Global CO_2 Emissions in 1997

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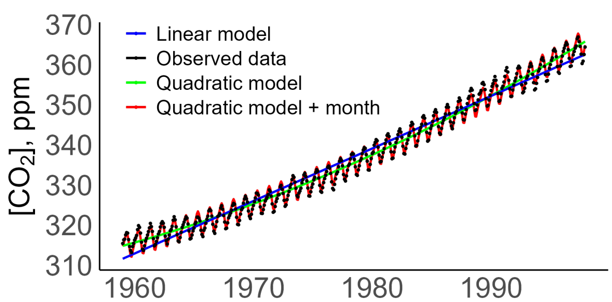
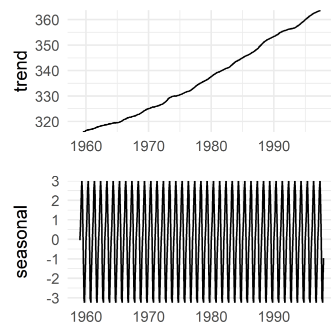
In this report we assess data from the Mona Loa observatory to model and predict atmospheric CO_2 concentrations. Assuming all forces that currently influence atmospheric carbon remain unchanged, our model predicts a grim future for the global climate.



(a) Historic trend and the models.



(b) Series decomposition.

Figure 1. : Monthly mean $[CO_2]$ time series and its models.

I. Introduction

This report aims to elucidate trends in the atmospheric CO_2 concentration, a question that has received considerable attention in recent years. At this time, the data seem to show a trend of increasing CO2 emission levels year over year, raising concerns in the scientific community.

It is therefore imperative that we determine if there is enough evidence that this recent rise 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 for future research on ways to measure and address the adverse causes and effects of this rise in CO_2.

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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.

This raise 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. Current 90% confidence estimate places CO2 level at 425-785 ppm for 1.5 °C increase in average Earth temperature as compared to pre-industrial levels.

II. Atmospheric CO_2 Measurement and Data

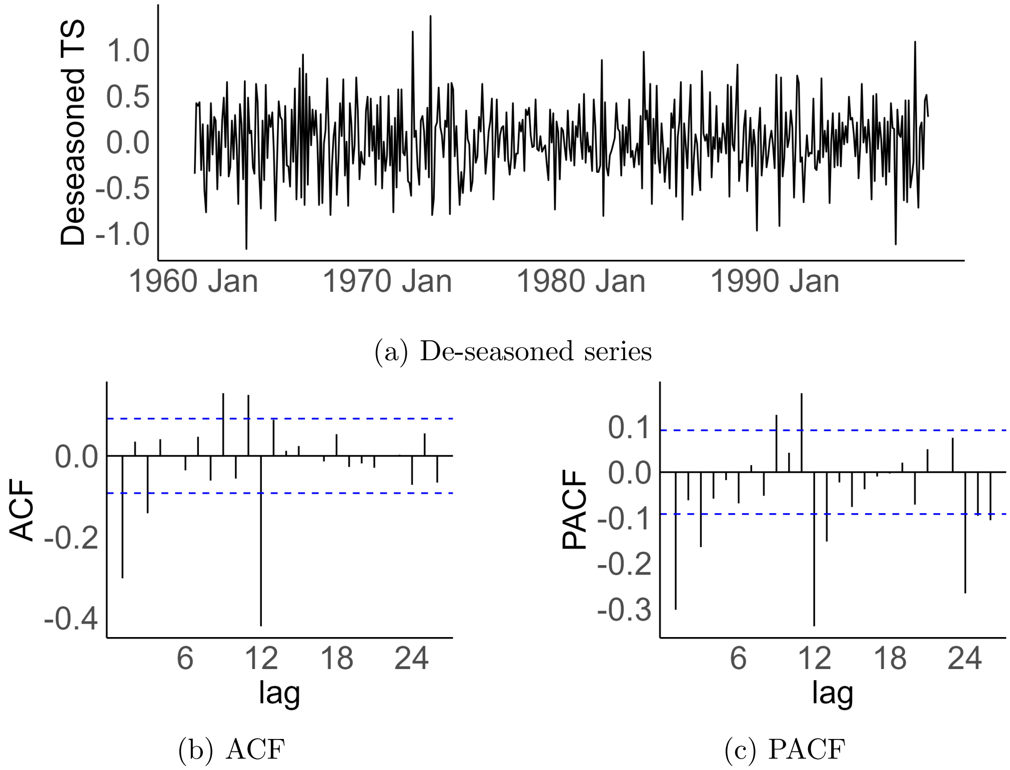
The data we will be using for this analysis is the CO_2 measurements from a laboratory at Mauna Loa, Hawaii. This site has been collecting CO_2 longer than any other site in the world. It is also unique in that it is representative of air for the entire Northern Hemisphere as it is not affected by nearby vegetation as the site is surrounded be lava flows. All in all, the Mauna Loa data is the gold standard of atmospheric carbon measurements because of the amount *and* quality of the data collected.

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, and thus the degree of absorption is proportional to $[CO_2]$. 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.

III. Exploratory analysis of historical trends in atmospheric CO_2

Atmospheric CO_2 level is plotted in Figure 1a(black trace) and shows a worrisome increasing trend with strong seasonal component. In general, the plot shows a clear uptrend in the last several decades. In addition, the slope becomes steeper after 1990, an even more troubling sign.

Figure 2 shows diagnostic information for this time series. After removing yearly variability by differencing with lag of 12 months, the series remains non-stationary, with visible upward trend (not shown). Further de-trending with lag 1 brings it close to stationary (Figure 2a). ACF plot (Figure 2b) of this de-trended series shows significant peaks only at lags 1 to 3 and few peaks around lag 12, without slow-decaying pattern. This indicates an MA(3) process and the need for seasonal component in SARIMA model. Similarly, PACF plot (Figure 2c) has a few significant peaks up to lag 3 and a cluster of significant peaks at lag 12.



(a) De-seasoned series

(b) ACF

(c) PACF

Figure 2. : Diagnostic plots for de-seasoned series of $[CO_2]$

These features are indicative of AR(3) process, and also point towards the need for seasonal component in SARIMA model. A grid search of model parameters, including differencing parameter, will be required for precise model allocation.

IV. Models and Forecasts

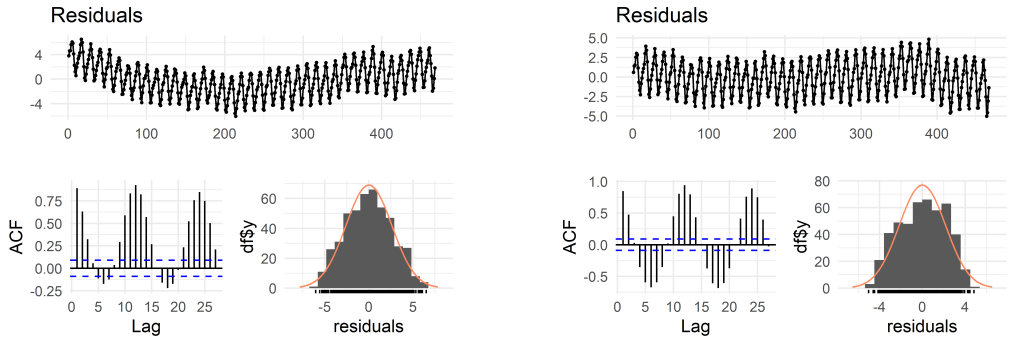
To gain insight into the driving forces behind observed data, it is often useful to generate a model of the process. In this section, we discuss simple polynomial as well as more advanced SARIMA models of the $[CO_2]$ trend.

A. Linear and Polynomial models

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

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 $\phi_2 =$



(a) Linear model (b) Quadratic model

Figure 3. : Diagnostic plots for residuals of polynomial models

0. While the residuals for this model appear to follow a normal distribution (Figure 3a), 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.

To remedy these issues, we estimated a quadratic model, which is a variant of Equation 1 with all $\phi_i \neq 0$. This model fares slightly better than a linear model. It captures inherent non-linearity of the trend (Figure 1a), but fails to capture seasonality. Diagnostic plots for this model (Figure 3b) show that residuals are not normally distributed and ACF plot shows strong osculations.

There is not much evidence to support that a logarithmic transformation is necessary. Figure 1b shows that the seasonality factor is not multiplicative and the overall trend does not appear to be exponential.

To address the issue of seasonality, we estimated a quadratic model augmented with the variable for the month. Figure 1a 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 4 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.

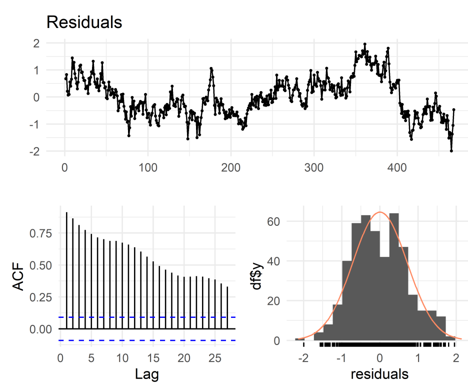
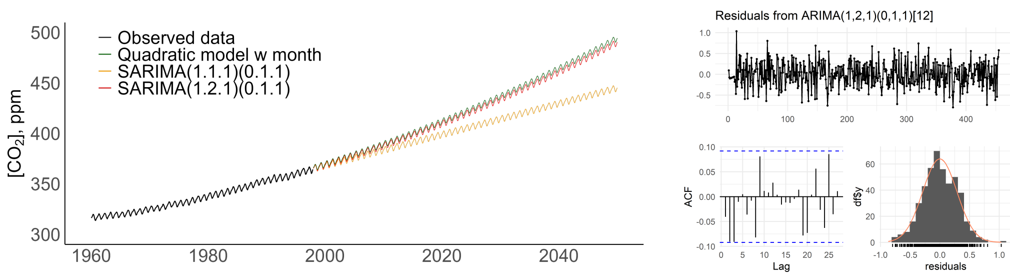


Figure 4. : Diagnostic plots for quadratic model with month variable

Figure 6 (green trace) 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*



(a) $[CO_2]$ forecast with linear and non-linear models (b) Model residuals

Figure 5. : Diagnostic plots for the selected ARIMA(1.2.1)(0.1.1)[12] model

We start with de-seasoning of the data by differencing with lag 12. We then conduct a grid search of ARIMA models, selecting model with the lowest BIC. The search yields $ARIMA(1.1.1)$ as the preferred model for de-seasoned data. We then fit a few SARIMA models to the original time series, only changing parameters in the range PDQ(0.0.0) to PDQ(2.2.2), again choosing the model with the lowest BIC. This way we arrived at $SARIMA(1.1.1)(0.1.1)_{12}$ that has BIC of 180.7. However, this model fails to capture non-linearity that we discovered in the analysis of polynomial models. Figure 5a shows that its predictions continue into the future almost linearly. To remedy this issue, we introduced additional differencing, hoping that double-differencing would eliminate growth acceleration, similar to how second derivative of distance over time removes acceleration.

Following this line of thought we selected $SARIMA(1.2.1)(0.1.1)_{12}$ as our final model. This update increased BIC to 216, which we consider a reasonable sacrifice to capture non-linearity. Figure 5b shows that ACF of the residuals does not have significant values and residuals are close to normally distributed, indicating reasonable quality of the model.

C. *Forecast atmospheric CO_2 growth*

Based on the chosen model, we can attempt to predict some important milestones. For the year 2100 we expect $[CO_2]$ to be 676ppm with 95% CI from 391ppm to 962ppm. We believe that even this wide confidence interval does not reflect true uncertainty in prediction, as it is highly unlikely that the driving forces behind CO_2 will remain stable. It is far more likely, that what we observe is the growth phase of a sigmoidal curve. Table 1 summarizes when 420 ppm and

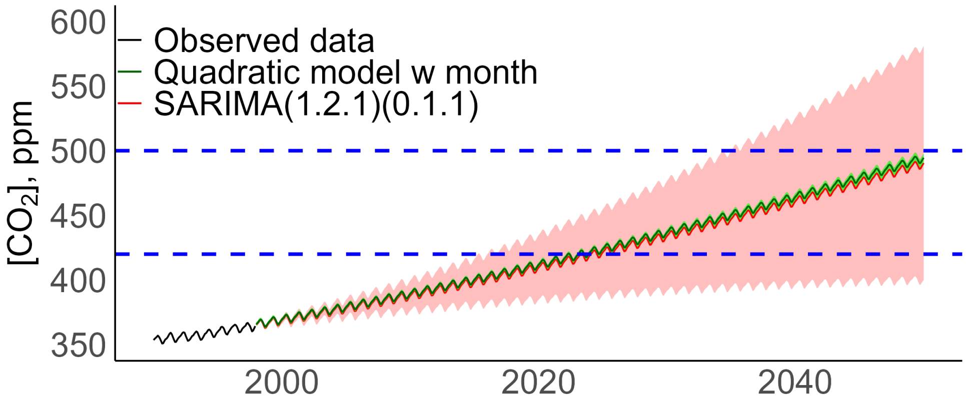


Figure 6. : $[CO_2]$ forecast

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 420 and 500 ppm thresholds. Horizontal lines on Figure 6 show these thresholds. It is evident from the picture that the lower boundary of 95% confidence interval for prediction levels out at approx 400 ppm and might never exceed 420 ppm.

V. Conclusions

Table 1—: $[CO_2]$ thresholds crossing

ppm	As early as	Expected	Last time
420	2015-05-01	2024-02-01	NA
500	2034-05-01	2053-01-01	NA

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 reasonable assumption, our model predicts a grim future for the global climate.