Global CO_2 Emissions in 1997

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In this report we assess data from the Mona Loa observatory to model and predict atmospheric CO_2 concentrations. Assuming all forces that currently influence atmospheric carbon remain unchanged, our model predicts a grim future for the global climate.

I. Introduction

This report aims to elucidate trends in the atmospheric CO_2 concentration, a question that has recieved considerable attention in the recent year. At this time the data seem to show an alarming trend of increasing levels year over year. This is alarming because CO_2 contributes to the "greenhouse effect", where certain gasses collect in the Earth's atmosphere and trap heat from leaving the Earth. As CO_2 levels increase we expect the Earth's temperature to increase leading to heat waves, drought and rising sea levels.

With the data at hand, it is imperative that we discover whether we have enough evidence to show that this recent rise in CO_2 levels is the result of a larger trend or could be explained by natural variation. If this trend is confirmed then it could pave the way to future research on ways to measure and address the adverse effects and causes of this rise in CO_2. This report will look into the existence of this larger trend of rising CO_2 levels and, if it exists, will also report on the magnitude of the rise as well as project future CO_2 levels.

A. Carbon Emissions

What are are carbon emissions, and why should anyone care about them? Briefly review what is known about the relationship between the burning of fossil fuels, atmospheric CO_2 What is the current understanding of the linkage between atmospheric CO_2 and global average temperatures.

II. Atmospheric CO_2 Measurement and Data

The data we will be using for this analysis is the CO_2 measurements from a laboratory at Mauna Loa, Hawaii. While there are other laboratories that collect

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CO_2 measurements, the Mauna Loa site has been collected CO_2 longer than any other site in the world which will give us the most data to work with as we conduct this analysis. The Mauna Loa site is also unique in that it is representative of air for the entire Northern Hemisphere due to its altitude and is not usually affected by nearby vegetation as the site is surrounded be lava flows.

The Mauna Loa data is frequently used because of the amount *and* quality of the data collected. Specifically, this dataset contains accurate and robust measurements of the number of CO_2 molecules per million in a cubic meter of *dry* air.

This site measures the concentration of CO_2 by funneling air through a cold chamber (to eliminate the effect of humidity) and then measuring how much infrared radiation is absorbed by the CO_2 in the chamber. Because CO_2 naturally absorbs infrared radiation, a higher density of CO_2 molecules will absorb more radiation. The researchers at the Mauna Loa site take great care to continually calibrate their equipment multiple times a day. In addition, the researchers are careful to account for any outside factors that may effect measurements such as the diurnal wind flow patterns present on Mauna Loa. Altogether, we can be confident that the data recorded at Mauna Loa is representative of global CO_2 concentrations.

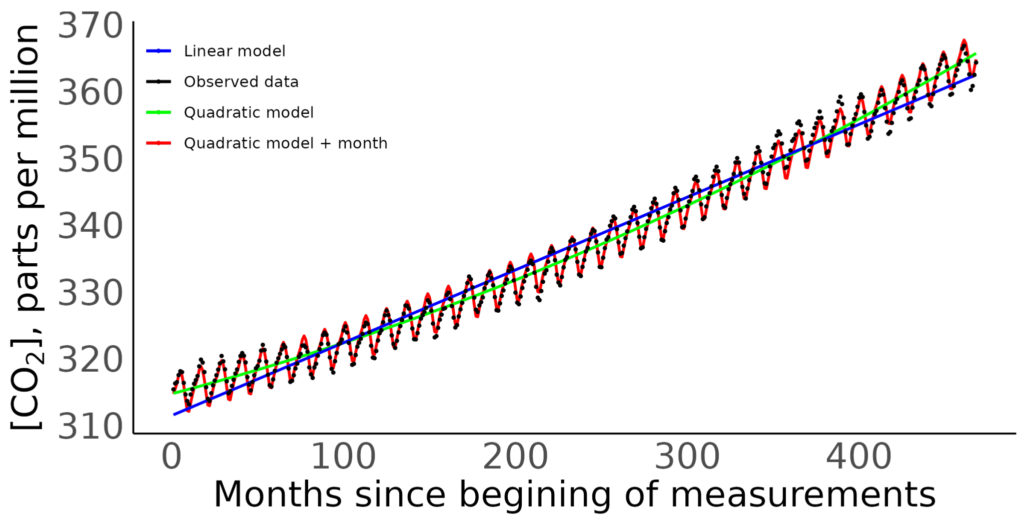

Figure 1. : Historic trend in monthly mean $[CO_2]$

Note: CO_2 concentration exhibits accelerating growth, with strong seasonal oscillations. Polynomila models capture these trends to varying drgree.

III. Exploratory analysis of historical trends in atmospheric CO_2

Description how, where and why the data is generated

Investigate the trend, seasonal and irregular elements. Trends both in levels and growth rates should be discussed

Atmospheric carbon is plotted in Figure 1, and shows some worrying trends. Just look at how wobbly that line is. How is it possible that we are not living in a simulation, when the lines that plots monthly average CO_2 looks like this?

IV. 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. Linear and Polynomial models

$$\text{CO}_2 = \phi_0 + \phi_1 t + \phi_2 t^2 + \epsilon_{eit} \tag{1}$$

Equation 1 is a general form of a polynomial model, where CO_2 concentration is modeled as a polynomial function of time and a random error.

We first estimate the linear model, which is a variant of Equation 1 with $\phi_2 = 0$. While the residuals for this model appear to follow a normal distribution (Figure 2), it is clear that a purely linear model does a poor job at modeling the seasonality of the data. There is also still clearly a trend in the remaining residuals which a linear model fails to capture. Overall, the a linear model does capture some of the trend but would not be sufficient to eliminate it entirely.

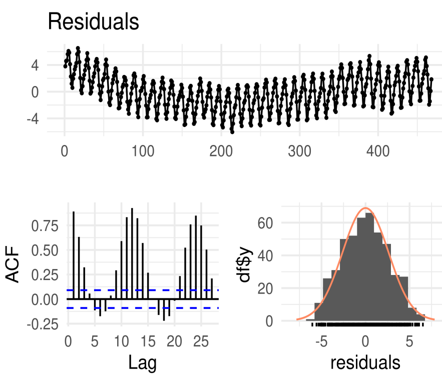

Figure 2. : Diagnostic plots for residuals of the linear model

In attempt to remedy these issues we estimated a quadratic model, which is a variant of Equation 1 with all $\phi_i \neq 0$:

A quadratic model fares slightly better than a linear model. It captures inherent non-linearity of the trend (Figure 1), but fails to capture seasonality. Diagnostic plots for this model (Figure 3) show that residuals are not normally distributed and ACF plot shows strong osculations.

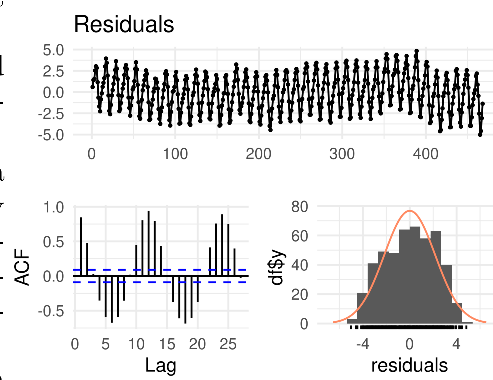

Figure 3. : Diagnostic plots for residuals of the quadratic model

There is not much evidence to support that a logarithmic transformation is necessary. Figure 4 shows that the seasonality factor is not multiplicative and the overall trend does not appear to be exponential.

```
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## to continuous.
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## to continuous.
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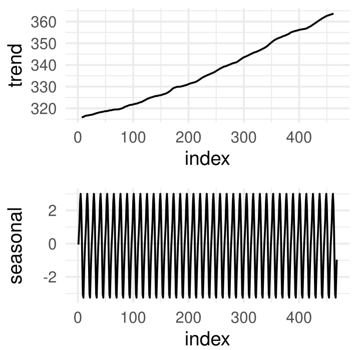

Figure 4. : Decomposition of the $[CO_2]$ time series

To address the issue of seasonality, we estimated a quadratic model augmented with the variable for the month:

Figure 1 show that the use of monthly dummy variables is a marked improvement over the linear and quadratic models, although it does not entirely capture the seasonality the data. Nevertheless, Figure 5 reveal that residuals of this model, although close to normally distributed, are far from white noise. Gradually decaying ACF plot indicates substantial AR component in the residual series.

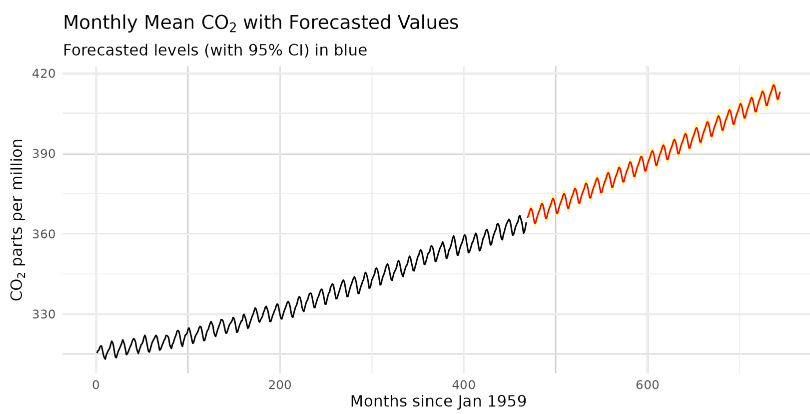

Figure 6. : Future [CO2], according to quadratic model w monthly variable

Note: Unrealistically narrow predication interval

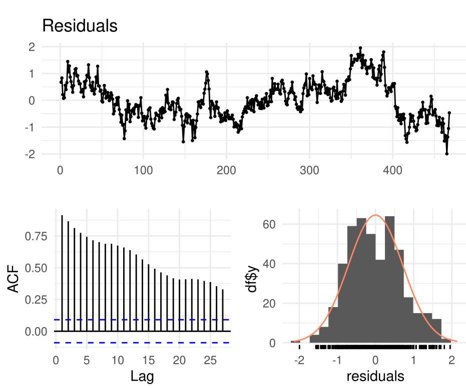

Figure 5. : Diagnostic plots for quadratic model with month variable

Figure 6 demonstrates predictive capabilities of the model. While the 95% predictive interval does appear somewhat small for a forecast so far into the future, the predicted values reliably follow the pattern of the historical data.

B. ARIMA times series model

Following all appropriate steps, choose an ARIMA model to fit to the series. Discuss the characteristics of your model and how you selected between alternative ARIMA specifications. Use your model (or models) to generate forecasts to the year 2022.

```
my_lag <- 12
co2_ts <- mutate(co2_ts, deseasoned = difference(value, lag = my_lag))
co2_ts <- mutate(co2_ts, detrended = difference(deseasoned, lag = 1))
co2_ts <- slice(co2_ts, my_lag + 2:nrow(co2_ts))
```

```
## Series: deseasoned
## Model: ARIMA(1,1,1) w/ drift
##
## Coefficients:
##          ar1     ma1  constant
##        0.254  -0.595    0.0014
## s.e.   0.127   0.108    0.0071
##
## sigma^2 estimated as 0.1381:  log likelihood=-193
## AIC=395   AICc=395   BIC=411
```

```
##
## Call:
## arima(x = co2_ts$value, order = c(1, 1, 1), seasonal = list(order = c(0, 1,
##     1), period = 12))
##
## Coefficients:
##          ar1     ma1    sma1
##        0.216  -0.547  -0.854
## s.e.   0.149   0.130   0.027
##
## sigma^2 estimated as 0.0816:  log likelihood = -81.2,  aic = 170
```

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## to continuous.
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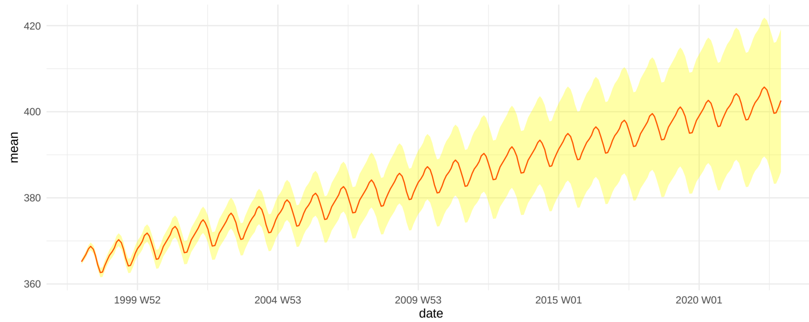

Figure 7. : Forecast for future CO2 concentration

Note: Residuals appear to be white noise

C. Forecast atmospheric CO_2 growth

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 2100. How confident are you that these will be accurate predictions?

V. Conclusions

In this report we assessed data from the Mona Loa observatory to model and predict atmospheric CO_2 concentrations. Our modeling takes into account only observed CO_2 data, with no attempt to bring into consideration other relevant information. Therefore the forecast from our modeling is only valid assuming all forces that currently influence atmospheric carbon remain unchanged. Given this reasobnable assumption, our model predicts a grim future for the global climate.

REFERENCES

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.