Simulation of city-level response to COVID-19 using EpiModel extension SEIQHRF (Susceptible-Exposed-Infectious-Quarantined-Hospitalized-Recovered-Fatal)

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1. Introduction

State and city-level response to COVID-19 varies across the United States. The timeliness of action and specifics of the directives can differ greatly. The response by citizens has also begun to diverge. Although most people, at least 316 million in 42 states, are staying home as much as possible, protests and demonstrations have started growing to defy stay-at-home orders [1]. A number of states have also started to allow businesses and restaurants to reopen. This is led most aggressively by Georgia Governor Brian Kemp. The state reopened on April 24th, an action that has drawn concern from mayors in the state who point to rising coronavirus cases in their cities as evidence it is too early to return to normal [2].

Without a vaccine, COVID-19 is being contained using stay-at-home and social distancing orders to flatten the curve. Because of this, the way in which states and cities respond and continue to respond will be crucial to combatting the virus. Following recommended protocols will reduce spread and ease the strain on health care systems, ultimately lowering deaths. To model timelines of interventions, I leveraged an extension of the SIR (Susceptible-Infected-Recovered) *EpiModel* package in R, SEIQHRF (Susceptible-Exposed-Infectious-Quarantined-Hospitalized-Recovered-Fatal) [3], and modeled two cities. An SIR model is an epidemiological model that represents a population of individuals who transition from susceptible, to infected, to recovered in a closed population over time. The SEIQHRF extension expands upon SIR by including additional parameters (see section 3.1). I chose Boston, MA and Atlanta, GA as my two simulation cities; a city that has clear timelines and detailed orders and a city that may be returning to business as usual too early.

2. Dataset

The Harvard Global Health Institute provides numbers on hospital capacity (see Table.1). The data is publicly available on *data.world* [4]. The information is broken out by Hospital Referral Region (HRR) for 305 local hospital markets in the country. At this granular level, it's possible to show how a region's resources may be stressed as COVID-19 infection rates rise. To note, because of the large population of the two cities, I scaled the numbers by 100 so I could run the simulations locally.

Table.1

Hospital Referral Region (HRR)	Specifying a market within which people generally go to the same hospitals
Total Hospital Beds	Count of all hospital beds within an HRR that are set up and staffed
Total ICU Beds	Count of all ICU beds within an HRR that are set up and staffed
Available Hospital Beds	Number hospital beds that are unoccupied at any given time, on average
Potentially Available Hospital Beds	Number beds that could be available if 50% of used beds could be free
Available ICU Beds	Number ICU beds that are unoccupied on average
Potentially Available Hospital Beds	Number beds could be available if 50% of used beds could be free
Adult Population	Number people over age of 18 living within the HRR

3. Methods

3.1 Definitions

Susceptible (S)	Adult population of the city
Exposed (E)	Exposed and infected, asymptomatic person who is potentially infectious to susceptibles
Infected (I)	Infected and symptomatic person who is infectious to susceptibles
Quarantine (Q)	An infected person who self-isolates
Hospitalized (H)	Rate of progression from Infected to Hospitalized
Recover (R)	Rate of progression from Hospitalized to discharge
Fatality (F)	Rate of progression from Hospitalized to death
Compartment	Terminology used for the above terms for the Individual Compartmental Model (ICM)

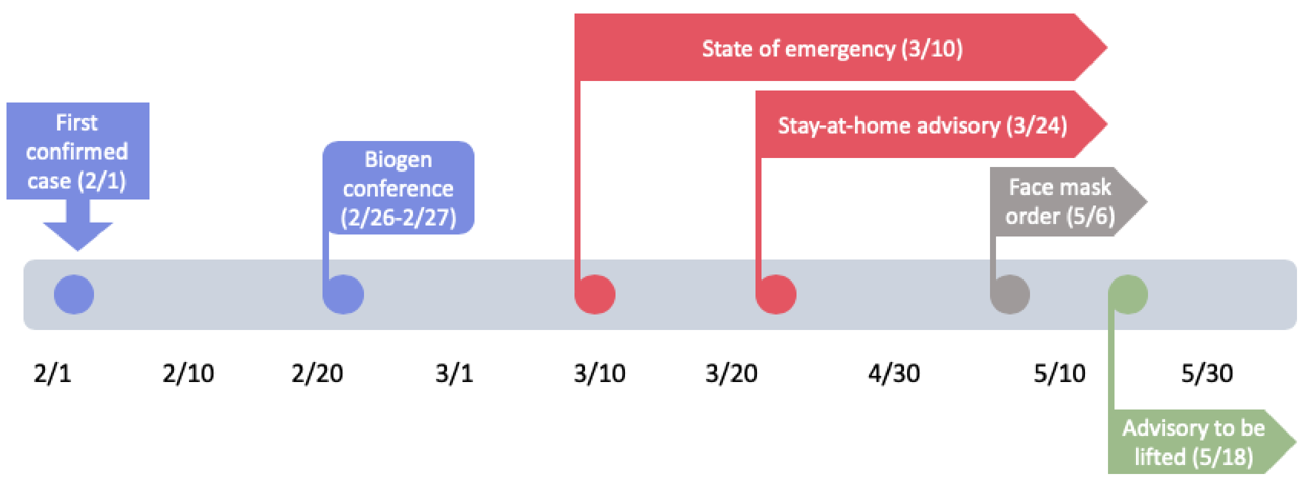
3.2 Baseline simulation parameters

The baseline is an average of 5 simulations generated for a full year with a business as usual approach, in which no COVID-19 policies are implemented. The same setup is used for both cities except for specifying hospital capacity and adult population numbers. To note, age-dependent fatality rates were not considered.

- **Progression rate** generated using random draws from a Weibull distribution with rate 1/10 (rate per day an Exposed becomes Infected); random binomial draws was computationally difficult
- **Average number of actions** between **E** and **S** person assumed to be 10 per day. To note, this is a high rate as residents go about their routine as normal.
- **Probability of passing on the infection** is assumed to be 0.05.
- **Progression from Infected to Quarantine** generated using a random sample with rate 1/30 (rate per day **I** go into **Q**). To note, this is a very low rate where most people do not self-isolate.
- **Progression from Infected or Quarantine to Hospitalized** using a random sample with rate 1/100 (1% of **I** or **Q** result in severe cases requiring **H**)
- **Progression from Hospitalized to Recovered** generated using a random sample with rate 1/15 (rate per day **H** is discharged)
- **Progression from Quarantine or Hospital to Recovered** generated using random draws from a Weibull distribution with shape parameter 1.5 and scale parameter 35
- **Progression from Hospitalized to Fatal** generated using a random sample with rate 1/50
- **Initial number of Infected** is 1 person

4. Results Boston, MA

The first confirmed case of COVID-19 in Boston was on February 1st. Over a month later, Governor Baker declared a state of emergency. By March 12th, over 100 people had tested positive for the virus, the majority of which were traceable to the Biogen conference held February 26-27th [5]. On March 24th, Baker announced a stay-at-home advisory effective until April 7th where non-essential businesses were ordered to close and restaurants and bars were restricted to takeout and delivery. Shortly after, the closure was extended to May 4th and then again to May 18th (as of May 8th).



4.1 Baseline simulation: business as usual

Using the baseline parameters, the simulation for a business as usual response to COVID-19 is as expected (see Fig.1). The surge in exposed and infected is exponential, peaking around day 40, with nearly 1 million people (25%) infected. The hospitalization and fatality curves seem reasonable and will be pulled out separately for analysis. There is a small proportion who self-quarantine, but without government intervention the assumption is most residents do not take precautions. Now that we have the baseline simulation and some plots, we can start to see how different actions can improve the baseline figures.

Fig.1 (a) baseline simulation

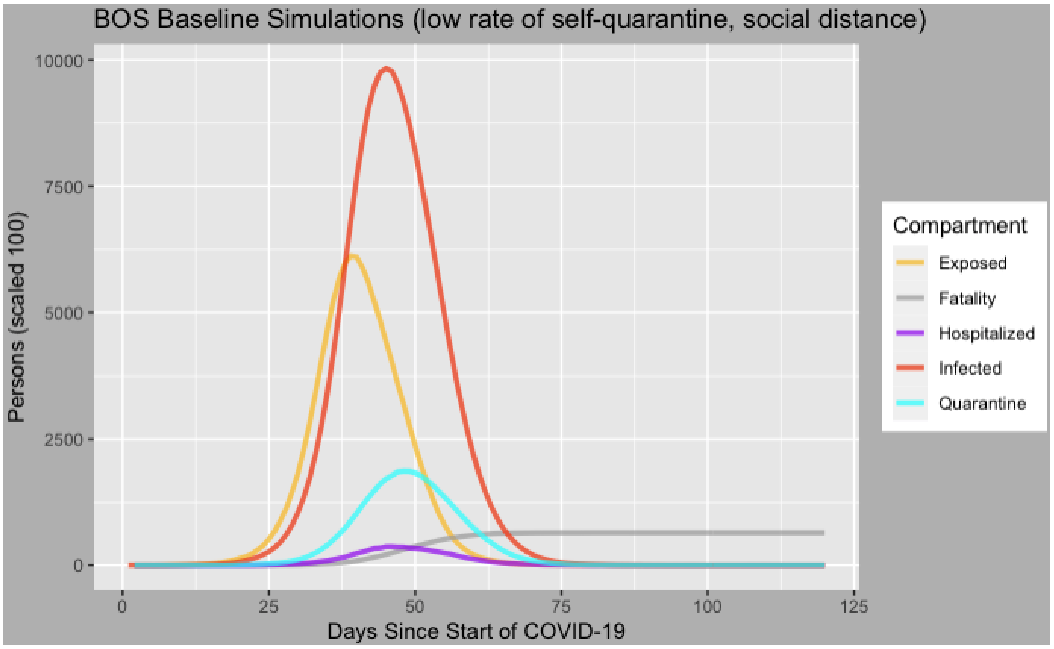
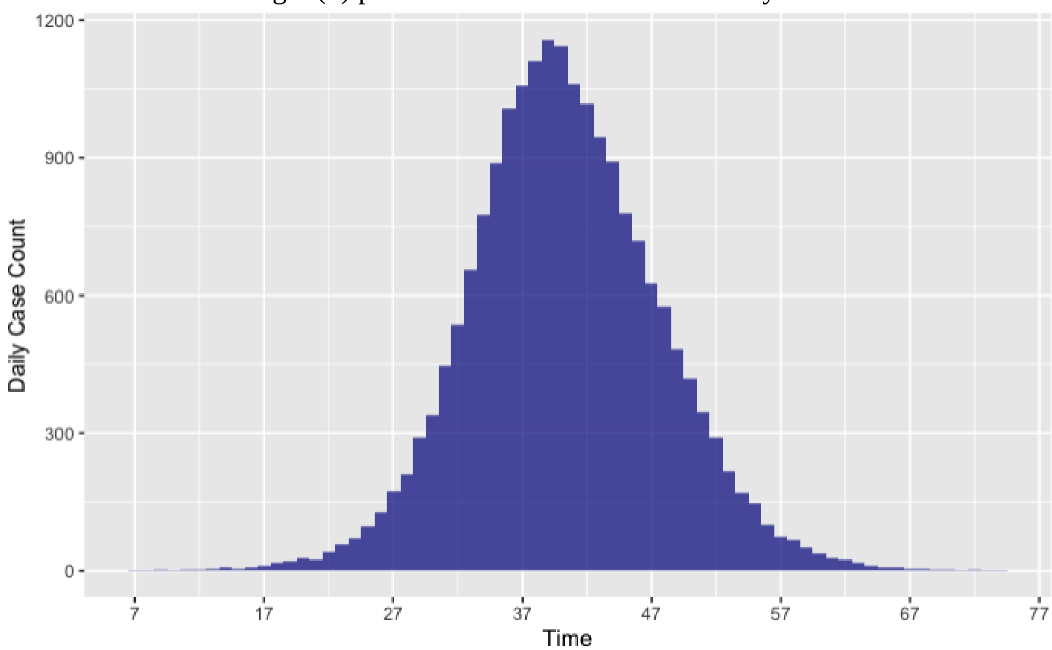


Fig.1 (b) peak of incidence curve around day 40



4.2 Intervention #1: majority of infected self-quarantine

The first intervention experiment models an increase in the self-quarantine rate over a two-week period. The parameter is gradually adjusted starting at day 15, about two weeks after the first confirmed case, from 1/30 to 7/10. This adjustment assumes that the majority of people did not begin to self-quarantine until after there were multiple confirmed cases and that the action would be implemented over a short period of time. The adjustment does not consider, however, those who were unaware of infection or "superspreading" events like the Biogen conference [5]. It is clear from the plot (see Fig.2), that advising self-quarantine for those who are sick significantly shrinks the peaks of the compartment curves. At the peak of the outbreak, the estimated number of active cases for exposed and infected are 85K (2%) and 10K (.3%) respectively.

Comparing the hospitalized and fatality curves against the baseline, self-quarantine helps to reduce the strain on hospitals and lowers the fatality rate. Although the hospitalization rates do exceed capacity at the peak, it is significantly improved from the baseline.

Fig.2 (a)

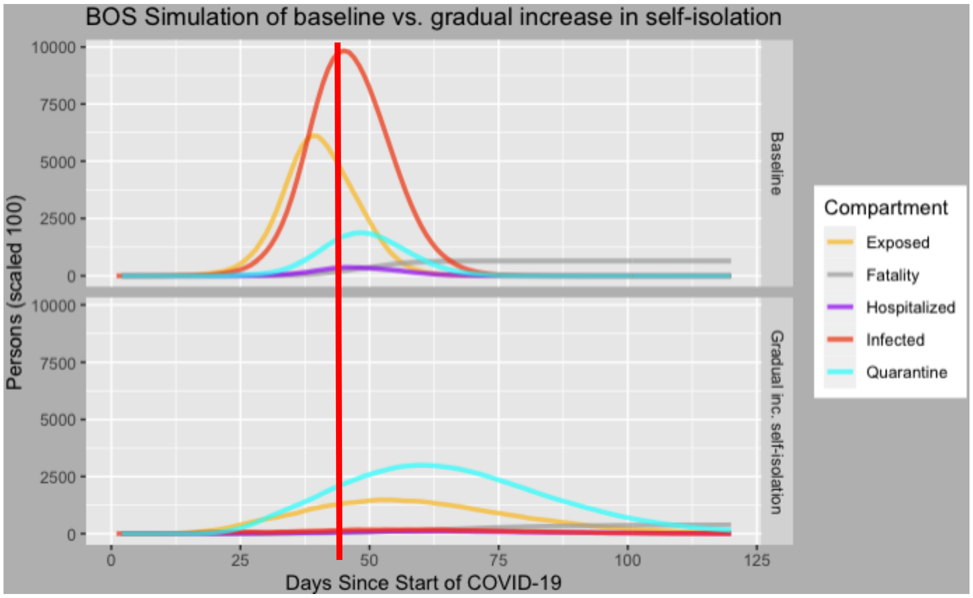


Fig.2 (b)

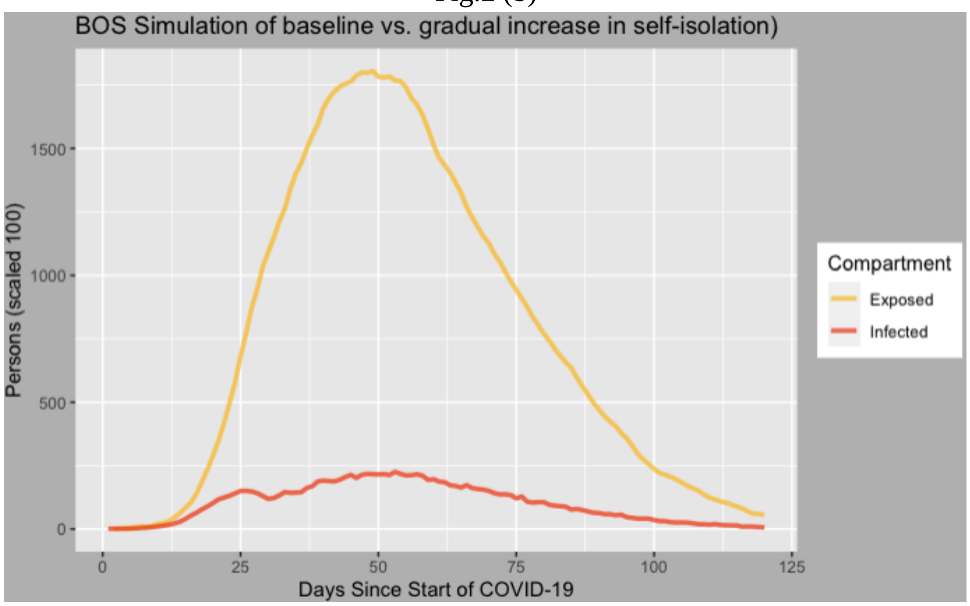
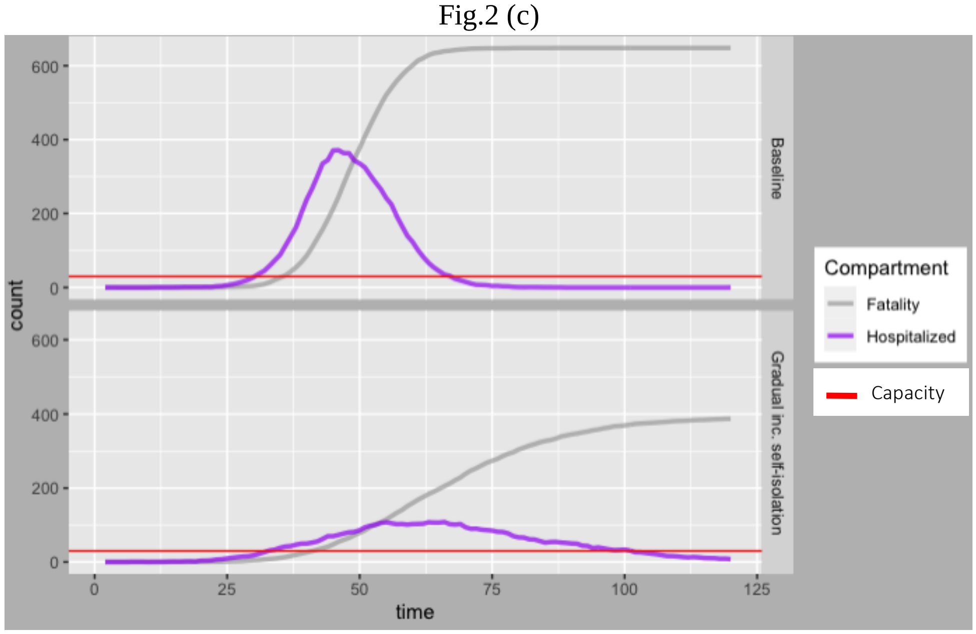


Fig.2 (c)



4.3 Intervention #2: majority of infected self-quarantine and hospital bed capacity is increased

The dataset includes an estimate for the number of hospital beds that could potentially become available if 50% of the non-COVID beds could free up. This figure was used for the second intervention experiment, which expands upon the first, simulating a gradual increase in self-quarantine rate and adding a gradual increase in number of available beds. The hospital capacity parameter is gradually adjusted at day 15 for 30 days.

Increasing hospital capacity while also considering an increase in self-quarantine rate, appears to substantially reduce the strain on hospitals in Boston (see Fig.3). Although still slightly exceeding capacity following the peak of active cases, the curve is flattening.

Fig.3 (a)

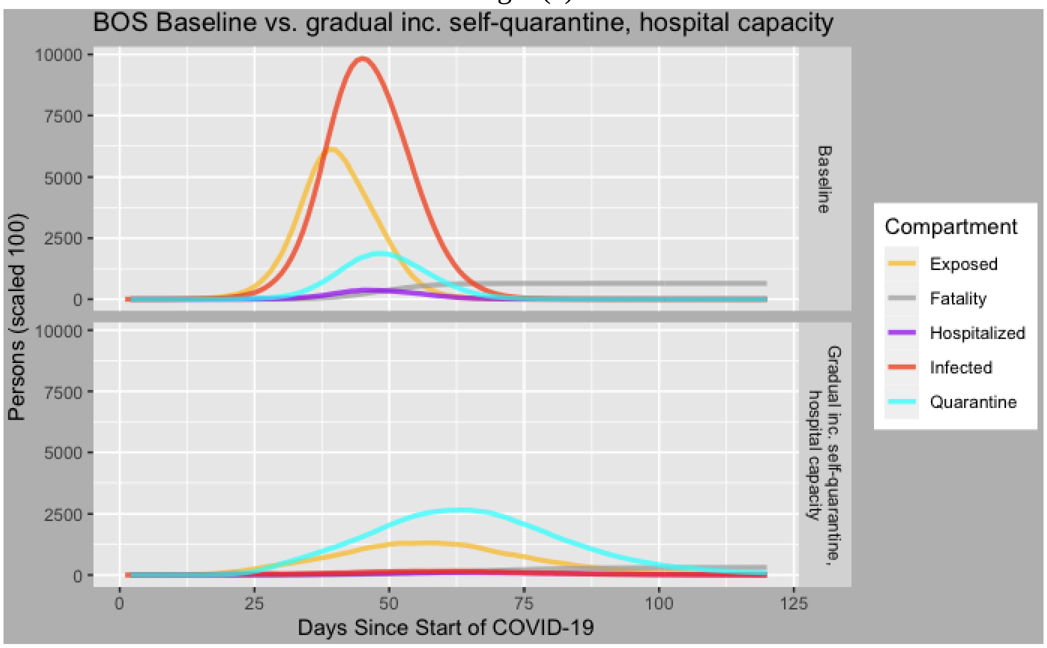
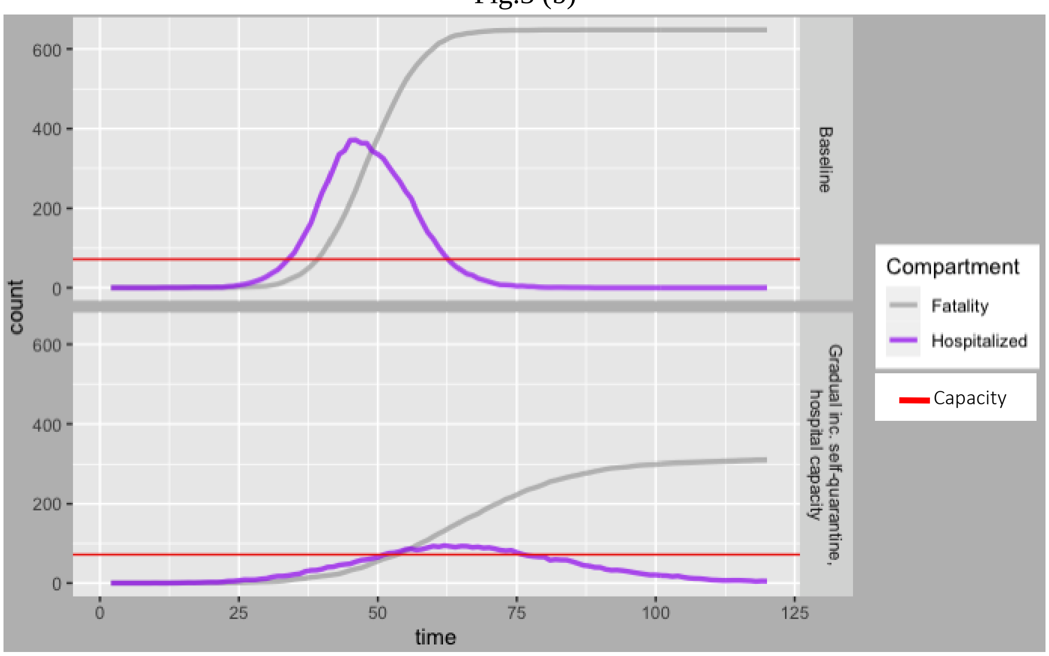


Fig.3 (b)



4.4 Intervention #3: majority of infected self-quarantine, hospital bed capacity is increased, and social distancing is implemented

Social distancing is an important containment measure as COVID-19 spreads mainly among people who are in close contact (within about 6 feet). Recent studies indicate that those who are exposed and asymptomatic likely play a large role in the spread of COVID-19 [6]. Social distancing helps limit contact with infected people and contaminated surfaces.

Therefore, the final intervention experiment for Boston combines self-quarantine, hospital capacity, and social distancing measures. The parameter is gradually adjusted starting at day 30, about a month after the first confirmed case, from 10 to 5. From the timeline, Boston was fairly slow in issuing a state of emergency after multiple confirmed cases were reported. The result is intuitive and clear from the plots (see Fig.4) that this is the ideal response to COVID-19. The compartment curves flatten, hospitalization projections meet capacity, and subsequently, fatality rates decline.

Fig.4 (a)

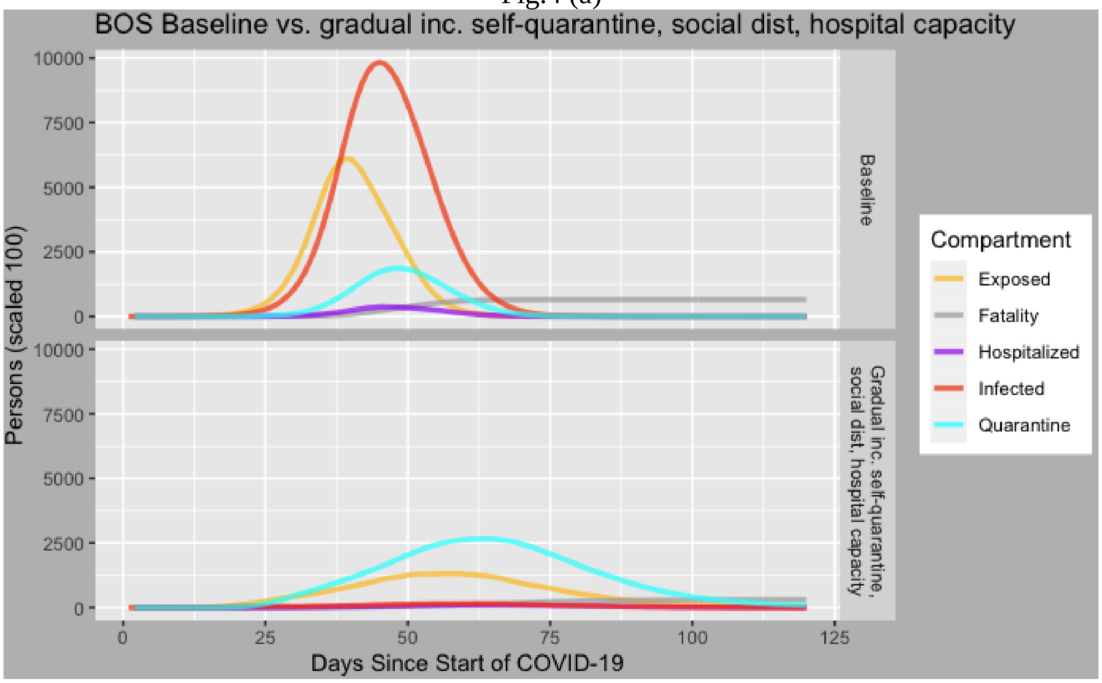
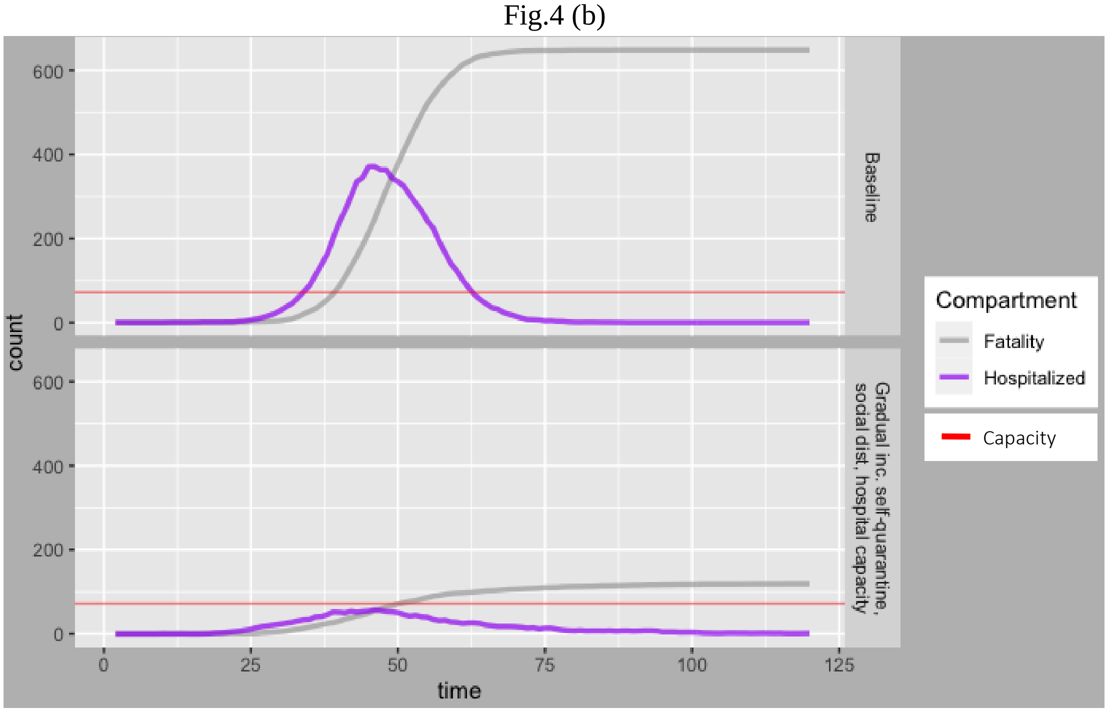


Fig.4 (b)



4.5 Comparison of the four simulations

The baseline model clearly articulates the consequences of ignoring the severity of COVID-19. The exponential growth of infection and the strain it causes on the health care system is evident. On the other hand, introducing interventions to the simulation has the best outcome in terms of lives impacted and saved. The four scenarios (see Fig.5) offer differing perspectives into the reality of the pandemic at the city-level.

Fig.5 (a)

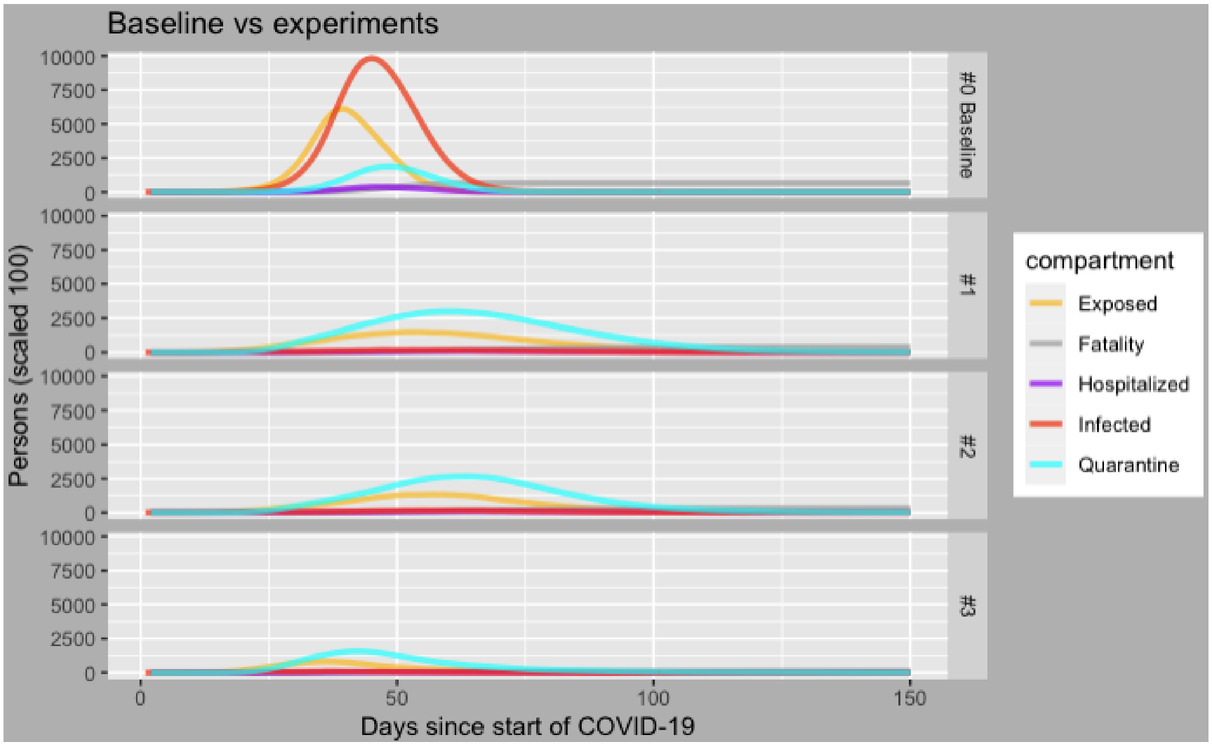
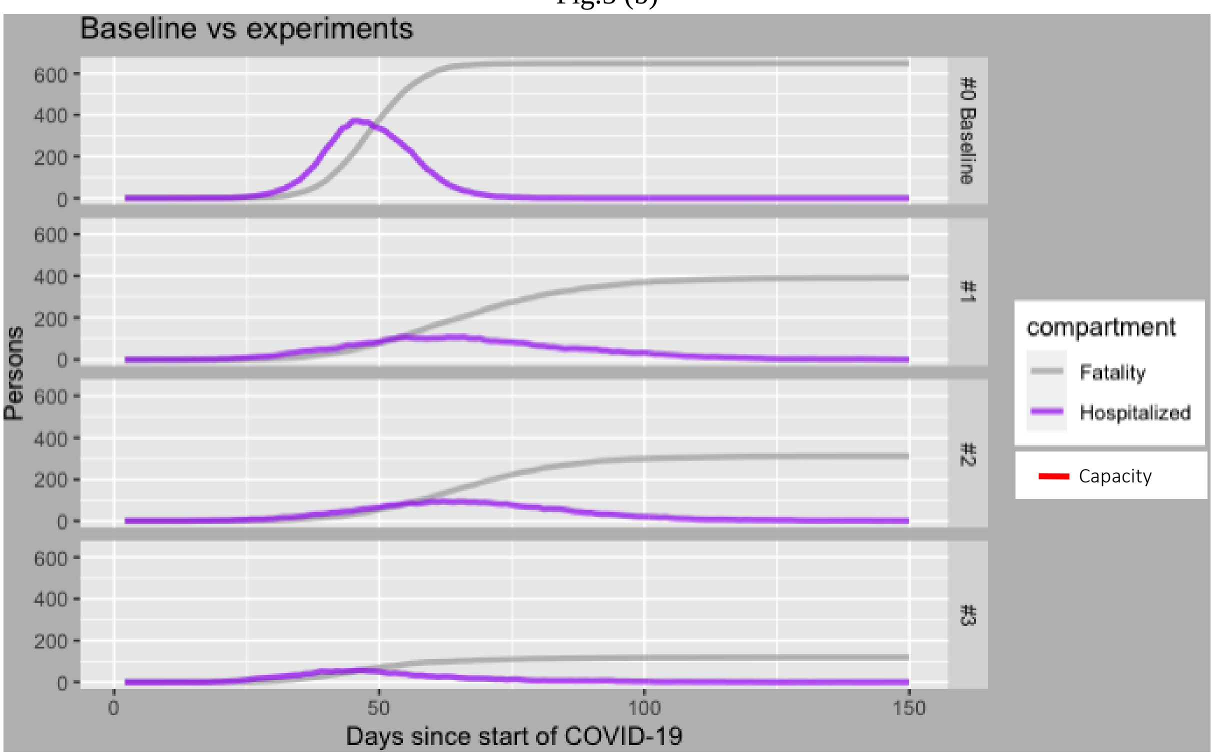


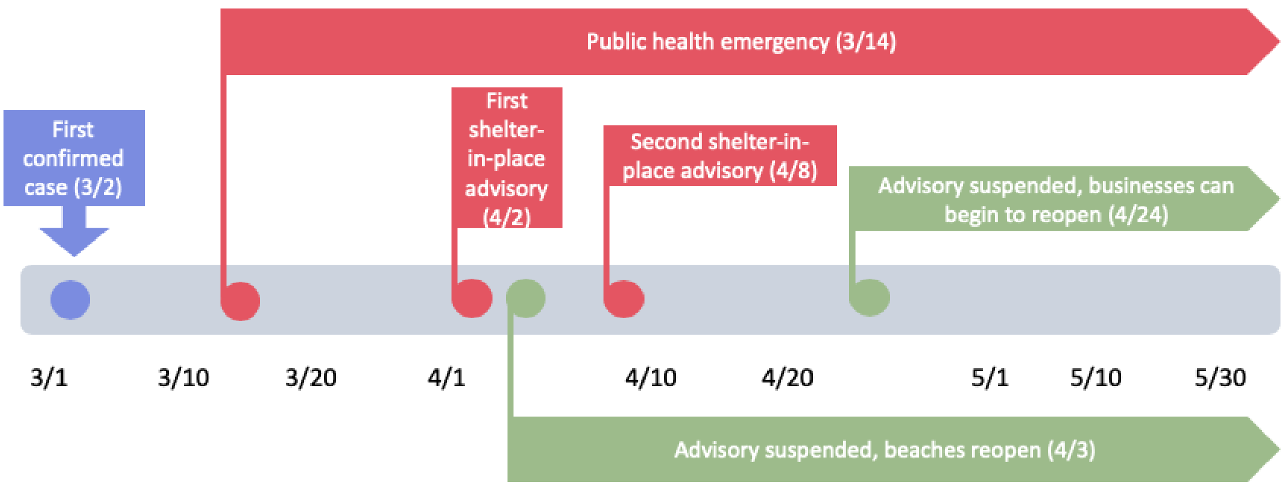
Fig.5 (b)



5. Results Atlanta, GA

Georgia's response to the outbreak is less linear than Massachusetts (see Fig.6). In Atlanta, the first confirmed case of COVID-19 was on March 2nd, although it was likely in the state much earlier [7]. Initially, Governor Kemp's actions were aligned with most states. He declared a public health emergency on March 14th followed by a statewide shelter-in-place order. Shortly after, however, Kemp's plan for the state began to deviate from others. A day after issuing the shelter-in-place mandate, Kemp suspended the order and reopened beaches. On April 8th, Kemp withdrew the decision and announced an extension of the shelter-in-place order through the end of April. But Kemp quickly reversed his stance again announcing that many businesses could begin to reopen on April 24th. The Governor's actions have been met by widespread criticism including Atlanta mayor Keisha Bottoms, who urged residents to continue to stay at home.

To understand the potential impact of reopening too early, an additional intervention experiment was simulated for Atlanta, in which social distance restrictions begin to return to near baseline levels after the advisory ends.



5.1 Baseline simulation: business as usual

Using the baseline parameters, the simulation for a business as usual response to COVID-19 is similar to what we saw in Boston (see Fig.6). The surge in exposed and infected is exponential and peaks around day 40 with 1.75M infected (34%).

Fig.6 (a)

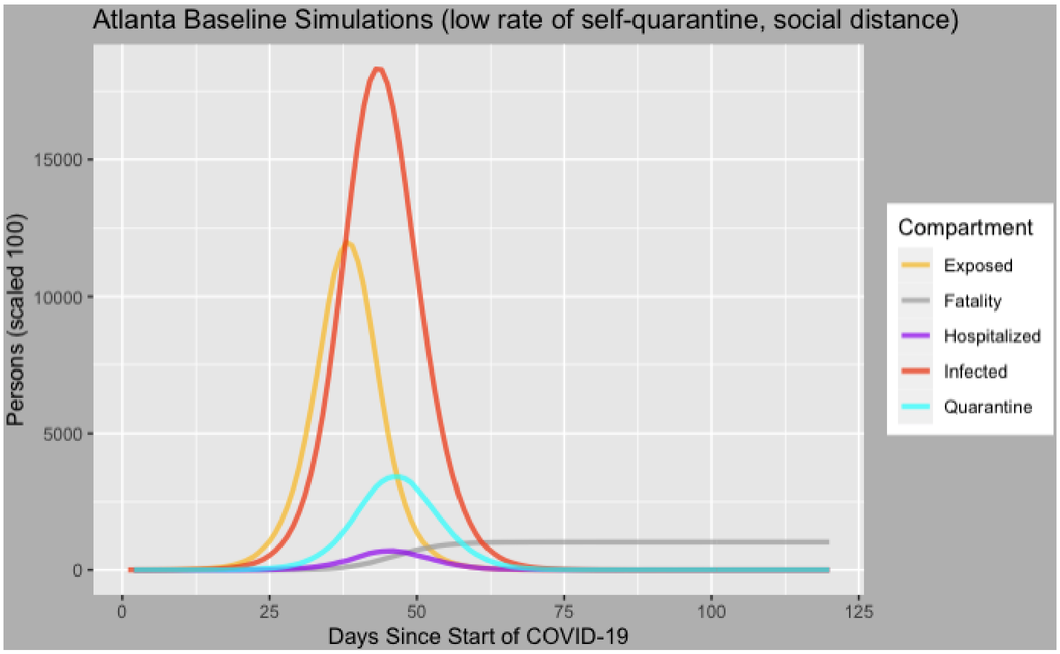
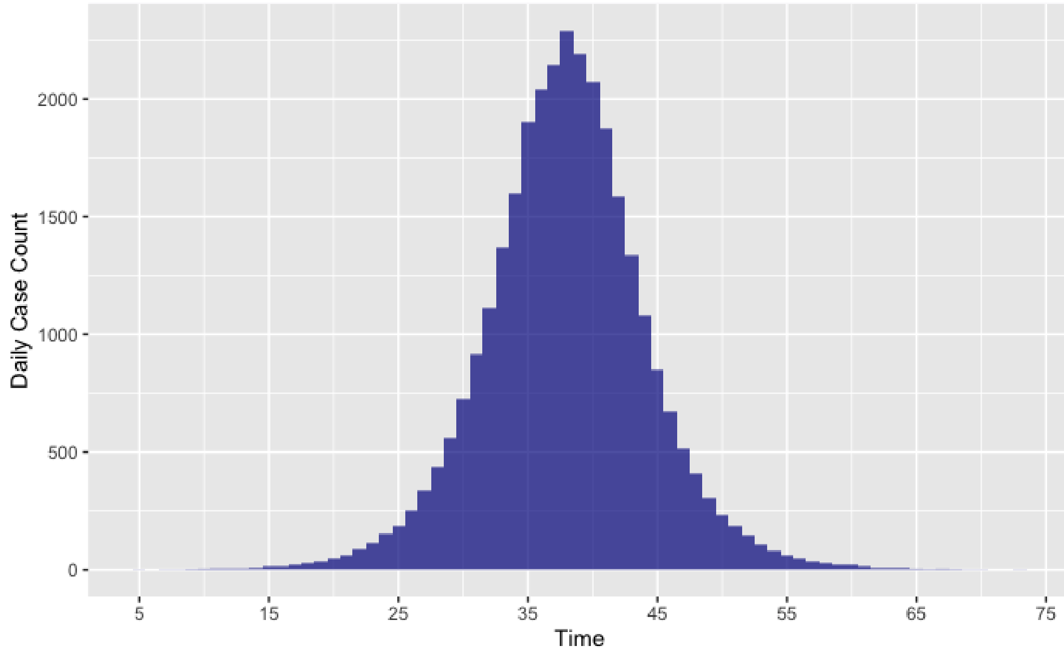


Fig.6 (b)



5.2 Intervention #1: majority of infected self-quarantine

The parameters for the first intervention experiment are the same as Boston. The model simulates an increase in the self-quarantine rate over a two-week period. The parameter is gradually adjusted starting at day 15, two weeks after the first confirmed case, from 1/30 to 7/10. At the peak of the outbreak, the estimated number of active cases for exposed and infected are 139K (3%) and 16K (.3%) respectively.

Fig.7 (a)

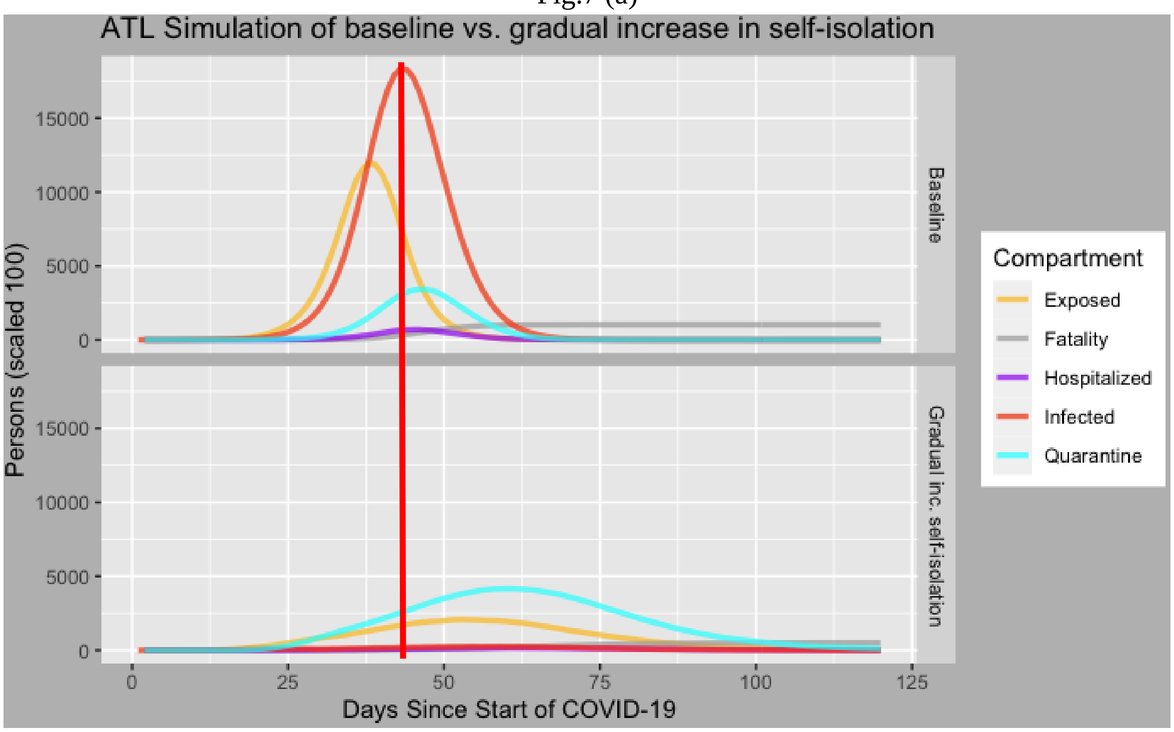


Fig.7 (b)

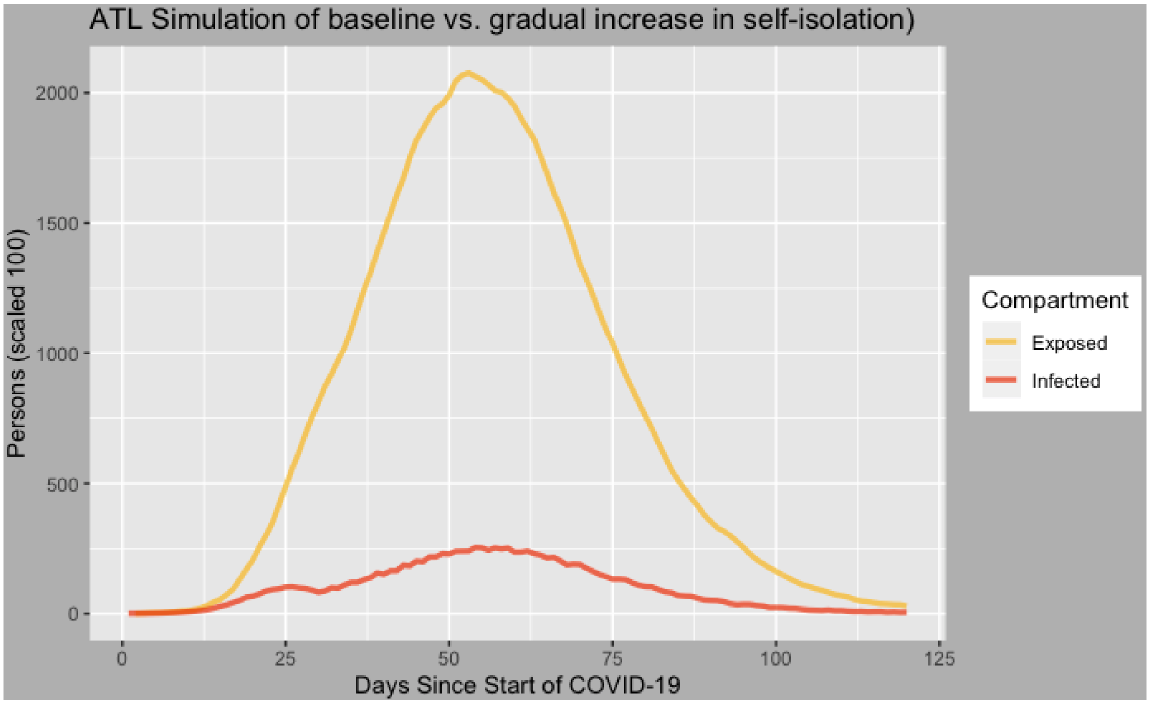
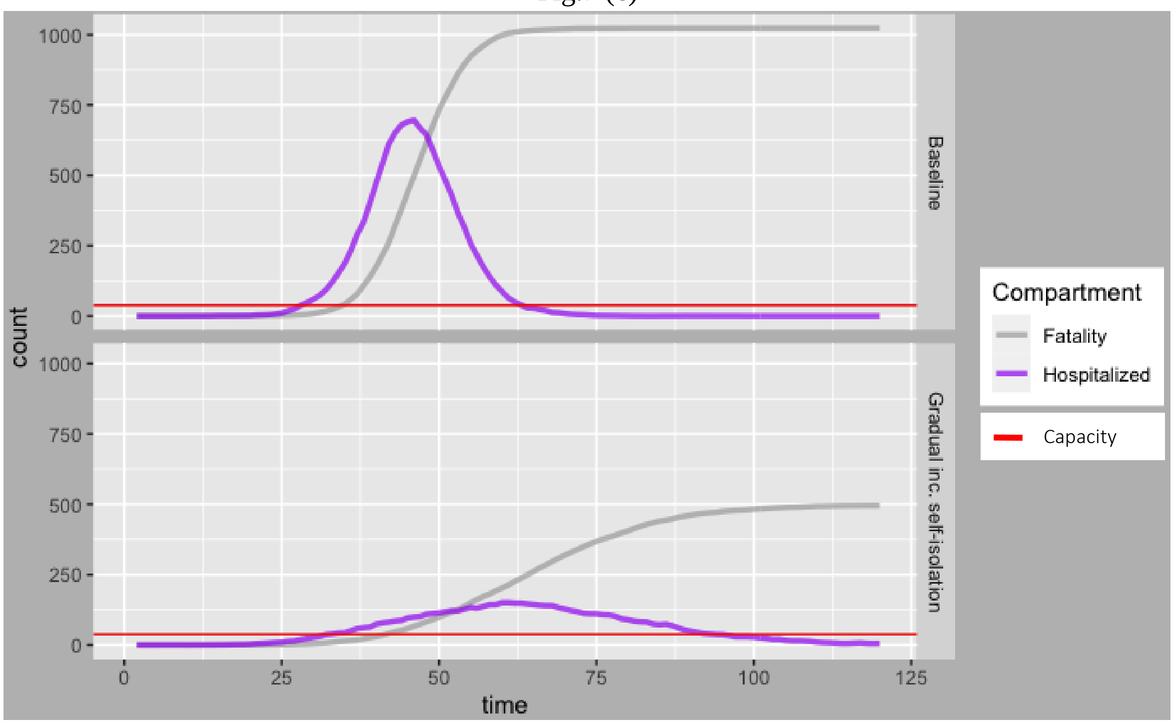


Fig.7 (c)



5.3 Intervention #2: majority of infected self-quarantine and hospital bed capacity is increased

Again, same setup as Boston as the two states had implemented similar policies at the onset. This experiment simulates a gradual increase in self-quarantine rate and gradual increase in number of available beds. The hospital capacity parameter is adjusted at day 15 for 30 days.

We see a similar trend as Boston, hospitalizations exceed capacity after the peak, but the curve is flattening (see Fig.8).

Fig.8 (a)

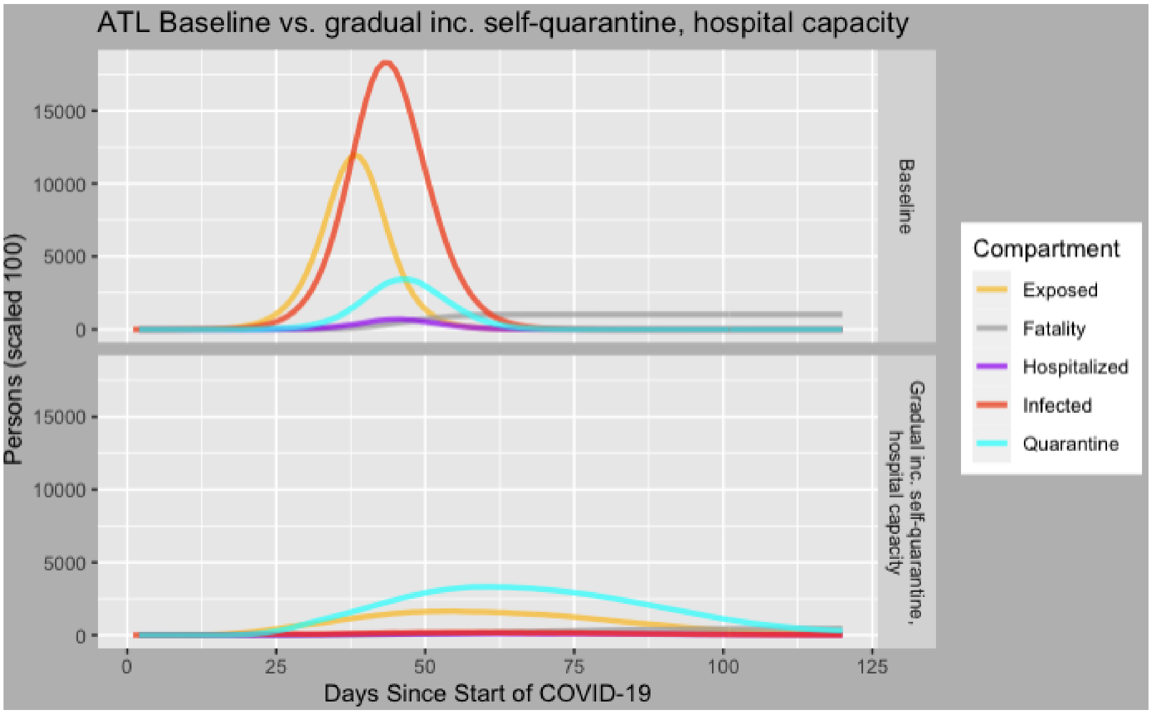
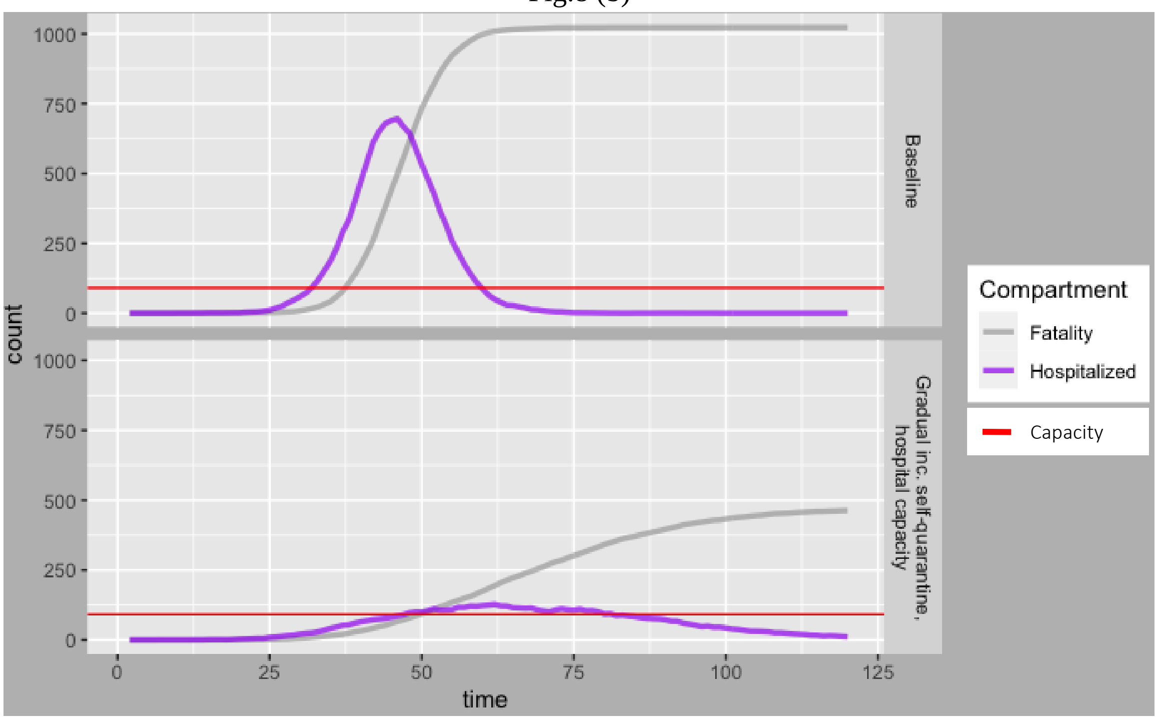


Fig.8 (b)



5.4 Intervention #3: majority of infected self-quarantine, hospital bed capacity is increased, and social distancing is implemented

The third intervention experiment for Atlanta combines self-quarantine, hospital capacity, and social distancing measures. As the timeline shows, although the state of emergency was declared sooner, the social distancing guidelines have been less strict than Massachusetts. Especially around tourist areas like beaches and parks. Since the reopening of Tybee Island on April 3rd, the beach has seen a spike in visitors. According to the *Georgia Recorder* out of Savannah, “tourists from the Northeast, Midwest and all over Georgia descended on Tybee Island over the weekend [May 2nd], creating scenes in the beach community typical of spring break or the height of summer vacation season, with little evidence of concern about catching or spreading the new coronavirus” [9]. For this reason, the social distancing parameter is slightly higher for the Atlanta simulation decreasing gradually from 10 to 7.5 over a two-week period. Following the timeline, the adjustment starts at day 15 versus day 30 for Boston.

It is clear that even with minimal social distancing measures, the intervention plays a significant role in a city's ability to manage the pandemic. The hospitalization projection is now within the city's hospital capacity (see Fig.9).

Fig.9 (a)

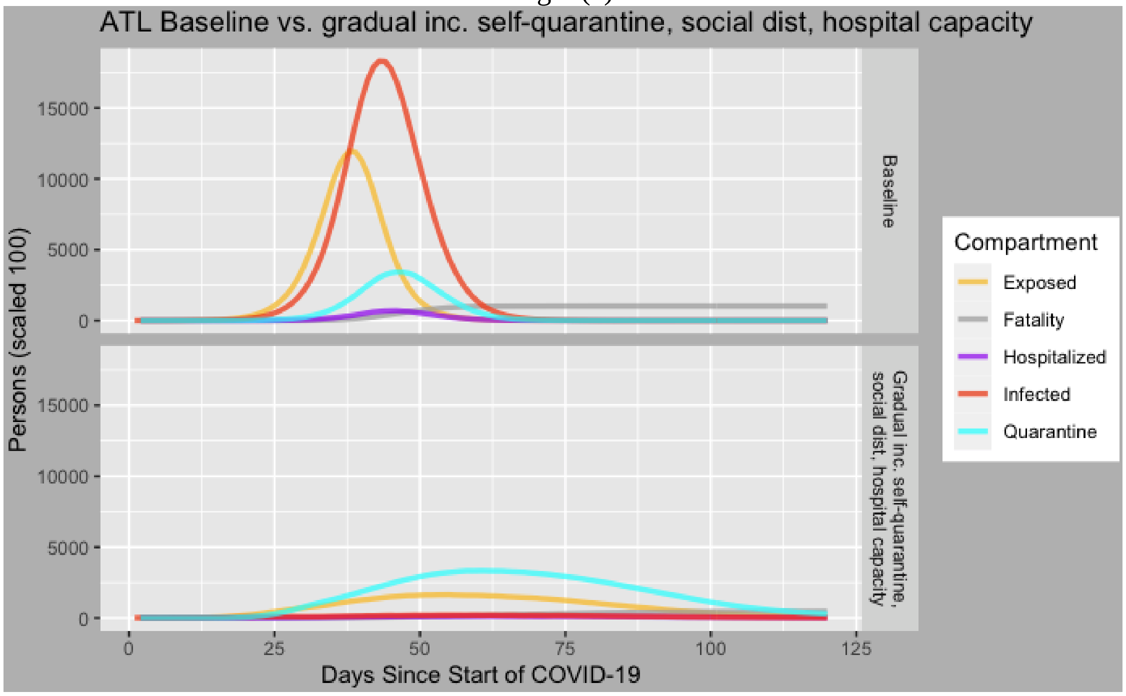
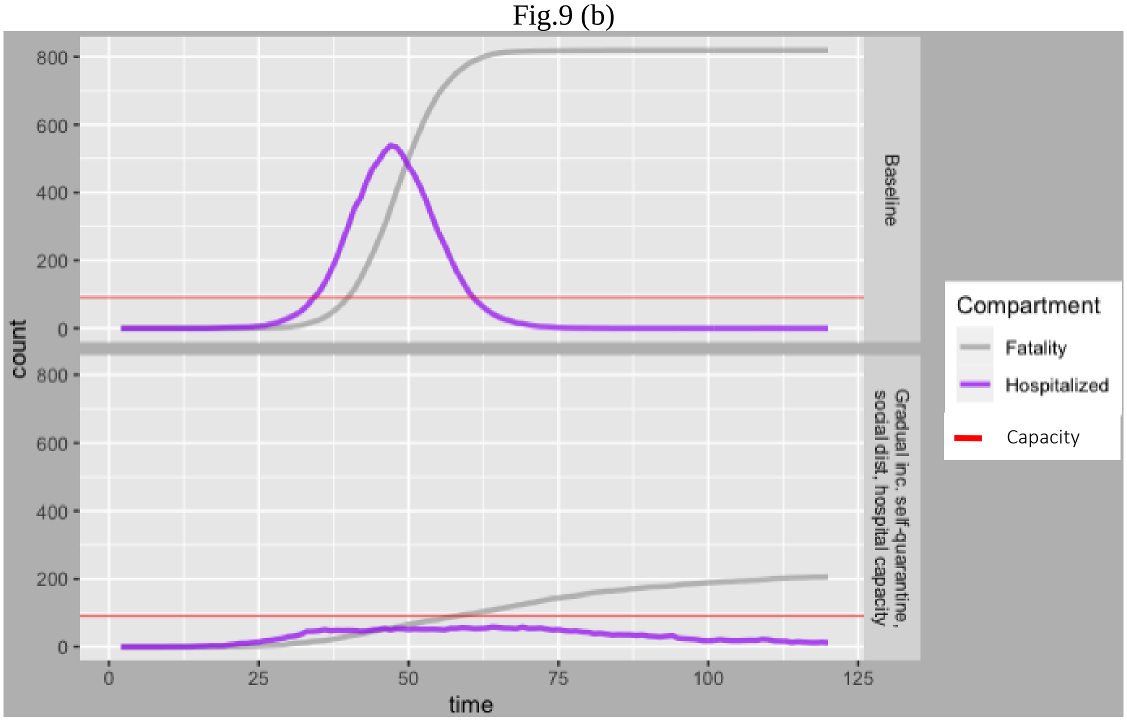


Fig.9 (b)



5.5 Intervention #4: majority of infected self-quarantine, hospital bed capacity is increased, but social distancing returns to normal

Although reopening Georgia has been met with criticism from many of the states' mayors and experts from around the country, Governor Kemp remains undeterred. While it has been reported that out-of-state visitors have "flocked" to Georgia, residents and business owners are conflicted over reopening [8]. The fourth intervention experiment simulates a gradual return to the social distance baseline over the span of 30 days starting at day 30. Many residents and business may remain cautious, but with so many traveling to Georgia after it reopened the assumption is, on average, social distancing returns to nearly normal levels.

From the plots (see Fig.10), reducing social distancing guidelines prolongs the pandemic. The flattening of the curves is expanded and the pandemic continues for an additional 2 months. The hospitalized projection exceeds capacity around day 75 after having successfully controlled the virus in experiment four.

Fig.10 (a)

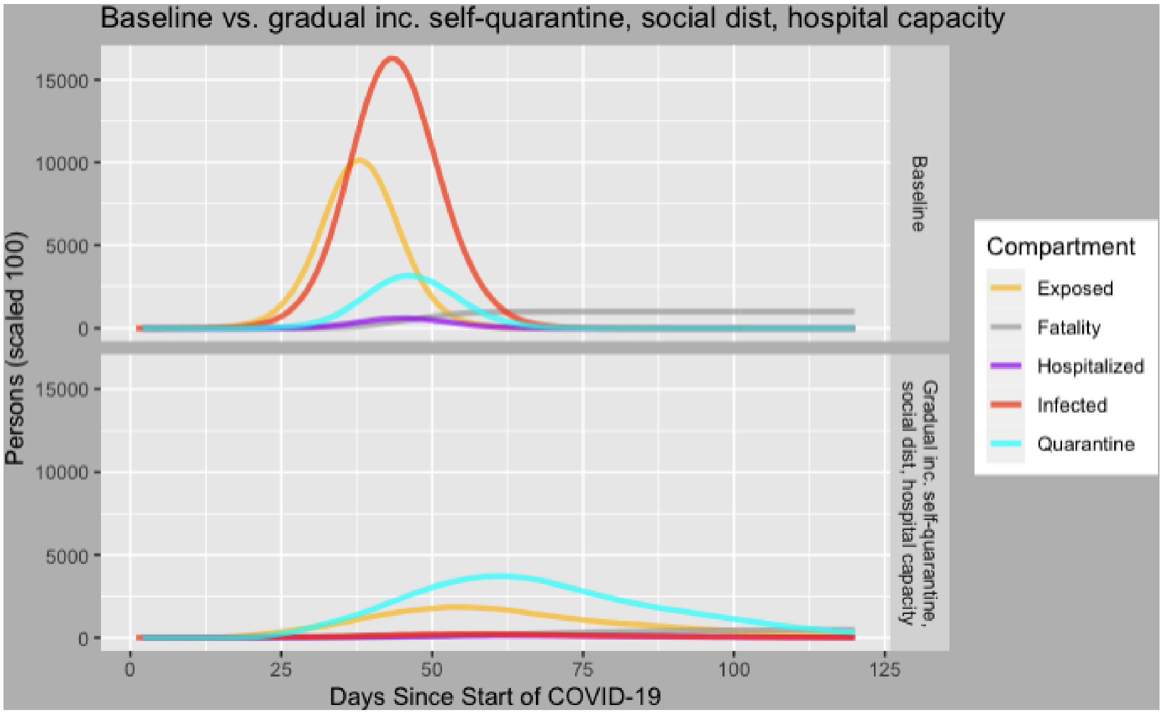
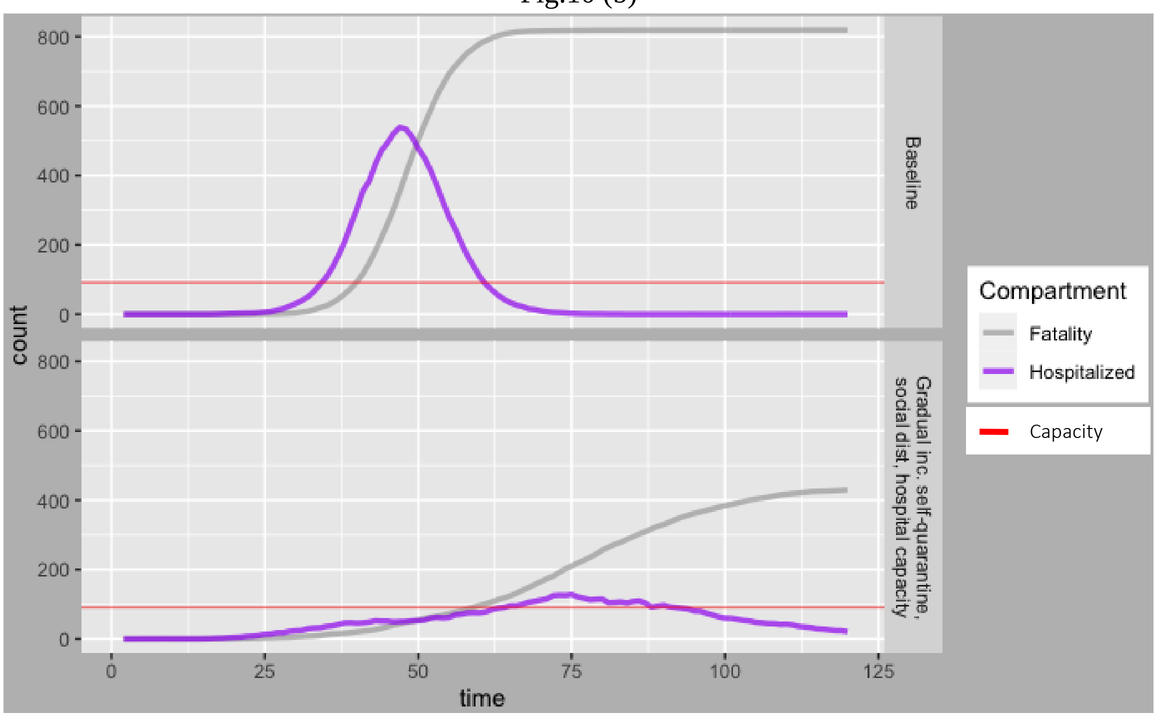


Fig.10 (b)



5.6 Comparison of the four simulations

Similar to Boston, without significant intervention, the exponential growth of infection is projected to strain the health care system. With Georgia open and the warmer weather bringing more visitors, the fourth experiment (see Fig.11) is the most relevant one. The second wave is a very real reality in which by the end of summer, the simulation indicates deaths could exceed 20,000.

Fig.11 (a)

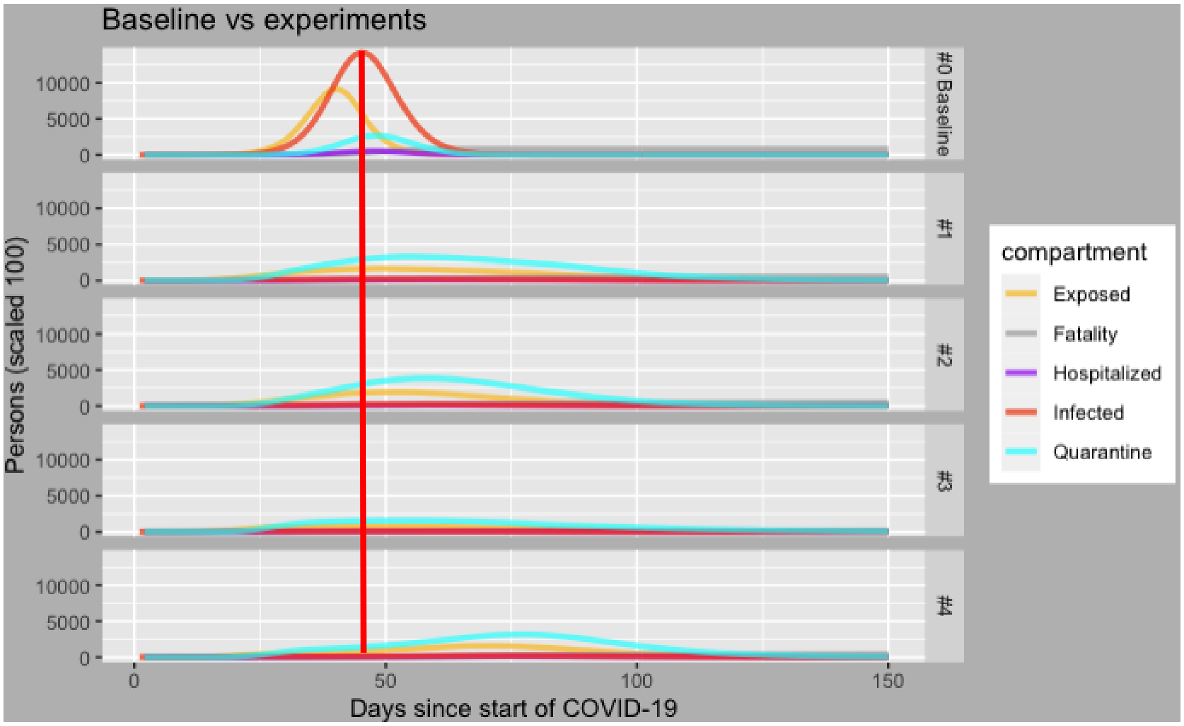
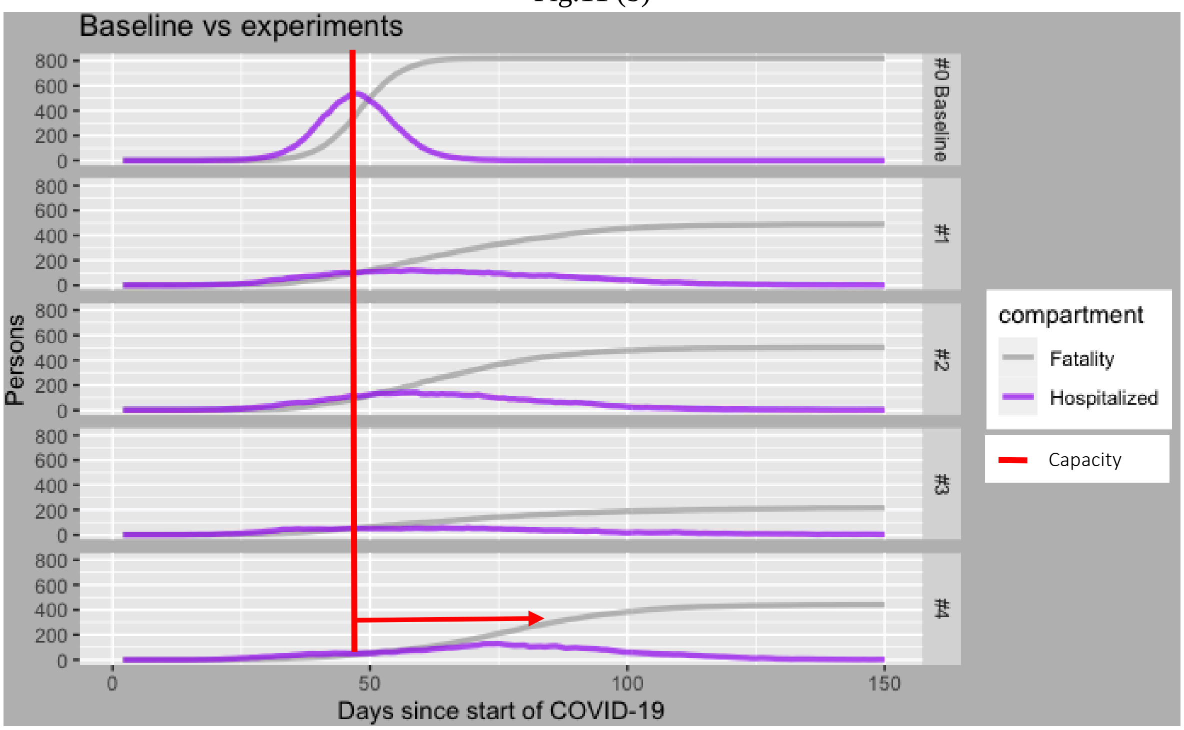


Fig.11 (b)



6. Conclusions

The purpose of this simulation was to assess the effectiveness of different response strategies to COVID-19 by modeling the timelines of two cities; Boston, MA and Atlanta, GA. This was done using an extension of the Susceptible-Infected-Recovered (SIR) epidemiological model in R called SEIQHRF (Susceptible-Exposed-Infectious-Quarantined-Hospitalized-Recovered-Fatal). At the start of the outbreak, the two states had similar approaches to containing the spread of the virus, but recent actions by Governor Kemp has the state diverging on policy. As was demonstrated by the different intervention experiments, guidance from local government is crucial to influencing individual behavior. The two cities have differing timelines, policy views, and as a result, different potential outcomes for its residents. For future analysis, it would be interesting to modify the model to reflect new timelines, different cities, and changing policies. It would also be more accurate to include an age-dependent fatality rate.

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[9] https://georgiarecorder.com/2020/05/04/social-distancing-takes-a-coastal-holiday-after-kemp-lifts-restrictions/