-seasonally-adjusted (NSA) series into training and test sets, using the last two years of observations as the test sets. For both SA and NSA series, fit ARIMA models using all appropriate steps. Measure and discuss how your models perform in-sample and (psuedo-) out-of-sample, comparing candidate models and explaining your choice. In addition, fit a polynomial time-trend model to the seasonally-adjusted series and compare its performance to that of your ARIMA model. 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.

```
# 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("2021-06-01"))
```

We first focus on seasolly adjusted data. As a first step we will perform a grid search of the model space, looking for the ARIMA model with the lowest BIC.

```
## Series: deseasoned
## Model: ARIMA(1,1,1) w/ drift
##
## Coefficients:
##          ar1      ma1   constant
##       0.1814  -0.8447    -0.0001
## s.e.  0.0356   0.0192     0.0028
##
## sigma^2 estimated as 0.388:  log likelihood=-1152.51
## AIC=2313.02   AICc=2313.05   BIC=2333.44
```

```
##
## Call:
## arima(x = co2_train$ppm, order = c(1, 1, 2), seasonal = list(order = c(0, 1,
##     1), period = 52))
##
## Coefficients:
##           ar1      ma1       ma2      sma1
##       0.08614  -0.67500  -0.09227  -0.81697
## s.e.  0.21123   0.21105   0.14537   0.02148
##
## sigma^2 estimated as 0.23105:  log likelihood = -830.66,  aic = 1671.33
```

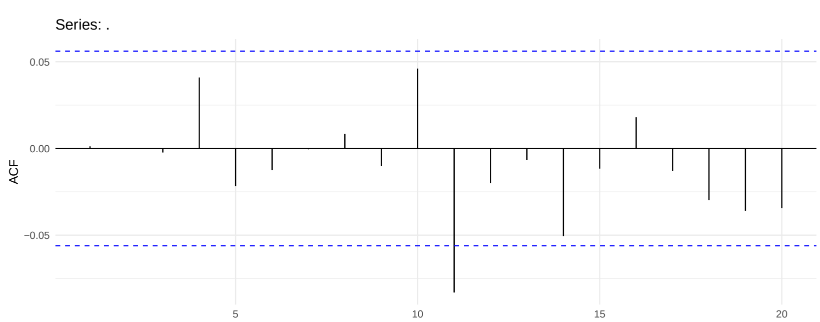


Figure 4. : ACF plot for SARIMA(1.1.1)(0.1.1)[52] residuals

Note: Residuals appear to be white noise

D. Forecasts: How bad could it get?

With the non-seasonally adjusted data series, generate predictions for when atmospheric CO2 is expected to be at 420 ppm and 500 ppm levels for the first and final times (consider prediction intervals as well as point estimates in your answer). Generate a prediction for atmospheric CO2 levels in the year 2122. How confident are you that these will be accurate predictions?

```
## Don't know how to automatically pick scale for object of type <ts>. Defaulting
## to continuous.
```

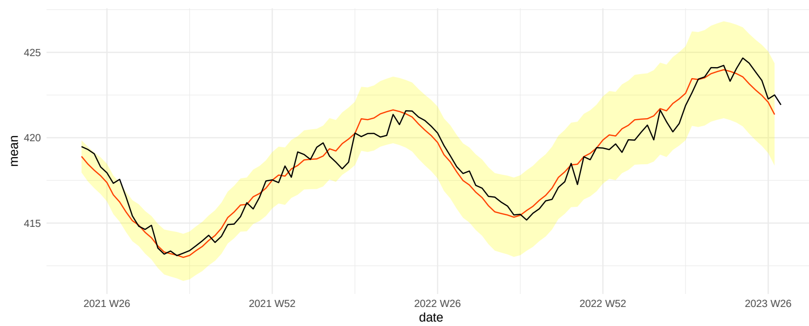


Figure 5. : Forecast for future CO2 concentration

Note: Residuals appear to be white noise

IV. Conclusions

What to conclude is unclear.

Appendix: Model Robustness

While the most plausible model that we estimate is reported in the main, "Modeling" section, in this appendix to the article we examine alternative models. Here, our intent is to provide a skeptic that does not accept our assessment of this model as an ARIMA of order (1,2,3) an understanding of model forecasts under alternative scenarios.