

Agent Based Modelling of COVID-19

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Abstract

COVID-19 is an incredibly complex problem that has been troubling the world for over a year. Part of humanities effort to combat the virus is to predict it using model. This project uses an Agent Based Model (ABM) to visualise different scenarios and see the effect of different current events. The model looks specifically into health care resources and vaccinations and how policy is affected.

Key Words:

- Agent Based Modelling
- REPAST
- COVID-19
- Epidemiology
- Pandemic
- Inoculation

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1 Introduction

1.1 Background

In December 2019, China detected a new type of viral pneumonia called COVID-19. Soon after, COVID-19 had taken the world by storm, becoming a global pandemic in March 2020 [1]. To date, the virus has infected over 130,000,000 individuals and taken over 2,500,000 lives around the world.

Individuals infected with the virus experience different symptoms as the virus attacks the body. Some cases are asymptomatic where individuals display no symptoms. Unless tested, the individual may not even know they carry the virus. Mild symptoms can then begin with the potential to worsen. Cases, where health does worsen, can lead to long-term negative health effects and in some cases, symptoms become more severe resulting in death. Individuals themselves are at a health risk and on top of that, they risk infecting others. Transmission most likely occurs from large infected droplets. Produced by infected individuals coughing, sneezing and breathing near a susceptible individual [2].

Large amounts of individual infections and deaths culminate to have catastrophic effects. Damaging everything from small communities to large global entities. Costing governments, companies and the general population large amounts of money. Estimates calculate that COVID-19 is likely to end up costing up-to \$15.8 Trillion [3]. Due to the repeated closure of schools, on average worldwide schools have lost two-thirds of an academic year [4]. Effecting those less fortunate, research estimates that COVID-19 will put 49 million into poverty [5].

The Plague of Justinian (541AD-542AD) was the first pandemic recorded [6] and there have been many pandemics and different infectious diseases since. Infectious diseases are not new to humanity but they still complex and multi-faceted. Humanity has developed new ideas and ways of battling infectious diseases gaining understanding and predicting the diseases. Daniel Bernoulli (1700-1782) developed what is considered the first epidemiology model, on vaccination against smallpox [7]. Many models have since been used to predicted and better understand infectious diseases, combating many different diseases through time.

1.2 Motivation

Countries have risen to combat COVID-19 in many ways. Experts have collaborated to discover solutions to the virus, finding biological, economic and social answers. Using vaccines, bailouts and lockdowns to hold society together. However, COVID-19 has spread viciously putting serious strain on the health care systems [8] limiting countries resources to fight the virus. One approach has been to model COVID-19 and forecasting how the virus will spread. If done accurately we can limit the damage done by the virus and help save lives. Using the predictive models, policies have been made to stop the spread. However, these models are challenging to create [9]. To reduce the spread epidemiologists have heavily relied on many mathematical models with many of these models affecting government policies. Computational simulations have also played a large role with modelling, predicting early on that the global pandemic was likely and already providing advice and potential strategies [10]. All these models have helped predict the spread of COVID-19 trying to predict different outcomes highlighting the importance these models have in reducing the spread of COVID-19.

The motivation of the project is to assist with these efforts. Provide a tool that can simulate and visualise the spread of COVID-19 providing insights into the virus and how it operates in different scenarios. The more realistic the simulations can be, the more useful they can be. There are many news areas of COVID-19 for example vaccinations. The project will tackle these new problems and incorporate them into the simulations. COVID-19 is constantly changing with cases decreasing in some countries and increasing in others, the problem will still be around for a long while. Scientist believes the virus will become an endemic circulating around pockets of the global population [11].

2 Methodology

To ensure this project was efficient and accurate clear methods were set up. There are four main areas development, project management, research and evaluation. Each section is important for the project and each one requires a clear plan of action.

2.1 Research Methodology

There are many different areas of the project that require research. The research will expand understanding and knowledge of the topics around the project. Setting up the project to be accurate and useful to the real world. The problem the project is tackling is very complex and some areas broad.

COVID-19 is an ongoing problem that is constantly changing and evolving. From new strains and vaccine advancements, constant changes are occurring. This requires constant research to be performed throughout all stages of the project. Some advancements may be too large to add or change nevertheless these features will be discussed as they may be future applications for the project.

Another factor is that there is a lot of research being done on COVID-19. With this different opinions and views requiring the research to be accessed. Avoiding misinformation from unreliable sources that could negatively influence the project.

2.2 Project Management

To ensure the project moves on time and work is completed correctly the project must be managed tightly. To do this a development methodology is needed and useful tools will be used.

2.2.1 Development Methodology

The important factors that are important in selecting a development methodology. The nature of the project is that there is potential for the requirements to change for example different scenario to simulate. The chosen methodology must allow for new ideas to be research and the changes to occur in the requirements. The planned time

frame of development is around 4 months which is relatively short. Implementing new features and making progress will therefore be measured in weeks. The shorter time frame and change in requirements suit either Agile or Lean development.

Agile is particularly useful as the scope is open to change. Treating weekly meetings with my supervisor as Scrum meetings would ensure that progress is being made and in the correct direction. The meeting would allow the project to also plan out the next sprint.[12]

The Lean methodology would make use of Kanban boards. Any new features or requirements could simply be added to the Kanban board and then implemented when there is capacity. Lean focuses on getting a minimum viable product out as soon as possible. This would mean the project could generate a simple model that is used as the base for the model. [13]

Both methodologies are incredibly useful. To make use of both the chosen methodologies, Scrumban has been chosen. Utilising Kanban workflow and then treating the weekly supervisor meetings as sprint cycles. To manage the project well it is important to follow the Kanban board and scrum meetings. Otherwise, parts of the project will fall behind schedule and other parts may be rushed. If this occurs it will reduce the effectiveness of the model created making it less useful.

2.2.2 Management Tools

As discussed it is very important to follow the methodology. To do this different tools will aid parts of management. Firstly to ensure a Kanban board is used and kept up to date trello.com will be used. This will keep track of task and features. Ensuring all parts are planned, developed, review and tested. As shown in figure 2.1 each feature will move through the board.

The second tool is Github. Github will be used for version control during the development of the program. Github tracks changes and ensures the project is safe. The weekly meetings will act as Scrums. Ensuring they are consistent, arranging a weekly recurring meeting with the supervisor is important. Covering current progress made and the plan for the next sprint. On top of this recording work done in a weekly diary writing up the progress made. This will ensure all work is documented extensively,

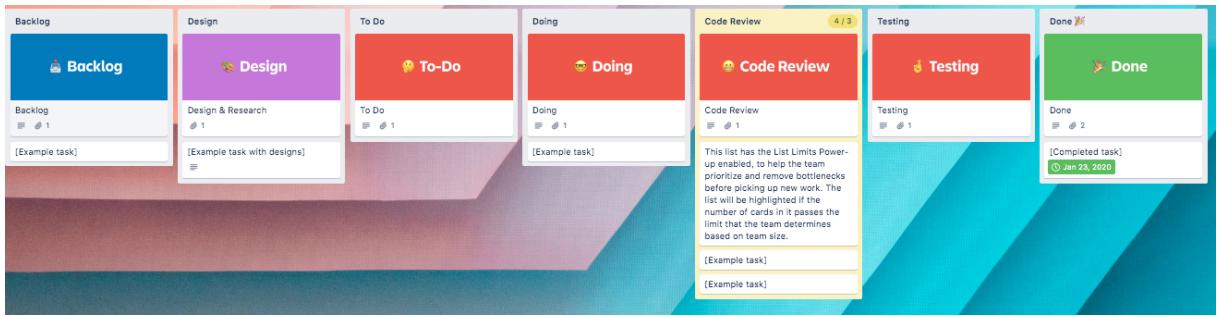


Figure 2.1: Empty Kanban board on trello.com

with justification.

3 Research

Modelling COVID-19 is a complex problem that requires different areas. The Research has been split into multiple sections.

3.1 COVID-19

My research has covered different factors and attributes that affect COVID-19 and COVID-19 spread. The importance of these different factors and how this will affect my model will be evaluated and then potentially used. COVID-19 is constantly changing with new problems and features occurring regularly for different countries. In turn, this means there is always new research being done to keep up with the virus. To ensure the project was moving initial research was done on COVID-19 and different areas of future research were highlighted.

3.1.1 Spread

COVID-19 is a respiratory virus that can be transmitted in three ways: contact transmission, droplet transmission and airborne transmission. It most likely occurs from large infected droplets produced by coughing sneezing and breathing in close proximity to another person[2]. Different social interactions have different chances of infecting members of the population. Spending more time and closer to infected people increases the chances of getting infected [14]. Research has found that reinfection is possible but very unlikely[15].

Social distancing will also affect the model with fewer social interactions occurring depending on the rules in place. The specifics of the rules are not essential as the level of social distancing rules can be placed on a low to high scale.

3.1.2 Symptoms and Death

When someone is infected with COVID-19 there are clear symptoms however, the majority of infected people are asymptomatic with research showing up to 76.5% of tested cases were asymptomatic[16]. With COVID-19 cases leading to serious illness and potentially death COVID-19 affects different members of the population

differently. There are underlying issues that can cause cases to worsen and increase their chances of being fatal cases[17].

This is interesting for the simulation as it may be beneficial to replicate the real world if each agent is not at the same risk of dying despite them all being at the same risk of catching the virus. As the project is looking into vaccination methods of COVID-19 it may prove better to vaccinate those more at risk.

3.1.3 Vaccinations

This brings on a recent issue for COVID-19, vaccinations. With new vaccines being discovered governments can vaccinate populations and build immunity without the virus spreading. The NHS has already said they are going to prioritise vaccinating cohorts who are at the highest risk [18]. However, it will take a while before vaccines are fully available with them coming at a big cost to governments and populations so not all the population will be vaccinated straight away. Some governments will have limited funds so careful consideration of the distribution will be essential in ensuring its effectiveness.

As this is a recent problem it makes it perfect for the project as my model could help guide policy in this new area. Offering insight into different scenarios that resemble particular situations simulating different constraints.

3.2 Epidemiology Modelling

To complete my project I need an idea of what makes a good epidemiology model. What makes the model accurate and what features should the model include.

Firstly, I researched different classes of computational models. I had decided on an agent-based model(ABM) also known as an individual-based model however, to ensure this was the best modelling approach for the problem I found helpful information. ABS allows for the simulation to be built bottom-up and large amounts of detail to be added[19], which greatly benefits its support for policy decision making. Dawid and Fagiolo claim that decision-makers might be more willing to trust findings based on detailed simulation models rather than abstract mathematical models[20]. However there are problems with ABS, as complexity increases it means that more assumptions

need to be specified. To combat these negatives I have researched specific COVID-19 features and any assumptions I make will be calculated and clearly stated.

There are three basic models for computational Epidemiology SIR, SIS, and SEIR[21]. The first is SIR one of the simplest models[22], in the SIR model any member of the population is in one of three states. Susceptible meaning the member is able to catch the virus, infected meaning the member currently has the contagious virus and finally removed meaning the member has recovered and is now immune or the member has died. Members in an infected state can spread the virus to other members. The SIS(Susceptible, Infected, Susceptible) model is very similar, however the members cannot gain immunity from the disease and can be reinfected. Finally, the SEIR model contains exposed. The state exposed describes a member who has come into contact with the disease but is not yet infected.



Figure 3.1: Diagram showing the basic SIR model

These three models are very simple and are a good starting point to develop from. As discussed before COVID-19 has displayed low cases of reinfection so all three models will be important in modelling COVID-19.

I have also researched some more complex models. They do not exactly relate to my problem however they do provide good inspiration for my model offering different ideas. The SIDARTHE model adds even more states shown in figure 3.2, it breaks the infected state into 5 different states. These include asymptomatic, symptomatic, detected, undetected and life-threatening condition. This model increases the complexity of the SIR model and its accuracy however, disease testing is not of much interest in the project so some of the added states are not as needed.

A feature of ABM is that they are able to represent heterogeneity. Increasing heterogeneity increases greater model complexity and in turn computational cost, this does allow for an accurate evaluation of preventive strategies[24]. If my model was homogeneous then all agents would have the same attributes this would be simpler to implement as the model would be less complex. For my project adding heterogeneity is more beneficial as COVID-19 affects individuals differently based on different

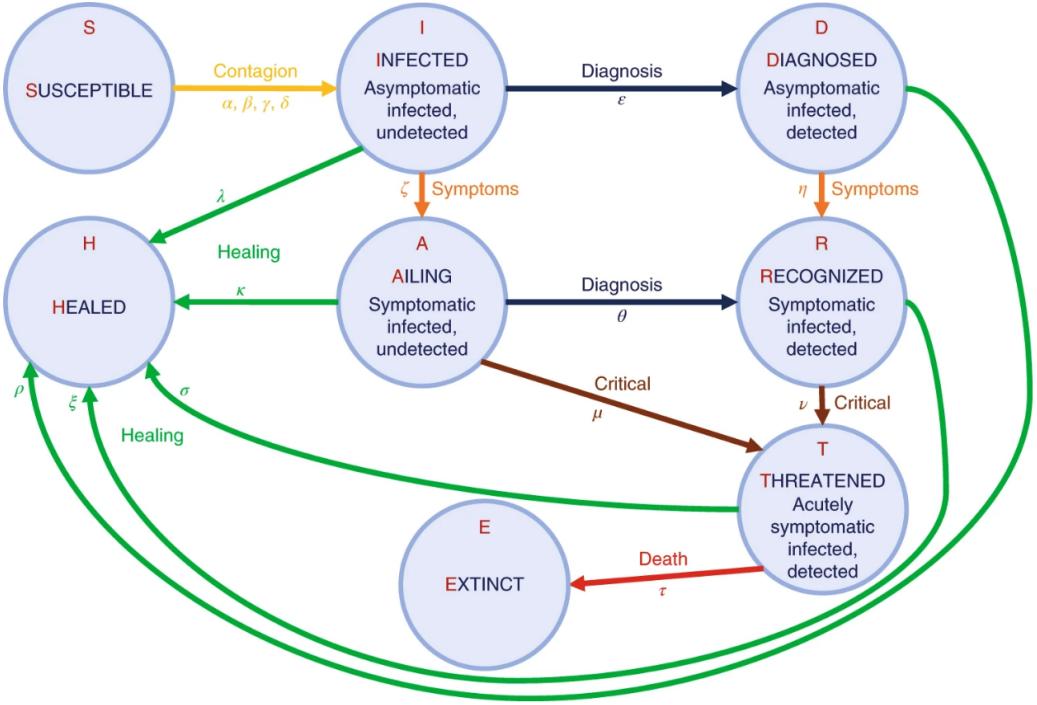


Figure 3.2: Diagram showing the SIDATHE model states and transitions[23]

factors and the vaccination plan that governments rely on heterogeneity in the population with some members being more at risk.

3.2.1 Agent Based Modelling Platforms (ABMP)

To implement the project a suitable software platform must be chosen for the development of the model. There is a couple of commonly used ABMP I will access their advantages, disadvantages and decide what relates best to the project. Information given in figure 3.3 has been collected from these sources.[25][26][27][28][29]

Most of the options do not have many limitations, their strengths will be more important in deciding on what software tool to use. Given the research and information in the table, I have concluded the best fit for the project is Repast. Repast requires good programming knowledge giving me the freedom to develop the code making the project more complex. Repast also has inbuilt visualisations of the simulation this benefits me as time can be spent focus on developing the model instead of getting stuck on programming a display. Repast also has large amounts of documentation and support, which will be beneficial due to my limited experience. I have tested using Repast on an example model. The model displayed the potential of Repast showing that certain elements of the model can definitely be implemented.

Software	Description	Advantages	Disadvantages
Repast	Agent-based simulation toolkit specifically designed for social science applications	<ul style="list-style-type: none"> • Greatest functionality • Allows for numerous languages(Java, Groovy, Python) • Data collection from simulations • Extensive analysis tools 	<ul style="list-style-type: none"> • Limited to social science models
MESA	Quickly create agent-based models in Python using built in core components	<ul style="list-style-type: none"> • Can make use of Python's data analysis tools • Visualisation of the models is done on a browser no need for cross platform GUI • Programmed in Python, which I have a-lot of experience with 	<ul style="list-style-type: none"> • Limited documentation and support • Extra code must be written for data extraction
NetLogo	Multi-platform general purpose complexity modeling and simulation environment.	<ul style="list-style-type: none"> • Easiest to implement models • Basic programming knowledge required • Extensive documentation 	<ul style="list-style-type: none"> • Mainly educational tool
MASON	Smaller and faster focusing on computationally demanding models	<ul style="list-style-type: none"> • Allows for 3D modelling • designed for fast execution speed • Can easily be used with other libraries 	<ul style="list-style-type: none"> • Limited analysis tools

Figure 3.3: Table showing different ABMP with their benefits and limitations

4 Planning

The project runs over a long period of time and requires large amounts of development and thought. To ensure the project is executed on time and to a high level this planning stage has been completed. Outlining what needs to be done for the project. The objectives of the project will be defined and dates for when these objectives will be met by will also be planned.

4.1 Objectives

My first objectives were very broad and did not describe the projects aims fully. Each individual objective was not precise enough and the objectives did not weigh the importance of each one it put them on the same level. Due to my first objective lacking, further research and advancements with COVID-19 my objectives have changed slightly. I will be using the MosCoW method for determining the importance of each objective. M representing MUST, C representing COULD and W representing WOULD. Depending on the time remaining the COULD objectives will hopefully be implemented there should be time to implement some of them but probably not all of them. Which objective I decide to follow up on will be decided when the project reaches that stage as some may be simple additions and others may not add to the model. Note the brackets highlight what the dependent objectives are.

1. Run models with a small population size simulate the spread of COVID-19. With agents that can be susceptible, infectious or recovered. Modelling the SIR model. (M) (0)
2. Visualise the simulations to the user to display the infections spreading. A non-technical user should be able to clearly understand what the simulation is showing and how it works. (M) (1)
3. Create heterogeneous agents that have attributes with differing values. (M) (2)
4. Expand the model to include vaccination and extinction agent states. (M) (3)
5. Program different scenarios that replicate the real-world situations populations

and replicate different pandemic measure. Then calculate and record what the impact is and predict what strategies work best for different scenarios. (M) (3)

6. Perform large repeated populations simulations on different scenarios storing results. Processing data generate from the simulations to find trends and draw conclusions from the models that could inform policy. (C) (4)
7. Add agent states to include reinfections. (C) (2)
8. Use the model accompanied by a Geo-Simulation to simulate a real-world location. (C) (2)
9. Add extra agent state for testing and incorporate a government testing scenario. (W) (2)

4.2 Timeline

Objective	Deliverable	Time
1/2	1.1 Create Roaming Agents	08/12/2020-16/12/2020 [1 Week]
	1.2 Add SIR attributes to agents	16/12/2020-23/12/2020 [1 Week]
	1.3 Add agent infections	23/12/2020-06/01/2021 [2 weeks]
	1.4 Test SIR model	06/01/2021-13/01/2021 [1 week]
3	2.1 Research and add health attributes	13/01/2021-20/01/2021 [1 week]
4	3.1 Add vaccination capabilities	20/01/2021-24/01/2021 [0.5 weeks]
	3.2 Add agent extinction	24/01/2021-27/01/2021 [0.5 Week]
5	4.1 Program and tweak scenarios	27/01/2021-03/02/2021 [1 week]
	4.2 Replicate pandemic measures	03/02/2021-10/02/2021 [1 Week]
	4.3 Run analysis on results generated	10/02/2021-17/02/2021 [1 Week]
Contingency	1 week for catch-up	17/02/2021-24/03/2021 [1 week]
Presentation	Create and perform	24/02/2021-10/03/2021 [1 week]
Additional Feature TBD	Choose a remaining objective and then implement it	10/02/2021-31/04/2021 [3 weeks]
Final Report	Create and finalise	31/03/2021-28/04/2021 [3 weeks]

Figure 4.1: Table showing tasks and the time frame of the project

As my project is linear with features clearly flowing on from each other the Gantt chart has proved futile as it is not that important for displaying dependencies. My schedule will aim to complete features in a week, moving onto the next one on Wednesdays after my weekly Scrum meeting with my supervisor. I have broken each objective down into a set of deliverables shown in figure 4.1. Some objectives have been combined as the task to implement them overlap. If all the deliverables are implemented for a given objective that objective should be complete. I have added a week catch-up week

before the presentation for unforeseen errors or tasks that may occur. The additional feature discussed will be one of the other objectives that have not been completed. I will decide at a later date what objective will add most to the project as I will have a better idea of what each feature will entail.

5 Implementation

This section describes the implementation and development of the project. It discusses the different features implemented and problems faced during development. The different features are discussed in chronological order in order that they were developed. Each feature is built on top of the previous features and adding to them in some cases.

5.1 Basic SIR Model

The first step of implementation is to develop a SIR model that will act as a type of minimal viable product. The SIR model will give the project the basis for all the other features and a good understanding of the REPAST platform.

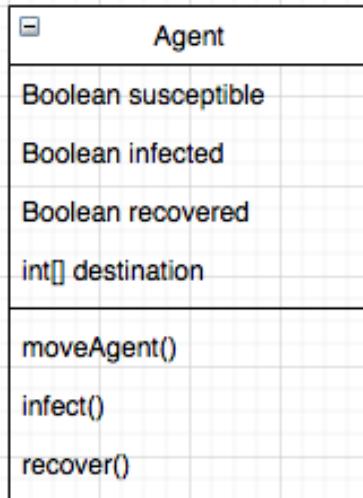


Figure 5.1: Single Class Implementation

The first step was to have agents that can interact with each other in a space. The agents must have three states. To get a basic SIR model working the first iteration was created. An agent class was created that contained all the attributes needed for the basic model shown in figure 5.1. The agents can randomly move about the space. There are a set number of infected agents hardcoded at the start of the simulation. Infected agents can infect susceptible agents and have a certain amount of time in simulation ticks until they recover. Currently, all agents are homogeneous and will respond to being infected in the same way. It is assumed that all agents currently who become infected are asymptomatic. Causing agents in all three states to act the

same way in their movement as each agent does not know if they have the disease or not.

However, this design was very limited. There was no way of distinguishing different agents in the space. REPAST records the number of agents of each class type however the current implementation does not make use of this as all different state comes under one agent class. The current iteration lacked scalability to further add more specific behaviour for each agent and further different agent states. To solve this a multi-class approach was adopted shown in figure 5.2.

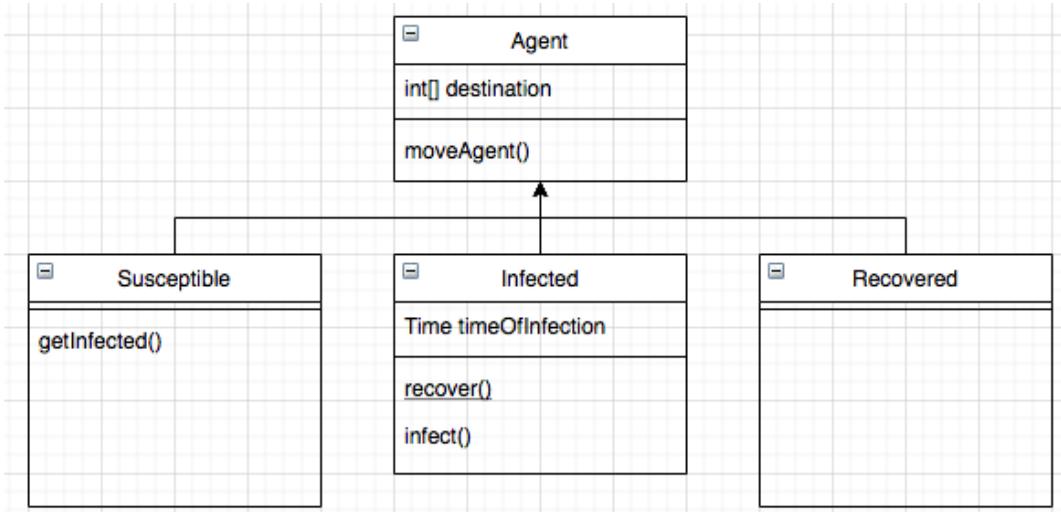


Figure 5.2: Multi Class Implementation

Each SIR state inherits from an Agent super-class. The Agent superclass controls the movement of the agents which is the same for each of the other agents. Agents in the susceptible can become infected. After a certain amount of time, infected agents recover and move to the recovered state. Agents can be initialised into any of the states if the user wants to simulate an environment with a different number split between the states. This structure also allows for specific behaviour for each agent allowing for more complex heterogeneous agents.

5.1.1 REPAST

REPAST works with having a context that all other objects are added to and controlled in. The context provides the infrastructure to define a population and the interactions that take place. [30] Contexts also contain projections that define the relationship between the agents. For example the distance between the agents or the

social relationship between agents.

The project uses REPAST projections to display space where the simulation can be shown while it is running. To create an environment in REPAST there are two useful projections Grid and ContinuousSpace. They each serve an essential purpose. ContinuousSpace allows objects to be projected visibly for the user. Allowing each stage of the simulation at each tick to be seen. Objects can be placed, moved and removed from the space. Grid allows for the agents to be projected on a grid space. With the Grids inbuilt functions, it can detect which agents are in the same grid space. This is needed for detecting transmittable interactions between the agents. The size of the space controls the density of the agents in the space with an increasing number of agents the size of the space will also have to increase to avoid too many instant interactions.

5.1.2 Context

In order to create the simulation, the context must be created. To do this REPAST uses a context builder. In this object, the context is initialised and the starting agents are created. We also define the size of the space that the agents exist in.

When any agents are added to the space their position is automatically randomised making each agent's position in the environment completely random. This does mean that in simulations with smaller population sizes the randomness of placement could impact the result of the model. If there is a scenario with 10 agents each interaction will be essential in shaping the results the random placement could be the difference between simulating an outbreak or the disease disappearing. To solve this the smaller the population size the more time the simulation must be run to improve the accuracy of the model and reliability of the results.

Infected agents starting positions can be changed to be less random and placed specifically on the board. Simulating the effect of the location of infected agents. Allowing for simulations where all agents start near each other compared to a simulation where agents are completely spread out in the space. This could allow for simulating when different geographical areas of the population have different severities of the disease. This route could also allow for the simulation of local quarantine.

5.1.3 Movement

Human beings and their lives are incredibly difficult to model. Each human is unique and makes seemingly random decisions. To add decisions on a large scale, to the model and programming for this would be too complex and take too much time. The focus of the model is the spread across a whole population rather than the individual agent. The movement of each agent will allow for the different agents to travel around the space and simulate real life. Agents are given random coordinates in the space, the agents move towards the coordinates at a set speed regardless of their state. The agents are given a random number. The random number controls how long the agents will travel to that destination. The time is generated between a range. Agents with longer times will travel further distance from their start location whereas agents with shorter times will travel a short while before changing direction causing them to stay nearer to their start location. The agents are given new directions if the time is met or they reach their end destination.

The longer the interval between changing direction the greater probability the agent has of being further from its start position. The agents that travel further away represent humans taking long journeys such as commuting. Other agents who are given shorter distances represent day to day movement like going to the supermarket. When the agents reach the edge of the space they wrapped around the edges appearing on the other side.

The movement is based on a simple implementation of 2-dimensional random walks shown in figure 5.3 [31].

Incorporating a more specific movement would greatly improve the project. Tracey et al highlighted the benefits of using movement data when creating an ABM for modelling disease spread in bobcats populations [32]. Finding interesting trends when the agents moved greater distances rather than moving about an established home range. Using data on human movement and behaviour would open up different areas to simulate precise human activity. This would require good data on human movement which is more complex than bobcat movement. The data would also have to be accurate and useful, this is an unfamiliar area that would require to must work and learning in an area that may not yield results for the project.

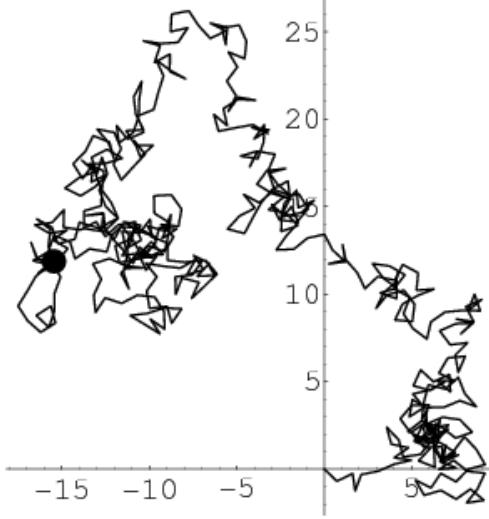


Figure 5.3: Random walk path similar to that of the agents paths [31]

5.1.4 Infections

When an infected agent collides with a susceptible agent it is treated as a transmittable interaction. Any interaction between an infected agent and a susceptible agent will spread the disease to the susceptible agent removing the agent and replacing it with an infected agent maintaining the same destination as before. To detect these collisions the grid interface is used any agents in the same grid sections as infected agents will check if the disease is spreadable to the agent. If multiple agents interact with an infected agent multiple infections can occur by one agent. The model assumes that any interaction between an infected agent and a susceptible agent is a transmission of the disease. As all the infections are currently asymptomatic the agents carry on as if they have not been infected.

5.1.5 Recovery

Initially, the recovery time was set to a fixed time however this meant any agents initially infected would recover at exactly the same time. This also lacks realism as recovery time is not constant but varies between different infected individuals.

There are two approaches to solve this problem. Firstly when running the simulations the start number of infected agents can be reduced so when the recovery time for them occur there is only a small change. However, this does not actually solve the problem only giving the perception that it has been solved. Also if the user wants to start the

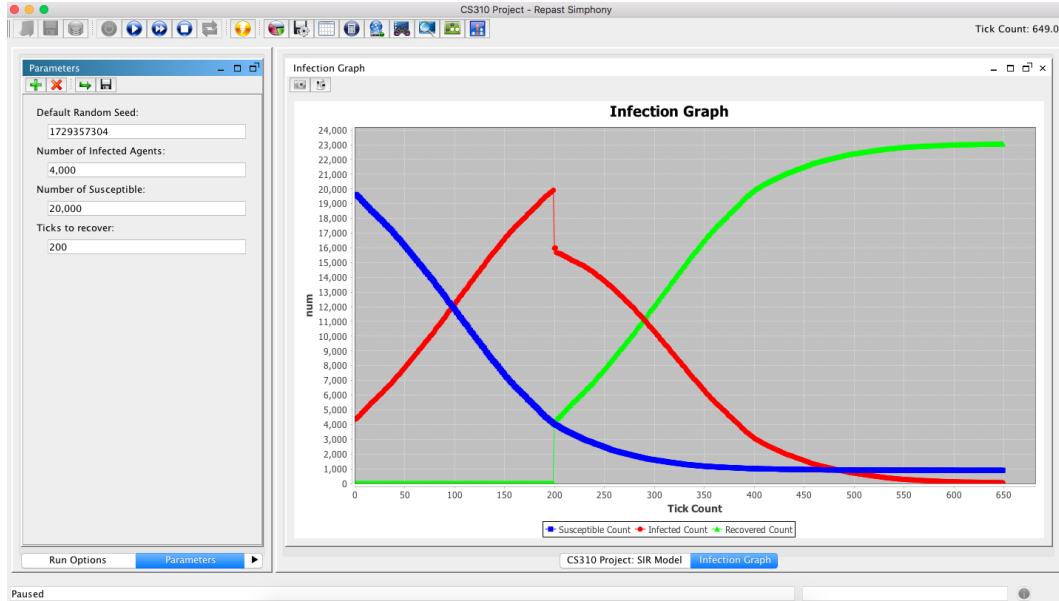


Figure 5.4: Infection graph showing a sudden drop off when 4000 agents start off infected

model with a large initial infection number then the issues will occur again. A second and better approach is to add randomness to the recovery time. To do this a random distribution can be used however it has limitations as it will evenly distribute the recovery time between the range given, Which is unrealistic as it will be distributed around the meantime to recover. Normally in social sciences, natural occurrences fall

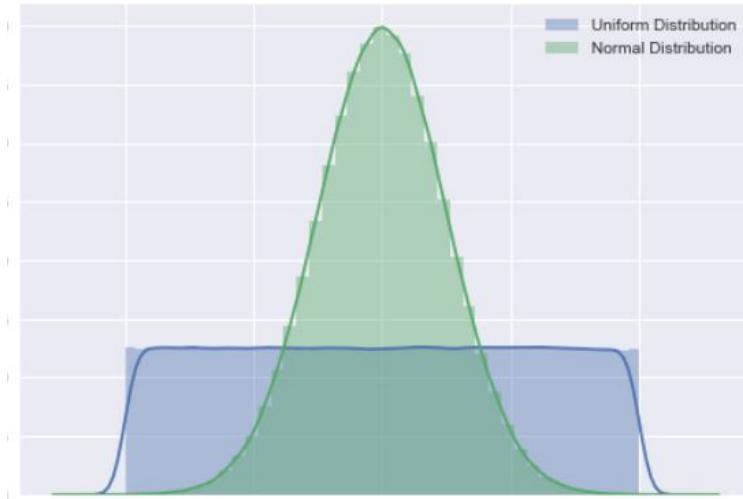


Figure 5.5: Normal Distribution vs Uniform Distribution [33]

on a Normal Distribution. Figure 5.5 show the two distributions. Using the Normal distribution we can estimate the infectious period of the infected agents. The normal distribution is of great importance because it is an excellent approximation for the

probability distribution of many random variables that arise in nature causing it to be widely used in social sciences [34]. To use Normal Distribution the mean and the standard deviation is required. For asymptomatic cases, recovery time is estimated to have a mean of 9.5 days[35]. The resulting implementation of variable recovery is shown in figure 5.6.

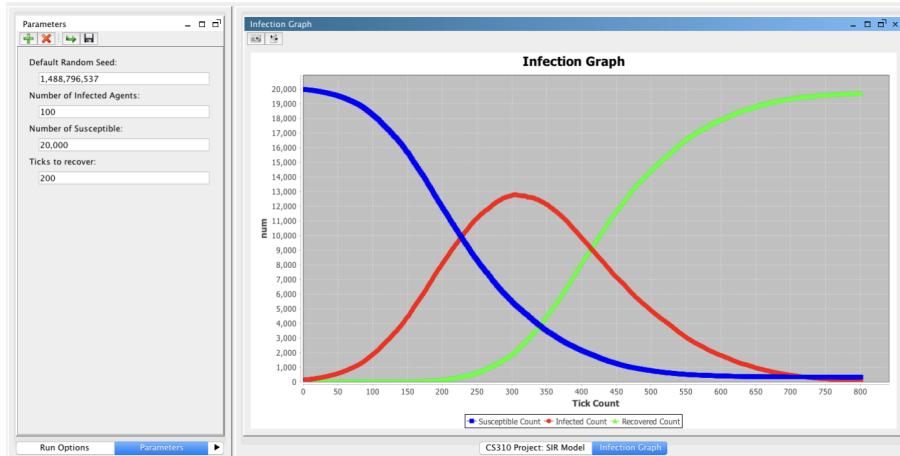


Figure 5.6: Recovery with Normal Distribution

5.1.6 Evaluation

All the planned features for the SIR model have been implemented correctly. There are susceptible, infected and recovered agents that can interact with each other in the environment. There is graphing output that shows the number of current cases at each tick of the simulation. The space has also been visualised. Figure 5.7 shows the infection spreading through the population then areas slowly recovering from the disease. There are 20,000 agents being visualised.

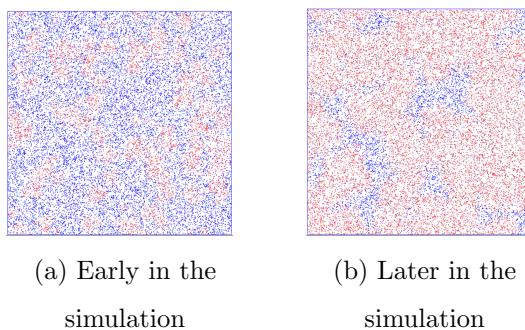


Figure 5.7: Spread Visualisation of the SIR model.

Blue - Susceptible, Red - Infected, Purple - Vaccinated, Green - Recovered

Discussions with the supervisor lead to the potential of implementing the SIDARTHE model [23] shown in figure 5.8. The SIDARTHE model is a complex mathematical model for COVID-19 that has many more agent state than the projects. The model has a focus on symptoms and diagnosing COVID-19. Along with the symptoms it models for worsened state and the extinction of agents. Features of the SIDARTHE model were implemented adding large amounts of complexity to the model and potential for many different features. The different infected class was split into infected, diagnosed, ailing and recognized states. It adds more features to the project however there wasn't much more added complexity as the classes were not very different and acted mostly in the same way. In addition, the model relies on testing whereas the aim of the project is to focus more on vaccinations. Ideally, both would be implemented however the project is limited by time. The model does provide helpful insights into implementing extinctions, symptoms and the worsening of symptoms. The desired implementation is shown in figure 5.9. On top of these adaptations to the model vaccinations will also be added. Implementing vaccinations on top of this will work as the vaccinations are another state that affects how the others work but do not change them.

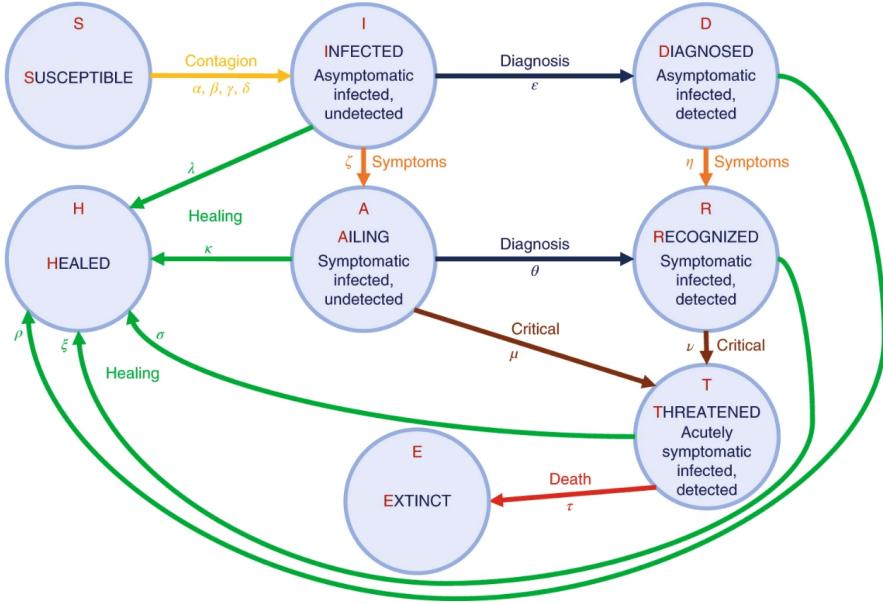


Figure 5.8: SIDARTHE Model [23]

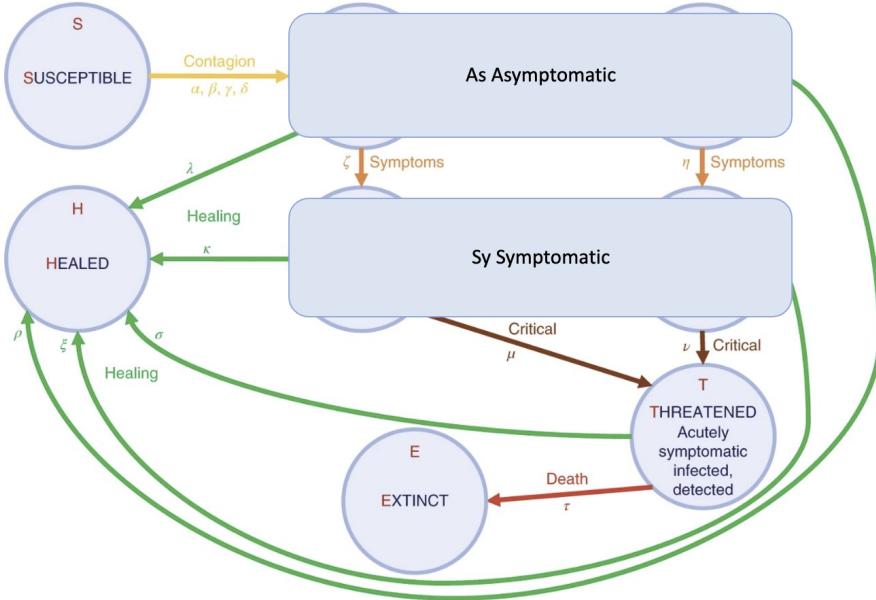


Figure 5.9: SIDARTHE Model Modified

5.2 Vaccinations

Vaccinations are a very current event. As many countries roll out their vaccinations to the general public there have been lots of different strategies. The vaccination of a population is a complex task that has many constraints such as cost and facilities. Countries have also ordered different amounts of these vaccines in most cases not having enough vaccinations for the whole population. To administer the vaccines, it takes a long time to roll out and requires skilled individuals to administer the vaccines. Many countries are prioritising vulnerable members of the population vaccinating them first [36].

Based on the research, to implement vaccinations the vaccines would need effectiveness, a rate at which they are administered and the max amount of vaccine there are for the population. A vaccination class was created that on scheduled intervals it will vaccinate a certain number in the population. Over time this will vaccinate susceptible members of the populations unless there are no more susceptible agents or if there are no longer any vaccinations left for the population. There is also a new class for vaccinated agents that inherits from the agent superclass. Figure 5.10 shows the latest class diagram in the model.

Figure 5.11 what happens when every tick 10 members are vaccinated so about 0.055% of the population per tick assuming that 8 tick corresponds to a day then that is about

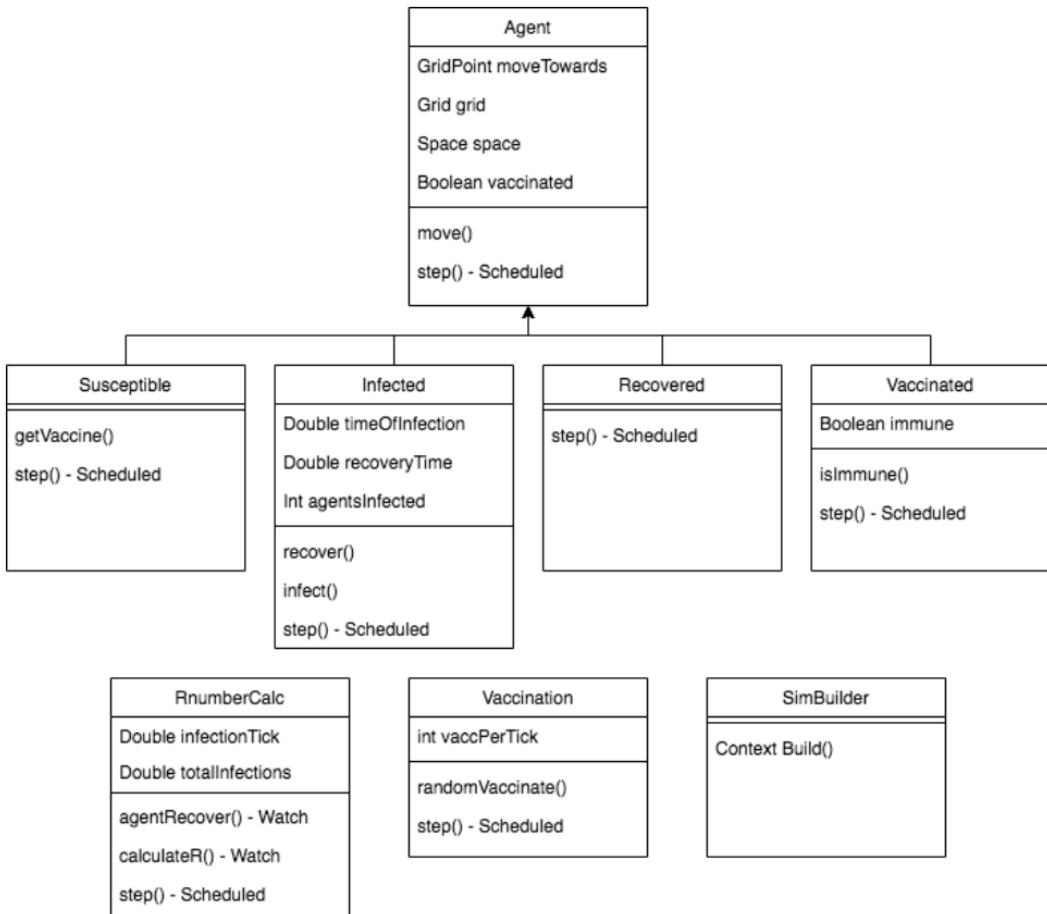


Figure 5.10: Class Diagram after Vaccinations have been implemented

1.25% of the population daily is getting vaccinated in this simulation. The simulation stops vaccinating individuals as everyone in the population is vaccinated or recovered from the disease. This number in the real world is different all around the globe with different countries vaccinating at different rates by the user can input different amounts for the simulation.

A more accurate implementation is to add targeted vaccinations. Where those who are at risk are vaccinated first providing immunity to those in more danger also those who are more likely to spread the virus [37]. The Current implementation is already targeted in that it doesn't vaccinate those who have already been infected but there is room for improvement. The second implementation checks if susceptible agents are at risk and will prioritise them first. Randomly selecting a group of agents from the context and vaccinating those at risk then if there are any vaccines leftover normal susceptible agents will be vaccinated. The implementation will not vaccinate all the vulnerable first as there is some randomness in the group it selects. In the group, it

selects there may only be a small amount of vulnerable. This adds a limiting factor that occurs in the real world where not all vulnerable members can be vaccinated straight away where there is limits in the vaccination process [38].

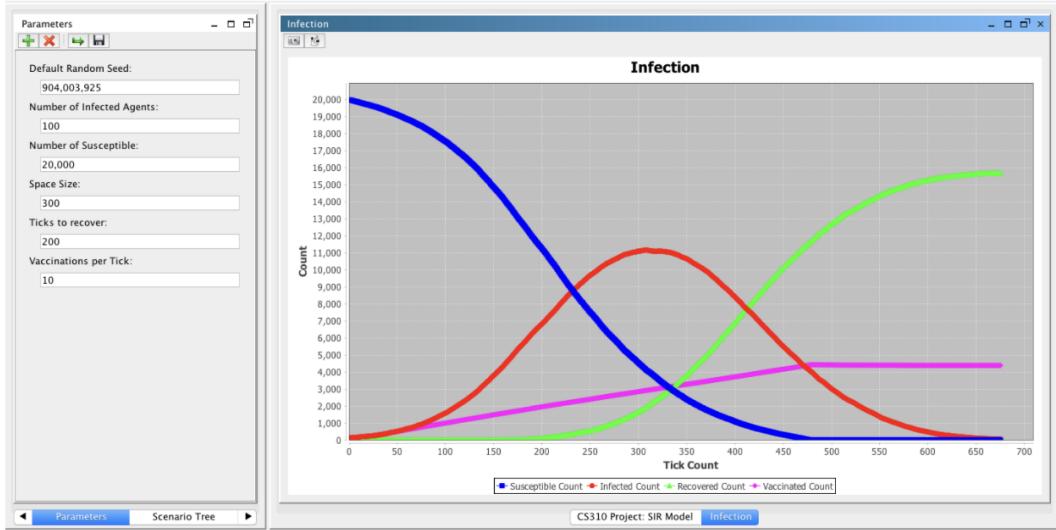


Figure 5.11: Simulation including vaccinations when there are no more susceptible agents

5.3 Symptoms and Extinctions

To implement extinctions two other features must first be implemented. First, the agents must be able to show symptoms and second, they must have vulnerability's that make them more at risk to COVID-19. Research has shown that some members of the population are more at risk of COVID-19 symptoms worsening and resulting in death [39]. Different populations will have varying amounts of at-risk individuals [40] affecting how much a population has the potential to be affected by COVID-19 related deaths. Individuals whose symptoms worsen and result in deaths has a mean of 14 days from symptom onset to death [41].

To implement this the agents would need to be able to develop symptoms and based on whether they are vulnerable they extinctions should occur. Rather than creating new classes for symptomatic and threatened agents, technically they are infected agents and come under the infected count. With the graphing and recording of infected agents, it makes no difference if they are symptomatic or their situation has worsened they should still be considered. Additional data sinks can be added to record the number of symptomatic and threatened if it is needed.

Firstly a new Boolean attribute was added to susceptible agents called vulnerable. This stores whether the agent is at an increased risk to COVID-19. When the context is initialized a certain number of selected agents will randomly be set to vulnerable. Being vulnerable guarantees the agent will become symptomatic the agent will develop symptoms around 1/3 of their infectious period. Simple randomness has been added to the onset of symptoms so for each agent it will be slightly different. If the agent is vulnerable they are also prone to then have their symptoms worsen after. When an agent's symptoms worsen if they are also vulnerable after a certain number of ticks the agent will become extinct. Not all cases in the real life that worsen result in deaths, however for the model the death number will be more of a measure of worst-case potential. Assuming that the country is ill-equipped to deal with any case worsening. Additionally, many people who are not at risk still display symptoms for COVID-19. To add this to the model when an agent is initially infected some will randomly display symptoms as if they were vulnerable agent would however, their symptoms will be unable to worsen. Figure 5.12 show the flow chart an agent will take to become extinct.

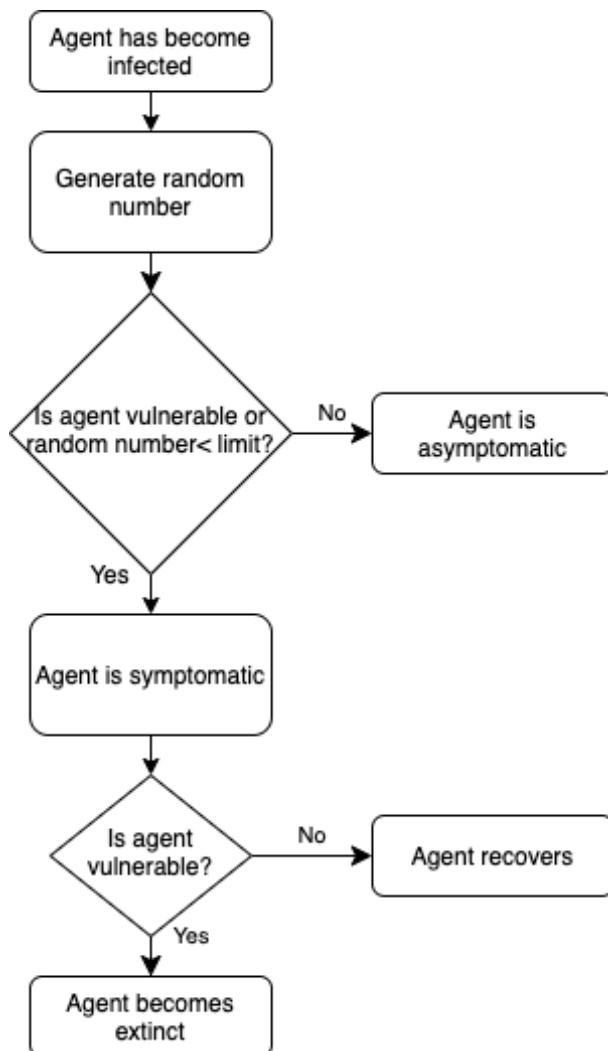


Figure 5.12: Flow chart showing the stages of infection to extinction

5.4 Hospitals

COVID-19 has put enormous amounts of strain on countries healthcare systems [8]. The ability for hospitals to cope with the disease and treat the general population is in part affected by the availability of hospital beds [42]. In some cases when the ICU is full the mortality risk increase by 20%, in most cases, the health care systems did not become full during the initial spread of the virus Wilde argues that even an increase in hospitalisations increases the mortality rate [43]. Different countries all have different healthcare systems with different amounts of spending, they also have different amounts of hospital beds. Different areas across different countries will also have different healthcare facilities with different amount of beds. There will be numerous healthcare resources that are likely to affect COVID-19 mortality including hospital resources and personnel. However only ICU beds were used as there is not a significant link between hospital beds in general [44]. Therefore the beds discussed in this section resemble ICU beds.

Currently, in the model all agents who become threatened become extinct. To adapt this all agents whose symptoms worsen will then require a bed in a hospital. There will a limited number of beds and agents will stay in bed until they have recovered if an agent is occupying a hospital bed then it is assumed they will recover from COVID-19. A new class for hospitals was created and a class for hospital beds was made. The OccupiedBed class is a template for a singular hospital bed, simply storing the agent currently in the bed. The Hospital class stores all the agents in the beds, the max bed count. It also sorts out agents on a first come first serve waiting list, when space frees up the agents are then placed in a free bed. The OccupiedBed class is needed to allow for REPAST to graph the number of beds occupied as REPAST graphing tools can only count the number of instances of a class that exist in the context. The instances of hospital and beds do not have a location and agents who are placed in hospitals remain on the space as even in hospitals the chance of infection is still possible[45].

There was an issue as there was a set recovery time for when the agents were administered to a hospital which was the same for each agent. This meant that there was a constant cycle of agents being taken into hospital then recovery, when the hospital became full other agents would almost reach the time of extinction. However, the

recovery time of the agents in a hospital would be before that of the waiting agent so as soon as one recovered in the hospital the waiting agent would enter a hospital for one day then recover straight after. To solve this, like with the other infection times more randomness was added to the hospital recovery time which is also more realistic. This result in the bed being occupied for different amounts of time and agents in the waiting list being unable to enter the hospital resulting in deaths.

There are issues with the assumption that anyone administered into hospital will recover from COVID-19 as it has been found that around 30% of COVID-19 hospital admission result in death[46]. To accommodate this agents who are in hospital still have a chance of becoming extinct. The stages an agent can take are displayed in 5.13

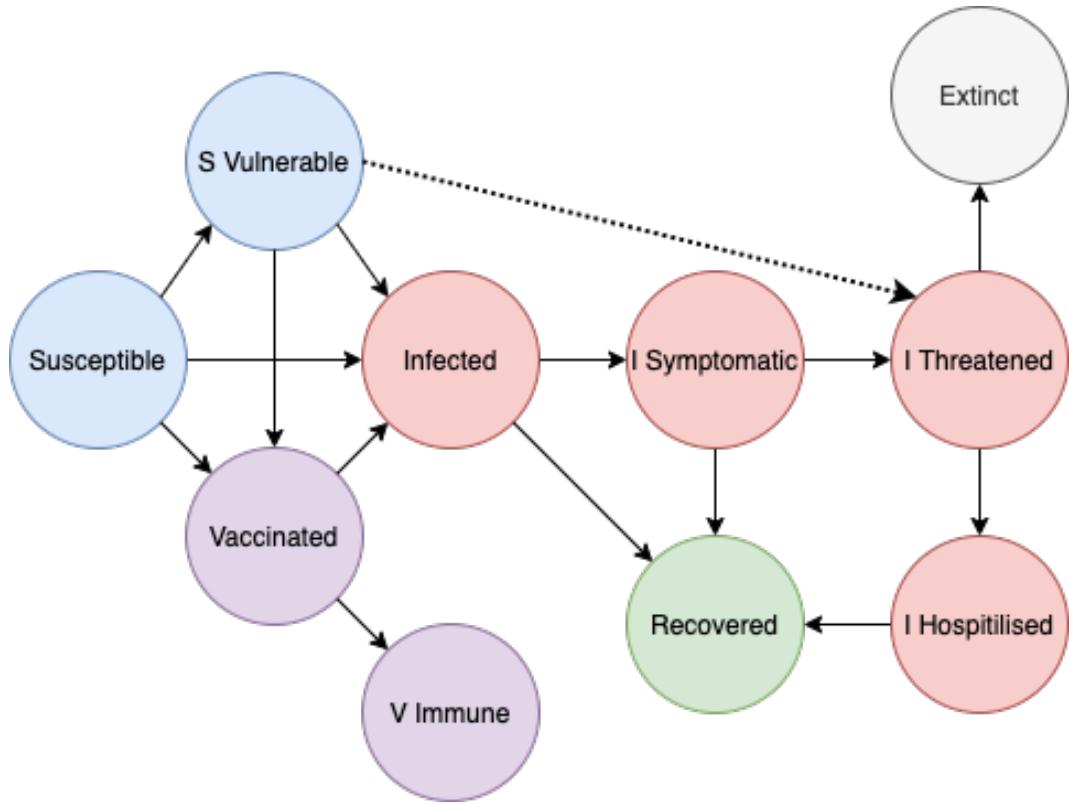


Figure 5.13: All the possible agents state and how the agent can move from one to another

5.5 Social Distancing Measures

To combat the spread of COVID-19 and deaths caused by COVID-19 governments have introduced isolating, social distancing measures and testing. These measures if done correctly can decrease the spread or delay the epidemic[47]. There are numerous measures that have been implemented around the globe and to different degrees. Not only are countries faced with the challenge of implementing successful restrictions that in the least way limit the populations lives they are tasked with easing the restrictions at the correct time. To correctly implement this there are different scenarios that will have to be programmed specifically. There are a number of factors that determine whether social such as R number, cases and health care capacity.

There are many ways in which interactions can be reduced during the running of the simulation. The agent's speeds and range of distances they travel can be altered. Reducing the speed will mean the agents cover less distance in the same amount of ticks reducing their chances of interacting with infected agents. The interactions in an infectious period for an agent will go down, therefore, reducing the number of agents it will spread the disease too. Reducing the range of distances the agents travel before changing direction means the agents have less probability of travelling further in the space. Another method is changing the movement for different types of agents. Making those who are infected slower will reduce their interactions with susceptible agents resembling real-life isolation measure. As these interactions are the most important.

When agents become infected their speed in the simulation remains the same. As there is no testing in the model in theory they should have no way of knowing they are infected and therefore will carry on with their normal programming. However, if an agent displays symptoms their speed is significantly reduced reducing the number of interaction they will have in the space. Additionally, when the agent's symptoms worsen or they have been admitted to the hospital their speed drops again. The model assumes everyone who develops symptoms is aware they have and then isolates reducing their interactions with other agents. The agents are not removed from the space to remove all interactions as in the UK despite having to isolate if displaying symptoms studies have shown many people do not follow the isolation guidelines[48].

The first social distancing measures were introduced based on the current R number

of the simulation. With the simulation checking the R number every so often checking if it meets a threshold then introducing different measures. The measures slow the agents down to a slower speed.

To really measure the infection rate during a simulation at different points scientist calculate the R number. R number is known as the basic reproduction number referred to as R_0 , this describes the average number of each infected person will infect. R_e describes the number of people that will be infected at any specific time[49]. R_e is what we will calculate to get a live record of infectiousness in the simulation. A new class has been created to calculate R_e . The interval that the R calculator runs can be changed by calculating the R_e number for that interval including the total number of infections that have occurred in that interval. The R number calculator does not provide much use on its own however used alongside slowing down the agents at certain points it proves very useful.

A developed scenario is shown in figure 5.14. Shows a scenario where the R_e number is checked every 60 ticks and if it is greater than 0.6 social distancing rules are implemented reducing the speed of all the agents in the population. If however at the next interval the R_e number drops below 0.6 it returns back to normal. You can see the movement of the graph as it reaches the intervals sharply changing as new rules are introduced but then as cases fall the rules are lifted and cause the virus to spread again. To change the interval it is hard coded in the step function as it does not allow variable to be in place of the step increment.

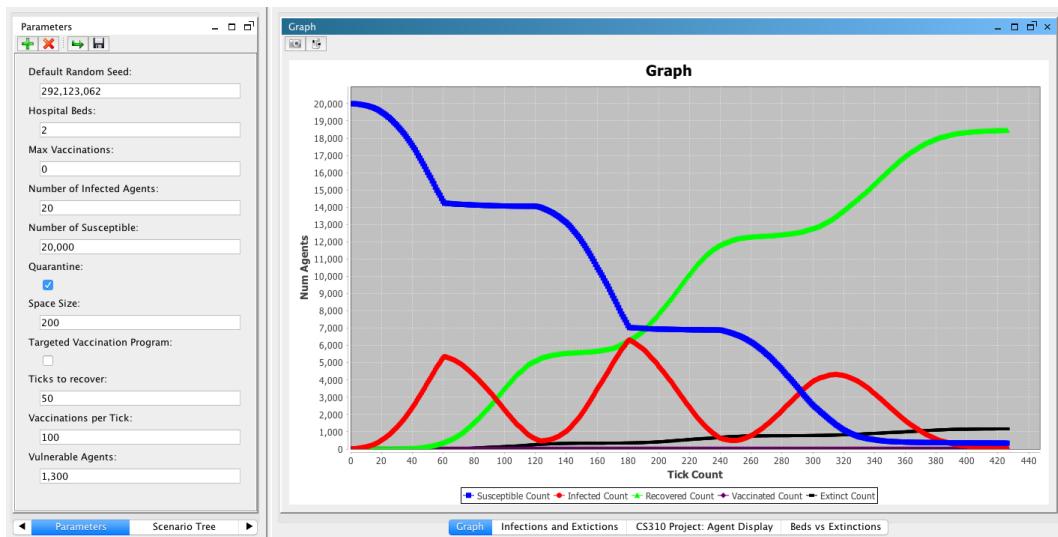


Figure 5.14: Simulating social distancing rules at different intervals.

6 Results

The aim of the results is to recreate real-world scenarios and support the current policies that have been put in place. The result will aim to also find areas that have not been touched on as much and provide more insight. The full power of the model will be showcased showing its potential for further results if developed further. To generate results from the model different parts of the model will be used to show its effect to on the results and what we can learn from this in the real world will be discussed.

6.1 Generating Different Scenarios

To show the power of the model different situation that occur in real life have been modelled. To show the different situations only the SIR features have been included. The results including the other features and their effect will be discussed after. An interesting idea that can be explored with the model is the outbreak threshold for a given environment. The outbreak threshold is defined as the number of infected individuals to ensure an outbreak is unlikely to go extinct [50].

6.1.1 Scenario 1: Single Sharp Peak

This scenario occurs in a dense population that implements no restrictions and life carries on as normal despite the virus spreading. This scenario does not occur very often however it is useful to model for the worst case. The simulation shown in figure 6.1 starts off with 0.1% of the population infected with 20 infected agents and 20,000 susceptible. The active cases shown in red follows a bell curve rising up infected most of the population then as there are fewer agents to infected and more agents start recovering the active cases drops naturally. This simulation uses a recovery time of 50 ticks using an estimate of the mean recovery time to be 9.5 days the whole virus spreads throughout the population in about 200 ticks, corresponding to about 38 days in real-time before everyone is recovered. With a peak of 7.2% agents being infected in one day, this is an extremely large amount of the population that has not really been seen in the real world. A contributing factor is the simulation records all cases not just positive test result to COVID-19 test so it gives the true number with

estimates this could be up to 57% in the UK of COVID-19 cases going undetected [51].

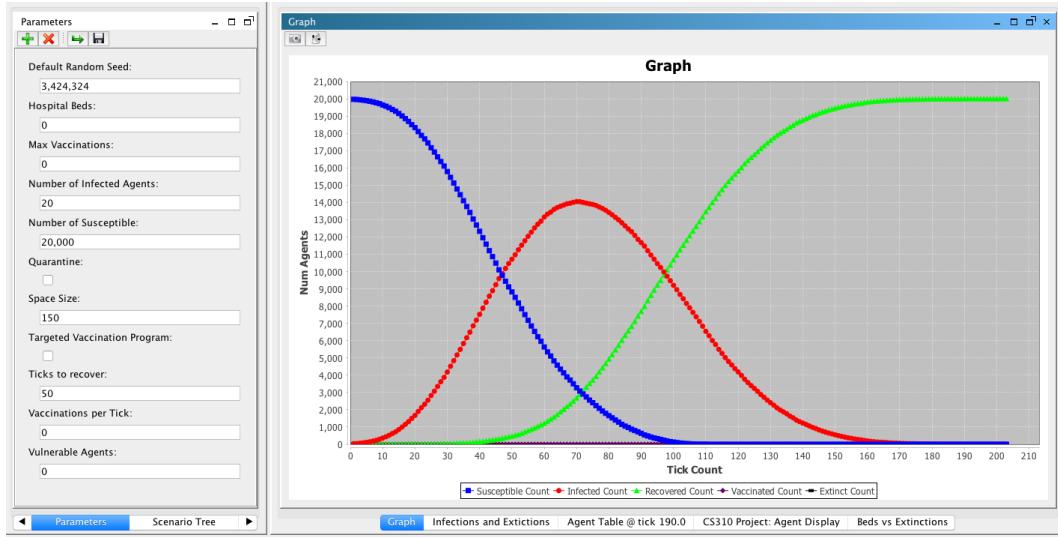


Figure 6.1: Simulating COVID-19 quickly spreading through a population

As shown in figure 6.2, given the scenario where we change the start number of infected agents to 1 the virus still breaks out and infects all the population. Meaning any number of infected agents in this environment meets the outbreak threshold. Despite the number of infected agents starting a lot lower the virus only takes roughly 1.9 times as long to spread through the whole population.

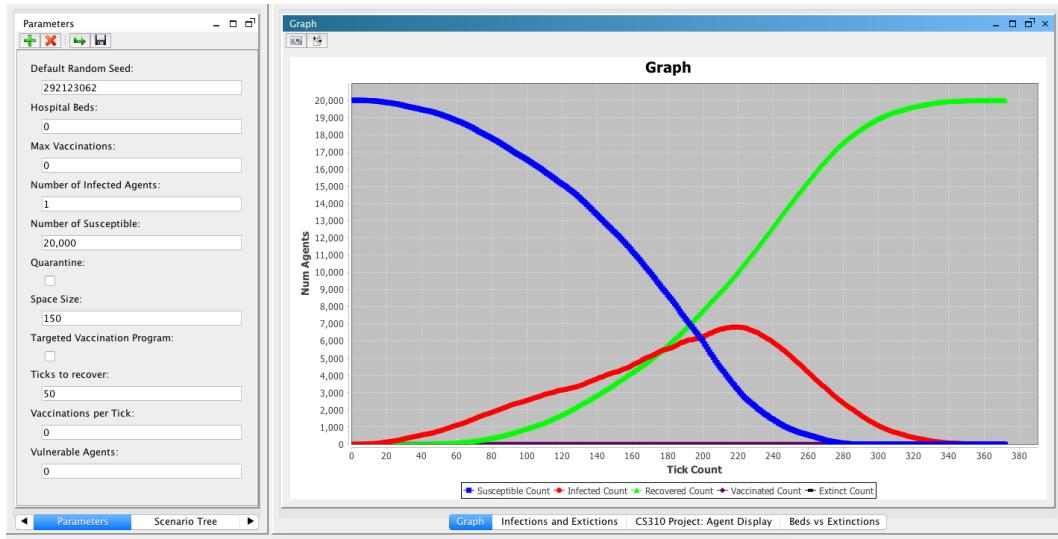


Figure 6.2: Steep infection rate starting with only one infected agent

6.1.2 Scenario 2: Medium Peak

In figure 6.3 the simulation runs in a slightly larger area and the effects can be seen below. The aim is to show how the simulation can be adjusted slightly and generate different outputs that may relate to different real-world populations. During this simulation, it takes longer for the peak to be reached and lasting about 50 days for all the cases to eventually recover. Similar to the previous simulation when this scenario starts with one infected agent it still causes an outbreak in figure 6.4.

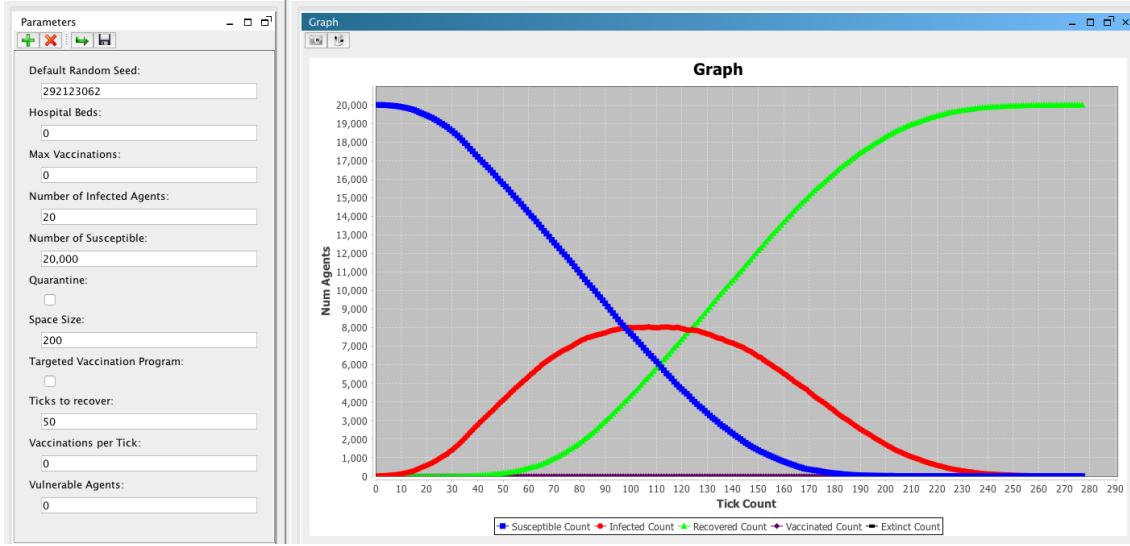


Figure 6.3: Simulating COVID-19 spreading through a population at a medium speed

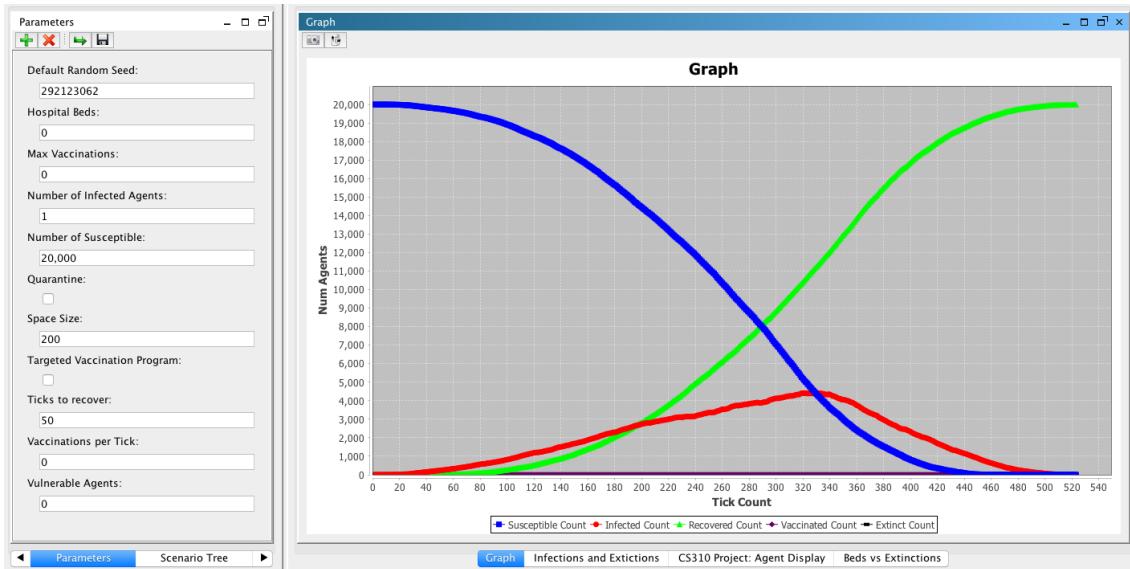


Figure 6.4: Simulating COVID-19 spreading through a population at a medium speed starting with one case

6.1.3 Scenario 3: Shallow Peak

A more realistic simulation is one that spreads through the population over a longer period of time. The simulation below simulates the spread over multiple months. Figure 6.5 shows the simulation lasts about 160 days which is around 5 months.

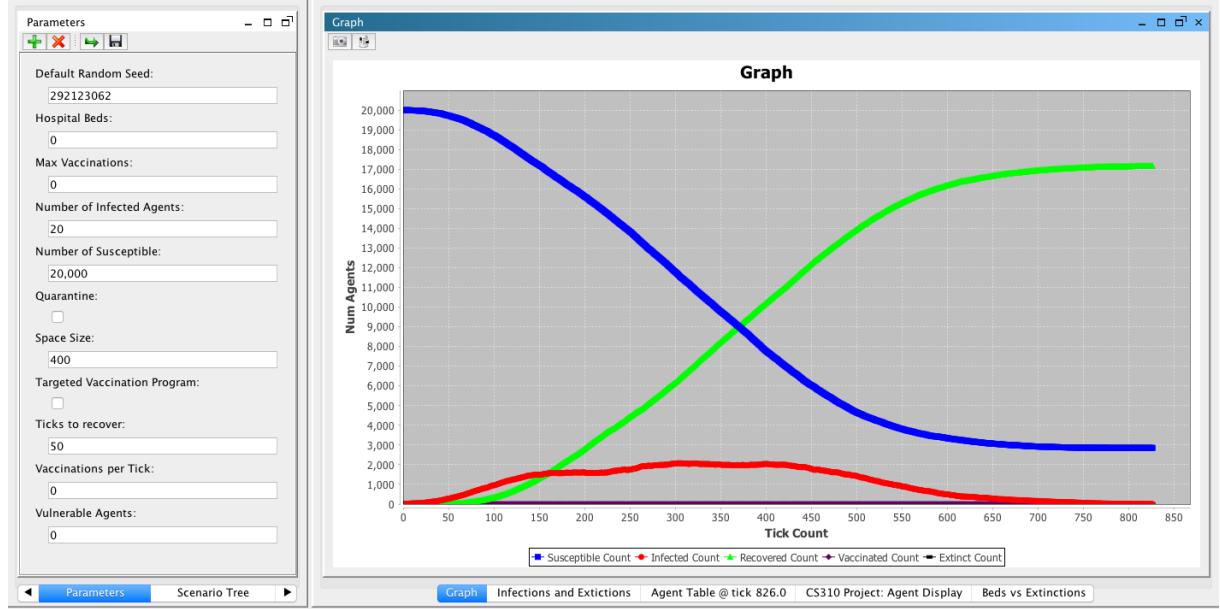


Figure 6.5: Simulating COVID-19 spreading through a population at a medium speed

The virus does not spread to all the population as 2850(14.25%) agents remained susceptible. Showing the more interactions between agents the increase in speed the virus will spread through the population and the greater probability more of the infection become infected. The graph is not smooth as the random placement of the agents will mean that different parts of the space will be more densely populated at different times result in some tick producing more infections than others. You can see from the daily cases that the at its peak there are about 1% of the population being infected every day

Using this scenario but starting off with one case over the course of about a year 85% of the population become infected and then the virus dies out. In most scenarios, the outbreak threshold is any amount of cases. For the virus to die out before everyone is infected shows that some of the infected agents do not pass the virus to any others in the space. Very rarely it is possible for the start agent to not interact with any agents and not cause an outbreak however this has not been found to happen in any of the simulations.

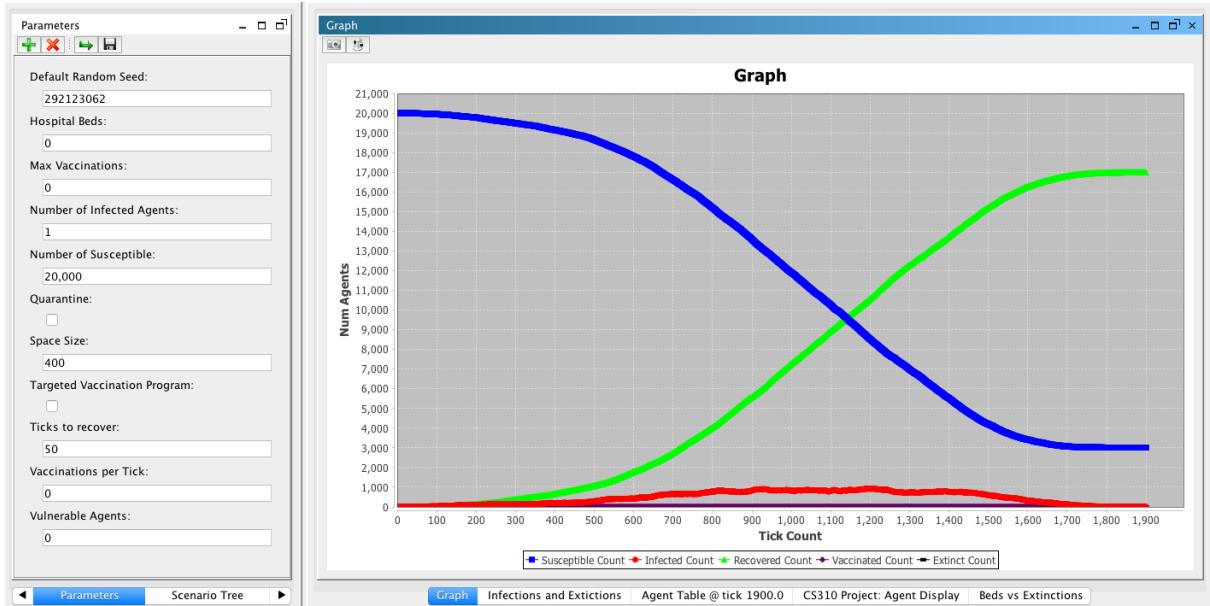


Figure 6.6: Same scenario but starting off with one case

6.2 Visualising Spread

The benefits of using REPAST is its visualisation of infections in the programmed space. It allows for an automatic visual representation of the space as it moves through each tick. With the other data produced by the model, it is very useful however it requires more knowledge of the topic to understand and it does not show how the model works behind the scenes. Visualising the agents in the space allows for better education for a non-specialist, it makes the data easier to understand and conclusions the model makes are easier to comprehend as visual feedback of the effects can be seen. Cause and effect can be spotted in the data produced especially where small changes in the environment cause large changes to the result [52]. However, to gain an understanding of why this happens, looking at the space at each tick is essential as it allows the user to see at what stage the changes occur and what are the particular causes of the changes are.

The visualisation of the space allows for the different agent interacts and their effect on the spread of COVID-19 to be viewed as they are happening. Whether it's simple and infected agents interacting with a susceptible agent and spreading the virus, or large amounts of infected agents recovering at a similar time completely halting the spread of the virus. Often in the real world, the spread of COVID-19 is hard to comprehend on large populations. When we talk about COVID-19 it is looked at on a global or

national level with population sizes in the millions, however, research has shown that humans are not great at understanding the repercussion on large scales [53]. Doing simulations with larger numbers allows for the effects to be understood better as it can be seen.

When developing the model it is often hard to test if the agents are performing in the desired way as getting the correct output does not ensure the agents are interacting correctly. Using the visualisation tool small scale simulations have been run during development to see the actual behaviour of the individual agents, ensuring the model is working as designed. This also holds true for future development, when new features are added to the model the visualisation tool will be essential in ensuring it is correct.

Figure 6.7 shows a simulation with a population of 20,000 agents, the size of a small UK town. It is difficult to understand how COVID-19 might spread through a town over time but the model shows how each individual becomes infected over time and eventually the whole population become infected.

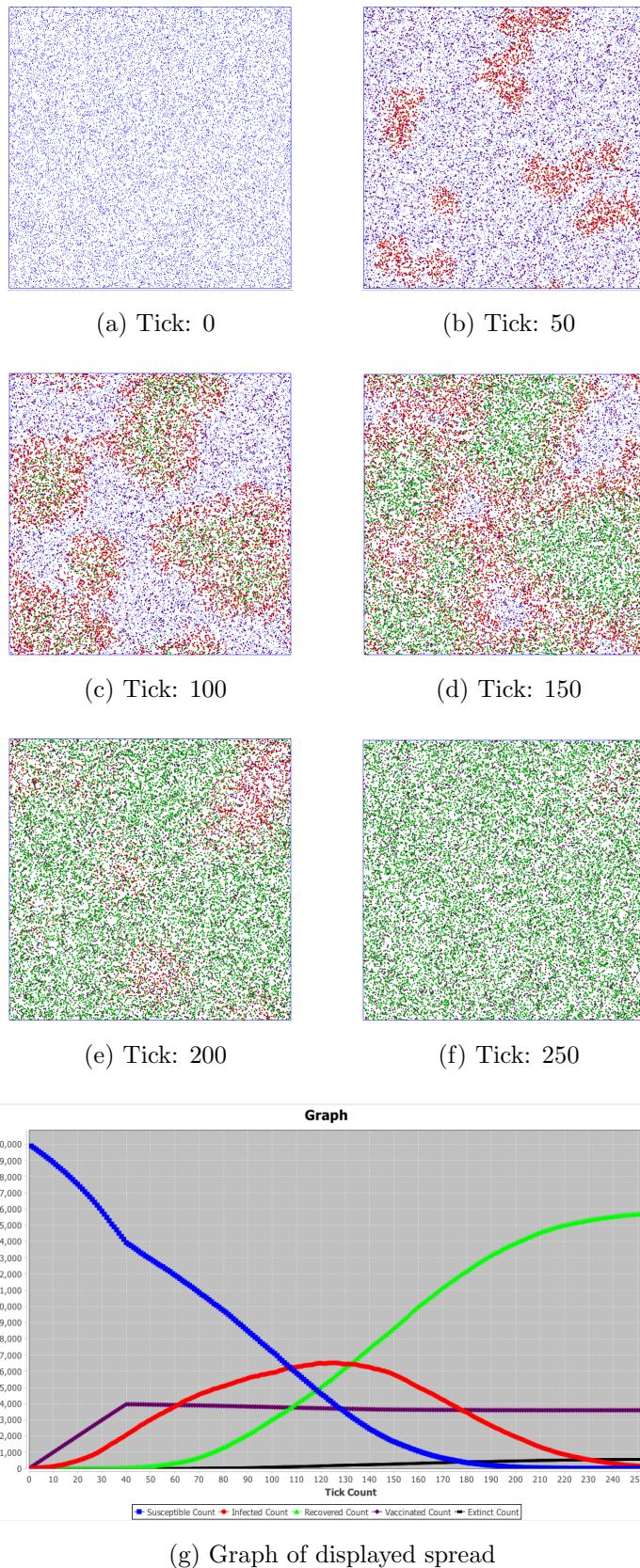


Figure 6.7: Visualisation of spread with graph.

Blue - Susceptible, Red - Infected, Purple - Vaccinated, Green - Recovered

6.3 Health Care

Three different scenarios have been created that simulate different speeds of spread in a population. It is useful to see how the different scenarios affect the spread of COVID-19.

Estimates suggest that 6.5% of Europe are at high risk to COVID-19 [40]. So using the same population numbers as the other simulations 20,000 around 1,300 agents in the simulation would be at high risk to COVID-19 assuming we are using the Europe at risk rate. Another feature is the number of hospital beds. An estimate put the UK ICU beds at around 7.3/100,000 inhabitants which is very low compared to the rest of Europe. Whereas Germany has 38.7/100000 ICU beds per inhabitants [54].

Using these numbers giving around 1.4 ICU beds per 20,000 inhabitants rounded up to 2 for the UK and 7.6 ICU beds per 20,000 for Germany rounded up to 8 we can see the effect of health care and ICU beds. For both simulations, we assumed the same number of vulnerable agents.

The result for the UK simulation is 1248 extinct agents at the end of the simulation. All 20,000 agents became infected so the final mortality rate is 6.24% (Figure 6.8). The result for the Germany based simulation is 1129 extinct agents with the whole population becoming infected (Figure 6.9). This gives a mortality rate of 5.645%. Giving a 0.595% increase in the estimated mortality rate in Germany than the UK. Both of these estimates are higher than the estimated mortality rate seen in real life but this is because the model used assumes all the population become infected within a short period of time. We can still see the relationship between ICU beds and mortality where the more ICU beds available the lower the mortality rate. This has been seen in the real world where governments have been increasing ICU beds to compensate for the virus [55].

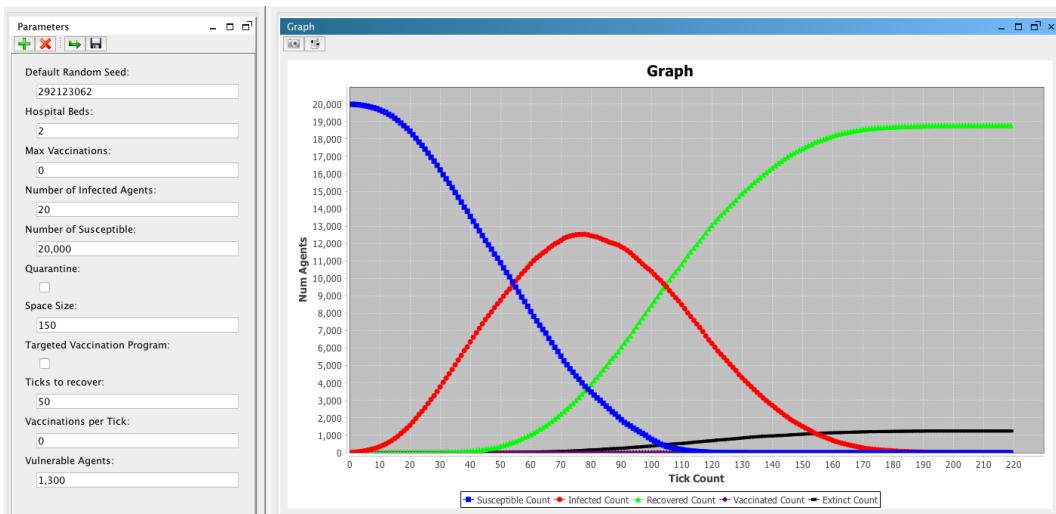


Figure 6.8: Simulation based of the UK using 1,300 vulnerable individuals and 2 ICU beds

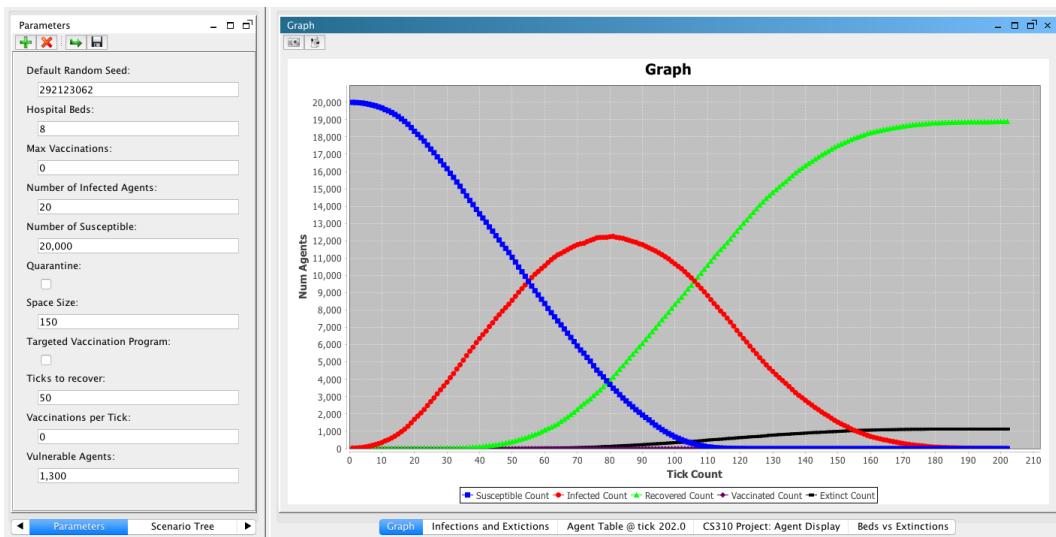


Figure 6.9: Simulation based of Germany using 1,300 vulnerable individuals and 8 ICU beds

Running similar simulations but using the scenario where the virus takes a longer time to spread through the population. For simulations based on the UK, figure 6.10 shows the result was 16825 infected individuals throughout the simulation and 906 extinct agents. Giving a 5.4% mortality rate a 0.84% decrease from the same ICU beds on a sharper curve. Basing the simulation of Germany, figure 6.11 The result was 17026 infected individuals and 541 extinct agents. Giving a 3.2% mortality rate 2.445% lower than the same ICU bed number than the sharp curve and 2.2% lower than the same scenario but using UK ICU bed numbers. In the real world, Germany's mortality rate is 2.44% whereas in the UK the mortality rate is 2.89%. The simulations support Germany having a lower mortality rate based on the ICU beds. However, Germany's and the UK's approach to the virus has been completely different. Both implementing different lockdowns at different times in the spread of the virus. There are so many factors that affect the mortality rate which makes it difficult to see the effect of one feature from one country to another. Regardless, the model's results do suggest the greater number of ICU beds and the longer the virus takes to spread through the population the better the lower mortality rate. As the hospitals as there is less demand for medical attention. Supporting the need for a greater number of ICU beds per individuals in the population and greater need for spending on the health care sector.

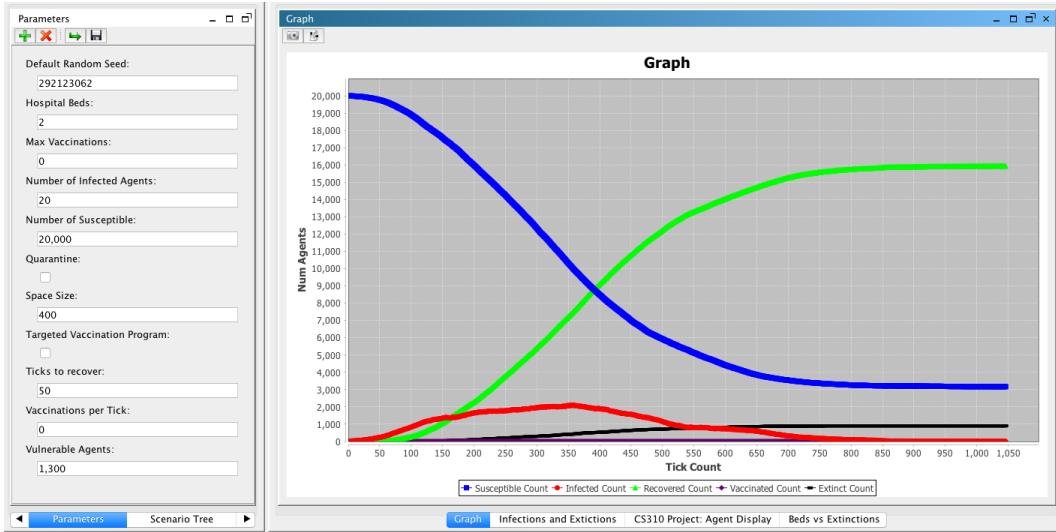


Figure 6.10: Simulation based of UK using 1,300 vulnerable individuals and 2 ICU beds over a longer period of time

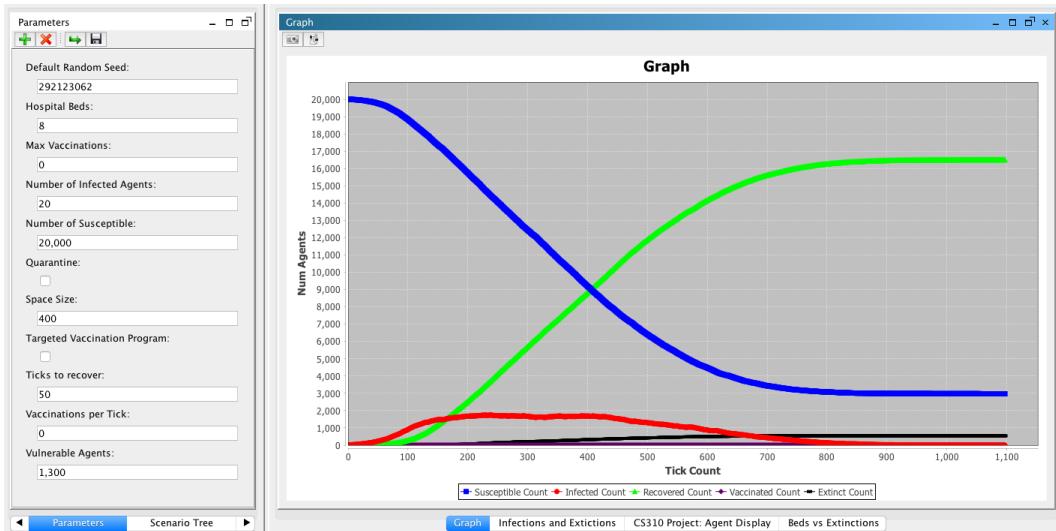


Figure 6.11: Simulation based of Germany using 1,300 vulnerable individuals and 8 ICU beds over a longer period of time

6.4 Vaccination Programs

As discussed before vaccinations have the potential to grant individuals in a population with immunity. When large numbers of a population have immunity against a disease gained from a previous infection or vaccination indirect protections can occur called 'Herd Immunity' [56]. Different diseases have different thresholds for herd immunity. Using the model we can see the effect of the vaccinations on the spread and the threshold for herd immunity. We can find the effect of different vaccination amounts in different ways. Agents can start off vaccinated or we can see the effect of gradual vaccinations. On the Sharp peak simulation where cases quickly spike it is interesting. It is assumed in the simulations below that the immunity level from the vaccinations was 90% chance of immunity.

6.4.1 Randomised Vaccinations

In this section all the vaccinations performed will be performed on random susceptible agents in the population not taking into account their vulnerability. This is not seen in real life however it will allow the benefits of targeted vaccinations to be shown. Using scenario 3 and the estimated UK ICU beds multiple simulations were run to find the effect of different amounts of the population being vaccinated before the virus spreads. To do this the simulation was run multiple times at different vaccination increments. From 0% to 100% in steps of 10% with three repetitions on each increment each with a different random seed. Figure 6.12 shows an example of a simulation with 25% of the populations the spread of the infections can be seen along with an increase of extinctions.

Firstly across the increments the total number of agents infected was recorded. As seen in figure 6.15 the values have been averaged across the three runs giving an estimate for the different vaccination percentages. Figure 6.16 visualises the numbers. What you can see is the change between intervals is not linear for example between 20% to 30% the average drops by 18% however the drop between 30% to 40% is 51%. This non-linear relationship between the number of vaccinated individuals and total infections showing that in vaccination effects against COVID-19 that certain thresholds must be met to fully start gaining the benefits from herd immunity. Counties may be able to vaccinate a further 10% of the population and have even greater ben-

efits than the other 10% increments. On the tail end it also shows that at a certain point there are diminishing returns as the majority of the population is vaccinated herd immunity plays a part in significantly reducing the spread. Scientist estimate that around 60%-70% of the population must be immune to achieve herd immunity [57] which is close to the data produced where at 70% the spread is very limited.

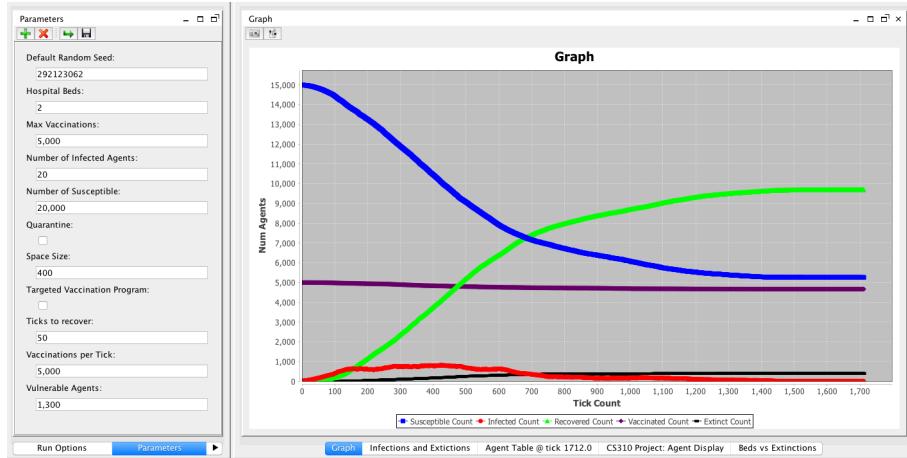


Figure 6.12: Example simulation ran with 25% of the population vaccinated

Percent Vaccinated (%)	Total infections simulation 1	Total infections simulation 2	Total infections simulation 3	Average
0	16139	15815	16270	16074.67
10	14087	14005	13822	13971.33
20	11604	11550	11367	11507
30	7977	8170	8235	8127.33
40	2956	3655	5397	4002.67
50	2316	2000	1450	1922
60	642	759	641	680.67
70	139	163	183	161.67
80	69	83	116	89.33
90	54	72	33	53
100	38	32	32	34

Figure 6.13: Table showing total cases generated from the simulations

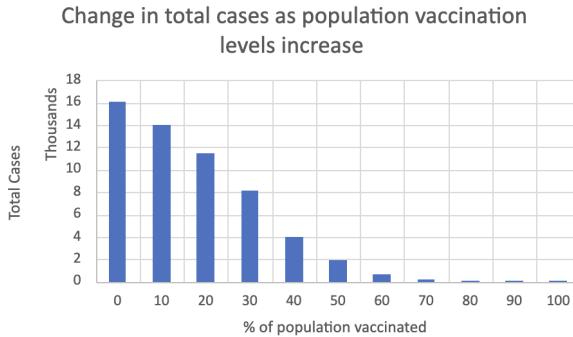


Figure 6.14: Graph showing total cases generated from the simulations at different vaccination percentages

The next data generated is the deaths at different vaccination levels. The data was retrieved in the same way as the total cases. The trends of the deaths follow a similar pattern as the cases where there is a big decrease in numbers from 30% to 40% before having little effect after 70%. If a country is purely trying to minimise deaths from COVID-19 whilst having limited resources to spend on vaccinations it may not be needed to vaccinate the population past a certain point as shown in 6.16.

Percent Vaccinated (%)	Total extinctions simulation 1	Total extinctions simulation 2	Total extinctions simulation 3	Average
0	940	939	883	920.67
10	781	784	722	762.33
20	549	589	550	562.67
30	346	307	316	323
40	43	102	213	119.33
50	61	44	23	42.67
60	15	10	9	11.33
70	0	1	1	0.67
80	0	0	0	0
90	0	0	0	0
100	0	0	0	0

Figure 6.15: Graph showing total cases generated from the simulations at different vaccination percentages

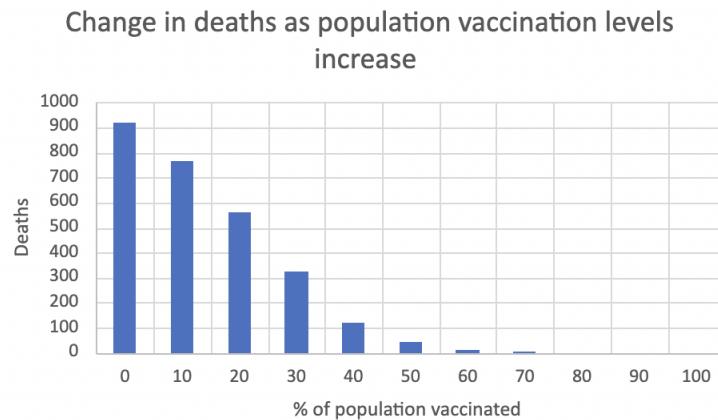


Figure 6.16: Table showing total cases generated from the simulations

A more useful measure that combines these two factors is mortality rate which is equal to extinctions/cases, which will give a percentage that shows the likely hood a case results in a death in the model. As shown in figure 6.17 it follows a similar trend as the other graphs but shows the increased benefits of vaccinating as much of the population as possible. Vaccinating 10% has little effect however if vaccinations are carried on from this much better benefit in mortality rates can be seen. The values

for higher vaccination percents are more likely to be inaccurate as they are working with increasingly small numbers. So realistically a mortality rate of 0% is incredibly unlikely but it still highlights the potentially increased safety for the population.

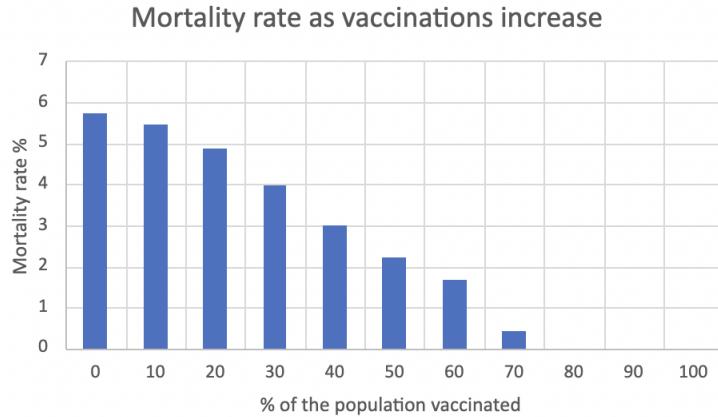


Figure 6.17: Table showing total cases generated from the simulations

Finally, the time the virus takes to spread through the population and die out was recorded. This is not as important as the other two metrics however they pose potential benefits with allow society to return to normal. Shown in 6.18 we see an interesting pattern where a slight bell curve forms. The cause of this is that as shown earlier with the different peaks and how they occur with the shallow to steep peaks changing the vaccination levels move the population from one scenario to another. Where low vaccination levels cause the virus to spread incredibly quickly infecting most of the population then struggling to carry one infecting and dying out due to lack of a host. Where incredibly high vaccination levels cause the virus to hardly spread and die out due to lack of interactions between susceptible and infected agents. The middle part is where the virus can spread slowly throughout a large portion of the population without having any agents infect or the needed agents to interact.

6.4.2 Targeted Vaccinations

Using the programmed targeted vaccinations we can see the effect of vaccination programs aimed at providing immunity to the vulnerable. It is not expected that the spread or the time of the simulations will change so these factors will not be observed focusing mainly on the effect on deaths.

Using the same process as before but instead using the targeted vaccination code. The

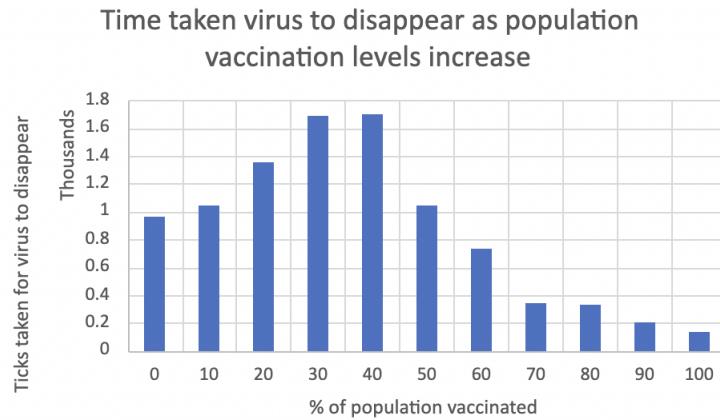


Figure 6.18: Table showing total cases generated from the simulations

vaccination code will take a sample of three times the given vaccinations for that tick then vaccinate all the vulnerable agents in the sample. Then with the remaining doses, it will randomly vaccinate individuals so the program is not 100% effective. Figure 6.19 shows the result of focusing on the vulnerable population when vaccinating. The deaths sharply decline the more people are vaccinated reducing deaths down to 0 when 50% are vaccinated. This is because the sample size for selecting the agents to be vaccinated will be larger than the whole population, vaccinating every vulnerable agent first then randomly vaccinating the others. Figure 6.20 show the comparison against the randomly vaccinating agents. What is interesting the model suggests that targeted vaccinations that are not 100% accurate it is still incredibly beneficial. The targeted vaccinations have the same effectiveness as randomly vaccinating twice the amount of individuals.

Percent Vaccinated (%)	Total extinctions simulation 1	Total extinctions simulation 2	Total extinctions simulation 3	Average
0	940	939	883	920.67
10	569	544	520	544.33
20	221	156	202	193
30	38	36	26	33.33
40	2	8	6	5.33
50	0	0	0	0
60	0	0	0	0
70	0	0	0	0
80	0	0	0	0
90	0	0	0	0
100	0	0	0	0

Figure 6.19: Table showing total cases generated from the simulations

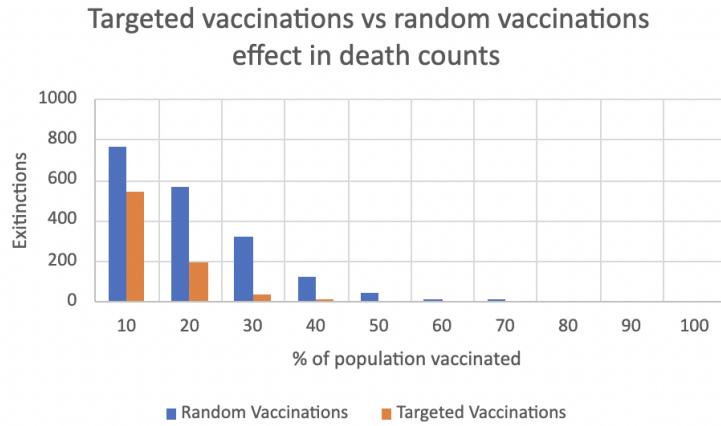


Figure 6.20: Table showing total cases generated from the simulations

6.5 Multiple Waves

The model can also generate simulations with multiple infectious waves. This has been a very common occurrence around the globe. As countries get through the first wave with lockdowns and social distancing reducing the cases to such a low number. As life then returns back to normal interaction increase and the virus then begins to spread again and in some cases worse than the first wave. Using the social distancing feature this can be simulated by changing the different thresholds that the different social distancing measures occur at.

In figure 6.21 the intervals for checking social distance rules were set to 60 ticks and the threshold for R_e number had to be greater than 0.6. Figure 6.22 shows just the active cases and the extinctions throughout the simulation. The simulation shows the benefit of introducing laws around social distancing and locking the population down for example at ticks 60 and 180 after a new policy is introduced the cases sharply fall. The simulation also highlights the dangers of returning the population back to normal even when the cases are low. The second peak is even worst than the second one in the model.

These multiple waves had been predicted by models [58] before they occurred. Predicting worse scenarios than the first wave. A similar thing happened in the simulation above where cases were low and restrictions were lifted however the threshold for another outbreak was still satisfied. So as soon as the restrictions were lifted another infectious wave broke out in the population.

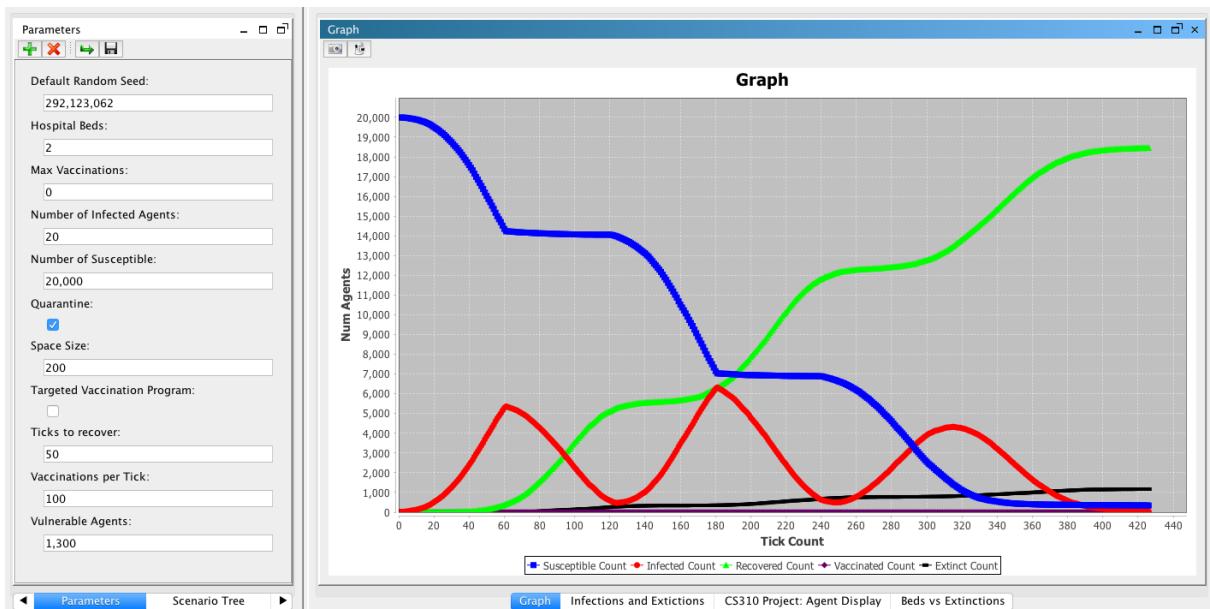


Figure 6.21: Graph with social distance measures in place

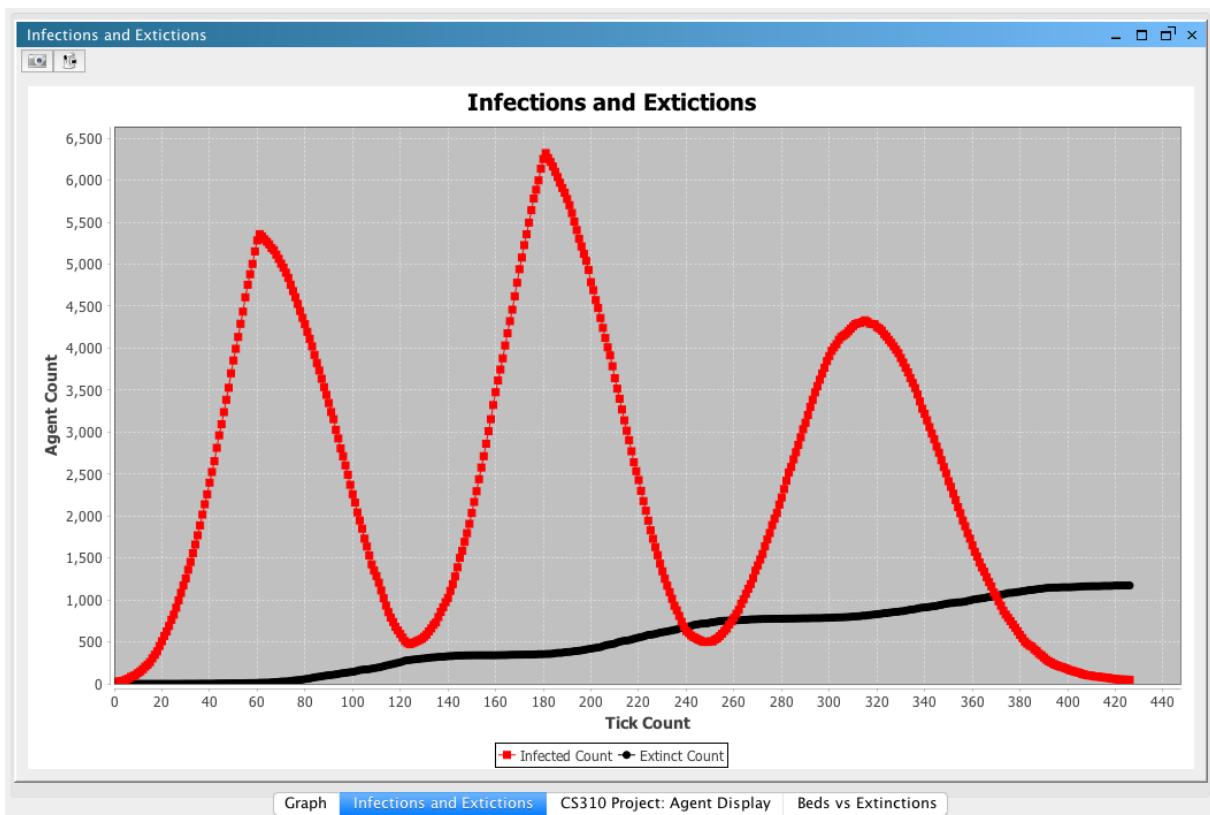


Figure 6.22: Graph looking at the active cases and extinctions only

6.6 Discussion

The findings from the results will now be summarised and applied to the real world. Discussing where my model supports any current policy and where the model may help improve and introduce new policy.

6.6.1 Health Care

The model shows the link between the number of ICU beds and COVID-19 extinctions. The model suggests a strong link between ICU beds and COVID-19 deaths where there are more beds the deaths are fewer. This is supported by other research, Janke et al found a significant association between hospital-based resources such as hospital beds and COVID-19 deaths in the early months of the pandemic. However no relationship was found in later months, it is argued that hospitals had adapted to the high demand[59]. Another study modelling ICU capacity in France, Germany and Italy found that beds were the most constrained ICU resource supporting the models use of beds as an indicator for the potential a health care system can provide aid during COVID-19 [60].

6.6.2 Vaccinations

Currently, vaccinations are being rolled out across the globe with some countries further ahead than others. Recently there has been an increase in anti-vaccine with many social media accounts gaining more and more followers [61]. A study was done by King's College London has found 1 in 6 people say they are unlikely to or definitely won't get a COVID-19 vaccine [62]. This is worrying as shown by the model there are certain thresholds that improve the vaccine benefits to a population and with the current anti-vaccine movements the thresholds may not be met and herd immunity may be achievable. As discussed the tool has the potential to provide educated through the results that it produces and its ability to visualise the virus. Members of these anti-vaccine groups could be shown different scenarios to display the benefits of members in the population getting vaccinated and building up immunity in the population. With different scenarios using different vaccination levels and the cause of this.

6.6.3 Critical Points

A common theme found in the results is the different thresholds in the different environments. Very similar to ecological thresholds where small changes result in a dramatic change in the outcome [63]. We can see this in almost all the results. Firstly if the conditions in the simulation are past the outbreak threshold small changes in the population's behaviour can greatly reduce the mortality rate and the spread of the virus. Secondly the critical point in achieving herd immunity where at certain thresholds, vaccinating slightly more of the population results in many more benefits to the whole population. These thresholds can be found in the model but the aim to find these thresholds in real-life populations. For some populations, this will allow them to save on vaccination cost and lift lockdown as soon as it is safe to do so.

6.6.4 Strengths

The results support a lot of the research on the topic with estimates on herd immunity being very close to that of another study [57]. The results also support the idea and benefits of an increased number of ICU beds.

6.6.5 Weaknesses

The problem with the results it is difficult to calculate the degree of accuracy of the results produced. The model has lots of random variables and from some of the simulations ran the results slightly differ. The solution to this is to average the results produce reducing the chance of the randomness in the model to skew the results. Ideally, a grid search type feature would allow for multiple runs of similar simulations with different input values such as different random seed. REPAST does not have the infrastructure to perform this type of processing so the results are limited in their accuracy.

7 Evaluation

The model's results have been generated and the project is almost complete. The success of the project and the usefulness will now be accessed. The evaluation has been broken down into different sections. Evaluating the model and its results and evaluating how the project went focusing on how the project was managed and ran.

7.1 Objective Evaluation

Early on in the planning of the project objectives were set. The objectives were the basis for the project being complete and a success. They were also used to form a plan of development.

- 1. Run models with a small population size simulate the spread of COVID-19. With agents that can be susceptible, infectious or recovered. Modelling the SIR model. (Must)**

Objective number 1 was completed fully and provided a base for the rest of the project. The SIR model was the first part that was developed and it was thoroughly evaluated and how the project should be taken further was discussed.

- 2. Visualise the simulations to the user to display the infections spreading. A non-technical user should be able to clearly understand what the simulation is showing and how it works. (Must)**

Objective 2 was completed successfully implemented using the inbuilt visualisation tools that REPAST provides.

- 3. Create heterogeneous agents that have attributes with differing values. (Must)**

Objective 3 was implemented during the health care phase of development with the addition of vulnerable agents that were more at risk to COVID-19

- 4. Expand the model to include vaccination and extinction agent states. (Must)**

Objective 4 consists of two features. The vaccinations were implemented with the full results showing the effect of different vaccination levels and the potential to achieve

herd immunity. Extinctions were added leading on from the vulnerable agents when their symptoms worsen and they are unable to visit a hospital.

5. Program different scenarios that replicate the real-world situations populations and replicate different pandemic measure. Then calculate and record what the impact is to then predict what strategies work best for different scenarios. (Must)

Objective 5 corresponds to the results section. The results contained a large number of different scenarios with data being generated from them.

6. Perform large repeated populations simulations on different scenarios storing results. Processing data generate from the simulations to find trends and draw a conclusion from the models that could inform policy. (Could)

Objective 6 was a stretch goal however it has been covered in the discussion section of the results. Large populations were not defined but during the simulations for vaccinations simulations of 20,000 agents were repeated ran and the data was then visualised and related to the policy and the benefit of educating and combating the anti-vaccine movement.

7. Add agent states to include reinfections. (Could)

Objective 7 was another stretch goal that was not taken further. The implementation of reinfections became less relevant as studies show that past infections provide 83% protection for 5 months [64]. For the project, vaccinations seemed more relevant and with lots of people becoming vaccinated in the UK, reinfection would be even less likely.

8. Use the model accompanied by a Geo-Simulation to simulate real world locations. (Could)

Objective 8 was another stretch goal that was not completed. This objective would be very interesting to take forward into the future. Allowing the model to simulate spread for specific towns or places such as airports. Given more time with the project, this would have been taken further.

Add extra agent state for testing and incorporate a government testing scenario. (Would)

Objective 9 was not developed and will not be taken into the future of the project. It further adds more features to the model that reduce the time and attention that could be used to focus on improving other features that have already shown relevance.

7.2 Model Evaluation

To evaluate the model there are many different areas that make it successful. Wallace et al have created an evaluation framework for policy-relevant agent-based models. The framework is broken down into four sections resources, activities, outputs and outcomes. Performing this evaluation will spot areas of development that need improving, help policymakers understand how to translate this model into more effective policies and help other modellers and scientist by suggesting new areas of research.[65]

7.2.1 Resources

Firstly the resources the ABM model has used is very important. It is necessary to have the correct knowledge and skills to execute the project. Looking at a range of previous models that are related and data surrounding the topic. Before any design or development occurred for the project clear research was performed in different areas.

Clear research was performed on COVID-19. Looking at the research performed over the past year on the virus. As specific knowledge was limited on the topic extensive research was performed initially and then throughout the development. The research was also performed into epidemiological models that are not specific to COVID-19 as ABM on COVID-19 are limited and looking into other disease's ABM more understanding can be applied to the project.

Many different modelling platforms were researched and REPAST was decided upon as the best for the project. REPAST provided good infrastructure that allowed the project to develop quickly and gave more time to focus on the model its self rather than developing visualisation tools and an input framework.

The project supervisor had experience in the general field so weekly meetings were had to make the best use of the expertise. These meetings could have been more consistently organised from the projects side with not utilising meetings as much later in the project.

Overall the research performed initially was sufficient however if no more was performed many assumptions would have been made that were not backed by science. The ongoing research that was performed during the project made sure each feature of the project was rigorously researched. One area that was lacking was the research into current social distancing measures and the policies that surround them. Only the UK's approach and the effect it had was researched further research on other countries should have been performed.

7.2.2 Activities

This section breaks down why the model was chosen, developed and tested.

ABM modelling as discussed in the research was chosen as the project expertise lined up best with ABM other modelling methods and ABM potential to educate and affect policy. During the development of the model full use of the research was made and extra research was performed. Any assumptions made were stated and backed up by research that supported the assumption for example values used for the health care section were all backed by empirical evidence. The timescale of the project was defined using data and related well to the real world. One area that lacked real-world backing was the density of the agents in the given space for each scenario. This proved to not be as important as population density in the space was not a variable that the project was interested in however it could have still provided some extra insight into the nature of the model.

The model did involve too many features that meant the specifics of the project were given less time and accuracy. Precision in the vaccination feature was traded off for implementing the potential for social distancing measures that kick in during the simulations. In hindsight just controlling the speed of the agents based on their state would have been efficient as to effectively use the social distancing it requires further programming after the scenario is created to truly add specifics to that scenario.

During development, each feature was tested as it was developed however this testing was not compared to real-world findings. This would have greatly improved the accuracy of the model during development as each feature could be tweaked accordingly.

7.2.3 Outputs

The model has numerous outputs including the discussion of the implementation.

The project includes clear documentation on the feature the model includes and the process they were created in. The documentation clearly gives interpretations for the results, discussing the model's strengths and weaknesses and the effect the model has on policy. The model generates a visualisation of COVID-19 spreading through a programmed population. Extracted data on the active cases, deaths, recoveries, vaccinations, social distancing and the effect of health care resources. The model supported other researches conclusions on policy and raised the importance of outbreak thresholds when exiting lockdowns. The results of the model are simple to understand and do not require knowledge of modelling disease however it does require basic knowledge of COVID-19 and how it spreads.

7.2.4 Outcomes

In this section the short term and long term outcomes of the project. The short term outcome of the project is that the current vaccination approach must be sustained to achieve herd immunity and best benefit the population. The visualisation part of the project can be used to educate the general population on the benefits of vaccinations and the benefits of social distancing. The data generation is limited in that it is hard to measure the accuracy of the data produced. The model can still be used by other epidemiologist and the results they produce can potentially add knowledge to different problems. To carry on the social distancing scenarios experience with programming in Java is needed as the reaction to the scenario must be coded into the model.

The longer-term effects of the model cannot be measure currently as the project has only just been completed. The potential is that model is used to educate and gain more understanding on COVID-19. The model also has the potential to have additional features integrated expanding the model even further.

7.3 Management Evaluation

The actual timeline of the project deviated from the planned timeline. The initial start of the development was slowed down by fear advancements in COVID-19 would nullify any development progress made. This meant that limited amounts of development was completed before 2021 started. The plan aimed to finish objectives 1/2 by 06/01/2021 however the actual finish date for the SIR model was 13/02/2021 significantly after the proposed date. Vaccinations and extinctions were supposed to be finished 2 weeks after the SIR model had been developed. The nature of the project meant that it did not make sense to develop the two features together concurrently. Less than two weeks later vaccinations were completed on 24/02/2021 this could have been sooner however there were issues with the SIR model that required extra work and tuning.

The plan then aimed for the project to use the model at this point and start generating scenarios and data. The project took a different turn as research into hospital resources looked like a better direction for the model. At this point, the path of the project had completely changed to that of the plan. The presentation was complete and presented on time showcasing what the project had completed up to that point. Giving demonstrations of the model in running simulations.

Early on in the project it was clearly stated that the project was open to change depending on research advancements but the timeline did not accommodate this. The timeline gave rigid dates for certain features to be implemented. A better approach would have been to base the timeline on creating any feature rather than creating a certain feature. This would have allowed the project to access what feature would be best to develop at that given time based on research and the current progress of the project. Overall the project could have been planned better and better time management could have been used.

Github was used throughout the development and kept up-to-date recording any features added to the model and any fixes that were performed. Trello proved very useful during the early phases of development keeping track of the different tasks. With the SIR model being recorded completely during the Trello. Soon after however as development sped up and there was less time. The tasks were not as thoroughly tracked on Trello.

8 Conclusion

The project created an Agent-Based Model for COVID-19 that successfully simulates the spread of the virus and the effects of different health care and vaccination methods have on mortality. The model is supported by numerous different items of research. The model can visualise the spread of the virus through a large population size. Producing data on infection, deaths, vaccination and health care resources. The model can simulate a large number of different scenarios that replicate the real world. Using the model the user can make estimates on the critical points in the environment and relate this to the real world.

9 Future Work

There are many areas in which the project can be taken further. The main area would be building geographical simulation similar to Truszkowska et al where a high definition model of New Rochelle was created then COVID-19 was a simulation in it as seen in figure 9.1 [66].

Another area of limitation in the current implementation is the use of ICU beds as the metric for measuring health care resource. This can be expanded to look into available ventilators or the number of skilled professionals.

The data produced by the project lacks accuracy an important future development will be to add the functionality of a grid search to the software. That allows repetitive running of the slightly different scenarios over and over again to extract accurate amounts of data. Providing a useful way to find the threshold in a given environment.

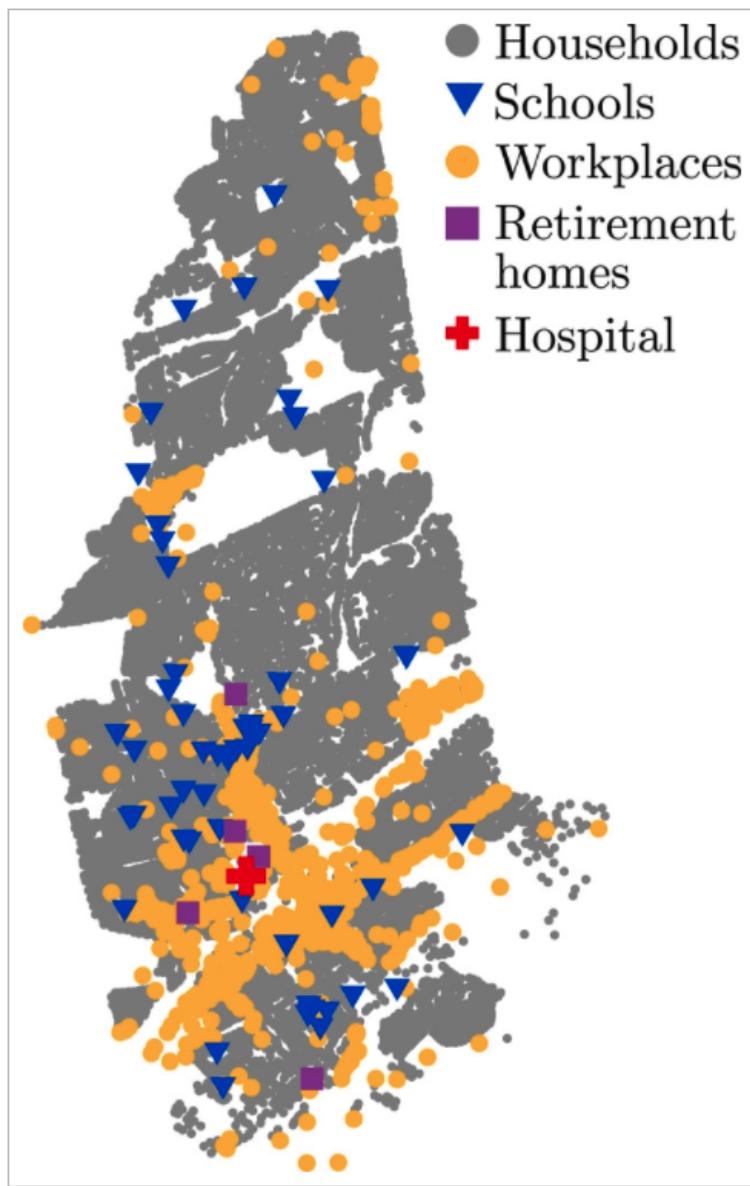


Figure 9.1: Map of New Rochelle created from database [66]

10 Author's Assessment of the Project

10.1 What is the contribution of the project?

The project provides another ABM to simulate COVID-19 and given the current climate as much research and help is needed. Contributing to the need for vaccinations and careful policymaking.

10.2 Why should this contribution be considered relevant and important for the subject of your degree?

ABM are a powerful simulation tool that is used frequently. The project uses an ABM on a current world problem highlighting the benefits and power of computational models.

10.3 How can others make use of the work in this project?

The results of the model can be compared to other results or real-world outcomes. The model can be taken on and extended by others or used to gain more understanding of the subject and help shape their model.

10.4 Why should this project be considered an achievement?

The project is an achievement as it met all the objectives it set out to do. In addition, the model itself support other research in this field given useful insights into the problem.

10.5 What are the limitations of this project?

The platform does not provide the infrastructure to recursively run simulations with slight changes to the environment.

References

- [1] Dr. Tedros Adhanom Ghebreyesus. *WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020*. Mar. 2020. URL: <https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020>.
- [2] The Lancet Respiratory Medicine. “COVID-19 transmission—up in the air”. In: *The Lancet Respiratory Medicine* (Oct. 2020). DOI: 10.1016/s2213-2600(20)30514-2. URL: [http://dx.doi.org/10.1016/S2213-2600\(20\)30514-2](http://dx.doi.org/10.1016/S2213-2600(20)30514-2).
- [3] Jeremy Schwab. *Fighting COVID-19 could cost 500 times as much as pandemic prevention measures*. 2020. URL: <https://www.weforum.org/agenda/2020/08/pandemic-fight-costs-500x-more-than-preventing-one-futurity/>.
- [4] UNESCO. *Total duration of school closures*. URL: <https://en.unesco.org/covid19/educationresponse>.
- [5] R. Andres Castaneda Aguilar Daniel Gerszon Mahler Christoph Lanker and Haoyu Wu. “The impact of COVID-19 (Coronavirus) on global poverty: Why Sub-Saharan Africa might be the region hardest hit”. In: (Apr. 2020). URL: <https://blogs.worldbank.org/opendata/impact-covid-19-coronavirus-global-poverty-why-sub-saharan-africa-might-be-region-hardest>.
- [6] Joshua Lederberg and David Relman. “5 Infectious Disease Emergence: Past, Present, and Future”. In: *Microbial evolution and co-adaptation: a tribute to the life and scientific legacies of Joshua Lederberg: workshop summary*. National Academies Press, 2009.
- [7] D. Bernoulli. “Réflexions sur les avantages de l'inoculation”. In: (1760).
- [8] Arush Lal et al. “Fragmented health systems in COVID-19: rectifying the misalignment between global health security and universal health coverage”. In: *The Lancet* 397.10268 (Jan. 2021), pp. 61–67. DOI: 10.1016/s0140-6736(20)32228-5. URL: [https://doi.org/10.1016/s0140-6736\(20\)32228-5](https://doi.org/10.1016/s0140-6736(20)32228-5).
- [9] Andrea L. Bertozzi et al. “The challenges of modeling and forecasting the spread of COVID-19”. In: *Proceedings of the National Academy of Sciences* 117.29

(July 2020), pp. 16732–16738. DOI: 10.1073/pnas.2006520117. URL: <https://doi.org/10.1073/pnas.2006520117>.

- [10] Chiara Poletto, Samuel V Scarpino, and Erik M Volz. “Applications of predictive modelling early in the COVID-19 epidemic”. In: *The Lancet Digital Health* 2.10 (Oct. 2020), e498–e499. DOI: 10.1016/s2589-7500(20)30196-5. URL: [https://doi.org/10.1016/s2589-7500\(20\)30196-5](https://doi.org/10.1016/s2589-7500(20)30196-5).
- [11] Nicky Phillips. “The coronavirus is here to stay — here’s what that means”. In: *Nature* 590.7846 (Feb. 2021), pp. 382–384. DOI: 10.1038/d41586-021-00396-2. URL: <https://doi.org/10.1038/d41586-021-00396-2>.
- [12] Gaurav Kumar and Pradeep Bhatia. “Impact of Agile Methodology on Software Development Process”. In: *International Journal of Computer Technology and Electronics Engineering (IJCTEE)* 2 (Aug. 2012), pp. 2249–6343.
- [13] Mary Poppendieck and Michael A. Cusumano. “Lean Software Development: A Tutorial”. In: *IEEE Software* 29.5 (Sept. 2012), pp. 26–32. DOI: 10.1109/ms.2012.107. URL: <https://doi.org/10.1109/ms.2012.107>.
- [14] Liling Chaw et al. “Analysis of SARS-CoV-2 Transmission in Different Settings, Brunei”. In: *Emerging Infectious Diseases* 26.11 (Nov. 2020), pp. 2598–2606. DOI: 10.3201/eid2611.202263. URL: <http://dx.doi.org/10.3201/eid2611.202263>.
- [15] Richard L Tillett et al. “Genomic evidence for reinfection with SARS-CoV-2: a case study”. In: *The Lancet Infectious Diseases* (Oct. 2020). DOI: 10.1016/s1473-3099(20)30764-7. URL: [http://dx.doi.org/10.1016/S1473-3099\(20\)30764-7](http://dx.doi.org/10.1016/S1473-3099(20)30764-7).
- [16] Irene Petersen and Andrew Phillips. “Three Quarters of People with SARS-CoV-2 Infection are Asymptomatic: Analysis of English Household Survey Data”. In: *Clinical Epidemiology* Volume 12 (Oct. 2020), pp. 1039–1043. DOI: 10.2147/clep.s276825. URL: <https://doi.org/10.2147%2Fclep.s276825>.
- [17] Ruchong Chen et al. “Risk Factors of Fatal Outcome in Hospitalized Subjects With Coronavirus Disease 2019 From a Nationwide Analysis in China”. In: *Chest* 158.1 (July 2020), pp. 97–105. DOI: 10.1016/j.chest.2020.04.010. URL: <http://dx.doi.org/10.1016/j.chest.2020.04.010>.

- [18] Emily Lawson and Sue Harriman. *COVID-19 vaccination deployment strategy and operational readiness*. Nov. 2020. URL: <https://www.england.nhs.uk/coronavirus/wp-content/uploads/sites/52/2020/11/covid-19-vaccination-deployment-strategy-and-operational-readiness-letter.pdf>.
- [19] Till Grüne-Yanoff. “Agent-Based Models as Policy Decision Tools: The Case of Smallpox Vaccination”. In: *Simulation & Gaming* 42.2 (2011), pp. 225–242. DOI: 10.1177/1046878110377484. URL: <https://doi.org/10.1177/1046878110377484>.
- [20] H. Dawid and G. Fagiolo. In: *Journal of Economic Behaviour Organization* 67 (2008), pp. 351–354.
- [21] Jason Weller and George Dimitoglou. “Survey of Models, Methods and Techniques for Computational Epidemiology.” In: (Jan. 2009), pp. 99–105.
- [22] Martin Kröger and Reinhard Schlickeiser. “Analytical solution of the SIR-model for the temporal evolution of epidemics. Part A: Time-independent reproduction factor”. In: *Journal of Physics A: Mathematical and Theoretical* (2020). URL: <http://iopscience.iop.org/article/10.1088/1751-8121/abc65d>.
- [23] Giulia Giordano et al. “Modelling the COVID-19 epidemic and implementation of population-wide interventions in Italy”. In: *Nature Medicine* 26.6 (Apr. 2020), pp. 855–860. DOI: 10.1038/s41591-020-0883-7. URL: <https://doi.org/10.1038/s41591-020-0883-7>.
- [24] Pieter Libin et al. “Efficient Evaluation of Influenza Mitigation Strategies Using Preventive Bandits”. In: *Autonomous Agents and Multiagent Systems*. Springer International Publishing, 2017, pp. 67–85. DOI: 10.1007/978-3-319-71679-4_5. URL: http://dx.doi.org/10.1007/978-3-319-71679-4_5.
- [25] Rob Allan. *Survey of Agent Based Modelling and Simulation Tools*. 2011. URL: <http://www.grids.ac.uk/Complex/ABMS/ABMS.html>.
- [26] Cynthia Nikolai and Gregory Madey. “Tools of the Trade: A Survey of Various Agent Based Modeling Platforms”. In: *Journal of Artificial Societies and Social Simulation* 12.2 (2009), p. 2. ISSN: 1460-7425. URL: <http://jasss.soc.surrey.ac.uk/12/2/2.html>.

- [27] Steven F. Railsback, Steven L. Lytinen, and Stephen K. Jackson. “Agent-based Simulation Platforms: Review and Development Recommendations”. In: *SIMULATION* 82.9 (2006), pp. 609–623. DOI: 10.1177/0037549706073695. eprint: <https://doi.org/10.1177/0037549706073695>. URL: <https://doi.org/10.1177/0037549706073695>.
- [28] David Masad and Jacqueline Kazil. “Mesa: An Agent-Based Modeling Framework”. In: Jan. 2015, pp. 51–58. DOI: 10.25080/Majora-7b98e3ed-009.
- [29] Leigh Tesfatsion. *Agent-Based Computational Economics (ACE), Agent-Based Modeling (ABM), and Complex Adaptive Systems (CAS): General Software and Toolkits*. <http://www2.econ.iastate.edu/tesfatsi/acecode.htm>. Oct. 2020.
- [30] URL: https://repast.github.io/docs/RepastReference/RepastReference.html#_repast_model_design_fundamental_concepts.
- [31] Eric W Weisstein. *Random Walk-2-Dimensional*. URL: <https://mathworld.wolfram.com/RandomWalk2-Dimensional.html>.
- [32] Jeff A. Tracey et al. “An agent-based movement model to assess the impact of landscape fragmentation on disease transmission”. In: *Ecosphere* 5.9 (Sept. 2014), art119. DOI: 10.1890/es13-00376.1. URL: <https://doi.org/10.1890/es13-00376.1>.
- [33] Ankit. *Normal Distribution Vs Uniform Distribution*. URL: <https://thatascience.com/learn-numpy/normal-vs-uniform/>.
- [34] J.P. Lehoczky. “Distributions, Statistical: Special and Continuous”. In: *International Encyclopedia of the Social & Behavioral Sciences*. Elsevier, 2001, pp. 3787–3793. DOI: 10.1016/b0-08-043076-7/00408-3. URL: <https://doi.org/10.1016/b0-08-043076-7/00408-3>.
- [35] Andrew William Byrne et al. “Inferred duration of infectious period of SARS-CoV-2: rapid scoping review and analysis of available evidence for asymptomatic and symptomatic COVID-19 cases”. In: *BMJ Open* 10.8 (Aug. 2020), e039856. DOI: 10.1136/bmjopen-2020-039856. URL: <https://doi.org/10.1136/bmjopen-2020-039856>.

- [36] Sam Moore et al. “Modelling optimal vaccination strategy for SARS-CoV-2 in the UK”. In: (Sept. 2020). DOI: 10.1101/2020.09.22.20194183. URL: <https://doi.org/10.1101/2020.09.22.20194183>.
- [37] Juan Yang et al. “Who should be prioritized for COVID-19 vaccination in China? A descriptive study”. In: *BMC Medicine* 19.1 (Feb. 2021). DOI: 10.1186/s12916-021-01923-8. URL: <https://doi.org/10.1186/s12916-021-01923-8>.
- [38] Melinda C. Mills and David Salisbury. “The challenges of distributing COVID-19 vaccinations”. In: *EClinicalMedicine* 31 (Jan. 2021), p. 100674. DOI: 10.1016/j.eclinm.2020.100674. URL: <https://doi.org/10.1016/j.eclinm.2020.100674>.
- [39] Fei Zhou et al. “Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study”. In: *The Lancet* 395.10229 (Mar. 2020), pp. 1054–1062. DOI: 10.1016/s0140-6736(20)30566-3. URL: [https://doi.org/10.1016/s0140-6736\(20\)30566-3](https://doi.org/10.1016/s0140-6736(20)30566-3).
- [40] Andrew Clark et al. “Global, regional, and national estimates of the population at increased risk of severe COVID-19 due to underlying health conditions in 2020: a modelling study”. In: *The Lancet Global Health* 8.8 (Aug. 2020), e1003–e1017. DOI: 10.1016/s2214-109x(20)30264-3. URL: [https://doi.org/10.1016/s2214-109x\(20\)30264-3](https://doi.org/10.1016/s2214-109x(20)30264-3).
- [41] Calum Semple Ewen M Harrison Annemarie Docherty. “COVID-19: time from symptom onset until death in UK hospitalised patients”. In: (Oct. 2020). URL: <https://www.gov.uk/government/publications/co-cin-covid-19-time-from-symptom-onset-until-death-in-uk-hospitalised-patients-7-october-2020>.
- [42] Bilal Akhter Mateen et al. “Hospital bed capacity and usage across secondary healthcare providers in England during the first wave of the COVID-19 pandemic: a descriptive analysis”. In: *BMJ Open* 11.1 (Jan. 2021), e042945. DOI: 10.1136/bmjopen-2020-042945. URL: <https://doi.org/10.1136/bmjopen-2020-042945>.

- [43] Harrison Wilde et al. “A national retrospective cohort study of mechanical ventilator availability and its association with mortality risk in intensive care patients with COVID-19”. In: (Jan. 2021). DOI: 10.1101/2021.01.11.21249461. URL: <https://doi.org/10.1101/2021.01.11.21249461>.
- [44] Brendon Sen-Crowe et al. “A Closer Look Into Global Hospital Beds Capacity and Resource Shortages During the COVID-19 Pandemic”. In: *Journal of Surgical Research* 260 (Apr. 2021), pp. 56–63. DOI: 10.1016/j.jss.2020.11.062. URL: <https://doi.org/10.1016/j.jss.2020.11.062>.
- [45] Reina S Sikkema et al. “COVID-19 in health-care workers in three hospitals in the south of the Netherlands: a cross-sectional study”. In: *The Lancet Infectious Diseases* 20.11 (Nov. 2020), pp. 1273–1280. DOI: 10.1016/s1473-3099(20)30527-2. URL: [https://doi.org/10.1016/s1473-3099\(20\)30527-2](https://doi.org/10.1016/s1473-3099(20)30527-2).
- [46] Annakan V Navaratnam et al. “Patient factors and temporal trends associated with COVID-19 in-hospital mortality in England: an observational study using administrative data”. In: *The Lancet Respiratory Medicine* 9.4 (Apr. 2021), pp. 397–406. DOI: 10.1016/s2213-2600(20)30579-8. URL: [https://doi.org/10.1016/s2213-2600\(20\)30579-8](https://doi.org/10.1016/s2213-2600(20)30579-8).
- [47] Laura Matrajt and Tiffany Leung. “Evaluating the Effectiveness of Social Distancing Interventions to Delay or Flatten the Epidemic Curve of Coronavirus Disease”. In: *Emerging Infectious Diseases* 26.8 (Aug. 2020), pp. 1740–1748. DOI: 10.3201/eid2608.201093. URL: <http://dx.doi.org/10.3201/eid2608.201093>.
- [48] Louise E Smith et al. “Adherence to the test, trace, and isolate system in the UK: results from 37 nationally representative surveys”. In: *BMJ* (Mar. 2021), n608. DOI: 10.1136/bmj.n608. URL: <https://doi.org/10.1136/bmj.n608>.
- [49] Elisabeth Mahase. “Covid-19: What is the R number?” In: *BMJ* 369 (2020). DOI: 10.1136/bmj.m1891. eprint: <https://www.bmjjournals.com/content/369/bmj.m1891.full.pdf>. URL: <https://www.bmjjournals.com/content/369/bmj.m1891>.
- [50] Matthew Hartfield and Samuel Alizon. “Introducing the Outbreak Threshold in Epidemiology”. In: *PLoS Pathogens* 9.6 (June 2013). Ed. by Glenn F. Rall, e1003277. DOI: 10.1371/journal.ppat.1003277. URL: <https://doi.org/10.1371/journal.ppat.1003277>.

- [51] Dankmar Böhning et al. “Estimating the undetected infections in the Covid-19 outbreak by harnessing capture–recapture methods”. In: *International Journal of Infectious Diseases* 97 (Aug. 2020), pp. 197–201. DOI: 10.1016/j.ijid.2020.06.009. URL: <https://doi.org/10.1016/j.ijid.2020.06.009>.
- [52] Alan Dorin and Nicholas Geard. “The Practice of Agent-Based Model Visualization”. In: *Artificial Life* 20.2 (Apr. 2014), pp. 271–289. DOI: 10.1162/artl_a_00129. URL: https://doi.org/10.1162/artl_a_00129.
- [53] Zheng Ye et al. “Brain imaging evidence for why we are numbed by numbers”. In: *Scientific Reports* 10.1 (June 2020). DOI: 10.1038/s41598-020-66234-z. URL: <https://doi.org/10.1038/s41598-020-66234-z>.
- [54] A. Rhodes et al. “The variability of critical care bed numbers in Europe”. In: *Intensive Care Medicine* 38.10 (July 2012), pp. 1647–1653. DOI: 10.1007/s00134-012-2627-8. URL: <https://doi.org/10.1007/s00134-012-2627-8>.
- [55] Denis Campbell. “NHS hospital bosses urge ministers to increase ICU beds in England”. In: *The Guardian* (Feb. 2021). URL: <https://www.theguardian.com/society/2021/feb/28/uk-government-must-increase-number-of-nhs-beds-hospital-bosses-warn>.
- [56] Saad B. Omer, Inci Yildirim, and Howard P. Forman. “Herd Immunity and Implications for SARS-CoV-2 Control”. In: *JAMA* 324.20 (Nov. 2020), p. 2095. DOI: 10.1001/jama.2020.20892. URL: <https://doi.org/10.1001/jama.2020.20892>.
- [57] Christie Aschwanden. “Five reasons why COVID herd immunity is probably impossible”. In: *Nature* 591.7851 (Mar. 2021), pp. 520–522. DOI: 10.1038/d41586-021-00728-2. URL: <https://doi.org/10.1038/d41586-021-00728-2>.
- [58] Elisabeth Mahase. “Covid-19: UK government must “get its act together” as modelling suggests 85 000 deaths in second wave, experts say”. In: *BMJ* (Oct. 2020), p. m4242. DOI: 10.1136/bmj.m4242. URL: <https://doi.org/10.1136/bmj.m4242>.
- [59] Alexander T Janke et al. “Analysis of Hospital Resource Availability and COVID-19 Mortality Across the United States”. In: *Journal of Hospital Medicine* Issue

2021-Jan ONLINE FIRST (Jan. 2021), E1–E4. DOI: 10.12788/jhm.3539. URL: <https://doi.org/10.12788/jhm.3539>.

- [60] R McCabe et al. *Report 36: Modelling ICU capacity under different epidemiological scenarios of the COVID-19 pandemic in three western European countries*. Tech. rep. 2020. DOI: 10.25561/84003. URL: <http://spiral.imperial.ac.uk/handle/10044/1/84003>.
- [61] Talha Burki. “The online anti-vaccine movement in the age of COVID-19”. In: *The Lancet Digital Health* 2.10 (Oct. 2020), e504–e505. DOI: 10.1016/s2589-7500(20)30227-2. URL: [https://doi.org/10.1016/s2589-7500\(20\)30227-2](https://doi.org/10.1016/s2589-7500(20)30227-2).
- [62] Ipsos MORI King’s College London. *Coronavirus uncertainties: vaccines, symptoms and contested claims*. July 2020. URL: <https://www.kcl.ac.uk/policy-institute/assets/coronavirus-uncertainties.pdf>.
- [63] Gary W. Luck. “An introduction to ecological thresholds”. In: *Biological Conservation* 124.3 (Aug. 2005), pp. 299–300. DOI: 10.1016/j.biocon.2005.01.042. URL: <https://doi.org/10.1016/j.biocon.2005.01.042>.
- [64] Elisabeth Mahase. “Covid-19: Past infection provides 83% protection for five months but may not stop transmission, study finds”. In: *BMJ* (Jan. 2021), n124. DOI: 10.1136/bmj.n124. URL: <https://doi.org/10.1136/bmj.n124>.
- [65] Institute of Medicine et al. *Assessing the use of agent-based models for tobacco regulation*. The National Academies Press, 2015. URL: <https://www.ncbi.nlm.nih.gov/books/NBK305912/>.
- [66] Agnieszka Truszkowska et al. “High-Resolution Agent-Based Modeling of COVID-19 Spreading in a Small Town”. In: *Advanced Theory and Simulations* 4.3 (Jan. 2021), p. 2000277. DOI: 10.1002/adts.202000277. URL: <https://doi.org/10.1002/adts.202000277>.