# Modeling Earth's CO2 Levels for Effective Policy-Making

Agent Based Modelling Project Report

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# Contents

# Chapter 1

# Introduction

## 1.1 Problem Domain

The industrial revolution in 1750 made the usage of steam machines more available and accelerated the rate at which society depended on coal. This massively increased the carbon dioxide ($CO^2$) levels in the atmosphere due to the mining and burning of fossil fuels. $CO^2$ concentration worsened with the world wars in the $20^{th}$ century, with the increasing urbanisation of populations and the modern trend of throw-away culture influenced by consumerism. Today, this is resulting in climate change, air pollution, food security and biodiversity loss. This has numerous impacts on the environment, including rising temperatures, melting of polar ice caps and ocean acidification which in turn has economic implications, such as the constant shifting of vineyard-suitable lands.

This resulted in organisations such as the European Union (EU) and treaties like the Paris Agreement imposing policies, energy targets and strategies to help mitigate the effects of these environmental changes. To make sure these objectives are achieved, each country is forced to monitor and forecast their current and future emissions based on real-life factors. This is where our ABM provides a powerful tool for policymakers and researchers to understand the ecological impact of human behaviour, business practices and deforestation within their governed areas.

## 1.2 Application Domain

The application domain of our agent-based model (ABM) is environmental sustainability. By the utilisation of a variety of agents representing some of the most polluting sources on planet Earth, our ABM can simulate different scenarios and interventions to inform decision-making for a more responsible future.

Since humans, deforestation and companies were responsible for 7%, 20% and 24% of the total global greenhouse gas emissions in 2010, respectively, we decided to implement these three agents in our model, named Humans, Trees and Companies. Each possesses numerous attributes which all affect their own and each other's net carbon emissions. In combination, a realistic ecosystem was formed which allows for the analysis and simulation of the carbon footprint of human activities (portrayed by human habits and company operations) and deforestation/reforestation.

There are multiple factors which can be investigated by interacting with the experiment, whilst looking at environmental sustainability. These can be the impact of various human behaviours; both psychological (such as influence and incentives) and physical, as well as the effects of policies or international actions on climate change and carbon emissions. For example, different enterprise taxes based on carbon output, incentives for the employment of renewable energy sources or rewards for reforestation efforts.

# Chapter 2

# Design

## 2.1 Technology Used

In this project, we utilized various tools to enhance our workflow and productivity. NetLogo was the primary software used for the design and implementation of our model. The collaborative nature of our project was aided by the use of GitHub repositories, where our team members could contribute to the code and track changes. We also used Google docs to centralize our ideas and drafts, making it easy for us to access and share information. In addition, we employed our normal channels of communication to facilitate team collaboration and ensure smooth progress throughout the project.

## 2.2 Model Structure

### 2.2.1 Human Agents

We model agents that represent humans interacting in the environment and have two key attributes: carbon emission and behavior. Carbon emission is a measure of how much carbon an agent emits per tick, while behavior represents whether an agent is classified as poor, average, or good in terms of their carbon emission rate. Behavior is initialized randomly, with good having the lowest emission and poor the highest. The number of humans on a patch can be set for each behavior type using the designated sliders.

#### Herd Behavior

The behavior of agents can change depending on the probability of influence, which determines how likely an agent is to be influenced by its surroundings (also known as herd behavior). If the probability of influence is set to 0, humans do not exhibit any herd behavior, but otherwise, depending on the probability, they may copy the actions of others. This change in behavior is linked with a change in carbon emission rate.

**Algorithm 1** Herd Behavior Design

```
num-good ← count of good humans in radius 5
num-poor ← count of bad humans in radius 5
num-average ← count of average humans in radius 5
majority ← behavior with highest proportion
if probability of influence ≠ 0 then
    current human ← majority
end if
```

#### Incentives

In addition to being influenced by their surroundings, humans can also be reward-driven. The idea behind this being that humans are more likely to have a better behavior if they get something out of it (e.g: More likely to bring their own grocery bag to avoid paying 30p or getting a reusable cup to get a discount on their coffee)

To do so, the model calculates the average carbon emission of an agent's neighbors using the mean function, and then calculates a penalty term by subtracting the agent's carbon emission $E_{a_1}$ from the average of its neighbors and squaring the result (to keep the herd behavior effect).

$$\text{penalty} = \left( E_{a_1} - \frac{1}{\#\text{neighbors}} \sum_{i \in \text{neighbors}} E_{a_i} \right)^2$$

The penalty term is then used to modify the reward function, which includes a base reward of 1 divided by the agent's carbon emission.

$$\text{reward} = \frac{1}{E_{a_1}} - \text{penalty}$$

The model also includes a carbon-tax variable to represent the cost per unit of carbon emission, and the cost of emitting carbon for each agent is calculated by multiplying its carbon emission by the carbon tax rate.

$$\text{carbon cost} = E_{a_1} \times \text{carbon tax}$$

The final reward for an agent is the base reward minus the penalty minus the carbon cost.

$$\text{reward} = \frac{1}{E_{a_1}} - \text{penalty} - \text{carbon cost}$$

This incentivizes agents to keep their carbon emissions close to the average of their neighbors while still striving to reduce their own emissions.

**Reproduction**

When reproducing, the model offers two possibilities. A human agent can reproduce with a neighboring human with a certain pre-set probability. The new born can then either inherit one of the parent's behavior and emission rate or be randomly assigned a behavior. This allows for variation in the population and potentially for the emergence of new behaviors or emission rates over time.

By incorporating both herd behavior and reward-driven incentives, the model may offer insights into how human behavior and emissions could be influenced in a real-world scenario and the impact it has on the environment.

### 2.2.2 Tree Agents

The tree agent plays a vital role in absorbing carbon in our environment and possesses three key attributes, namely age, absorption rate, and tree growth rate.

The Age parameter is used to simulate the entire lifespan of the tree, with each tree agent having a lifespan of 30 years. As the tree gets older, both its size and absorption rate experience a corresponding increase.

The growth rate determines the number of new trees replanted annually as well as the trees growing due to seed dispersal, reflecting the average level of increments each year. The number of trees is impacted not only by the tree growth rate but also by the cut speed of companies meaning that high-revenue or large-scale companies tend to cut trees at a faster rate. Also note that, seed dispersal in our model can only happen once a tree reaches the age of 5.

Our model features a plant policy that offers a viable means of increasing the number of trees in a specified period, thereby reflecting the positive action that humans can take to protect the environment. If the plant policy is activated, individuals with good behavior will commence planting baby trees, resulting in an overall increase in the tree population.

**Initialization**

We start by randomly generating some trees with different ages on the grid and give them some random initial attributes ( see Table 2.1).

**Implementation**

Trees agents take the whole responsibility of absorbing Co2 in the system. Each tree will absorb a certain value of Co2 at each tick.
The trees regrowth function is a basic way to increase the number of trees'. The amount of trees created at each tick is given by:

$$\text{New Trees} = \text{Num Trees} * (\text{Regrowth Rate})/100$$

| Attributes | Value |
|---|---|
| Age | random 0-30 |
| Growth rate | 0.01 |
| Absorption rate | random 0-20 |

Table 2.1: Attributes and Value

Another potential way to increase the number of trees is to switch on the plant policy function which will grow trees as a linear function of the number of good behaving humans:

$$\text{Planted New Trees} = \#\text{Good} * 0.1$$

As will be discussed in the next section, the cut rate is related to the scale of the Company Agents such that the number of trees cut is given by:

$$\#\text{Trees Cut} = \sum_{i=1}^{n} (\text{Scale} * 0.0001)$$

### 2.2.3 Company Agents

The third kind of agents in our model represent companies. They possess the following attributes - scale (which quantifies the size of a company as time passes), age, net revenue, net carbon emissions, net penalty and the net number of trees cut.

We assume that as time passes, the revenue of each company grows as a Brownian Motion. The scale is directly proportional to the revenue and age and the number of trees cut and $CO_2$ emissions are also directly proportional to the scale, i.e, a larger company would cut more trees and pollute the environment more than a smaller one.

Companies influence $CO_2$ levels by directly adding to the emissions by way of air pollution. By indulging in deforestation, they also reduce the amount of $CO_2$ absorbed by trees. Moreover, we assume that the revenue of a company indirectly caters to the consumerism in society by changing people's daily habits, thereby affecting carbon dioxide emissions.

In addition to this, our model also works under the assumption that as $CO_2$ levels in the environment increase, external entities such as governments and environmental agencies levy penalties on companies in order to reduce their revenue (and in turn their scale). There are three levels of penalties which increase in severity as the net emissions in the environment increase.

**Initialisation**

We generate a fixed number of companies in the bottom half of the model window. We initialise the attributes for the Company Agents as follows:

| Attributes | Value |
|---|---|
| age | 1 |
| revenueAmt | 100 |
| netPenalty | 0 |
| scale | revenueAmt - netPenalty |
| emissionQty | scale * 0.10 |
| numTreesCut | 0 |
| emissionQtyPerTick | 0 |

Table 2.2: Attributes and Values

### Implementation

With the passage of each tick, the variable age is incremented by 0.1. We define the scale of a company as a function of it's age and revenue. This is because it is reasonable to assume that when a company has been established long enough, it can sustain a larger hit to its revenue. During the early stages of their inception, age plays a greater factor when looking at the scale of companies. This is why we take the natural logarithm (see Figure 2.1) of the age and increment it by 1.

In the real world, the revenue of a company may increase or decrease randomly. To simulate this randomness, we ensure that the revenue grows as Lognormal Random Walk at each tick in the following way:

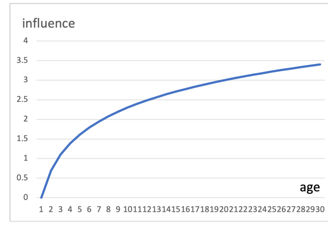



Figure 2.1: Plot of the influence as a function of the logarithm of the age

$$\text{tickRevenueGrowth} = \exp\{(\mu - \frac{\sigma^2}{2})t + \sigma\phi\sqrt{t})\}$$

where

$$t = 1,$$

$$\sigma = 0.01,$$

$$\mu = 0.01005$$

$$\phi = N(0, 1)$$

thus giving us the equation in our code as

$$\text{tickRevenueGrowth} = \exp(0.01 + 0.01\phi)$$

Companies influence the net $CO_2$ emissions as follows. In order to increase their revenue and thrive, they have to cut down trees thereby reducing the total absorption done by them. As revenues increase, the scale (a function of the revenue) also increases and so larger companies pollute more. This behavior is synonymous with the real world. For a single Company Agent, the number of trees cut per tick is assumed to be 0.01% of the scale while the emission quantity is assumed to be 20% of the scale.

When the total $CO_2$ emissions are alarmingly high, we assume that external entities like governments and The United Nations Environment Programme (UNEP) enforce penalties on the companies. Our model accounts for three different penalties of varying severity at three different levels. These penalty levels and rates are user inputs. For each company, the penalty amount is calculated per tick and is subtracted from the net revenue. It is defined in the following way:

$$\text{penPerTick} = \begin{cases} \text{revenue} * \text{pen-rate-3} & (CO_2 >= \text{pen-lvl-3}) \\ \text{revenue} * \text{pen-rate-2} & (CO_2 >= \text{pen-lvl-2}) \\ \text{revenue} * \text{pen-rate-1} & (CO_2 >= \text{pen-lvl-1}) \end{cases}$$

where

$$\text{pen-rate-3} = 0.05$$

$$\text{pen-rate-2} = 0.02$$

$$\text{pen-rate-1} = 0.01$$

In addition to this, the model also accounts for consumerism amongst Human Agents with the help of an Economy Indicator defined as follows:

$$\text{EconomyIndicator} = \frac{\sum_{i=1}^{n} \text{revenueAmt}(x_i)}{n} \div \text{InitialRevenuePerCompany}$$

where

$$x_1, x_1, ..., x_n$$

are the Company Agents. As the revenue of the Company Agents increases causing the economy to do well, a new human will be born with poor behavior with a certain probability defined as

$$P = \begin{cases} 0 & (\text{EconomyIndicator} < 1) \\ 0.5 & (\text{EconomyIndicator} > 1) \end{cases}$$

If the average revenue of companies is higher than the standard initial revenue, it means the society is developing rapidly and more Humans are likely to fall prey to consumerism. We thus include this probability in the section of the code where humans reproduce. Examples of this kind of consumerism are a family choosing to commute in private cars instead of walking or using public transport and Humans using disposable cups to coffee shops instead of bringing their own ones.

**Algorithm 2** Companies-Human-behavior Design

economy-indicator $\leftarrow \frac{revenueAmt}{companies} * \frac{1}{init-rev-per-company}$
**if** economy-indicator >1 **then**
    randNum $\leftarrow$ random$(0, 1)$
**end if**
**if** randNum = 1 **then**
    human $\leftarrow$ "bad behavior"
**end if**

### 2.2.4 Full Diagram

The diagram presented in Figure 2.2 provides a comprehensive illustration of our model, which includes all of the agents and their corresponding attributes, as well as the global environment attributes. It is worth noting that the agents interact with each other and the environment in diverse ways, but what's particularly noteworthy is the role of the environment in influencing the agents in a feedback loop.

In other words, the environment does not merely serve as a passive backdrop to the agents' activities, but rather, it actively affects the agents and their behavior. This feedback loop can be understood as a continuous cycle of reciprocal influence, in which the agents' actions and decisions affect the environment, which in turn feeds back into the agents' subsequent actions and decisions. By examining this interplay between the agents and the environment, we can gain valuable insights into the dynamics of the system as a whole.

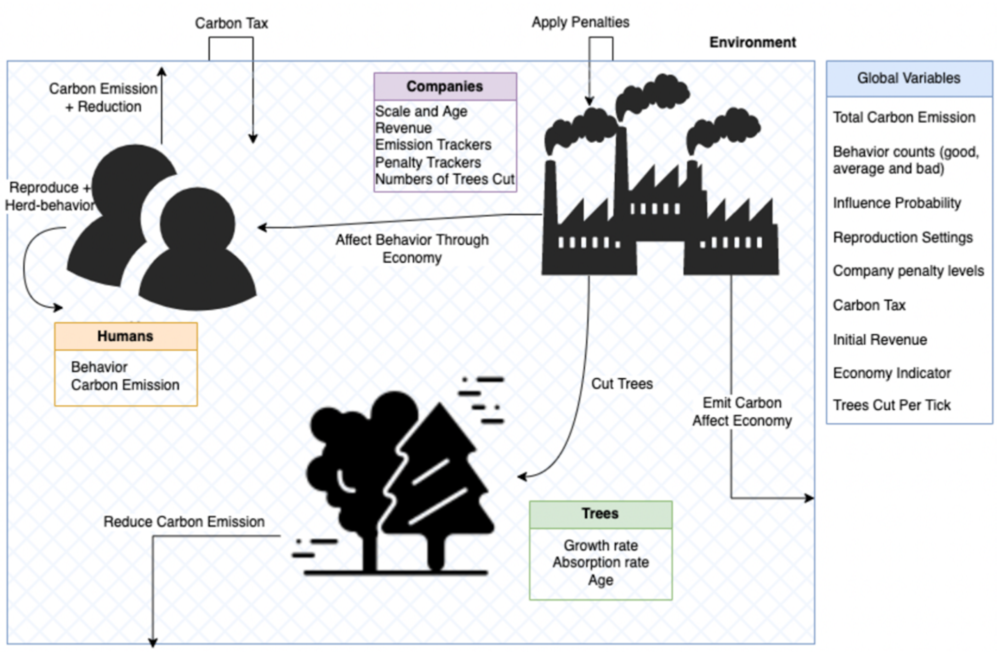



Figure 2.2: Full Infrastructure of our Model

# Chapter 3

# Analysis and Observations

The following experiments have been conducted using the Behavior Space tool on NetLogo.

## 3.1 Experiment 1: Changing the number of trees

In this experiment (A.1), a sensitivity and perturbation analysis was performed on the tree agents (The evolution of the number of trees can be seen in Figure A.1c). The results indicated that a decrease in the number of trees led to dangerously high CO2 levels (see Figure A.1a) and consequently, more severe penalties. This resulted in an instantaneous decrease in the companies' revenues (see Figure A.1b).

On the other hand, an increase in the number of trees resulted in oscillations with smaller amplitude and higher frequency, leading to more range-bound carbon levels due to a higher absorption rate.

As penalties were applied based on the total emissions, the companies experienced cycles of high and low profits. When there were fewer trees available, the competition among companies intensified, causing revenues to rapidly fall to zero. Conversely, an increase in the number of trees led to less competition, resulting in high revenue and range-bound carbon emissions.

Our model proves to be sensitive to the initial setting for the number of trees with rather extreme perturbations when the latter is set too high or too low.

## 3.2 Experiment 2: Changing the number of companies

For our second experiment (A.2), we examined the impact of varying the number of company agents in the model. Through our observations, we discovered that a decrease in the number of companies led to an increase in the overall "health " of both the companies and the trees in the simulation. This phenomenon was attributed to the principles of supply and demand, as the reduced number of companies resulted in less competition for resources, thereby enabling both parties to thrive (A.2b, A.2c).

Furthermore, we noticed that fluctuations in emission levels were more pronounced when there were fewer companies (A.2a). This was due to the presence of penalties in the simulation, which created cycles of high and low revenue. These findings suggest that economic conditions and competition play a critical role in the health of an ecosystem, and can have a significant impact on its long-term sustainability.

Our model also shows interesting insights (A.2d) into the relationship between consumerism and human behavior. This is due to our simulation's assumption that a thriving economy leads to greater consumerism and, consequently, a decrease in desirable behavior. Hence, we observed an increase in the number of bad behaviors. However, it is worth noting that other factors such as reproduction and herd behavior play a role in these numbers.

## 3.3 Experiment 3: Human Behavior

This is the only experiment that was not run using Behavior Space (A.3). Rather it was done to see how the different human attributes reacted to change. To do so, we've isolated the humans to observe their behavior.

The initial number of humans does not play an important role in the model as through reproduction and herd behavior we will see the emergence of new behaviors. However, it is a useful tool if we wanted to start with settings that are closer to what we would expect in the real world (i.e a higher number of bad and average behaviors).

The observed patterns were as follows. If we turn inheritance on, then depending on the random positions of the humans this will create behaviors with higher counts (A.3). The same phenomenon is observed if we increase the probability of being influenced (A.4). Finally when we turn on rewards, we observe an immediate drop of bad behaviors and a higher number of average behaviors as humans will tend to be more environmentally friendly if they get something out of it (A.5).

## 3.4 Experiment 4: Revenue Penalization

For our fourth experiment (A.6, A.7), we examined the impact of changing the severity of the revenue penalties imposed on the company agents.

On increasing the "pen-rate-3" variable from 0.05 to 0.10 (A.6d), we observed that the total carbon emissions started limiting themselves to a tighter range. The graph still looked like a sine wave but started decreasing in both amplitude and frequency. (A.6a) The existence of this waveform can be attributed to the fact that due to their greedy nature, companies start cutting down more trees as soon as penalties are revoked, thereby increasing their emissions.

Additionally, the severe penalties also caused a rapid fall in the revenues of companies and the oscillations in this graph also decreased in amplitude (A.6c). This was because heavier penalization meant that the revenues of the company agents would be kept in check more aggressively. With higher penalties, we also noticed that the revenue graph became more and more downtrending. A lower value of the average company revenues could signify economic collapse in the system as the "economy-indicator" variable has been defined as a function of the company revenues.

Conversely, decreasing the "pen-rate-3" variable from 0.05 to 0.02 (A.7d) resulted in carbon levels that pose a significant threat to human existence. This was due to the fact that higher revenues resulted in a higher scale which meant companies needed to cut down more trees to survive, thus resulting in higher emissions by the company agents and lower capability for the trees to absorb $CO_2$.

The revenue graph also had a larger range (A.7c) as the penalties, though less severe, lasted for a longer time thus causing more variation. Due to the lenient penalties and the resulting increase in revenues and scale, we also saw an increase in the amount of deforestation being conducted by the companies (A.7b).

Through this experiment, we were able to discern the relationship between penalizations imposed by governments and the condition of the economy. Harsh penalties cause a risk of severely damaging the economy while punishing companies with less severity poses a threat to the environment. To conclude, a good balance is important for a sustainable future so that all three agents can thrive.

# Chapter 4

# Conclusion

## 4.1 Future Work

The model we have developed provides a valuable tool for exploring the potential benefits of policy interventions aimed at mitigating the effects of climate change. However, it is important to acknowledge that like any model, it has limitations that must be taken into account when interpreting the results.

One of the main limitations of our model is its simplification of some real-world complexities. As a result, there may be some aspects of the system that are not fully captured by the model, leading to potential inaccuracies in the predictions.

Despite these limitations, we believe that our model can still provide valuable insights into the dynamics of the climate system and inform decision-making around climate change mitigation strategies. By simulating different policy interventions, we can identify potential areas for action and evaluate their likely effectiveness in reducing emissions and limiting the impacts of climate change.

To improve the accuracy and utility of our model, several potential enhancements could be considered. For example, we could implement measures to prevent total CO2 rates from going below zero, as this is physically impossible and could impact the reliability of the model's predictions.

Furthermore, incorporating a larger variety and number of agents, with more attributes per agent, such as industry attributes for factories, could help to capture more of the complexity of real-world systems and provide a more comprehensive understanding of the impacts of policy interventions.

Finally, we could also consider implementing additional ways for the agents to interact with each other, which could further increase the realism of the model and improve its predictive power.

## 4.2 Lessons Learnt as a Team

Throughout our project, our team learned a multitude of valuable lessons that have contributed to our success. One of the most important takeaways was the significance of establishing effective communication channels as well as setting regular meetings to ensure timely and efficient completion of the project.

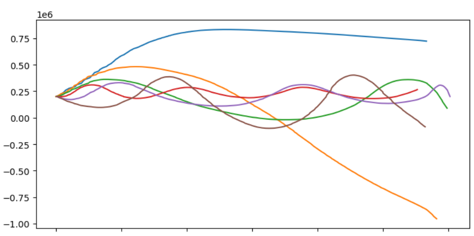
We also recognized the importance of fostering an environment where every team member's ideas are heard and valued. By encouraging active participation in debriefs and brainstorming sessions, we were able to generate innovative solutions and approaches that might have otherwise gone unnoticed. Working with individuals possessing a diverse set of skills was another invaluable lesson that we learned. By tapping into the unique strengths and perspectives of each team member, we were able to leverage our collective expertise to drive our project forward.

Finally, we discovered the utility of NetLogo as a highly user-friendly tool for designing agent-based models. This experience has not only provided us with a deeper understanding of the value of these models in policy-making, but has also highlighted the importance of visual aids in communicating complex ideas and insights to stakeholders.

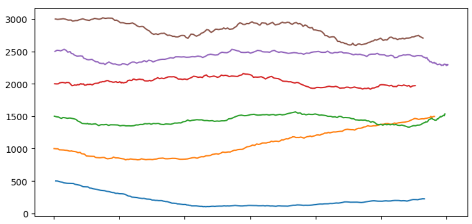
# Appendix A

# Experiment Results

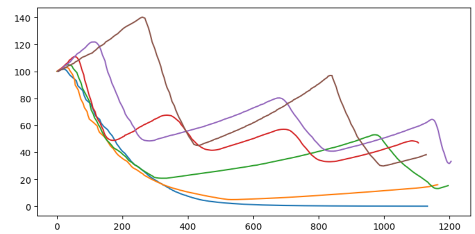
## A.1 Experiment 1



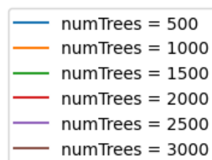
(a) Total Carbon Emissions



(b) Total Number of Trees



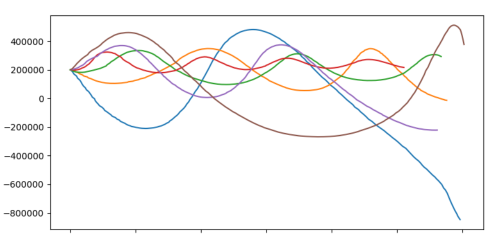
(c) Average Company Revenue



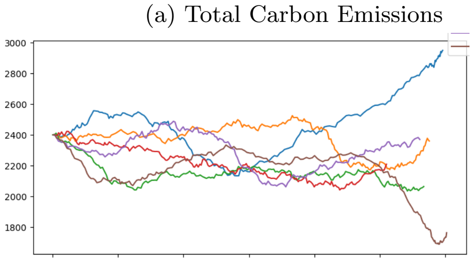

(d) Legend

Figure A.1: Model Behavior Upon Changing Initial Number of Trees

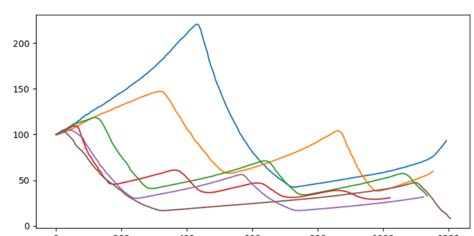
## A.2 Experiment 2



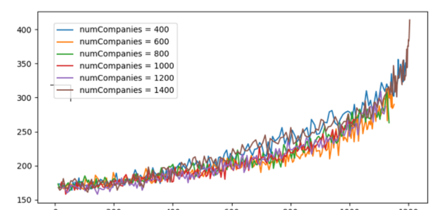
(a) Total Carbon Emissions



(b) Total Number of Trees



(c) Average Company Revenue




(d) Bad Behavior Counts + Legend

Figure A.2: Model Behavior Upon Changing Initial Number of Companies

## A.3 Experiment 3

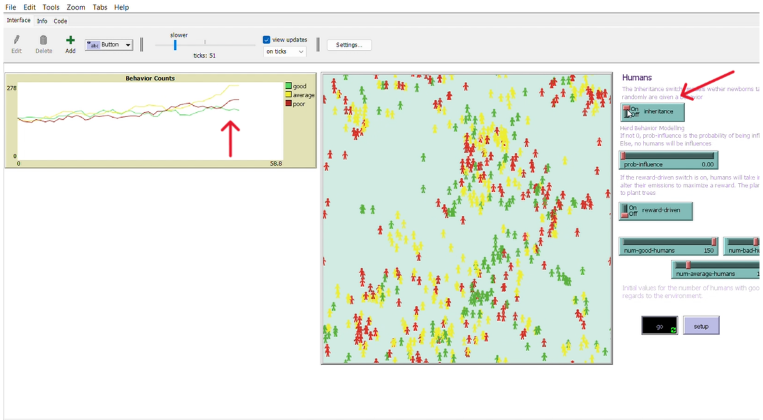


Figure A.3: Behavior when Inheritance is on

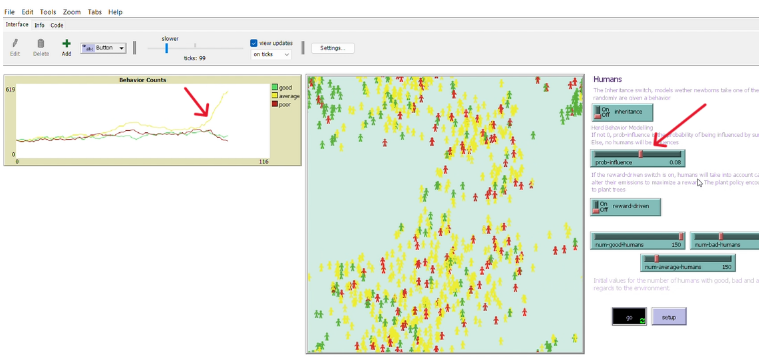


Figure A.4: Herd Behavior

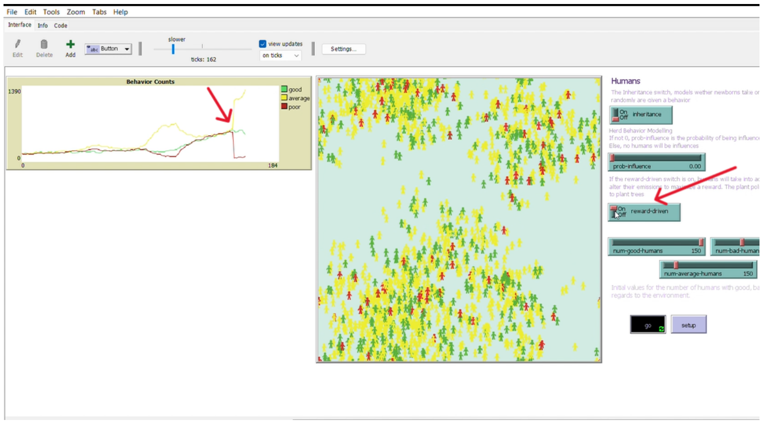
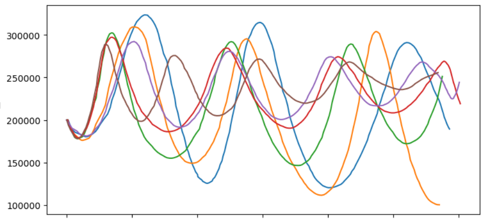


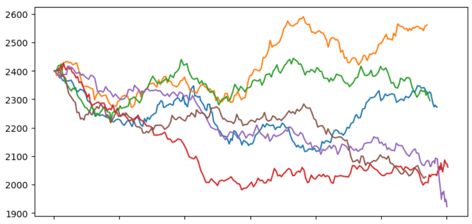
Figure A.5: Behavior when we add incentives

## A.4 Experiment 4

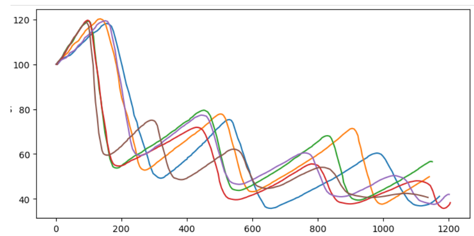
### A.4.1 Increasing Penalty Severity



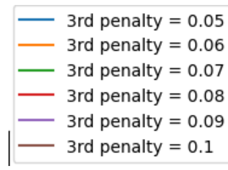
(a) Total Carbon Emissions



(b) Total Number of Trees



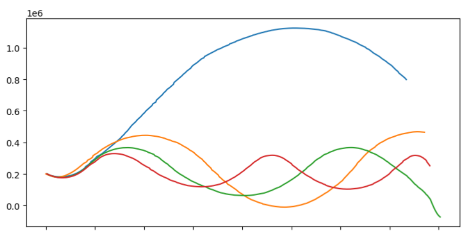
(c) Average Company Revenue



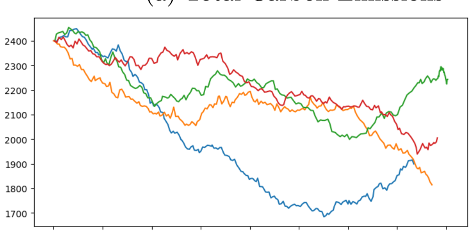

(d) Legend

Figure A.6: Model Behavior Upon Increasing Penalty Severity

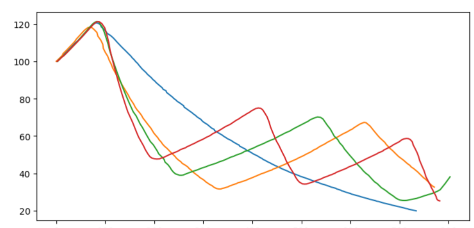
### A.4.2 Decreasing Penalty Severity



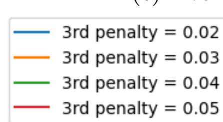

(a) Total Carbon Emissions



(b) Total Number of Trees



(c) Average Company Revenue




(d) Legend

Figure A.7: Model Behavior Upon Decreasing Penalty Severity