Impact of Vaccine Hesitancy on COVID-19 Spread in a SIRV Model of a Scale-Free Network

LIFE DATA EPIDEMIOLOGY PROJECT

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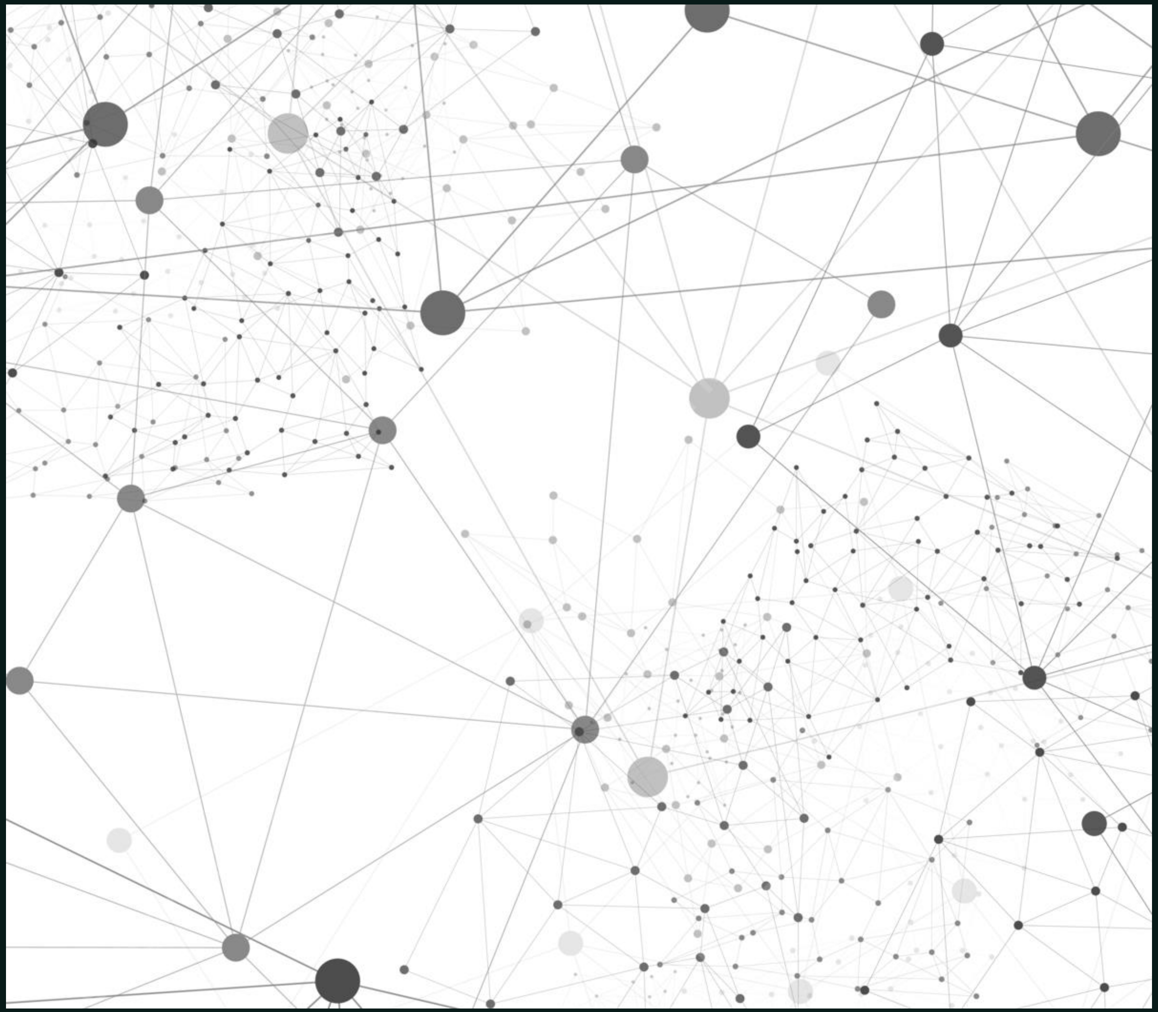


Main question and goals

The question?

WHAT ARE THE EFFECTS OF **VACCINE HESITANCY** ON THE EPIDEMIC DYNAMICS? UNDERSTAND WICH SOCIAL STRATEGIES COULD LEAD TO A POSITIVE RESOLUTION OF THE EPIDEMIC

Main goals of project

1. Examine how **hesitancy in vaccination** influences spreading behaviors in static social networks, by altering :

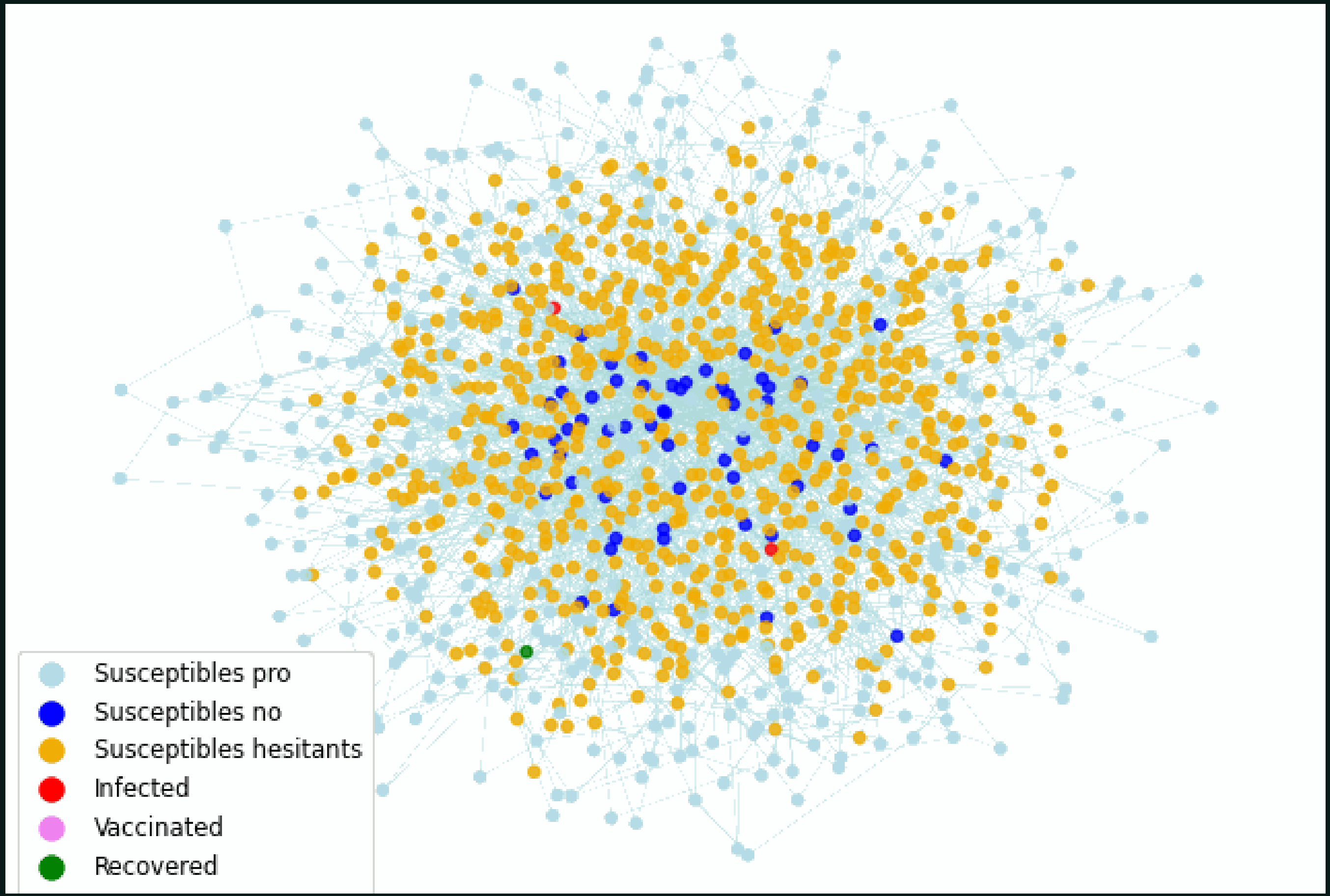
- **proportions of hesitants, infected and no-vax in the initial population**
- the weights that represent each state's influence on the probability for an hesitant to change their idea (explained later).

2. Assess effects of hesitancy on spreading dynamics, specifically focusing on:

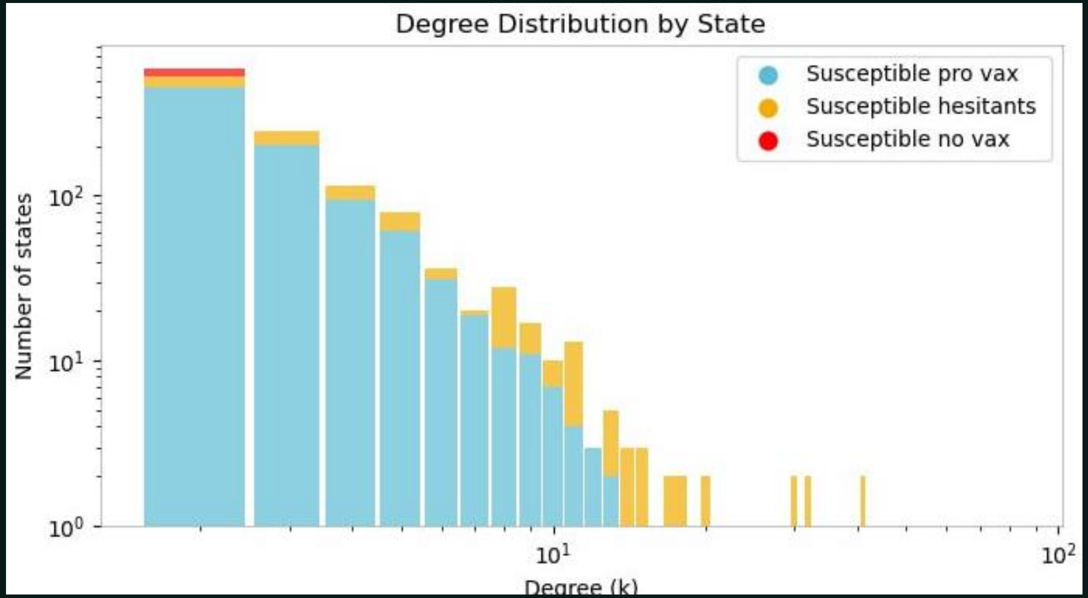
- changes in the **number of deaths** and **infections**
- analysis **of infection peak** in terms of both **timing and intensity.**

General approach

- Barabási–Albert network model;
- SIRV compartmental model;
- Mean-field approximation;
- Sourced some contagion data from real COVID-19 pandemic observations (beta, mu, time for the vaccine to be effective).



Network specifications

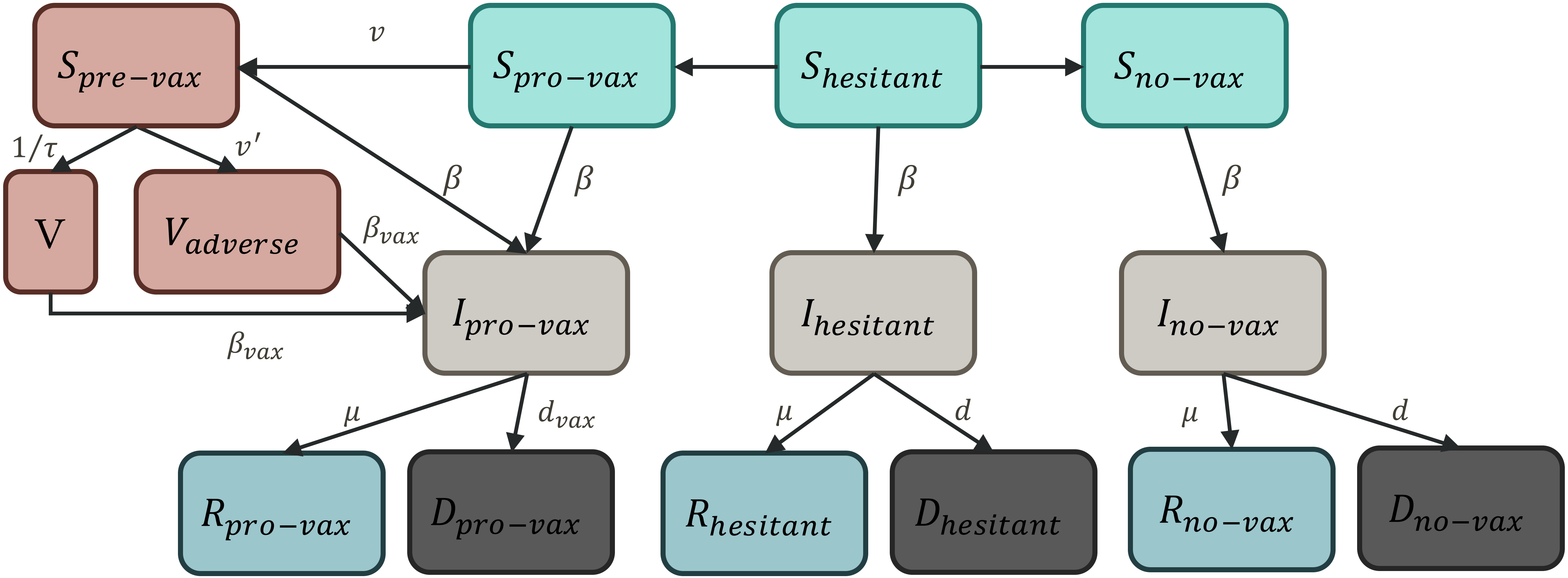


Weighted links 0.1 - 0.6 (social distancing)

1200 nodes

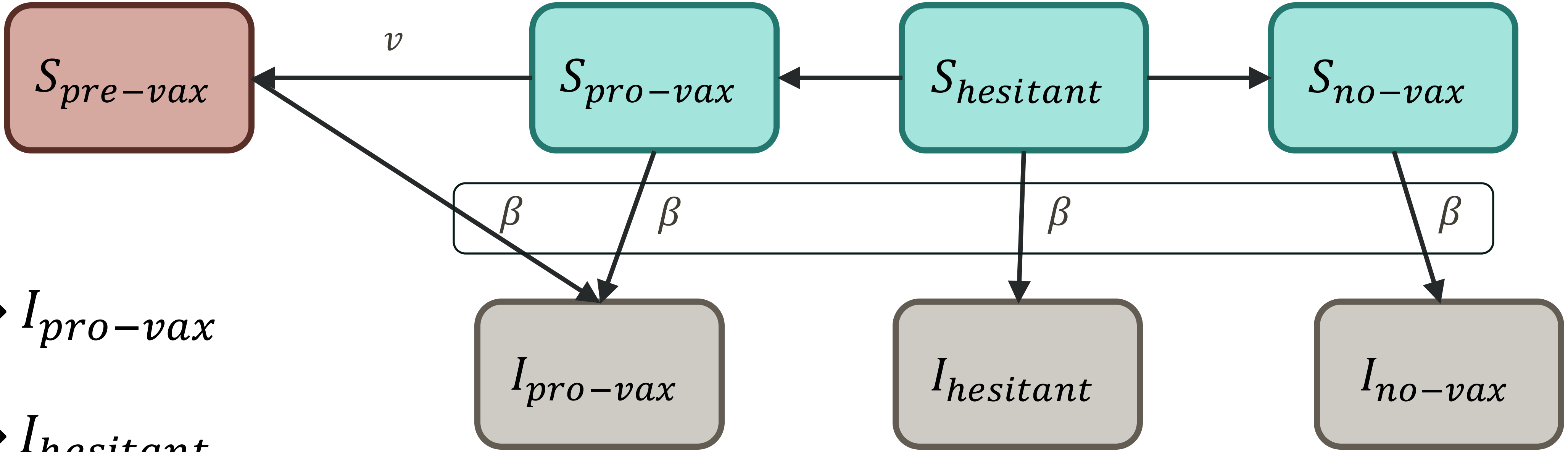
Initial states are susceptible and infected

Overview on the SIRV model



SIRV model

Compartment definition



$$S_{pro-vax} \xrightarrow{\beta} I_{pro-vax}$$

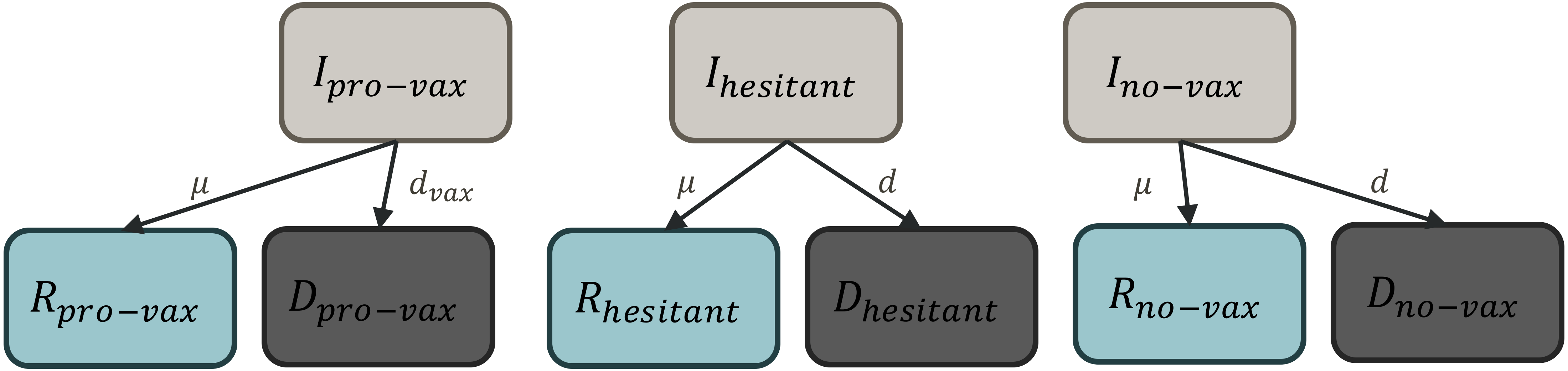
$$S_{hesitant} \xrightarrow{\beta} I_{hesitant}$$

$$S_{no-vax} \xrightarrow{\beta} I_{no-vax}$$

HYP: transition rates are fixed leading to exponential occupation time!

Transition rules: infection

β is the **infection rate** for all susceptible categories, including pre-vaccinated individuals.



$$I_{pro-vax} \xrightarrow{\mu} R_{pro-vax} \qquad I_{pro-vax} \xrightarrow{d_{vax}} D_{pro-vax}$$

$$I_{no-vax} \xrightarrow{\mu} R_{no-vax} \qquad I_{no-vax} \xrightarrow{d} D_{no-vax}$$

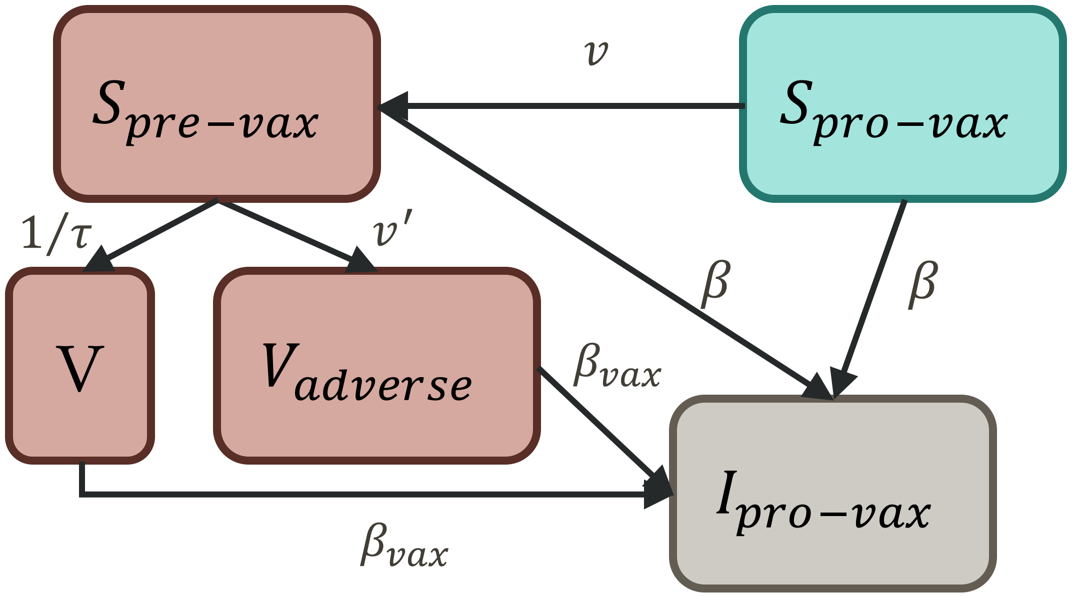
$$I_{hesitant} \xrightarrow{\mu} R_{hesitant} \qquad I_{hesitant} \xrightarrow{d} D_{hesitant}$$

Transition rules: recovery and death

-**μ** is the recovery rate for all the infected

-d is the death rate for no-vax infected

-$\boldsymbol{d_{vax}}$ is the death rate for vaccinated infected (smaller)



$$S_{pro-vax} \xrightarrow{v} S_{pre-vax}$$

$$S_{pre-vax} \xrightarrow{1/\tau_v} V$$

$$S_{pre-vax} \xrightarrow{v_{adverse}} V_{adverse}$$

$$\mathrm{V} \xrightarrow{\beta_{vax}} I_{pro-vax}$$

$$V_{adverse} \xrightarrow{\beta_{vax}} I_{pro-vax}$$

Transition rules: vaccine

-v is the vaccination rate for the pro-vax

-v' is the rate of the vaccinated with adverse reaction

-1 / τ is the rate of conversion from pre-vaccine to fully vaccinated

-β_{vax} is the (smaller) rate of infection for vaccinated people

Parameters

FIXED

- β=0.18
- β vac = 0.3·β
- μ=0.037
- d_no_vac = 0.05
- d_vac = 0.01
- τ_vac = 12 days
- vaccine_time = 120 days
- Vaccine availability = 700 doses

VARIABLE

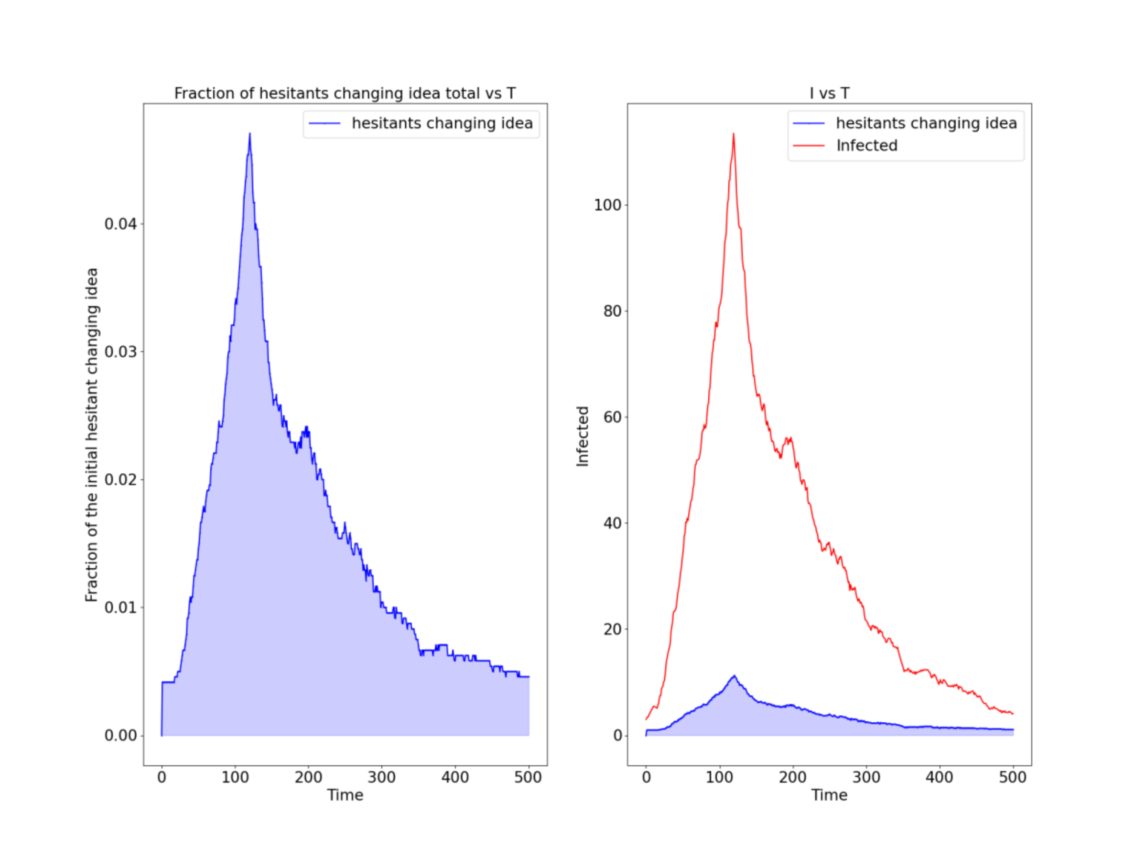
- i0 = 3
- frac_hesitant = 0.2
- frac_no_vax = 0.05
- weights of fear

Colored values are taken from real COVID-19 data

Fear modelization

Dynamic changes in hesitancy: transition rules

1. Initially, we determine how many hesitants should switch their stance at each time step.



Fixed rate unsatisfactory: all hesitants changed minds before infection peak, with exponential probability.

Hesitants change minds only during active epidemic, not before.

2. **Solution**: number hesitant that change mind directly proportional to the current pandemic status, randomly selecting from hesitant list.

Dynamic changes in hesitancy: transition rules

$S_{pro-vax}$

⇑ currently infected people
⇑ deaths of no vax

$S_{hesitant}$

⇑ deaths of pro vax
⇑ vaccinated with adverse reaction

S_{no-vax}

3. We determine the probability for an hesitant to become pro-vax or no-vax.

Probability is determined by:

- Local contribution
- Global contribution

Dynamic changes in hesitancy: transition rules

LOCAL CONTRIBUTION

At **time t node i** is **hesitant.**

1. Identify neighbors of i (denoted as N)
2. Count nodes that are infected, dead with and without vaccination and the ones that had adverse reaction to vaccine.
3. Assign different weights [0,1] for every possible state. Higher weights = higher probability of becoming pro-vax

This weights for ⅔ of the total contribution

Infected

$$Local\ factor = \sum_i \left(\boxed{(N_i = S_3) + (N_i = S_4) + (N_i = S_5)} \right) * W_0$$

Adverse reaction $+ \boxed{(N_i = S_8)} * W_3$

$+ \boxed{(N_i = S_{12})} * W_2$ Death pro-vax

Death no-vax $+ \left(\boxed{(N_i = S_{13}) + (N_i = S_{14})} \right) * W_1$

$+ \left(\boxed{(N_i = S_0) + (N_i = S_1) + (N_i = S_2)} \right) * W_4$ Susceptible

Recovered $+ \left(\boxed{(N_i = S_{11}) + (N_i = S_{10}) + (N_i = S_9) + (N_i = S_6)} \right) * W_4$

Pre-vax

$$Normalization = \sum_{state \in network\ states} \frac{W_{state}}{\#\ nodes}$$

Dynamic changes in hesitancy: transition rules

GLOBAL CONTRIBUTION

It takes into consideration the global influence of the pandemic: we don't work with neighbors anymore but with the rates of the compartment occupation.

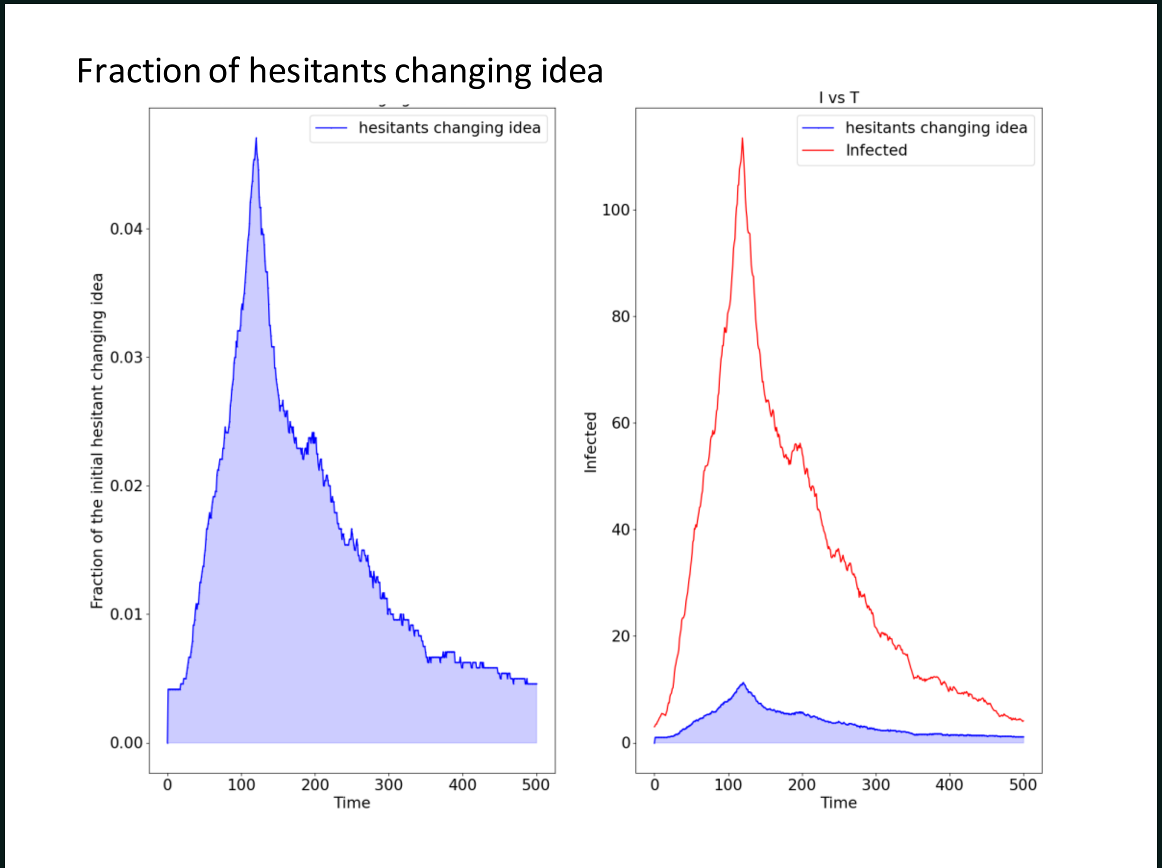
The weights used here are the same used for the local contribution.

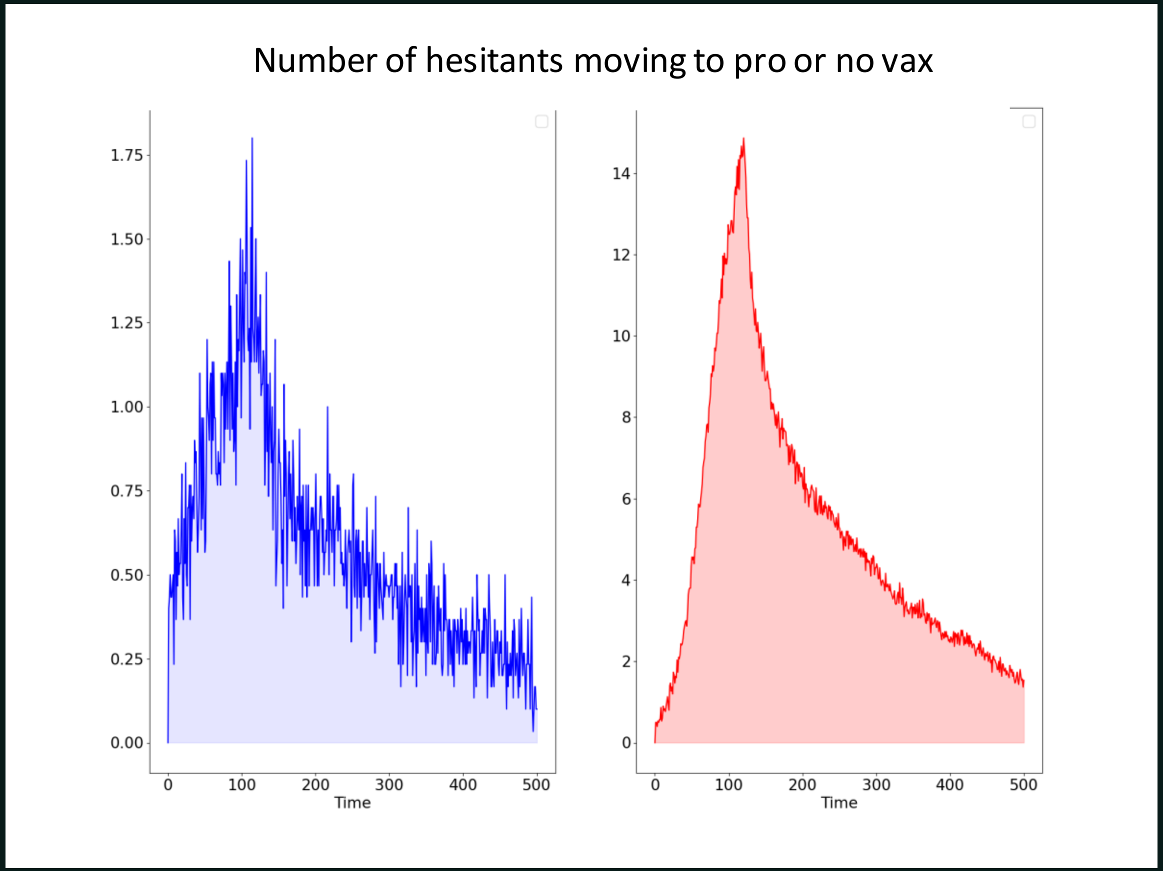
This contribution accounts for ⅓ of the final decision.

$$
\begin{aligned}
Global\ factor = \sum_i &\big((G_i = S_3) + (G_i = S_4) + (G_i = S_5)\big) * W_0 \\
&+ (G_i = S_8) * W_3 \\
&+ (G_i = S_{12}) * W_2 \\
&+ ((G_i = S_{13}) + (G_i = S_{14})) * W_1 \\
&+ ((G_i = S_0) + (G_i = S_1) + (G_i = S_2)) * W_4 \\
&+ ((G_i = S_{11}) + (G_i = S_{10}) + (G_i = S_9) + (G_i = S_6)) * W_4
\end{aligned}
$$

$$
Normalization = \sum_{state \in network\ states} \frac{W_{state}}{\#\ nodes}
$$

Dynamic changes in hesitancy: transition rules





Simulations overview

Process Flow

Initialization

Define the network

Use real-world COVID data on hesitancy and no-vax presence in population + vaccination rates

Population initialization

Use different initialization for the population in the network:
- random
- no-vax in hubs, hesitant as neighbors
- no-vax in periphery, hesitant as neighbors

Optimization

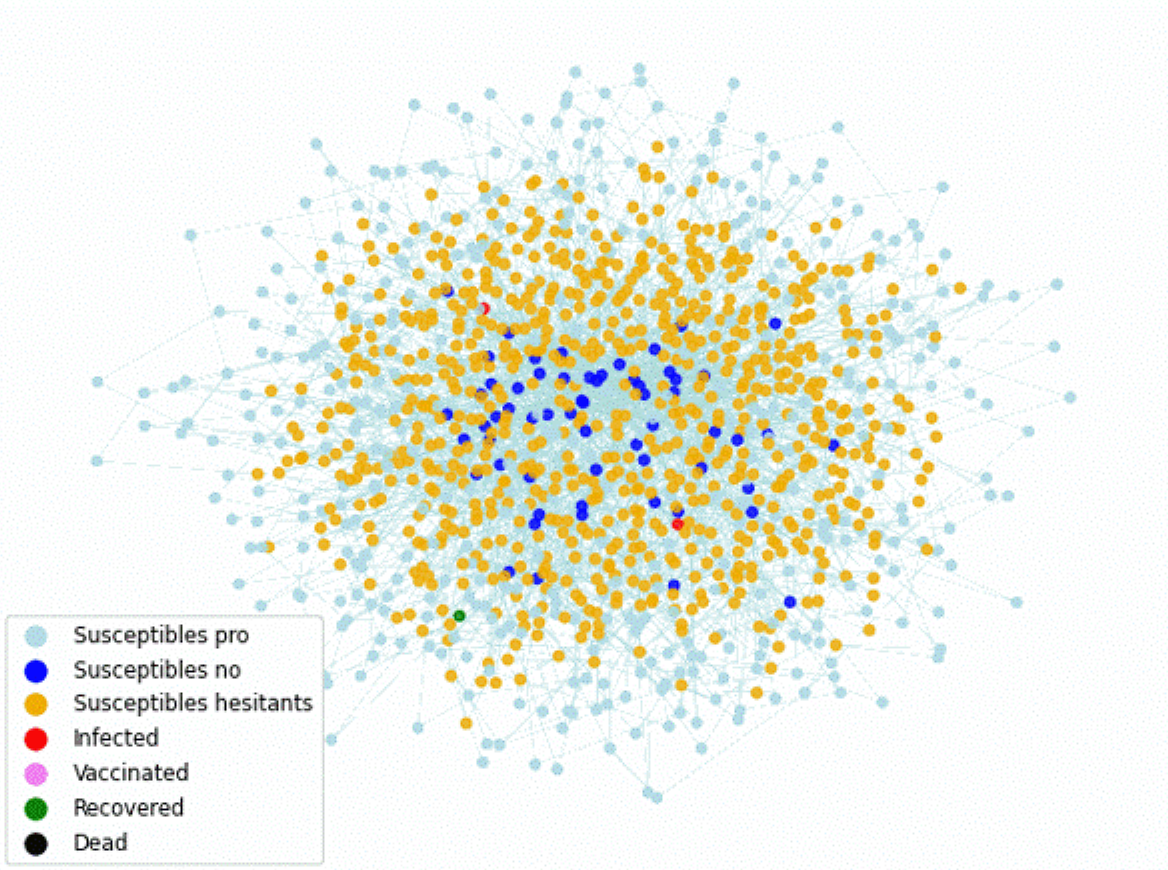
Search for the weights of the “fear function”

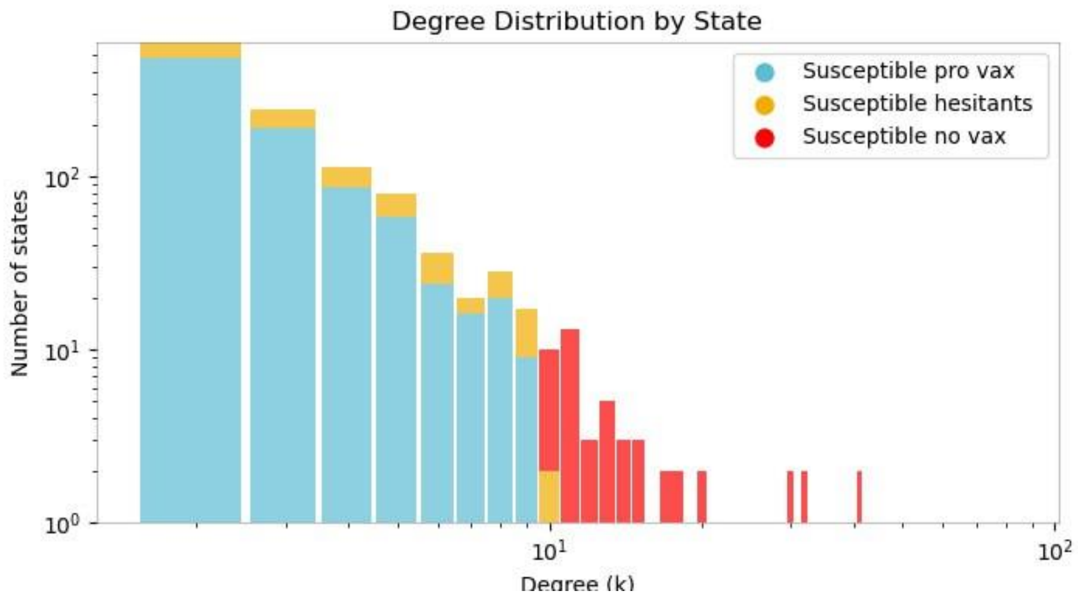
Choose the middle ground solution (median value) and use it for the subsequent analysis

Sensitivity analysis

Varying:
- initial infected i0
- fraction of hesitants
- fraction of no-vax

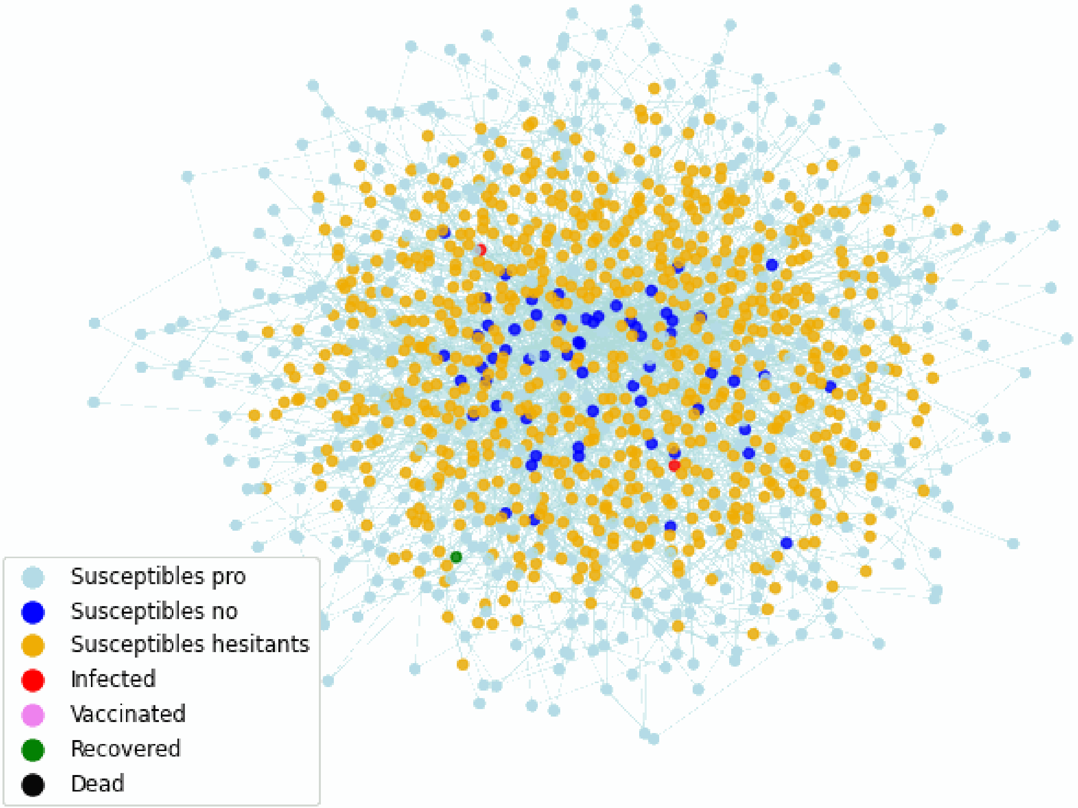
Explore the impact of said parameters on the number of infected, time of peak infection, final attack rate, number of death

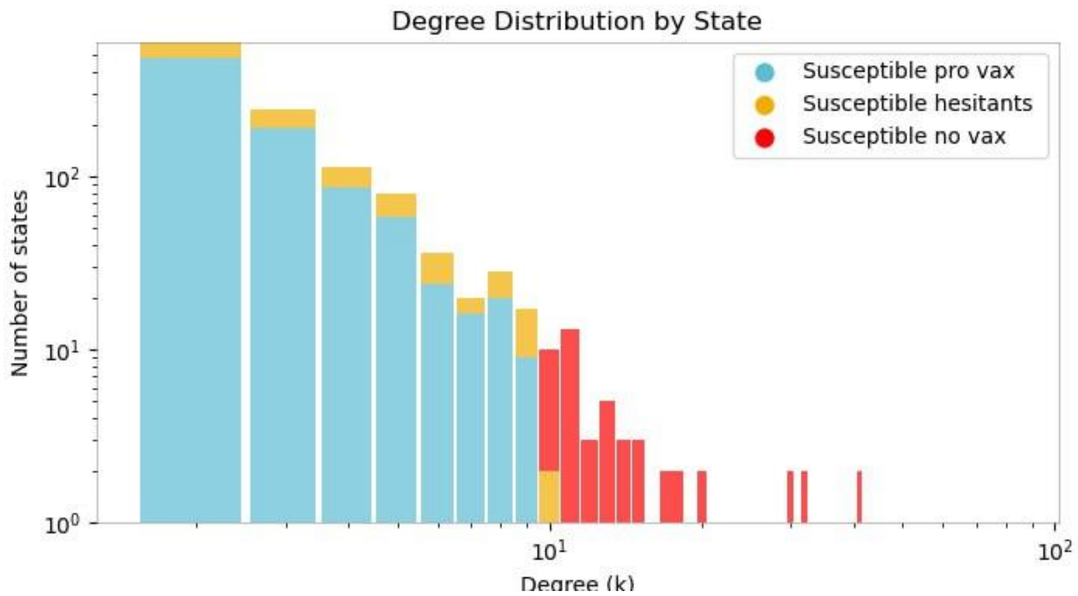




Network initialization: hubs

- No vax in hubs
- Hesitant as neighbors





Network initialization: hubs

- No vax in hubs
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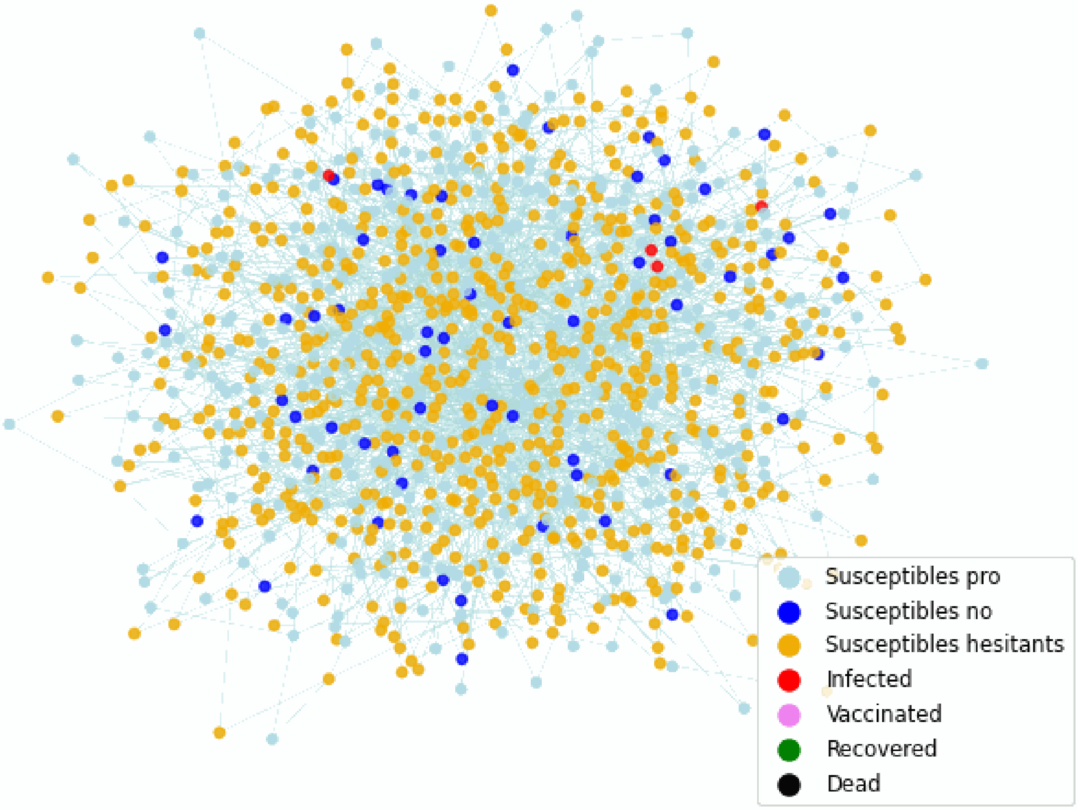
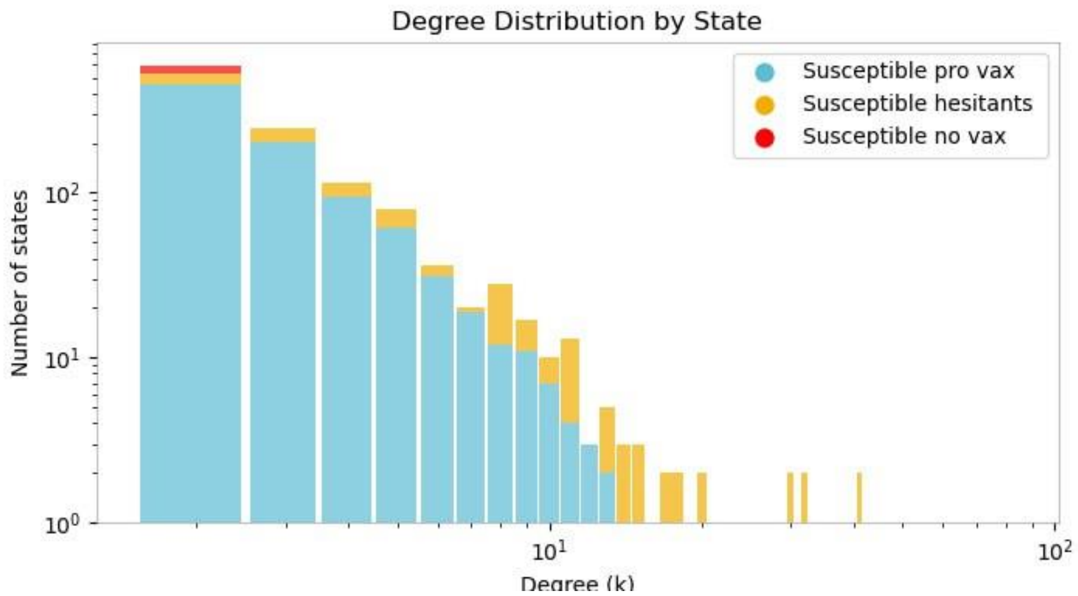
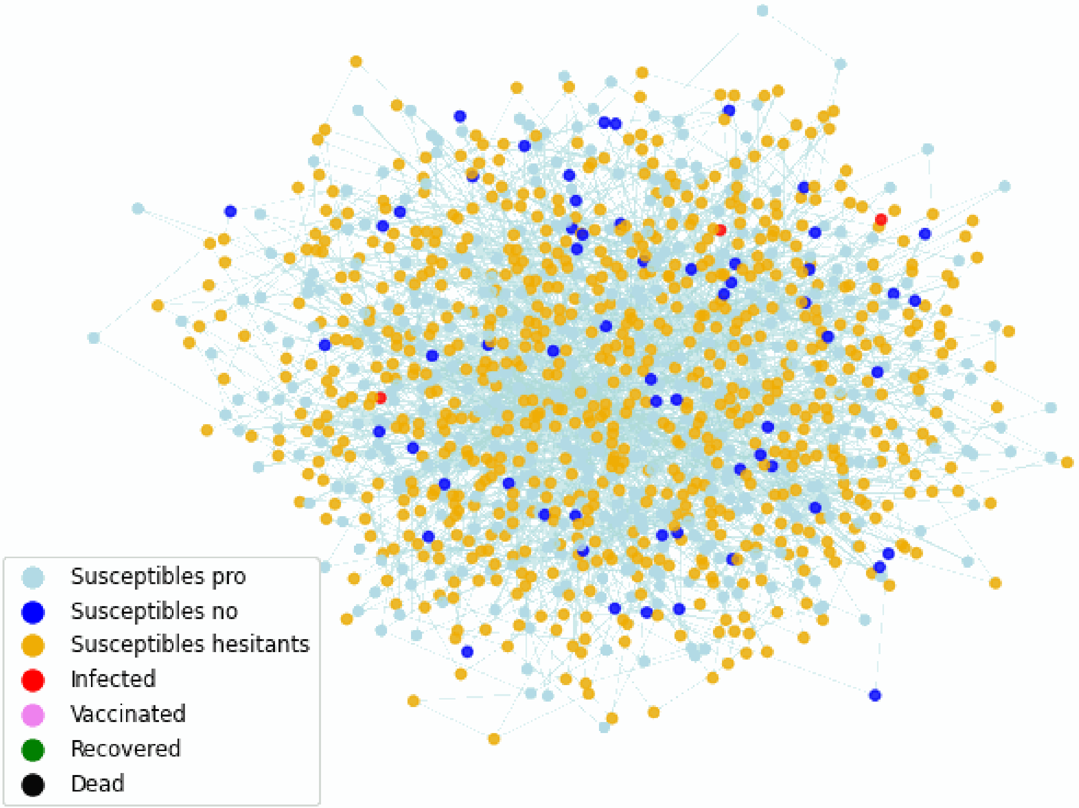
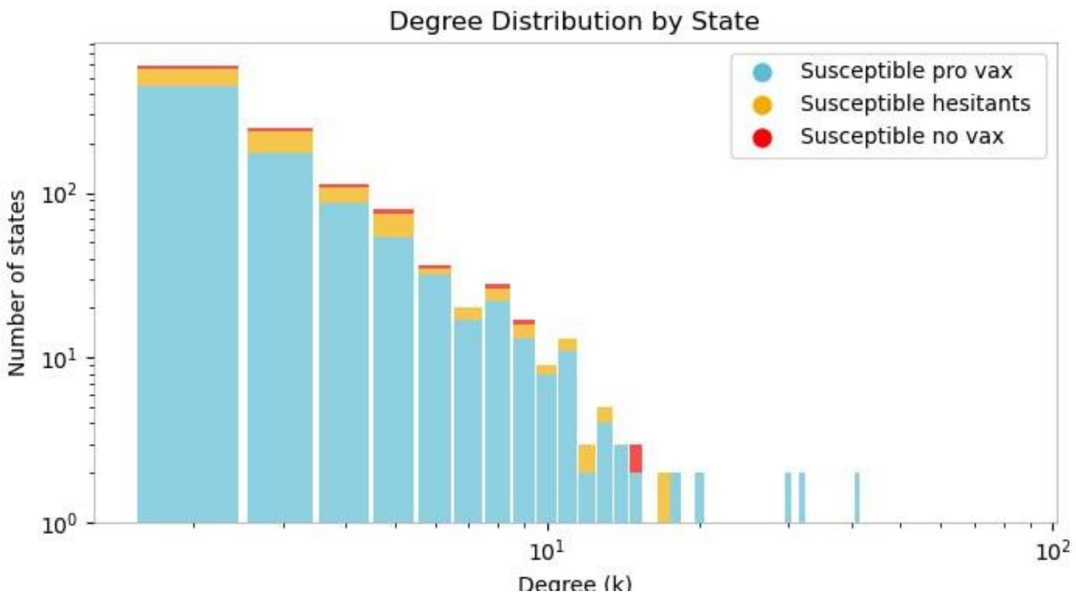




Network initialization: periphery

- No vax in peripheral nodes
- Hesitant as neighbors





Network initialization: random

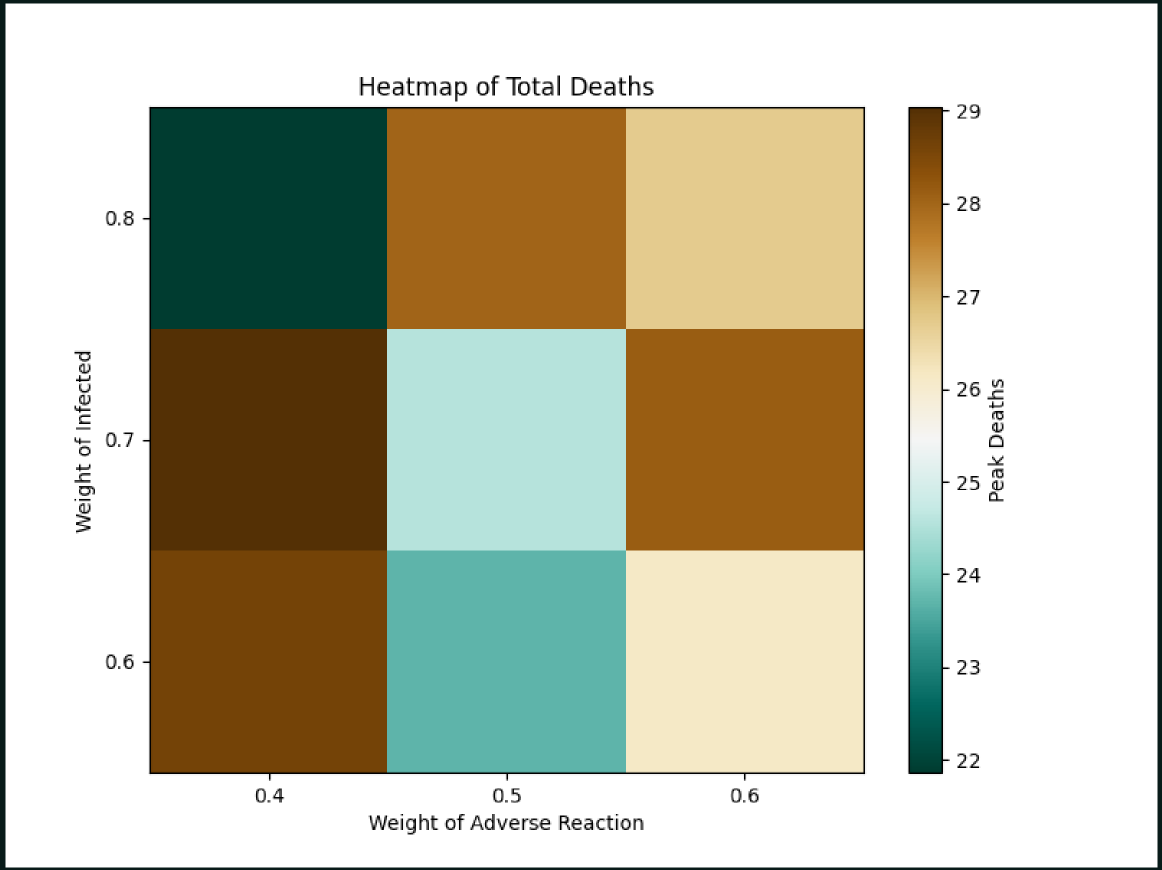
- All nodes positioned randomly

RESULTS OF SIMULATIONS

Gridsearch on The Weights of Fear

- 3 initialization, 30 iterations
- Others parameters are fixed
- Weights are between 0 - 1
- Weight of infection [0.6 , 0.7 , 0.8]
- Weight of death non vaccinated [0.85 ,0.9 ,0.95]
- Weight of death of vaccinated [0.2 , 0.3 , 0.4]
- Weight of adverse reaction [0.4 , 0.5 , 0.6]
- Weight of other states [0.5]
- Value of guesses are from the hypothesis of fear in real life scenario
- Take the median value for future test

More fear of Covid =
More pro vax

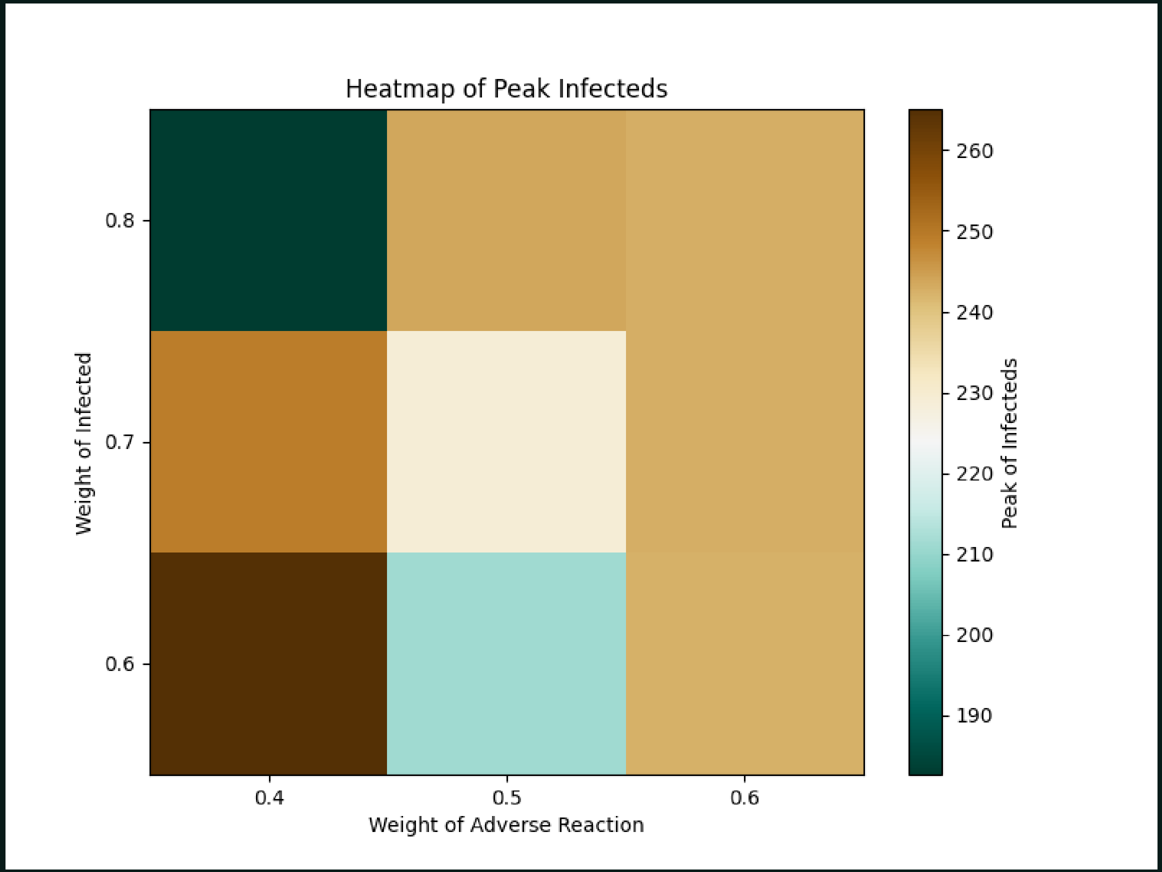


More fear of Covid =
More pro vax

- Best scenario top – left;
- Worst scenario, middle– left;

Hubs initialization

More fear = more pro vax



More fear of Covid = More pro vax

- Best scenario top – left;
- Worst scenario, bottom– left;

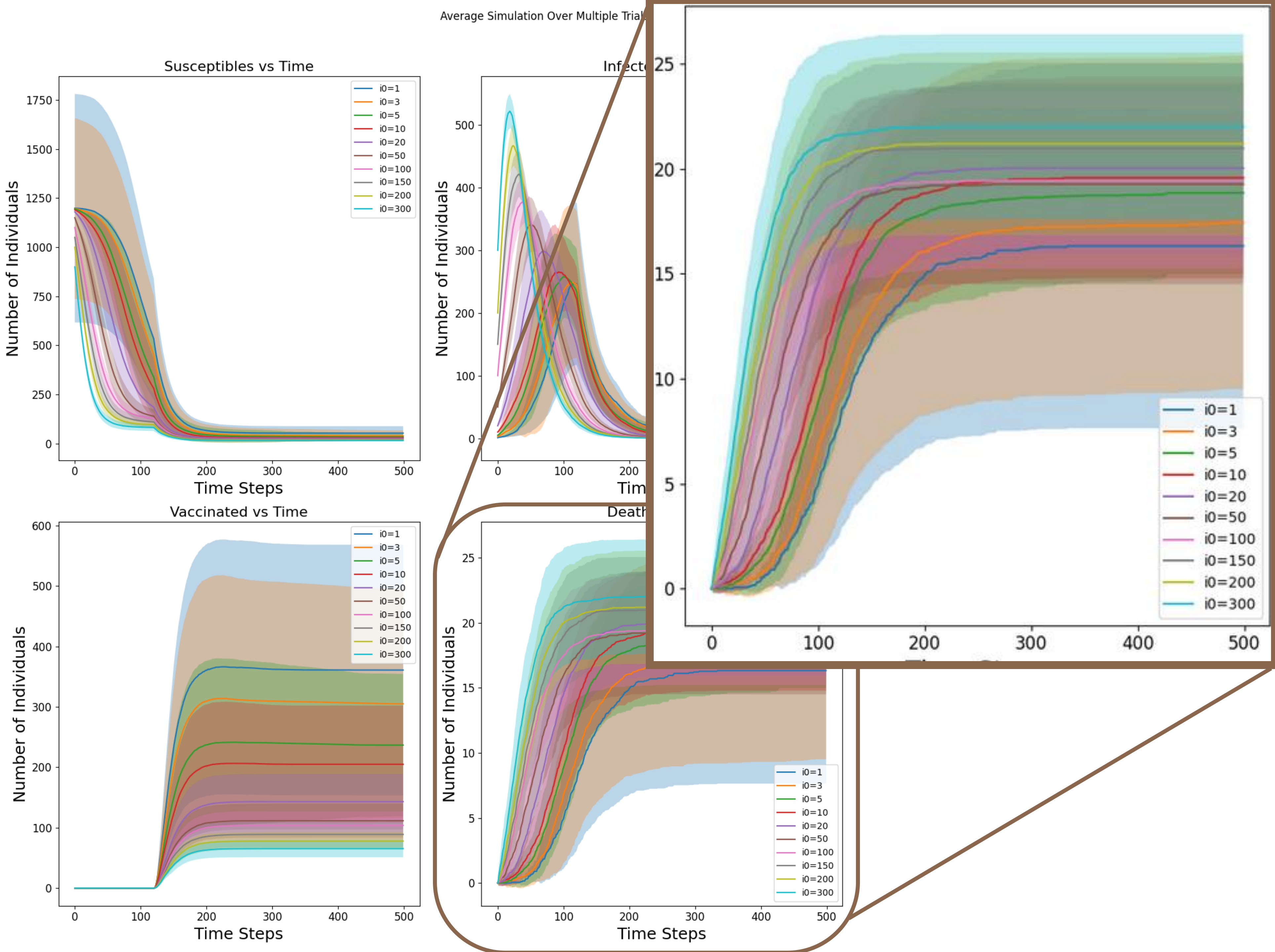
Hubs initialization

Sensitivity Test

- 3 initializations, 50 iterations
- Median weights from gridsearch
- Variation of i0_values
  [1, 3, 5, 10, 20, 50, 100, 150, 200, 300]
- Variation of frac_hesitant_values
  [0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4, 0.5, 0.7, 0.9]
- Variation of frac_novac_values
  [0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4, 0.5, 0.7, 0.8]
- Fixed values i0 = 3, frac hesitant = 0.2, frac novac = 0.05

Periphery

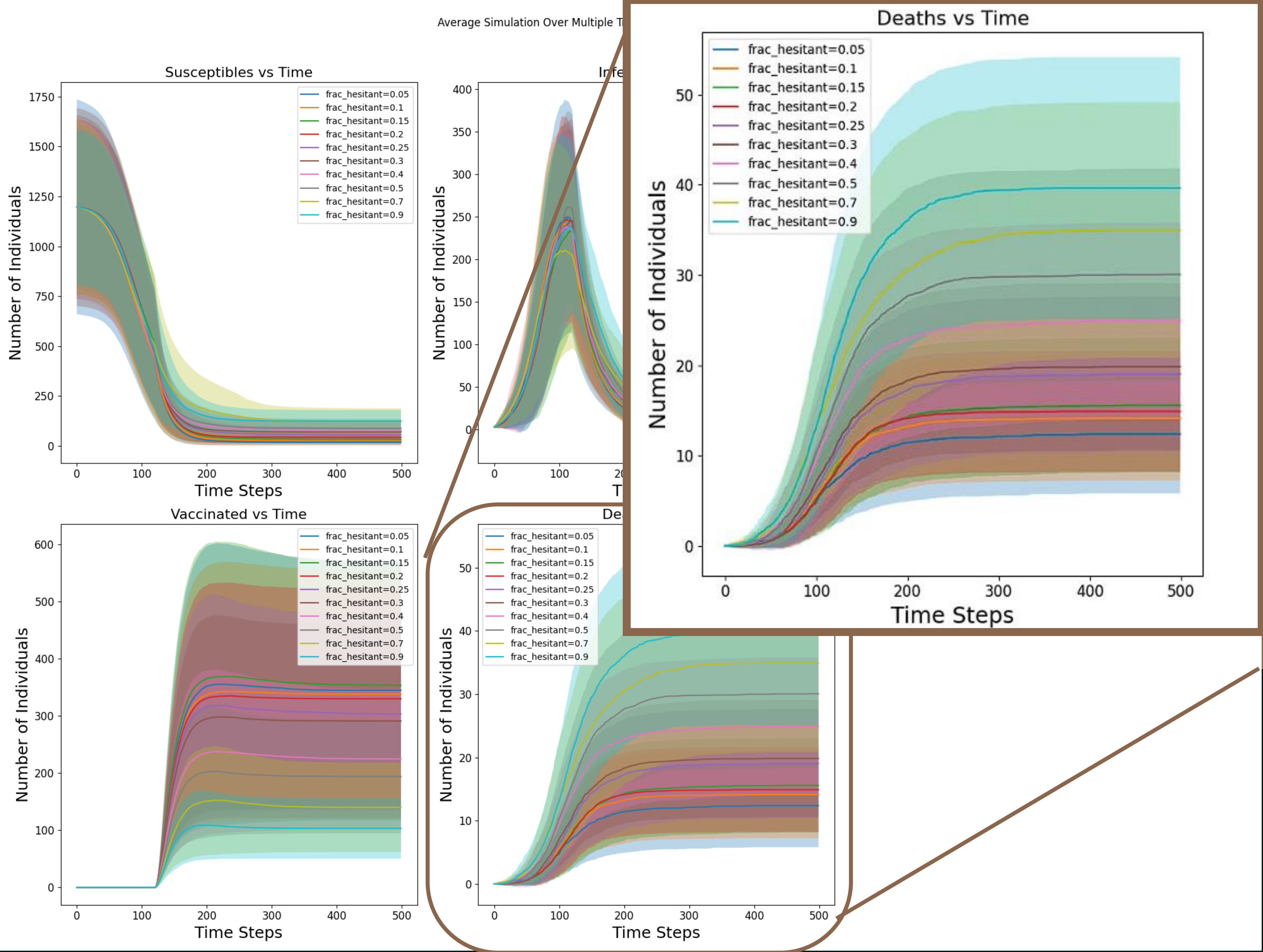
INITIAL INFECTION (I0)



Periphery

FRACTION

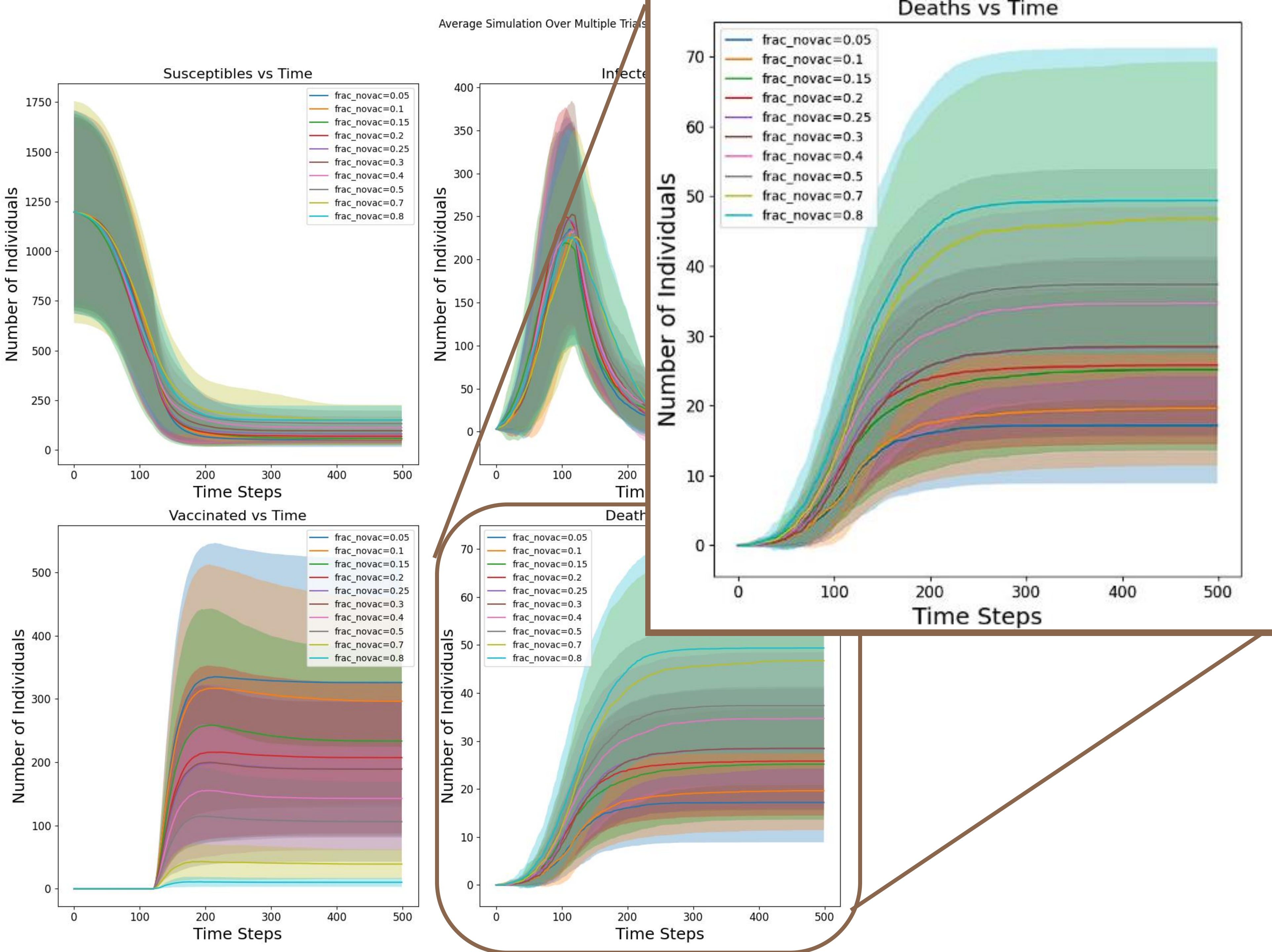
HESITANT



Periphery

FRACTION

NON-VACCINATED



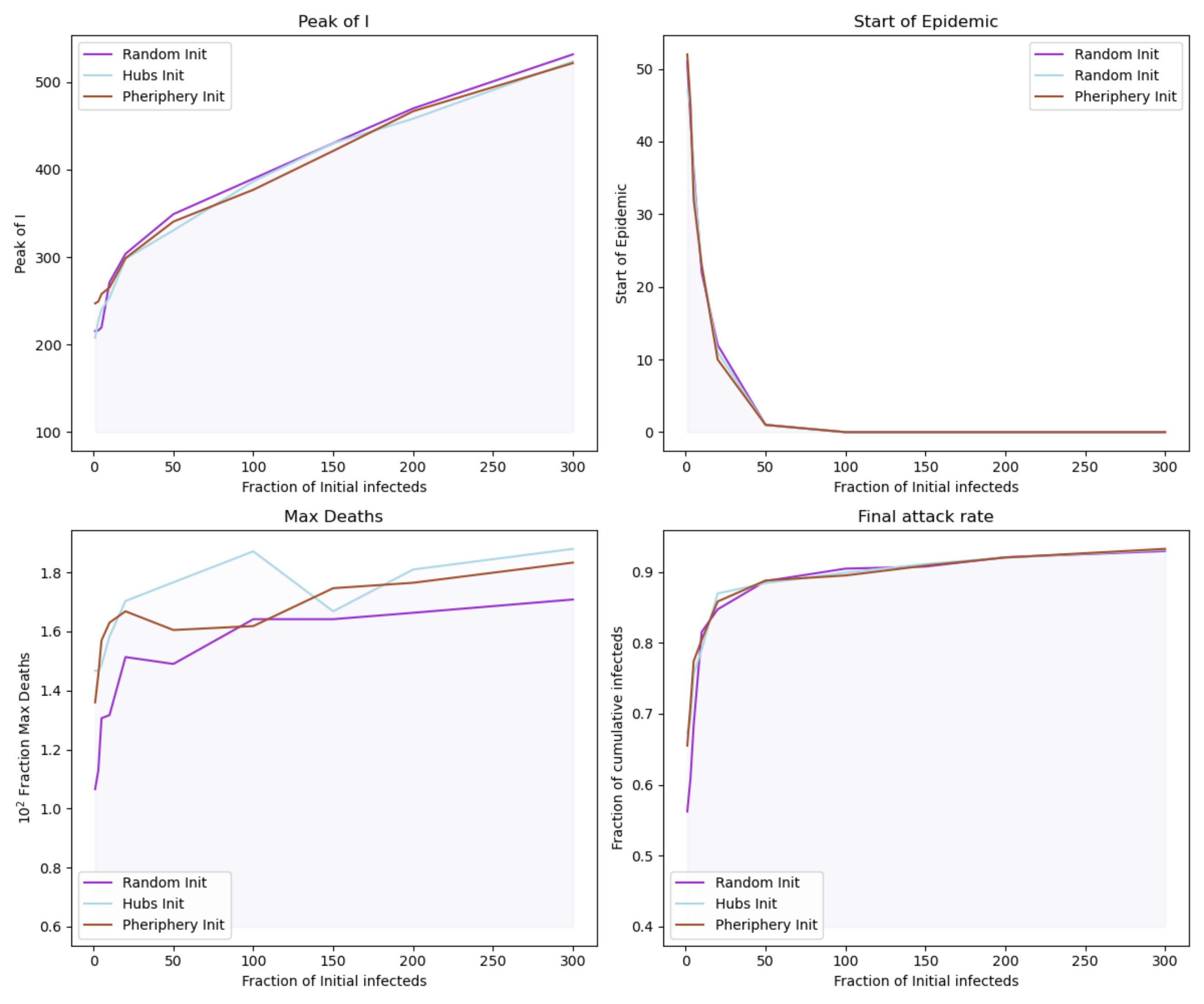
Initialization comparison

To compare the different initializations we plot:

- peak of infection $\longrightarrow$ max(I);
- starting time of the epidemic $\longrightarrow$ $I>50$;
- total deaths $\longrightarrow$ max(D);
- Final attack rate $\longrightarrow$ $(I(\infty) + D(\infty) + R(\infty))/N$;

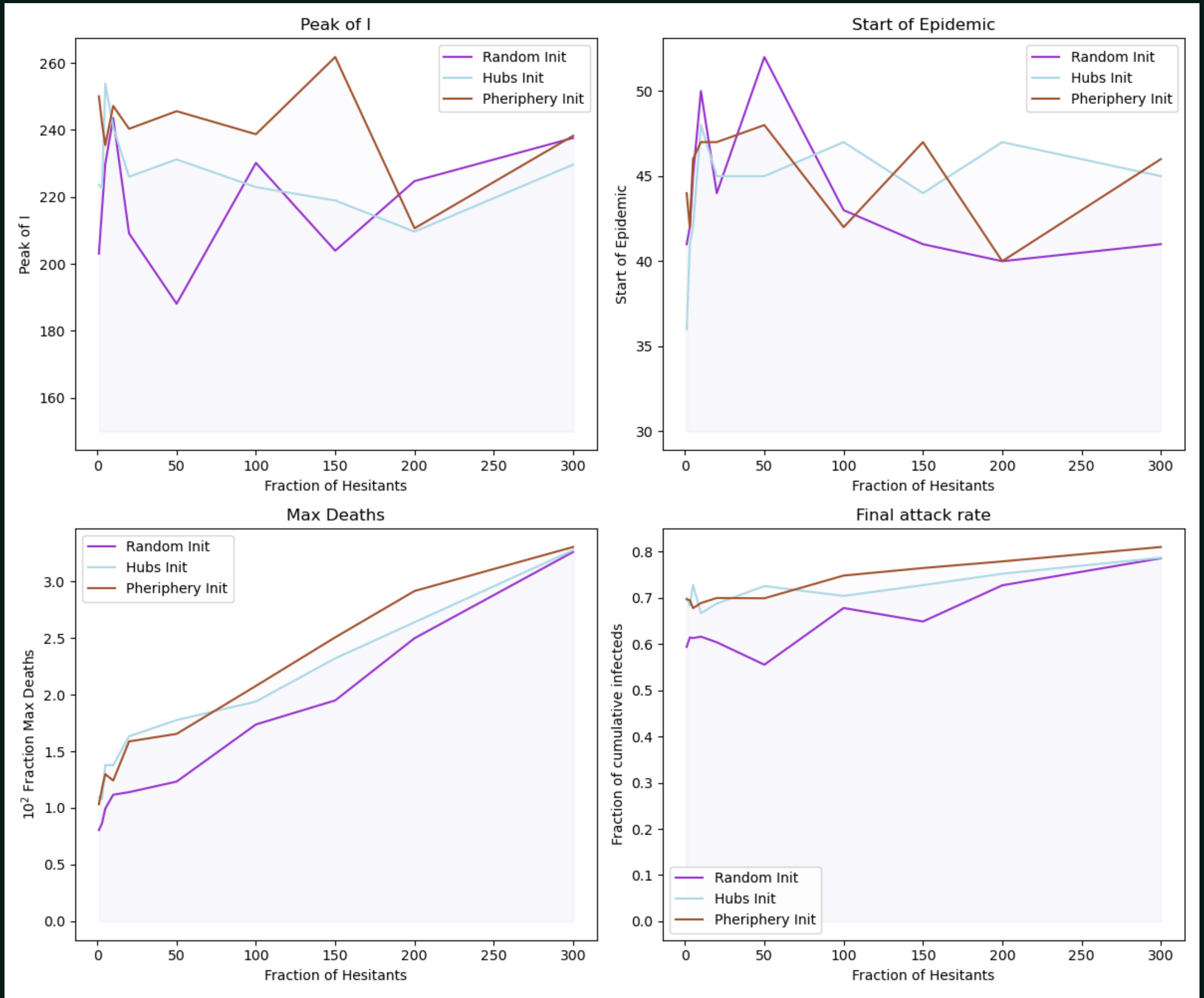
VS

- The different fraction of initial hesitants;
- Fraction of initial no-vax;
- Number of initial infecteds;



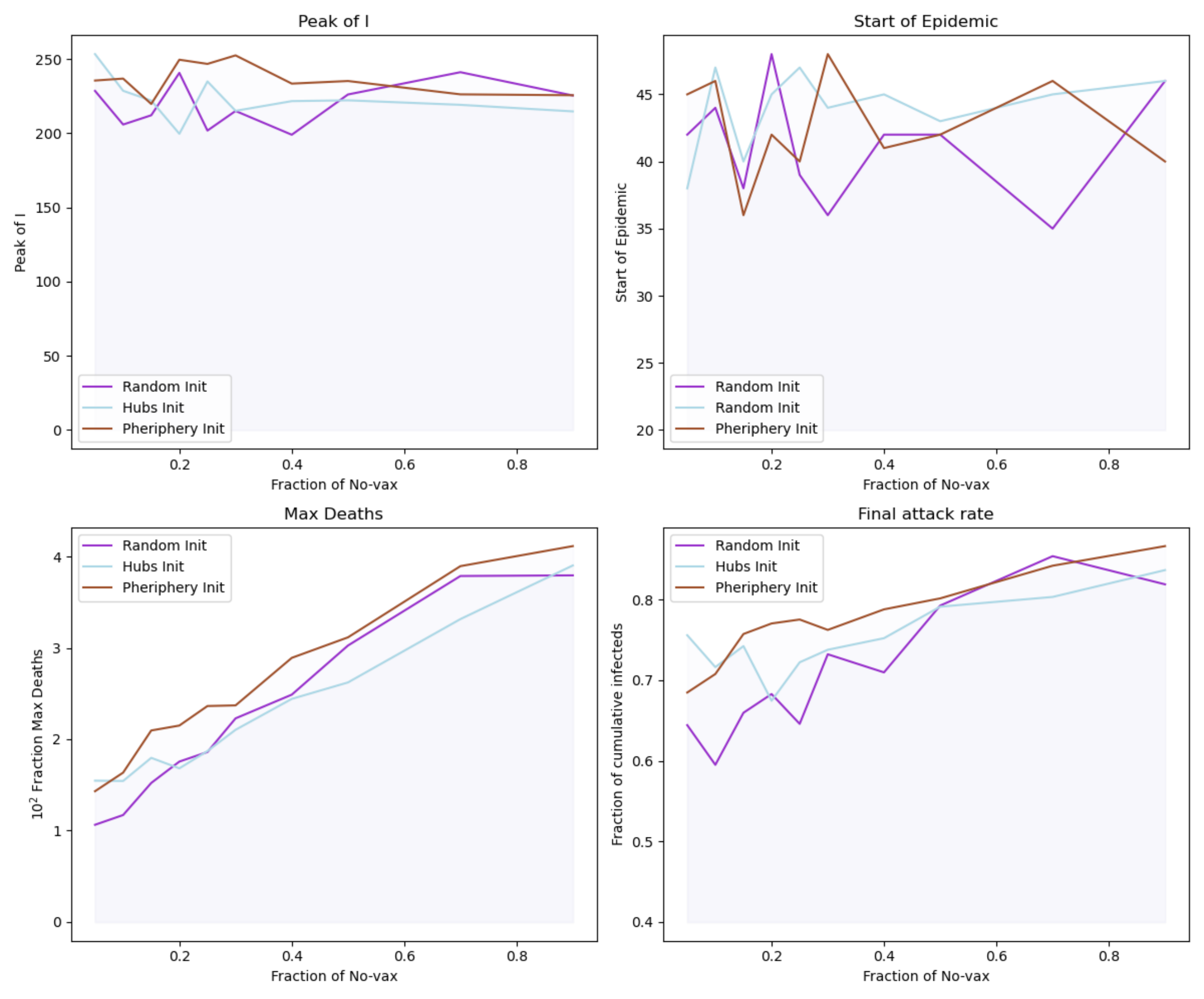
Initial infected (i0)

- ALL THE PARAMETERS ARE SENSIBLE TO CHANGES IN THE INITIAL NUMBER OF INFECTEDS;
- THE TIME OF THE START OF THE EPIDEMIC DROPS IMMEDIATLY TO ZERO.



Fraction of hesitants

- PEAK OF INFECTED AND START OF EPIDEMIC ARE NOT SO SENSIBLE TO CHANGES IN HESITANTS AND INITIALIZATIONS
- THE DEATHS AND THE FINAL ATTACK RATE ARE PROPORTIONAL TO THE HESITANTS.



Fraction of non-vaccinated

- PEAK OF INFECTIONS AND START OFEPIDEMIC ARE NOT SO SENSIBLE TO CHANGES IN NOVAX AND INITIALIZATIONS
- THE DEATHS AND THE FINAL ATTACK RATE ARE PROPORTIONAL TO THE NOVAX FRACTION.

Conclusions

- We were able to implement a novel model of contagion on a network;

- Our analysis suggests that variations in hesitant individuals, infected cases, and non-vaccinated individuals generally have a noticeable impact on deaths and the cumulative number of infections. However, the peak of infections appears to be less sensitive to these factors;

Conclusions

- Our analysis suggests that assigning higher weights to infected compartments in modeling fear and consequently influencing the decisions of hesitant individuals decreases the final number of deaths and the height of the infection peak;

- In our model, the quantity of hesitant or non-vaccinated individuals matters more than their network positions; three different initializations produce similar outcomes.

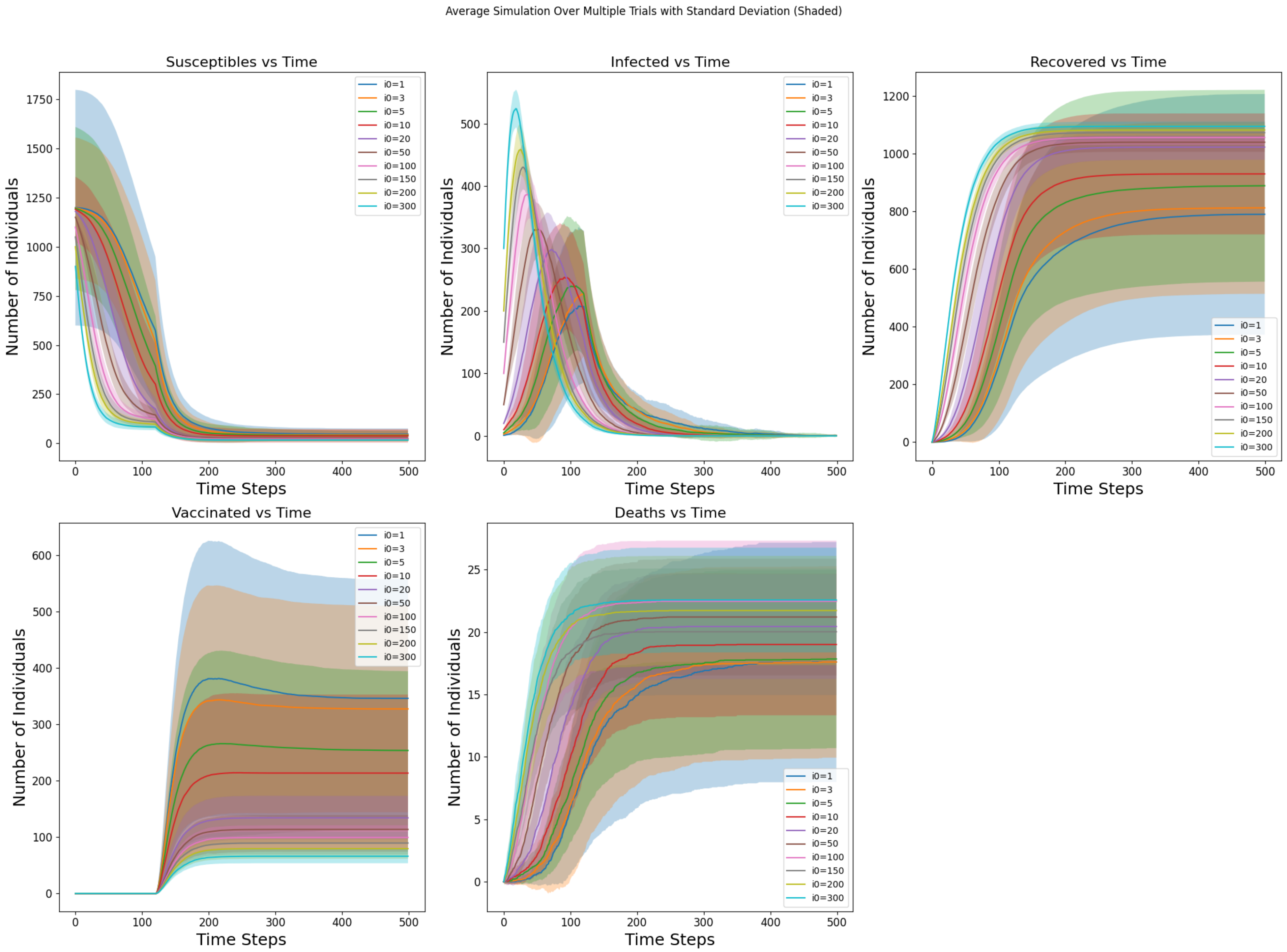
Further improvements

- Repeat the analysis using a bigger number of nodes and averaging over more realizations;
- Put more stress on the social distance, encoded in the weight of the links;
- Refine the modelization of the fear by extracting the weights *a posteriori* from real contagion data and apply them to our model.
- Refine weights with finer gridsearch and more realizations;
- Explore various network models, both simulated and real-world, for analysis.

Additional material

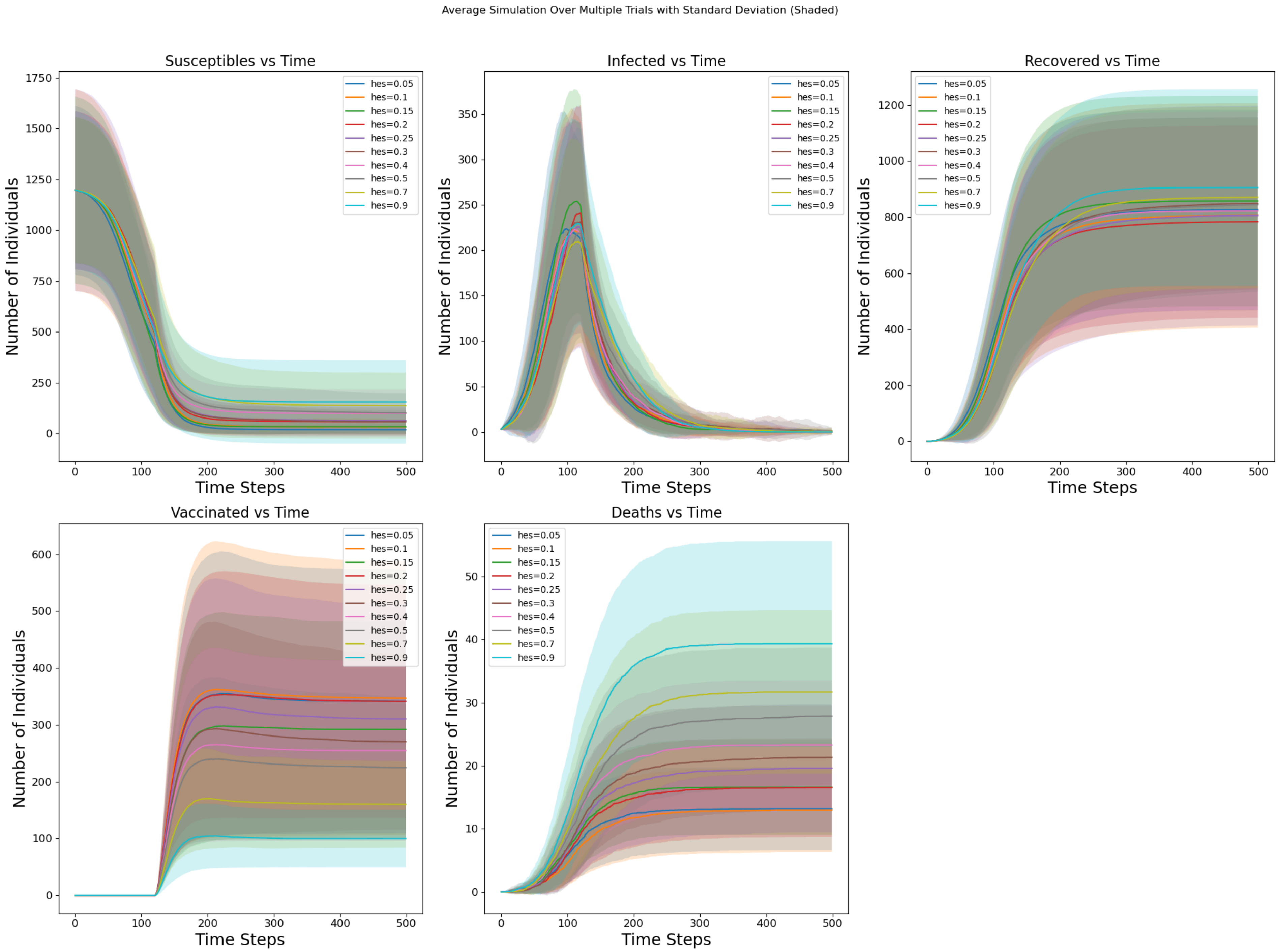
Hubs

INITIAL INFECTION (I0)



Hubs

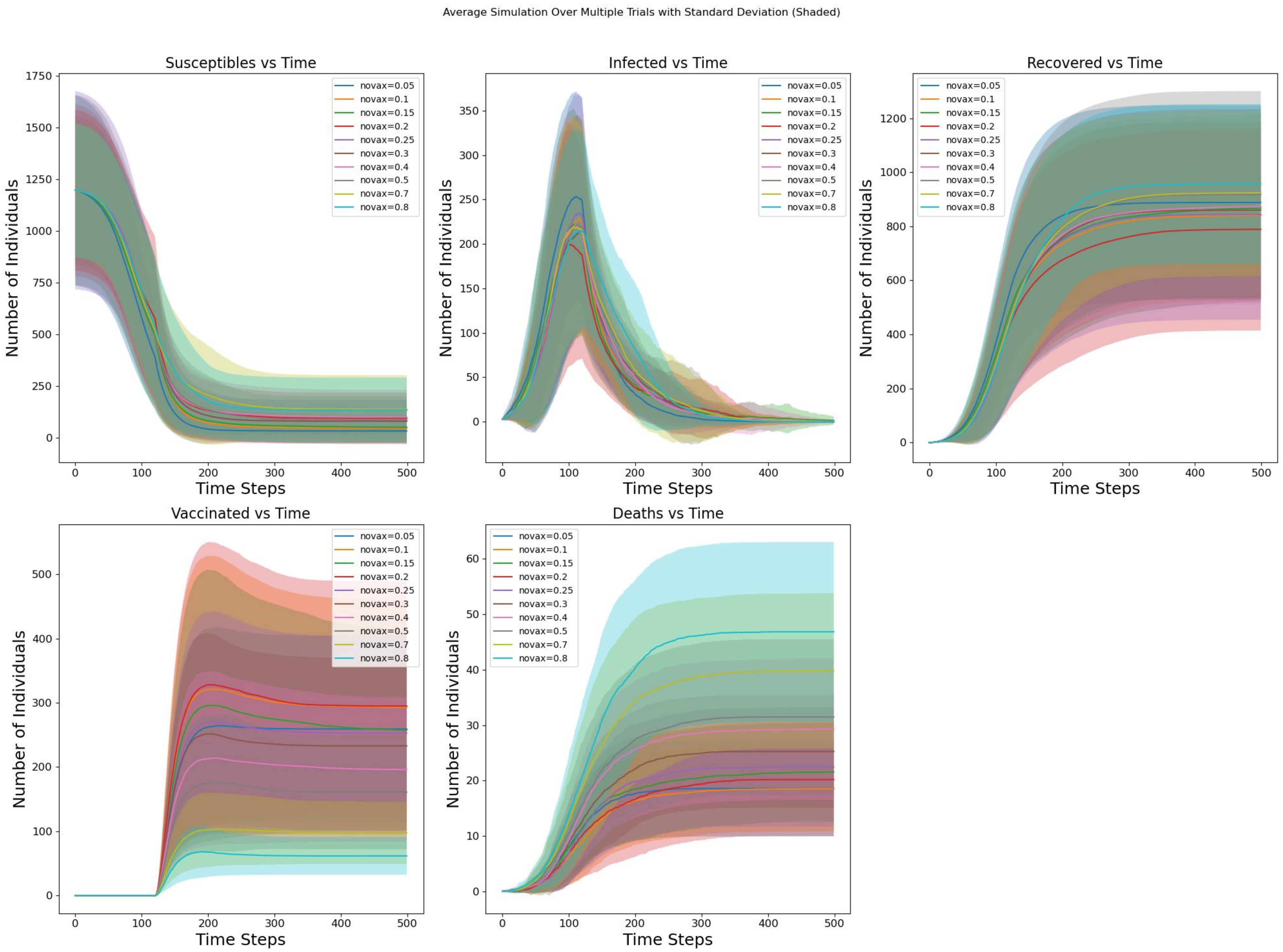
FRACTION HESITANT



Hubs

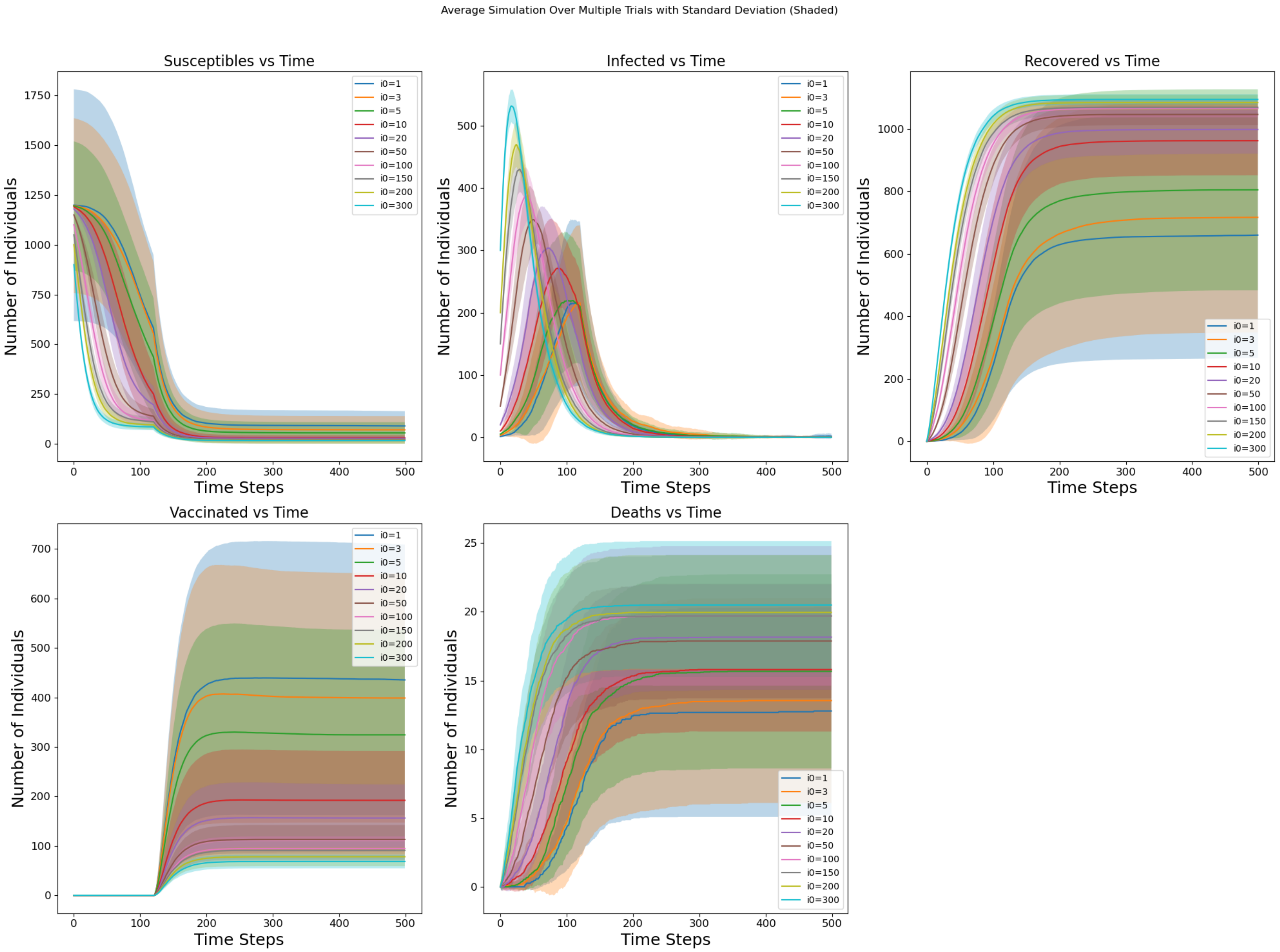
FRACTION

NON-VACCINATED



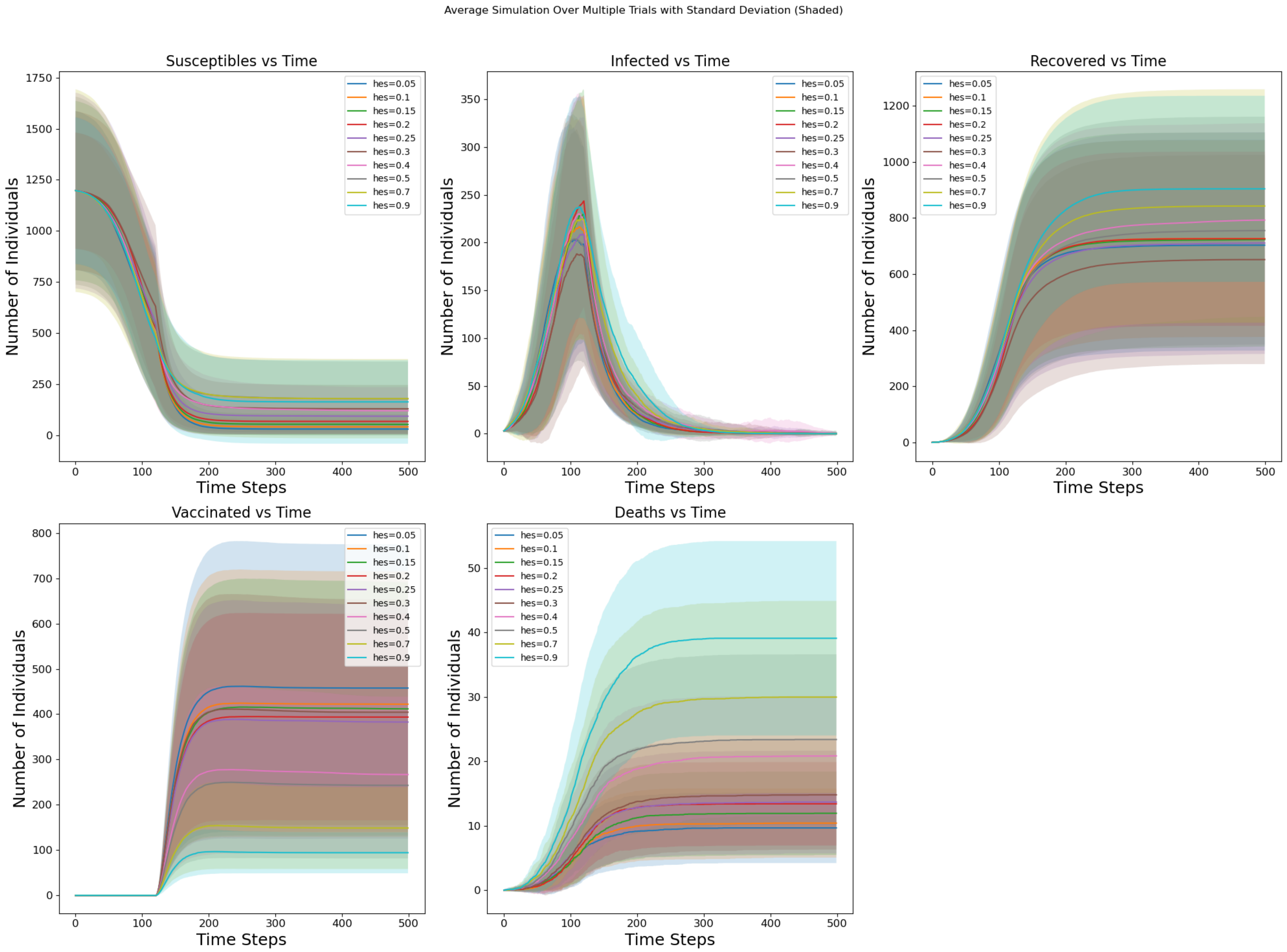
Random

INITIAL INFECTION (I0)



Random

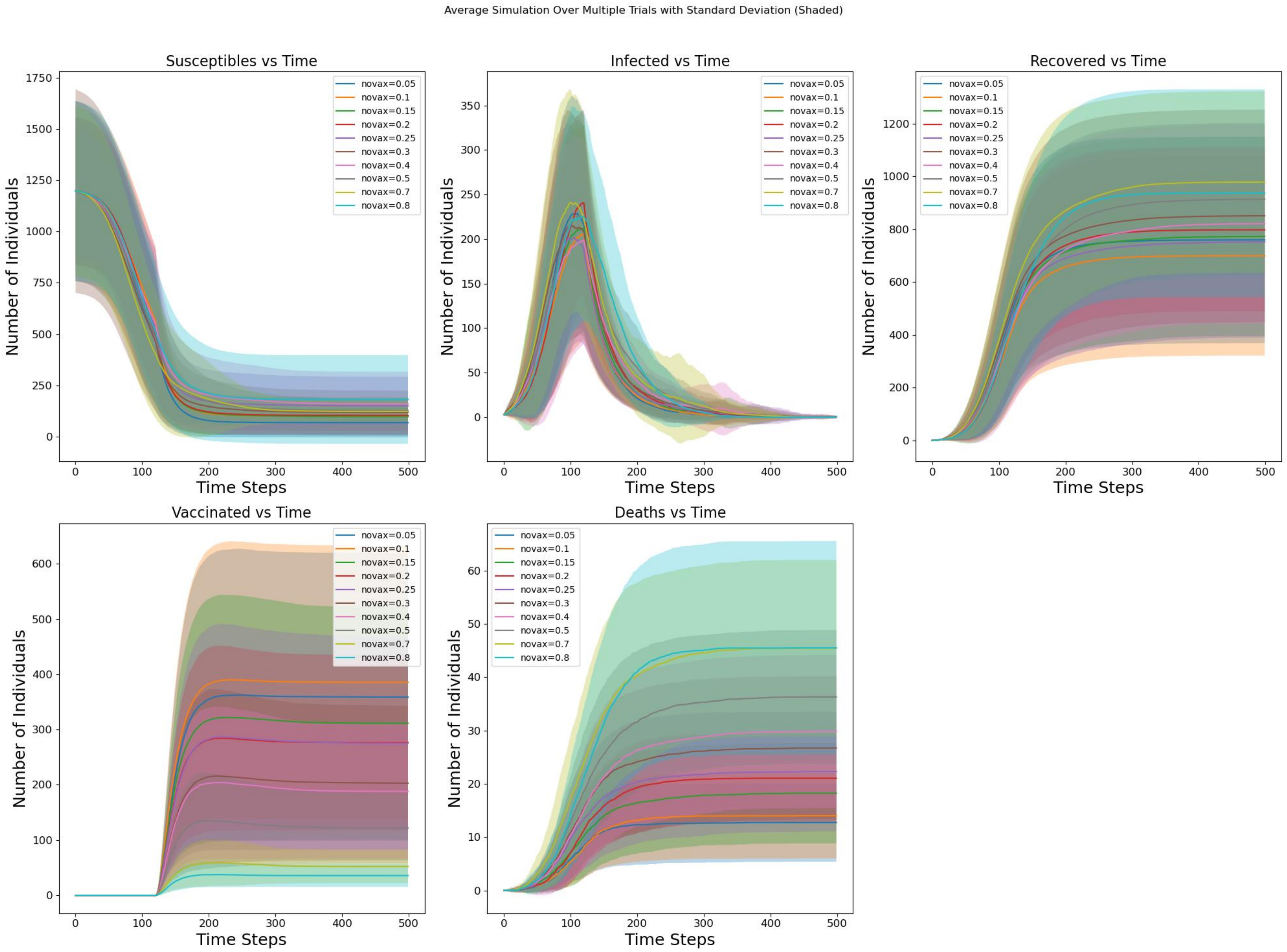
FRACTION HESITANT



Random

FRACTION

NON-VACCINATED



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- Fraction of hesitants to vaccine in Italy retrieved from: https://www.sciencedirect.com/science/article/pii/S0033350621000834?casa_token=Z_4s7x6Zw5UAAAAA:Qhfh1r7Pqif5IjnJKMZVIvawvBlLZku35ap9oVNAyy1gnknxnSK58jyD_tpx7GUlMOn_wpcs2w
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