Information Travel and Pandemics

Working Group III: Lisa Beckmann, Mela Eckenfels,
Nathanael Gutknecht und Zuzanna Mielczarek

Agenda

Introduction

Research Question

The Model

Results

Limitations

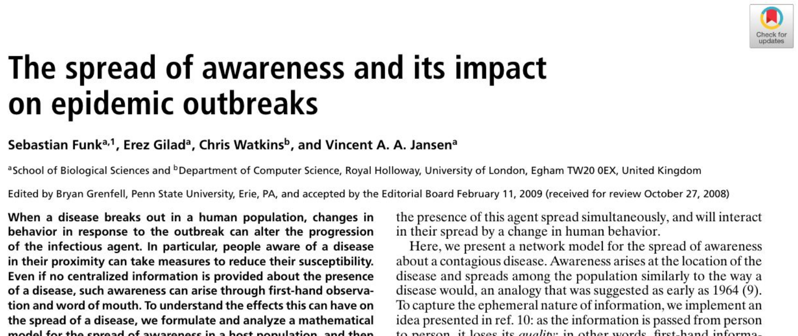
Summary and Outlook

Introduction

- Paper of choice:
    - **Funk et al (2009)**: The spread of awareness and its impact on epidemic outbreaks

- Two aspects of epidemic spread: **information** and **illness**

- Research: Influence of awareness on epidemic spreading



The spread of awareness and its impact on epidemic outbreaks

Sebastian Funk[a,1], Erez Gilad[a], Chris Watkins[b], and Vincent A. A. Jansen[a]

[a]School of Biological Sciences and [b]Department of Computer Science, Royal Holloway, University of London, Egham TW20 0EX, United Kingdom

Edited by Bryan Grenfell, Penn State University, Erie, PA, and accepted by the Editorial Board February 11, 2009 (received for review October 27, 2008)

When a disease breaks out in a human population, changes in behavior in response to the outbreak can alter the progression of the infectious agent. In particular, people aware of a disease in their proximity can take measures to reduce their susceptibility. Even if no centralized information is provided about the presence of a disease, such awareness can arise through first-hand observation and word of mouth. To understand the effects this can have on the spread of a disease, we formulate and analyze a mathematical model for the spread of awareness in a host population, and then link this to an epidemiological model by having mor hosts reduce their susceptibility. We find that, in a well- ulation, this can result in a lower size of the outbreak, b affect the epidemic threshold. If, however, the behavior is treated as a local effect arising in the proximity of ar it can completely stop a disease from spreading, altho the infection rate is below a threshold. We show that of locally spreading awareness is amplified if the social potential infection events and the network over whic als communicate overlap, especially so if the networks l level of clustering. These findings suggest that care r taken both in the interpretation of disease parameters in the prediction of the fate of future outbreaks.

mathematical model | rumor spread | behavioral response | soci

Human reactions to the presence of disease abour

the presence of this agent spread simultaneously, and will interact in their spread by a change in human behavior.

Here, we present a network model for the spread of awareness about a contagious disease. Awareness arises at the location of the disease and spreads among the population similarly to the way a disease would, an analogy that was suggested as early as 1964 (9). To capture the ephemeral nature of information, we implement an idea presented in ref. 10: as the information is passed from person to person, it loses its *quality*; in other words, first-hand informa-

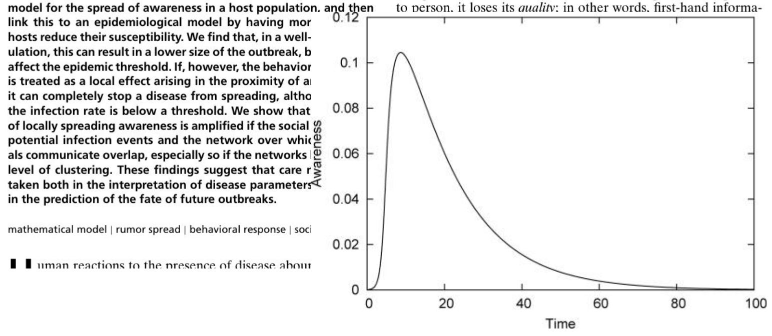


Fig. 1. Awareness $g(\rho,t)$ in the well-mixed population as a function of time for a given $\rho < 1$ if information is not replenished by the presence of the disease.

Research Question

1. Which **conditions** can help to contain outbreaks through information spreading?

2. What is the impact of **self-isolation** of knowingly infected individuals on the spread of a disease and under which **conditions** is it most impactful?

The Model

- Implementing **SIR-Model** for disease as a (30x30) **grid** with **four neighbours** for each person
  - each individual is associated to the states of SIR with **probabilities**

- Including **Awareness** into the Model
  - People with a **high rates of awareness** are less likely to get infected
  - Information wanes with **time** and **number of passages**
  - Information is generated by **infected individuals**

The Model

Legend:
β: normal infection rate
ϱ: decay rate
γ: Recovery rate
ω: Information generation rate
i: awareness (0 is highest)

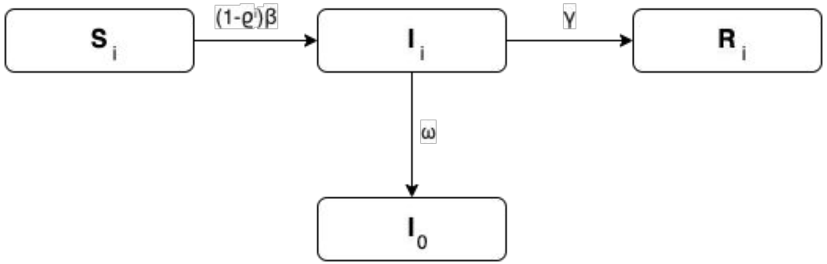


Fig.2 Flowchart of the SIR model. The boxes describe individuals having one of three possible conditions: being susceptible, infected or recovered. The arrows show the transition rates.

The Model

Legend:
β: normal infection rate
ϱ: decay rate
γ: Recovery rate
ω: Information generation rate
i: awareness (0 is highest)

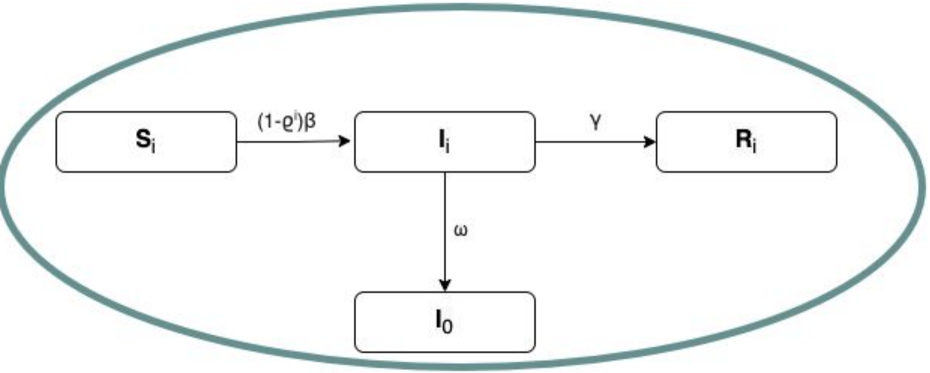


Fig.2 Flowchart of the SIR model. The boxes describe individuals having one of three possible conditions: being susceptible, infected or recovered. The arrows show the transition rates.

The Model

Legend:
β: normal infection rate
ϱ: decay rate
γ: Recovery rate
ω: Information generation rate
i: awareness (0 is highest)
α: Information transmission rate
λ: Information fading rate

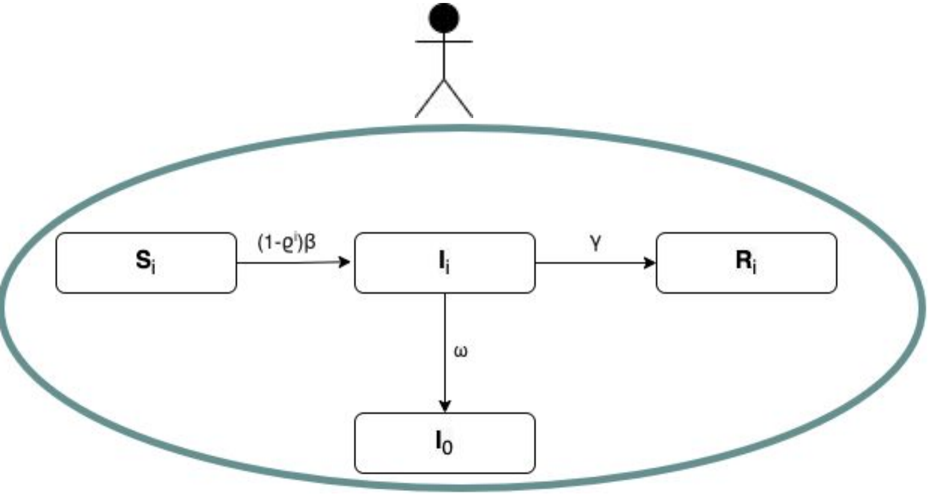


Fig.2 Flowchart of the SIR model. The boxes describe individuals having one of three possible conditions: being susceptible, infected or recovered. The arrows show the transition rates.

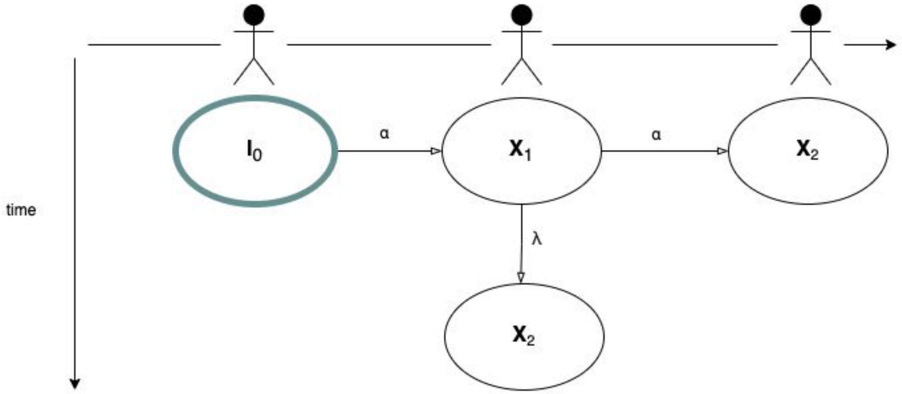


Fig.3 Flowchart of the awareness generation. The boxes describe the individuals and the arrows describe the information transmission/fading with time. The index describes the grade of awareness.

The Model

Basic Model

- only susceptible individuals act based on information received from neighbors

Extension

- Self-isolation of knowingly infected individuals with a probability κ
- **+ also the infected individuals (acting on information generated by themselves)**

Awareness without Infections

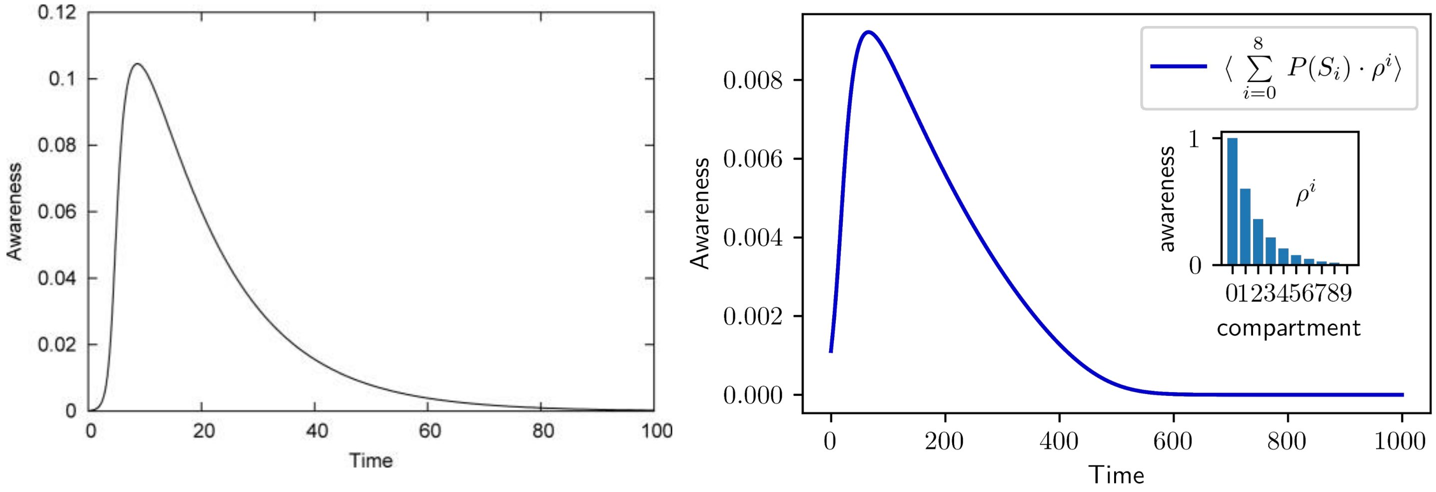
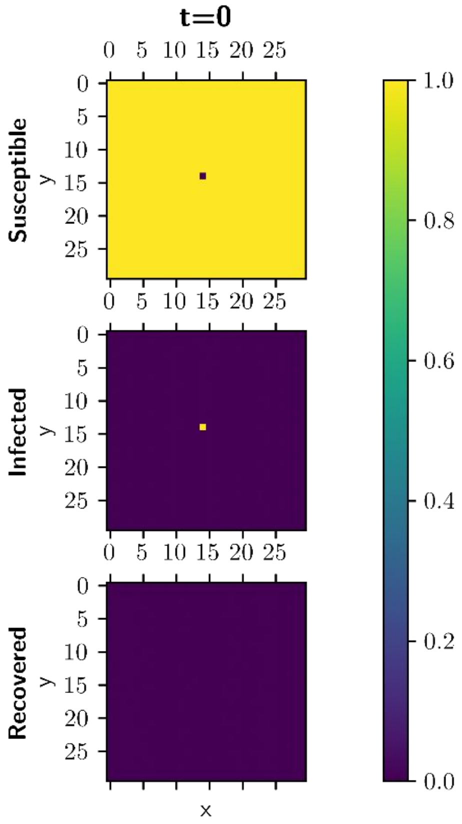
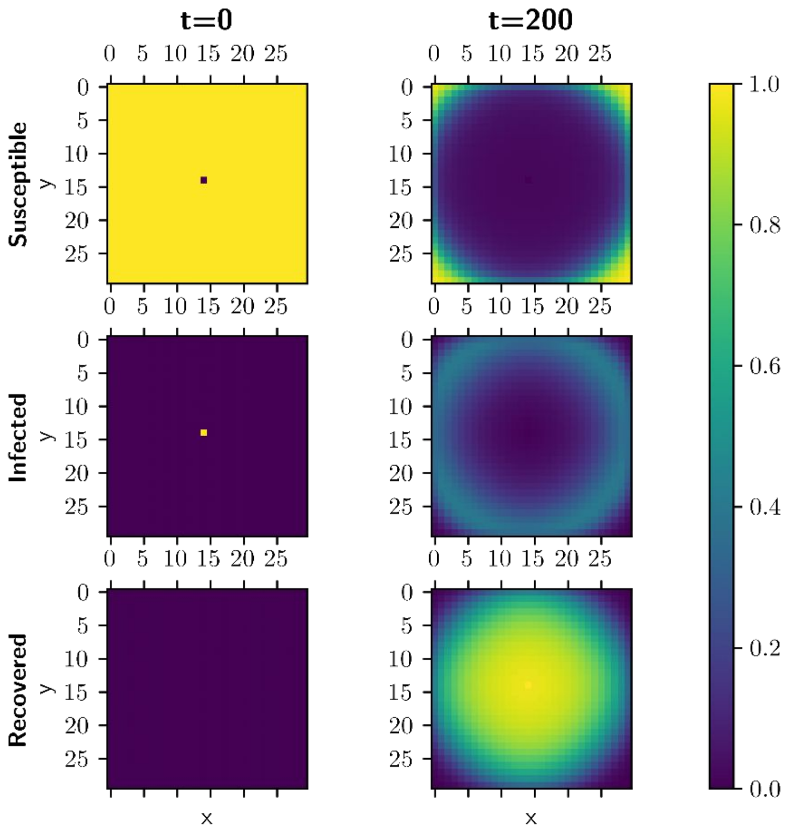
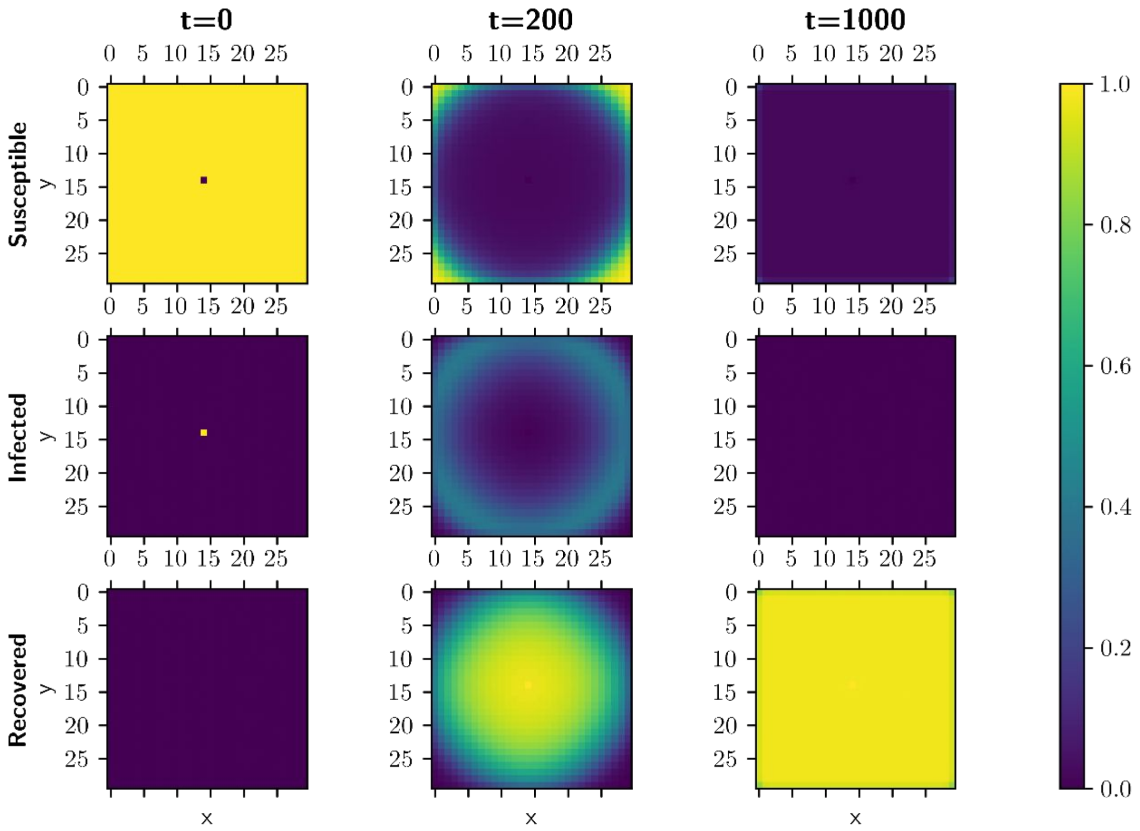


Fig. 4. Comparison between the awareness level $g(\rho,t)$ in the population when no infections are present to generate new awareness.
Left: original figure from *Funk et al (2009)* for a well-mixed population (mean field analysis);
Right: own recreation on a square lattice with interactions between nearest neighbors only.


t=0
Susceptible
Infected
Recovered
y
x
0
5
10
15
20
25
1.0
0.8
0.6
0.4
0.2
0.0


t=0
t=200
Susceptible
Infected
Recovered
y
x
0 5 10 15 20 25
1.0
0.8
0.6
0.4
0.2
0.0



t=0
t=200
t=1000
Susceptible
Infected
Recovered
y
x
0 5 10 15 20 25
1.0
0.8
0.6
0.4
0.2
0.0

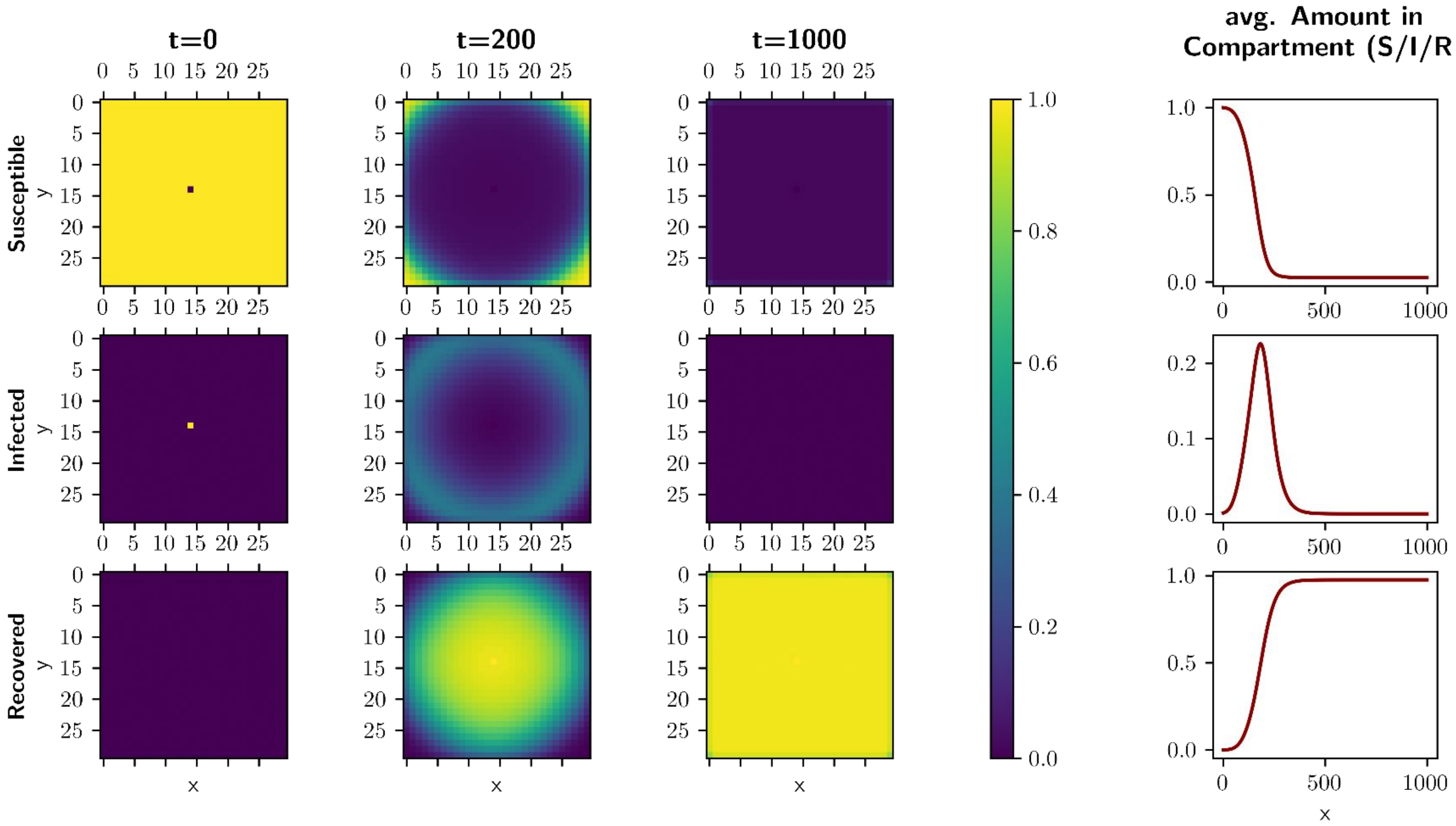
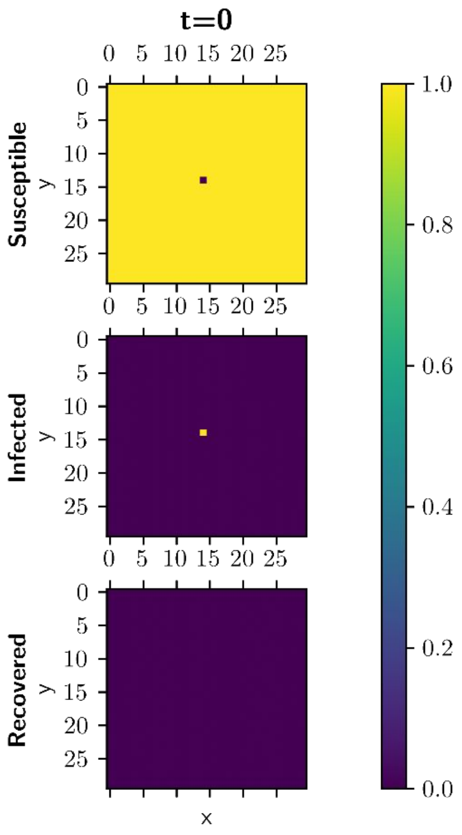
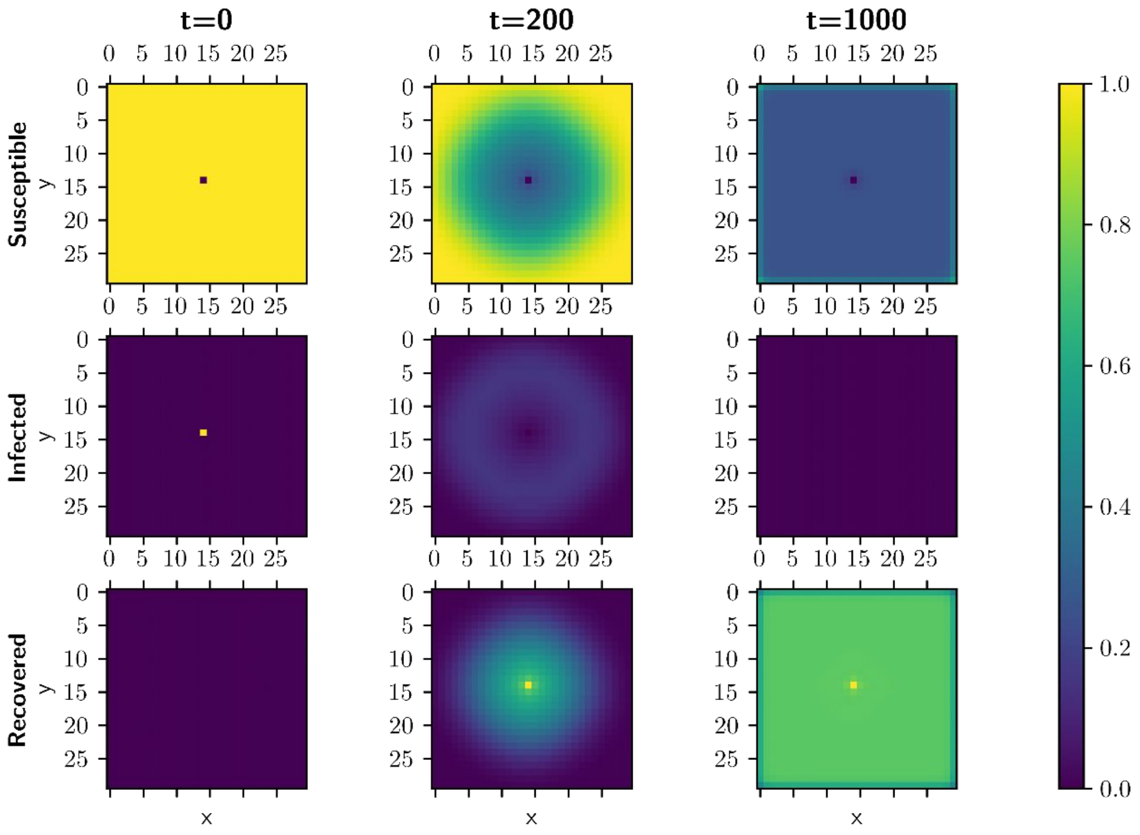


Fig. 5 spread of infections based on an SIR model without awareness


t=0
Susceptible
Infected
Recovered
y
x
0
5
10
15
20
25
1.0
0.8
0.6
0.4
0.2
0.0


t=0
t=200
t=1000
Susceptible
Infected
Recovered
y
x
0 5 10 15 20 25
1.0
0.8
0.6
0.4
0.2
0.0

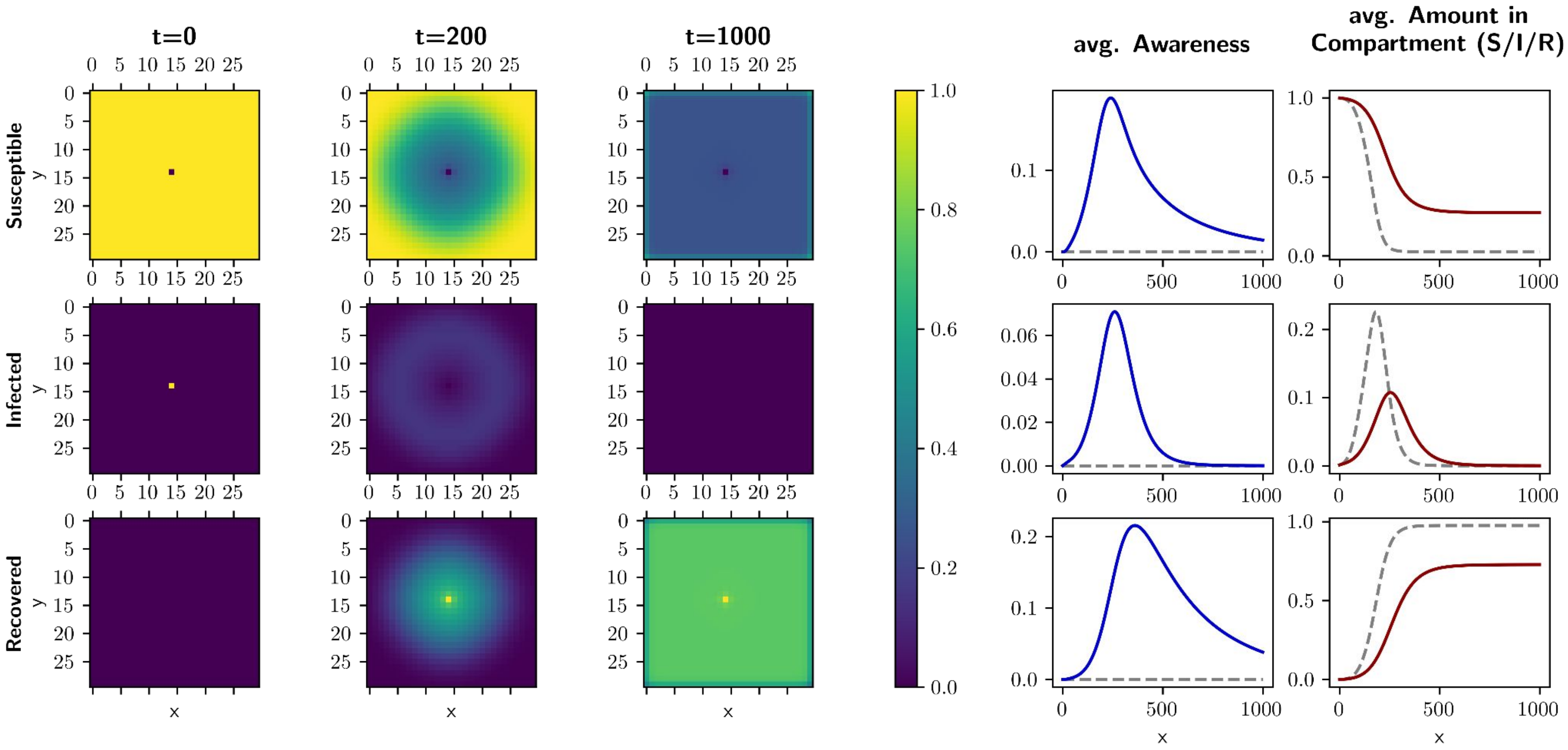
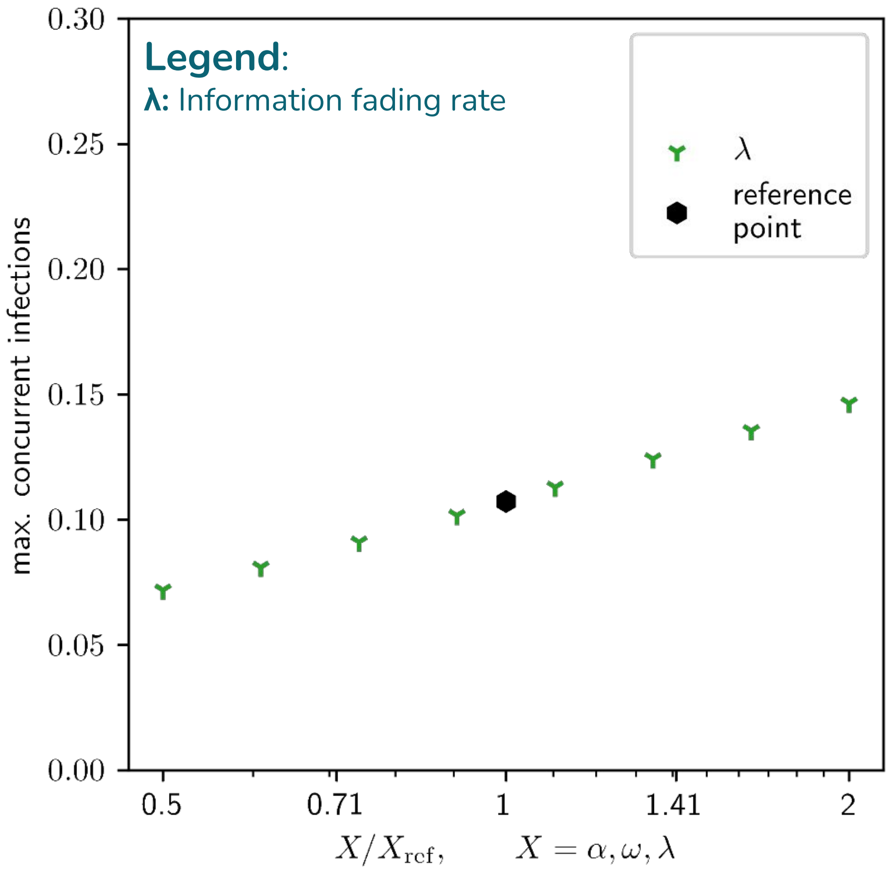
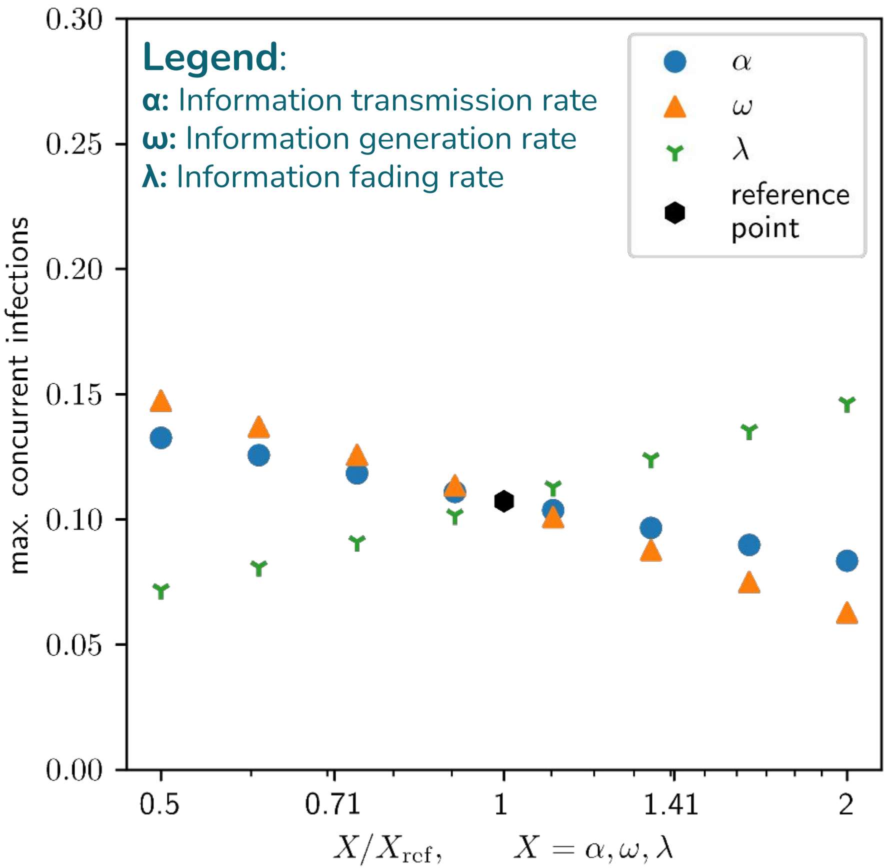


Fig. 6 Spread of infections on a rectangular lattice based on an SIR model with awareness, which causes people to reduce their susceptibility.
Left: Spatial distribution of infections on the grid at the beginning, during and after the outbreak. Right: The spread is reduced both in speed and intensity compared to the case without awareness (gray line, dashed).


Legend:
λ: Information fading rate
0.30
0.25
0.20
0.15
0.10
0.05
0.00
max. concurrent infections
λ
reference point
0.5
0.71
1
1.41
2
$X/X_{\mathrm{ref}}, \quad X = \alpha, \omega, \lambda$


Legend:
α: Information transmission rate
ω: Information generation rate
λ: Information fading rate
α
ω
λ
reference point
max. concurrent infections
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0.5
0.71
1
1.41
2
$X/X_{\mathrm{ref}}, \quad X = \alpha, \omega, \lambda$

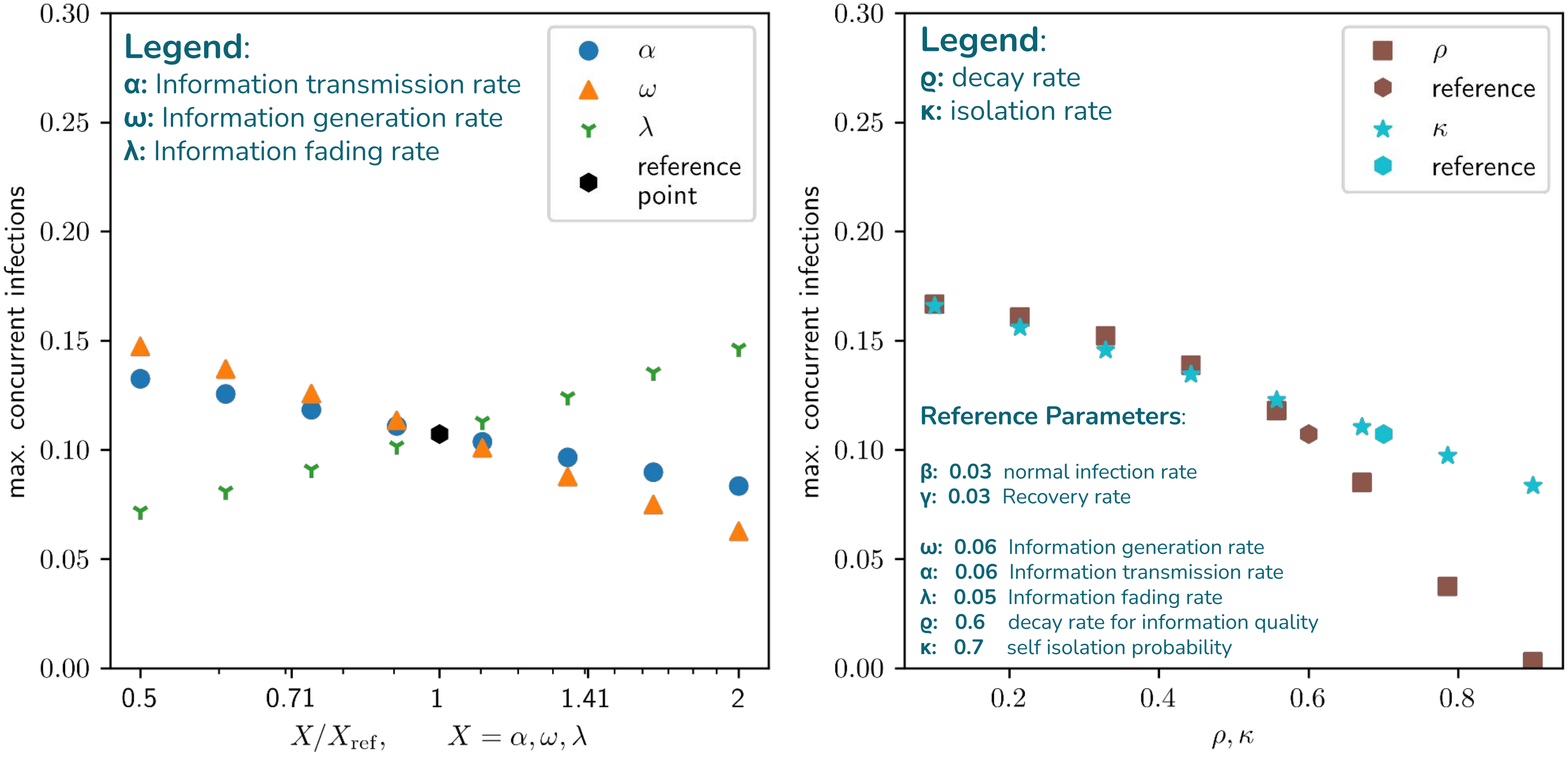


Fig. 7 Sensitivity analysis for rates and parameters related to creation and decay and impact of awareness.

Main Results

1. Which **conditions** can help to contain outbreaks through information spreading?

Big impact: High **ϱ** (decay rate) can “freeze” the outbreak
→ if awareness stays long

2. What is the impact of **self-isolation** of knowingly infected individuals on the spread of a disease and under which **conditions** is it most impactful?

Self-isolation will help limit the spread of the disease, yet it is harder to discern the ideal condition.

Limitations

- **Time constraints led to**
  - … a very **basic** model
  - … a **non-realistic** contact pattern
  - … the **lack** of complex approaches.
  - … a **limited** population size
  - … the **percentual approach** does not allow a straight cut for the end of the disease
  - … parameter sweep only around one reference point
  - … neglecting correlations between neighbours leads to deviations compared to a Monte Carlo Simulation

Summary and Outlook

Conclusion:

- this combination of parameters can lead to a **containment** of the **disease**
- self-isolation leads to a **decline** in **infections**
- we think our model can be used to **deepen** the **understanding** how information influences infection patterns

Summary and Outlook

Conclusion:

- this combination of parameters can lead to a containment of the disease
- self-isolation leads to a decline in infections
- we think our model can be used to deepen the understanding how information influences infection patterns

Enhancing the model with influencing factors like:

- certain nodes dispersing **higher quality** information (influencers)
- clusters dispersing **dis- or misinformation** (anti-vaxxers e.g.)
- clusters of people **ignoring information** (blunters[1])
- disseminating information prior to infection (pre-bunking)

[1] The Psychology of Pandemics — Steven Taylor

Thank you for your attention!
Any Questions?

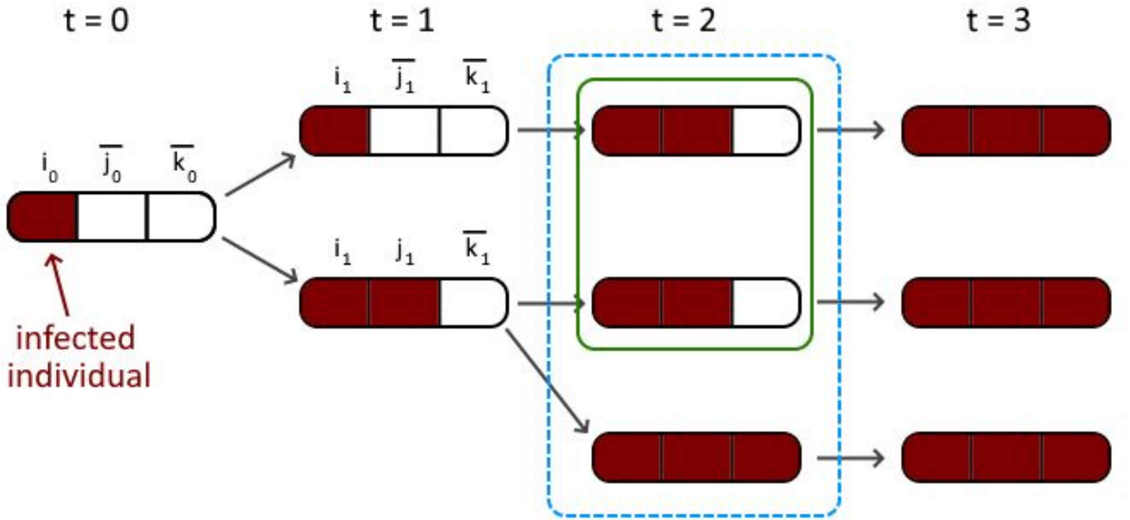
Conclusion:

- this combination of parameters can lead to a containment of the disease
- self-isolation leads to a decline in infections

Enhancing the model with influencing factors like:

- certain nodes dispersing higher quality information (influencers)
- clusters dispersing dis- or misinformation (anti-vaxxers e.g.)
- clusters of people ignoring information (blunters[1])
- disseminating information prior to infection (pre-bunking)

Extra Slides



$$
\begin{aligned}
P(k_3) &= P(k_2) + P(k_3|\overline{k_2}) \cdot P(\overline{k_2}) \\
&= P(k_2) + \beta\Delta t \cdot P(j_2 \cap \overline{k_2}) \cdot P(\overline{k_2}) \\
&\leq P(k_2) + \boxed{\beta\Delta t \cdot P(j_2)} \cdot P(\overline{k_2})
\end{aligned}
$$

Fig. 8: Simplifications in the model (correlations between neighbors are not respected) lead to both a larger and faster epidemic outbreak compared to a Monte Carlo simulation. The example shown here is a chain of three people with the first one being infected.
Blue (dashed) line: assumptions used in the model. Green (solid) line: actual expected behaviour, which corresponds to a Monte Carlo simulation.

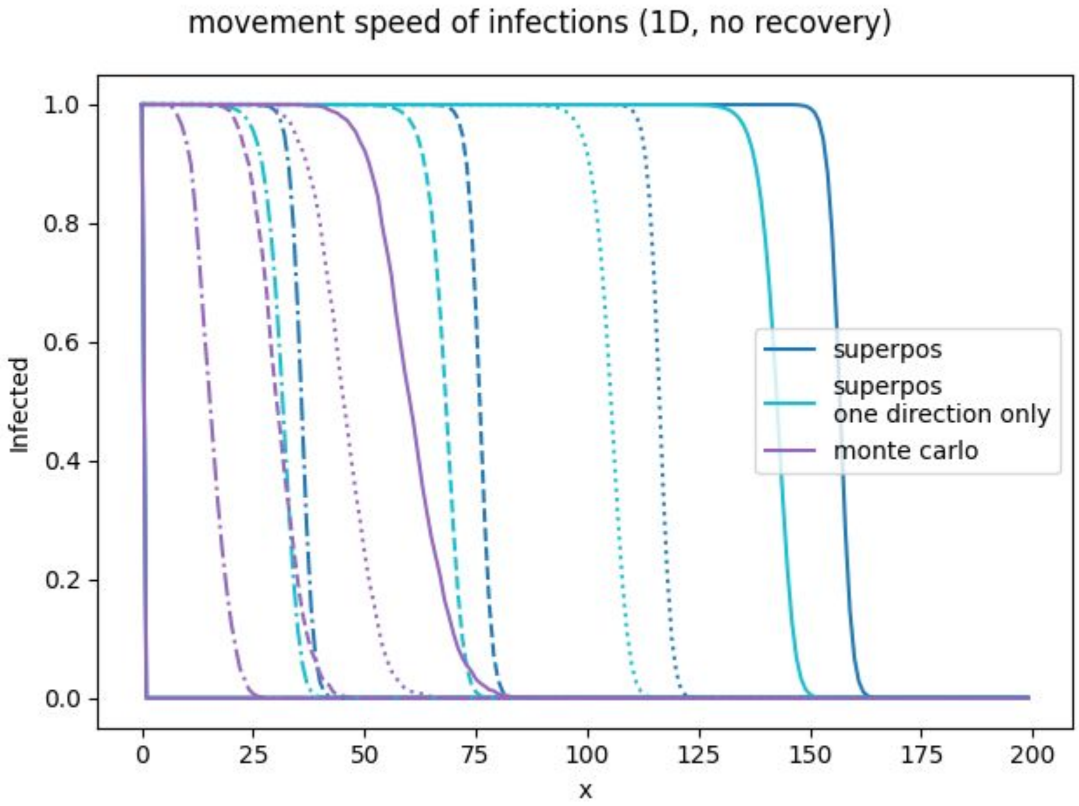


Fig. 9: Movement speed for a 1D chain of people. At t = 0 only the individual at x = 0 is infected. The figure shows the infected people at different time stamps (t = 250, 500, 750, 1000) with linestyles: (mixed, dashed, dotted, solid). Blue: Our model. Cyan: A restricted model where infections can only travel from left to right. Purple: A Monte Carlo Simulation with 1000 passes. β = 0.06, γ = 0. It can be seen that our model leads to a much faster spread than the Monte Carlo Method.

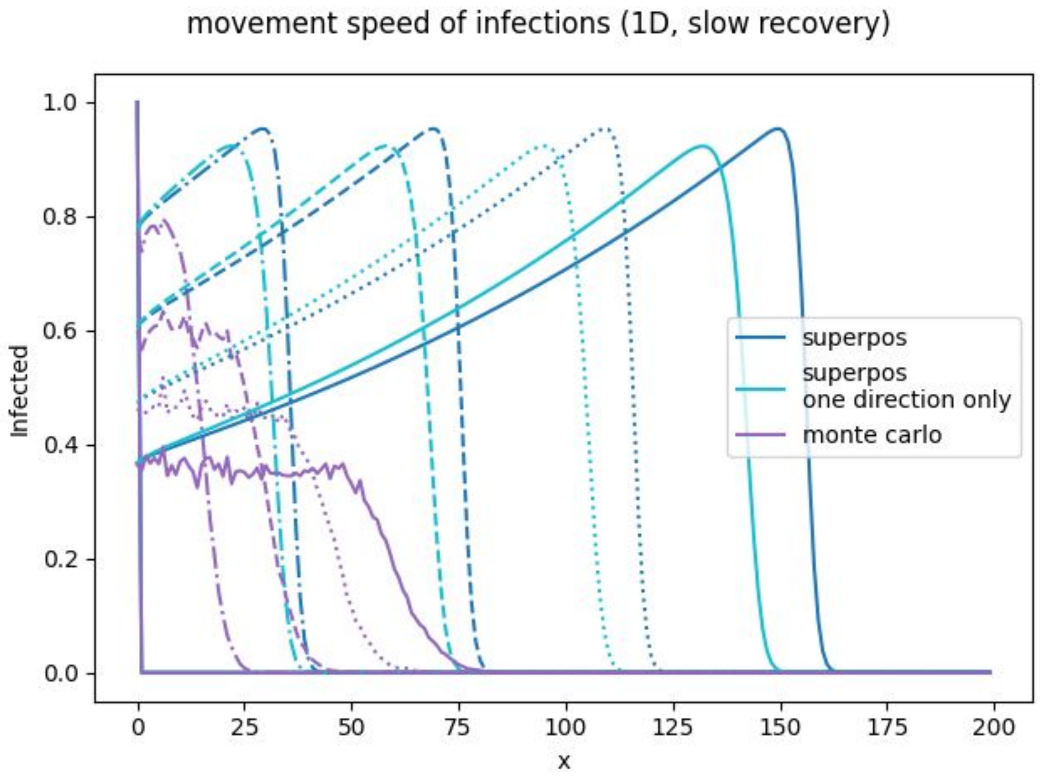


Fig. 10: Movement speed for a 1D chain of people. At t = 0 only the individual at x = 0 is infected. The figure shows the infected people at different time stamps (t = 250, 500, 750, 1000) with linestyles: (mixed, dashed, dotted, solid). Blue: Our model. Cyan: A restricted model where infections can only travel from left to right. Purple: A Monte Carlo Simulation with 1000 passes. $\beta = 0.06$, $\gamma = 0.001$. It can be seen that our model leads to a much faster spread than the Monte Carlo Method. The recovery does not limit the speed of the spread but it can heavily reduce the reach of the spread as there is always a chance of the infection not being passed on.

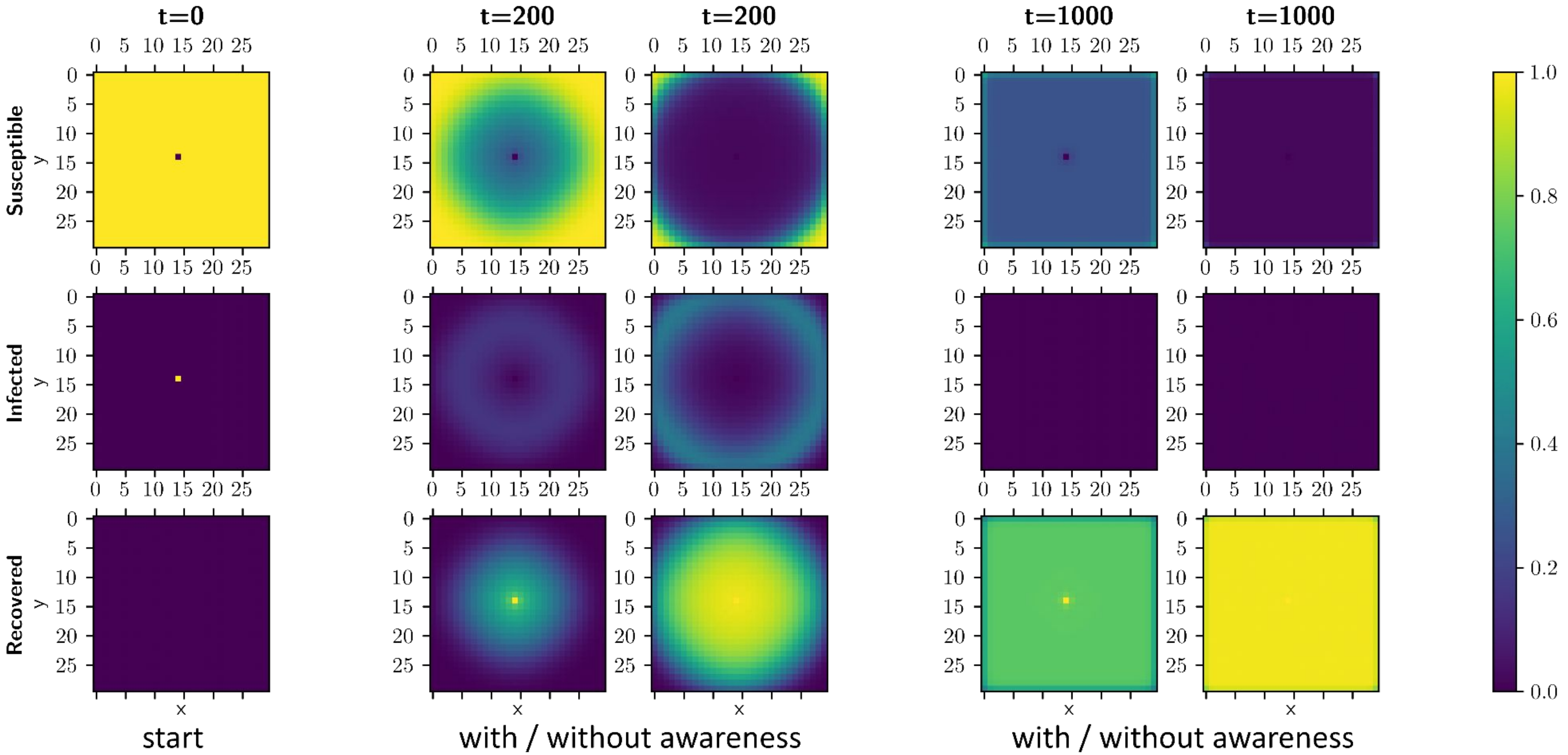


Fig. 11: Comparison for an outbreak with and without awareness.

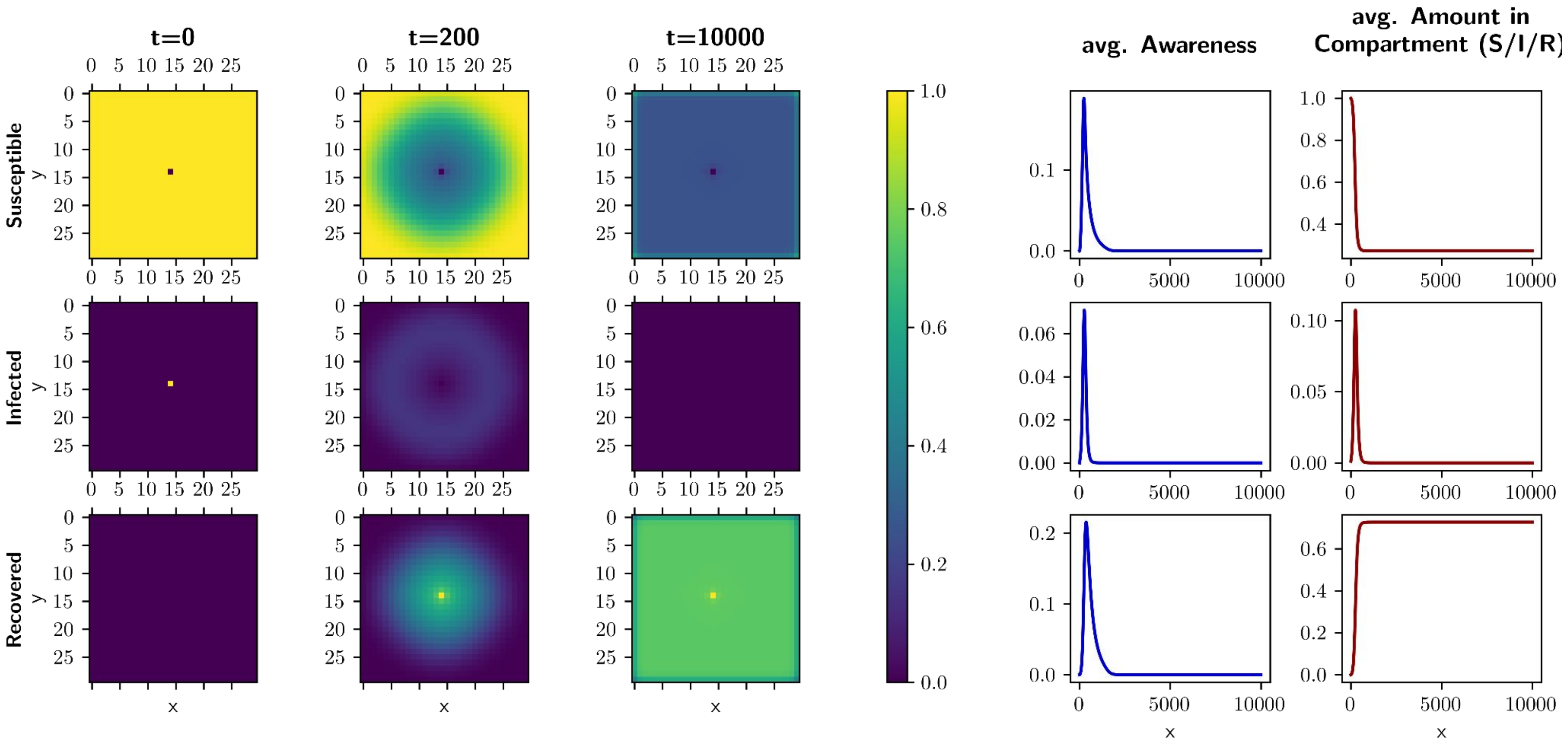


Fig. 12: The outbreak is contained even though the awareness has faded if the number of recovered people is above the threshold of 1 - 1/R_0 (= 75 % in this example).

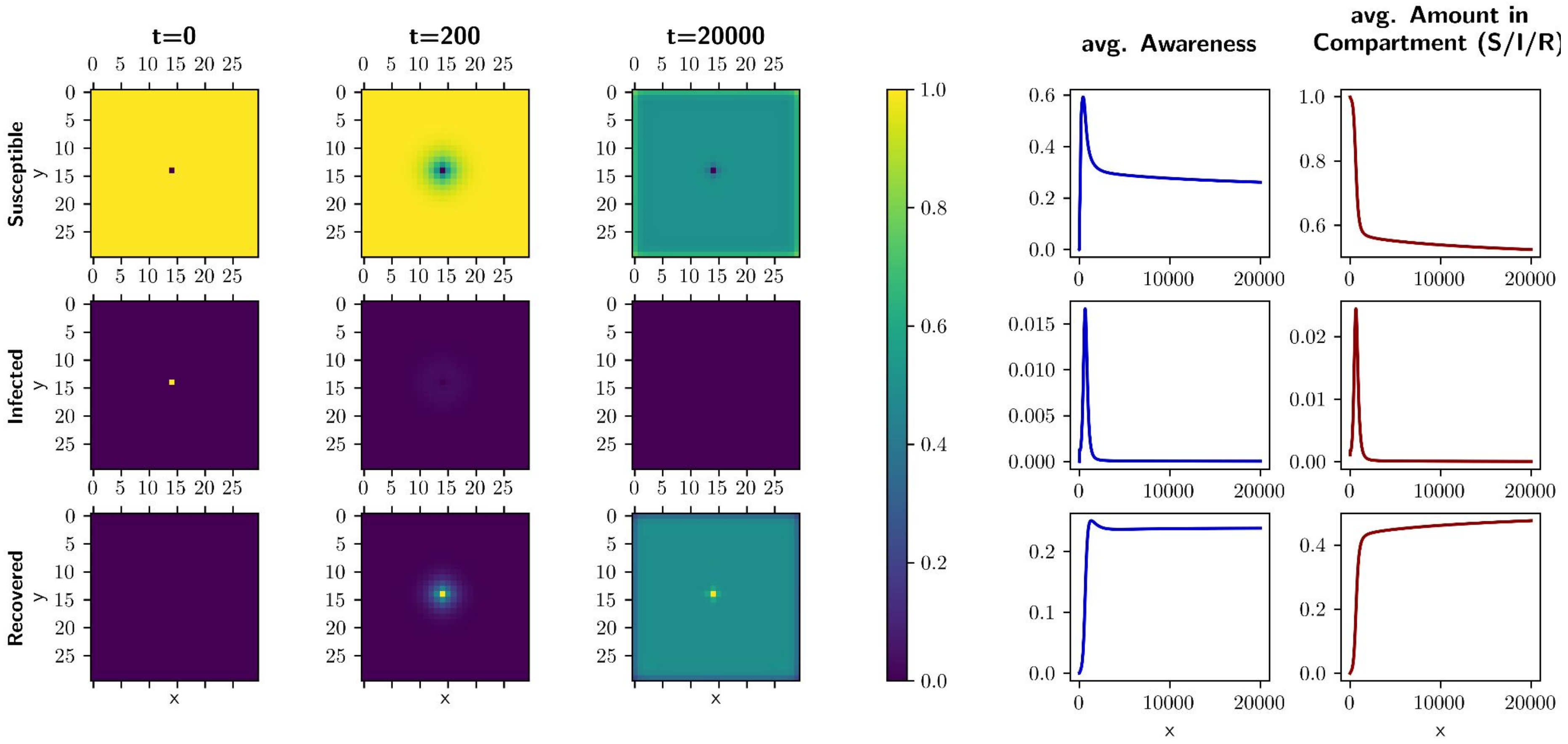


Fig. 13: The outbreak is contained for a long time by awareness present in the susceptible population even if the the threshold of 1 - 1/R_0 recovered people (= 75 % in this example) has not been reached.

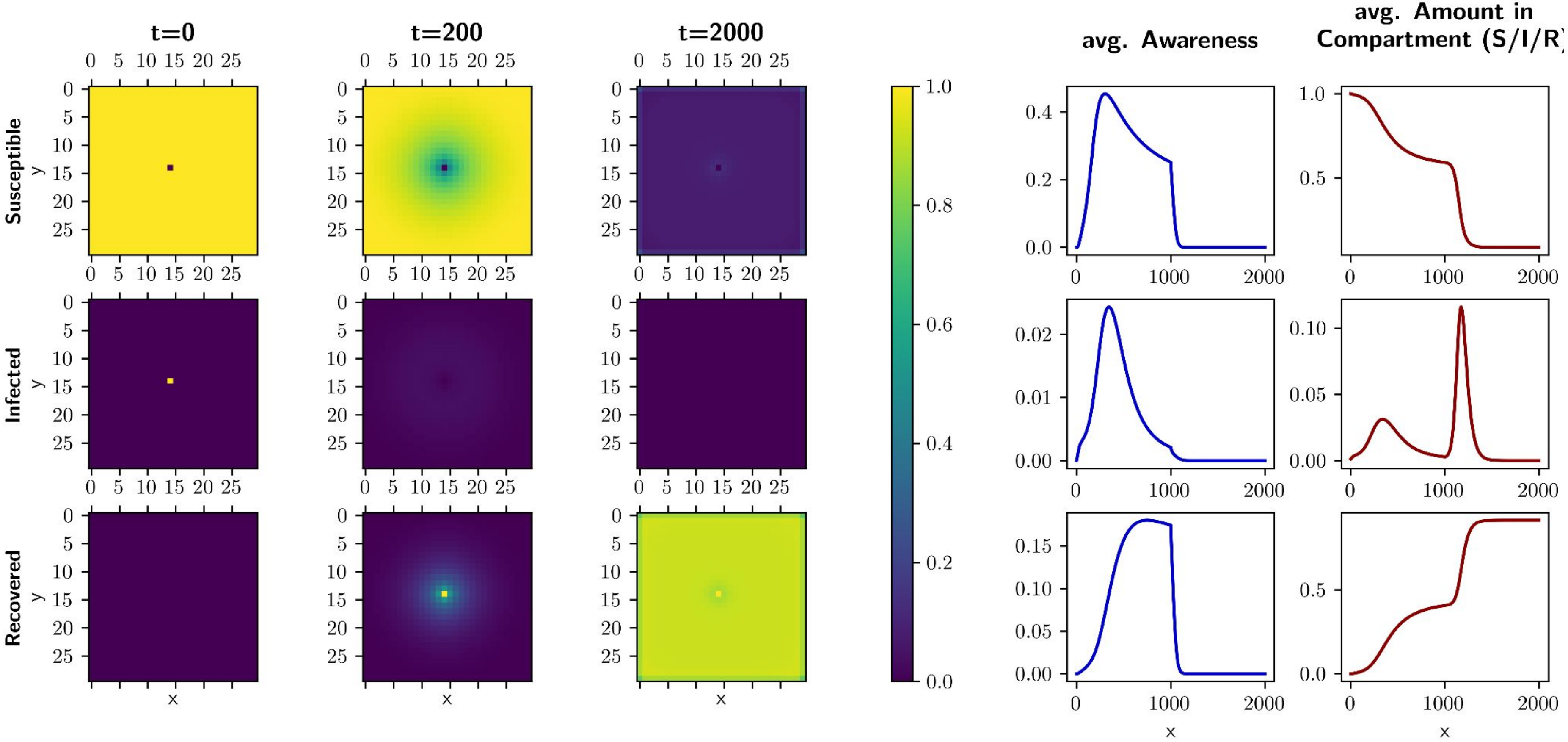
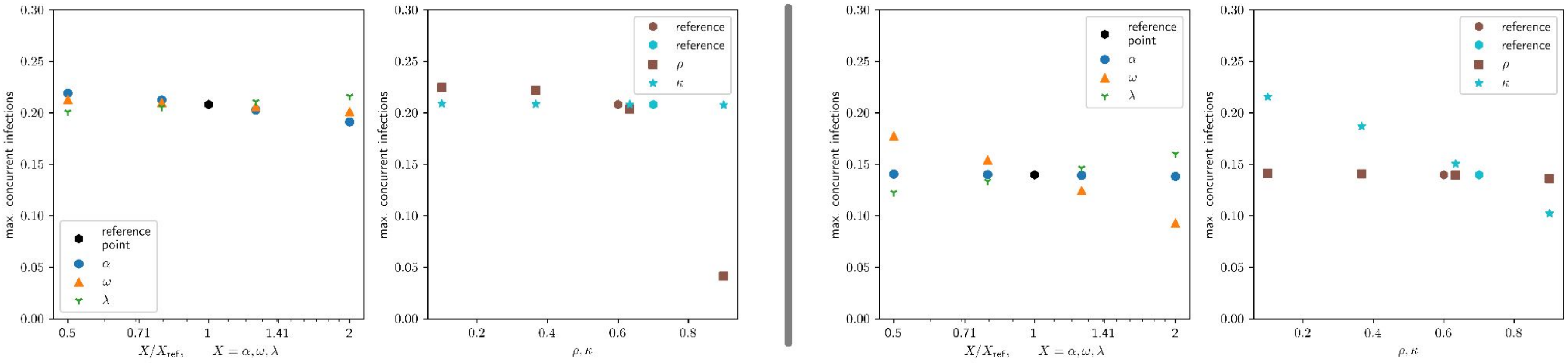


Fig. 14: If the awareness suddenly drops, a second wave is possible if the the threshold of 1 - 1/R_0 recovered people (= 75 % in this example) has not been reached.

Default Parameters:

β: 0.03 normal infection rate
γ: 0.03 Recovery rate

ω: 0.06 Information generation rate
α: 0.06 Information transmission rate
λ: 0.05 Information fading rate
ϱ: 0.6 decay rate for information quality
κ: 0.7 self isolation probability



α: 0.1 Information transmission rate
ω: 0.001 Information generation rate

α: 0.001 Information transmission rate
ω: 0.1 Information generation rate

Fig. 15: Comparison of the sensitivity analysis done with respect to different reference points.
Left: Here the spread is dominated by a fast transmission of information while the information is generated at a slow rate. Therefore self isolation only has a little impact as the spreading of the virus is much faster than the virus is being detected.
Right: Here the transmission of information is very slow but the detection rate for generating new information is large, which leads to self isolation having a much greater impact in this scenario.

Parameters:

β: 0.03 normal infection rate
γ: 0.03 Recovery rate

ω: Information generation rate
α: Information transmission rate
λ: 0.05 Information fading rate
ϱ: 0.6 decay rate for information quality
κ: 0.7 self isolation probability

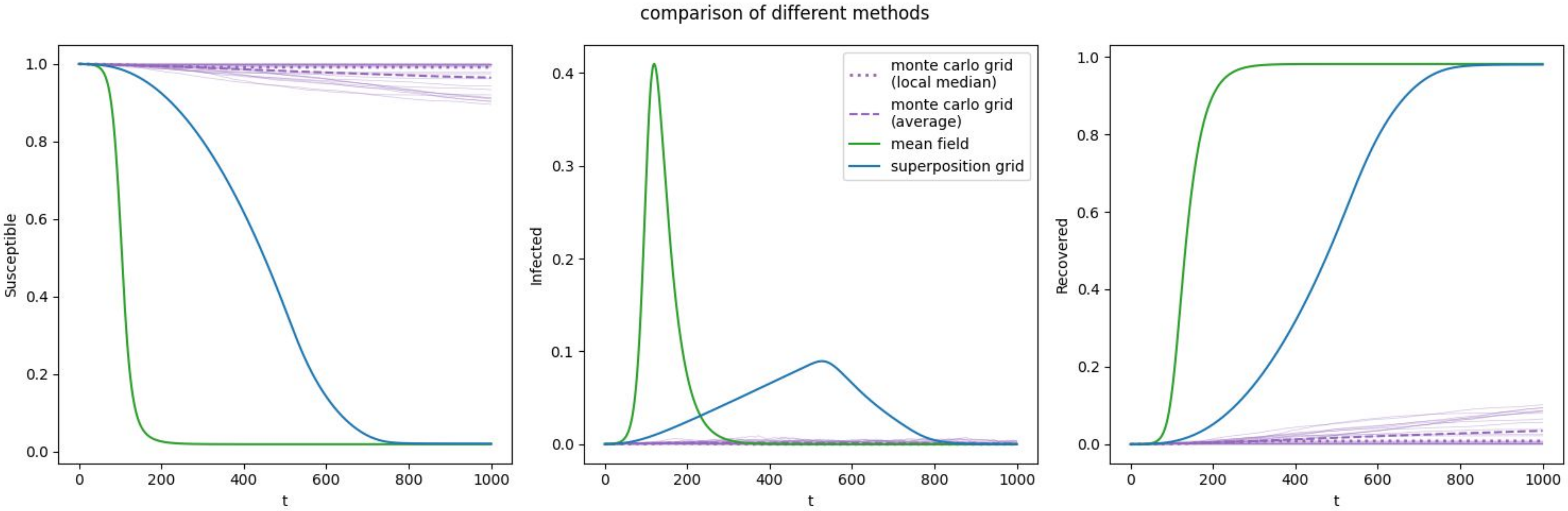


Fig. 16: Comparison between mean field approach (green), our model (blue) and a Monte Carlo simulation (purple) on a square lattice with size 100x100 for an SIR model (no information/awareness). $\beta = 0.03$, $\gamma = 0.03$. Our model leads to a linear increase in active cases because of the circular pattern moving outwards. The Monte Carlo simulation (25 passes) leads to a slower spread as the correlations between neighbours are not respected in our model. Here, the Monte Carlo simulation has the possibility to freeze out at low numbers and thus significantly reduces the total number of infections.

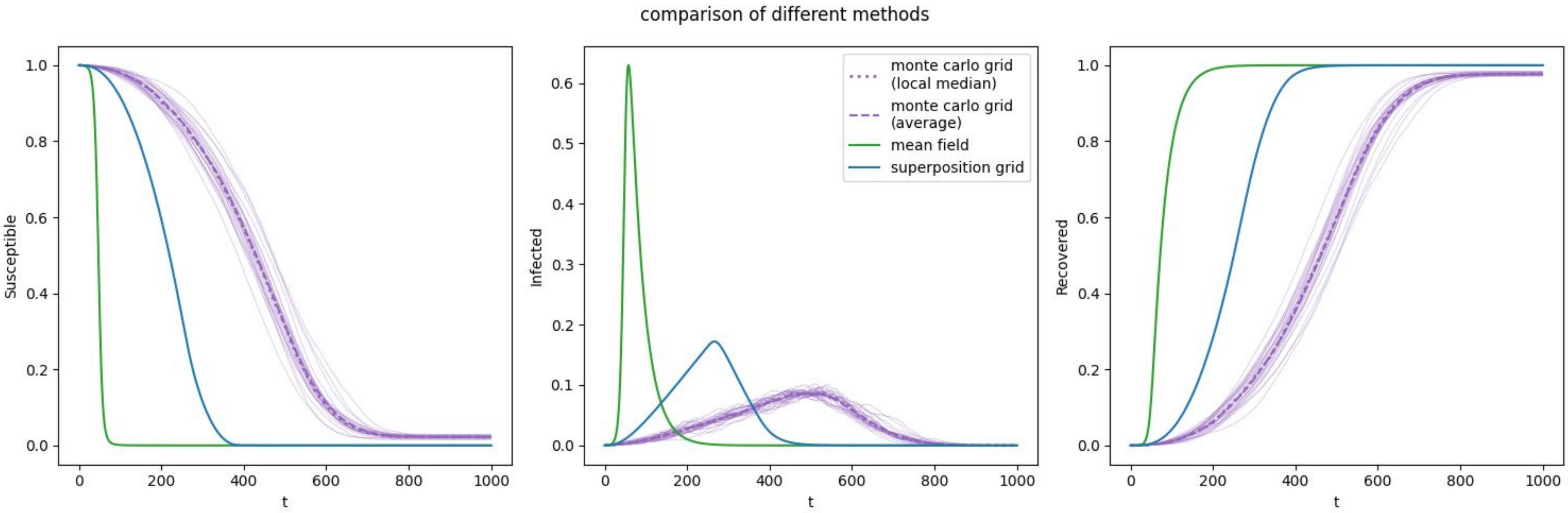


Fig. 17: Comparison between mean field approach (green), our model (blue) and a Monte Carlo simulation (purple) on a square lattice with size 100x100 for an SIR model (no information/awareness). $\beta = 0.06$, $\gamma = 0.03$. Our model leads to a linear increase in active cases because of the circular pattern moving outwards. The Monte Carlo simulation (25 passes) leads to a slower spread as the correlations between neighbours are not respected in our model.

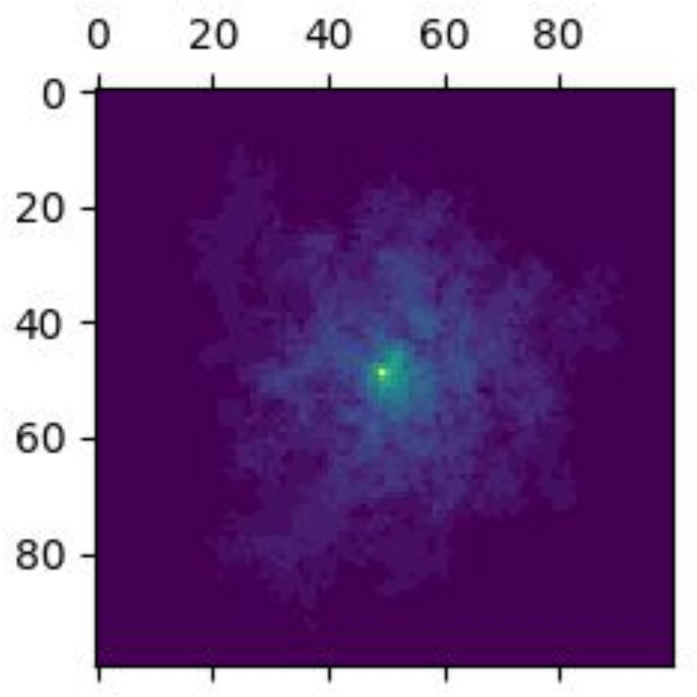


Fig. 18: Overlay of 25 Monte Carlo simulation on a square grid for = 0.03, γ = 0.03 at t = 1000, SIR only.

Extra Slides