The effect of rumor dynamics on disease dynamics

Abstract

In this model, we want to study the influence of misinformation about COVID-19 on its dynamics and propagation and see how lack of valid information can fasten the spreading of disease and consequently, increase numbers of mortality.

1 Introduction

In the early stage of this epidemic, there were many rumors and conspiracy theories like "it's a hoax", "it's not airborne", "it's is just similar to a light flu" and so on. This kind of misinformation spread in social media and communities. As a result, people who do not follow news from valid sources, might accept those fake news and so do not follow safety protocols and when they get infected, do not use standard medical treatments. On the other side, when the numbers of infected and mortality increase, the fear also increases and people can see the intensity of disease with their own eyes. In addition, the disease attracts more attention, and valid sources like news agencies will inform people and fact-check rumors.

2 Model

In our model, we study the propagation of misinformation and a disease simultaneously. We assume the disease and rumor have respectively SEIR and SIR dynamics. The rumor model has three classes: (i) ignorant, which represents individuals that have not heard the rumor; (ii) spreader, which refers to agents that are aware of the rumor and are actively spreading it further, and (iii) stifler, who are those subjects that already know the rumor, but are not disseminating it any longer. So, every state of disease has three different states of the rumor that are denoted by X_1, X_2, and X_3. These combined states mean respectively an agent in X state of disease that is also "Ignorant", "Spreader" and "Stifler". Now we explain the Dynamics and interactions between agents.

Dynamics of the disease is shown in image 1. We can see:

- S_i get infected from I_j with the rate $\beta_{i,j}$ and goes to E_i state.
- E_i goes to I_i state with the rate σ_i.
- I_i recovers and goes to R state with the rate γ_i.

Also, assuming $X, Y \in \{S, E, I, R\}$, the dynamics of the rumor is shown in images 2, and we can see:

- X_{ig} gets rumor with the rate λ from Y_{sp} and with probability η goes to X_{sp} state or with probability $1-\eta$ goes to X_{st} state.
- X_{sp} losses its interest with the rate α and goes to X_{st} state.
- X_{st} recovers its interest with the rate α and goes to X_{sp} state.

3 Dynamical Equations In Mean-Field Approximation

In mean-field approximation we assume that the nodes are completely interacting with each other or in other words we assume our network to be a complete network. Additionally, in this problem, we deal with two different dynamics that can affect each other, on the same network. If we take a look on these dynamics, separately, we have following graphs:

but when we mix this two dynamics, we confront with a more complicated situation.before we write the mean-field equations, note that in the simulation of this network, we don't use simultaneous synchronization but first we update one of dynamics and then the other one. we know that as Δt goes to zero, we should get the same result for the simultaneous synchronization. if we write mean-field equations(indeed master equations) we find the followings. Here, ig, sp, st represent the ignorant, the spreader and the stifler:

$$
\begin{aligned}
\frac{dS_{ig}}{dt} &= -\frac{\beta_{11}S_{ig}I_{ig}}{N} - \frac{\beta_{12}S_{ig}I_{sp}}{N} - \frac{\beta_{13}S_{ig}I_{st}}{N} - \frac{\lambda S_{ig}Y}{N} \\
\frac{dS_{sp}}{dt} &= -\frac{\beta_{21}S_{sp}I_{ig}}{N} - \frac{\beta_{22}S_{sp}I_{sp}}{N} - \frac{\beta_{23}S_{sp}I_{st}}{N} + \frac{\lambda\eta S_{sp}X}{N} + \frac{\beta S_{sp}Z}{N} - \frac{\alpha S_{sp}Z}{N} \\
\frac{dS_{st}}{dt} &= -\frac{\beta_{31}S_{st}I_{ig}}{N} - \frac{\beta_{32}S_{st}I_{sp}}{N} - \frac{\beta_{33}S_{st}I_{st}}{N} + \frac{\lambda(1-\eta)S_{sp}X}{N} - \frac{\beta S_{st}Y}{N} + \frac{\alpha S_{st}Y}{N} \\
\frac{dE_{ig}}{dt} &= \frac{\beta_{11}S_{ig}I_{ig}}{N} + \frac{\beta_{12}S_{ig}I_{sp}}{N} + \frac{\beta_{13}S_{ig}I_{st}}{N} - \sigma_{ig}E_{ig} - \frac{\lambda E_{ig}Y}{N} \\
\frac{dE_{sp}}{dt} &= \frac{\beta_{21}S_{sp}I_{ig}}{N} + \frac{\beta_{22}S_{sp}I_{sp}}{N} + \frac{\beta_{23}S_{sp}I_{st}}{N} - \sigma_{sp}E_{sp} + \frac{\lambda\eta E_{sp}X}{N} + \frac{\beta E_{sp}Z}{N} - \frac{\alpha E_{sp}Z}{N} \\
\frac{dE_{st}}{dt} &= \frac{\beta_{31}S_{st}I_{ig}}{N} + \frac{\beta_{32}S_{st}I_{sp}}{N} + \frac{\beta_{33}S_{st}I_{st}}{N} - \sigma_{st}E_{st} + \frac{\lambda(1-\eta)E_{sp}X}{N} - \frac{\beta E_{st}Y}{N} + \frac{\alpha E_{st}Y}{N} \\
\frac{dI_{ig}}{dt} &= \sigma_{ig}E_{ig} - \gamma_{ig}I_{ig} - \frac{\lambda I_{ig}Y}{N} \\
\frac{dI_{sp}}{dt} &= \sigma_{sp}E_{sp} - \gamma_{sp}I_{sp} + \frac{\lambda\eta I_{sp}X}{N} + \frac{\beta I_{sp}Z}{N} - \frac{\alpha I_{sp}Z}{N} \\
\frac{dI_{st}}{dt} &= \sigma_{st}E_{st} - \gamma_{st}I_{st} + \frac{\lambda(1-\eta)I_{sp}X}{N} - \frac{\beta I_{st}Y}{N} + \frac{\alpha I_{st}Y}{N} \\
\frac{dR_{ig}}{dt} &= \gamma_{ig}I_{ig} - \frac{\lambda R_{ig}Y}{N} \\
\frac{dR_{sp}}{dt} &= \gamma_{sp}I_{sp} + \frac{\lambda R_{sp}X}{N} + \frac{\beta R_{sp}Z}{N} - \frac{\alpha R_{sp}Z}{N} \\
\frac{dR_{st}}{dt} &= \gamma_{st}I_{st} + \frac{\lambda(1-\eta)R_{sp}X}{N} - \frac{\beta R_{st}Y}{N} + \frac{\alpha R_{st}Y}{N} \\
X &= S_{ig} + I_{ig} + E_{ig} + R_{ig} \\
Y &= S_{sp} + I_{sp} + E_{sp} + R_{sp} \\
Z &= S_{st} + I_{st} + E_{st} + R_{st} \\
N &= X + Y + Z \\
\beta &= \beta_{misinformation}
\end{aligned}
$$

And $\beta_{infectious}$ matrix is: $\begin{pmatrix} \beta_{11}=0.1 & \beta_{12}=0.2 & \beta_{13}=0.1 \\ \beta_{21}=0.15 & \beta_{22}=0.25 & \beta_{23}=0.15 \\ \beta_{31}=0.1 & \beta_{32}=0.2 & \beta_{33}=0.1 \end{pmatrix}$

In this dynamics, we have following assumptions:

- We didn't consider natural mortality because in early stage of epidemic, the specific dynamics time is small.

- Initial Conditions: $S = 300000, I_1 = 80, I_2 = 10, I_3 = 10$

- σ is the rate of latent individuals becoming infectious. For simplicity, we assume that $\sigma_1 = \sigma_2 = \sigma_3$ and is equal to 3 days.

- In misinformation dynamics, We considered ignorant class and stifler class to be almost the same, Meaning that γ_1=γ_3=1/14(days), γ_2=1/25(days) (Recovery rate) and β_{i1}=β_{i3}, β_{1i}=β_{3i} (Infectious rate).

- Transition rate of the infected who is spreader, is bigger than Transition rate of the susceptible who is spreader. Because it is more dangerous if patient with COVID-19 doesn't follow safety protocols.

- To better show the dynamic effect of the rumor, we considered people very uncultured!!

4 Analyses

4.1 Mean-Field Approximation

In the following , we investigate three cases, one considering SEIR dynamic only, the second, the information dynamic is added and the third , again is a combination of both.In order to emphasize the effect of the fake news spreading, we have exaggerated in evaluating the spreading parameter(η) so that the effect caused by the rumors would be clear. SEIR figures are as follow 3:

The other figures are not plotted since are constant.

and mix dynamic 4:

and mix dynamics with exaggerated parameters 5 6 7 8 9:

An interesting result was the changes of recovered individuals, as the α parameter varies. as you can see in fig 11 10, there is a minimum that means that, for an specific amount of α the epidemic is small. The physical significane of the phenomenon is not clear to us yet but it would be an interesting topic for further investigations.

4.2 Simulation

We simulated this dynamics on a double layer network

5 conclusion

As was explained, we saw that there is a meaningful difference between the case when there is a high flow of misinformation and rumor and the case when people tend to avoid spread the fake news and are in stifler state.

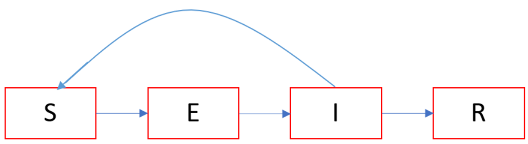

Figure 1: Infectious Dynamics

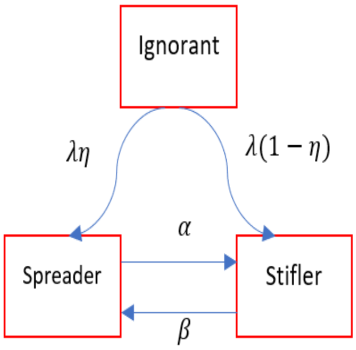

Figure 2: Misinformation Dynamics

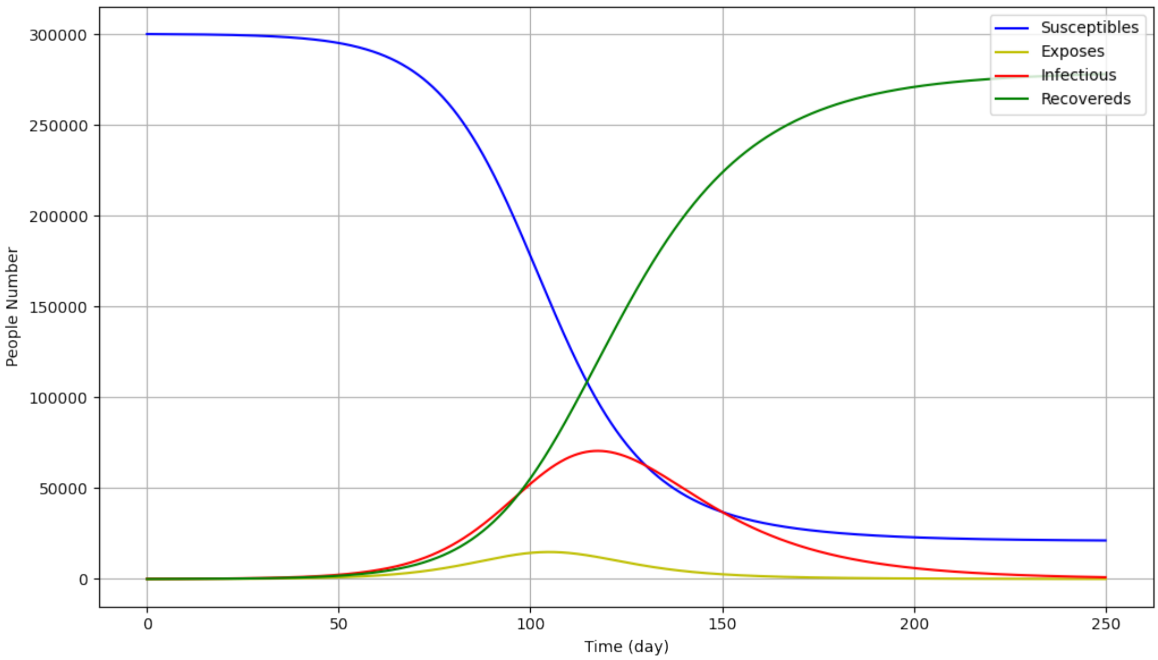

Figure 3: In this case all information parameters are set to zero.

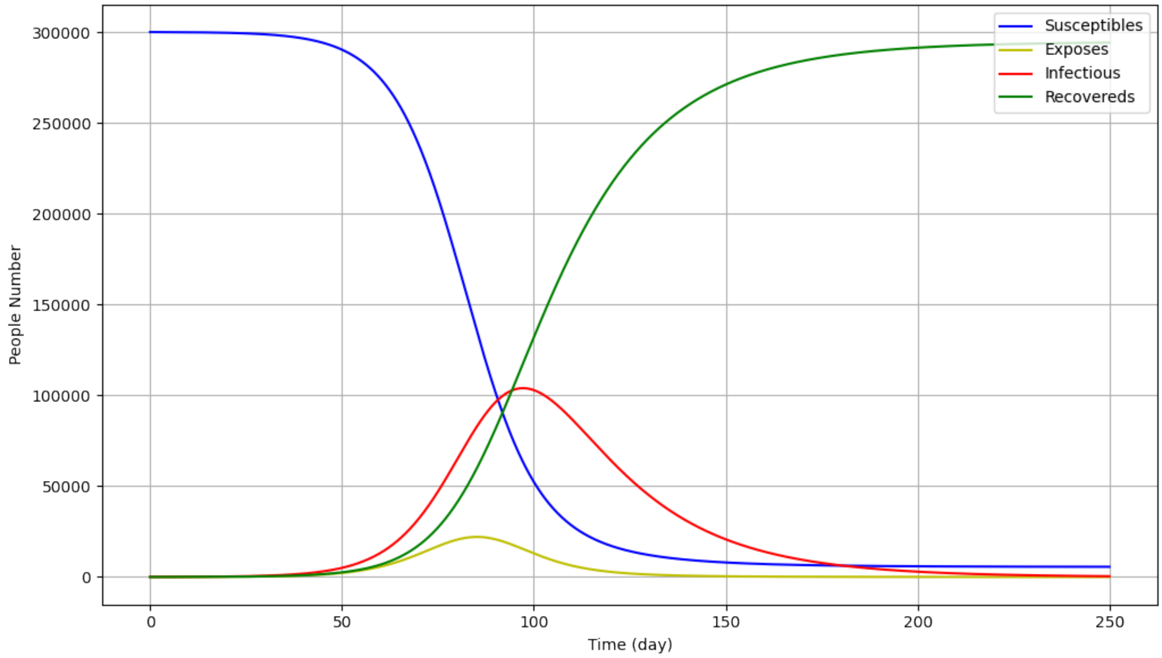

Figure 4: In this case the dynamics are mixed but the information parameters are reasonable and not extreme. The parameters are:$\lambda = 0.1$, $\eta = 0.8$, $\alpha = \beta_{so} = 0$

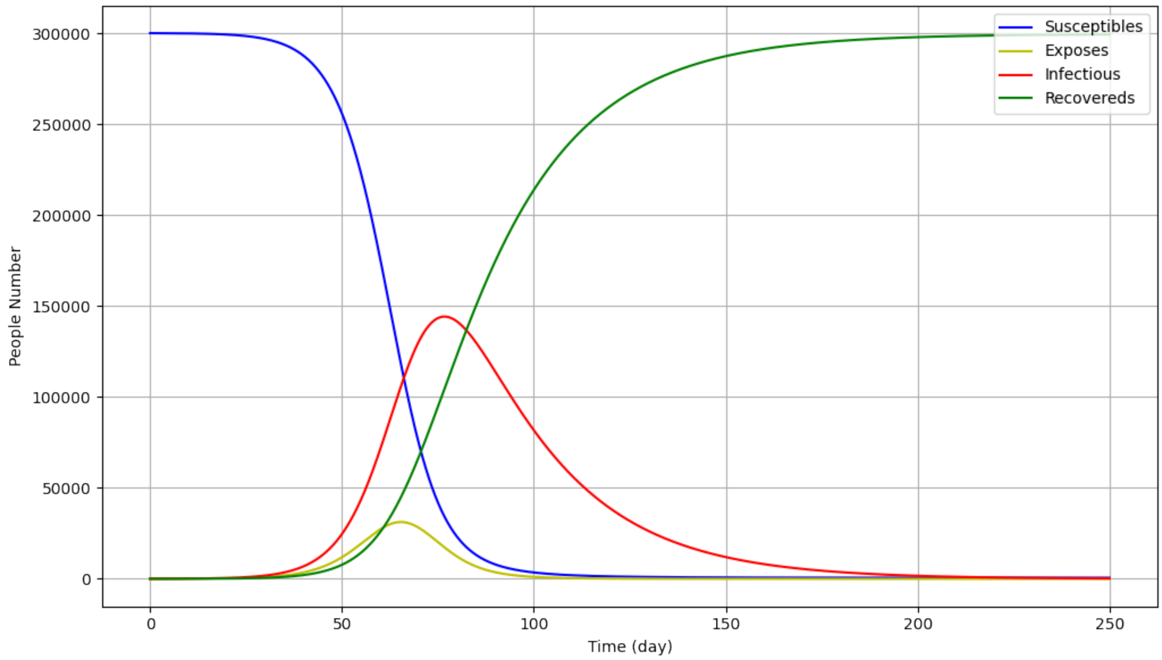

Figure 5: SEIR dynamic for uncultured people while the information dynamic is on as well with parameters:$\alpha = 0.01, \beta_{so} = 0.5, \lambda = 0.1, \eta = 0.8$

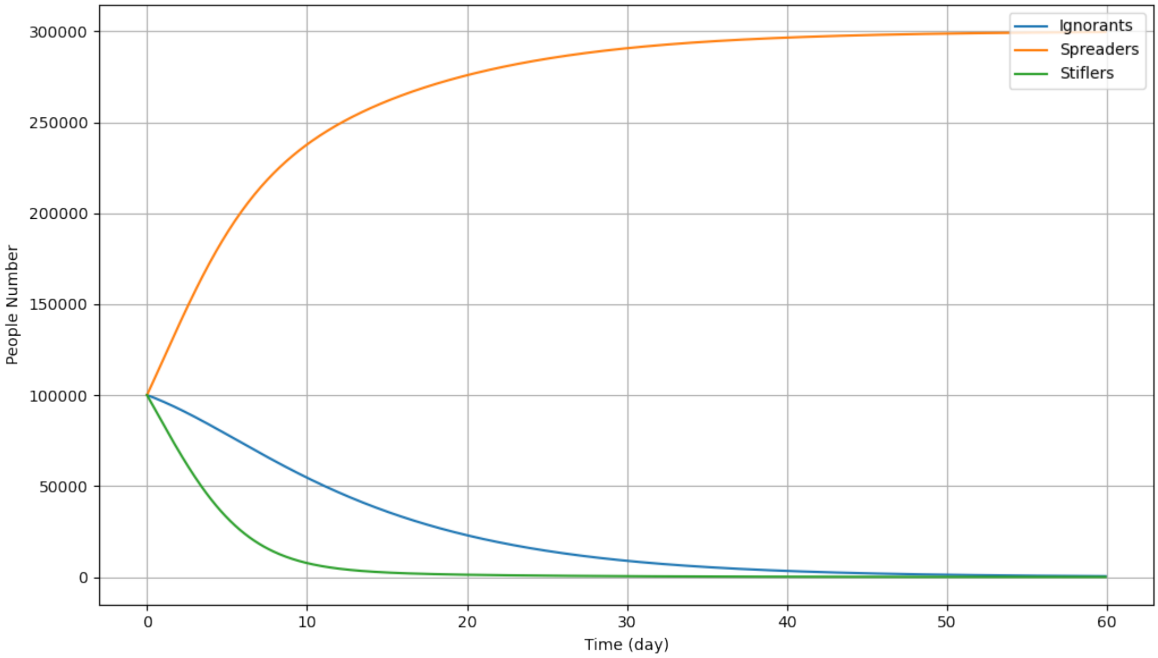

Figure 6: Misinformation dynamic for uncultured people while the information dynamic is on as well with parameters:$\alpha = 0.01, \beta_{so} = 0.5, \lambda = 0.1, \eta = 0.8$

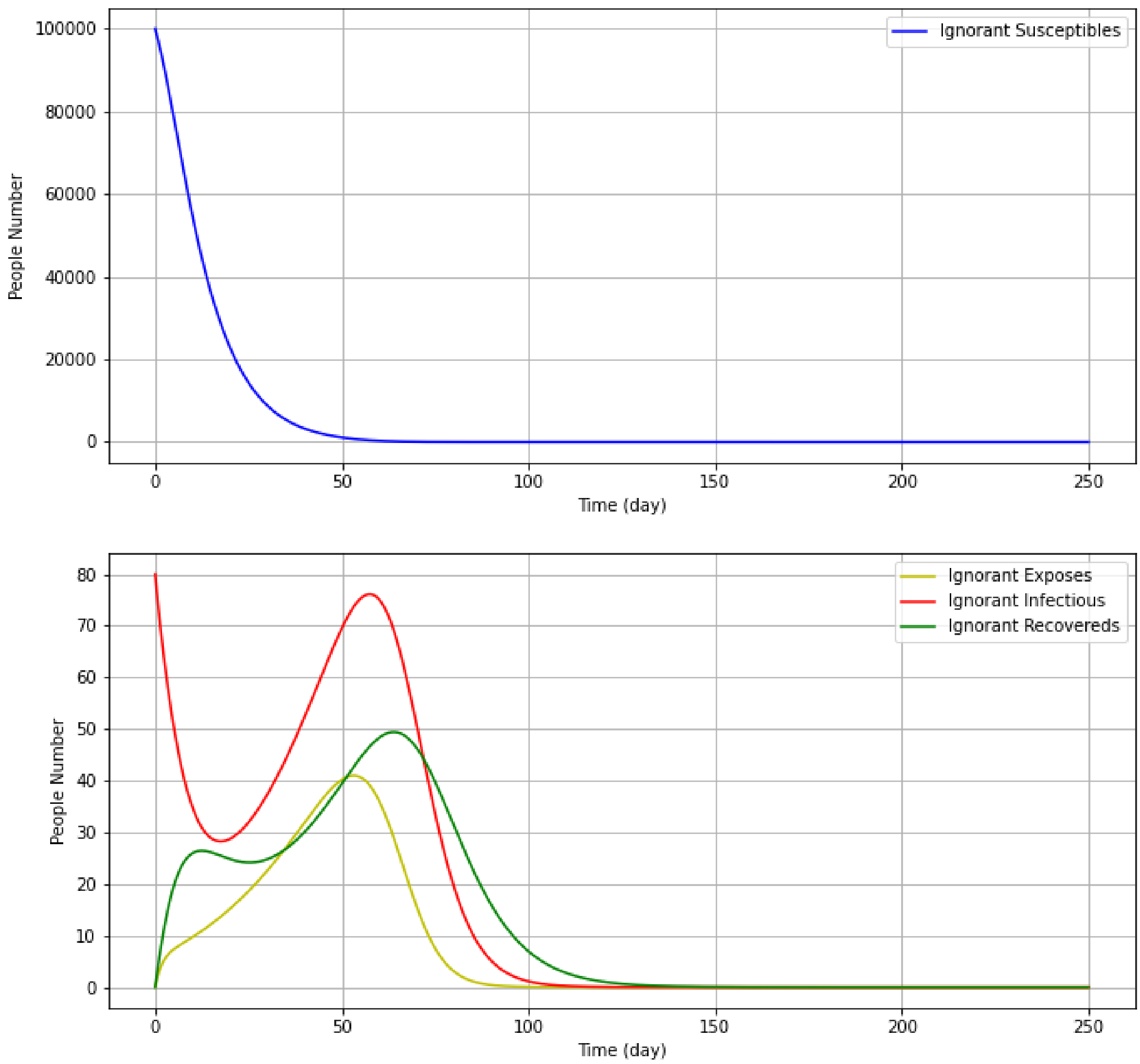

Figure 7: Ignorant people under SEIR dynamic while the information dynamic is on as well with parameters:$\alpha = 0.01, \beta_{so} = 0.5, \lambda = 0.1, \eta = 0.8$

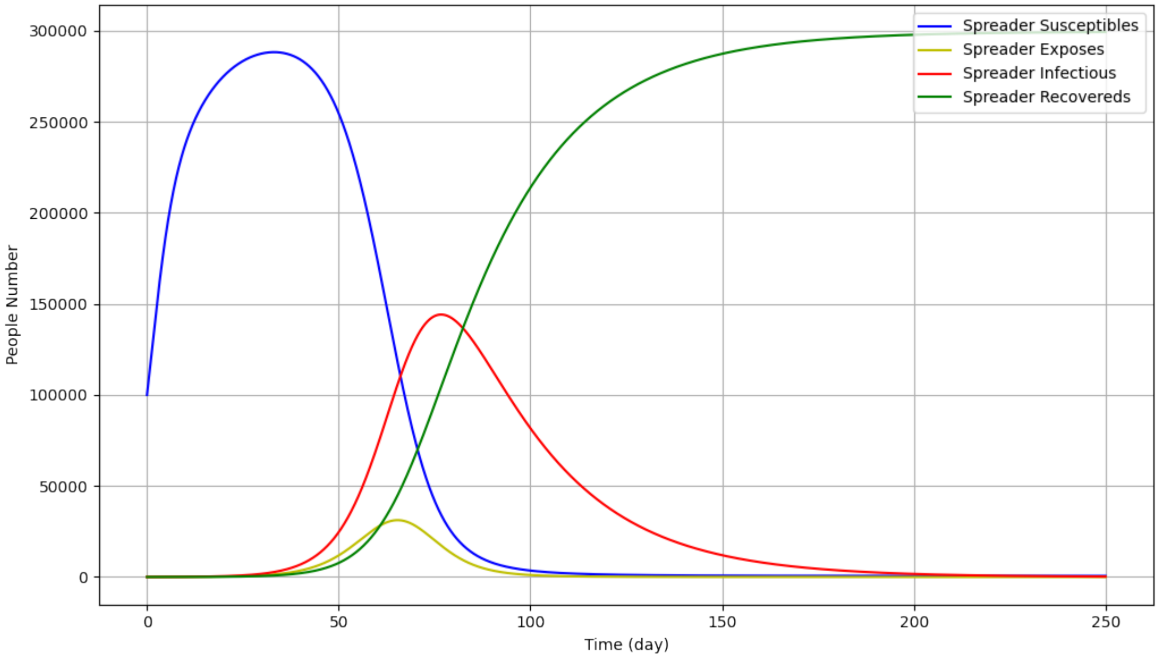

Figure 8: Spreader people under SEIR dynamic while the information dynamic is on as well with parameters:$\alpha = 0.01$,$\beta_{so} = 0.5$,$\lambda = 0.1$,$\eta = 0.8$

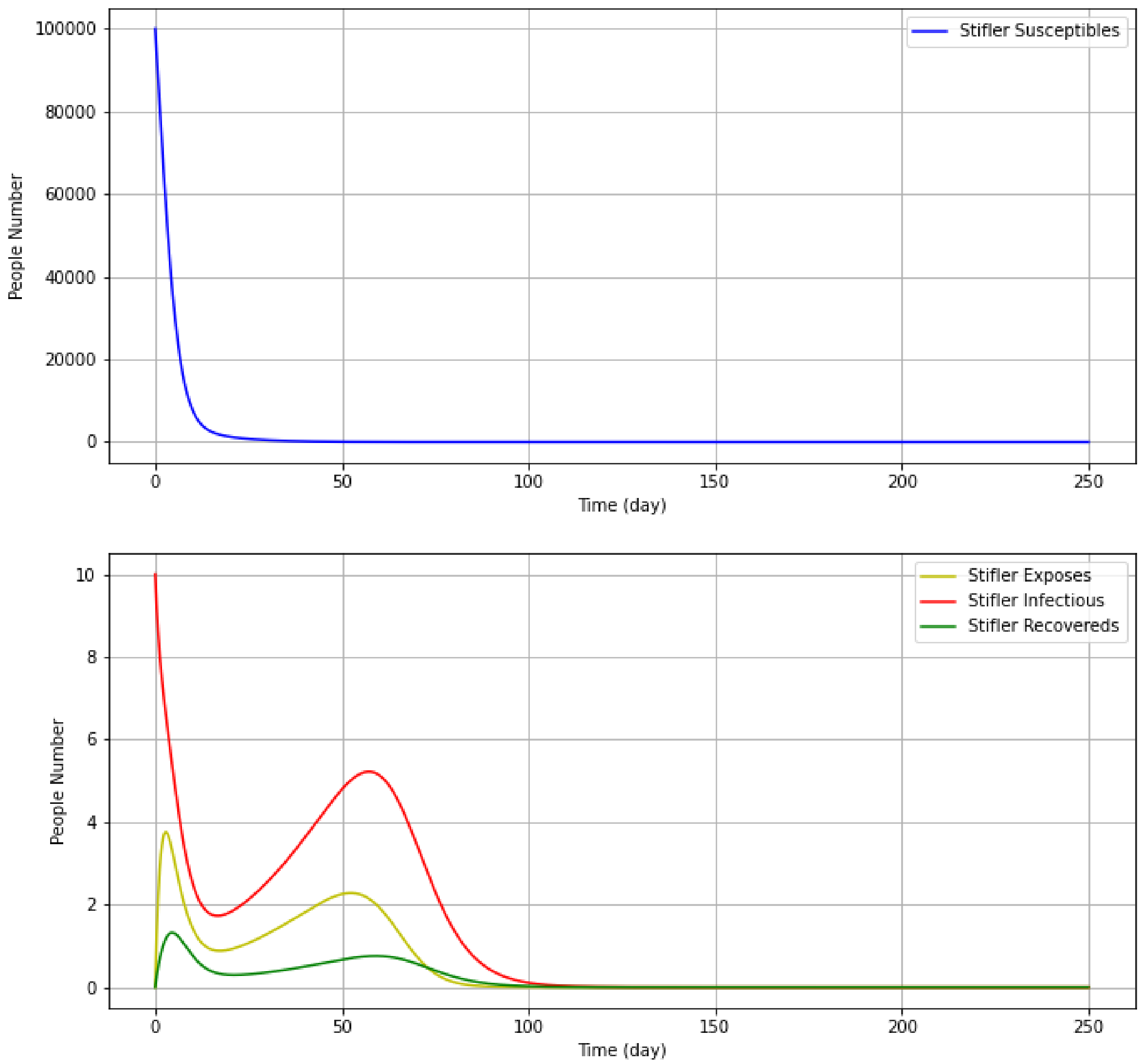

Figure 9: Stifler people under SEIR dynamic while the information dynamic is on as well with parameters:$\alpha = 0.01, \beta_{so} = 0.5, \lambda = 0.1, \eta = 0.8$

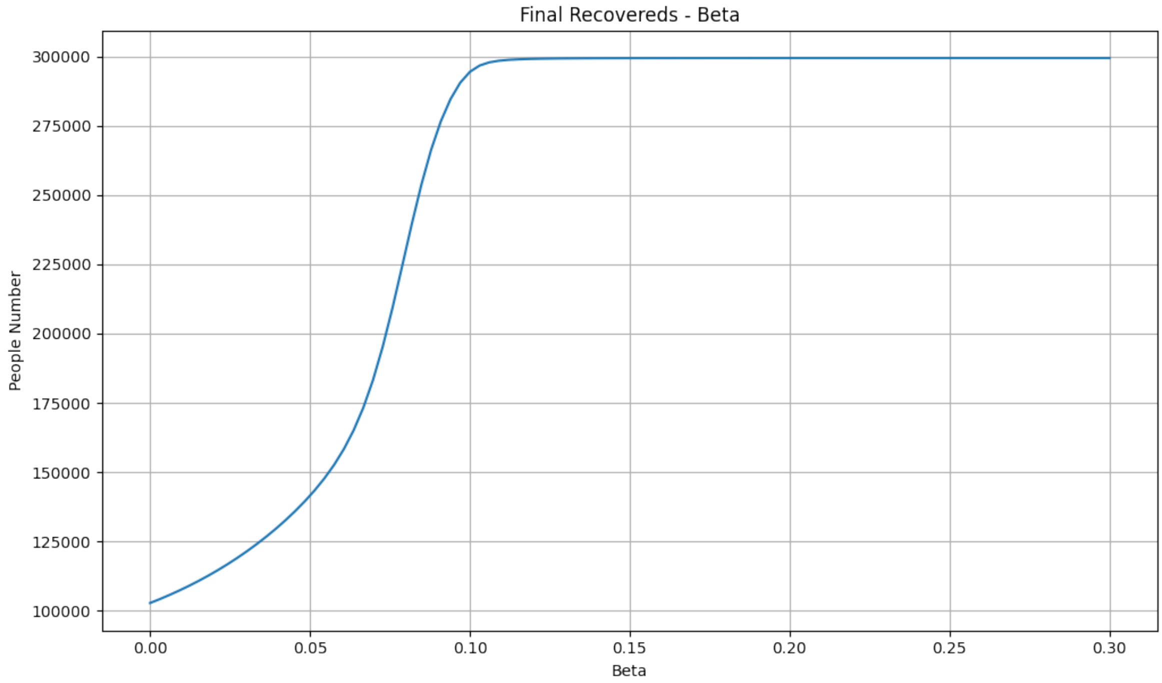

Figure 10: This result validates our intuition that says with increase in spreaders, we have increase in disease

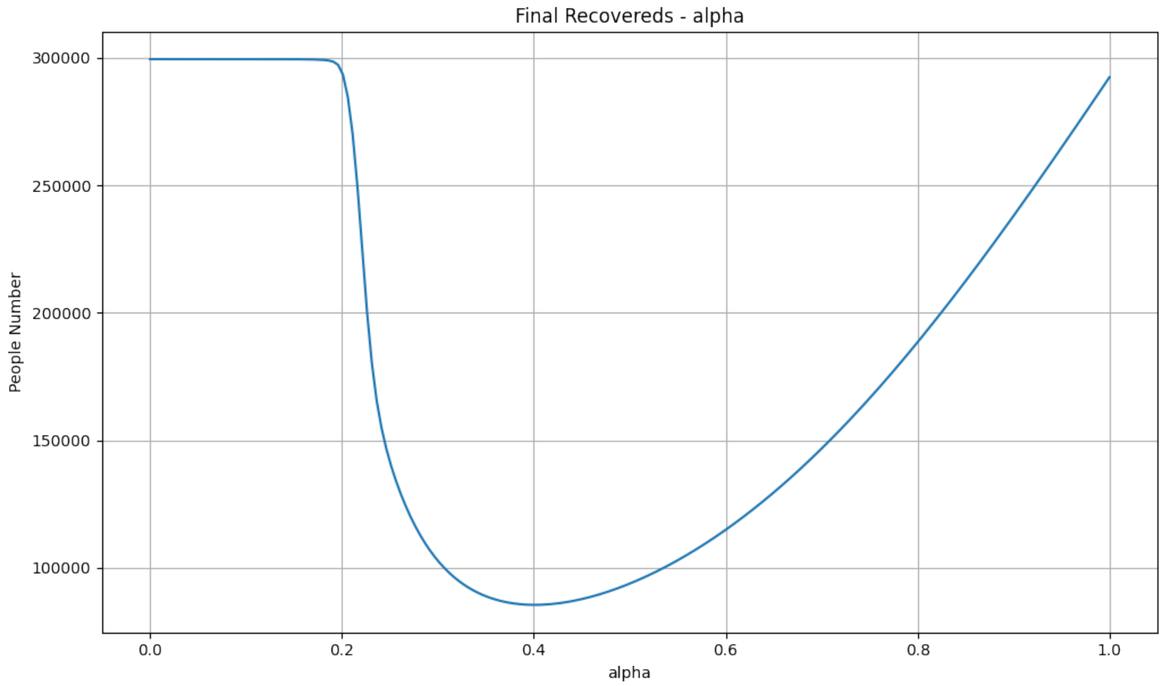

Figure 11: The physical significance of this minimum is still unknown to us

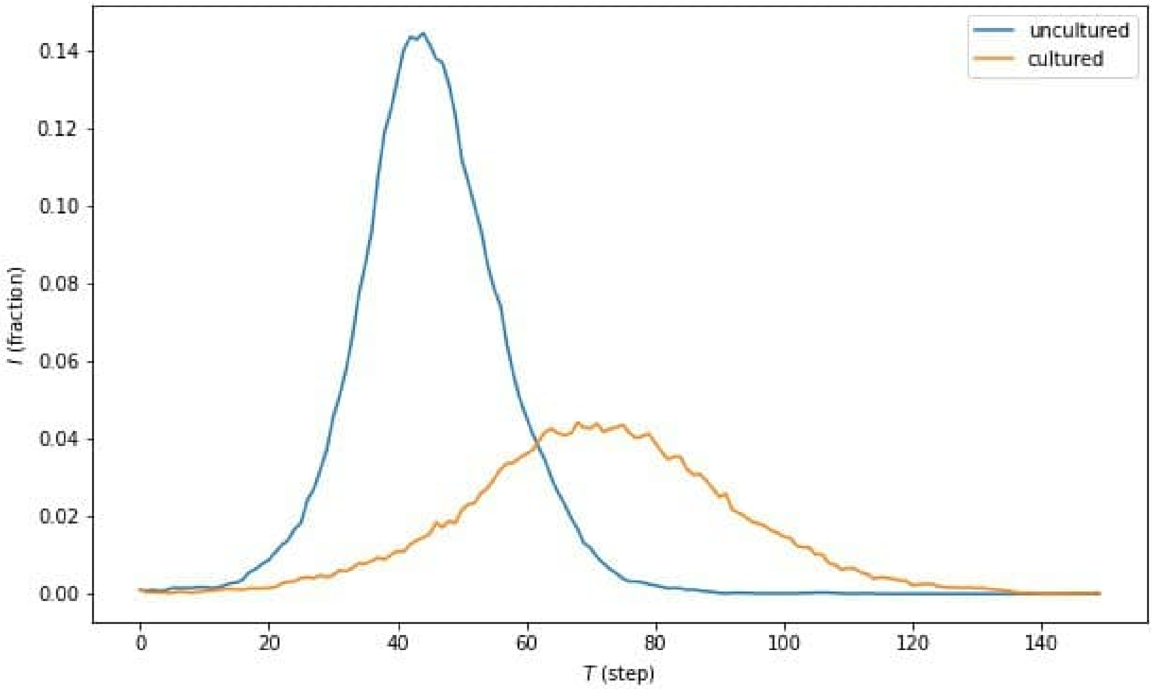

Figure 12: $\beta = 0.1$, $\eta = 0.3$

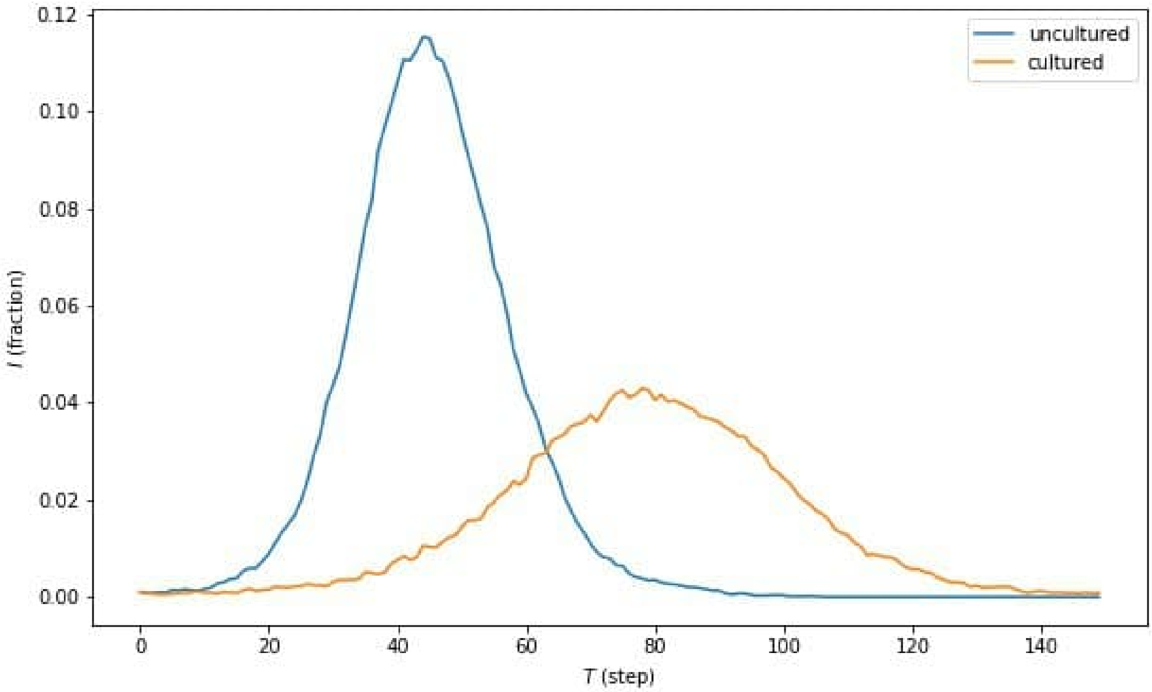

Figure 13: $\beta = 0.05$, $\eta = 0.3$

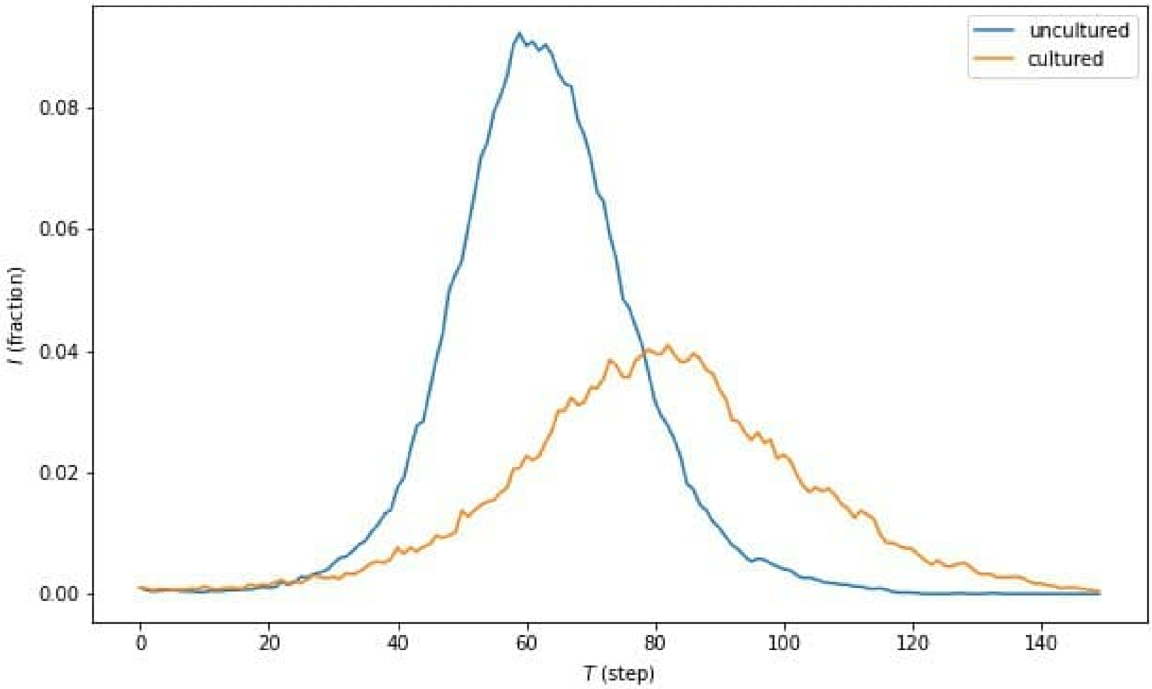

Figure 14: $\beta = 0.03$, $\eta = 0.3$

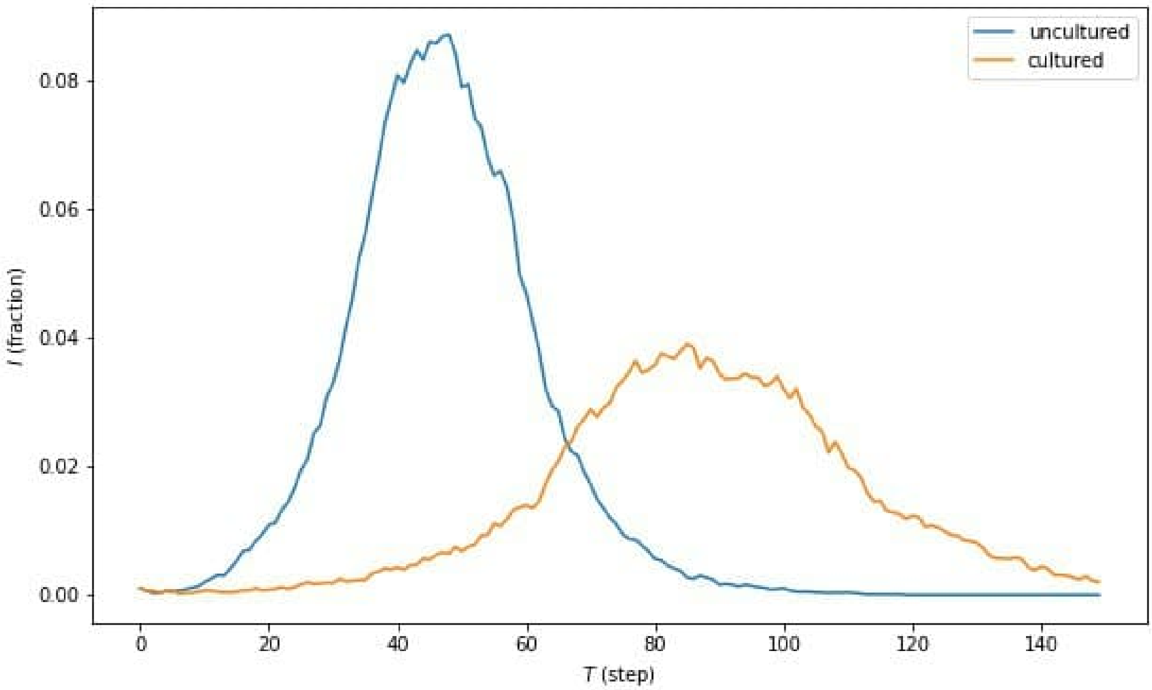

Figure 15: $\beta = 0.03$, $\eta = 0.8$

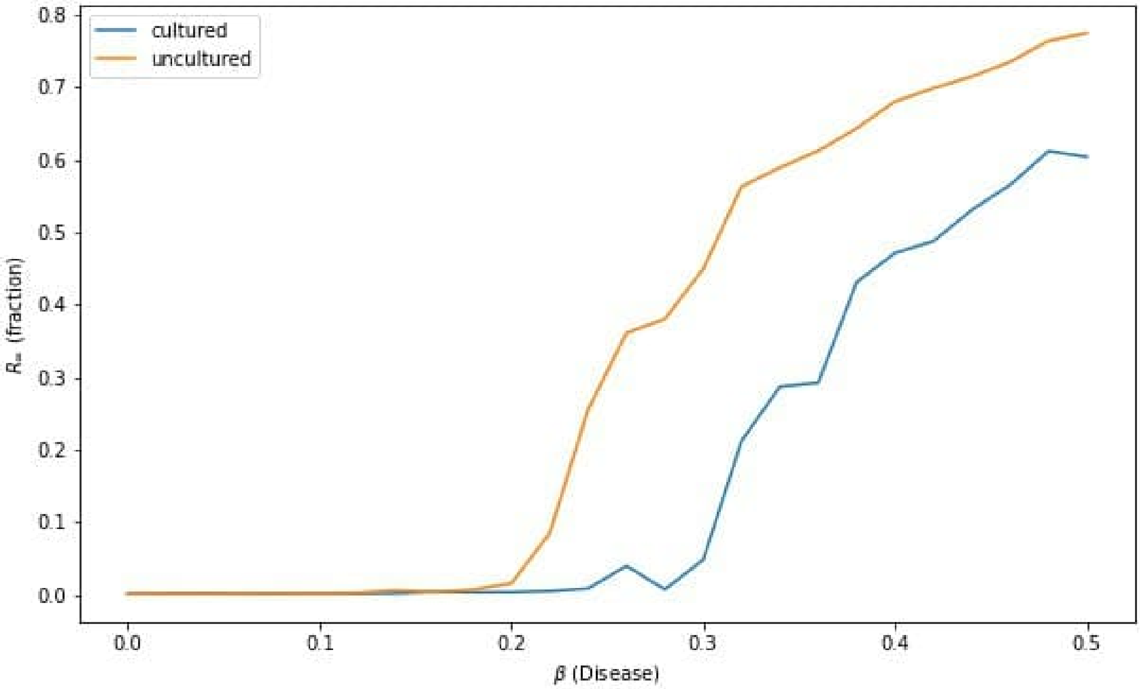

Figure 16: $\beta = 0.03$, $\eta = 0.3$

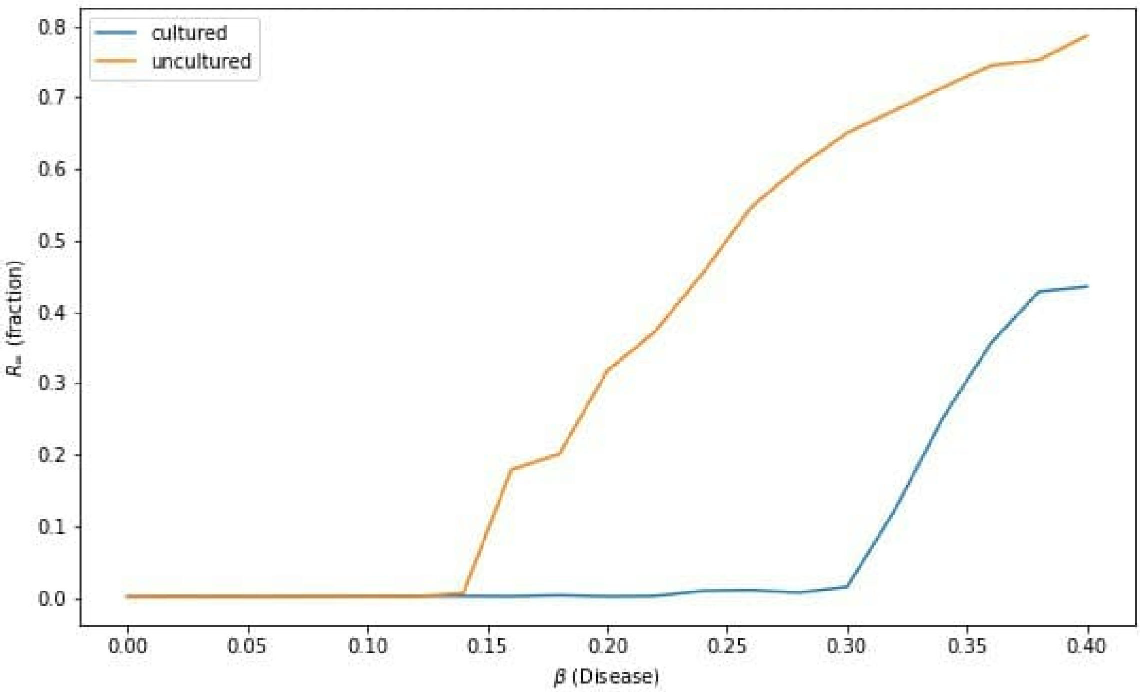

Figure 17: $\beta = 0.06$, $\eta = 0.3$