CO_2 Forecasting Project – Mauna Loa April 2025 by Kevin Hernandez

Accurate forecasting of CO_2 levels in the atmosphere is essential for understanding long-term climate trends, as Dr. Keeling showed the world. This project analyzes monthly CO_2 concentration data from February 2015 to February 2025 (collected by the Mauna Loa Observatory) using multiple time-series models, including Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), and Exponential Smoothing (ETS) models. In addition to fitting and evaluating these models, we ran simulations to refine our predictions and account for uncertainty. Model selection was based on statistical diagnostics, residual analysis, and forecast accuracy, ultimately determining the best approach for predicting CO_2 levels in April 2025. The reliability of our forecast is assessed using 95% and 99% confidence intervals to ensure that our chosen model is robust and provides the most accurate prediction.

Preliminary Data Analysis

Before fitting our models, we cleaned the data and performed exploratory analysis to ensure that the dataset was complete and free of anomalies. A preliminary time-series plot revealed a positive trend in CO_2 levels over time, with stable variance. A seasonal plot further confirmed a recurring annual cycle, with CO_2 levels decreasing from May to September and increasing from September to May.

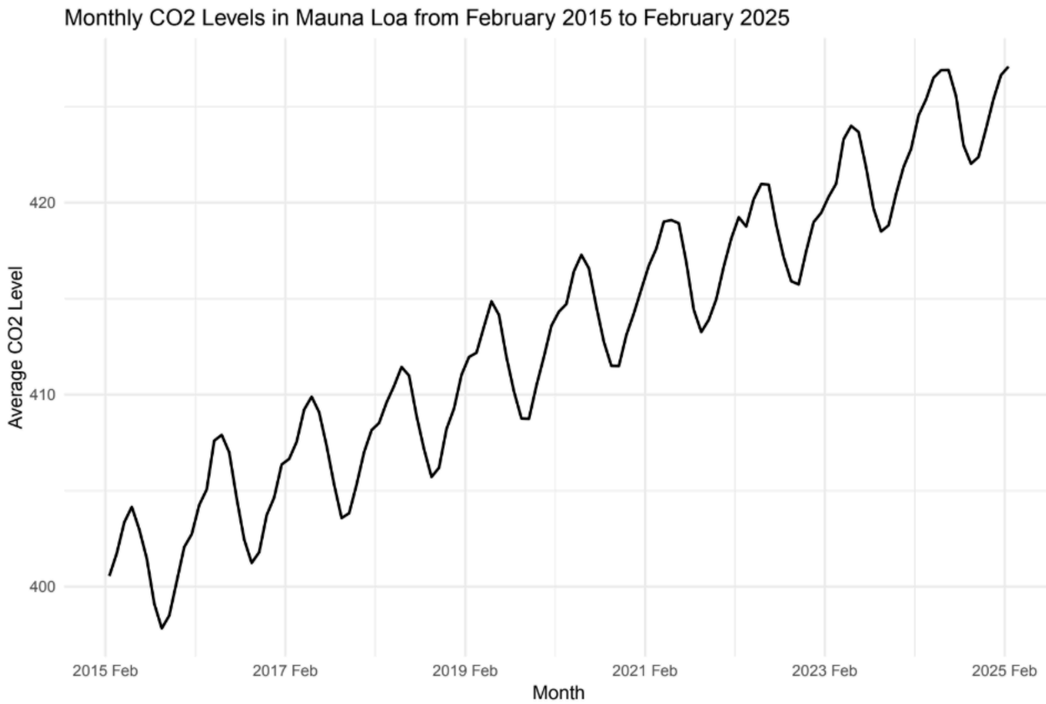

Figure 1. Monthly average CO_2 levels at Mauna Loa from February 2015 to February 2025. A clear upward trend is visible, with regular seasonal oscillations corresponding to annual environmental cycles.

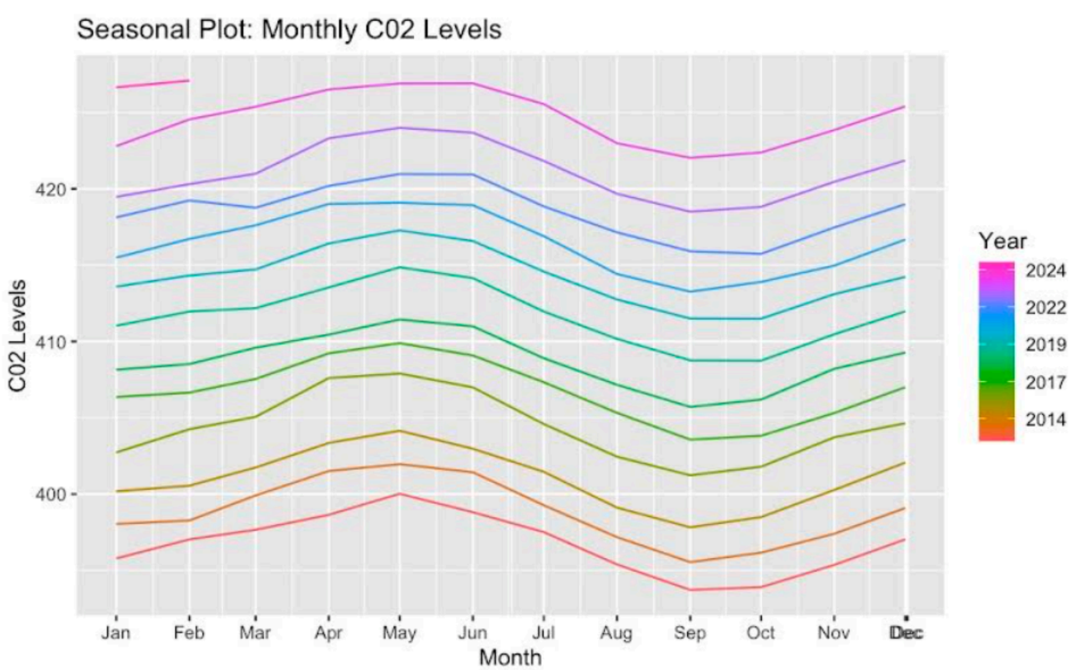

Figure 2. Seasonal patterns of monthly CO_2 levels across different years. Each line represents a year, illustrating the recurring pattern of CO_2 levels decreasing from May to September and increasing from September to May.

To prepare the data for modeling, we assessed stationarity using the KPSS test, which failed to reject the null hypothesis at a 0.05 significance level and thus confirmed that the series was stationary. We applied a lag-12 differencing operator to remove seasonality and ensure the series was suitable for AR, MA, ARMA, and ARIMA modeling. A first-order backward shift operator was tested for trend removal but deemed unnecessary, as the trend appeared linear and was effectively handled by differencing.

Model Selection and Estimation

To determine the best forecasting model, we compared the multiple approaches above to a Seasonal Naïve (SNAIVE) benchmark model in order to give us a baseline standard for our model selection. The dataset was split into train (80%) and test (20%) sets so that we could validate each of our models on new data (i.e. data not used to train the models) and determine the predictive accuracy of each. Given our 10 years of monthly CO_2 report data, we put the most recent two years into the test set to refine our models and ensure up-to-date accuracy.

For the AR, MA, and ARMA models, we analyzed Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots to guide model selection. A significant spike at lag 1 in the ACF suggested a non-seasonal MA(1) component, while a significant spike at lag 1 in the PACF suggested a non-seasonal AR(1) component. Additionally, a significant spike at lag 12 in the ACF suggested a seasonal MA(1) component. Based on these findings, we initially tested MA(1), AR(1), ARMA(1,1), and ARMA(0,2) models. While the MA(1) and AR(1) models performed reasonably well, neither outperformed ARMA(1,1). The ARMA(0,2) model then outperformed all three of these, while also meeting the causal, identifiable, and invertible conditions since our theta values were less than 1 and did not sum to 1. Additionally, the Ljung-Box test yielded a non-significant p-value, confirming that trend and seasonality had been successfully removed. To further validate our model selection, we measured model accuracy based on the sum of squared residuals (SSR). A function called arar() was also tested, which estimated an optimal AR model with built-in confidence intervals. Surprisingly, this function selected an AR(14) model, though not all lags were statistically significant. We decided to fit an ARIMA model with seasonal differencing, given the seasonality and trend that were present. The initial model structure was ARIMA(1,1,1)(0,1,1)[12], which included a non-seasonal AR(1) and MA(1) component, as well as a seasonal MA(1) component, based on our previous results. Additionally, an ETS model was fitted to capture patterns in the data in a different way than all of our previous models had done.

To compare model performance, we evaluated one-step forecasts on the test set using accuracy metrics. Based on resulting values of Mean Average Error (MAE) and Root Mean Squared Error (RMSE), ETS outperformed both our ARIMA model and our initial champion ARMA(0,2) model, making it the best choice for forecasting. While ARIMA captured key statistical properties of the series, ETS provided superior short-term predictive accuracy, which we felt was more important for predicting a couple of months in the future of the data. To further refine our forecast, we ran simulations, generating multiple possible future paths for CO_2 levels. These simulations incorporated random noise and parameter uncertainty, allowing us to quantify any potential variations in our predictions. The simulated trajectories confirmed that both the ETS model was the most accurate and that our forecasted value was robust, with most simulated paths remaining within our 95% prediction interval. The wider 99% prediction interval captured all of our simulated future predicted values, reinforcing confidence in our projection. Since the ETS model performed better than the other models, it is evident that this data has very clear trend and seasonality, thus meaning there are not really any other significant or influential predictors.

Forecast and Prediction Intervals

Using the ETS model, supported by simulations, we forecasted the monthly average CO_2 concentration for April 2025, with confidence intervals to account for any potential variance:

- **Predicted CO_2 for April 2025: 429.47 ppm**
- **95% Prediction Interval: (429.10, 429.84) ppm**
- **99% Prediction Interval: (428.98, 429.96) ppm**

The 95% prediction interval provides a high-confidence estimate, while the wider 99% interval accounts for variance and will definitely include the actual value. These intervals are derived from the ETS model's residual variance and confirmed by the distribution of simulated forecasts. A time-series plot visualizes the forecasted CO_2 levels along with confidence intervals, confirming the model's ability to capture long-term trends and seasonal fluctuations.

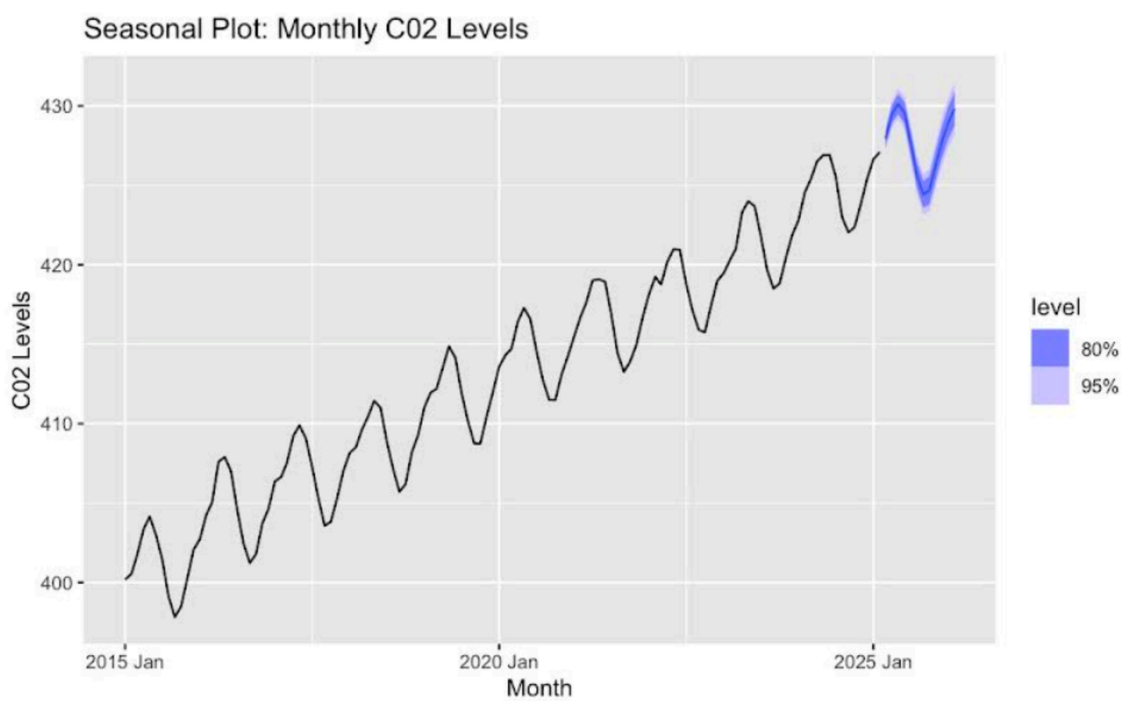

Figure 3. ETS model forecast with 80% and 95% prediction intervals. The model captures long-term trend and seasonality, providing high-confidence short-term predictions.

Conclusion

Our analysis predicts that the monthly average CO_2 concentration in April 2025 will be approximately 429.47 ppm. This forecast is based on a comprehensive comparison of AR, MA, ARMA, ARIMA, and ETS models, with ETS emerging as the best fit. The ARMA(0,2) and ARIMA models also performed well, but ETS provided superior predictive accuracy on test data. The observed CO_2 increase in our prediction aligns with global climate trends, while seasonal variations reflect natural atmospheric cycles.