Modeling the Relationship between Atmospheric Carbon Dioxide Concentrations and the Human Population

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Spring 2023, Math-150: Mathematical Modeling
May 6, 2023

Contents

1 Introduction

1.1 Background Research

Carbon dioxide and other greenhouse gases function as a thermal blanket that traps the heat radiating from the Earth's surface, which contributes to a naturally occurring process known as the greenhouse gas effect. Rising concentration levels of greenhouse gases in the atmosphere amplify the greenhouse gas effect, resulting in increased exacerbating effects of global warming. The primary factor responsible for global warming is widely regarded to be the heightened levels of CO2 concentration in the atmosphere as carbon dioxide is the primary greenhouse gas that constitutes 79% of the total U.S. greenhouse gas emissions [1]. With increasing concentration of CO2 in the atmosphere, contributes to rising global temperature on the planet, thereby leading to the frequent occurrence of severe weather events, disruption of natural ecosystems and wildlife, degradation of the environment, and negative impact on human health.

The rapid development of modernization caused by the human population is the primary contributor to global warming as human activities have increased atmospheric CO2 concentration by 50% since the industrial revolution [2]. The burning of fossil fuels, such as coal, oil, and natural gas, that are used for power transportation, energy production, and industrial processes is the primary source of CO2 emissions as the burning of fossil fuels is responsible for approximately 87% of CO2 emissions produced by human activities [3]. The combustion of fossil fuels releases a vast amount of carbon dioxide into the atmosphere at a rate that is significantly faster than natural processes can remove it, which gives rise to the detrimental effects of global warming as the excess CO2 in the atmosphere accumulates over time [2]. In addition to the burning of fossil fuels, the other remaining percentage of human-caused CO2 emissions include increased deforestation efforts and farming of livestock animals (9%) as well as the development and expansion of industrial processes (4%) [2].

Global warming is one of the most urgent issues we are still facing today, where the increasing CO2 concentration in the atmosphere is a major contributor to global warming. Human activities are the root cause of this problem as it has led to the over-accumulation of excess CO2 in the atmosphere, such that human activities have been attributed to the increase in the global average temperature by approximately 1.8F [4]. Furthermore, human activities contribute to the depletion of natural resources, loss of biodiversity, as well as increased levels of water and air pollution, waste disposal, and severe degradation of the environment [5]. Environmental degradation includes increased wildfires, severe droughts, ocean acidification, and soil erosion [6]. As the human population continues to grow, there is a constantly growing demand for energy, food, and other resources, which leads to increased human activities that contribute to more CO2 emissions. Thus, it is essential to understand the relationship between the human population and atmospheric CO2 concentration to alleviate the negative effects of global warming that are mainly caused by human activities.

1.2 Motivations

My interest in exploring the relationship between CO2 concentration in the atmosphere and the human population is motivated by the increasing concern and urgent need to understand the impact of human activities and the associated potential consequences on human health. Human activities contribute to global warming, climate change, and other environmental issues. These changes have significant implications for the human population as exposure to high levels of carbon dioxide can have adverse health effects. Human-produced CO2 emissions release airborne particles from pollutants, which can give rise to respiratory problems, cardiovascular disease, and cognitive impairment. Thus, it is vital to understand the relationship between CO2 concentration in the atmosphere and the human population in order to develop mitigation strategies to combat the negative impacts of global warming and reduce our carbon footprint in an effective and sustainable manner.

There are many current research studies aimed at analyzing the relationship between the human population and atmospheric CO2 concentration. As human activities are the primary factor behind the rapid increase in CO2 concentration in the atmosphere, the main focus of current research studies is understanding the contribution of human activities to the increase in atmospheric CO2 concentration and their overall impact on the Earth's climate system. The limitation of these studies do not account for CO2 concentrations caused by natural processes in their models [6]. The variability in naturally occurring CO2 concentrations is caused by the carbon cycle, volcanic activity, plant respiration, and absorption by oceans. Without consideration of these naturally occurring CO2 concentrations, it contributes to uncertainty in understanding the driving factors of CO2 concentration in the atmosphere. This work formulates a mathematical model that aims to understand the relative factors associated with rising CO2 concentration in the atmosphere, as well as explore the complex relationship between the impact of the human population on the dynamics of the increasing CO2 concentration in the atmosphere.

2 Methods

2.1 Mathematical Model

My proposed compartmental model, shown in Figure 1, outlines the relationship between atmospheric CO2 concentration and the human population, taking into account both natural and human-caused emissions of carbon dioxide. Let $C(t)$ and $N(t)$ represent the CO2 concentration in the atmosphere and the human population at any time t, respectively. Assume that both $C(t)$ and $N(t)$ are greater than 0 as the concentration of CO2 and population cannot be negative nor can be 0. If there were initially no carbon dioxide in the atmosphere (i.e., assume $C(0) = 0$), the Earth would become too frigid to support life. Similarly, if the population is initially 0 (i.e., assume $N(0) = 0$), there would be no human activities that could lead to anthropogenic CO2 emissions. I assumed the growth rate of CO2 concentration caused by natural sources to be constant because natural processes, such as the carbon cycle, decomposition of organic matter, as well as weathering of rocks and minerals, generally release and/or absorb carbon dioxide at a relatively steady rate over long periods of time [7]. This assumption allows me to simplify the model to have a better view of the impact of human activities on the concentration of CO2 in the atmosphere. The decay rate of CO2 concentration caused by natural sinks, such as photosynthesis and absorption by the oceans and soils, is proportional to the relative level of CO2 concentration in the atmosphere. As human activities lead to increased levels of CO2 emissions, the growth rate of anthropogenic CO2 emissions is proportional to the interaction with the human population. Furthermore, the increasing CO2 concentration in the atmosphere can deplete the overall health of the human population. I assumed there is an inverse relationship between the human population and atmospheric CO2 concentration, such that the human population declines as atmospheric CO2 concentration increases. Thus, I assumed that the human population and atmospheric CO2 concentration follow a predator-prey relationship, where atmospheric CO2 concentration is considered to be the "predator", and the human population is the "prey". I further assumed that the human population follows a logistic growth in the absence of carbon dioxide in the atmosphere because the Earth has limited resources to sustain the rapidly growing population, which ultimately constrains the growth of the population to the carrying capacity that the Earth can withstand.

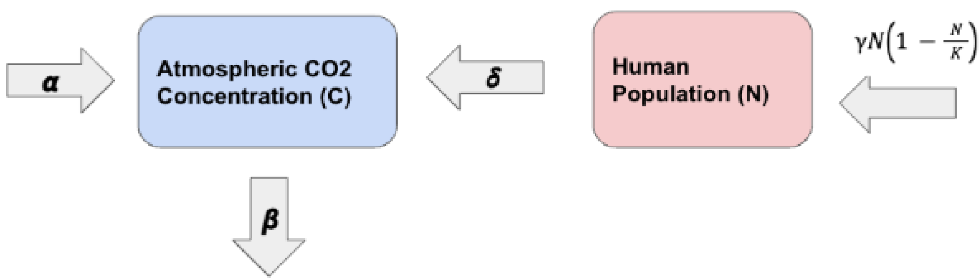


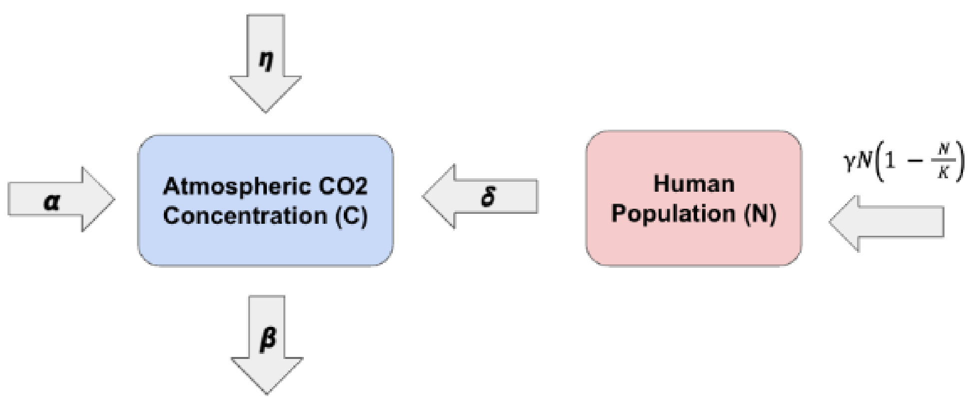
Figure 1: Compartmental Model between atmospheric CO2 concentration and human population

$$\frac{dC}{dt} = \alpha - \beta C + \delta NC \qquad \frac{dN}{dt} = \gamma N\left(1 - \frac{N}{K}\right) - \delta NC$$

Figure 2: The corresponding system of ordinary differential equations describes the rate of change in both the atmospheric CO2 concentration and the human population with respect to time and is characterized by the following equations: System of ordinary differential equations for Original Model. Where $C(0), N(0) > 0$. All the parameters in the modeled system are assumed to be positive. The constant growth rate and decay rate of atmospheric CO2 concentration caused by natural sources correspond to α and β, respectively. The net growth and decay rate of atmospheric CO2 concentration caused by anthropogenic factors is represented as δ The intrinsic growth rate and carrying capacity of the human population are represented by γ and κ, respectively.

2.2 Modified Model

The previous model made the assumption that naturally occurring CO2 concentrations were constant over time. This assumption can lead to inaccurate predictions of future CO2 concentrations since natural processes are subject to variation. To address this issue, a new term η was introduced to represent the growth rate of atmospheric CO2 concentrations caused by natural sources. The term α was redefined as the intrinsic CO2 concentration level already in the atmosphere in order, which considers the level of CO2 concentration in the atmosphere starting from 1960 as the baseline value. The modified model includes both the growth and decay rate of atmospheric CO2 concentration as dependent on the relative level of CO2 concentration in the atmosphere and the size of the human population. Through this approach, the modified model can effectively account for the effects of natural processes and human activities on atmospheric CO2 concentration. This can lead to more accurate predictions compared to the original model as the new model considers the variability of naturally occurring CO2 concentrations over time and their impact on the overall growth rate of atmospheric CO2 concentrations. The modified mathematical model is illustrated as a compartmental model in Figure 3.



$$\frac{dC}{dt} = \alpha + \eta C - \beta C + \delta NC$$

$$\frac{dN}{dt} = \gamma N\left(1 - \frac{N}{K}\right) - \delta NC$$

Figure 3: Compartmental Model and System of Ordinary Differential Equations for Modified Model

2.3 Numerical Methods

The ODEINT function in Python allowed us to numerically solve the system of differential equations, which was necessary to make predictions about the behavior of our system. However, in order to use this function, we needed to have accurate values for the parameters in our model. This is where nonlinear regression analysis proved to be invaluable. By refining our model through trial and error and comparing it graphically to the experimental data, we were able to find the optimal values of the parameters that resulted in the best fit. The estimated global human population, measured in billions, was obtained from the Carbon Dioxide Information Analysis Center (CDIAC) [8], and the global fossil-fuel CO2 emissions data, expressed in million metric tons of carbon, was obtained from Kaggle [9]. We processed the data by scaling it to the same units and covered within the same time frame of 1960 to 2014 in order to facilitate the numerical analysis of the relationship between atmospheric CO2 concentration and the human population during this time period. This time period covers recent rapid modernization and industrialization during which humans began using fossil fuels as their major source of energy to power industrialization in the 1960s, which led to a significant increase in the annual growth rate of atmospheric CO2 from 0.80.1 ppm in the 1960s to around 2.4 ppm in the 2010s [10]. Once we had these parameters, we were able to use them in the ODEINT function to simulate the behavior of the system under different conditions and make predictions about its behavior.

3 Analysis and Results

3.1 Overview of the model optimization process

We used regression analysis to determine the optimal parameters for our model, utilizing the least squares optimization method due to its suitability for nonlinear models. We made initial guesses for the parameters using our understanding of the system and experimental data and refined the model through trial and error until it produced satisfactory results that eliminated the need to adjust equations or add parameters. Python's SciPy library was used to perform all numerical calculations. To ensure that our optimized parameters were valid, we included an optional bounds parameter in the least squares function. To calculate the difference between the real data and the model solution, we defined an objective function that used the ODEINT function to simulate carbon emissions and population under different conditions. To improve the accuracy of the regression analysis, we interpolated the y values to fill in any gaps in the data. We called the least squares function, which ran the objective function until the difference was minimized and returned the optimal parameters for our model. With these parameters, we were able to use the ODEINT function to simulate the behavior of the system and make predictions about its behavior under different conditions or test hypotheses about it.

```
[ 0.01   0.01   0.025  0.016 10.     0.01 ]
[ 0.01000001  0.01        0.025       0.016      10.         0.01      ]
[ 0.01        0.01000001  0.025       0.016      10.         0.01      ]
[ 0.01        0.01        0.02500001  0.016      10.         0.01      ]
[ 0.01        0.01        0.025       0.01600001 10.         0.01      ]
[0.01       0.01       0.025      0.016      9.99999985 0.01      ]
[ 0.01        0.01        0.025       0.016      10.         0.01000001]
```

Figure 4: Here is a display of the first 6 iterations of the optimization process

3.2 Optimizing Accuracy

The initial parameter guesses are crucial for the success of the least squares optimization, as they serve as the starting point for the optimization process. If the initial guess is significantly different from the true optimal value, it can cause the optimization process to take more iterations to converge, and if poorly chosen, the algorithm may converge to a local minimum rather than the global minimum, leading to inaccurate parameters and reduced model accuracy [11]. To address this, we made educated guesses based on experimental data for the growth rate of the human population and the net growth/decay rate of carbon emissions, using the CAGR (compound annual growth rate formula) [12]. We also made assumptions about the carrying capacity of the human population, based on resource limitations. For the growth/decay rate of emissions, we selected a rate of 0.01, assuming that rates are either positive or negative depending on growth or decay. We incorporated bounds to prevent invalid parameters and ensure positivity for rates, assigning a maximum of 1 and a range of [-1,1] for the net growth/decay rate. To ensure compatibility between the human population and CO2 emissions data, we cleaned and converted the units before running our model. The human population data were measured in billions, while the CO2 emissions data were measured in millions of metric tons of carbon. We multiplied the CO2 emissions values by 3.667 and divided them by 1000 to convert them to billions, matching the human population units. This preprocessing step was critical for running our predator-and-prey model accurately. This is why for our initial guesses we made some education guesses.

$$\mathrm{CAGR} = \left(\frac{V_{\mathrm{final}}}{V_{\mathrm{begin}}}\right)^{1/t} - 1$$

CAGR = compound annual growth rate

V_{begin} = beginning value

V_{final} = final value

t = time in years

Figure 5: Here is the formula for Compound Annual Growth Rate (CAGR)

3.3 Optimal Parameters

After executing the code, the analysis yielded the best-fit parameters for the modified model. The optimal values obtained are as follows: Alpha (Intrinsic Initial CO2 concentration level) = 0.3238, Beta (Decay Rate of CO2 concentrations caused by natural sources) = 0.01, Delta (Net Growth/Decay of CO2 emissions) = 1.58e-05, Gamma (Intrinsic growth rate of the human population) = 0.0327, K (Carrying Capacity of the human population) = 10, and Eta (Growth Rate of atmospheric CO2 caused by natural processes) =

0.0166. These parameters can be used to predict the behavior of the system under various conditions or to test hypotheses related to it.

```
Alpha (Intrinsic Initial CO2 concentration level) = 0.3238
Beta (Decay Rate of CO2 concentrations caused by natural sources) = 0.0100
Delta (Net Growth/Decay of anthropogonic emssions of CO2) = 1.58e-05
Gamma (Intrinsic growth rate of the Human Population) = 0.0327
K (Carrying Capacity of the Human Population) = 10.0000
Eta (Growth Rate of atmospheric CO2 caused by natural processes) = 0.0166
```

Figure 6: Here are the Optimal Parameter Values of our Modified Model

After running the model with optimized parameters, we observed graphically that the model performed well. However, to provide numerical evidence, we utilized the r2 score function in Python's sklearn library to compute the $R\hat{2}$ metric (coefficient of determination) to evaluate the accuracy of the model's predictions. This metric indicates that a large proportion of the variability in the CO2 emissions and human population data can be explained by the model's optimal parameters. The resulting $R\hat{2}$ value was 0.9806, which is a strong indication that the model is performing well. We also computed the $R\hat{2}$ values separately for the human population and CO2 emissions. The R-squared value for the CO2 emissions model was 0.9647, indicating 96.47% accuracy, while the R-squared value for the human population model was 0.9966, indicating 99.66% accuracy.

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \overline{y})^2}$$

Figure 7: Here is the formula for the coefficient of determination, R^2

4 Discussion/Conclusion

4.1 Strengths and Weaknesses

Although our developed model achieved an accuracy of over 98% when compared to the real experimental data we collected, indicating good perfor-

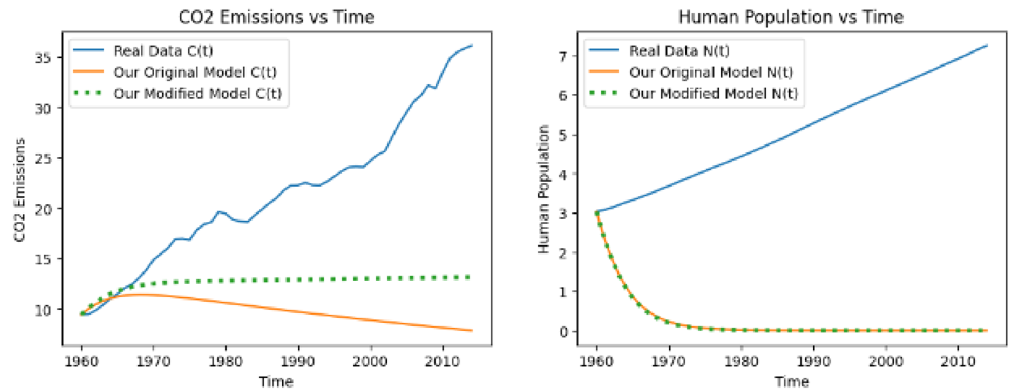


Figure 8: Here is our Original and Modified Models before finding optimal parameters

mance, it is important to note that generalizing and using the model to predict future outcomes is limited. This is because the R^2 value is only indicating how well our model is able to fit with the real experimental data. This is why we decided to truncate the data from the last 20 years to evaluate the model's performance in predicting future CO2 emissions and human population without access to actual data. When we did this, our R^2 value from 1994 to 2014 was roughly 0.24. When we reduced this time span to 1994 to 1999, the accuracy was increased to roughly 0.70. The low accuracy in our model is likely due to the fact that our model does not consider factors such as new technology, nor does it incorporate enough parameters to fully represent the complex interactions within the human population or carbon emissions. Additionally, our model assumes that the growth rates of carbon emissions and the human population are constant. Despite the disappointing results, our model provides a 0.72 level of confidence in predicting 5 years into the future. It may not be perfect, but it is a useful tool for understanding the relationship between human population and carbon emissions. The initial mathematical model achieved an R^2 value of 0.9604. This indicates that our model fits well with the experimental data used to find the parameters. However, when looking at the long-term behavior of our original model, we found that the model plateaued at around 6.5 billion, which is not an accurate prediction. This led us to investigate the model's long-term performance, and we recognized that a modification was necessary to provide a more comprehensive understanding of the factors affecting atmospheric CO2

```
151 Iterations
Alpha (Intrinsic Initial CO2 concentration level) = 0.8060
Beta (Decay Rate of CO2 concentrations caused by natural sources) = 0.0222
Delta (Net Growth/Decay of anthropogonic emssions of CO2) = -2.93e-04
Gamma (Intrinsic growth rate of the Human Population) = 0.0233
K (Carrying Capacity of the Human Population) = 9.9902
Eta (Growth Rate of atmospheric CO2 caused by natural processes) = 9.3727e-07
R^2 for both model = 0.9884
R^2 for CO2 emissions model: 0.9739
R^2 for human population model: 0.9944
```

concentration and human population dynamics.

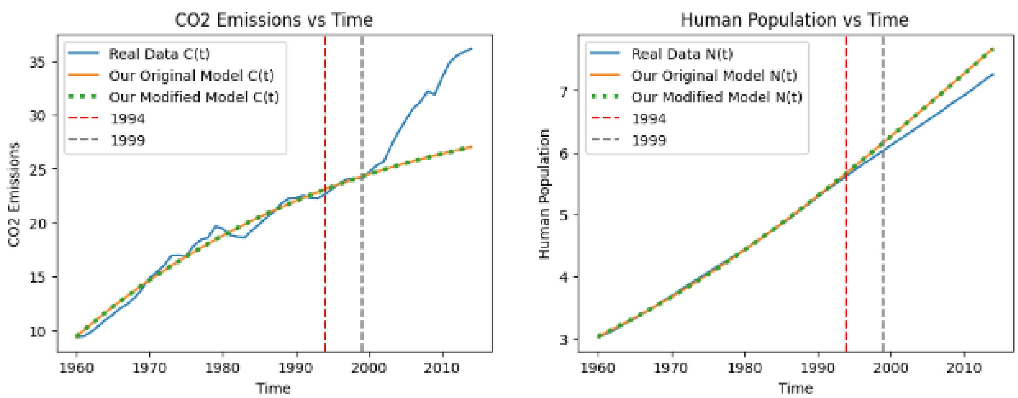


Figure 9: Here our the results after truncating the last 20 years of our dataset

4.2 Comparison of the Two Models

After the incorporation of our newly defined Eta parameter, the modified model's R^2 value increased to 0.9806. The modified model, shown in Figure 3, predicts that the human population will reach the carrying capacity of 10 billion people by 2100, followed by a significant decline in population size. Despite the predicted decrease in population size, CO2 emissions continue increasing, as shown in Figure 4. The model indicates that atmospheric CO2 concentration is likely to surpass 2000 billion metric tons of carbon, thus highlighting the limitation of the model's assumption of an exponential increase in CO2 emissions.

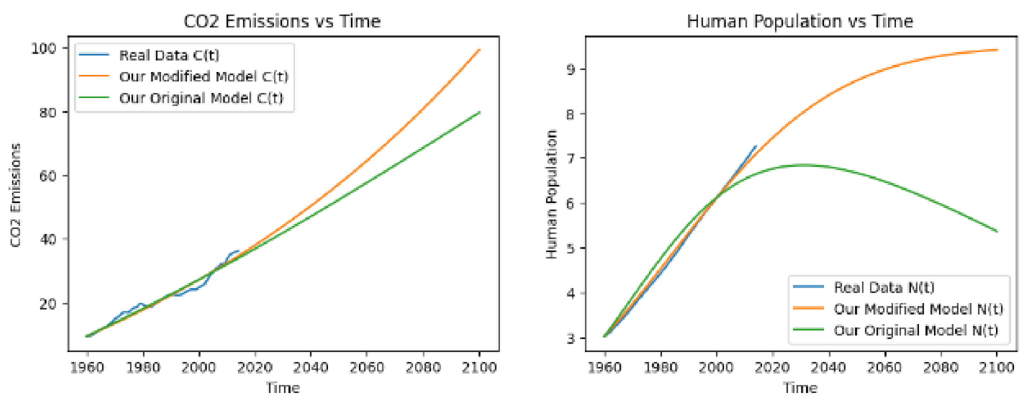


Figure 10: Long-term behavior of Original vs Modified Model with optimal parameters

4.3 Analysis and Findings

We applied the model to address our initial question of whether the human population affects CO2 emissions. Our model suggests that the impact of the human population on CO2 emissions may not be as significant as we had initially hypothesized. Upon analyzing the long-term behavior of the model, we observed that the population size is expected to reach its peak by around the 2100s and then start to decline. On the other hand, CO2 emissions are projected to continue to increase, despite the declining population. This indicates that our model may not accurately predict the decline in CO2 emissions. Our expectation was that a decrease in human population would contribute to a decrease in CO2 emissions, however, it appears our model's growth rate for carbon emissions is too high causing the decay rate to be irrelevant. We believe this could be attributed to the model formulation lacking enough factors to fully capture the future outcomes. After attempting to adjust our model equations to better fit the data, we found that improving the accuracy of one model results in a decrease in the accuracy of the other. By changing the Eta term to be multiplied by N instead of C, we were able to achieve greater accuracy in our emissions model. However, this adjustment led to a decrease in the accuracy of our human population model.

One major drawback of our model is the lack of consideration for the impact of new technology as time progresses. This makes it challenging to predict future outcomes accurately. In terms of short-term predictions

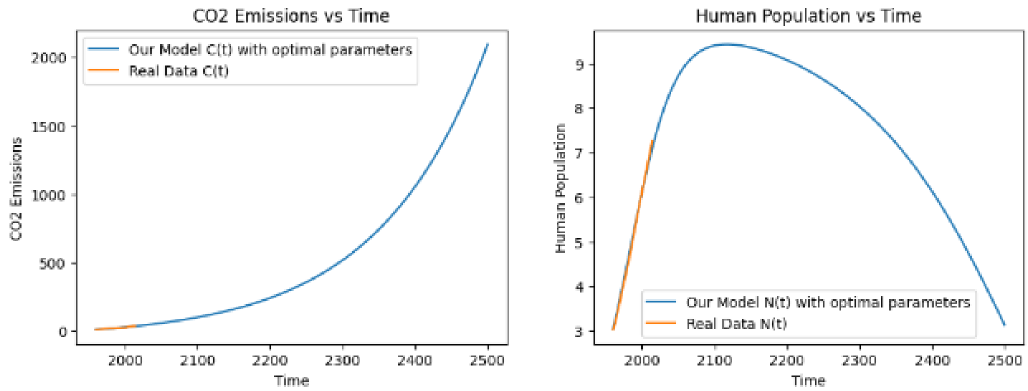


Figure 11: Long-term behavior of Original vs Modified Model with optimal parameters

(within the next 20 years), our model indicates a steady increase in CO2 emissions while the human population is expected to approach a plateau-like behavior. However, our model's limitation lies in the sensitivity of each parameter. Even a slight alteration of these parameters can result in a significant change in the overall behavior of the plot. To improve the accuracy of our model, we can consider incorporating additional parameters that provide a more comprehensive representation of CO2 levels and population size. It is also important to mention that if we had more data it is likely that our approximation to our model would be more accurate, in our case we only had around 70 years of data. Another approach to enhance our model is by modifying the growth rate of the carbon emissions equation. The main complication of our current model is its reliance on prey and predator-model, which makes it difficult for the model to coexist. A possible improvement is to adjust the growth rate to have a stronger connection to the human population. Currently, the model struggles to accurately represent the growth of carbon emissions and exhibits unbounded growth as time progresses. Future research aimed at improving the model should explore the incorporation of additional parameters, more extensive datasets, and dynamic parameters that account for changes over time. Moreover, the model should consider the impact of potential interventions and policies that may influence the trajectory of both CO2 emissions and human population growth.

In conclusion, a mathematical model exploring the relationship between the impact of the human population on the dynamics of increasing CO2 concentration in the atmosphere was developed. The model showed good performance in predicting CO2 emissions based on population size but had limitations in generalizing and predicting future outcomes due to the complexity of interactions within the human population and carbon emissions. As the human population continues to grow, there is a constantly growing demand for energy, food, and other resources, leading to increased human activities that contribute to more CO2 emissions. While the developed model suggests that the impact of the human population on CO2 emissions may not be as significant as initially hypothesized, it lacks consideration for new technology and enough parameters to fully represent the complexities of CO2 emissions and population size. To improve the accuracy of the model, incorporating additional parameters that provide a more comprehensive representation of CO2 levels and population size and modifying the growth rate of the carbon emissions equation are possible approaches. However, the model's sensitivity to parameter alterations is a significant challenge that needs to be addressed. Overall, the study highlights the importance of developing more comprehensive models that consider various factors for predicting future CO2 emissions and population size accurately and emphasizes the need for sustainable practices to combat the negative impacts of global warming, reduce carbon footprint, and preserve the environment for future generations.

5 Appendix

General Algorithm

Below is the Python code used in our analysis:

```
import numpy as np
import pandas as pd
from scipy.integrate import odeint
from scipy.optimize import least_squares
from scipy.interpolate import interp1d

def model(y, t, alpha, beta, delta, gamma, K, eta):
    C, N = y # unpack y values as C and N
    dCdT = alpha + eta*C + delta*N*C - beta*C # DE for C
    dNdT = gamma*N*(1 - N/K) - delta*N*C # DE for N
    return [dCdT, dNdT]
```

```
def objective(parameters, t, y):
    y0 = [y[0,0], y[0,1]]
    sol = odeint(model, y0, t, args=tuple(parameters))
    return (y - sol).flatten()

data = pd.read_csv("dataset.csv")
t_data = data.iloc[:,0]
y_data = data.iloc[:,1:]

parameters = [0.01, 0.01, 0.025, 0.016, 10, 0.01]

t = np.linspace(t_data[0], t_data[54], 55)
y_interp = np.zeros((len(t), y_data.shape[1]))
for i in range(y_data.shape[1]):
    f = interp1d(t_data, y_data.iloc[:, i].values, kind='cubic')
    y_interp[:, i] = f(t)

bound = ([0, 0, -1, 0, 9.0, 0], [1, 1, 1, 1, 10, 1])

coef = least_squares(objective, parameters, bounds=bound, args=(t, y_interp))
```

Full version of the code and dataset can be found using the links below:
Full Code on Google Colab
Dataset Spreadsheet

5.1 Bibliography

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