Exploring Agent Based Models

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Abstract
The purpose of this whitepaper is to introduce the practice of agent-based modeling (ABM) and agent-based simulation (ABS) (together, ABMS) to a technical but unfamiliar audience. Section one gives an overview of the background of ABMS; section two describes the essential characteristics of ABMSs, including agency, choice, and environment; section three discusses recent uses of ABMSs in light of the COVID-19 pandemic and includes a walk-through of simple ABMSs; section four provides resources for further reading.

Keywords
Agent-based Modeling, Agent-Based Simulation, Game of Life, COVID-19, Forecasting

1. Overview and Background

Agent-based models and agent-based simulations (collectively denoted as ABMS) are algorithmic artifacts that are designed to depict scenarios by simulating independent ‘agents.’ As opposed to other kinds of mathematical models which may take static inputs, ABMSs are executed in a series of timesteps wherein agents make decisions, receive inputs from the simulation environment, and go on to affect the decisions of other agents.

‘Agent’ in this context may refer to any independently operating unit of an environment. Agents may be representative of people, groups of people, vehicles, or other kinds of machinery that may ‘act’ independently within the environment.

ABMS should be distinguished from two other kinds of modeling. First, most traditional kinds of modeling and forecasting involve the use of static, and often probabilistic, inputs. To forecast the spread of a disease throughout a population, a traditional model may simply use only static inputs such as the infection rate, recovery rate, and susceptibility (assuming no vaccine exists). This model would simply calculate the population’s status at each interval of time based on these initial variables. ABMSs, on the other hand, simulate the actions of agents at each time interval, as opposed to treating the entire population as a single unit.

Second, ABMS takes a different orientation toward systems than techniques such as Discrete Event Simulation (DES). While ABMS focuses on the choices, actions, and consequences of agent behaviors, DES focuses on events and their consequences. DES models the flow and interactions of processes, rather than the agentic behaviors. Majid et al. [1] have discussed the pros and cons of ABMS and DES, showing that although DES models may be easier to construct and implement, ABMS allow for more variability in model scenarios and outcomes. Figures 1, 2, and 3 show the difference in complexity between ABMSs and DES of a customer-staff try-on room scenario.

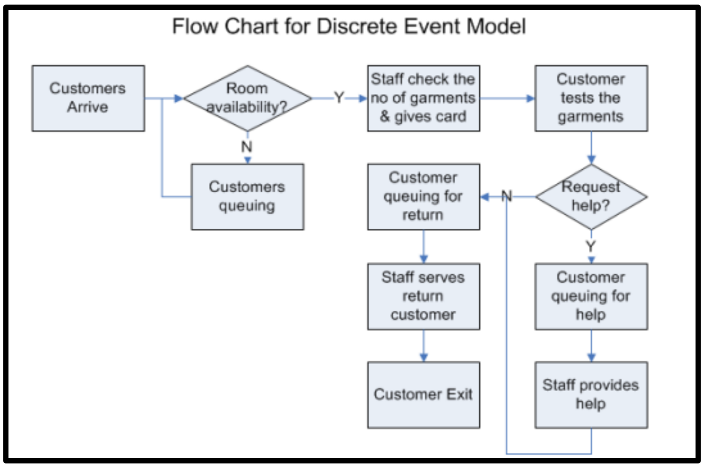

Figure 1: Flow chart for DES model [1]

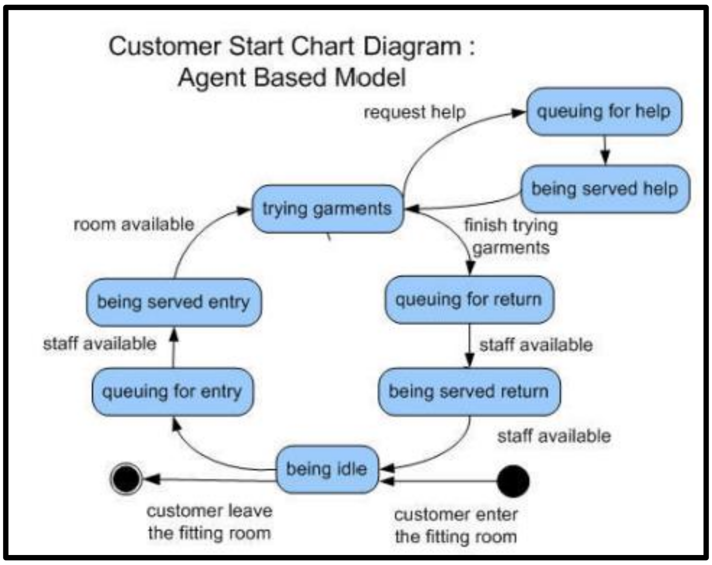

Figure 2: State chart for ABMS model customer [1]

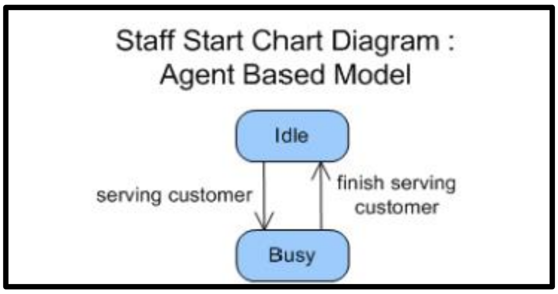

Figure 3: State chart for ABMS model staff [1]

ABMS became mainstream over the course of the 1970s. Despite earlier implementations, two notable models became academically renowned at this time: Thomas Schelling's segregation model [2], and James Sakoda's checkerboard model [3]. Designed to represent generic social interaction, Sakoda introduced a 'checkerboard model' for representing group membership based social interactions in which individual units on an 8x8 checkerboard interact based on group membership—team square or circle—and that group's attitude toward the opposing group. Schelling's model of group segregation, which had a similar set up as Sakoda's checkerboard, had a major impact in sociological modeling going forward.

1971 also saw the creation of the most popularly known ABMS: the Game of Life. Inspired by John Von Neumann's self-replicating cellular automata (CA), the Game of Life consists of a grid of independent cells that are affected by the state of their neighbors. In this game, each cell may be alive or dead, and that state is affected by the state of their neighbors. The rules are as follows:

1. If a dead cell has exactly three living neighbors, it becomes alive.
2. If an alive cell has exactly two or three living neighbors, it stays alive.
3. All other living neighbors without exactly two or three living neighbors die.

Figure 4 shows the Game of Life being run for seven iterations.

Schelling, Sakoda, and Conway's models all operate in a similar way: independent units arranged in a grid acting upon the state and proximity of their neighbors. However, not all ABMSs need to represent populations, group membership, and spatial proximity. Axelrod's 1984 Tit-for-Tat model simulates the emergence of cooperation in a world without a central authority [4].

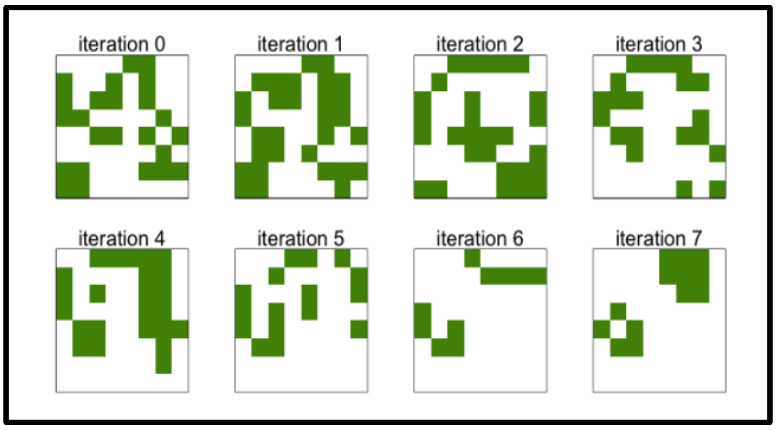

Figure 4: Game of Life board [5]

Today, ABMSs are used across practically every discipline, from immunology, economics, and war games to anthropology, political science, and logistics (and much more). Section 4 contains a short guide for further reading.

2. The Functions and Components of ABMSs

In this section, I describe the functions and components of ABMSs. First, I discuss the purposes of ABMSs and how different models serve different ends. Then, I discuss the important and essential qualities of agents and their behavior that is unique to ABMS.

2.1. Models and their Functions

Models and simulations are always models ***of*** or ***about*** something—regardless of whether the something in question is a past event, ongoing event, future event, or hypothetical scenario. Not only are models about scenarios and events, but they are also designed with distinct purposes. In this section, I explore what it means for a model to represent, describe, and predict different scenarios.

All models represent. All models are about scenarios and represent them. These scenarios may be past events—such as using models to explain how historical events transpired-ongoing events, such as the COVID-19 pandemic—and future events, such as economic markets. Other models, however, may be about idealized or completely fictitious scenarios, such as modeling alternative histories or even science fiction scenarios. Even in these cases, the representative function of models still holds.

Further, models are typically descriptive or predictive. Descriptive models have the purpose of making salient, or obvious, aspects of scenarios. Descriptive models also serve the purpose of explanation, of expressing the causes or factors of how a scenario might unfold. This includes diagnostic models, whose purpose is to replay a scenario to discover the root causes of some consequence.

Alternatively, predictive models have the purpose of forecasting future events and actions. These models assume some factors of a scenario play a causal role in the unfolding of those scenarios such that model users may gain an insight into the outcome of those scenarios.

A small set of models might have a prescriptive function. A prescriptive model might show how a system is intended to act, and agents within that system. These kinds of models might be used as educational tools or by researchers to determine what course of action agents should take in certain scenarios to achieve certain outcomes—much like predictive models.

2.2. Agents, Actions, Environments

In this subsection, I survey three essential aspects of all ABMSs: the agency of agents, the actions and consequences of those agents, and the environment.

2.2.1. Agency and Action

The essential feature of agent-based models and simulations is, well, agents. To be an agent minimally means to be an independent unit able to execute one or another action. Agents with no choice in action are not agents, but mere bots. Of course, the agency that computational agents possess is different than the kind of agency organic and living being possess. Rather than flatly deny computational systems may possess agency, philosophers, such as Leonard Dung, have proposed 'agency profiles,' a method of distinguishing the attributes of agency and ranking entities according to their high or low possession of each attribute. Table 1 shows each attribute and examples of how animals, humans, and machines might rank for each.

Table 1
Five-Dimensional Agency Profile [6]

Dimension of Agency	Description	Example
Goal-Directedness	Having preferences and acting on them; goal-directed control	All living beings; chess engine
Autonomy	Ability to propel itself to behavior; learning about the world	All animals; game-playing reinforcement learning agent
Efficacy	Ability to affect the world without someone else's mediation or intervention	All animals; game-playing reinforcement learning agent
Planning	Long-term planning; learned sensitivity to instrumental value	Intelligent animals; reinforcement learning agents
Intentionality	Acting for reasons; having propositional attitudes	Humans; perhaps intelligent animals

No matter how 'thoughtful' or 'intentional' an agent is, agents must **act** at some point. Every ABMS incorporates some course of action into the unfolding of the simulation, and agents have the unique ability to choose A or B. Those actions, in turn, may affect the actions of other agents in the model environment. In Schelling's segregation model, agents have the choice to stay or move; in Conway's Game of Life, cells may be alive or dead; and in Axelrod's model, agents may be more or less selfish.

Another important aspect of action in ABMSs is whether the actions and state of an agent influences the actions and states of other agents. While in the Game of Life, the state of each cell *always* affects the state of the neighboring cells, in Schelling's segregation model, the state of each cell *may* affect the actions of that cell, depending on that cell's preferences.

In both the Game of Life and the segregation model, agent-agent interaction occurs between spatially proximate agents, that is, cells that directly share an edge. The ability the 'view' other agents, and to view agents beyond one's immediate boundaries, raises another essential element of ABMSs: the environment.

2.2.2. Environment

Agents are always situated in an environment. Some environments might be as simple as simple agent-to-agent interfaces (such as Axelrod's Tit-for-Tat model). Other environments, such as Schelling and Sakoda's models, might minimally represent spatial proximity to other agents. As computers have become more powerful in the last 50 years since the field began to take off, models have been able to craft increasingly complex environments. Miyasaka et al., for example, recently developed and agent-based model that represents social-ecological feedback mechanisms in spatially, temporally, and socially complex environments [7].

Distinct but related to the complexity of the environment is the ability of the agent to change or operate within their environment. Some models, such as the Game of Life, do not allow agents to move from one location to another. Others, like Sakoda's, allow agents to migrate from one location to another. Neither, however, allow agents to change or act upon their environment, as opposed to Miyasaka's, which is specifically designed to represent agent-environment interactions.

3. COVID-19 ABMSs

The ongoing COVID-19 pandemic has brought ABMSs to the popular consciousness. In spring 2020, healthcare and public health professionals encouraged the public to 'stomp the curve' and 'stop the spread' of the infection using various safety measures (including wearing masks and social distancing among other things). These professionals used agent-based models and simulations to forecast how quickly the infection would spread throughout the population based on compliance with these safety measures. Once a vaccine was developed, new models incorporated vaccine effectiveness predictions and vaccine adoption rates into their models as well.

A brief survey of the available literature and code on GitHub reveals many publicly available ABMSs designed to forecast the spread of COVID-19. One model developed by Silva et al. early on in 2020 was designed to forecast the effectiveness of lockdowns, accounting for factors such as: the severity of the lockdown, severity of isolation, and degree of compliance with safety measures such as wearing facemasks and social distancing [8]. Another model developed in 2021 has the purpose of forecasting the effectiveness of contact tracing in a population [9]. Even more models have focused on the dynamics of social interaction and points of interest, from large cities—such as New York City and the Bronx [10]—to small towns such as New Rochelle, New York [11]. Still, other, even more complex models were developed that allowed researchers to tailor model scenarios which incorporate all the above [12].

3.1. Simple COVID-19 Models and Simulations

In this section, I present a 'Game of Life' style COVID-19 agent-based simulation. This model was generated with the help of Microsoft's generative AI model Bing. In this scenario, each agent begins as 'susceptible,' and may be infected by a neighboring agent depending on that agent's contact rate and the disease infection rate. During each simulated timestep, an agent may move to a random cell on the map if their neighbor is infected and swap places with the agent whose cell they moved to.

Figure U shows the approximate model architecture for each of the models. In general, the model begins by initializing the population (of size **N**). Each agent is given a pre-defined set of attributes including their likelihood of moving away from an infected neighbor, their susceptibility rate, contact rate, recovery rate, whether they are immune, and whether they are vaccinated (including the effectiveness of the vaccine). The simulation then executes a pre-set number of timesteps during which (1) each agent's movement behavior is executed (to move or not), (2) whether they contact their neighbor, and if they are infected (3) whether they recover.

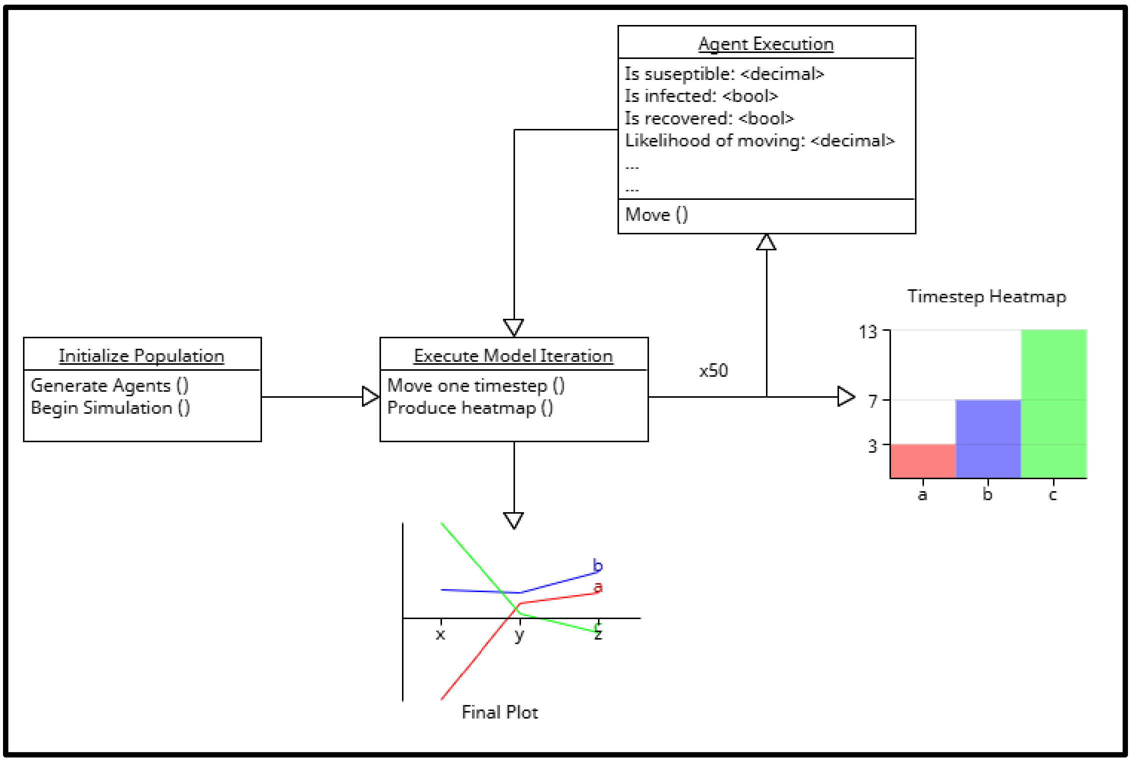

Figure 5: UML Diagram of Model Architecture

Figures 6, 7, and 8 show a heatmap of the scenario at various points along the simulation's execution. This scenario was executed with the following parameters:

- Population size = 100
- Infection Rate = 0.3
- Recovery rate = 0.1
- Move probability = 0.99

Where no agent was vaccinated.

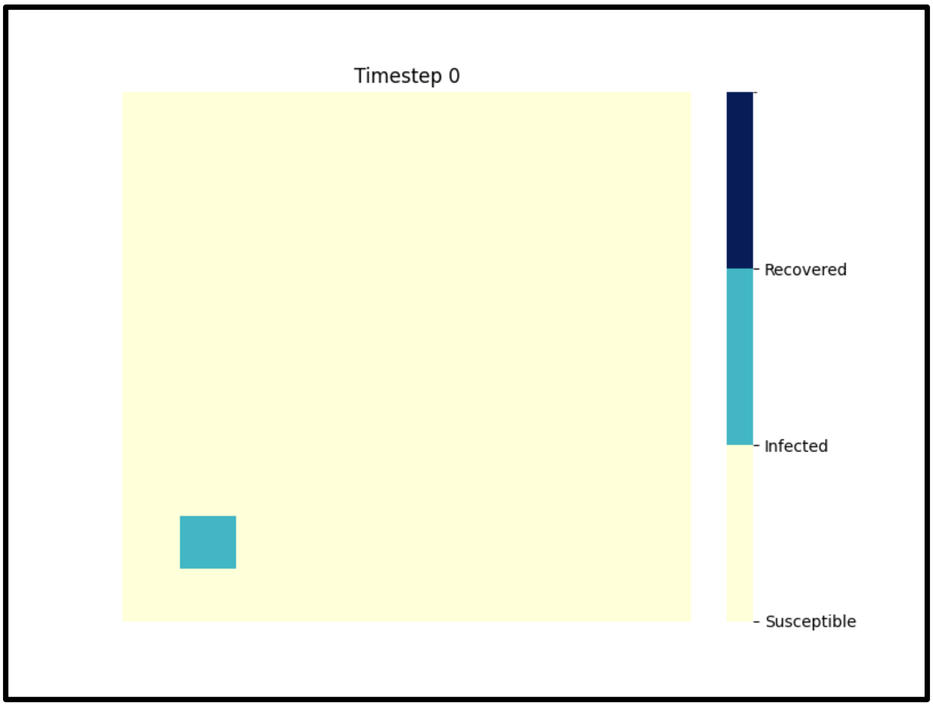

Figure 6: Timestep 0 (Initial Population State) of COVID-19 ABM

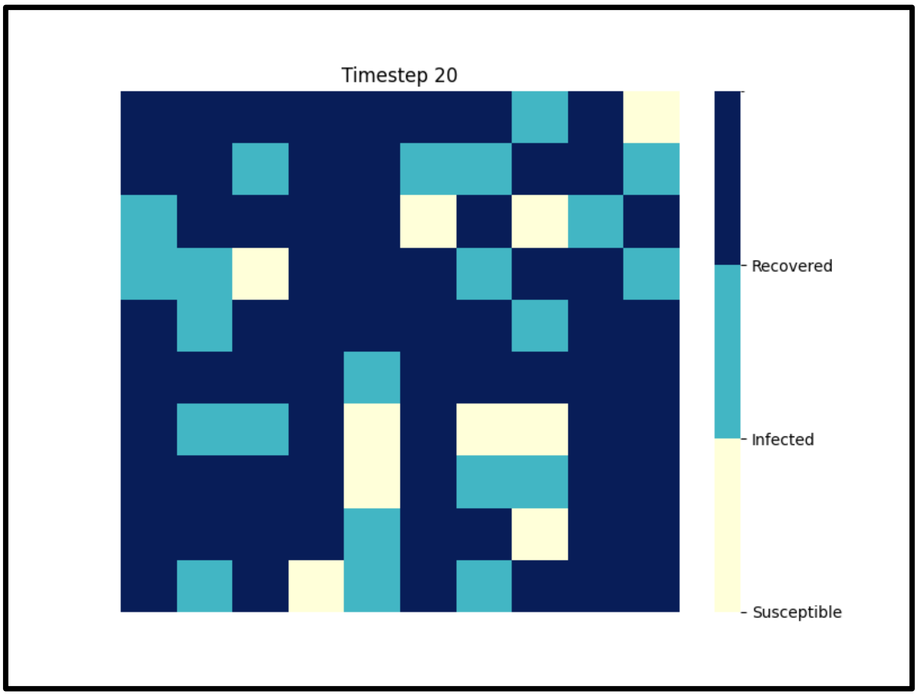

Figure 7: Timestep 20 of COVID ABM

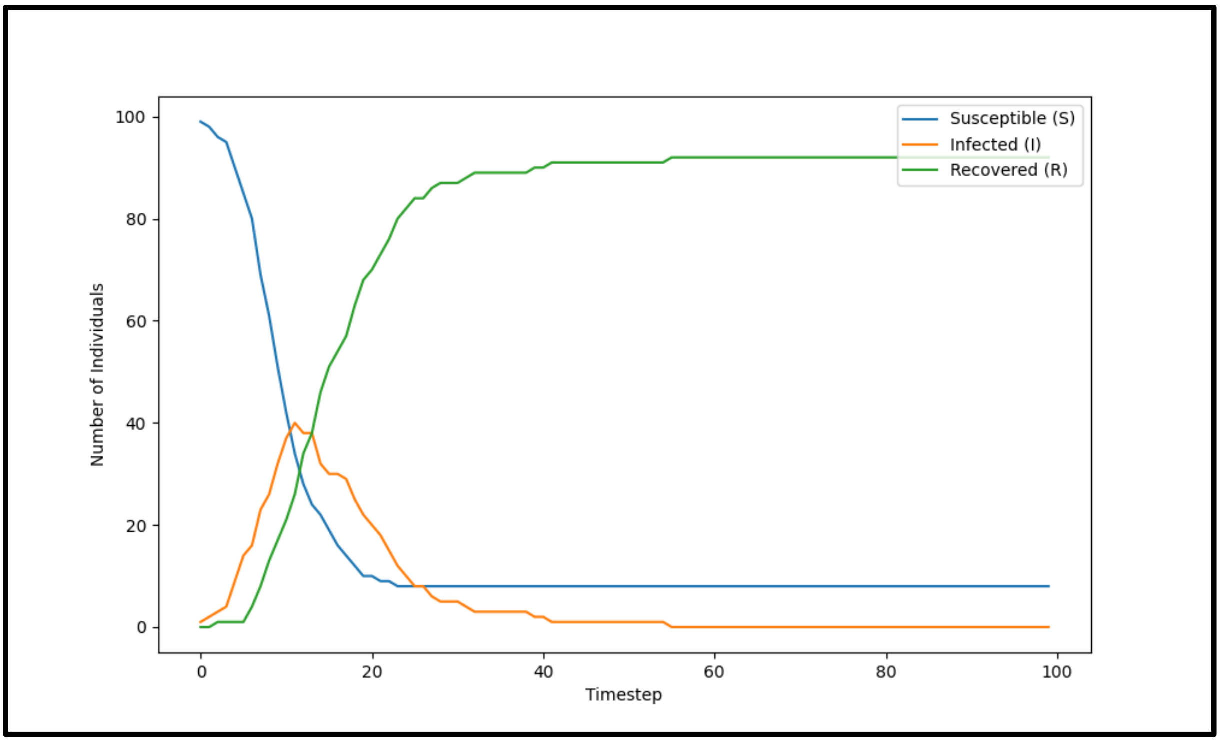

Figure 8: Overall COVID-19 ABM Execution

The models displayed in Figures 5-8 display the results of highly contrived model. Although similar in overall design and parameter type, models crafted by professional researchers are designed to incorporate more nuance and geospatial complexity into agent-agent interactions—indeed, the world is not a perfect grid.

4. Further Resources

For a general overview of agent-based modeling, see Macal [13]. For a recent example of COVID-19 agent-based modeling, see Nitzsche and Simm [14]. For a brief history of applied military agent-based simulation, see [15]. For more on agent-based models of social movements, see [16]. For an example of agent-based election models, see [17]. For an example of macroeconomic agent-based modeling, see [18].

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