MODELING AND PREVENTING VIRUS SPREAD MODEL

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ABSTRACT

This model shows how to prevent the spread of a virus through preventative measures, which can be applied to the current COVID-19 pandemic. Agent based modeling is useful for this topic because interactions between individual people and the individual decision making process is difficult to represent without an ABM. This model is unique because it has a geospatial element. Other COVID-19 models take into account hundreds of factors, but they do not include a geospatial element that actually shows the agents as they are moving and interacting with each other. Through various experiments, I have found that using both masks and vaccines as preventative measures are more effective in reducing deaths, while just masks as a preventative measure works best in reducing virus spread.

Keywords: agent-based modeling, COVID-19, preventative measures, GIS, Herndon, VA, Reston, VA.

1 INTRODUCTION

The spreading of viruses is a complex system. It is fully dependent on the movements of people, which are different, random, and hard to model. It is important to examine this system, however, because learning which preventative measures work best in models can be quickly applied to real life and reduce deaths/infections. This paper summarizes the agent-based model called 'Preventing Virus Spread' developed to explore and understand this phenomena. The specific research question or objective that guided this project is: How can preventative measures such as masks and vaccines affect virus spread and virus deaths?

2 BACKGROUND

2.1 The Topic

This model focuses on how to model the spreading of a virus in a community. It also explores how using preventative measures can change the death rate and spread rate of the virus. This topic is important to discuss because it is modeled after the COVID-19 pandemic. The COVID-19 virus caused many deaths, and spread very fast. However, many people were reluctant to implement preventative measures - for whatever reason - and as a result, the deaths and spread were higher than they should have been. This model shows how implementing preventative measures could have made the impact of COVID-19 much less.

2.2 Related Research

The COVASIM model by Cliff et al. is an agent based model that models COVID-19 spread. It accounts for many detailed factors, such as social layers. Social layers are layers that connect agents that would normally randomly interact or not interact at all. Examples of social layers that Cliff et al. used in their model are school, household, and workplace networks. However, one downside of this model is that it does not have a visual/spatial element. The model does not actively show agents contracting COVID-19 and interacting with other agents.

Another related model is the Fire Spreading/Segregation model by Cuevas. This model was highly mathematical. However, it also had the same problem as the COVASIM model. It did not spatially or visually represent interactions between the agents, only using scatterplots as the visual output.

2.3 Why Utilize Agent-based Modeling?

Agent-based modeling is important for this topic because it shows us just exactly how individuals interact and how a virus is spread. Additionally, the premise of an agent based model is that each agent is an individual person who makes individual “choices” (Bonabeau, 2002). In this model, each agent has to make a decision not only about where to move, but which preventative measures to use. This would have been difficult without an agent based model!

3 DATA

The only data used in this model was geospatial data from the Virginia Department of Transportation’s Traffic Volume Database (Virginia Department of Transportation). This database was used to create the roads that the agents would traverse upon. QGIS was used to clip the roads to the areas of Herndon, VA, and Reston, VA. That shapefile was then moved to Netlogo and used to draw the roads.

I also used The New York Times’ ‘A Detailed Map of Who Is Wearing Masks in. the U.S.’ (Katz et al) to assign the original mask percentages when setting up the agents. To set up the percentage of people infected/vaccinated, I used the CDC’s COVID Data Tracker. Finally, I used the ‘COVID-19 deaths reported in the U.S.’ page by Statista to set the cutoff age for deaths caused by the virus. Statista’s dataset stated that people over age 50 were more likely to die from COVID-19 than people below 50, so 50 became the age cutoff for the ‘death’ method.

4 MODEL DESIGN

The key model components include a move function, mask and vaccine functions, and death functions.

The move function randomly determines the amount that the person will move, given that they stay on the road. If they move off road, they correct themselves by rotating.

The mask and vaccine functions change the mask and vaccine status depending on how many people around the agent have their mask on/off or are vaccinated. It is important to note that vaccines can only be administered, they cannot be removed. So once an agent is vaccinated, they cannot be unvaccinated. This is not true for masks, however. Masks can be put on or taken off depending on the mask status of the current neighbors.

Appendix A includes a detailed description of the model following the Overview, Design concepts, and Details (ODD) protocol (Grimm et al., 2006). The ODD enables transparency of the model components and to both reproducibility and reuse of the model (Grimm *et al*, 2020).

4.1 Model development

To develop the agent-based model, the modeling framework of Netlogo (Wilensky, 1999), version 6.2.1, was used. In addition to its robust coding language to support agent-based model development, Netlogo provides users with a graphical user interface to view the model and conduct experiments in real time during each model iteration. For this model, the GIS extension for Netlogo was used to enable display and utilization of spatial datasets to inform agent and environment attributes as well as model parameterization.

A screenshot of the geographical area was also added underneath the roads, which was taken from OpenStreetMap. To allow the agents to move on the roads, patches underneath the roads were set to a specific color. This is because the agents cannot recognize the GIS data, they can only recognize patches and the color of those patches.

4.2 Model Components

4.2.1 Model Initialization and Parameters

This agent-based model enables the user to adjust parameters to setup initial conditions and to experiment with different model scenarios. The user-controlled parameters and interactions are noted in Table 1. By adjusting the preventative measures used, the user can note the effects of each parameter separately or all together.

Table 1: User input parameters and controls

Parameters	Range	Meaning
use-masks	true/false	A switch that allows the user to setup the environment with masks as a preventative measure
use-vaccine	true/false	A switch that allows the user to setup the environment with vaccines as a preventative measure

4.2.2 Agents

This model only has one overall type of agent - people. And for simplicity, I am only defining one group of agents and the attributes and decision making processes in Table 2. However, the people are split into two main categories: people without the virus and people with the virus. Let's discuss the differences between agents with the virus and healthy agents.

The main difference between these two categories is that the people with the virus have a chance to die, while healthy people cannot die. Additionally, people with the virus are able to transmit the virus if they themselves are unmasked and the person near them is unmasked and unvaccinated.

Other common traits that both of these types of agents share are the ability to be masked and vaccinated. Once a person is vaccinated, however, they cannot be infected with the virus. So the category of healthy people also includes the group of people with their vaccine.

For both of these types of agents, a key decision making process is deciding whether or not to wear their mask and get their vaccine. In this model, masks can be taken on and off depending on the masking status of the majority of the agent's neighbors. If half or more of the neighbors are wearing masks, the agent will also wear their mask and vice versa. Vaccines are determined similarly, but it only takes two or more neighbors that are vaccinated for the agent to decide to get their vaccine. Once the vaccine is administered, it does not change.

Table 2: Agents and key attributes and behaviors used in the model

Agents	**Select attributes**	**Key Decisions**
People	mask, vaccine, virus	wearing a mask, getting vaccinated, transmitting the virus

4.2.3 Environment

The model incorporates a spatially-explicit environment for the geographic area of Herndon, VA and Reston, VA. The area represented in the model is shown in Figure 1. Spatial data for the roads are loaded into the model during setup. The spatial extent represented in the model is an area of about 12 sq miles.

Figure 1: Geographic area of the model is Herndon, VA and Reston, VA.

4.2.4 Sub-models

The key sub-models incorporated in this agent-based model are the agent-agent interactions and the decision-making processes for masks and vaccines. These are briefly summarized.

Healthy-Infected: The infectious agent can transmit the virus to a nearby healthy agent if both are unmasked and the healthy agent is unvaccinated. The agent remains infected for 240 ticks. Once the 240 ticks are over, they are healthy again.

Mask: If 4 or more of the agent's neighbors are wearing a mask, the agent wears a mask. Alternatively, if 4 or more of the agent's neighbors are not wearing masks, the agent does not wear their mask.

Vaccine: If 2 or more of the agent's neighbors are vaccinated, the agent gets vaccinated. The agent cannot become "unvaccinated" after the vaccine has been administered.

4.3 Model logic and flow

The processes that take place during each model iteration are summarized as a flow diagram in Figure 2.

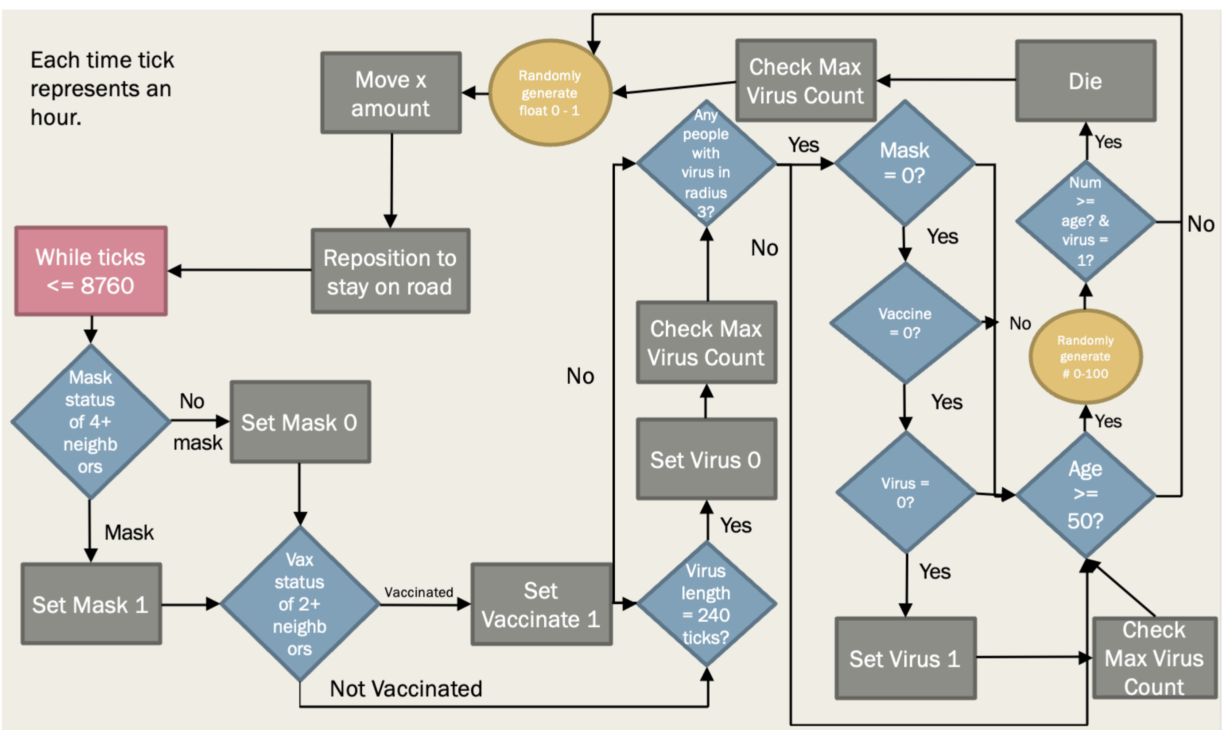

Figure 2: Model flow diagram.

4.4 Model interface

A screenshot of the model interface and results during a sample run are shown in Figure 3.

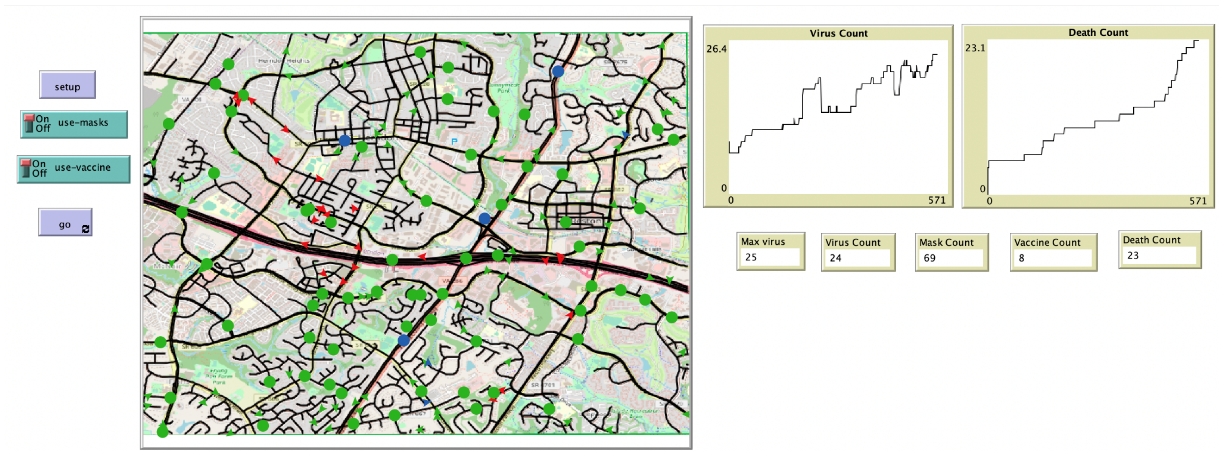

Figure 3: Graphical user interface of the Preventing Virus Spread model.

5 EXPERIMENTS AND RESULTS

The model was tested by running a baseline and three experiments, each testing a different configuration of the preventative measures.

In the baseline, 97 people died on average. Additionally, no more than 78 people were carrying the virus at one time. The trends in deaths and virus transmission are shown in Figures 4 - 6. As shown, the end virus count never reaches 0. This is due to the lack of protective measures like masks or vaccines. Additionally, the deaths chart plateaus in all 3 figures. This is because the model only has people die if they are older than 50, which is the population most affected by the COVID-19 virus. If the deaths method included all ages, the deaths chart would most likely be linear.

The first experiment was with only masks as a preventative measure. With a death count of 52, the death rate decreased from the baseline by 46.39%. The maximum number of people with the virus at any given time also decreased by 75.64%, from 78 to 19 on average. This shows exactly how effective masks are, and how having many people wear masks reduces the risk of death and catching the virus. The graphs for these experiments are shown in Figures 7-9. Interestingly, the virus count was able to reach 0 in all three trials. Once this happened, people stopped dying (which is why the death graph shows a plateau).

The third experiment with just the vaccine as a preventative measure, was predicted to have the same results. However, this was not the case. The deaths mirrored the baseline experiment, with 92 deaths (a decrease of 5.15% from the control). The maximum number of people with the virus at any given time was lower, however, at 55 people on average (29.49% decrease from the control). These results do not present a compelling argument for vaccines. However, with this experiment, the figures tell a much more interesting story. The figures for this experiment are Figures 10-12. In all of the other figures, there is visible fluctuation in the virus counts graphs. With this experiment, on the other hand, the virus counts sharply increase and then sharply decrease at almost the same rate. Additionally, the virus counts reached 0 much earlier than any of the other experiments so far. This proves that vaccines work to eradicate the virus much faster than just masking.

The final experiment combined both masks and vaccines. There were 40 deaths, on average (a 57.73% reduction from the baseline), and at most 24 people who had the virus at any given time, on average. That is a 69.23% reduction from the baseline value. Looking at Figures 13-15, the same pattern of sudden increase and sudden decrease that was observed in the vaccine experiments is visible here as well. The virus was also eradicated early on with both masks and vaccines implemented.

In conclusion, the experiment with both masks and vaccines implemented had the most success in decreasing the amount of people who died from the virus, while the experiment with just masks was more successful in reducing the infection rate at any given time.

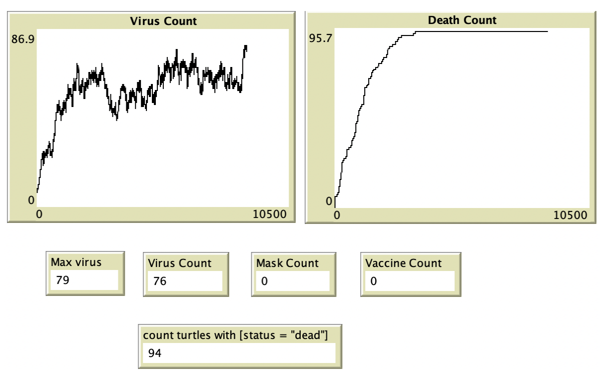

Figure 4. Trial 1 of Control Experiment

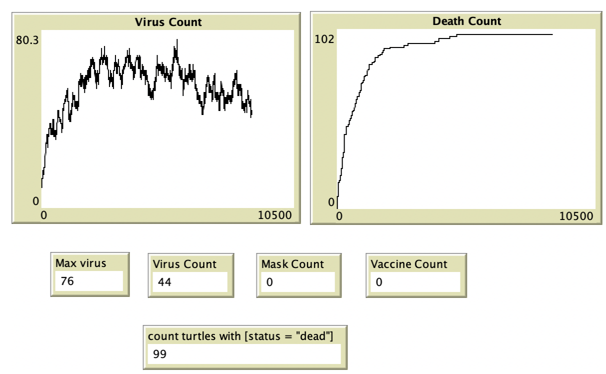

Figure 5. Trial 2 of Control Experiment

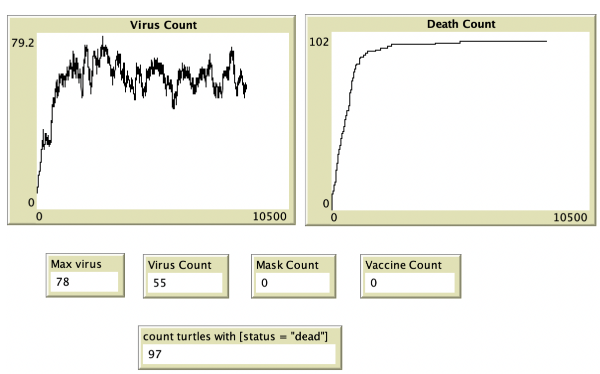

Figure 6. Trial 3 of Control Experiment

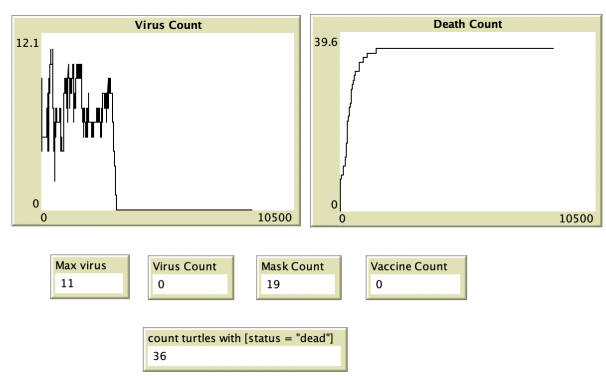

Figure 7. Trial 1 of Masks Experiment

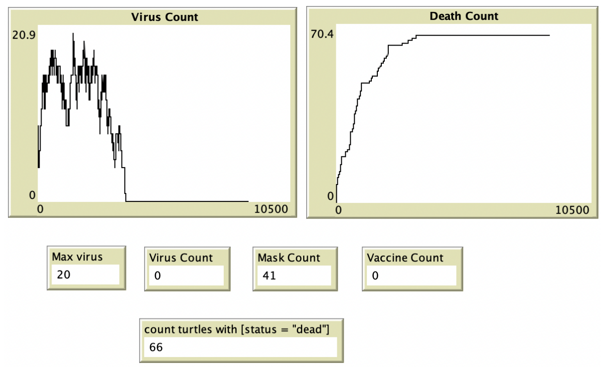

Figure 8. Trial 2 of Masks Experiment

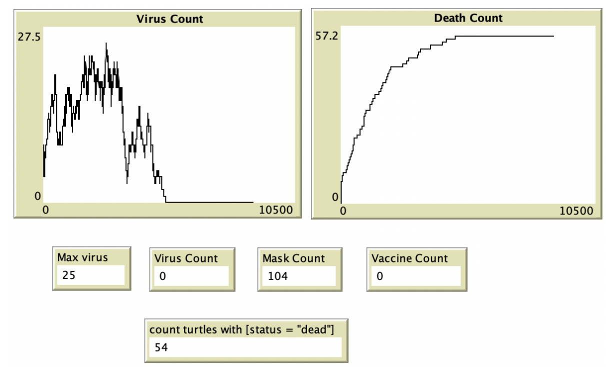

Figure 9. Trial 3 of Masks Experiment

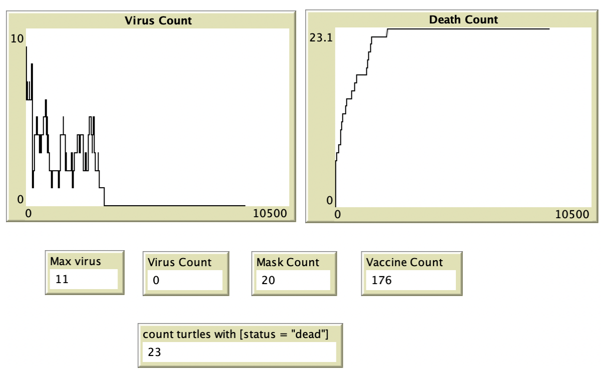

Figure 10. Trial 1 of Vaccine Experiment

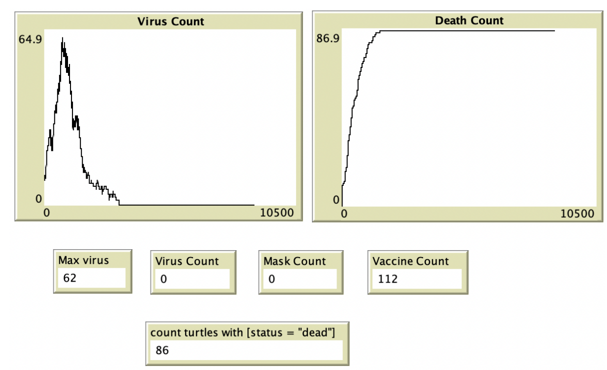

Figure 11. Trial 2 of Vaccine Experiment

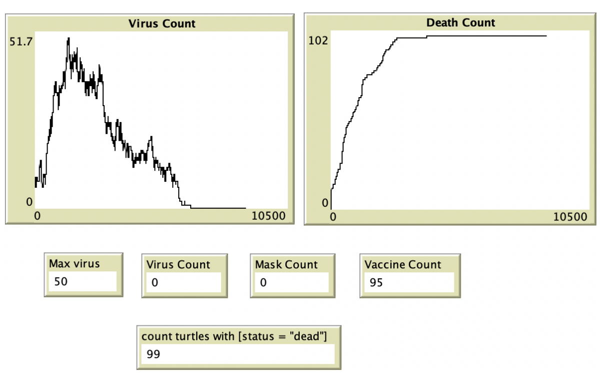

Figure 12. Trial 3 of Vaccine Experiment

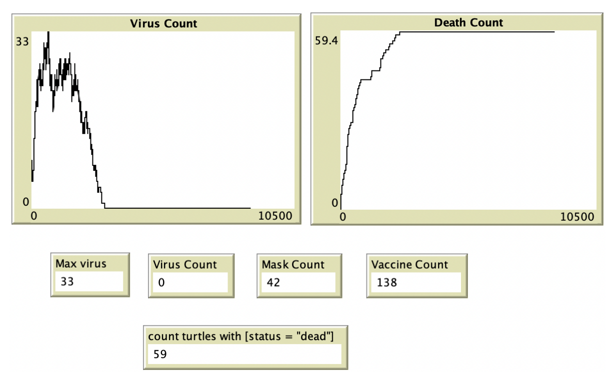

Figure 13. Trial 1 of Masks + Vaccine Experiment

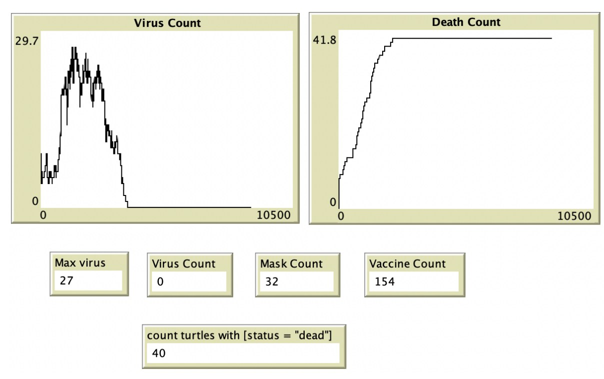

Figure 14. Trial 2 of Masks + Vaccine Experiment

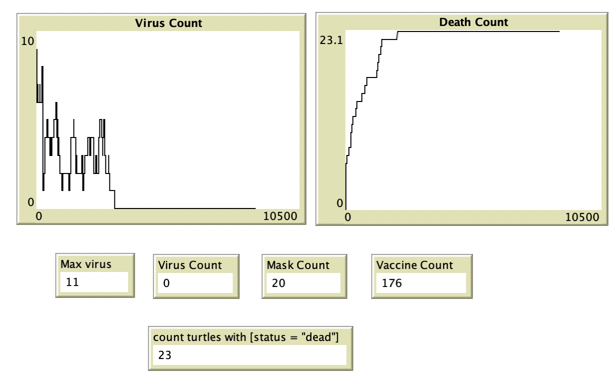

Figure 15. Trial 3 of Masks + Vaccine Experiment

6 CONCLUSION AND AREAS OF FURTHER WORK

This model shows us the importance of implementing preventative measures to combat a virus. Even the bare minimum (just masks) had an impact on the virus spread. This is useful not only to model the COVID-19 virus, but any other virus provided that some small elements of the model are changed to fit that specific virus. Two areas for improvement on this model include adding additional networks and expanding the region mapped out in order to make the model more accurate. Additional networks refer to social networks such as schools, workplaces, and homes. Currently, the agents in this model move randomly, but having them come into contact with a specific group of people might change how the virus spreads and how preventative measures work.

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Appendix A

ODD: Preventing Virus Spread

This document provides the detailed overview, design concepts, and details (ODD) of the agent-based model on preventing virus spread.

1 Overview

1.1 Purpose and Patterns

The overall *purpose* of this model is to test how a virus spreads through a community and if we can implement preventative features. Specifically, we are addressing the following question: How does implementing fear of the virus affect the rate at which the virus spreads throughout the community and number of deaths? Additionally, how does implementing preventative measures such as vaccination status and masks change this rate as well? To consider our model realistic enough for its purpose, we use *patterns* in vaccination rates and COVID-19 case rates.

1.2 Entities, State Variables, and Scales

The model includes the following *entities*: people and square grid cells, which have the *scale* of 0.01 x 0.01 mile^2. The *state variables* characterizing these entities are listed below in Table 1. People can have and spread the virus, but they can avoid catching it by having a mask or vaccination. Also, people with the virus are more likely to die if they are 50+ years old. The virus is spread through movement, as most of the agents will be moving along the roads.

For the *spatial* and *temporal* resolution and extent: A tick in the model represents 1 hour and the model is run for 12 months - or 8760 ticks. The model was run on a 180 x 140 cell structure in NetLogo. The structure represents areas in Herndon, VA and Reston, VA.

Table 1. Entities and state variables of the virus model

Entity	Variable	Description	Possible Values	Units
Person	virus?	If the person has the virus or not	True/False	--
	mask?	If the person wears a mask or not	True/False	--
	vaccine?	If the person has a vaccine or not	True/False	--
	age	Age of a person	0-99	Years
	virus-start	The tick count when the agent first got the virus	1-8760	Ticks
	amt-moved	The amount the agent moved	1+	Units
	status	Living status of the agent	dead/alive	--
Road	road-here	If a road crosses over that patch	0/1	--

1.3 Process Overview and Scheduling

The most important *processes* of the model, which are repeated every *time step,* are the movement of the people and the viral status of the people. A person can transfer their viral status to another by being neighbors with them (passing them on the street) and if they are both unmasked and unvaccinated. A person has the virus for 240 ticks - this represents the 10 days a person is infectious with COVID-19. Within those 240 ticks, they may die if they are above age 50, as that is the population that is most susceptible to death from COVID-19. The *scheduling* of my model is as follows:

The environment sets up the roads, the agents, and their properties using the 'setup' function. It then executes its 'go' function, which contains references to other functions - 'move', 'death', 'mask-on', 'virus-transmit', 'virus-length', and 'vaccination'.

Movement is determined based on a combination of variables. The people move along the roads by using the road-here variable. The amount of movement is determined by random number generation.

Death is determined based on the age and viral status of the person. Death is possible for people above 50 who have the virus, but the probability increases as the age increases - this mirrors the COVID-19 trends of death (Statista).

The mask variable can change depending on the neighbors' mask variables. I will use the 'herd mentality' theory to set the mask variable. Therefore, if more than 4 of a person's neighbors do not wear masks, then they won't wear one either. I will set vaccination status similarly, except it only takes 2 neighbors for an agent to decide to get vaccinated. However, once it is set, it cannot change.

The virus is transmitted as stated above. Before transmitting, however, we check to see how long the agent has had the virus for. If they have had the virus for 240 ticks, they can become healthy again.

The display and output are updated.

2 Design Concepts

2.1 Basic principles

The *basic principle* of this virus model is to demonstrate how a virus spreads among a population, and predict if preventative measures can reduce the spread of the virus and deaths. Does implementing only masks change the number of deaths? What about just vaccinations? Does combining the two methods save more lives? Demonstrating the effectiveness of these preventative measures in a model can show people the importance of utilizing these preventative measures in their daily lives.

2.2 Emergence

The key *emergent* behaviors are the amount of people with the virus and the amount of deaths. By tracking the patterns of these behaviors, we can see which combination of preventative measures works the best in reducing virus transmission.

2.2 Adaptation

The *adaptive* behavior that agents adopt in this model is determining how much to move based on the viral status of neighbors and also whether to wear a mask or not based on the mask status of their neighbors.

2.2 Objectives

The *objective* of this model is to track the number of cases and deaths caused by the virus in different scenarios. I would consider my model a success if there is a correlation between the trends of virus cases and the preventative measures.

2.2 Learning

This model does not implement *learning*.

2.2 Prediction

This model does not implement *prediction.*

2.2 Sensing

The agents in this model use *sensing* to sense the viral status, mask status, and vaccination status of their neighbors. For simplicity's sake, we are assuming that the agents know these statuses with 100% accuracy throughout the entire model.

2.2 Interaction

Additionally, the agents in this model use *direct interactions* with each other to transmit the virus, as well as mask and vaccination statuses. These interactions occur randomly, just based on the agents that are "in the neighborhood" of the current agent.

2.2 Stochasticity

Stochasticity is a very important factor in this model. The locations of the agents are determined randomly, as are the initial viral status, mask status, and vaccination status. The length of the "steps" that each agent takes are also determined randomly. Stochasticity is important in this model because it represents the randomness of people, and it makes the model more realistic.

2.2 Collectives

This model does not implement *collectives.*

2.3 Observation

The key *observations* that are made in this model are the number of cases and deaths. These will both be shown graphically. By tracking these graphically, we can see the trend of cases and deaths over time.

3 Details

3.1 Implementation

Netlogo 6.2.0 is used in this model.

3.1 Initialization

For the user to set up the model, they just need to click the 'setup' button. The roads will be taken from the VDOT Traffic Volume database (Virginia Department of Transportation). Approximately 200 agents will be randomly placed on the map, with 9 agents with the virus. I chose 9 agents because the current percent positivity rate in Fairfax County is 4.56% (CDC). A similar number of agents will be vaccinated, but 67% will be masked (Katz). This is the approximate masking rate in Fairfax County.

The rates of vaccination, viral status, and masking status will remain the same across multiple runs of the model. The roads will also remain the same. This is a generic model. However, the locations of the agents will differ, as they are chosen randomly.

3.2 Input data

This model only uses spatial data from the VDOT Traffic Volume database (Virginia Department of Transportation) to create the roads. It does not take any other *input data*.

3.3 Submodels

There are two main *submodels* in this model, however, there are additional subcategories to these submodels. The first main submodel is healthy agents.

Healthy agents are free to move as much as they want. They cannot transmit the virus, they can get it if they are not either masked or vaccinated. If at least one of the agents' neighbors has the virus, the agent will get the virus.

Agents with viruses have free movement as well. Agents with viruses can also have masks, but they cannot be vaccinated. They can transmit it to any agent without a vaccination and mask. As soon as their 240 ticks are over, they are healthy agents. Each agent at or above age 50 has a chance of dying with the virus, but as the age of the agent increases, their chance of dying increases as well. Death will be decided with random numbers. These are the two main submodels, but there are also submodels within each submodel - masks and vaccination status.

Masking status is determined by the agents' neighbors as well. If 4 or more of the neighbors wear masks, the agent will also wear a mask.

Vaccination status is determined similarly. If 2 or more of the neighbors are vaccinated, the agent will also get vaccinated. However, it cannot be reversed.

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