Project 14: "Advanced" Pandemic Flu Spread

Project Group 204

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Project 14 Abstract

Our study presents a discrete-event simulation model of the 2020 SARS-CoV-2 pandemic flu spread. This approach uses agent-based modeling to analyze the effects of population density, healthcare infrastructure, and vaccination logistics on the disease's outcomes. We ran two scenarios of Monte Carlo simulations, one with 300 agents and 4 hospitals (S1) and another with 3000 agents and 40 hospitals (S2) holding all other variables the same. Shorthand results show that population density is a key driver of infection spread, with S2 exhibiting a much higher infection rate (99% vs. 29.7%) from the drastic increase in agent interactions and hospital strain. The model additionally incorporates the following to show nuance between runs: age stratified infectious rates, vaccination uptake, and hospital capacity. Ultimately, both scenarios reveal that immunity and mortality are consistent despite differing infection rates, thus vaccine logistics and healthcare capacity in urban areas must have a greater epidemic preparedness.

General Simulation Strategy

A successful simulation required three different normal distributions: (a) Infectious Rate; (b) Vaccination Rate; and (c) Mortality Rate. Each normal distribution was constructed using actual historical data from Fulton County, Georgia from 2020. The data set included the number of COVID cases present in the population on a daily basis (i.e., number of cases on May 1, 2020, number of cases on May 2, 2020, etc.)

A percentage change formula was used to determine growth or decline for each rate.

$$\frac{X_i - X_{i-1}}{X_{i-1}} = \frac{\text{date}_i - \text{date}_{i-1}}{\text{date}_{i-1}}$$

After finding the percent change for each day, the mean and standard deviation for each distribution was also calculated. Having the mean and standard deviation values available made using normal distributions a logical choice for interpreting this data for the purposes of future disease prevention.

Infectious Rate Distribution

The Infectious Rate distribution defined whether an individual contracted COVID-19 once he or she was exposed to another infected individual. The data set began with the number of individuals contracting COVID-19 in Fulton County, Georgia on a daily basis. From there, the set was divided into ten different age groups (01-04, 05-09**,** 10-17, 18-29, 30-39, 40-49, 50-59, 60-69, 70-79, and 80 & older)**.** A different normal distribution was generated for each different age group, as demonstrated below:

Age Group	Mean	Standard Dev	~ nor(μ,σ)
01-04 years	0.271	1.562	~ nor(.271, 1.562)
05-09 years	0.276	1.585	~ nor(0.276, 1.585)
10-17 years	0.235	1.351	~ nor(0.235, 1.351)
18-29 years	0.168	1.110	~ nor(0.168, 1.110)
30-39 years	0.176	1.281	~ nor(.176, 1.281)
40-49 years	0.167	1.149	~ nor(0.167, 1.149)
50-59 years	0.155	1.223	~ nor (0.155, 1.223)
60-69 years	0.162	1.150	~ nor(0.162, 1.150)
70-79 years	0.170	1.175	~ nor(0.170, 1.175)
80 & Older years	0.209	1.355	~ nor(.209, 1.355)

Using the percentage change formula, more growth represented a greater number of infected individuals, while more decline indicated fewer infected individuals.

Vaccination Rate Distribution

The Vaccination Rate distribution determined whether an individual received the COVID-19 vaccine.[1] This data set similarly began with the number of individuals contracting COVID-19 in Fulton County, Georgia on a daily basis. However, the data was not divided by age. All age groups had the same normal distribution.

	Mean	Standard Dev	~ nor(μ,σ)
Vaccinations	-0.749	8.838	~ nor(-0.749, 8.838)

Using the percentage change formula, more growth represented a greater number of vaccinated individuals, while more decline indicated fewer vaccinated individuals.

Mortality Rate Distribution

Finally, the Mortality Rate distribution evaluated the likelihood of an infected individual passing away from COVID-19. This data set also began with the number of individuals contracting COVID-19 in Fulton County, Georgia on a daily basis. However, as with the Vaccination Rate Distribution, no adjustments were made for the age of the affected individuals. All age groups had the same normal distribution.

	Mean	Standard Dev	~ nor(μ,σ)
Mortality	- .0189	0.848	~ nor(-.018, 0.848)

Using the percentage change formula, more growth represented a greater number of individuals passing away from COVID-19, while more decline indicated fewer individuals passing away from COVID-19.

[1] For purposes of this simulation, vaccines were not mandatory. Each individual had the choice of whether or not to receive the COVID-19 vaccine.

The Simulation Program

The simulation was created in Python using agents (to represent individuals) randomly moving around a grid. This grid represents the area where a group of individuals reside and includes different hospitals where agents can be healed and/or vaccinated.

The Grid

The grid measures 40 by 40 and functionally acts as a 160 square mile city or town. The grid is where agents move and reside during the simulated public health event.

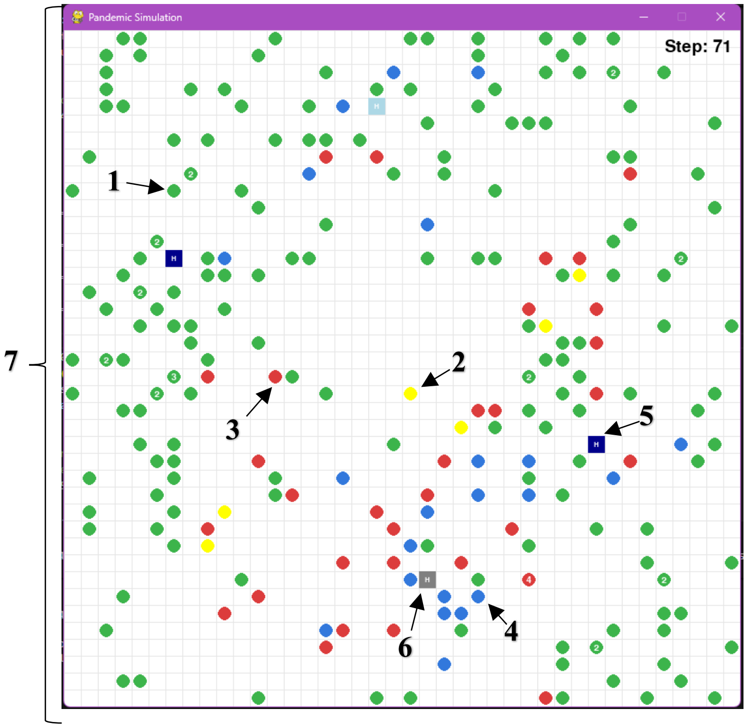
The agents

Agents represent individuals. As the Markov chain simulation runs, the agents move throughout the grid. These movements are intended to simulate daily activity in the grid. Each agent has 5 different parameters: ID, Name, Age, Location, and Health Status. An agent can have one of four different health statuses: Green (representing a healthy person); Yellow (representing a person who is infected but not yet contagious); Red (representing a person who is infected and contagious); and Blue (representing a person who is immune, either through vaccination or building immunity to COVID-19). An agent with a Yellow health status transitions to a Red health status after five (5) days without vaccination.

The Hospitals

The hospitals in the grid serve two essential purposes. First, the hospitals administer COVID-19 vaccines to agents with a Green health status. Second, the hospitals treat agents with a Red health status with the COVID-19 vaccine.

Hospitals are placed randomly throughout the grid. As in real life, hospitals have a limited capacity. In the simulation, when a hospital reached full patient capacity, the hospital closed and did not admit any new agents. Similarly, if a hospital ran out of COVID-19 vaccines, the hospital closed until the vaccine supply was replenished. When a hospital is closed, it turned gray in color.



1. Healthy Agent (Green)
2. Infected but not Contagious Agent (Yellow)
3. Infected and Contagious Agent (Red)
4. Immune Agent (Blue)
5. Open Hospital
6. Closed Hospital
7. Grid Area

Monte Carlo Simulations Progression

As the Monte Carlo simulation runs, the following progression takes place: Agent Movement, Disease Transition, Imunity, and Death.

Agent Movement:

Throught the simulation, agents are capable of two different movement behaviors. The first movement behavior (Standard Movement) occurs when an agent moves randomly from one box in the grid to another adjacent box. Standard Movement is intended to represent the daily movement of a healthy individual. The second movement behavior (Non-Standard) occurs when an infected agent has a 50 % change of moving to the nearest open hospital. In a Non-Standard movement behavior, the agent is simply trying to get care in the same way an infected individual would seek care from their doctor or an emergency room.

Disease Transition:

During the simulation, COVID-19 is transmitted when an infected agent encounters a non-infected agent. Based on the agent's individual infection rate, the agent either (a) retains a Green health status and remains healthy; or (b) receives a Yellow health status and is infected without being contagious.

Immunity:

Imunity occurs when an agent is no longer able contract COVID-19. An agent can achieve immunity in several ways. First, a healthy agent can receive the COVID-19 vaccine to proactively prevent the disease. 100% immunity occurs after the receipt of two COVID-19 vaccine shots; only receiving one COVID-19 vaccine shot decreases immunity to 70%. Second, an infected agent can become immune to the disease after becoming infected and surviving (either through reliance on a strong, healthy immune system or through seeking care from a hospital).

Death:

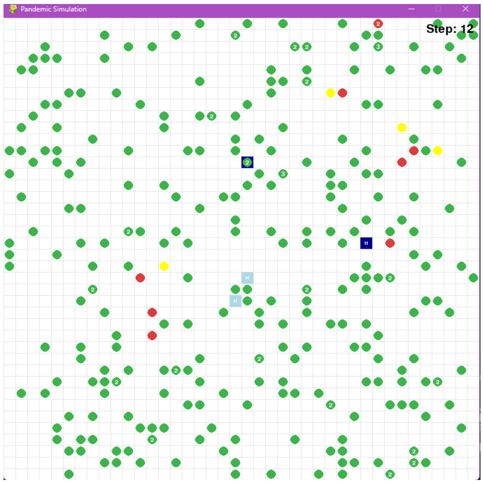
Certainly not the desired outcome, death occurs when an agent is infected and refuses or does not otherwise receive hospital care. Upon death, an agent's death rate will become a factor of the normal distribution for Mortality.

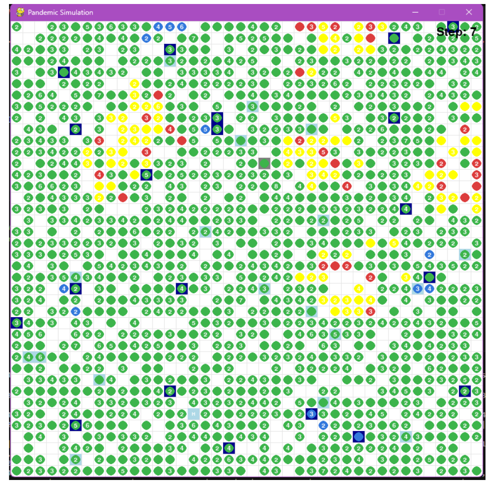
Running the Simulation

Once the simulation program was created, two different Monte Carlo simulations were run. The first simulation (S1) represented an area with less population density comprised of 300 agents and 4 hospitals. The second simulation (S2) represented an area with a much greater degree population density comprised of 3000 agents and 40 hospitals. Following the establishment of each simulation's individual parameters, S1 and S2 were each run for 1000 iterations. Each iteration began with five infected agents and ended when there were no more infected agents (due to either immunity or death).

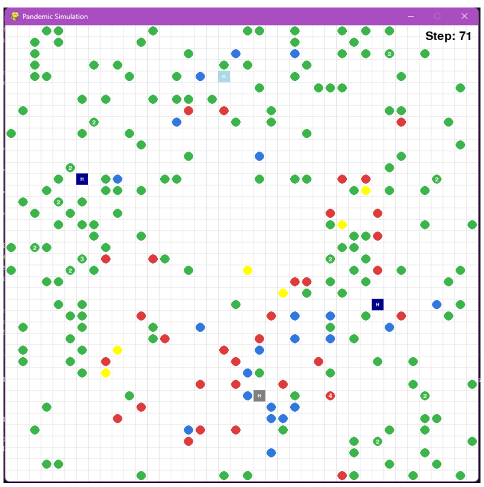
Because both simulations appear to be scaled copies on their face, it is logical to predict similar outcomes for each simulation. However, while S1 had an average infection rate of 30%, S2 had an average infection rate of 99%. These results demonstrate the effect of population density on the spread of infectious disease.

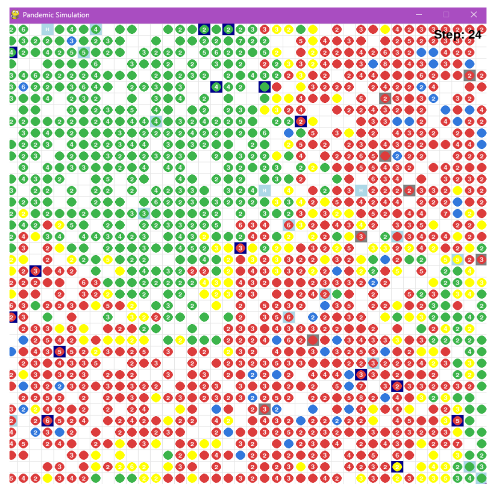
Simulation 1 | Simulation 2



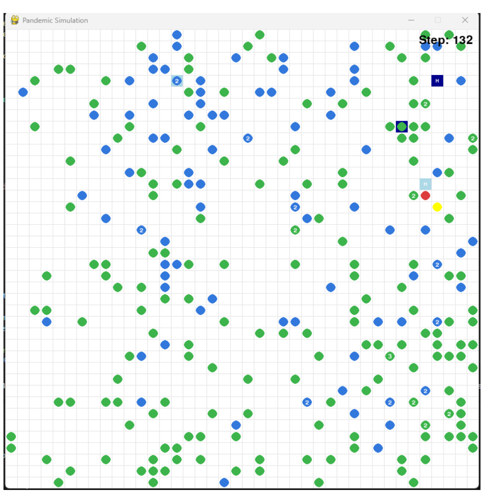


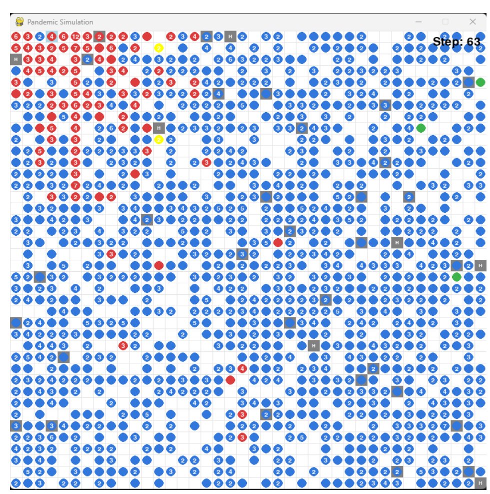
The beginning stages of the simulation with few red agents and hospitals are all open





The middle stage of the simulation where there are many infected red agents and the strain on hospitals are shown. Note how may more infected agents are in simulation 2 than 1



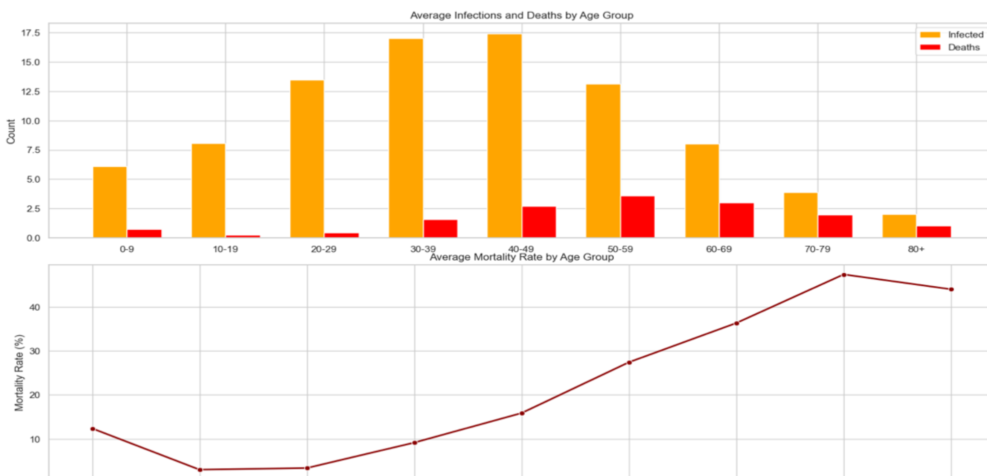


The end stages of the simulation where blue immune agents far outnumber the red infected agent. Note how in simulation 2 the red infected agents are surrounded by the blue immune agents.

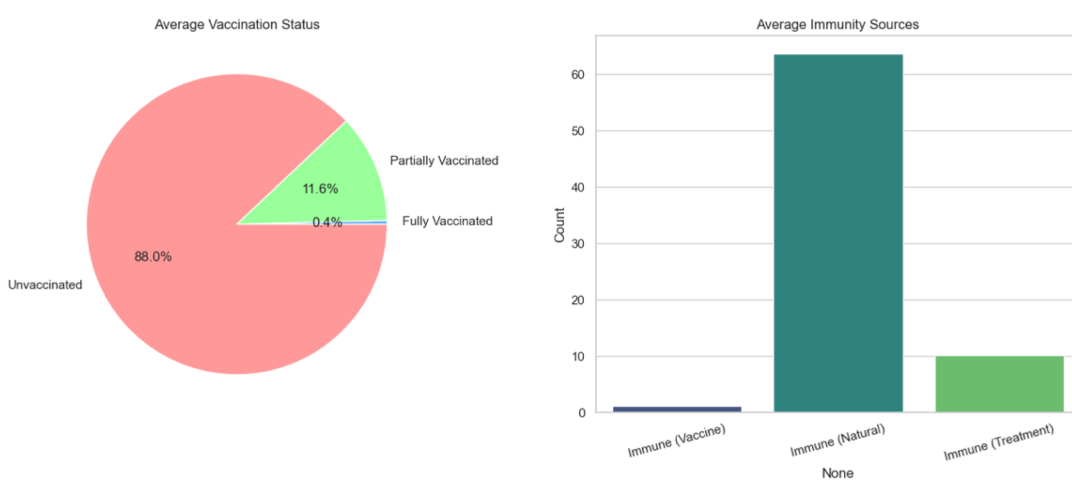
RESULTS

S1 (less population density):

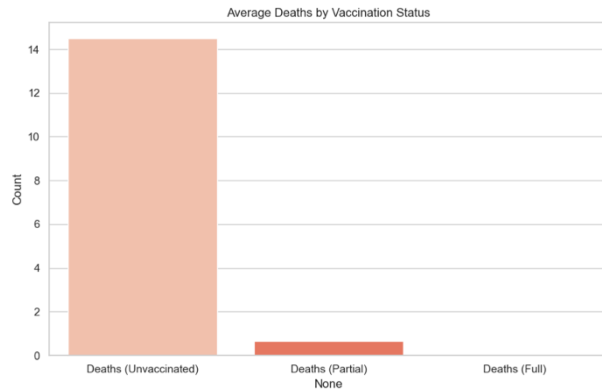
S1 included a mean of 89.18 infected agents (representing 29.7% of the population). With respect to vaccinations, S1had a mean of 34.85 agents receiving at least one of the two vaccines. Only 2.67% of the total immune agents (1.236 agents) were fully vaccinated against COVID-19. The remaining sources of immunity came from natural immunity (75.33%) and treatment immunity (22.00%), respectively. The mean of immune agents came out to 75.05 (representing 25.01% of the overall population). S1 saw a mortality rate of 17.25% (a mean of total deaths of 15.36 agents). Generally speaking, the mean result of agents achieving immunity and the mean result of agents who died did not add up to the full population. This means many agents were not impacted by COVID-19 in any way under S1's conditions.



A breakdown of the average infected and mortality by agent age. The elderly had the highest mortality percentage of about 40%.



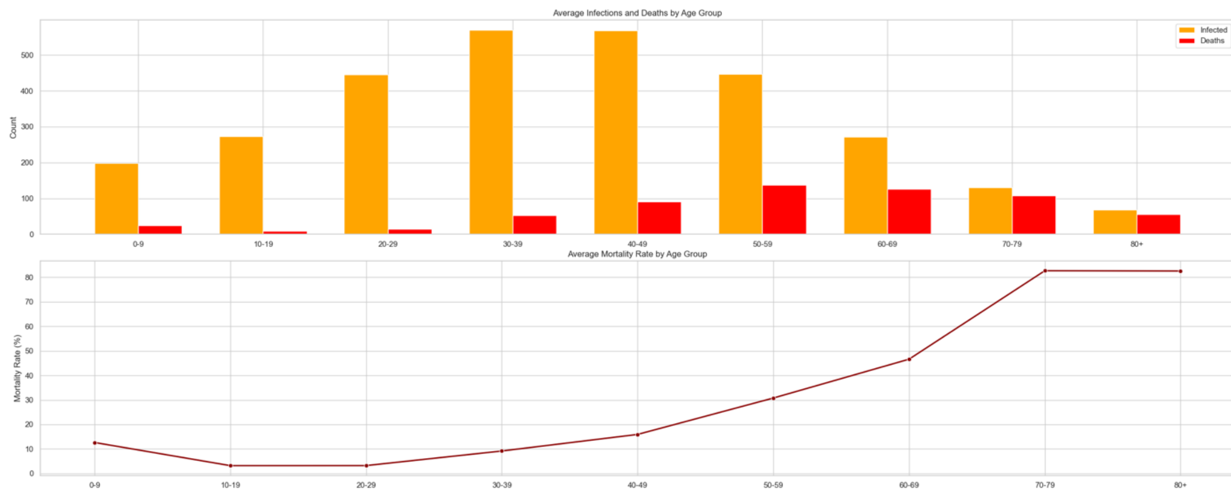
A breakdown of vaccination status and immunity sources. The majority of the population remained unvaccinated, likely due to a lack of consistent vaccine supplies (i.e. the 40% stock out rate). Most immunity in S1 was natural due to the significant unvaccinated population.



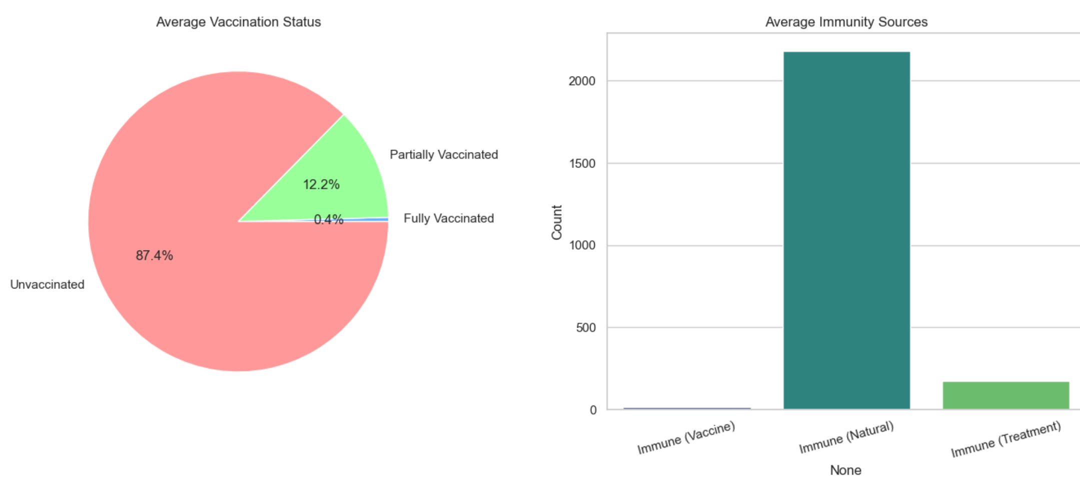
A breakdown of the deaths by vaccination status. The vast majority of deaths occurred when the agent was completely unvaccinated. Notably, another small number of agents died despite receiving the first dose of the COVID-19 vaccine. Nevertheless, no agent receiving full immunity via two doses of the COVID-19 vaccine died during S1 conditions.

S2 (more population density):

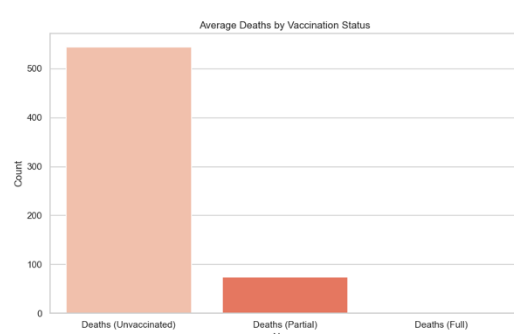
S2 included a mean of 2970.22 infected agents (representing 99% of the population). With respect to vaccinations, S2 had a mean of 365.48 agents receiving at least one of the two vaccines. Only 13.273 agents (0.56% of the total immune agents) became full vaccinated and received two shots (a much lower rate than in the S1 simulations). The lower full vaccine rate could be due to an increase in hospitals running out of vaccines (i.e. the 71.63% stock out rate). The remaining immunity sources came from natural immunity (92.14%) and treatment immunity (7.30%). The mean of the immune agents came out to 2364.38 (representing 78.81% of the overall population). S2 saw a mortality rate of 20.84% (a mean of total deaths of 619.10 agents). While large portions of the population in the S1 simulations were unaffected by COVID-19, the opposite was true in the S2 simulations. Roughly 99% of the total population in the S2 simulations were impacted by COVID-19 to some degree.



A breakdown of the average infected and mortality by agent age. The elderly had the highest mortality percentage reaching 80%



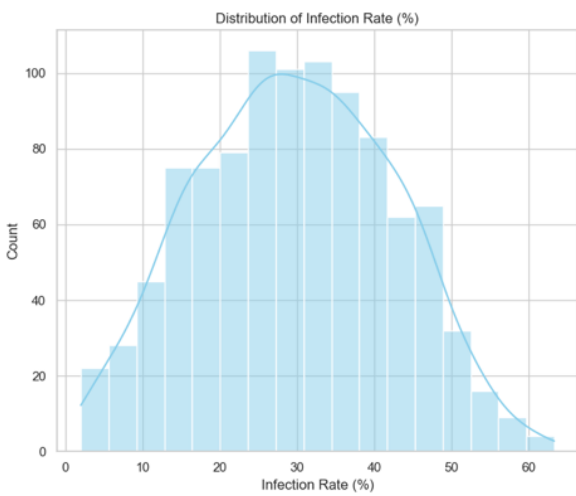
A breakdown of vaccination status and immunity sources. The majority of the population remained unvaccinated, likely due to a lack of consistent vaccine supplies (i.e. the 71 percent stock out). The majority of immunity was natural due to the large unvaccinated population.



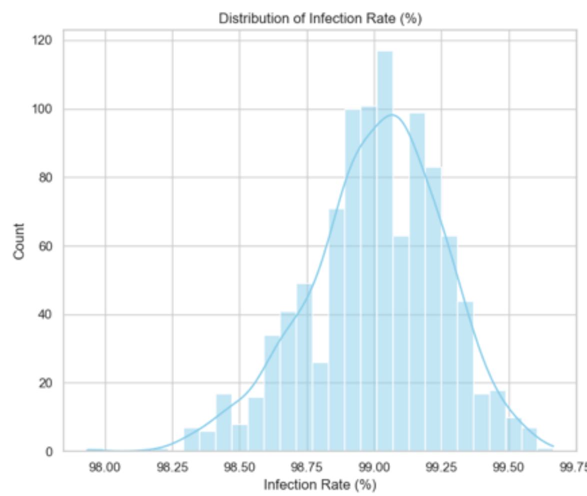
A breakdown of the deaths by vaccination status. The vast majority of deaths occurred when the agent was completely unvaccinated. Notably, another small number of agents died despite receiving the first dose of the COVID-19 vaccine. Nevertheless, no agent receiving full immunity via two doses of the COVID-19 vaccine died during S2 conditions.

Standard Deviation Differences

One of the key differences between S1 and S2 was the variations present among the simulations' various iterations. For example, when examining the amount of infected agents, S1's iterations were stochastic. S2's iterations were more stable and consistent. In S1, the standard deviation for total inflected agents was 37.82. This value represents a substantial degree of variability in the number of total infected agents among S1 iterations. Conversely, S2 only saw a standard deviation of 7.49, demonstrating a smaller degree of variability. This lower value indicates that the number of infected agents in S2 remained relatively consistent throughout the different iterations. The two graphs below demonstrate the difference in standard deviation between S1 and S2.



Simulation 1 – with a much thicker bell curve due to the low standard deviation.



Simulation 2 – with a much tighter bell curve due to the low standard deviation.

These simulations demonstrate that areas that are less densely populated present fewer changes of exposure to COVID-19. However, an infected agent in a less densely populated area is more likely to have a consistent mortality-related outcome. In contrast, agents in areas that are more densely populated are more likely to be exposed to or infected by COVID-19. Despite high infection rates, these agents have a wider range of options when it comes to surviving the disease.

Conclusion

The S1 and S2 simulations demonstrate how the COVID-19 pandemic affected different areas of the country. Rural areas with lower levels of population density experienced lower levels of infection and even fewer deaths. More urban areas with higher levels of population density saw higher levels of infection and a higher average mortality rate. Despite these differences, both simulations showed consistent trends, such as the impact of low vaccine supplies on health outcomes. Running these simulations emphasizes the importance of a well-run logistics and manufacturing program during public health crises and allows decision-makers to better prepare for the next severe disease outbreak.

Citations

- Covid Cases Data

Georgia Department of Public Health. (n.d.). *Epicurve age group report date (CSV dataset)*. Georgia COVID-19 Status Dashboard. https://ga-covid19.ondemand.sas.com

- Vaccines Data

Fulton County Government. (n.d.). *DPH Covid vaccinations: Persons fully vaccinated by county by day (DPH_Covid_Vaccinations__Persons_fully_vaccinated_by_county_by_day_20251103)* [Dataset] . Fulton County Open Data Portal. https://sharefulton.fultoncountyga.gov/dataset/Daily-COVID-19-Cases-Deaths-Hospitalizations-and-C/q86g-ze2n/about_data

- Deaths Data

Georgia Department of Public Health. (n.d.). *Epicurve by symptom date (epicurve_symptom_date.csv)* [CSV dataset]. Georgia COVID-19 Status Dashboard. https://ga-covid19.ondemand.sas.com