# Spatial Analysis of COVID-19 Risk Based on Different Lockdown Strategies - a Case Study for Storrs Campus Community, University of Connecticut

Weijia Wang[1]

[1]Affiliation not available

January 7, 2021

## 1. Introduction

In the United States, the number of cases of COVID-19 is continuously increasing. Until October 28, 2020, according to John Hopkins Coronavirus Resource Center, there were 8,856,413 confirmed cases in the United States, and 72,183 cases were reported in one day. After a few months of the lockdown in March, most states are reopening, including retail stores, restaurants, and recreation. As a college student, COVID-19 is affecting everyday student life and residence life.

According to the CDC, seasonal influenza viruses are expected during the late fall and peak between December to February [1]. There are some explanations about why flu season usually spreads in the winter. First, people spend more time indoors, which increases the chance to closer contact others who might be carrying the virus. Students, for example, would prefer using public transportation, such as buses, instead of walking to class. Second, in the short days of the winter, people may run low on Vitamin D and weaken our immune system [2]. UConn is located in the northeast of the United States; the temperature is low during the fall and winter. Students and the university need to be prepared and preclude the new wave from spreading. Typically, international students and out-of-state students are more vulnerable to get infected due to limited access to testing [3].

The government of Connecticut announced the reopening policy phase 2 began on June 17, which up to 50% capacity indoors with 6 feet spacing for restaurants, personal services, libraries, and indoor recreation and up to 25% capacity capped at 100 people for indoor religious gatherings. Phase 3 began on October 8. Restaurants, personal services, and libraries are up to 75% capacity indoors and up to 50% capacity for indoor and outdoor religious gatherings. However, due to the increasing number of cases of COVID-19 in Connecticut, the Connecticut government updated the latest reopening rule, which was phase 2.1 started on November 6. Phase 2.1 is slightly different from the phase 2 version, in which restaurants can accommodate up to 50%, while personal service and libraries can accommodate up to 75% [6].

This article focuses on a local scale, which is the UConn main campus. It is important because college campuses are places with high dense population and easily get infected. From a student's perspective, building spatial models of campus areas are necessary and help us create a safe community. This study article focuses on building a mathematical model, the Susceptible-Infected-Recovered (SIR) model, and estimates the infectious rate and recovery rate at the University of Connecticut (UConn) Storrs. The model generates the number of cases from August 16, when students who live on campus check-in, to September 7. After finding out the parameters using SIR, we use Agent-Based Modeling (ABM) to simulate different cases to predict and evaluate the risks of different places on campus.

UConn, located in Storrs, has approximately 5,000 students living on campus. Such a population would increase the chances of interaction between students in public places such as academic buildings, dining halls, grocery stores, residential halls, and apartments. Before the semester began, UConn had already announced reopening policies. Most of the classes are moving online or distance learning to prevent the spreading of disease. In-person classes require students wearing a mask and maintaining at least six feet of physical distancing from others. Dining halls are switching to take-out and limited dining models. However, for those students who live in residential halls, even though UConn policy requires one person per dorm room, they are still sharing bathrooms. For those who live in apartments or off-campus, students have approximately one to four roommates, which increases the chance of infection.

Our primary goal is to extend the SIR model into the spatial form and using QGIS and NetLogo to visualize the spreading. Because the covid-19 disease varies a great deal with places, we consider leveraging this when we estimate covid information for policy-makers to make lockdown or reopening business strategies. We extend the traditional mathematical SIR model into a spatially-explicit model to simulate the spatial dynamics of covid-19 over discrete-time and across discrete space at the Uconn Storrs campus. The spatially-explicit models may provide useful insights into the epidemiological characteristics of the disease and identification of disease hotspots across the campus, thus can inform and guide policy-makers for targeted interventions and targeted reopening the business in specific locations of the campus. This paper focuses on a specific area, rather than a state or a country, with a smaller population size. We are using the data to predict the cases and infection rates in the next few months, evaluating each building's risk and ranking the score with a higher chance of getting infected. Based on the policies that have been implemented at UConn, we also make some suggestions to the university about forestalling the new wave coming in winter.

## 2. Data and Methodology

To simulate the spreading of epidemics, we are building the SIR model. The SIR model was first introduced by Kermack and McKendrick by separating people into three different categories: susceptible (S), infected (I), and recovered (R) [4]. In this case, the population in Storrs is susceptible (S). Individuals who get infected move from susceptible stage to infected stage (I). Eventually, people who were removed from the infected status recovered (R). The SIR model using the parameters $\beta$, the infection rate, and $\gamma$, the recovery rate, can be presented by the ordinary differential equation (ODE).

$$\frac{dS}{dt} = -\beta IS$$

$$\frac{dI}{dt} = \beta IS - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

$$R_0 = \frac{\beta S}{\gamma}$$

The Agent-based modeling (ABM) is based on a set of autonomous agents who make decisions based on a series of rules we set [5]. Each agent-based model can simulate a real-world situation, which provides essential information. In this article, we are creating six public places with higher risks of interactions between people, including school, church, office, bus, café, and sub. In the program, the number of susceptible individuals in the initial population is 1,000 people compared to the approximately 5,000 who are living on campus. The ratio of parameters and the real population is 1:5. We set the two parameters, $\beta$ and $\gamma$, constant which $\beta$ equals to 0.602 and $\gamma$ equals to 0.527. Three scenarios are created based on varying restrictions. The baseline scheme means that all restrictions will be enforced. The second scenario depends on the Phase 2 Reopening Rules, which were 50% of its regular indoor capacity. The third scenario follows the Phase 3 Reopen Rules by

Sector in Connecticut, which has a maximum 50% capacity of religious gatherings, and 75% indoor capacity of restaurants [6].

# 3. Results

Figure 1 shows the number of cases changing from August 16 to September 7, with a total of 25,817 population in Mansfield. We also transform the y-axis scale to a log scale with base 10 to make the graph look better in Figure 2. Based on the data we collected, Figure 3 predicts S, I, and R changes in the next 30 days, from September 8 to October 7. However, this figure is not practical to see the changes because the susceptible and recovered lines are at the bottom. To improve it, we transform the y-axis to a log scale and get a more straightforward plot in Figure 4. We can see the red line, which is infectious, increases until September 23 and starts decreasing. The green line represents infectious, which is increasing at a relatively fast rate. Thus, in the long run, the infectious cases will decrease, and susceptible individuals are increasing at a slower rate. R0 = 1.1441 estimates the initial reproduction number, and $\beta = 0.6024$ and $\gamma = 0.6265$ estimate the infected rate and recovery rate.

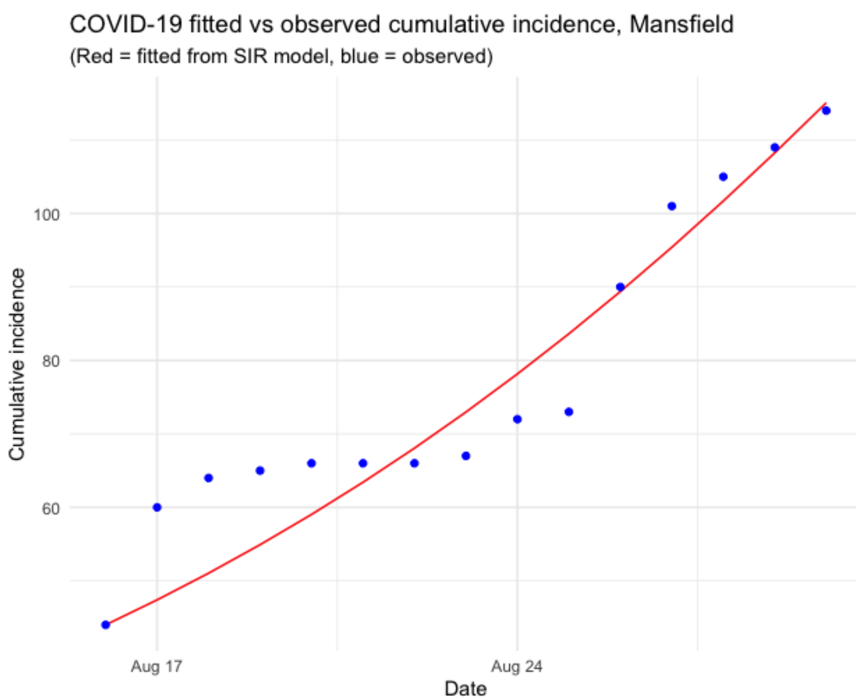


Figure 1: The blue dots are the number of cumulative cases

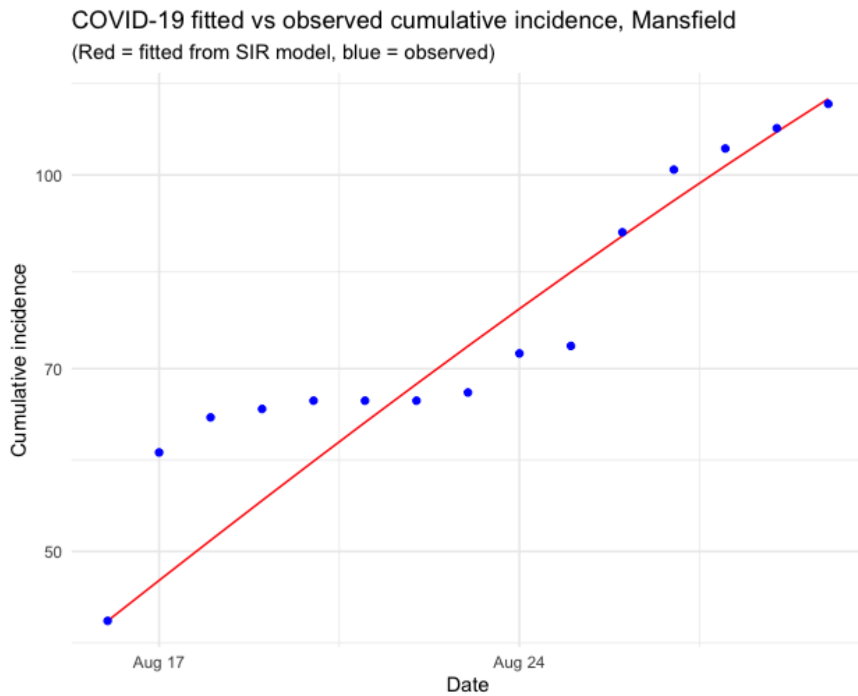


Figure 2: We transform the y-axis from Figure 1 to a log scale

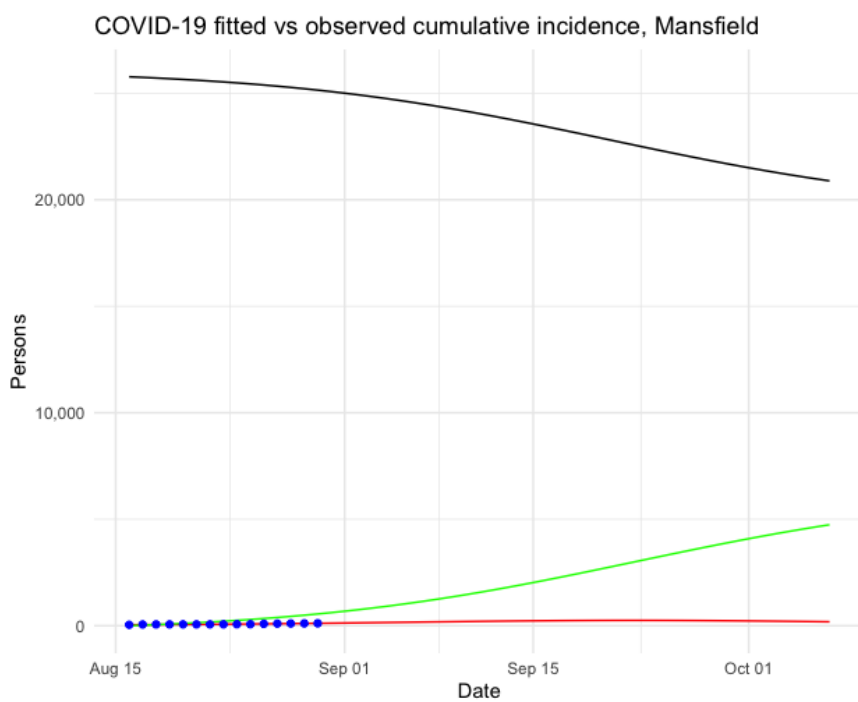


Figure 3: The blue dots are the confirmed cases and the SIR model shows the prediction in the next 30 days

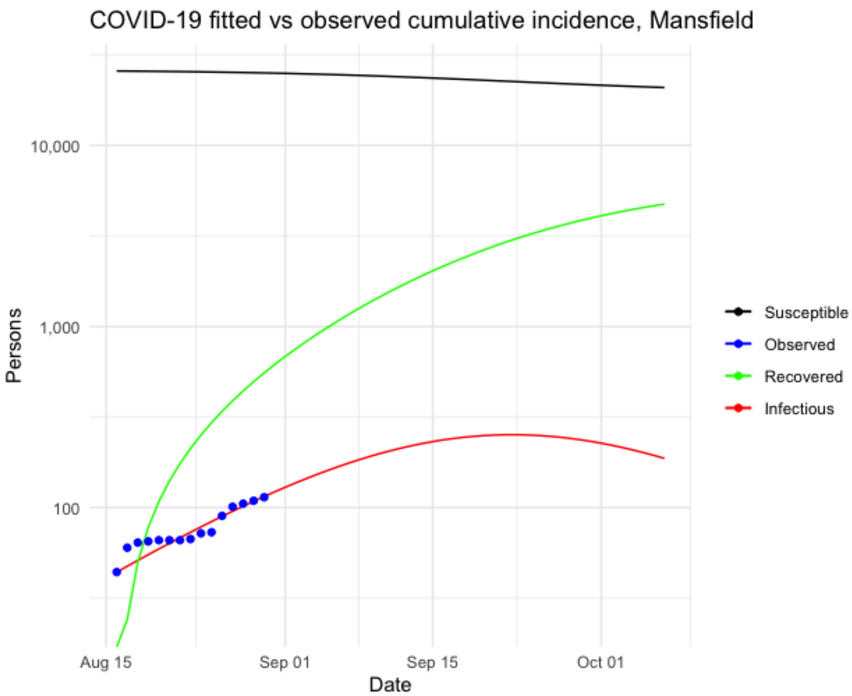


Figure 4: Figure 4 is transforming y-axis from Figure 3 to a log scale

Figures 5, 6, and 7 show different levels of lockdown based on the policies. These results are using QGIS to locate the University of Connecticut, arranged with 1000 individuals for 200 days. It is essential to know that we assume there will be an intersection between individuals in the day and night. Thus, we are simulating 200 steps, which are 100 days. We are using the parameters 0.6024 and 0.6265 as the infectious rate and recovery rate. To run the simulation, we are adjusting six different parameters according to different policies. The baseline scenario shown in Figure 5 displays that all the parameters are set to zero, which means the whole campus and public places are locked down. After 200 days, we can see 27% infected, 14% recovered, and 592 out of 1000 individuals are still in suspected status. Figure 6 presents a phase 2 reopening policy in Connecticut, with up to 50% capacity indoors with 6 feet social distancing. The results show the infected and recovery rates are 30% and 18%, and 520 out of 1000 individuals are in susceptible status. Depending on phase 3 reopening policy from the Connecticut government, we adjust the parameters and run the third case (Figure 7), which up to 75% capacity indoors, including restaurants, personal services, and libraries. The results display that 498 out of 1000 individuals are in susceptible status, and the infection rate and recovery rate are 35% and 15%. Based on these results, it is clear that case 3 has higher risks and infection rates than the baseline case and case 2.

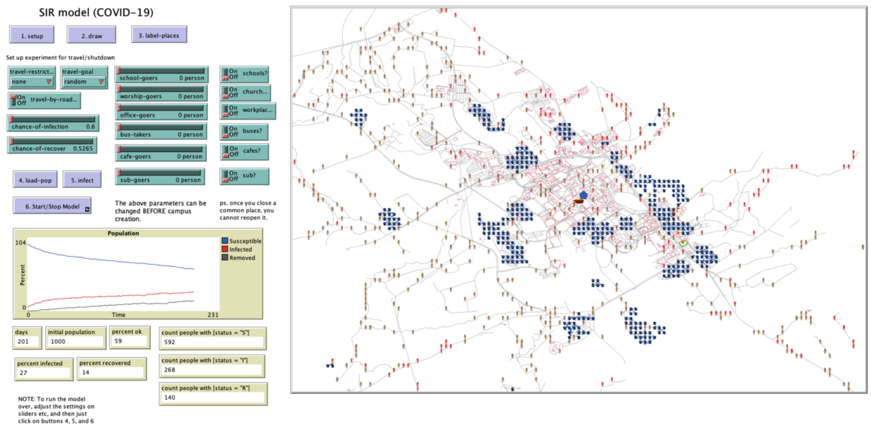


Figure 5: This is a baseline scenario

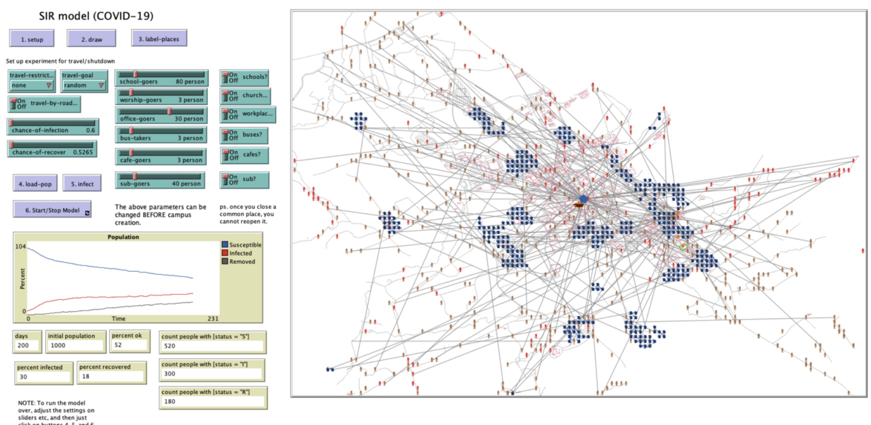


Figure 6: Figure 6 presents a phase 2 reopening policy, with up to 50% capacity indoors

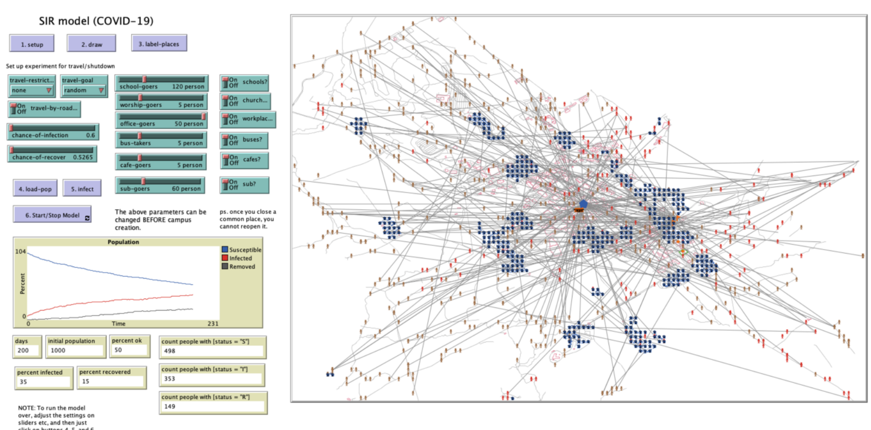


Figure 7: Figure 7 is phase 3 reopening policy, with up to 75% capacity indoors

# 4. Discussion and Conclusion

We have conducted one SIR model and three agent-based modelings to predict and address the COVID-19 spreading at the UConn campus. We extend the SIR model to a spatial dimension, using RStudio, QGIS, and NetLogo software. Results present that phase 2 of the reopening policy is the most effective way to decrease virus transmission. The spatially-explicit models may help policy-makers for targeted interventions and targeted reopening business in specific locations. Areas free from infection can be free of restrictions if it is deemed safe to do so. The spatially-explicit simulation results would make it easier for decision-makers to locate the hotspots of covid-19 and take proper intervention actions in these hotspots areas while open business in other less affected areas.

In this paper, we demonstrate that phase 2 of the reopening policy can minimize the virus's spreading while ensuring the regular operation of campus and businesses.

This paper analyses the risk level of different policies, which are commonly used in public health services on campus, to give suggestions to campus policymakers with evidence about what can be minimized the spread and safely quarantined when students are tested positive. We show that the prediction of the SIR model may be a useful input into campus policy, which evaluates which buildings are safe to allow quarantine and which have potential risks.

More detailed data is needed for improving the accuracy of models. Since COVID-19 has much uncertainty, we still need to collect the data and modify our models to fit the real situation better. Using the UConn data instead of Mansfield data would significantly improve the models' accuracy and help us have a better understanding of the models. We do not need to wait for the next outbreak before building and analyzing the model.

Currently, UConn is doing an excellent job of providing hand sanitizer, wearing masks, and quarantine buildings. The policies including quarantined students' need to eat during design hours, providing medical needs and free testing, and residential buildings are quarantined once there are positive cases.

Still, the policies right now are not sufficient to address the rising number of infections. Accordingly, as policymakers move forward with plans for further steps, it is essential that they focus on providing adequate and sufficient tests while safely reopening campus in order to prevent the spread of disease. Students who go back home during the semester need to get tested before going back to dorms or classrooms. Also, people who are not living on campus cannot go to dorms or classrooms without permission.

Isolate people confirmed positive cases to apartments such as Northwood apartment, Charter Oak apartment, or Busby suites. As confirmed cases increase, it will be significant to stop further spreading, especially in residential halls. The population density in residential halls is different from houses. Students' interactions in the building before quarantine are high, such as elevators, bathrooms, and lounges. Once there is a confirmed case, other students who live in the same building have higher chances of getting infected. Currently, the residential policy quarantines the whole building, and students cannot attend in-person classes [7]. However, it only decreases the exposure in classrooms, but still has risks to infect in the residential halls. Students who confirmed positive should be isolated somewhere with a lower population density and far from the central campus.

As the vaccine for COVID-19 coming available, UConn needs to make a list of the allocation priority. Minority groups such as International students and out-of-state students are more vulnerable because they are far from home and having less access to local resources. Compared to long-term residents, who live on campus, transfer students and off-campus students have higher risks of carrying viruses. We can easily trace whom the students who live on campus have interaction with. In contrast, it is hard to track who had contact with the student who transferred or live off-campus. Before the new semester begins, students and staff who come to campus need screening and testing.

There are limitations to our paper. First, due to there is no public data on UConn students' confirmed cases, we estimate the cases at UConn by the proportion of Mansfield's population and the number of infected people. Second, the age group of UConn is mainly young people, which is different from Mansfield. Thus, the recovery rate at UConn may be higher compared to Mansfield. Because of the data uncertainty issue, the models fitted to covid-19 confirmed case data in this study are probably not very reliable. Model parameters associated with covid-19 transmission rate probably also have uncertainty. The parameter uncertainty may propagate through the models, therefore, unavoidably generated uncertainty in the simulation results. Despite these limitations, we believe that this paper helps arrange the reopening policy, providing risk scores of buildings and shops, especially when the holiday is approaching. There are many factors related to covid-19 transmission such as from political and societal issues to ethical and cultural standards, which are difficult or impossible to be represented in any model. It is impossible for any model to predict the situations of the covid-19 epidemic very accurately. Our simulated results can only serve as a guiding tool for policy-makers. We may incorporate more factors to better simulate the complex covid-19 situation. However, we also realize that the increased complexity of a model usually comes with increased difficulty for manipulation, analysis, computation, and implementation. The complexity of a model does not mean it could increase the accuracy of the simulation results.

## Reference:


1. The Flu Season. (2018, July 12). Retrieved October 24, 2020, from https://www.cdc.gov/flu/about/season/flu-season.htm

2. Robson, D. (2015, October 18). The real reason germs spread in the winter. Retrieved October 24, 2020, from https://www.bbc.com/future/article/20151016-the-real-reason-germs-spread-in-the-winter

3. Benjamin Rader, MPH, Christina M Astley, MD, ScD, Karla Therese L Sy, MS, Kara Sewalk, MPH, Yulin Hswen, ScD, MPH, John S Brownstein, PhD, Moritz U G Kraemer, DPhil, Geographic access to United States SARS-CoV-2 testing sites highlights healthcare disparities and may bias transmission estimates, Journal of Travel Medicine, , taaa076, https://doi.org/10.1093/jtm/taaa076

4. Satsuma, J., Willox, R., Ramani, A., Grammaticos, B., & Carstea, A. (2004, January 24). Extending the SIR epidemic model. Retrieved October 27, 2020, from https://www.sciencedirect.com/science/article/pii/S0378437103012287?casa_token=AtYHM_-q6Ca8AAAAA%3AmV4r9_ZTsQPeLX9_2fNxmu8kgQU5_U3CmrPauCUNYNSLS_e7IgfMS_-0cvaH8eoDyT33EQxvXoEIM

5. Bonabeau, E. (2002, May 14). Agent-based modeling: Methods and techniques for simulating human systems. Retrieved October 29, 2020, from https://www.pnas.org/content/99/suppl_3/7280

6. CT.gov. (2020). Sector Rules for Reopen. Retrieved October 29, 2020, from https://portal.ct.gov/DECD/Content/Coronavirus-Business-Recovery/Sector-Rules-and-Certification-for-Reopen

7. Hubbell, D. (2019, December 23). Novel Coronavirus Disease (COVID-19) Information. Retrieved November 17, 2020, from https://studenthealth.uconn.edu/updates-events/coronavirus/