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Epidemiology modeling report

Task 1: Aspect of epidemic outburst to explore

In this project, we extend the traditional Susceptible-Infected-Recovered model by incorporating a Quarantined compartment. This new compartment represents individuals who have been identified as infected and isolated from the general population. The purpose of this model is to analyse the effects of quarantine measures on the control of epidemic outbreaks.

Task 2: Implemented properties and data

2.1 Implemented Properities

The key objective of this model is to evaluate the efficacy of quarantine measures in controlling disease transmission. The model will incorporate the following strategic modifications:

1. Introduction of a Quarantined compartment (Q) to segregate the identified infected individuals from the susceptible population.

2. Implementation of transitions from the Infected (I) to the Quarantined (Q) compartment based on a defined rate of quarantine (αiq).

3. Analysis of the recovery or progression of disease in quarantined individuals through a separate recovery rate (αqr).

These parameters are crucial as they directly influence the model's dynamics and can be used to simulate different public health strategies.

2.2 Sources of Data for Parameter Estimation

To estimate the parameters of this extended SIR model, we will consider the following sources of data:

1. Public Health Records: Data on the rate at which infected individuals are quarantined and their outcomes post-quarantine.
2. Clinical Studies: Information regarding the recovery rates and effective- ness of quarantine measures from detailed clinical studies.
3. Epidemiological Surveys: Surveys and studies providing insights into the behavior of the disease and the effectiveness of different quarantine strategies.

Task 3: Model Parameters and Compartments

3.1 Key Elements of the Model

The model incorporates various compartments to represent different stages and outcomes of the disease and vaccination process. Each compartment is defined as follows:

- Susceptible (S): Individuals who are not yet infected but can contract the disease.
- Exposed (E): Individuals who have been exposed to the disease but are not yet infectious.
- Infected (I): Individuals who are currently infectious.
- Recovered (R): Individuals who have recovered from the disease and gained immunity.
- Quarantine (Q): Individuals who have been tested and sent on quaran- tine.

3.2 Model Parameters

The model includes several parameters that influence the dynamics of disease spread and vaccination outcomes:

- β: Infection rate - influenced by the number of contacts and probability of infecting.

- γ: Recovery rate for people not on quarantine.

- σ: Infection rate in exposed individuals.

- αqi: Rate at which individuals leave the Infected compartment and are sent on quarantine.

- αqr: Rate at which individuals leave the Quarantine compartment because of recovery.

Task 4: Initial Conditions

The initial conditions for the epidemiological model are crucial as they set the starting point for the simulation and influence the model's behavior throughout its course. These conditions are based on realistic assumptions to ensure the model's applicability to real-world scenarios.

4.1 Population Setup

- Population size (N): The total population is assumed to be 100,000 individuals.

- Initial number of infected individuals (I_0): At the start of the sim- ulation, there is 1 infected individual.

- Initial number of susceptible individuals (S_0): Initially, all other individuals in the population, 99,999, are susceptible.

- Initial number of recovered individuals (R_0): There are initially no recovered individuals (0).

4.2 Parameters

The parameters set for the model, which are fixed and will not be explored further, include:

- Probability of infecting (β): Calculated as the product of the average number of contacts per individual (50) and the probability of infecting (1/200), normalized by the population size. This results in $\beta_{true} = \frac{1}{4000}$.

- Recovery rate (γ_{true}): Set at 1/14, indicating that it takes on average 14 days for an infected individual to recover.

- Incubation rate (σ_{true}): The incubation period is set at 7 days, resulting in $\sigma_{true} = 1/7$.

- Immunity waning rate (ρ_{true}): Immunity is assumed to wane at a rate of 1/60 per day.

- Rate from Infected to Quarantined ($\alpha_{IQ\ true}$): Set at 1/28, indicat- ing a transition rate from infected to quarantined status every 28 days.

- Rate from Quarantined to Recovered ($\alpha_{QR\ true}$): Set at 1/14, re- flecting the recovery rate from quarantined status.

4.3 Simulation Time Frame

The simulation starts at time t = 0 and ends at t = 360 days, with time steps of 1 day.

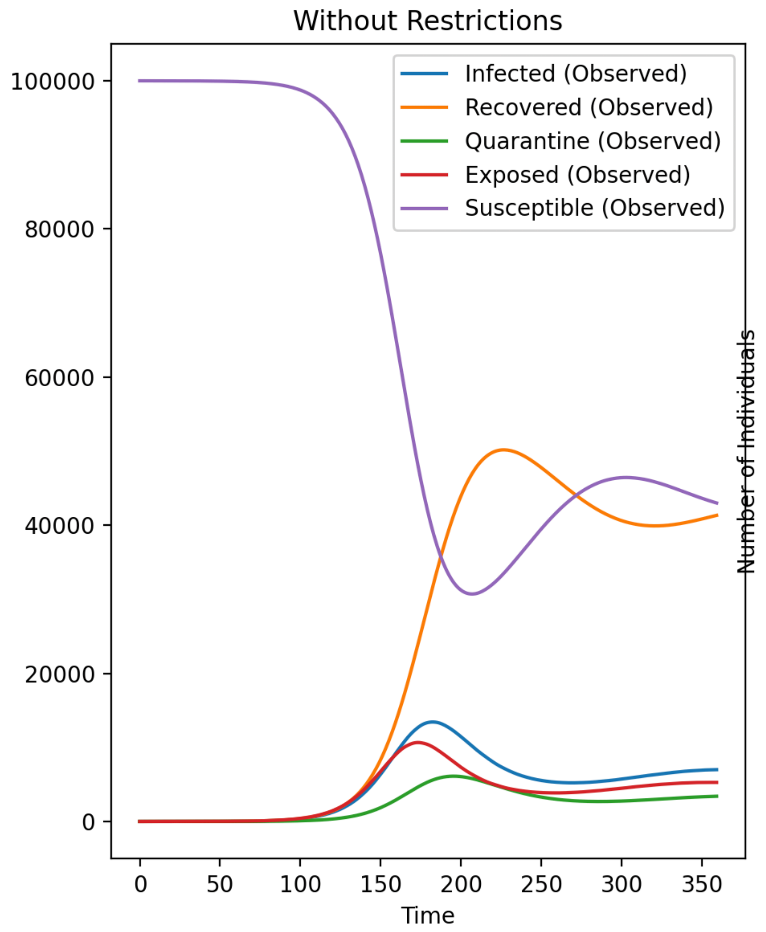
Task 5: Exploratory Scenarios

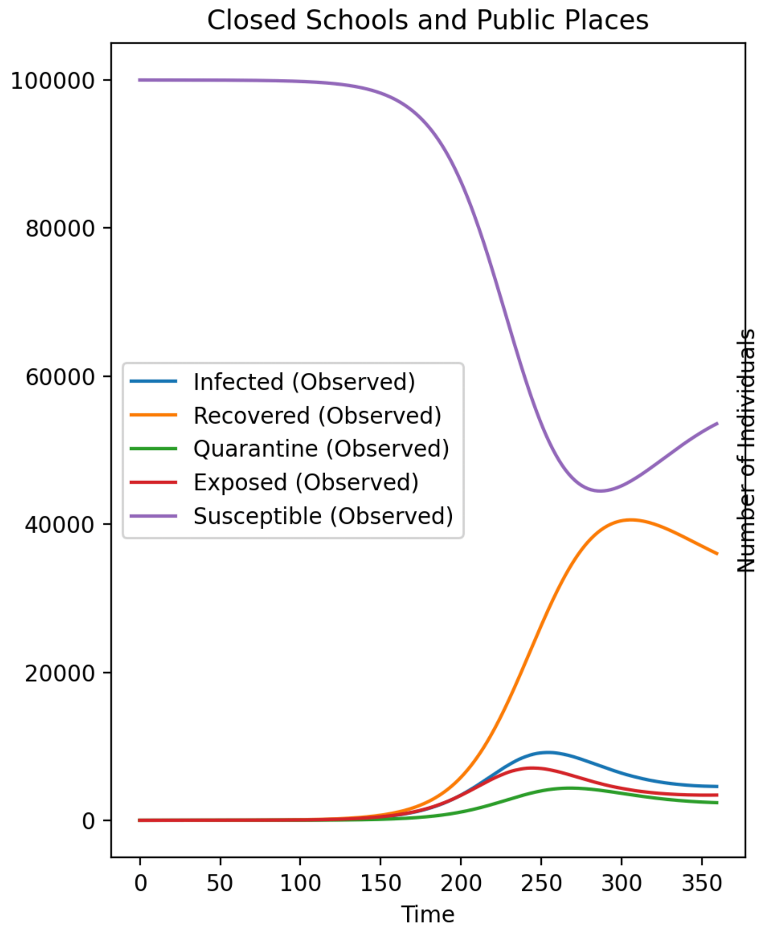
Scenario 1: Hospital Capacity and Social Restrictions

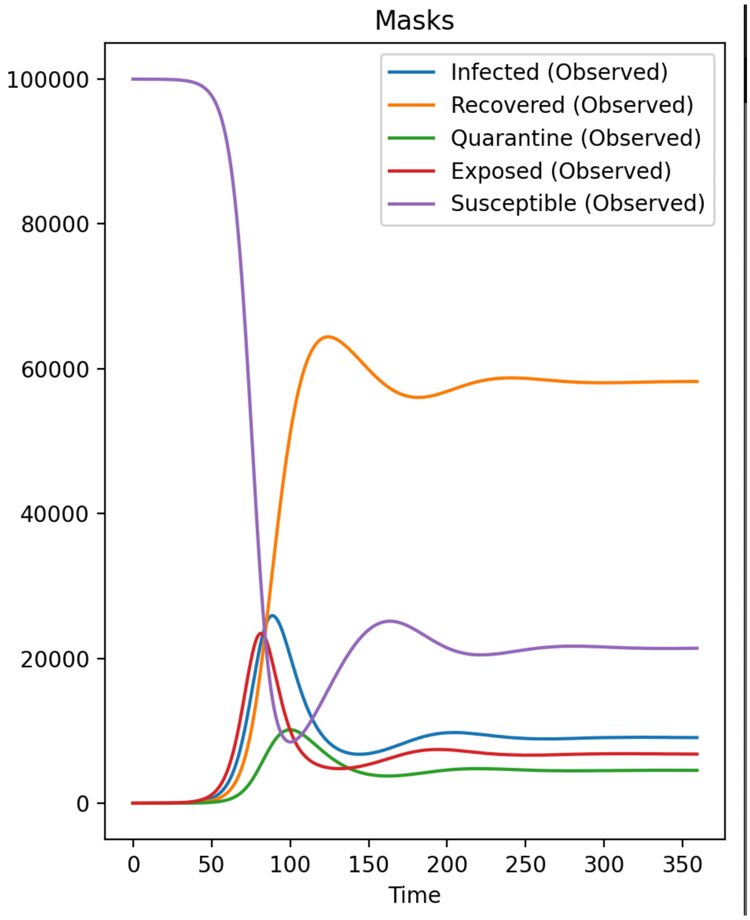
In this scenario β parameter is directly correlated with 2 parameters below:

The parameters which are represented by social restrictions:

- prob_of_infecting: Probability of Infecting — represents taken actions by the government (masks, social distancing, desinfectants)
- avg_no_contacts_per_individual: Average Number of Contacts per Individual — reduced in case of quarantine and simply by not being in public places.


Without Restrictions
Infected (Observed)
Recovered (Observed)
Quarantine (Observed)
Exposed (Observed)
Susceptible (Observed)
Number of Individuals
Time


Closed Schools and Public Places
Infected (Observed)
Recovered (Observed)
Quarantine (Observed)
Exposed (Observed)
Susceptible (Observed)
Number of Individuals
Time

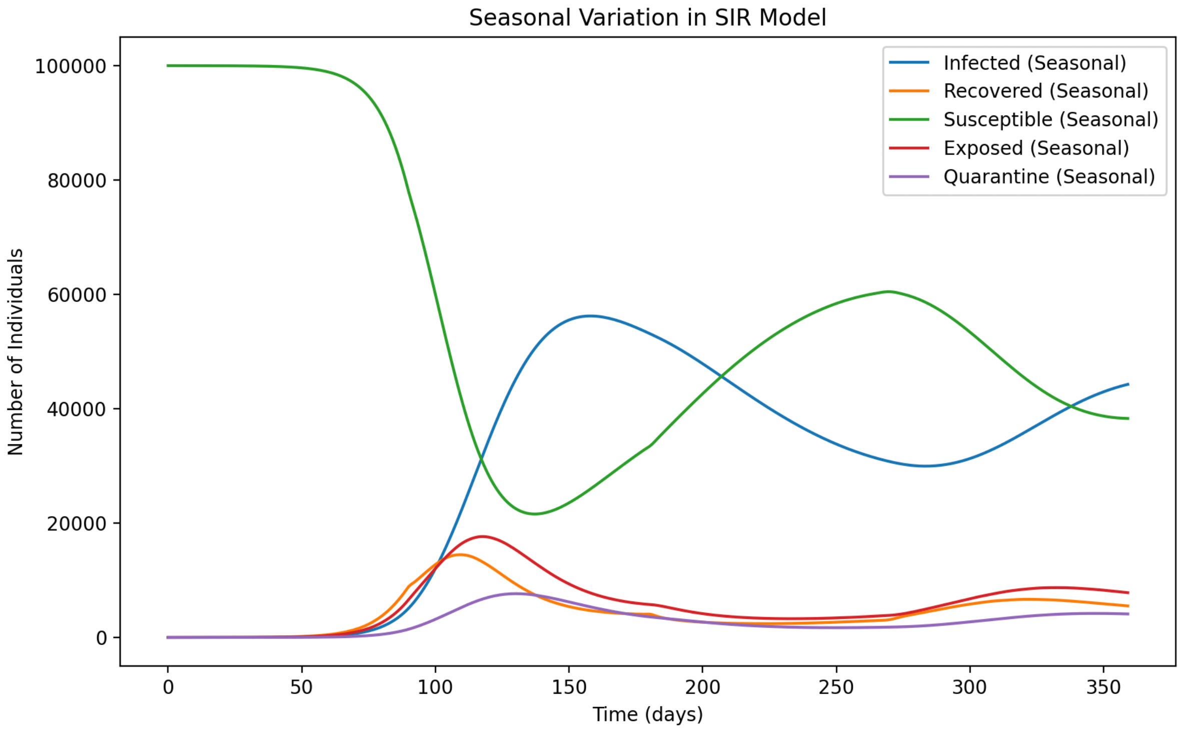


As we can see from the figures above, the least peak of infected individuals was spotted in the variation „Closed Schools and Public Places". Thus, we can say it is the most effective way to fight an epidemic. However, the biggest one (above 20 000 individuals infected was in the variation with wearing masks. Although, the probability of infecting is lower, the average number of contacts is still high. In our simulation, this evidently caused such a big peak but at the same time the number of susceptible individuals is distinguishably different. (Much lower in the scenario with wearing masks)

Scenario 2: Seasonal Variation

To simulate the seasonal changing of β parameter, it will be adjusted periodically:

- Winter: Increased by 50%.
- Spring: Increased by 20%.
- Summer: Decreased by 20%.
- Autumn: Normal beta.



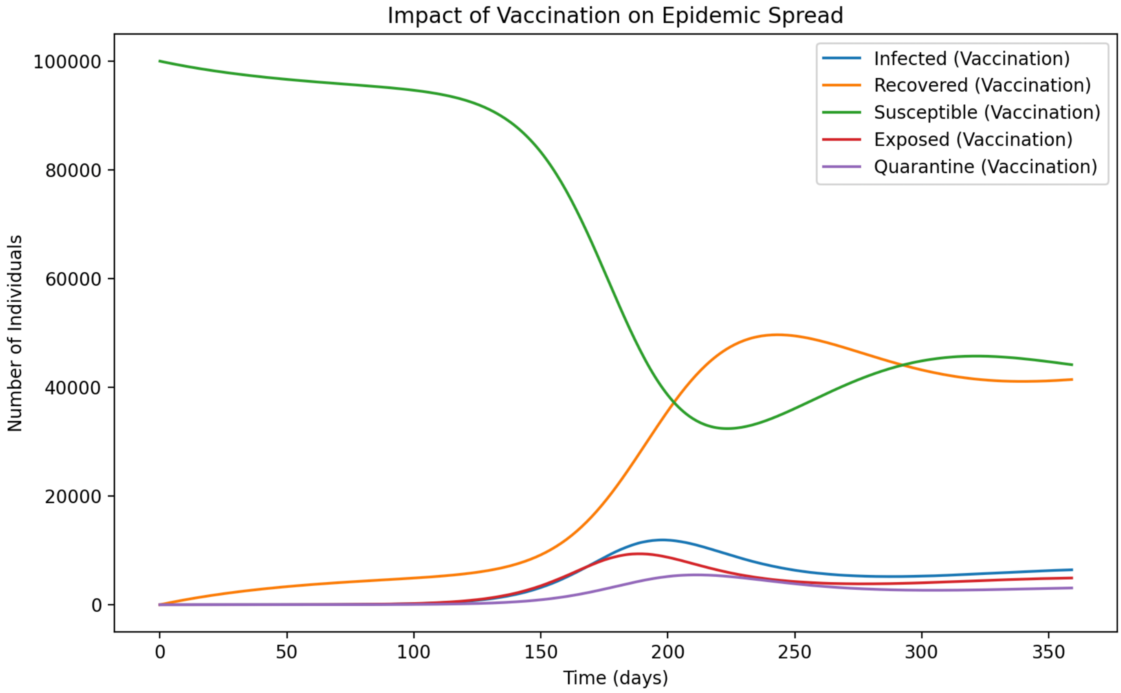
Here we can easily see, that the highest number of infected individuals is around day 150 (Middle of Spring in our model). Lower is in late Summer - beginning of Autumn. And then heading to higher value closer to Winter.

The transmission rate is still relatively high in the spring, leading to more infections. What's more, the exposed individuals (E) during the high transmission period in winter may become infectious in the spring, contributing to a peak. In Summer, the reduced beta decreases the transmission rate, leading to a decline in the number of new infections. This corresponds to the lower number of infections around day 280. However, as Fall progresses, beta returns to its normal value, leading to a gradual increase in the transmission rate again.

Scenario 3: Vaccination

In this scenario the impact of vaccination rates on the dynamics of epidemic spread will be investigated. A new variable appears — vaccination rate parameter v.

v reduces the susceptible population over time. This new parameter is be incorporated into the SIR model to observe how varying vaccination rates influence the dynamics of the epidemic spread.



In this figure numbers of infected, exposed and quarantined people is relatively low. Vaccination directly reduces the number of susceptible individuals (S). This means fewer individuals are available to contract the disease, thus lowering the overall transmission rate. Moreover, vaccination increases the number of individuals moving directly to the recovered category (R), contributing to herd immunity and further reducing the spread of infection. With fewer susceptible individuals, the rate at which people get exposed (E) and infected (I) decreases. This leads to a lower peak and overall number of infected individuals. The reduction in infection rates also means fewer individuals need to be quarantined (Q).

Task 6: Data generation tool

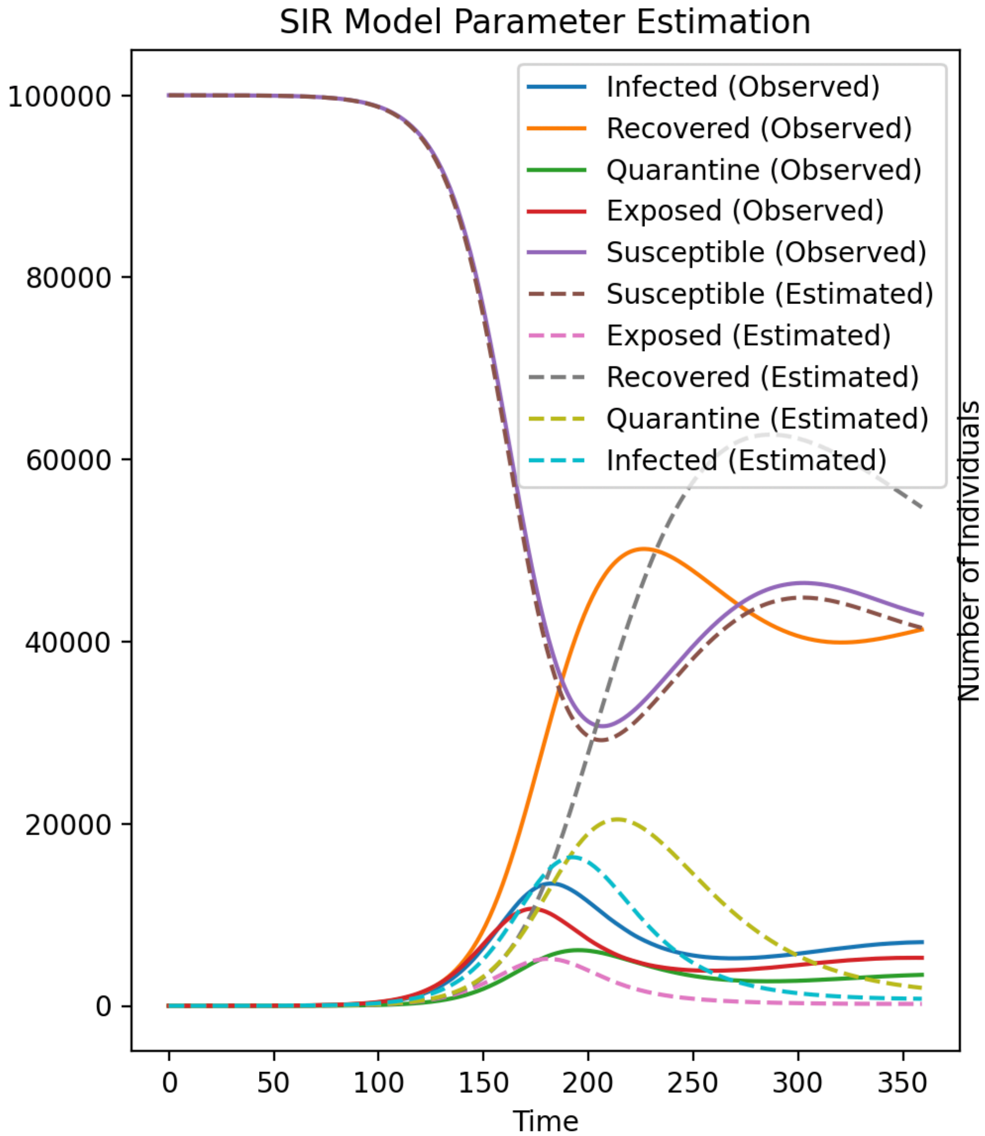
Data generating functions (with seasonal variations and random noiser either) are present in the code.

Task 7: Prediction using optimalisation

Predictions for each scenario will be presented below.

Scenario 1:

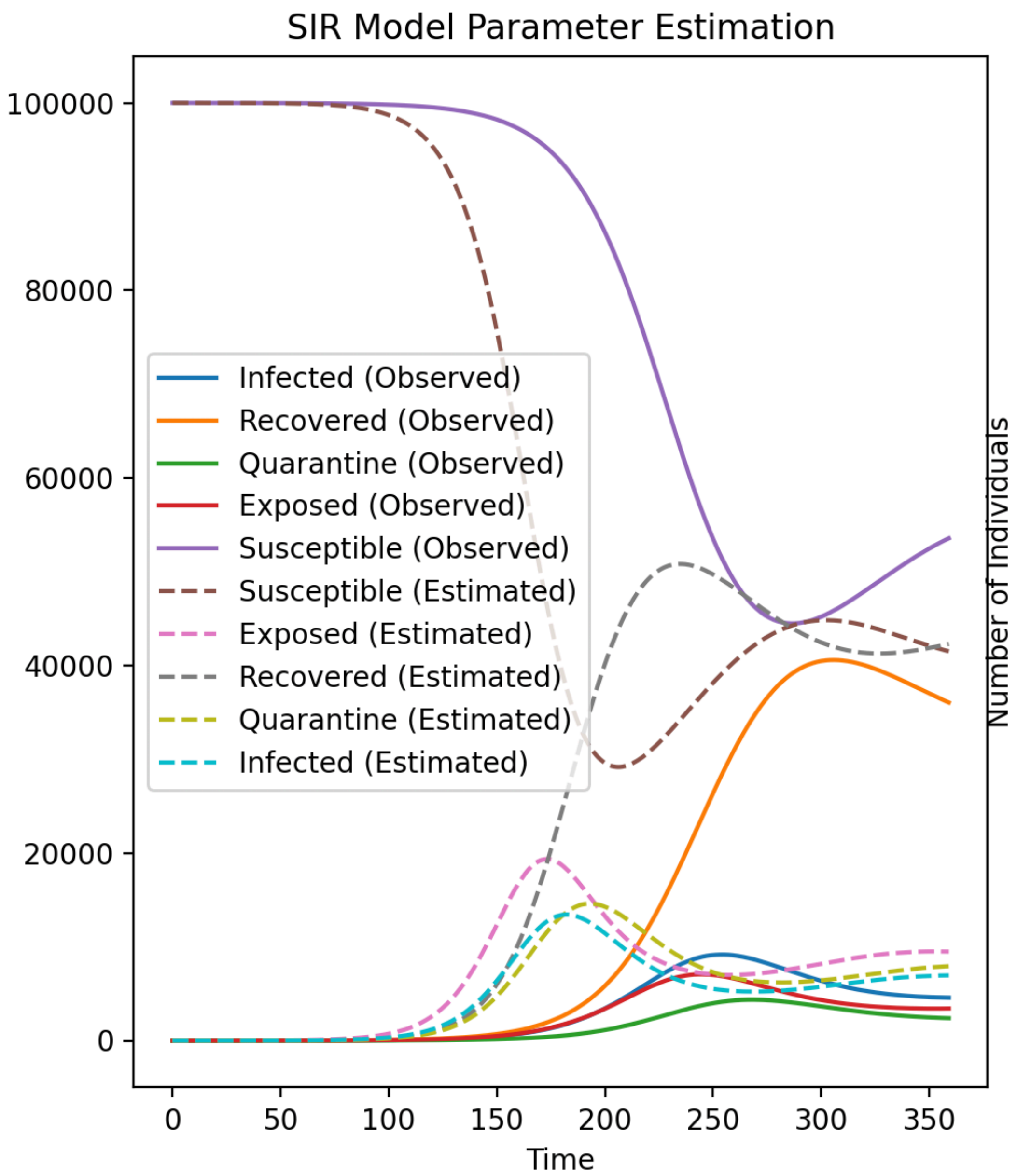
Estimating for the variation without restrictions:



True Parameters: beta = 2.5e-06, gamma = 0.07142857142857142, sigma = 0.14285714285714285, rho = 0.016666666666666666

Estimated Parameters: beta = 1.6297046786758248e-06, gamma = 0.015118245998533522, sigma = 0.24929185129253242, rho = 0.004346214901646817

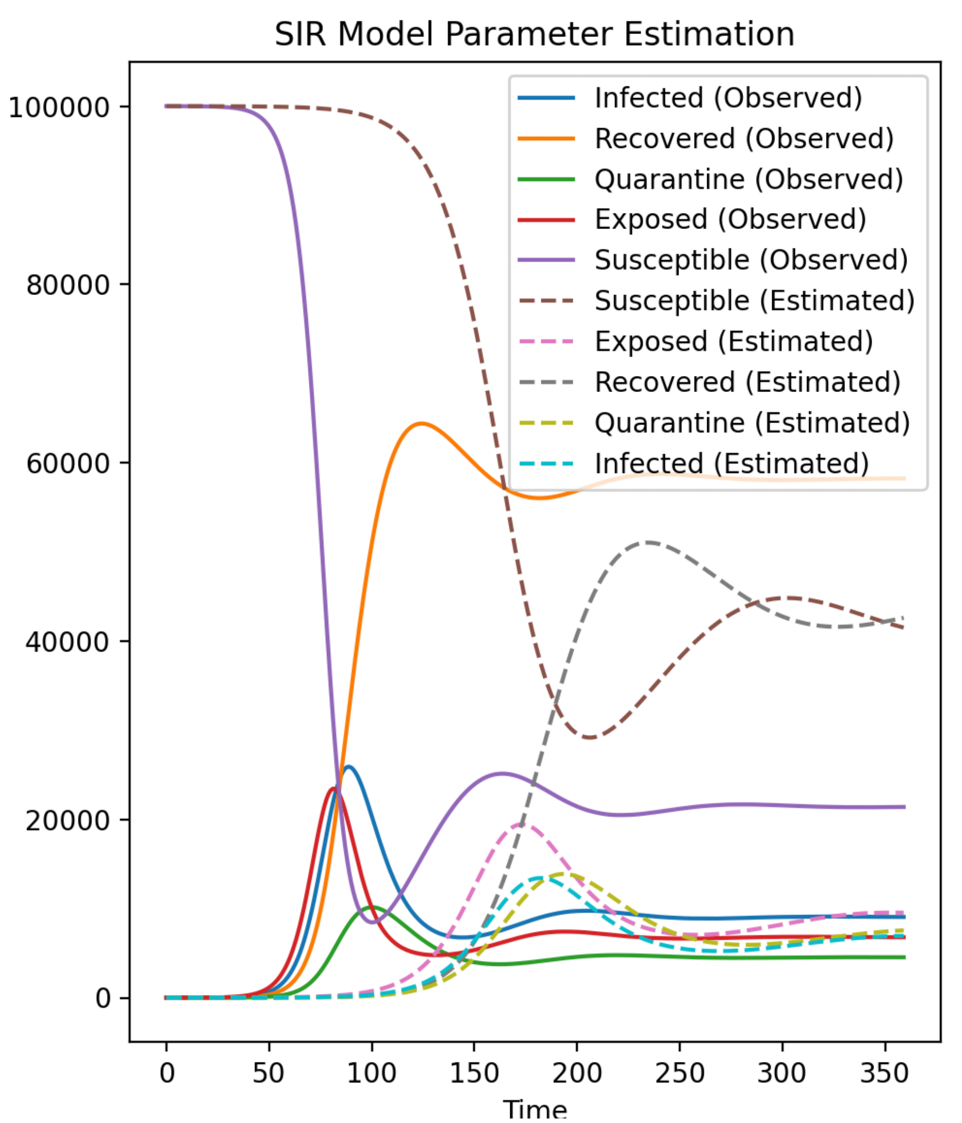
Estimating for the variation with closed schools and public places:



True Parameters: beta = 2e-06, gamma = 0.07142857142857142, sigma = 0.14285714285714285, rho = 0.016666666666666666

Estimated Parameters: beta = 3.1838734655303243e-06, gamma = 0.002268070260503377, sigma = 0.07809327175900262, rho = 0.016005797519353944

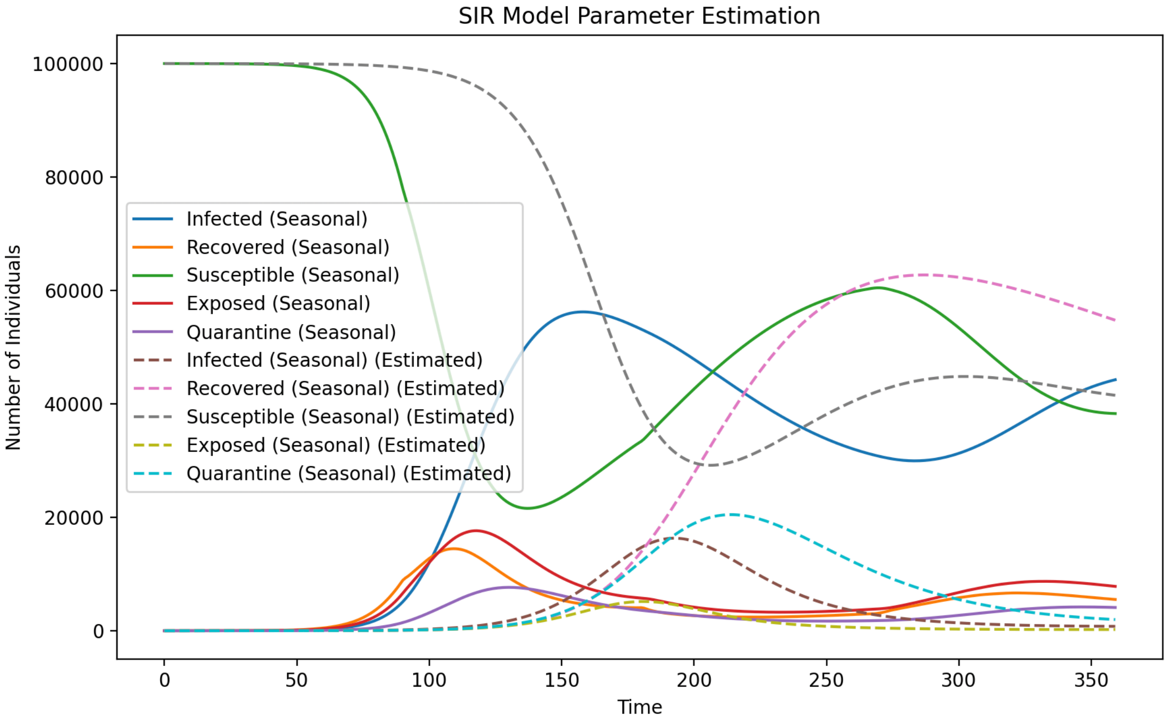
Estimating for the variation with masks:



True Parameters: beta = 5e-06, gamma = 0.07142857142857142, sigma = 0.14285714285714285, rho = 0.016666666666666666

Estimated Parameters: beta = 3.1954929321033032e-06, gamma = 0.011540682029019957, sigma = 0.07794998868761252, rho = 0.015953019848520697

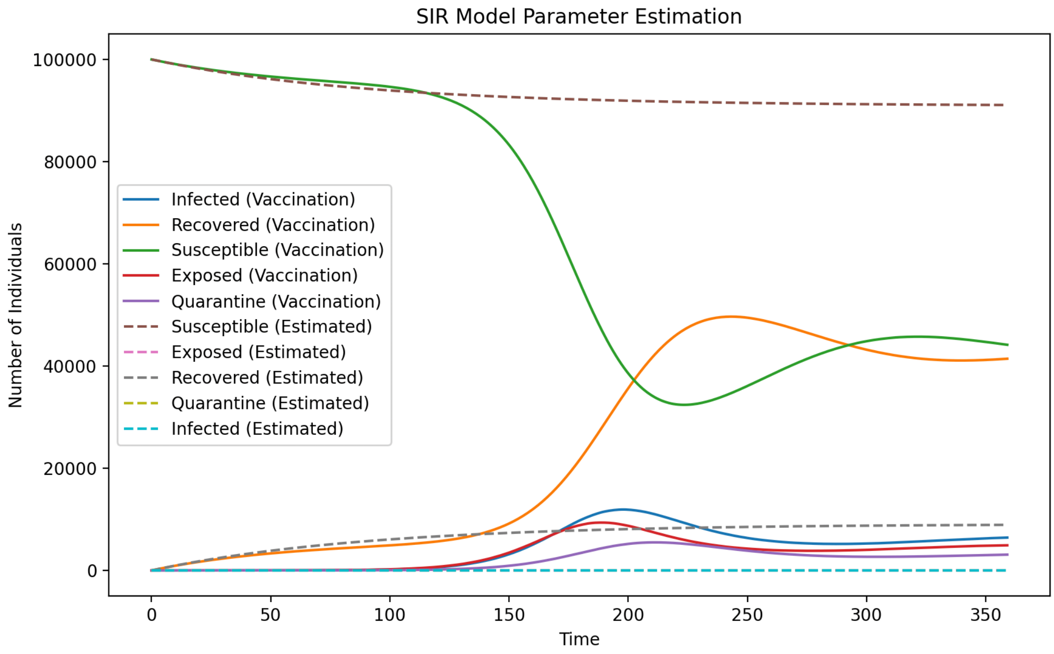
Estimating for the scenario 2: Seasonal variations



True Parameters: beta = 2.5e-06, gamma = 0.07142857142857142, sigma = 0.14285714285714285, rho = 0.016666666666666666

Estimated Parameters: beta = 1.6297046786758248e-06, gamma = 0.015118245998533522, sigma = 0.24929185129253242, rho = 0.004346214901646817

Estimating for the scenario 3: Vaccination



True Parameters: beta = 2.5e-06, gamma = 0.07142857142857142, sigma = 0.14285714285714285, rho = 0.016666666666666666

Estimated Parameters: beta = 1e-06, gamma = 0.01, sigma = 0.1, rho = 0.01

Conclusion:

As we can see from the estimations above, estimation is not quite good. There must be several issues in estimation process that can explain why there is a discrepancy between the true parameters and the estimated parameters. In my opinion, the initial guess for the parameter values plays the most significant role in the convergence of the optimization algorithm. If the initial guess is too far from the true parameters, the algorithm may converge to a local minimum rather than the global minimum.

Scaling of parameters may also cause the problem. Parameters that vary over different scales can cause numerical difficulties during optimization.