D2.3 – Coupled epidemiological models and scenario analyses

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Executive Summary

The goal of deliverable 2.3 (D2.3) is to develop a coupled model and conduct a scenario analysis. The coupled model combines the agent-based model (ABM from deliverable 2.1 with a susceptible-exposed-infected-recovered dead (SEIRD) system dynamics model (sd). The scenario analysis focuses on the impact of travel on the spread of the virus. Besides, we build a GIS dashboard to visualise the model outcomes.

We present the methodology of how one can couple an ABM with a SD-like model. We extensively discuss the coupling and additions we construct to make the models interact. For instance, we introduce a new *SEIRD-based progression model* and two new transmission models: *distance* and *probability-based*. We are also "opening up" the previously closed system of D2.1 and include travel between the cities and countries. While the resulting model covers The Hague, the Haaglanden region and two European countries: Belgium and Germany, one can extend it to include more countries. We further explain how we built a GIS dashboard.

The *coupled model* (COOL) allows us to examine the impact of local (within the Haaglanden region) and international travel (from Belgium and Germany to The Hague). With the COOL, we analyse three scenarios: *business-as-usual*, a *highly infectious city* and a *highly infectious country*. From the first scenario, we found that several social groups significantly contribute to the spread of the disease—for instance, workers and kindergarten and school pupils. Because of that, there is a substantial difference in the total number of infections in cities/countries. Satellite cities and countries stop at 42-64%, while The Hague reaches 92%. Such a finding highlights the importance of non-pharmaceutical interventions aimed at social groups with more extensive contact networks. In a highly infectious city scenario, satellite cities get infected faster, especially the highly infectious city Rijswijk itself. The infection rate factor of 16 (the worst case scenario) makes infection happen around ten days earlier. It also leads to more infections compared to the business-as-usual. In the worst case scenario, the increase for the satellite cities is 42.78% and 39.92% for Rijswijk. The impact on The Hague is however limited. Due to limited interactions between The Hague's and other entities' agents, a higher IRF does not "shift the curve" or increase the total number of infected in The Hague agents. Therefore, again we argue in favour of other NPIs that will help prevent the virus's spread within The Hague. The last scenario, a highly infectious country, significantly "shifts the curve." A double increase in infection rate makes an outbreak happen 20 days earlier. Such an impact highlights the importance of limiting travel or extensive testing policies for countries with a high infection rate. We visualise the scenarios in a GIS dashboard.

Thus, we have observed a need for the pandemic response across all resolutions: neighbourhood, city and country. Both local and international travel have an impact on the spread of the virus. We recommend limiting travel and a comprehensive testing policy to avoid "**shifting the curve**" and overwhelming the healthcare system. However, limiting the travel is not a sufficient measure to "**flatten the curve**." There is a need for the NPIs discussed in D2.1 to combat the pandemic in its early stages.

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List of Acronyms

Abbreviation / acronym	Description
ABM	Agent-based model
BCS	Base case scenario
CM	Compartment model
COOL	Coupled model
CTS	The Hague to satellite city worker
DBIM	Distance-based infection model
GIS	Geographic Information System
ICU	Intensive care unit
IF	Infection rate
IFR	Infection rate factor
IM	Infection matrix
JSON	JavaScript Object Notation
LTC	Long-Term Care
NCTC	Neighbouring country to The Hague worker
NPI	Non pharmaceutical intervention
PBIM	Probability-base infection model
PHP	Hypertext Preprocessor
POI	Point(s) of interest
RAI	Resident Assessment Instrument
RDBMS	Relational Database Management System
REST API	Representational State Transfer Application Programming Interface
SARS-CoV-2	Covid
SD	System dynamics
STC	Satellite city to The Hague worker
STS	Satellite city to satellite city worker
TPDF	Triangular probability density function
WCS	Worst case scenario

1 Introduction

The SARS-CoV-2 (Covid) pandemic has affected the globe in waves for over two years. On 25 September 2022, worldwide mortality reached 6,536,643 deaths (*Coronavirus (COVID-19)*, n.d.). In contrast to what was expected by WHO and other officials initially, it has spread across the globe. No country in the world has not experienced the consequences of the global pandemic. The first to take a hit was the local healthcare systems. What is known now as the "*wild type variant*" put hospitals and intensive care units (ICU) at the edge and beyond their capacity. From there, the consequences of the pandemic reached other elements of a global society: transport (travel bans), supply chain (lack of resources), economy (GDP drop), ecology (temporary drop in C02 emissions), politics (protests due to Covid-19 measures) and many more. Many countries still struggle to recover from the damage afflicted by Covid.

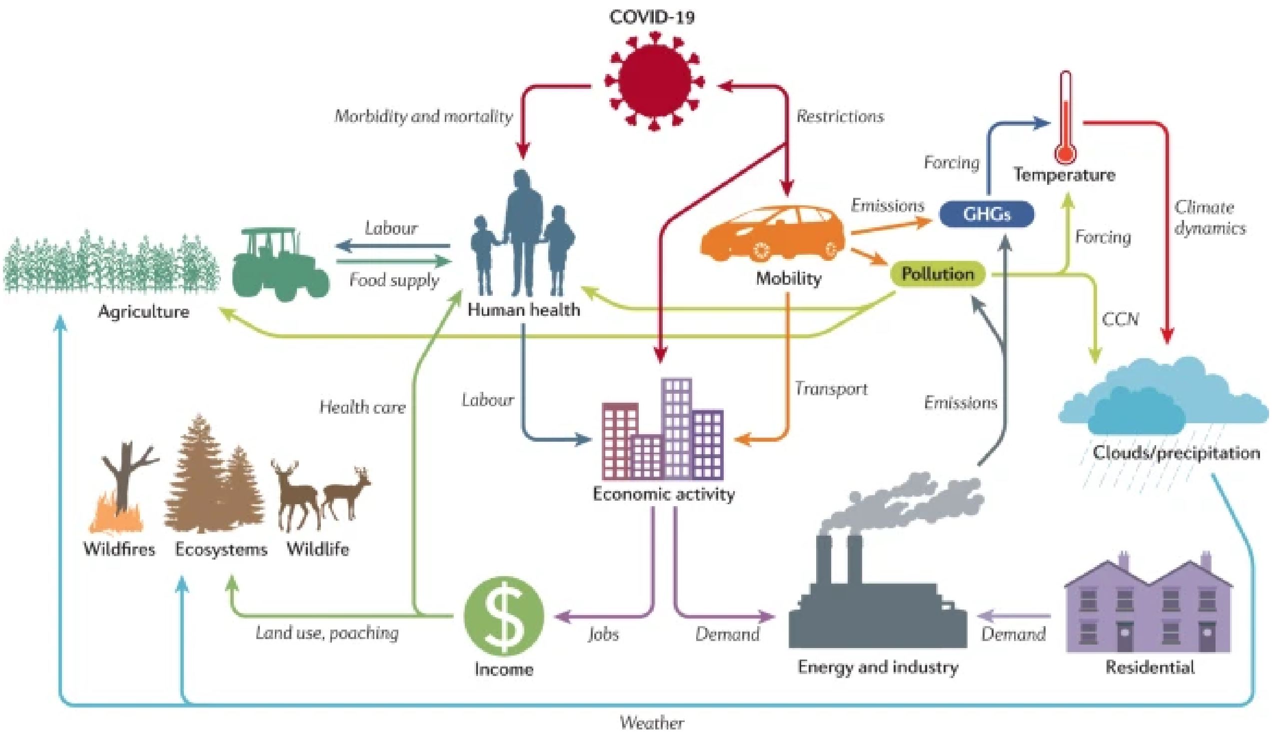

Figure 1. Earth System interactions linked to the COVID-19 socioeconomic disruption (Diffenbaugh et al., 2020).

Another issue which Covid highlighted is how ***heterogeneous*** (different) the population within a country is. (Nations, n.d.) reports that the largest cities were hit the most. During the first wave of the pandemic Italy was one of the countries with the highest number of cases and mortality. Also, when analysing the number of positive tests on a map, it became clear that certain regions have higher numbers. This phenomenon is now known as a ***hotspot***. Therefore, it is essential to "zoom-in" into the country and recognise geographical differences. Going further, (Sharifi & Khavarian-Garmsir, 2020) reported that cities are also heterogeneous. Certain districts and communities were hit most. Empirical evidence points us at: unemployment, number of people living together, health problems, elderly and others. Some modern cities are segregated (Guzman et al., 2021). As a result people who have some or even all of those attributes live in the same district. This results in an amplifying effect. Besides, some people do low-paid jobs and have to be essential workers (e.g. cashiers at a supermarket). These findings highlight the importance of the ***model's scale*** (resolution). That is it, what are the units in the model: countries, regions, cities or their residents?

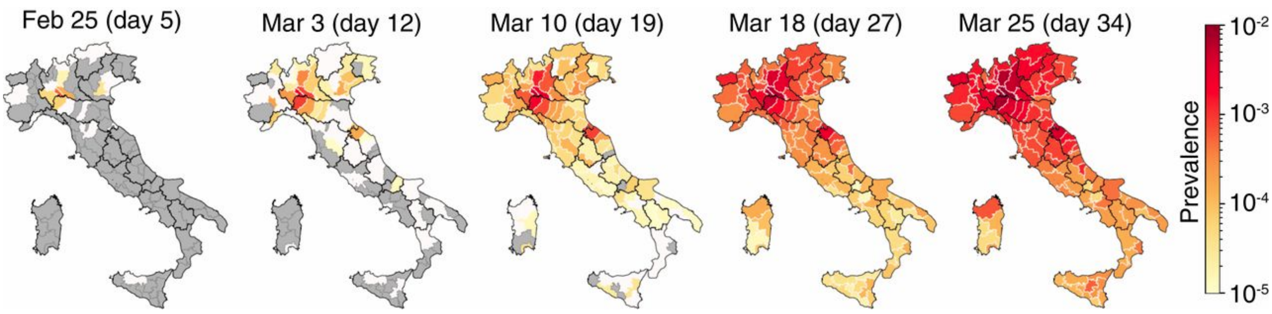

Figure 2. Evolution of the ratio of confirmed cases/resident population in Italy. The spatial spread over time of COVID-19 is plotted from February 25 to March 25, 2020 (Gatto et al., 2020).

A population group that requires extra attention is the eldery. Covid mortality risk in the first wave of the pandemic was more than 62 times higher for an individual aged over 65 compared to one under 50 (Yanez et al., 2020).

Another complication related to Covid is the presence of many ***uncertainties*** about the virus and its effects on individuals. At the beginning pandemic, we knew little about how the virus spreads: via droplets or aerosol transmission (Jayaweera et al., 2020) and what are its parameters: incubation period, viral load, etc (Wang & Flessa, 2020). Scholars reported these numbers with a significant variance around them. Such uncertainty complicated the policy response. What should the government do if it is unknown how the virus spreads? Can it advise people to meet and interact in an open space where everyone "feels" healthy, or does it bring too much risk since people can be infectious but asymptomatic?

People's ***behaviour*** plays a significant role in how Covid spreads. At the beginning of the pandemic, when we knew little about the virus (virus uncertainties), the majority of the population in some countries took advice from the government seriously. As a result, there was a high level of "compliance." Later on, the situation started to change. In the Netherlands, for example, already during the second wave, some population groups began to "bounce back" to normal: more frequently meeting friends, not keeping social distance. Such a trend continued, especially after vaccines were made available and vaccination rates started picking up. A term to describe such behaviour is *pandemic fatigue*. Scholars are trying to explain why people behave in a certain way: *rational*, *Homo economicus, fear,* and others. Such knowledge can help governments design more effective policies.

To address these uncertainties, researchers employed ***models*** and got involved in the policy-making process. There are different models: mathematical, machine learning, and agent-based, with an overall goal to either predict or better understand how the virus spreads. For example, Reich Lab COVID-19 Forecast Hub uses an ensemble of models to forecast COVID-19. The Imperial College COVID-19 Response Team proposed an ABM to combat the pandemic in the UK (Ferguson et al., 2020). The findings are usually presented in a ***dashboard***: an app or a website with the key model outcomes (Figure 3). Based on the findings from these models, governments can propose a new policy: people cannot gather in groups of more than three people, or plan “reopening” (lifting the measures): schools can open.

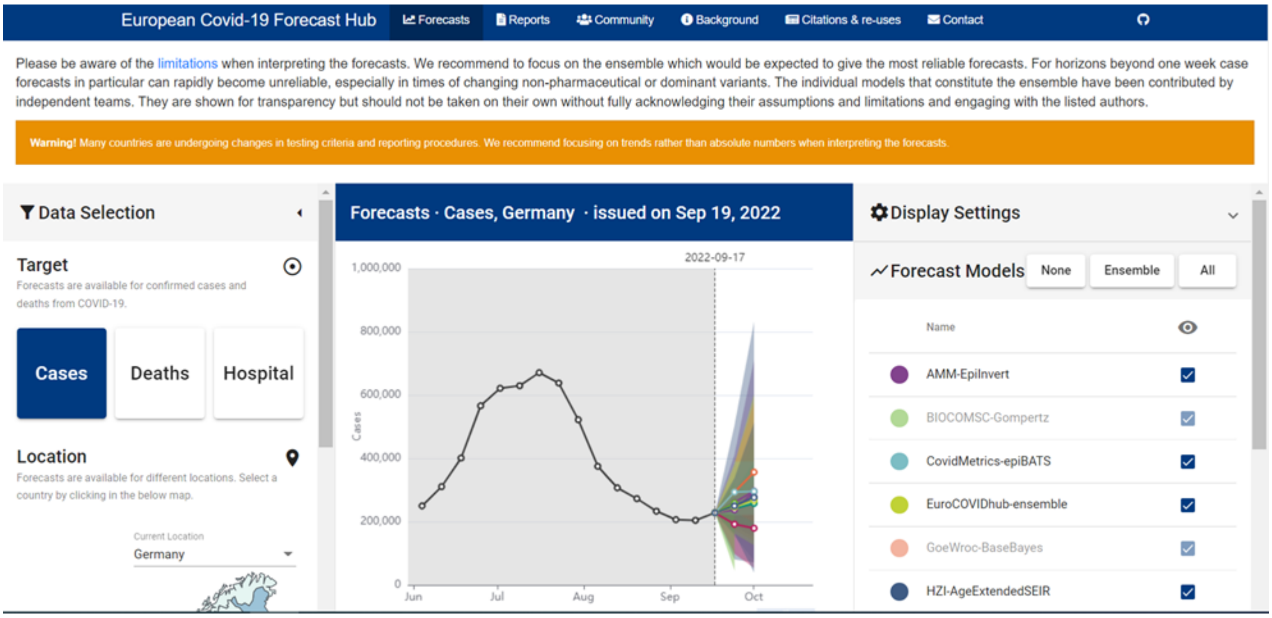

Figure 3. Example of website visualising models’ outcomes. Dashboard of The European Covid-19 Forecast Hub; available online at https://covid19forecasthub.eu/visualisation.html; screenshot date: 20 September 2022.

The policy response to Covid varied. Before a certain point in time, there was no vaccine (first, second and third waves); therefore, only *non-pharmaceutical interventions* (NPIs) were available. There is a variety of NPIs and their combinations (Haug et al., 2020). One major category aims to limit mobility*:* external (from other countries) and internal (within the country and smaller geographical regions). China, for example, issued a *“full lockdown*”: no one can leave the house, and only a limited number of essential workers are operating. The Netherlands implemented an “*intelligent lockdown”,* requiring people (only prescribes) to stay home as much as possible. Sweden used a different approach, the so-called “Swedish experiment.” In short, the government imposed fewer measures than other European countries, e.g. Germany. The effectiveness of these measures is still an open debate. However, what became clear is that both types of mobility matter: external and internal (Alessandretti, 2022). Macro mobility (e.g. air traffic from the UK to the Netherlands) and micro mobility (daily commute within The Hague for shopping) result in a complex set of interactions. **It is unclear whether one should combine these measures with other NPIs (e.g. kindergarten and school closures) to be more effective.**

The aims of deliverable 2.3 (D2.3) are:

- Develop a SEIRD-based system dynamics-like (SD) model to understand how the virus spreads globally,
- Couple the SD model with the agent-based model (ABM) from D2.1 and conduct a scenario analysis,
- Visualise the outcomes of the model in a GIS dashboard.

Additionally, we examine the impact of Covid on the elderly in Long-Term Care (LTC) in Finland. We analyse the change in their health status by comparing two periods: during the national social distancing policy and pre-Covid. We conduct analyses utilising the Resident Assessment Instrument (RAI) that measures the functional, cognitive, social, and mental health and wellbeing of the elderly.

Modelling efforts result in policy advice. As we previously discussed, some models played an essential role in policymaking. However, there is still a lack of knowledge about the interplay between micro and macro level "interactions" under uncertainty. The coupled model can help understand the complex interplay between limiting macro and micro-mobility and the need of other NPIs. To answer this question, we propose a two-step methodology. We start by developing a compatible SD-like model. The proposed model operates on two resolutions: mid-resolution for cities and low-resolution for countries. Next, we present the way to model the elements of this model: agents, locations, activities and transport. Further, we explain the epidemiological model, which consists of three submodels: an extended SEIRD-based progression model and distance-based and probability-based infection models. Because the coupled model operates on three resolutions, its infection models must differ.

The report consists of 4 sections. The Methodology section explains how we built the SD-like model, coupled it with the ABM model, and conducted scenario analysis on it. The section continues with a description of the GIS dashboard. The Methodology ends with a subsection on analysis of the impact of Covid on the elderly. The Results section presents the main findings from the analysis and presents the dashboard. Conclusion summarises the work, brings the findings into a broader context and reports advice for policymakers.

2 Methodology

We propose a two-step methodology followed by analysis and visualisation. First, we explain how we do the *coupling*: combining system dynamics (SD) and agent-based models (ABM). This process can be done in multiple ways depending on the purpose of the coupled model. We aim to explore the impact of local (national with a small region) and international travel on the SARS-CoV-2 spread. Second, we introduce a SEIRD-based (Susceptible-Exposed-Infected-Recose-Dead) system dynamics-like model of Covid spread. This model is a simplified but compatible version of a full-scale SD model. It helps to understand how the virus spreads on a city/country level and allows us to examine individual infections among city visitors. Subsequently, we introduce scenario analysis and explain how we build an interactive dashboard.

Coupling agent-based and system dynamics models

Agent-based modelling is a simulation modelling formalism which proposes to model complex systems “bottom-up”, see D2.1. A modeller creates agents – the primary entities of a model that interact -, defines a set of rules of how these agents interact, and adds the environment in which they interact.

SD is an alternative simulation modelling formalism. SD models complex systems “top-down” as a combination of stocks, flows, feedback loops and delays. The modeller does not specify either individual agents or their behaviour. Instead, they use more general mechanisms. SD often assumes that a system of interest is homogeneous. For example, instead of considering differences in the behaviour of various social groups during the pandemic, SD models them as a single ‘stock’.

SD and ABM have pros and cons, and the choice of formalism depends on the problem. One of the pluses of SD is that one does not specify numerous rules for different agents: one of the core ABM’s activities. This makes the modelling process simpler and faster. On the other hand, it limits the analysis. We cannot analyse agent groups anymore but instead use aggregated numbers.

To benefit from both, and as outlined in the description of work, we can ***couple*** them. In simple words, the model coupling is a process of combining several models. For example, one can combine a SEIRD epidemiological model and a transport model to study the impact of transport on disease spread.

One of the reasons for coupling is that building a high-resolution ABM model[1] is complicated and data-intense. Ideally, it requires *microdata* (or its sample) which has an extensive set of attributes about each person living in a city of interest or elsewhere. This data is very privacy sensitive and not available for public use. As an alternative, we propose to couple a high-resolution and data-intense ABM with less complicated but still useful mid and low-resolution models. The mid and low-resolution models are more homogeneous (SD-like). We assume that there is no need to capture the whole population of a city as we did for the ABM, but only a fraction of it. Therefore, the agents of those models will not be involved in all activities that the ABM agents have. Instead, we model only the two core ones: Work and Personal care. To account for details related to infection, we connect the mid-resolution model’s probability-based infection model to the ABM distance-based infection model via the infection rate factor (see subsubsection Probability-based infection model). Our coupled model (COupled mOdeL - COOL) operates at three spatial resolutions: country, city, and neighbourhood (Figure 4).

[1] A high-resolution model has a great level of detail. In our case, it is an ABM model from task 2.1. It has a number of agents approximately equal to a city's population, which perform activities over a representative number of places of interest (POI).

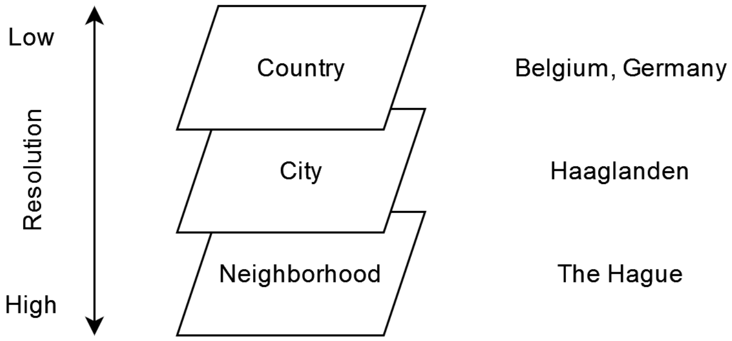

Figure 4. Schematic representation of spatial resolutions of the model.

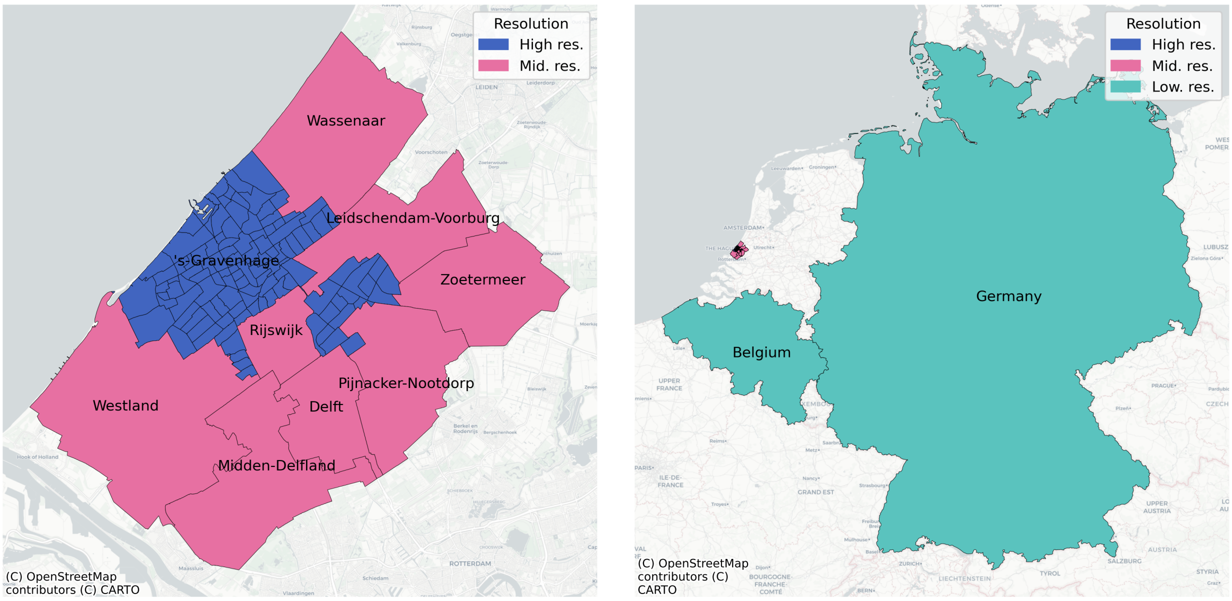

Figure 5. Spatial representation of two (left) and three resolutions (right).

The coupled model combines *a city*: The Hague, cities nearby: Haaglanden region, which we call *satellite cities* and two bordering countries: Belgium and Germany, which we call *neighbouring countries* (Figure 5).

There are plenty of difficulties in model coupling. One of the first issues a modeller has to resolve is to ensure that the models are *compatible* and that their elements can interact. For example, if agents are getting infected in an SD model and the transport model is an ABM, one should create a mechanism allowing agents to travel. Another issue is aligning simulation time. SDs operate with a fixed usually large (e.g. a day) time 'tick', but the agents of an ABM can execute many actions within a short period (e.g. every 10 minutes). Finally, if we build two models using different software, they need to be technically connected.

With the coupled model, we seek to analyse the impact of travel on the spread of Covid. While the model from task 2.1 is a model of a “closed system”: agents cannot leave The Hague for whatever reason (e.g., for work), the coupled model “opens” the system up (Figure 6). To capture the travel, we introduce four new social groups: *The Hague to satellite city worker*, *Satellite city to The Hague worker*, *Satellite to satellite city worker*, and *Country to The Hague worker*. The first social group represents agents living in The Hague but who travel and work in one of the neighbouring cities (e.g. Delft), and the rest of the activities they perform in The Hague. The second category is the opposite: an agent lives in Delft but works in The Hague. The third one captures the travel between the satellite cities (e.g. from Delft to Rijswijk). Furthermore, the final category represents people living in a neighbouring country, like Belgium, and working in The Hague. We assume work to be the purpose with the highest number of travellers.

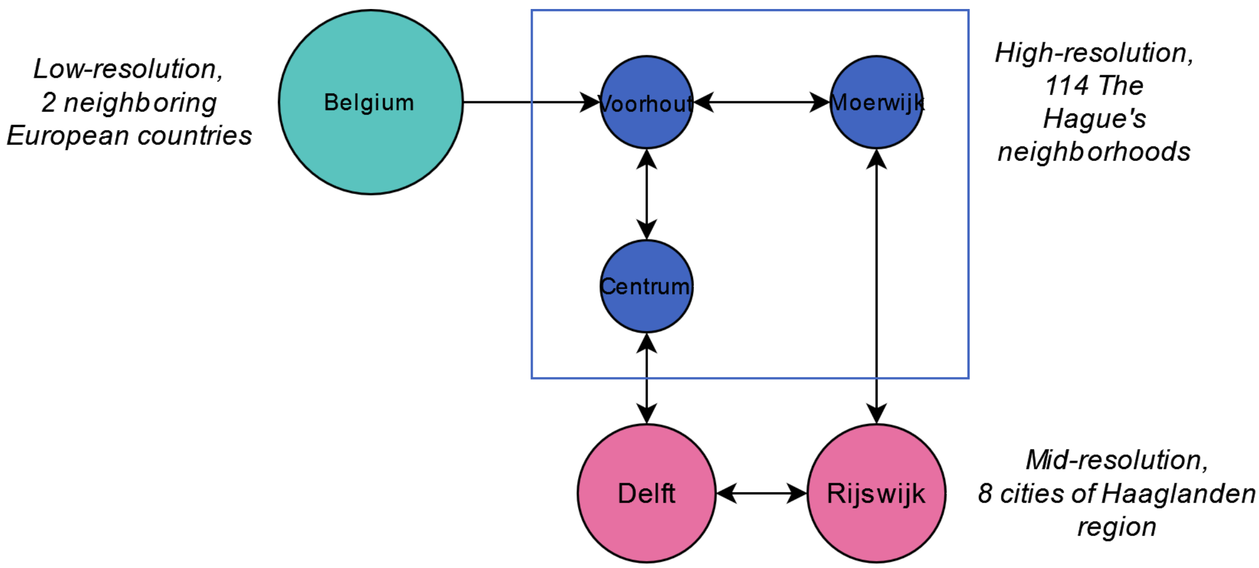

Figure 6. Schematic representation of how models of different resolutions interact. An arrow denotes travel from an entity to an entity.

To model the travel between The Hague (neighbourhoods in blue in Figure 6) and satellite cities, we use ODiN data provided by Statistics Netherlands (Statistiek, n.d.). Using ODiN we model the Origin-Destination Matrix (OD matrix) for the Haaglanden region. The OD matrix allows us to estimate how many agents within each of the newly defined social groups travel from a city to a city (Figure 7, Figure 8).

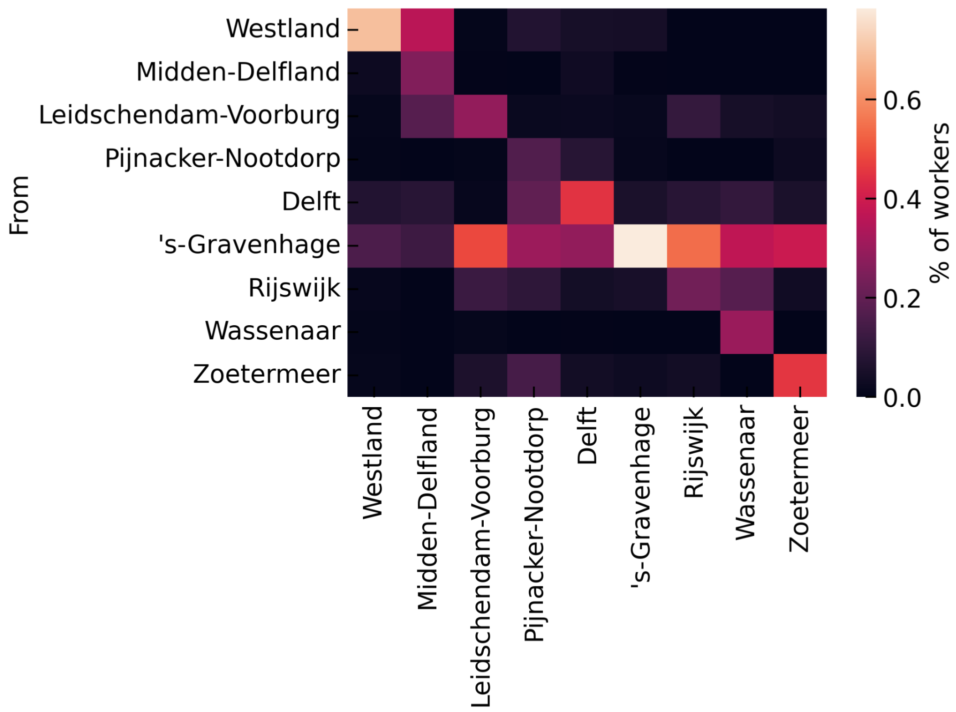

Figure 7. OD matrix for the Haaglanden region: workers travelling for work.

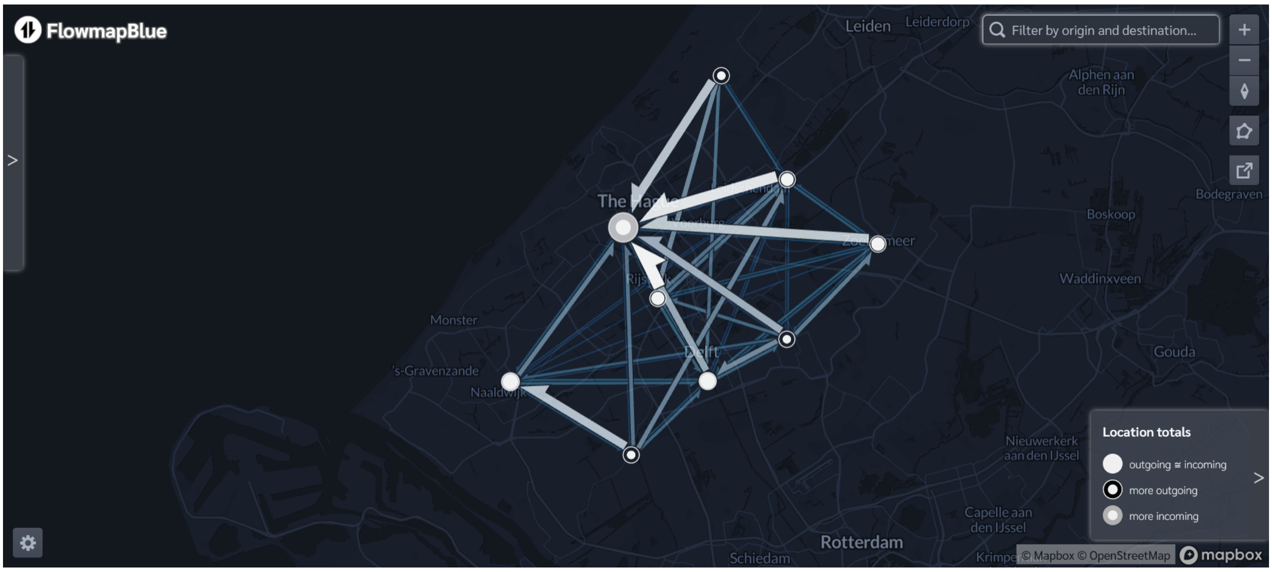

Figure 8. Workers travel for work within the Haaglanden region. The thickness and colour of the arrow represent the number of agents. A geographic flow map with FlowmapBlue (*FlowmapBlue – Flow Map Visualization Tool*, n.d.).

We estimate the number of workers travelling from Belgium and Germany to The Hague using Grens data provided by Statistics Netherlands. While the data reports the total number of people travelling to a bigger region, for the sake of simplicity, we assume 500 workers from Germany and 500 from Belgium to have a permanent workplace in The Hague and commute daily *to* The Hague. Importantly we do not model mobility from The Hague to neighbouring countries.

We use an approach similar to the one in task 2.1 (see D2.1) to build both the mid and low-resolution models. First, we generate a synthetic population: agents living in each satellite city. However, we limit ourselves to only a few attributes: age and social group. For each satellite city, we generate a part of its population: within the 18-65 age group and assign them the worker social group. To further identify what kind of worker it is: Satellite to The Hague worker or Satellite to Satellite worker, we OD matrix. This process results in the number of agents-workers by satellite city with a workplace elsewhere. While the type of workplaces may differ (e.g. Delft agents work in education in The Hague), we assume that it is likely that they can work at a workplace of any type. Next, we model the locations of mid and low-resolution models. We introduce two new types of locations: Satellite workplace and Satellite accommodation. These locations do not have the key attribute of the ABM model: area. Instead, they play the role of a “sink.” Agents go to Satellite workplaces to execute work activities for around 8 hours and then move to stay at Satellite accommodation until the end of the day. Thus, their activities are Work and Personal care. Notably, we do differentiate between the weekdays and weekends for these agents.

The key difference between the models with different resolutions is how infections happen. The high-resolution model uses a "distance-based" infection model, while the mid and low-resolution models use system dynamics like a probability-based infection model. We discuss all necessary details in the following subsection.

SEIRD-based system dynamics-like model of Covid spread

The high-resolution model and mid/low-resolution models have different levels of detail. Each location in the ABM has an area, while SD-like models do not have locations as such. Therefore, their infection models differ. The Hague uses the "distance-based" infection model, and satellite cities and neighbouring countries use the "probability-based" infection model. We structure this subsection as follows. We first explain the epidemiological model. It has two main parts: progression and infection models. Then we zoom-in in on each of the submodels: distance-based and probability-based infection models.

Epidemiological model

The epidemiological model of the COOL consists of two parts: *progression* and *infection* models (Figure 9).

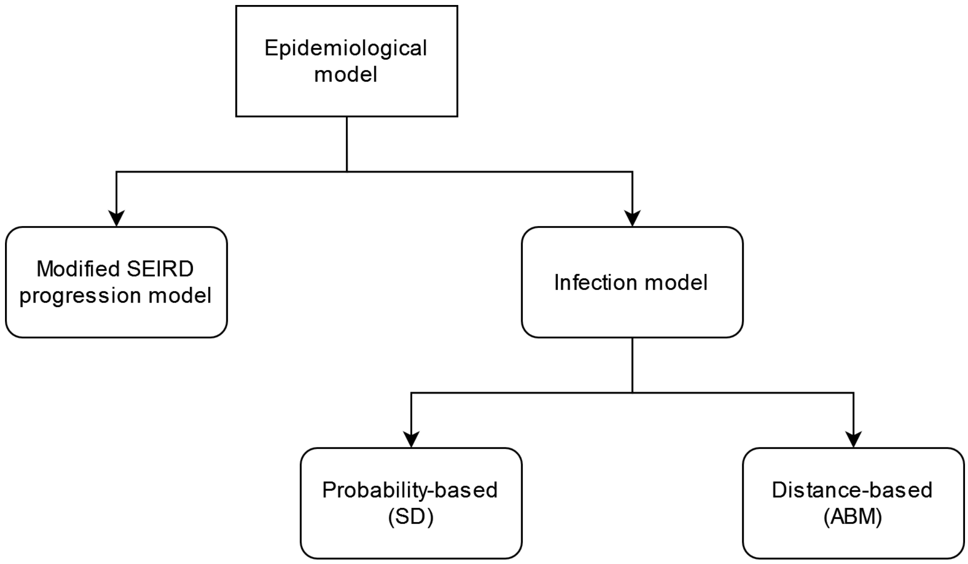

Figure 9. Epidemiological model.

Modified SEIRD progression model

There are different models to understand how a virus spreads. One of the basic categories is ***compartmental models*** (CM). A compartmental model in epidemiology is a mathematical model formulated as a set of differential equations. The population of, e.g., a country split into a set of compartments: Susceptible, Infected, and Recovered in the case of a simple SIR model. One must specify a set of parameters to predict how the virus progresses: population size and *transmission rates.* Once done, we can observe "infection curves" and potentially plan policy interventions. For example, the social distancing policy leverages parameter β (number of contacts between susceptible and infected individuals) and, therefore, can decrease infections (Figure 10).

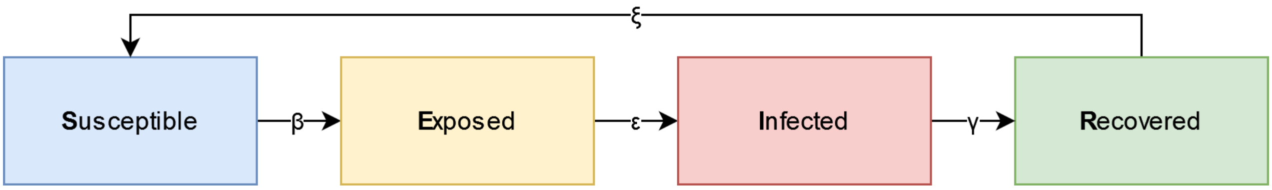

Figure 10. A simple SEIR Susceptible-Exposed-Infected-Recovered compartmental model.

There are different types of CM. For example, for Covid modelling, scholars often use a modified-SEIRD model (Figure 11), which accounts for symptomatic and asymptomatic infections. It also has Hospitalised and ICU states which help to plan hospital and ICU capacity. Of course, having more compartments requires us to specify more parameters and makes the model more complicated to calibrate.

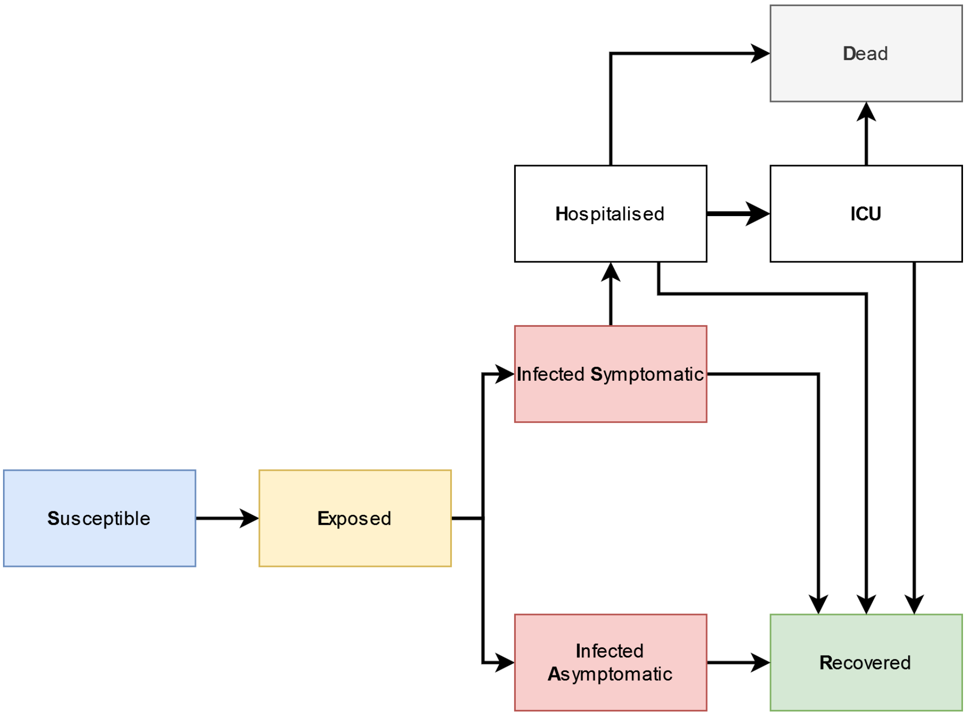

Figure 11. A modified SEIRD Susceptible-Exposed-Infected-Recovered-Deceased model of the coupled model.

First introduced by (Ross, 1916), CM is now perceived as a very general modelling technique and has been extensively criticised for being "*top-down*" (Carlson et al., 2020), but some argue that compartmental models can still be useful (Araújo et al., 2020). CM may serve as a base for an SD model (Gel et al., 2020). In such a case, one can more easily explore the impact of different policies on the progression of the disease.

The progression model of COOL aligns with the state-of-the-art Covid compartmental models. It is a modified SEIRD-based model which accounts for asymptomatically infected individuals and has two additional compartments: Hospitalised and ICU (Figure 11). The main difficulty of any progression model is the specification of its transition rates. Put simply, how many people will move from, e.g. Infected-Symptomatic to Hospitalised, and how long they will stay in the latter (Table 1 and 2). Note that the infection model defines the transition from Exposed to either Infected-Symptomatic or Infected-Asymptomatic. The progression model describes the "social" or "behavioural" aspect of the disease. Indeed, whether or not a person will go to a hospital depends not only on the virus's epidemiology but also on other social and behavioural factors. For example, a person can go to a hospital long after the clinical disease period is over because of the complications.

From/To	Hospitalised	ICU	Dead	Recovered
Infected-Asymptomatic				TPDF(12,16,20)
Infected-Symptomatic	TPDF(7,9,11)			TPDF(12,16,20)

Hospitalised		TPDF(1,3,5)	TPDF(1,3,5)	TPDF(11,13,15)
ICU			TPDF(2,4,6)	TPDF(28,30,32)

Table 1. Example of data on days it takes to transit from compartment to compartment.

From/To	Hospitalised	ICU	Dead	Recovered
Infected-Asymptomatic				
Infected-Symptomatic	0.44038			
Hospitalised		0.14674	0.0	
ICU			0.08393	

Table 2. Example data on probability to transit from compartment to compartment of 60-69 age group. Constructed from the RIVM data on the number of people by compartment (*RIVMdata*, n.d.).

Distance-based infection model

To model infections in the ABM, we propose a *distance-based infection model* (DBIM). This model takes into account an extensive set of parameters, including NPIs: social distancing and mask use. As a base, we use the work of (Phillip Stroud, 2007).

First we model **viral load (ν)** as a function of *time* in days (t) since infection (Kissler et al., 2021; Sun et al., 2022). Viral load depends on *latent period* (L), *incubation period* (I), *clinical disease period* (C) in days and *viral load peak* (ν_{max}) in log10 copies per mL.

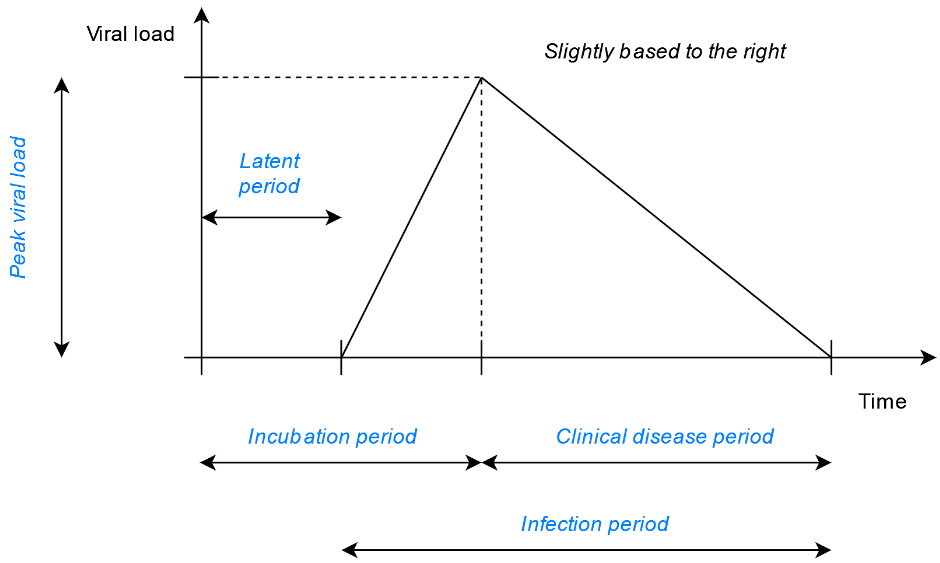

Figure 12. Theoretical model of the viral load changes over time.

These are epidemiological parameters and they differ by variant. Here is a set of parameters for alpha variant:

L = 2

I = 3.4

C = 6.2

if t >= L and < I:

ν = ν_{max} * ((t - L) / (I - L))

elif t >= I and t <:

ν = ν_{max} * ((I + C - t) / C)

else:

ν = 0

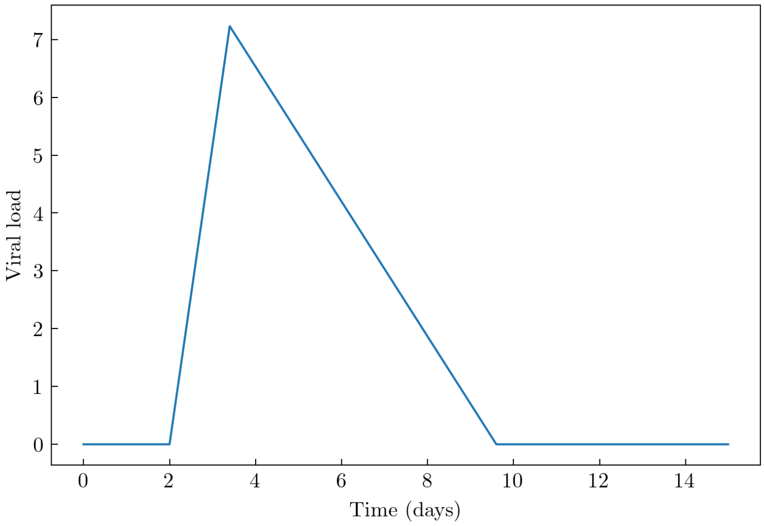

Figure 13. Development of the viral load of the alpha variant over time.

Second, we have to convert the viral load into what we call **transmission probability P**. P captures how likely an infected person can transmit a virus to a susceptible person in close contact (0 m distance between people). P must be dependent on time: we need to know how long the close contact lasts to estimate P correctly. For now, let us loosen this dependency. Relations between transmission probability and viral load are sigmoid-like:

$$P(t) = \frac{1}{1 + e^{-k \times (\nu_t - \nu_0)}}$$

where *k* is transmission rate, ν_t is viral load given *t* days since infection and ν_0 is reference viral load (calibration factor). After we calibrate this model the values are:

k = 2.294

ν_0 = 4.0

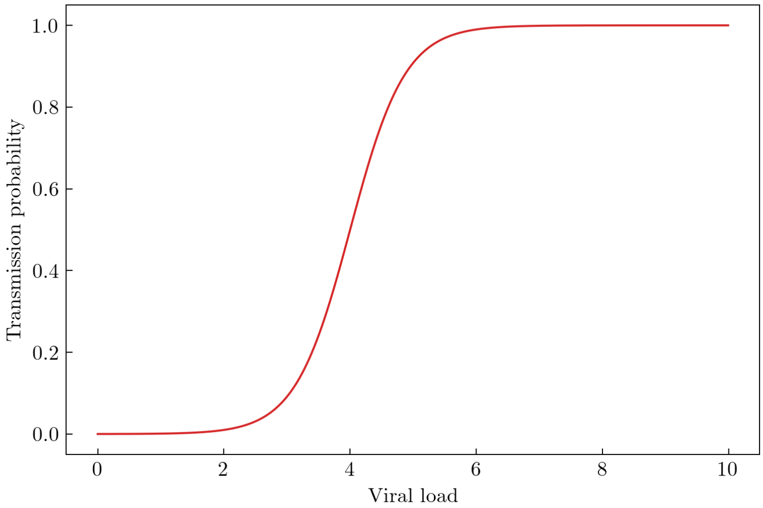

Figure 14. Relations between viral load and transmission probability.

Transmission probability over time becomes:

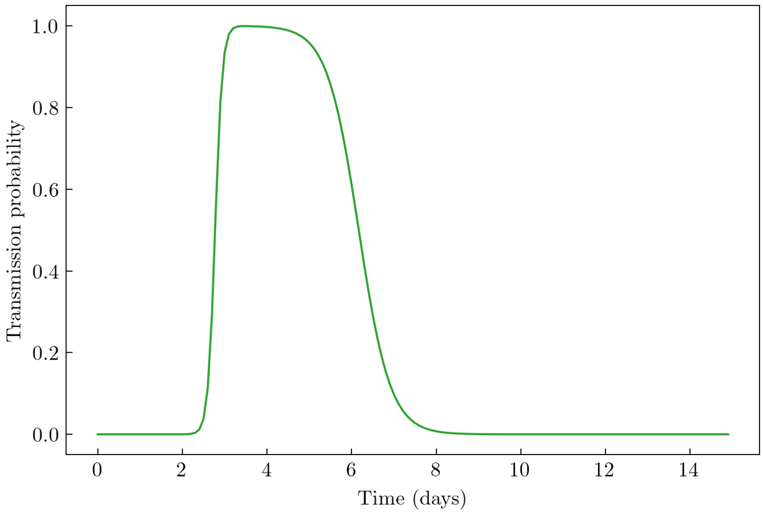

Figure 15. Development of transmission probability over time.

Finally, we formulate **infection probability** $p_{i,j}$, where *i* is the index of the susceptible person and *j* is the index of the infected person.

$$p_{i,j} = 1 - e^{-\sum_{j=1}^{M_k}} (1-\mu)^2 \times P_j(d) \times t_{i,j} \times \sigma(max(\Delta(A_k, N_k), \psi)) \times \alpha$$

where

- M is the number of infected individuals in the *k*-th location
- μ is a factor for mask effectiveness
- $P_j(d)$ is transmission probability of the infected person *j* at *d* days since infection
- $t_{i,j}$ is the time person *i* and *j* spent together
- σ is a factor for distance
- Δ is the average distance between people
- A is the area of the *k*-th location
- N is the total number of people in *k*-th location
- ψ is a factor for social distancing
- α is a calibration factor

To calculate the average distance we use a simple formula:

$$\Delta = \sqrt{\frac{A}{N}}$$

Social distancing ψ spreads people apart. Here ψ is the distance after which there is no infection. Let us assume that there is no infection after 3 metres. If we use a corresponding policy, then we compute $\sigma(\psi)$, and not $\sigma(A, N)$.

To define a factor describing relations between distance and transmission probability**,** we come up with a simple theoretical model:

$$1 - \frac{1}{1 + exp(-3 \times (max(\Delta(A_k, N_k)), \psi) - 1.5))}$$

Which given $\psi = 0$, $A_k \in [1, 100]$ and $N_k = 5$ converts into

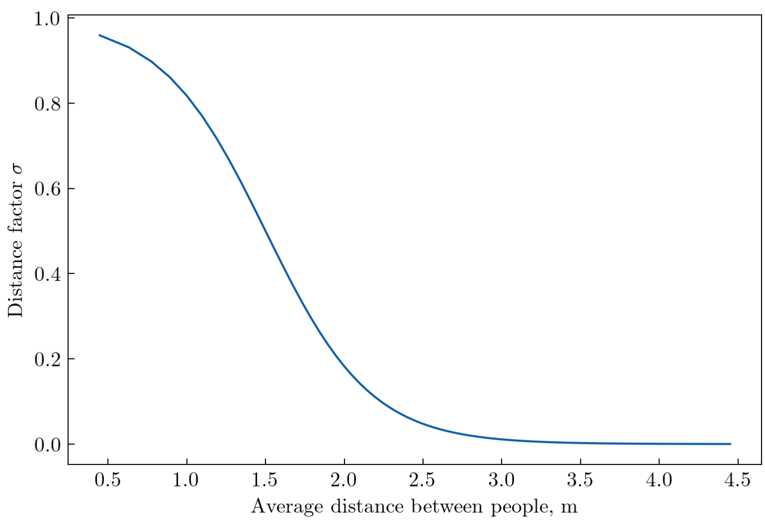

Figure 16. Relations between average distance and distance factor σ.

Importantly, the current version of the formula has to be calibrated with the use of α. There is a lack of literature on how

To verify the model we do a series of experiments:

```
Experimental setup
Number of infected people in the room M: 1
Mask effectiveness mu: 1e-05
Days since infection of the infected person d: 3.4
Time spent together t_i,j: 8
Room of A m2: 25 m2
Number of people in the room N: 7
Social distancing psi: 1 m
Calibration factor alpha: 0.025
```

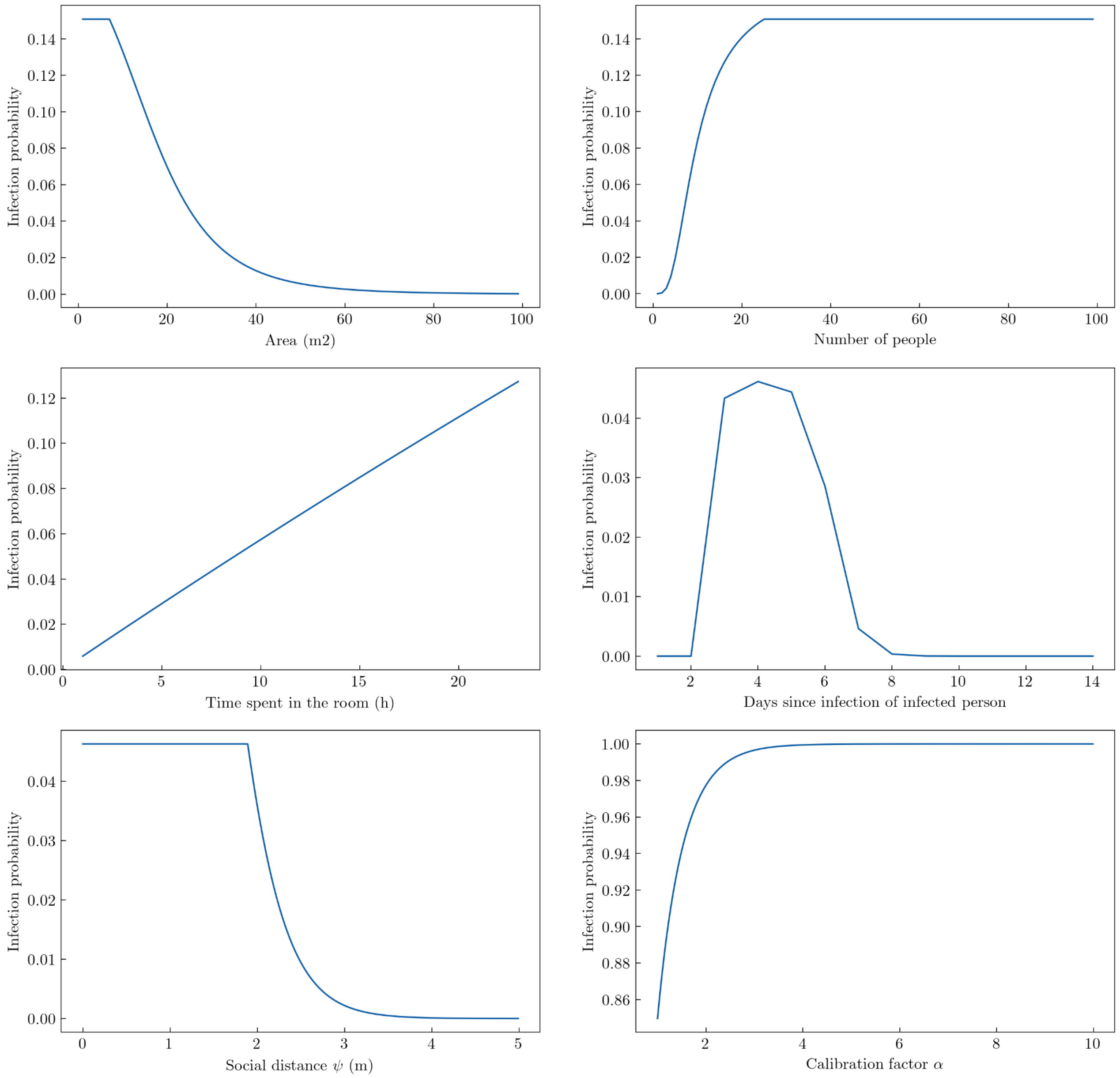

Figure 17. Experiments with infection probability $p_{i,j}$

Name	Symbol	Value	Model(-s)	References
Latent period	L	2	Viral load	(Goyal, Reeves, Cardozo-Ojeda, et al., 2021; Goyal, Reeves, Thakkar, et al., 2021; Kissler et al., 2021; Peng et al., 2021; Sun et al., 2022)
Incubation period	I	3.4	Viral load	
Clinical disease period	C	6.2	Viral load	
Peak viral load	ν_{max}	7.23	Viral load	
Reference viral load	ν_0	4	Transmission probability	

Transmission rate	k	2.294	Transmission probability	
Factor for social distancing	ψ	1	Infection probability	
Calibration factor	α	0.025	Infection probability	

Table 3. Epidemiological model parameters.

Probability-based infection model

We propose simplifying the SEIRD-based system dynamics model to model infections in mid and low-resolution models: a *probability-based infection model* (PBIM). PBIM uses a single value - an *infection probability*, to infect susceptible agents. However, infection probabilities for satellite cities and neighbouring countries are different. The first one is based on the *infection rate factor* and uses infection probability for the worker social group from the ABM. The second one is based on *the infection rate* of a country and is independent of the ABM.

An infection rate factor (IRF) of a city is the number of positively tested individuals divided by the city's population. To calculate IRF we use RIVM's data on positively tested individuals from 1 September 2020 to 1 December 2020 (*RIVMdata*, n.d.). Figure 18 shows infection rate factors for different cities.

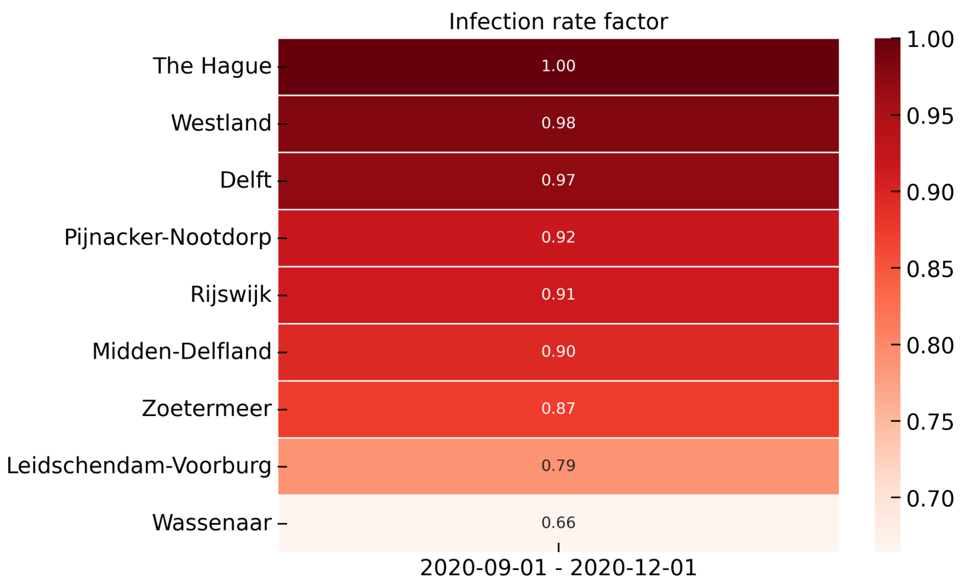

Figure 18. Infection rate factors for satellite cities.

For the neighbouring countries, we calculate an infection rate (IR) equal to the number of positively tested individuals divided by the country's population. To calculate IRs we use open data on positively tested individuals from 1 September 2020 to 1 December 2020 (*Covid19-Eu-Zh/Covid19-Eu-Data: Automated*

Data Collection: COVID-19/SARS-COV-2 Cases in EU by Country, State/Province/Local Authorities, and Date, n.d.).

PBIM will not change in which compartments an agent is. That is, once exposed, they will go through the whole Progression model: from Exposed to Recovered or Dead.

Scenario analysis

To understand the impact of local and international travel on Covid spread, we formulate three groups of scenarios of interest: *business-as-usual*, a *highly infectious satellite city* and a *highly infectious neighbouring country*.

Business-as-usual scenario aims to demonstrate what can happen to a highly interconnected region such as Haagalden when there is no policy in place. In this case, we run the simulation model with a default set of parameters derived from the literature (see Annexes). Highly infectious city scenarios allow us to explore the impact of local travel on the spread of the virus. We experiment with the IRF and Rijswijk, a city closest to The Hague. Note that we are interested in studying *first* and *second-order* effects. Three social groups will be affected directly (first order): The Hague to satellite city workers (CTS), Satellite to The Hague workers, and (STC) Satellite to satellite workers (STS). These agents can get infected either at work in a highly infectious city or at home if they live there. Other social groups will experience the second-order effect: e.g., an infected CTS brings the disease home and infects their family members. In the last group of scenarios, a highly infectious neighbouring country allows us to investigate whether there is a need to close the country's borders. Especially when the number of travellers is relatively low. We do this by sampling the IR of a single country: Belgium.

Visualisation of model outcomes

The Covid pandemic has stimulated the development of tools to communicate pandemic-related data (Bernasconi & Grandi, 2021). Especially the online ones and with a spatial dimension. Examples are so-called dashboards - a web-based graphical user interface that provides insight into relevant indicators. Those dashboards were developed not only by national or international agencies, institutions, and research centres but also by private companies and individuals and have become an essential source of information during the pandemic (Kamel Boulos & Geraghty, 2020).

It also has proved that simulation models can help inform the general public and serve as a tool for policymakers. However, not the models are of interest, but their outcomes. Since the model outcomes have the same characteristics as the data, we use similar tools to visualise them. We need to find a way to explain the outcomes with state-of-the-art data visualisation techniques. And dashboards seem the most efficient and effective solution for timely and comprehensive access to information. Model outcomes should, however, meet the requirements and deal with the limitations of both: data visualisation techniques and dashboards.

The first step in building a comprehensive data visualisation is understanding its motive and purpose, which are closely related to end-users. The process of visualisation design is end-user-driven, and the knowledge of who the target audience is is crucial from the very beginning. The information on end-user needs and visual perceptual skills enables proper identification of the motive and purpose of visualisation, hence the appropriate selection of its content and functionalities (Figure 19).

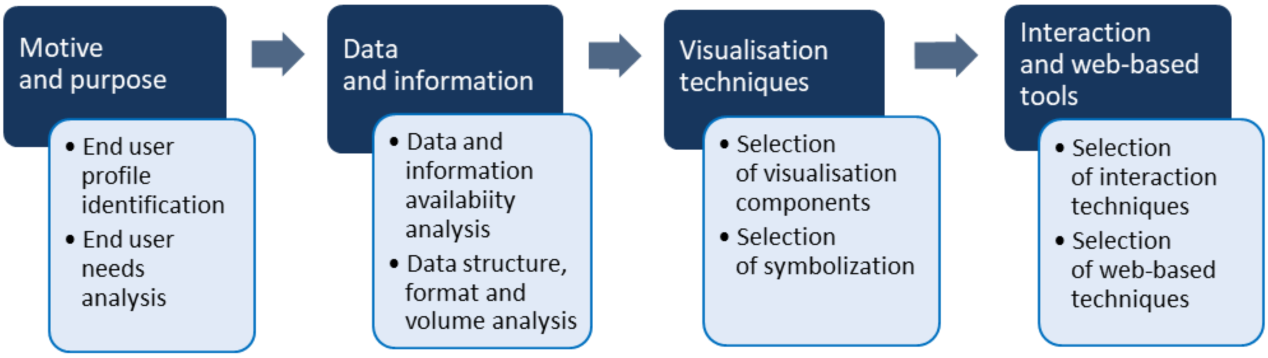

Figure 19. General workflow of creating data visualisation.

We can present data and information in various ways, for example, through charts and maps. Whichever approach is chosen, the content should be easy to read and comprehend. Therefore the visualisation should:

- be simple (without irrelevant details and complex components),
- be effective – give answers to all questions the audience may ask (if available data can provide required information),
- use custom meaningful, and standardised symbology,
- be consistent with the visualisation message (e.g. use purposeful colours).

Furthermore, the web-based approach, as exemplified by dashboards, can improve data and information sharing to support decision-making if the tool allows for:

- filtering across time and relevant data,
- presenting geospatial distribution of data and area identification,
- zooming the area of interest,
- comparing various outcomes of the model.

Analysing the impact of Covid restrictions on Long-Term Care

Since the Covid restrictions were imposed and data began to accumulate, several studies have been published for different populations to explore the effects of the restrictions. There was a particular focus on the impact of restrictions on vulnerable groups such as the elderly. Research on the impact of restrictions on the elderly (e.g. people living in nursing homes) has shown that although the restrictions might have had positive effects on the health of the elderly, negative impacts could also be detected. Previous studies have shown that the restriction might have had a negative impact on memory, anxiety (Paananen et al., 2021), depression (De Pue et al., 2021), and mental health (Curran et al., 2022). Furthermore, sleep quality, and activity levels, induced weight loss and loneliness could be detected (Levere et al., 2021).

The comprehensive long-term impact of some restrictions can only be detected in longitudinal analyses in the future since some countries are still implementing restrictions at the time of writing. However, in this study, we analysed the first period of Covid restrictions. More specifically, we focus on the change in the health status of the elderly in Long-Term care (LTC) in Finland compared to the pre-Covid health status.

The analysis was conducted utilising the Resident Assessment Instrument (RAI), which measures **the functional, cognitive, social, and mental health and wellbeing** of the elderly.

Compared to the earlier published research on the impact of Covid restrictions on people living in nursing homes, this study presents many contributions. We analyse extensive individual-level longitudinal data on the well-being of the elderly (from the RAI) collected before and after Covid restrictions. The data allows us to use the difference-in-differences method to study the causal effects of the restrictions. The results are based on the changes of individual LTC clients in functional, cognitive, mental, and social functionality and well-being before and after the Covid restrictions were set in Spring 2020. External caregivers and nurses collected the RAI, and the assessment form is based on the mature international protocol. To complete statistical analyses for estimating the effect of Covid restrictions on the elderly in the LTC, we use the Difference in Differences (DiD) method (Lechner, 2010). DiD estimates the differences between the changes in outcomes before and after the restriction in "restriction" versus "control groups" (Figure 20).

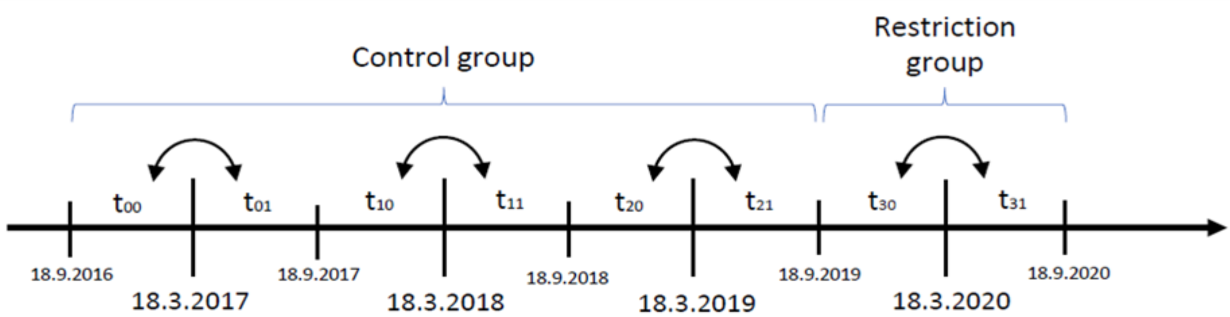

Figure 20. Methodology.

Data was gathered between 2016-2020 for a cohort of 65 228 long-term care clients, with one group of 16 668 clients who experienced restrictions and three control groups (no restriction), constituting 26 233 clients

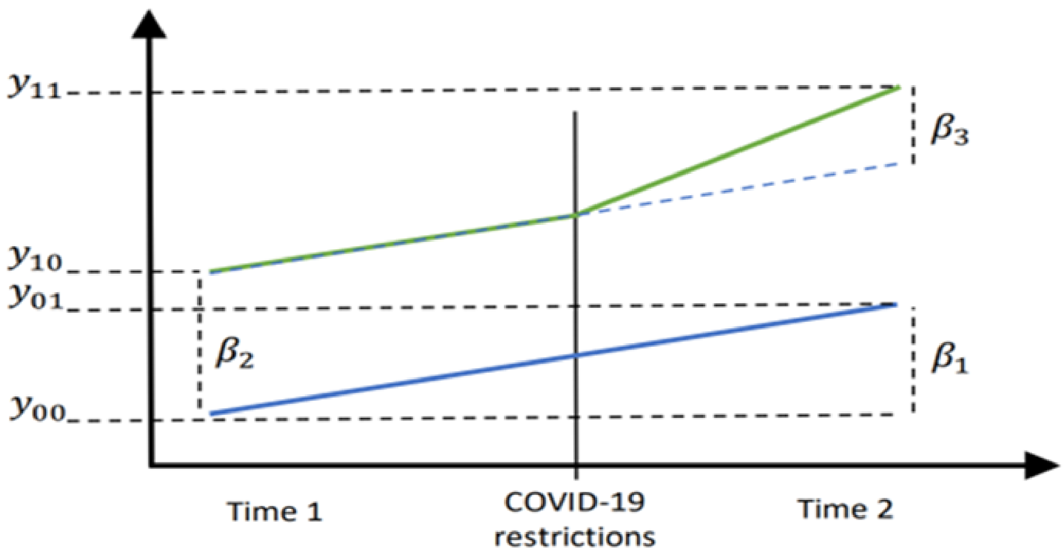

Figure 21. COVID-19 restriction effect was calculated as the difference in differences of the outcomes of the restricted group (green line) and control group (blue line).

Preliminary results show that effect was detected for several indicators of wellbeing.

	Variables with negative effect	Variables with no effect
Activity	Physical activity outside of facility	Walking, Independent use of toilet, Personal hygiene
Mood and behavior	Decline in social activities	Depression, Mood swings, Sleeplessness, Complains, Pain, Sadness
Psychosocial well-being	Involvement in life of facility, Establishes own goals, Personal contact with family or friends	Conflict, Aggression, Preforms activities independently
Memory	Cognitive skills for making every day decisions	Remembers staff names, Confused, Short term memory, Long term memory
Treatments	Therapy, Emergency room visits, Hospital stay	Changes in medicine prescription

Figure 22. Effect on wellbeing

3 Results

This section is structured as follows. We first show and discuss the model outcomes, which we split by scenario. Then we present interactive dashboard solutions for these model outcomes.

Scenario analysis

This subsection presents the model outcomes. We first run the model business-as-usual using default parameters. Then we simulate a highly infectious city scenario. We make Rijswijk, the city closest to The Hague, a highly infectious city. Finally, we study the impact of a highly infectious country on the spread of the virus. In our case, this country is Belgium. The combinations of these scenarios will help us understand the impact of local and international travel on the spread of the virus and provide relevant policy advice.

Business-as-usual

We start the analysis by looking at the number of agents by the compartment of the SEIRD model (Figure 23). There are eight components in total. The total number of agents in the model is 738,131 (553,677 living in The Hague), and as we can see from the first subplot called "Susceptible", not all of them got infected. Notably, under the business-as-usual, we do not apply any policy. Agents performing their routines as usual: worker agents go to work, pupil agents go to school, etcetera. However, if an agent gets infected and is symptomatic, it will change its schedule to stay at home. Such behaviour can explain why not every agent in the model got infected. We can also observe many agents at the hospital and ICU (subplots 5 and 6). Undoubtedly, given such an experimental setup, it becomes impossible for the healthcare system to operate.

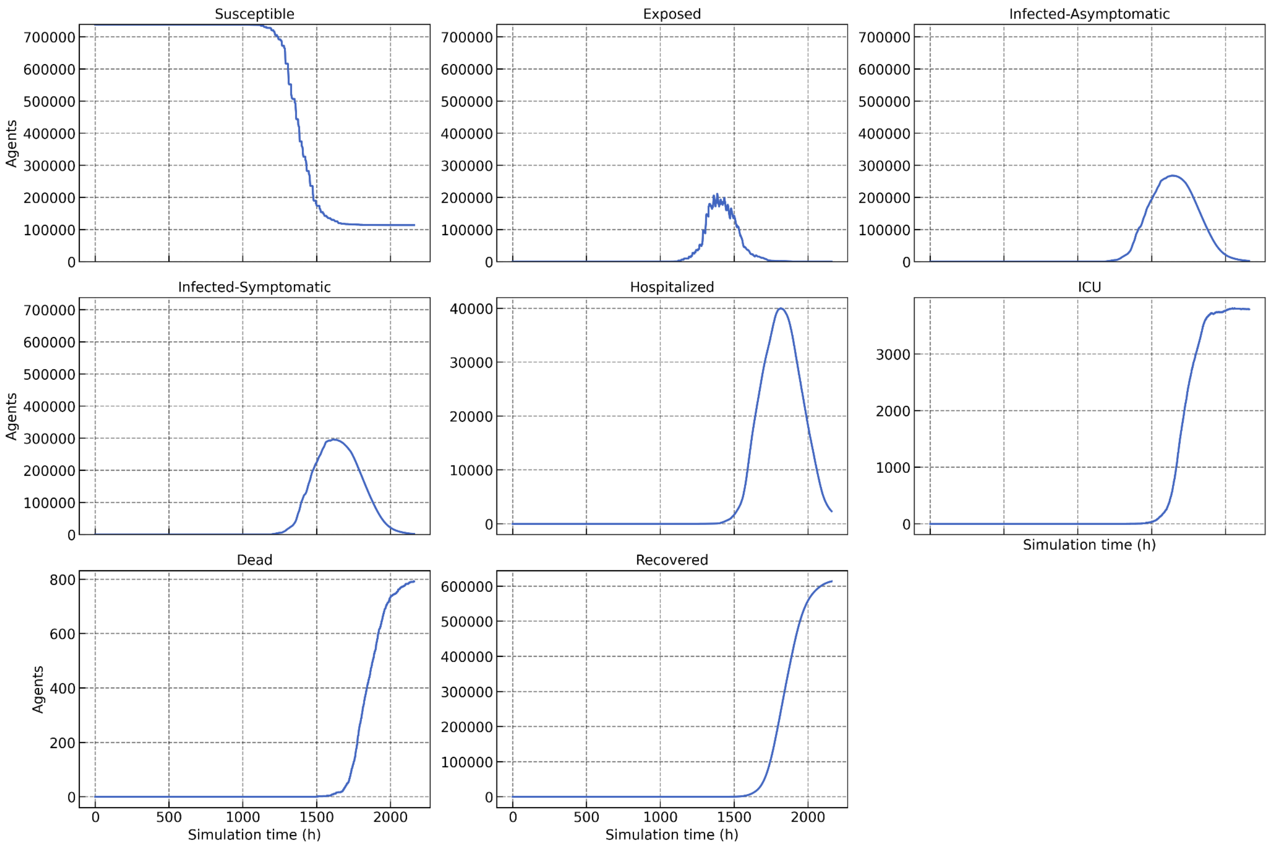

Figure 23. Number of agents by compartment.

Next, we zoom in into infections (both symptomatic and asymptomatic) at individual entities: The Hague, some of the satellite cities, and neighbouring countries. Recall that we use different infection models for high, mid, and low-resolution models. For example, in Westland, IRF is the highest and equal to 0.98. It means that Satellite workers working or living in this city will get infected at almost the same rate as workers in The Hague. When we look at the first and the second subplots, we can see that the infection peak in satellite cities happens slightly later than in The Hague. Depending on the IFR of a city, the first wave covers a different fraction of the population: for Westland, with IFR=0.98, it is 0.21, and for Wassenaar, with IFR=0.66, it is 0.15. Infections in Belgium and Germany do not follow a similar pattern, they develop more independently. Infections in Belgium and Germany do not follow a similar pattern and develop more independently. Higher IR for Belgium translates into earlier infections, while even though IR is lower, the second infection peak is higher than that of Belgium.

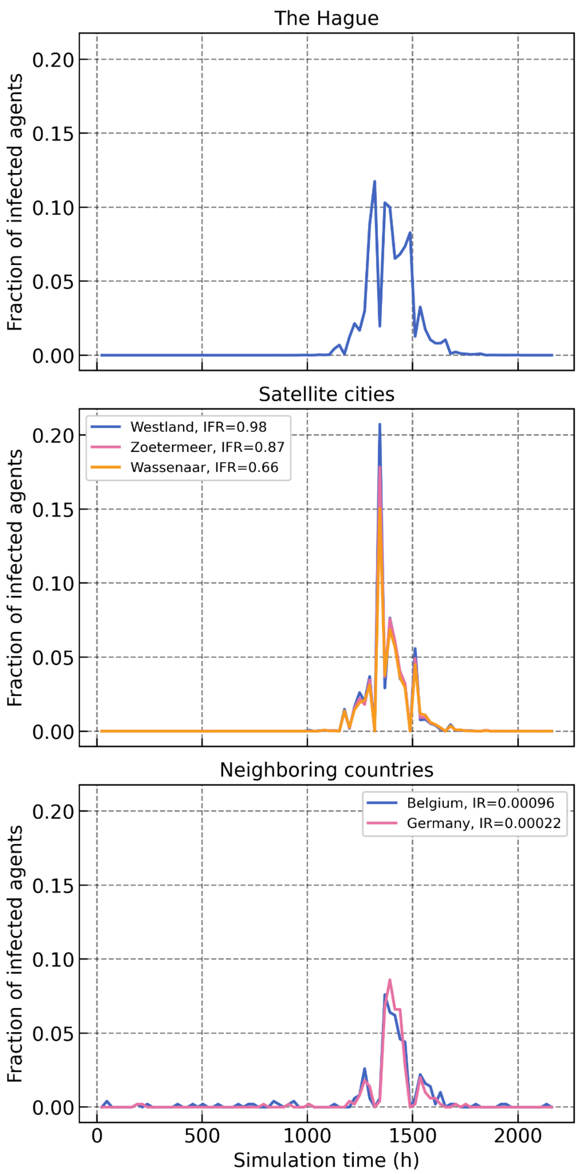

Figure 24. Fraction of infected agents from an entity: The Hague, satellite cities and neighbouring countries.

Remarkably, the total number of infections differs by the entity at the end of the simulation run (Figure 22). The Hague got 92% of its citizens infected, in satellite cities from 57 to 64% depending on their IRF and 42 and 46% for Germany and Belgium, respectively.

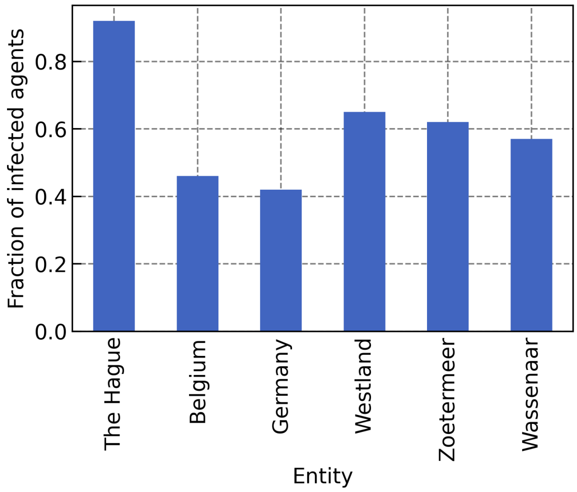

Figure 25. Fraction of infected agents by entity at the end of the simulation run.

Let us explain the reasons for that. We plot *infection matrices* on the next set of graphs: Figure 26 - Figure 29*.* An infection matrix (IM) shows agents of which social group infect agents in other social groups at locations of a specific type. For example, Figure 26 is an IM for the Workplace locations. We can see that most of The Hague workers are infected by the workers from neighbouring countries (NCTC workers). The same applies to the workers from the satellite cities (STC workers). NCTS workers infect them at workplaces in The Hague.

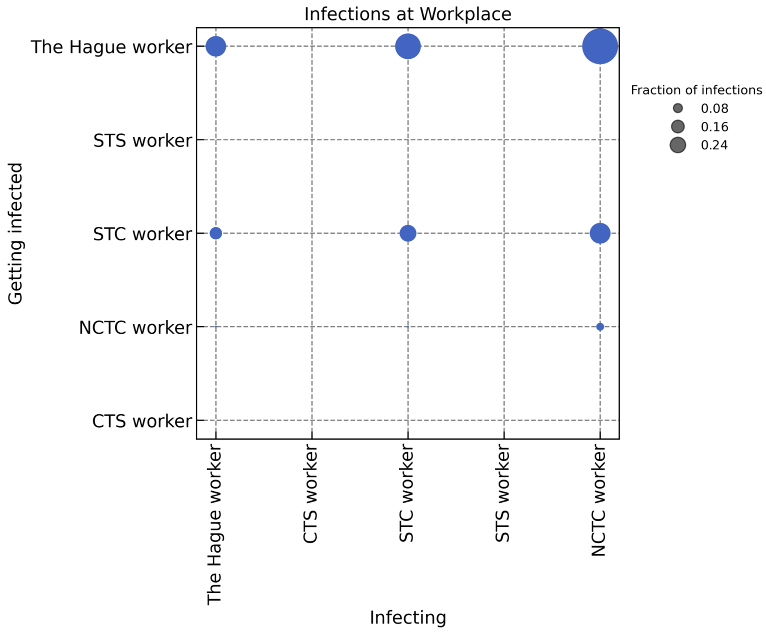

Figure 26. Infection matrix: agents of which social groups infect other social groups at the Workplace type of location.

Agents from the three new social groups: STC, STS, and NCTS, have two activities to execute: Work and Personal care. And besides Workplace locations in The Hague, they can do the first activity at Satellite workplaces. Figure 27 shows the IM for Satellite workplaces. The second activity is Personal care which they do Satellite accommodation. The following Figure 28 depicts the IM for Satellite accommodation. Only certain social groups meet there and infect each other. By comparing these three plots (Figure 26-28), we can see that more infections happen at Satellite accommodations than at Satellite workplaces and workplaces for STC and STS workers.

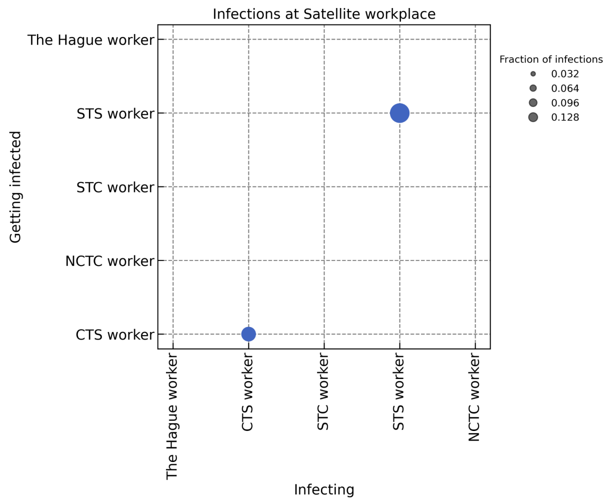

Figure 27. Infection matrix for Satellite workplace.

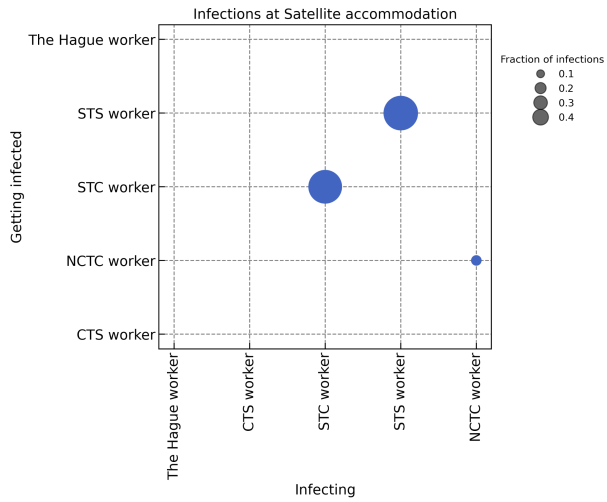

Figure 28. Infection matrix for Satellite accommodation.

Let us explore IM for Accommodation to understand how disease propagates further (Figure 29). Each Worker has a place to stay where they interact with other household members. For example, a household can consist of Worker A, another Worker B, a partner of Worker A, and three school pupils who are their children. Each of those agents may get a disease at any other location. School pupils can get infected at School, whereas Worker B can get infected at a Supermarket. Figure 26 highlights the unequal impact of different social groups on each other. Now, let us continue with the Worker social group. Kindergarten and School pupil infections are the highest, up to 60% of the total number of Workers infections. Such a finding indicates a need for a specific policy measure to prevent the spread of the disease. Interestingly, many Kindergarten and School pupil agents infect other agents from the same social group.

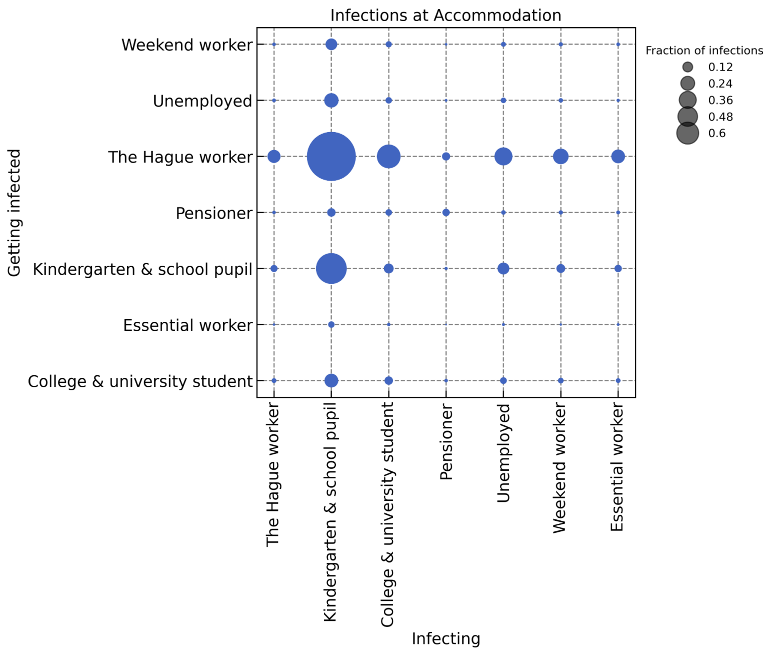

Figure 29. Infection matrix for Accommodation.

The COOL operates at three spatial resolutions: neighbourhood, city and country. Figure 30 shows two types of outcomes: the ratio of infected agents by their residence (e.g. Centrum neighbourhood has 40% of its residents infected) and the number of infections in a particular area (e.g. 1000 infections happened in Delft) at the end of the simulation run. Importantly, these two outcomes are not equal (Figures 31-32). The reasons are differences in the number of places of interest (POI) and what they are, the preferences for the POIs to visit (e.g. does an agent go to the closest bar or search for a random one within 2.5 km), number of agents per entity, etc.

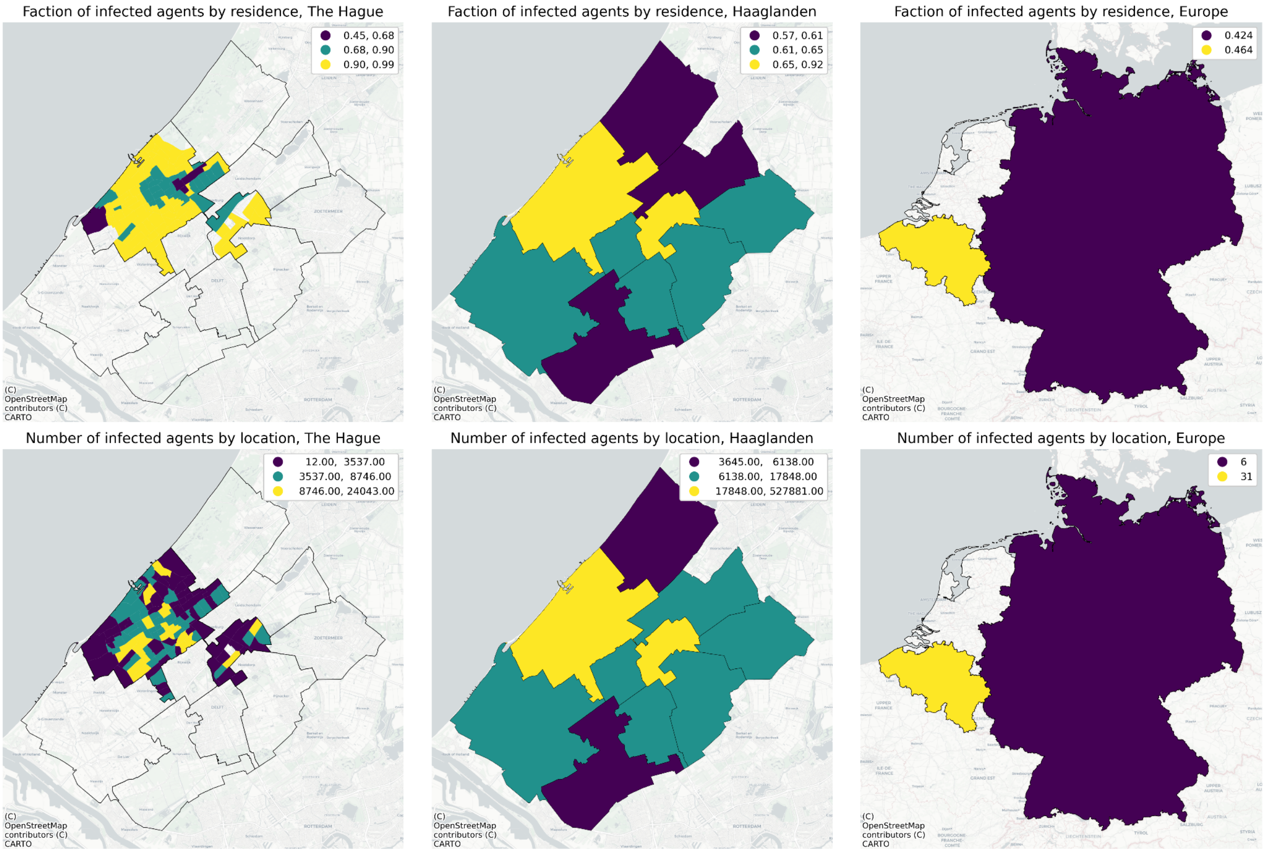

Figure 30. Spatial distribution of infections by residence (fraction of the total population) and by location.

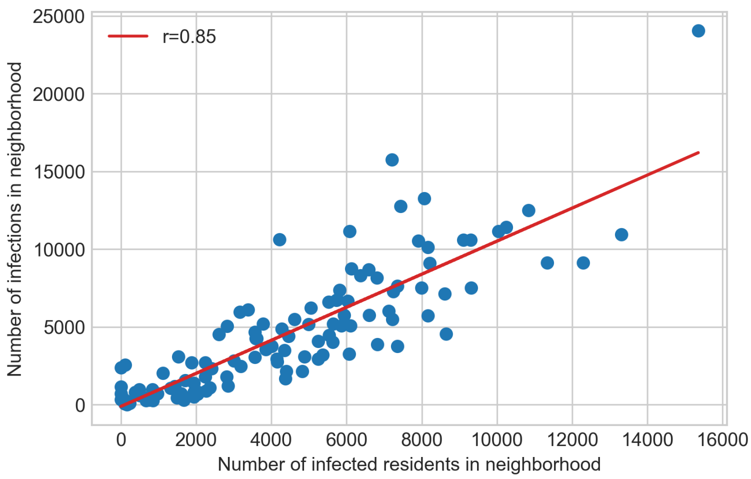

Figure 31. A linear regression model correlating the number of infected residents (x) with the number of infections in a neighbourhood (y).

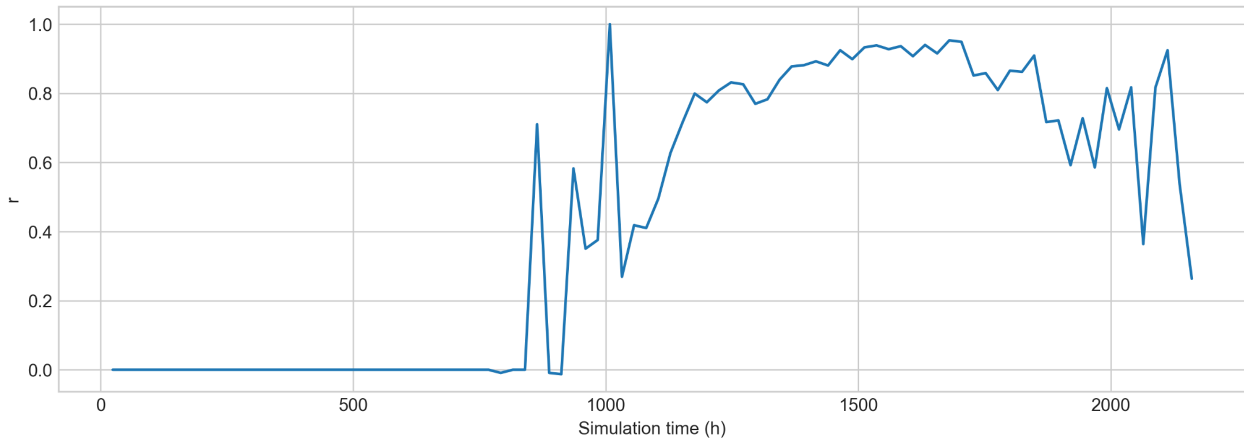

Figure 32. corr(x,y) over the simulation run.

The coupled model without any non-pharmaceutical intervention (NPI) results in a considerable number of infected agents at the end of the simulation run in The Hague, satellite cities, and neighbouring countries. An initial setup of 100 infected agents and a moderately infectious virus variant results in 92% of the population in The Hague infected, whereas the percentage of infected population in other entities ranges from 42% to 64%. Remarkably, workers are not the only contributors to the spread of the virus. By looking at the infection matrix, we learn that the highest number of worker infections at home is through kindergarten and school pupils. Thus, we have a feedback loop/infection chain. That is, the kindergarten and school pupil agents get infected at their study places. They further infect each other and workers at home, and workers spread the disease further at all types of locations that they visit. Therefore, we argue in favour of the policy measures which we have covered in task 2.1, e.g. closing up kindergartens and schools to "flatten the curve."

A highly infectious satellite city

The first category of scenarios explores what can happen to a highly populated city, given that its satellite city is highly infectious. For that, we select a single closest to The Hague city: Rijswijk (Figure 33). We sample its IFR from the business-as-usual value of 0.91239 to 16.

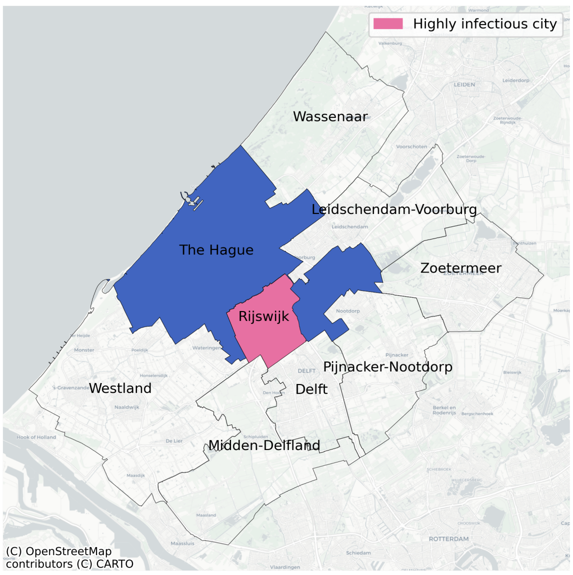

Figure 33. A highly infectious satellite city Rijswijk.

We start the analysis by looking at the number of agents by compartment. This time, we look at four scenarios of interest: from business-as-usual aka *base case* (BCS) to *mid* and *worst case* (WCS) with IRF=16. A higher IRF pushes the curves to the left, indicating that the pandemic spreads faster. Remarkably, the difference in time is relatively smaller: the peak in the second subplot in the first row (Exposed) for the base case happens at 1385.5 and for the worst case it is 1361.5 hours - a day.

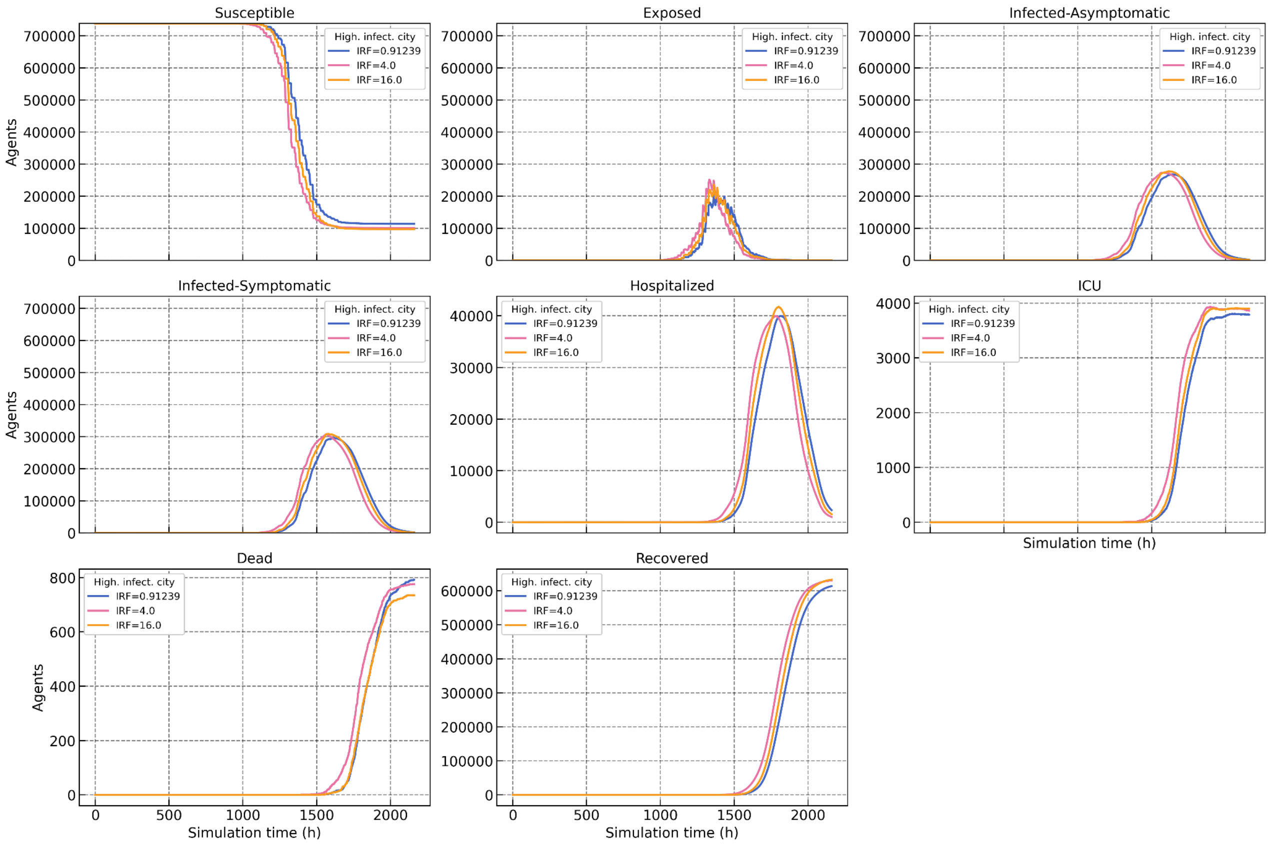

Figure 34. Number of agents by compartment.

Next, we zoom in on infections by entity: how the fraction of infected agents varies given different scenarios (Figure 35). At first glance, there is no significant difference between the scenarios. However, with a closer look, we see that the infection curve scales up with the IRF. With IRF=4.0 and IRF=16, The Hague will get infected slightly faster. The second plot for Rijswijk has a set of notable differences. In the case of two scenarios when IRF=4 and IRF=16, the Rijswijk population gets infected earlier. The worst-case IRF of 16 at the start leads to fewer infections in The Hague and neighbouring countries. In satellite cities, the infection peak occurs around 1600. Mid-case IRF=4.0 pushes infections to happen earlier and has a milder peak value.

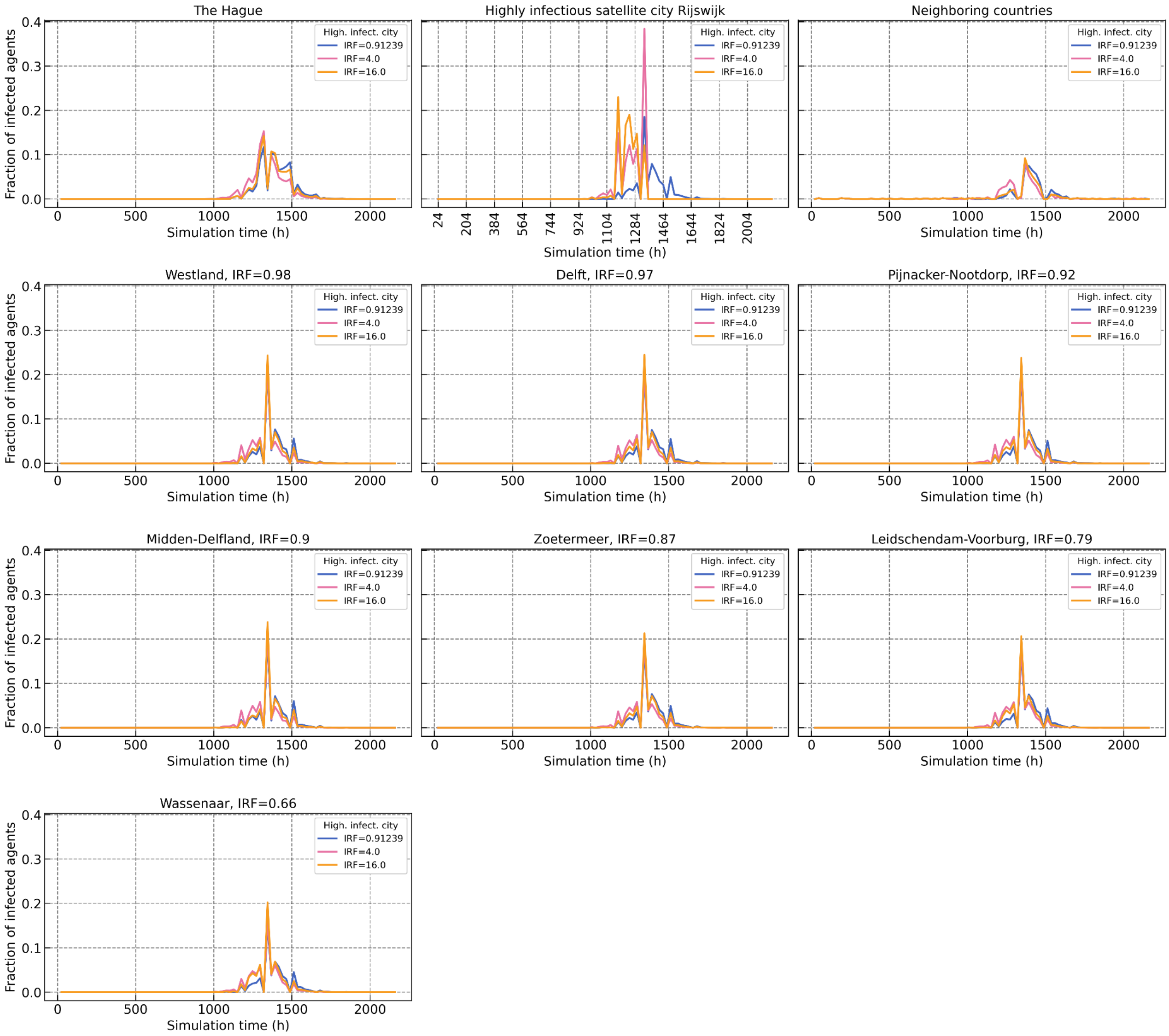

Figure 35. Fraction of infected agents by entity.

Let us investigate the impact of Rijswijk's scenarios individually. As we previously saw, WCS makes infections happen faster. However, from Figure 36, we also learn that the WCS leads to more infections in the highly infectious city Rijswijk (39.92%) and other satellite cities (42.78%). For The Hague to Rijswijk workers (CTS), the difference in infections is not as big as for Rijswijk and satellite cities: only 4.81%.

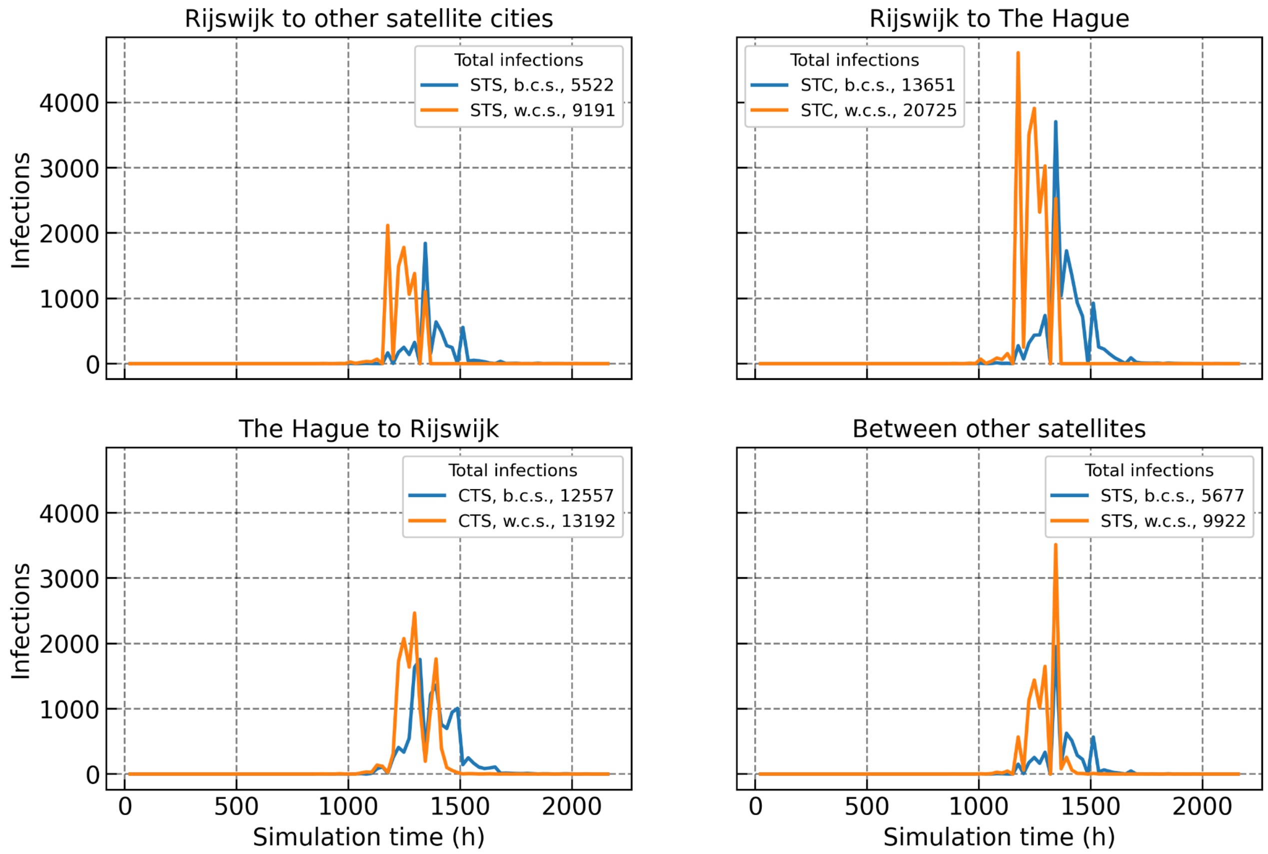

Figure 36. Differences in the number of infections with different rate factors. B.c.s. - business-as-usual scenario with the rate factor of 0.91239, W.c.s. - worst case scenario with the rate factor of 16.

Figure 37 shows the fraction of infected agents at the end of the simulation run by an entity and scenario. With a higher IRF, the total fraction of agents infected at the satellite locations increases. Notice that a higher IRF has the opposite effect on the neighbouring countries. The larger the IRF, the smaller the fraction. NCTC workers interact with other agents either in The Hague's Workplaces or at Satellite accommodations in their own countries. Thus, if the disease spreads faster locally and the population recovers, there are fewer chances for NCTS workers to get infected.

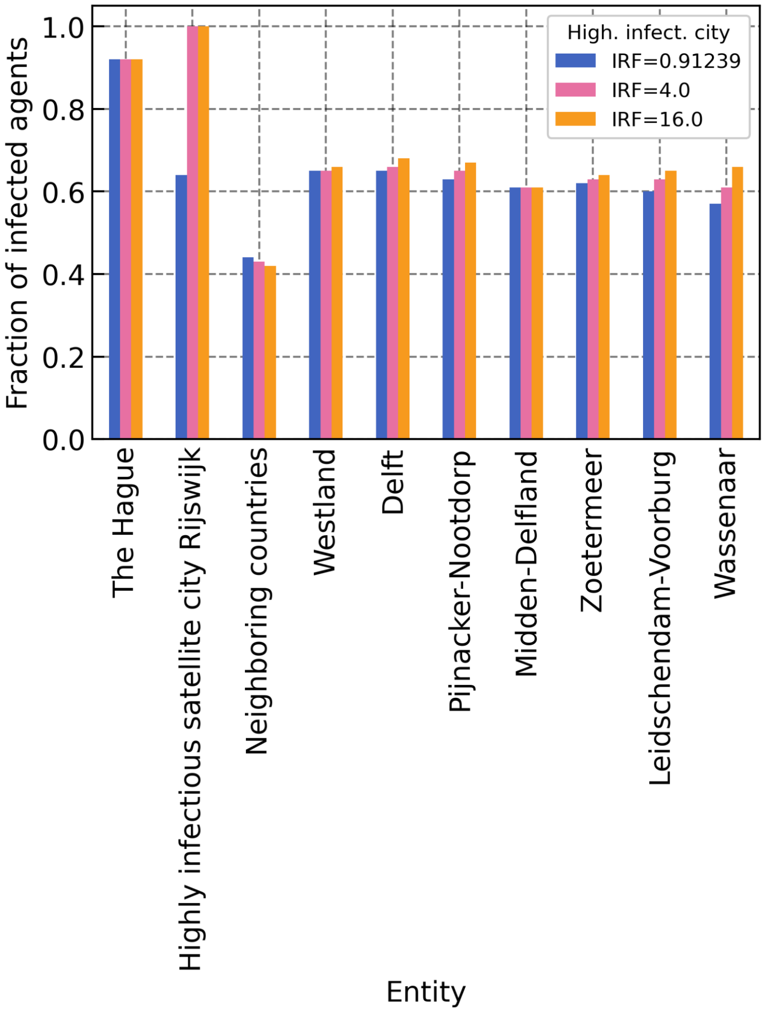

Figure 37. Differences in the total number of infections by entity and scenario.

Figure 38 illustrates the differences in IM between two scenarios: BCS and WCS. As we can see, there are no differences in the structure of the IM. It was instead minor differences in the number of infections that scaled with the increase in IRFs.

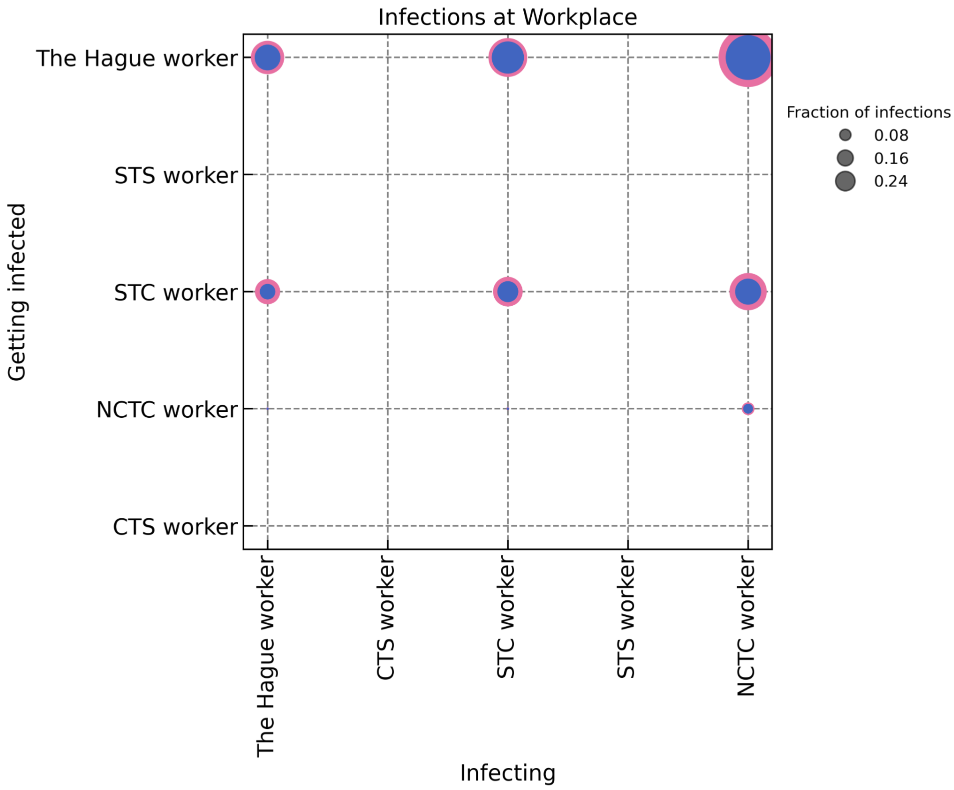

Figure 38. Infection matrix for Workplace.

Making one of the satellite cities (Rijswijk) highly infectious speeds up the progression of the disease; however, the impact is limited. First of all, it affects the city itself. As we see, the outbreak in Rijswijk happens earlier, and the number of infections doubles under the worst-case scenario. Secondly, it impacts other satellite cities since there is a constant flow of workers visiting Rijswijk. The impact on The Hague is, however, limited. As we have seen in the business-as-usual scenario, workers are not the only social group that spreads the disease. Due to limited interaction between the agents from satellite cities and The Hague residents, a highly infectious satellite city results in almost the same number of infections as business-as-usual. Thus, cutting down the local travel can help reduce infections across satellite cities and delay the disease spread. However, it is an insufficient measure for flattening the curve and reducing the burden on the healthcare system.

A highly infectious neighbouring country

The last set of scenarios explore the impact of international travel on the spread of the virus. We simulate four scenarios where we make one of the neighbouring countries highly infectious (Figure 39): IR=0.0009 - the base case scenario (BCS), IR=0.0019, IR=0.09 and IR=0.36 - the worst case scenario (WCS).

Figure 39. A highly infectious neighbouring country: Belgium.

Figure 40 shows the number of agents by compartment under the four scenarios. Opposite a highly infectious satellite city, we can see how much a higher IR speeds up the disease spread. For instance, a doubled IR of 0.0192 shifts the infection curve by 20 days. In the WCS, with an IR of 0.36, the outbreak happens almost 40 days earlier. However, when we look at the total number of agents by compartment, we do not yet see an immediate increase in the number of infected agents.

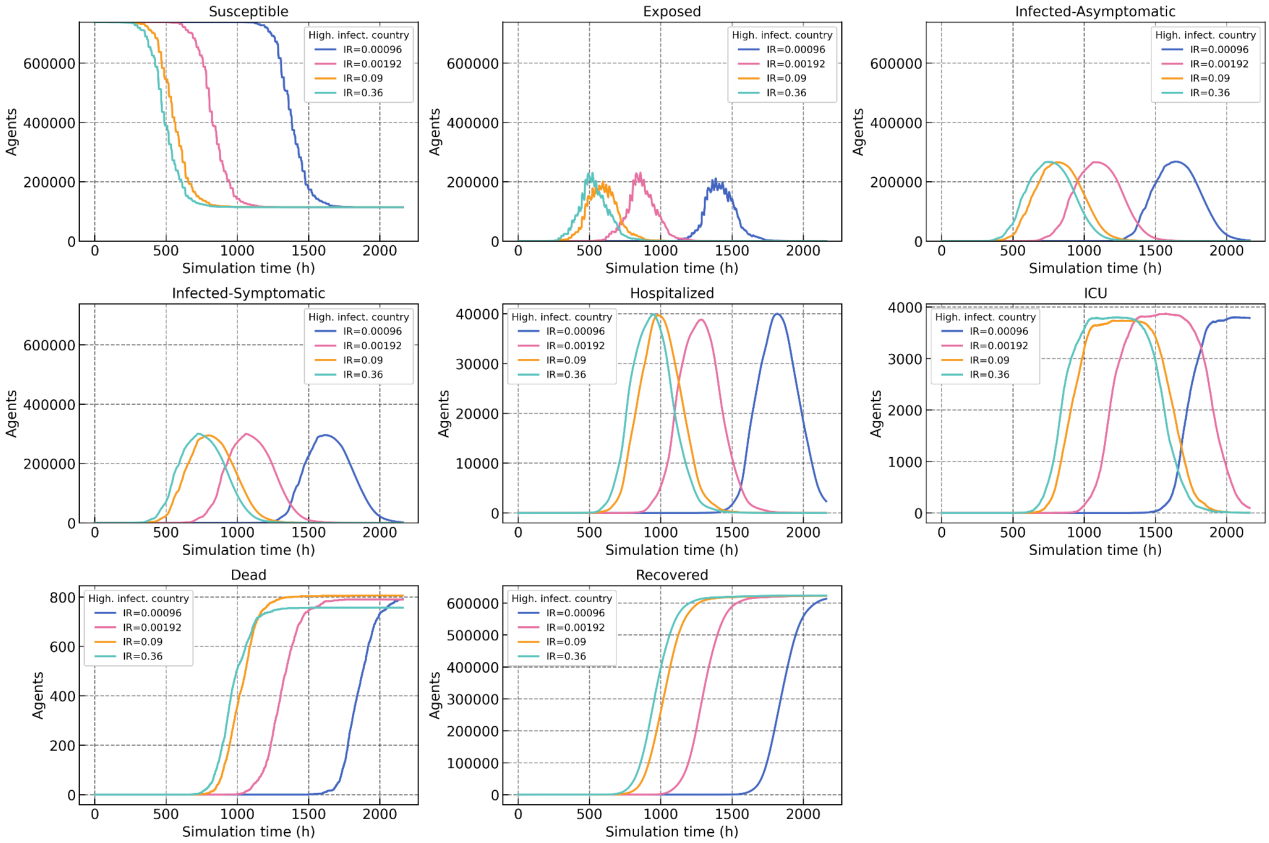

Figure 40. Number of agents by compartment.

Figure 41 with infection fraction by the entity demonstrates a similar dynamic. With the increase in IR, the infections start to appear earlier across all of the entities. Remarkably, the IR of 0.09 does not have a spike in infections, while the rest of the scenarios do.

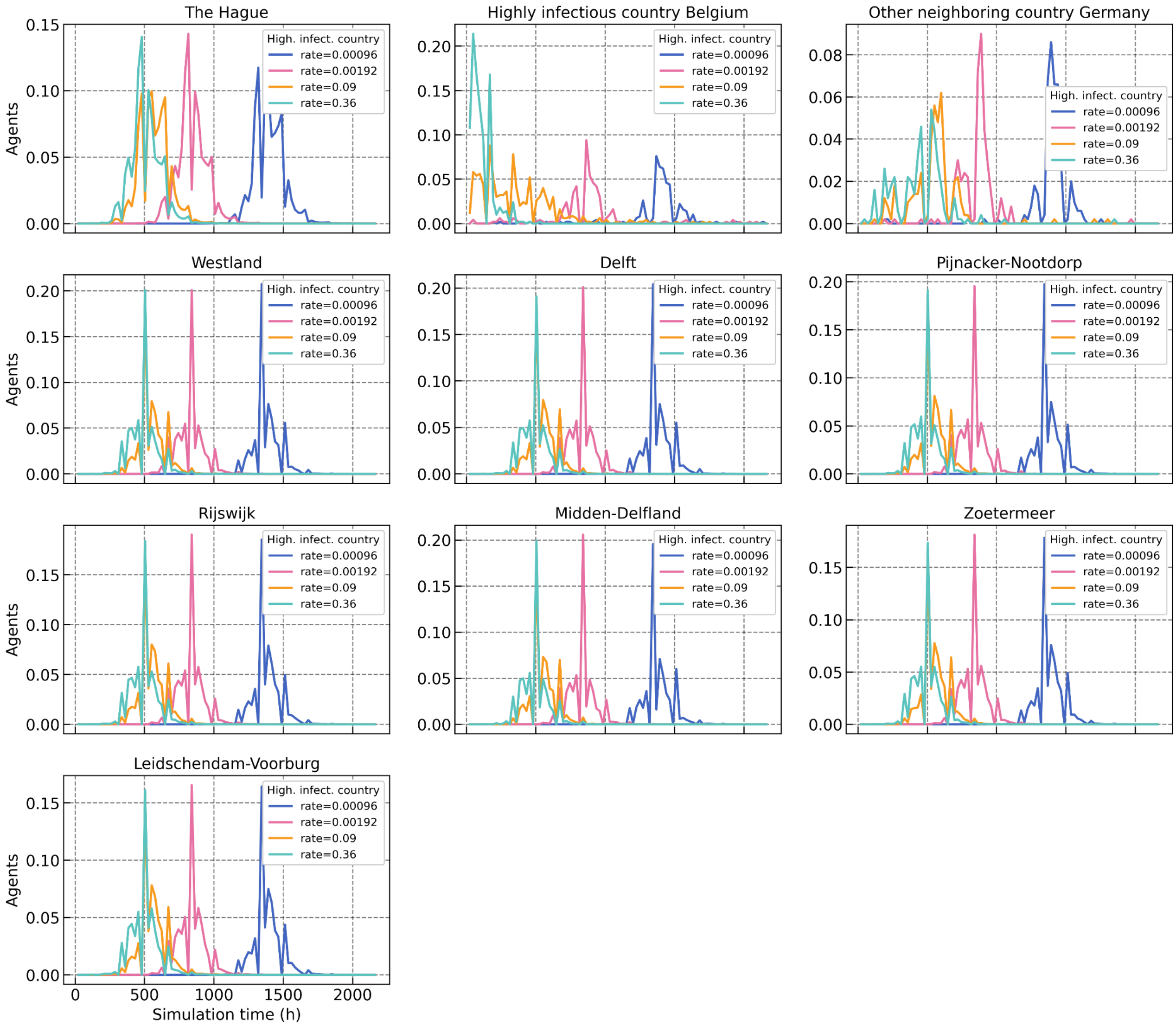

Figure 41. Fraction of infected agents by entity.

Analysis of the impact at the entity level follows the same pattern (Figure 42-43). However, it also shows that the total number of infections does not change significantly for any entity besides Belgium. In a highly infectious country, it reaches its maximum relatively quickly. Infected agents stop travelling, so the disease becomes localised. This is possible only in practice, given responsible behaviour and a thorough testing policy.

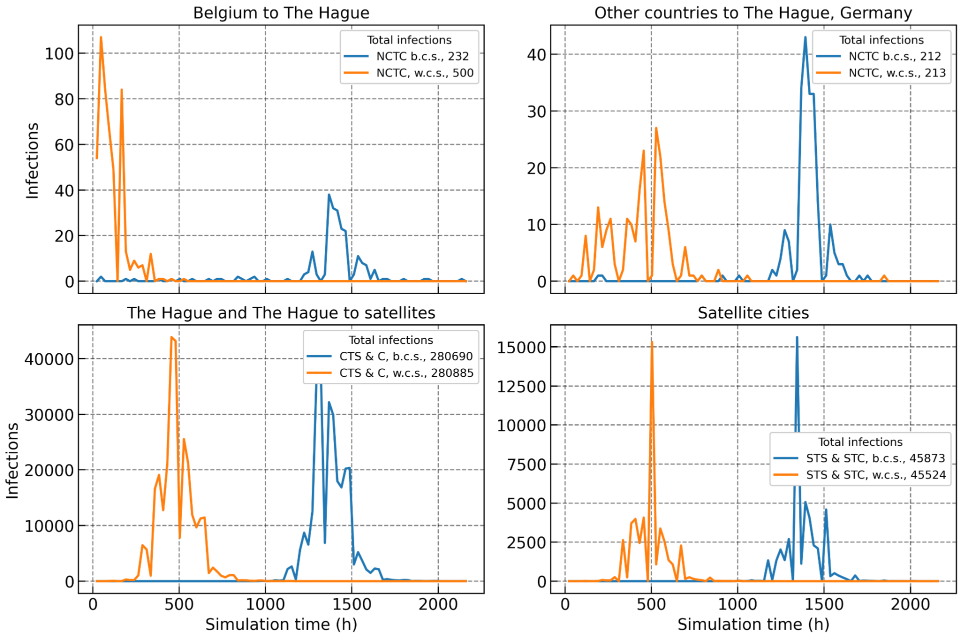

Figure 42. Differences in the number of infections with different rates. B.c.s. - business-as-usual scenario with the rate of 0.00096, W.c.s. - worst case scenario with the rate of 0.36.

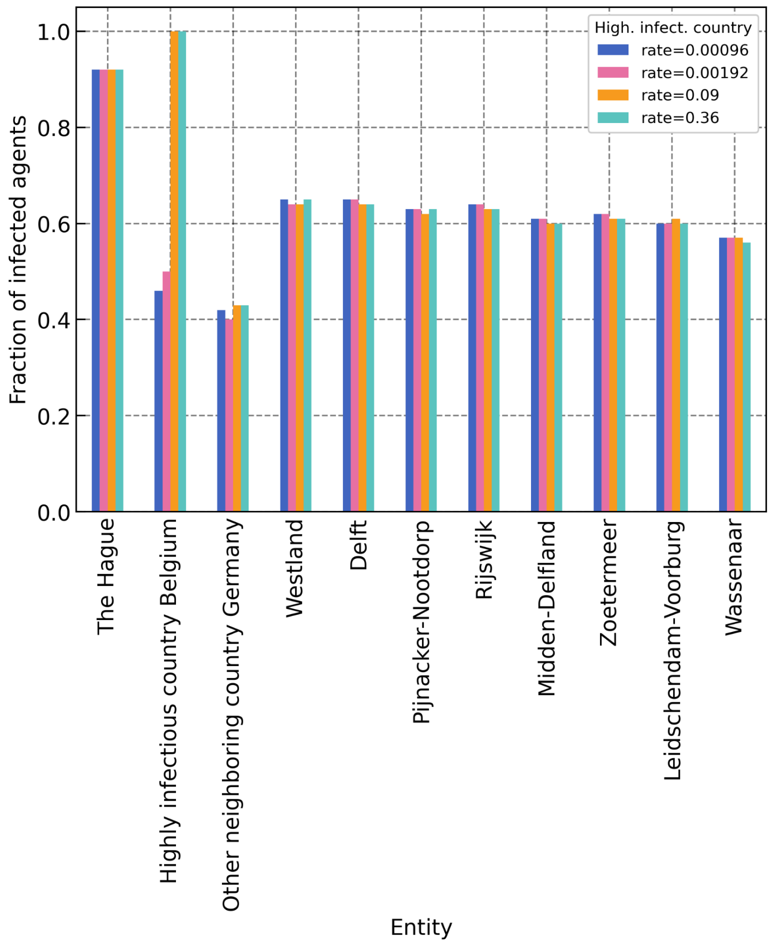

Figure 43. Differences in the total number of infections by entity and scenario.

The scenarios that include travel from a highly infectious country (Belgium) witness a more rapid spread of the virus in every entity: The Hague, satellite cities and neighbouring countries. A double increase in the infection rate (IR=0.0192) makes the infections happen around 20 days earlier. The above result highlights the importance of closing up the borders if a country's IR is above a certain threshold and the need for testing. However, similar to the highly infectious city, the increase in the IR does not affect the total number of infections in The Hague. Thus, to "flatten the curve," one should limit not only the international travel and introduce rigorous testing but also use other non-pharmaceutical interventions on the city scale (such as, closing kindergartens and schools).

An interactive dashboard for model outcomes

The primary users of dashboards are policymakers and healthcare operation leaders. It is imperative for these stakeholders to monitor the spread of diseases and their effects in their area of responsibility. This will enable them to take appropriate preventive measures and prepare the system appropriately for such disease outbreaks. Therefore the dashboards design, components, and functionality should give a quick and comprehensive response to the specific questions regarding the function of policy applied in the model and the date of its implementation:

- how many people will be infected on date x,
- how many infected people will require hospitalisation on date x,
- how many hospitalised patients will need admission to ICUs on date x,
- how many people will die due to infection by the date x,
- how many people will recover by the date x,
- what the rates of change in the number of people infected/hospitalised/admitted to ICU are on the date x or when the respective rate of growth will start to decrease,
- what the spatial distribution of people infected/hospitalised/admitted to ICU will be on date x.

Two web-based solutions and an additional application that dynamically visualize the virus transmission were developed to satisfy these expectations.

The first solution was created using the ArcGIS Online tool as a web application visualising the ABM outcomes for The Hague on two administrative levels of the city. The ArcGIS application can be accessed at https://experience.arcgis.com/template/9ad93be58bb646779ad56e7895667b33.

On separate subpages, the outcomes of the BM model, like the number of individuals currently infected, hospitalised, admitted on the ICU agents, dead, or recovered, are presented on graphs and maps. All visualisations are related to "Policy 0" - a no-lockdown strategy and two policies implemented on the 1st day, 7th and 15th of the pandemic: "soft lockdown" - closure of restaurants, bars, and recreational and educational institutions, "hard lockdown" - closure of all public services and establishments, except for parks and essential services. The user can choose a line graph or a logarithmic graph, and maps aggregated to the urban districts (Stadsdelen) or neighbourhoods (Buurten). Additionally, by using the appropriate button, the user can see the number of agents in a given state on the 7th, 35th, 63rd, 91st or 119th day of the pandemic.

The development and testing of the above solution revealed several disadvantages of the web application using a cloud-based software-as-a-service model. For example, the solution provides limited room for customisation of the web interface, fewer visualisation components and their distribution on a webpage, and require longer times for downloading and processing latest data.

The second version of the web-based interactive application (available at http://heros.cbk.waw.pl) was written in PHP, using the Laravel framework (version 9). The data is stored in the relational database (RDBMS) – MariaDB, compatible with MySQL. The application provides REST API and a web-based graphical user interface. The API retrieves data in JSON and GeoJSON formats and provides data feed for scripts that perform visualisation. For developing the charts, we use Plotly.js and for the maps, we use Leaflet.

The charts and maps are built dynamically and depend on the input parameters selected by the user on the application page. Scripts send requests to the REST API and receive data in response. After downloading the data from API, scripts generate the appropriate visualisations. The application has a built-in cache option, which enhances both the efficiency and speed. After the API's first data retrieval ("first hit"), the prepared data is cached in files on the server side. Subsequent data downloads with the same parameters are served from cached files, thus avoiding time-consuming data retrieval from the database and calculations.

The application also provides the used a feature to compare the spatial spread of Covid over time on two maps using an interactive time slider. The features that can be selected are:

1. epidemiological state of agents, i.e. number of agents, which are susceptible/exposed/infected symptomatic/infected asymptomatic/hospitalized/admitted on the ICU/infected in all states/dead/recovered;
2. map coverage (The Hague or The Hague conurbation (Haaglanden)) and administrative division (districts (Stadsdelen) or neighbourhoods (Buurten)),
3. policy,
4. scenario within a given policy.

Hovering over a polygon reveals specific details regarding the chosen features, such as the area name, agents' state, policy, scenario and the value corresponding to the map's legend (Figure 44).

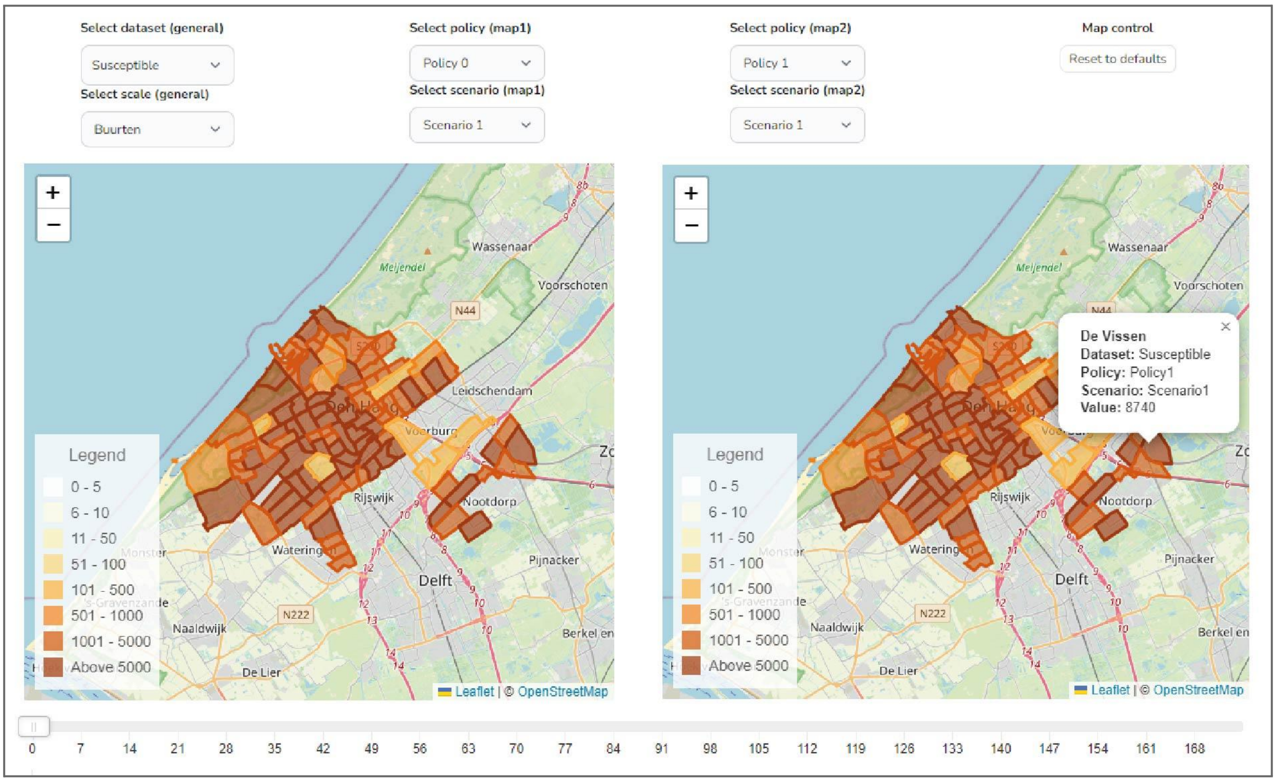

Figure 44. The map component of the web-based interactive application enabling users to compare the ABM model's outcomes.

Below the map component, the model outcomes over time are shown in charts on a linear or logarithmic scale to choose from. The uncertainty is presented in the form of multiple line charts with time series data, which show the projections from each scenario within one policy. The area between the line representing the "best-case" and "worst-case" scenarios at a given time is shaded.

A completely new approach to ABM model outcomes visualisation has been adopted by creating an agents interaction simulation model (Mrozek, 2021/2022). This version of the web-based application has the advantage of giving a dynamic perspective showing the process of infection transitions and places where people are most likely to be infected. The 180-day simulation tracks the hourly location and epidemiological state of 534 638 agents within the Hague. In this way, the animation reflects the agent's individual behaviour patterns in the function of the age group, family role etc., according to a given disease prevention policy. Thus, the person-to-person interactions enable tracing of the potential Covid spread within a specific community.

In order to explore the visualisation effectively and efficiently, the user has the options to pause, change the animation speed and time, zoom in or out, move the map view, and filter the agents by epidemiological states. Furthermore, since the statistics are shown on the legend, the user can track the current number of agents at a specific state (Figure 45).

Figure 45. The agent-based simulation model as a web-based interactive application.

Additionally, the smooth operation of the user's hardware is ensured by the possibility to select the low, medium or high level of detail.

4 Conclusion

With deliverable 2.3 (D2.3), we aimed to investigate the impact of local and international travel on the spread of Covid. More specifically, the goals of D2.3 were:

- Develop a SEIRD-based system dynamics-like (SD) model to understand how the virus spreads globally,
- Couple the SD model with the already developed agent-based model (ABM) from D2.1 and conduct a scenario analysis
- Visualise the outcomes of the model in a GIS dashboard.

Additionally, we examine the impact of Covid on the elderly in Long-Term Care (LTC) in Finland. This section summarises the work, brings the findings into a broader context and reports advice for policymakers.

A coupled model and scenario analysis

We present the methodology of how one can couple an *agent-based model* (ABM) with a *system dynamics-like* (SD) model. We discuss in detail the coupling and additions we construct to make the models interact. For instance, we introduce a new *SEIRD-based progression model* and two new transmission models: *distance* and *probability-based*. We are also “opening up” the previously closed system of D2.1 and include travel between the cities and countries. While the resulting model covers The Hague, the Haaglanden region and two European countries: Belgium and Germany, one can extend it to include more countries.

The *coupled model* (COOL) allows us to examine the impact of local (within the Haaglanden region) and international travel (from Belgium and Germany to The Hague). With the COOL, we analyse three scenarios: *business-as-usual*, a *highly infectious city* and a *highly infectious country*.

From the first scenario, we found that several social groups significantly contribute to the spread of the disease—for instance, workers and kindergarten and school pupils. Because of that, there is a substantial difference in the total number of infections in cities/countries. Satellite cities and countries reach 42-64%, while The Hague reaches 92%. Such a finding highlights the importance of non-pharmaceutical interventions aimed at social groups with more extensive contact networks.

In a highly infectious city scenario, satellite cities get infected faster, especially the highly infectious city of Rijswijk. The infection rate factor of 16 (the worst case scenario) makes infection happen around ten days earlier. It also leads to more infections compared to the business-as-usual scenario. In the worst case scenario, the increase for the satellite cities is 42.78% and 39.92% for Rijswijk. The impact on The Hague is however limited. Due to limited interactions between agents in The Hague and other entities, a higher IRF does not “shift the curve” or increase the total number of infected in The Hague agents. Therefore, again we argue in favour of other NPIs that will help prevent the spread of the virus within The Hague.

The last scenario, a highly infectious country, significantly "shifts the curve." A double increase in infection rate makes an outbreak happen 20 days earlier. Such an impact highlights the importance of limiting travel or extensive testing policies for countries with a high infection rate.

Thus, we have observed a need for the pandemic response across all geographic resolutions: neighbourhood, city and country. Both local and international travel have an impact on the spread of the virus. We recommend limiting travel and a comprehensive testing policy to avoid "**shifting the curve**" and overwhelming the healthcare system. However, limiting the travel is not a sufficient measure to "**flatten the curve**." There is a need for the NPIs discussed in D2.1 to combat the pandemic in its early stages.

Web-based GIS applications

We developed three web-based GIS applications to visualise and explain the outcomes of the coupled model. These applications provide actionable information since policymakers and healthcare professionals use visualisations to facilitate decision-making.

In the case of the first two applications, dashboards were employed, as their interactive nature makes the information scope comprehensive and understandable for non-technical users. Both approaches included map components (geo-dashboards), which enable stakeholders to answer the questions not only about the quantitative and time aspects of the disease spread, but also about the geographic distribution, and hence help to plan the appropriate preparation of the health care system in the right place at the right time.

The third application was developed in the form of agents' animation within a city. This approach allows the stakeholders to improve process model comprehension in particular regarding the behaviour patterns resulting in rapid spread of the pandemic.

Regardless of the chosen visualisation technique, the user must be aware that despite the employment of the same dashboard components as in the case of presenting the real data, the modelling outcomes are always subject to some degree of uncertainty. As such, the related charts and maps shouldn't be treated as a 100% prediction, but as indicators of possible trends.

Impact of Covid policies on elderly in Long-Term Care

We found that Covid restrictions had a negative impact on the elderly in Long-Term Care (LTC). For instance, there is a decline in indicators related to activity, mood and behaviour, psychosocial well-being, memory, and treatments. However, other indicators, such as independent use of the toilet, sleeplessness, depression, pain, and sadness, did not show any significant change. These results indicate that Covid restrictions aimed at positive health impact can cause a more long-term negative impact on the well-being of the elderly in the LTC. We recommend a more comprehensive assessment of the potential impacts of Covid restrictions on all population groups. For instance, the elderly in LTC. We also argue for more research on which exact aspects of restrictions negatively impact each indicator (e.g. memory or mood), longitudinal analysis and cross-country comparison.

Limitations and future work

The coupled model (COOL) generated several insights which can be helpful in policy making. However, we would like to stress that COOL is an exploratory model and does not predict the future. Instead, we use it as a "sandbox" to test scenarios that are not feasible otherwise.

Another critical aspect of the model is that it is still a "closed" system, even though a bigger one than in deliverable 2.1 (D2.1). Therefore, to better understand how disease spreads, we propose to scale up the model to the whole country. This will require work on the components of the model which we described in D2.1: people, locations and activities.

Additionally, more neighbouring countries and other reasons for travel and events will make the model more realistic. Indeed, the differences in Covid measures between the neighbouring countries generated controversial travel behaviour. For example, while the Netherlands was experiencing a lockdown: shops, bars and restaurants were closed, Belgium had them open. It led to a massive influx of Dutch travellers, overcrowded trains and places of interest. Once studied, the impact of these events can open up discussion on the alignment of policy measures between the neighbouring countries. That is why we want to stress the importance of good travel data. For the current version of the model, we use aggregated data. To further improve the model and make the findings more precise, we propose to use more detailed data on the number of people travelling from city to city and for what reason. Additionally, the model can benefit from including other social groups travelling for different purposes (such as students for studies, workers for shopping, etc.)

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This is not an extensive list and we will not be able to name all of the contributors. Still, we want to sincerely say that we appreciate all the inputs given to us throughout the project.

Read more about the team behind the model here https://www.heros-project.eu/.

Annexes

Source code

We store the source code of the city generation algorithm, simulation model and web-based application on GitHub.com. For the city generation algorithm visit https://github.com/mikhailsirenko, for the simulation model look at https://github.com/averbraeck/medlabs-heros and for the web-based application refer to https://github.com/Michsior14/covis.

Simulation model

Entity	Agents
The Hague	553667
Zoetermeer	32443
Rijswijk	29916
Leidschendam-Voorburg	29521
Delft	27935
Pijnacker-Nootdorp	22571
Westland	18958
Midden-Delfland	12139
Wassenaar	9981
Germany	500
Belgium	500
Total	**738131**

Table 4. Number of agents by entity.

Experimental setup

For a complete overview of the default parameters see https://github.com/averbraeck/medlabs-heros/tree/main/src/main/resources.

Default parameters

Parameter	Value
Number of infected people	100
Minimum age of getting infected	0
Maximum age of getting infected	100

Table 5. Default parameters of the coupled simulation model.

Business-as-usual

Parameter	Value	Entity
Infection rate factor	0.873904964	Zoetermeer
Infection rate factor	0.98115211	Westland
Infection rate factor	0.972391824	Delft
Infection rate factor	0.789487656	Leidschendam-Voorburg
Infection rate factor	0.917706398	Pijnacker-Nootdorp
Infection rate factor	0.912397133	Rijswijk
Infection rate factor	0.66418901	Wassenaar
Infection rate factor	0.895938413	Midden-Delfland
Infection rate	0.00096209	Belgium
Infection rate	0.000220074	Germany

Table 6. Parameters used in the businesses-as-usual scenario.

A highly infected satellite city

Parameter	Value	Entity
Infection rate factor, base case scenario	0.91239	Rijswijk
Infection rate factor, mid case scenario	4.0	
Infection rate factor, worst case scenario	16.0	

Table 7. Parameters used in the highly infected satellite city scenario.

A highly infected neighbouring country

Parameter	Value	Value
Infection rate, base case scenario	0.0009620898197102	Belgium

Infection rate	0.0019241796394204	
Infection rate, mid case scenario	0.09	
Infection rate, worst case scenario	0.36	

Table 8. Parameters used in the highly infected neighbouring country scenario.

Are preparedness indices reflective of pandemic preparedness?

As a continuation of the health care system analysis in task 2.1 a sub-study was conducted in D2.3 on how the reported cumulative mortality rates, during the spring of 2020 and in the 60 days after the date of a country's first COVID-19 related death, compared to the expected preparedness rank according to the existing global preparedness indices (IHR and GHSI) on a country level.

The analysis strives to understand crisis and disaster preparedness and effective response, via the lens of the ongoing global pandemic and responding to the questions: do the current measures for pandemic preparedness reflect preparedness adequately, and what does pandemic preparedness mean? We analysed how the reported cumulative mortality rates, during the spring of 2020 and in the 60 days after the date of a country's first COVID-19 related death, compared to the expected preparedness rank according to the existing global preparedness indices (IHR and GHSI) on a country level. We found, at country level, that the health-related outcomes from the first wave of the pandemic were primarily negatively correlated with the expected preparedness. We contend that our results indicate a need to investigate further development and enhancement of the preparedness indices.

Sub-indicator	**Category**	**Indicator**	**Specific question/item**	**GHSI scoring/scale**	**Pearson correlation**	**P-value**
4.6.2a	**4. Health System** - Sufficient & Robust Health System To Treat The Sick & Protect Health Workers	Capacity to test and approve new medical countermeasures	Is there a government agency responsible for approving new medical countermeasures (MCM) for humans?	Yes = 1 No = 0	−0.463	0.003**

5.5.3b	**5. Compliance with International Standards -** Commitments To Improving National Capacity, Financing And Adherence To Norms	Financing	Is there evidence that the country has, in the past three years, either invested finances (from donors or national budget) or provided technical support either to • Support other countries to improve capacity to address epidemic threats? • Improve the country's domestic capacity to address epidemic threats? Needs to meet at least one of the criteria to be scored a 1 on this measure.	Yes = 1 No = 0	−0.250	0.119
3.1.1c	**3. Rapid Response -** Rapid Response To And Mitigation Of The Spread Of An Epidemic	Emergency preparedness and response planning	If this plan is in place, does it include considerations for pediatric and/or other vulnerable populations?	Yes = 1 No/no plan in place = 0	−0.250	0.120

5.5.2a	**5. Compliance with International Standards -** Commitments To Improving National Capacity, Financing And Adherence To Norms	Financing	Is there a publicly identified special emergency public financing mechanism and funds which the country can access in the face of a public health emergency (such as through a dedicated national reserve fund, an established agreement with the World Bank pandemic financing facility/other multilateral emergency funding mechanism, or other pathway identified through a public health or state of emergency act)?	Yes = 1 No = 0	−0.242	0.133
6.2.3a	**6. Risk Environment -** Overall Risk Environment And Country Vulnerability To Biological Threats	Socio-economic resilience	Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population)	Yes = 1 No = 0	−0.184	0.255

2.3.2a	**2. Detection & Reporting -** Early Detection & Reporting For Epidemics Of Potential International Concern	Epidemiology workforce	Is there public evidence that the country has at least 1 trained field epidemiologist per 200,000 people?	Yes = 1 No = 0	−0.180	0.266
2.1.2a	**2. Detection & Reporting -** Early Detection & Reporting For Epidemics Of Potential International Concern	Laboratory systems	Does the country participate in a regional or international laboratory network?	Yes = 1 No = 0	−0.177	0.274
4.5.1a	**4. Health System -** Sufficient & Robust Health System To Treat The Sick & Protect Health Workers	Infection control practices and availability of equipment	Has the country published a publicly available plan, strategy, or similar document to address personal protective equipment (PPE) supply issues for both routine national use and during a public health emergency?	Yes = 1 No = 0	−0.138	0.396
1.2.1c	**1. Prevention -** Prevention Of The Emergence Or Release Of Pathogens	Zoonotic disease	Is there a department, agency, or similar unit dedicated to zoonotic disease that functions	Yes = 1 No = 0	−0.130	0.424

			across ministries?			
3.6.4a	**3. Rapid Response -** Rapid Response To And Mitigation Of The Spread Of An Epidemic	Access to communications infrastructure	Percentage point gap between males and females whose home has access to the Internet	Yes = 1 No = 0	−0.122	0.453

Table 9. Ten most negatively correlated Global Health Security index (GHSI) sub-indicator items against COVID-19 mortality data for 40 countries with highest mortality data in GHSI.

Sub-indicator	Category	Indicator	Specific question/item	GHSI scoring/scale	Pearson correlation	P-value
4.3.1c	**4. Health System -** Sufficient & Robust Health System To Treat The Sick & Protect Health Workers	Healthcare access	Out-of-pocket health expenditures per capita, purchasing power parity (PPP; current international $)	31.5–2325.7	0.473	0.002**
6.5.1b	**6. Risk Environment -** Overall Risk Environment And Country Vulnerability To Biological Threats	Public health vulnerabilities	Healthcare Access and Quality (HAQ) Index frontier score	35–96.6	0.459	0.003**
1.2.4a	**1. Prevention -** Prevention Of The Emergence Or Release Of Pathogens	Zoonotic diseases	Number of veterinarians per 100,000 people	0–229	0.458	0.003**

6.5.1a	**6. Risk Environment -** Overall Risk Environment And Country Vulnerability To Biological Threats	Public health vulnerabilities	Total life expectancy (years)	62.47–89.4	0.423	0.007**
6.3.1a	**6. Risk Environment -** Overall Risk Environment And Country Vulnerability To Biological Threats	Infrastructure adequacy	What is the risk that the road network will prove inadequate to meet needs?	1, 2, 3, 4	0.414	0.008**
6.4.3a	**6. Risk Environment -** Overall Risk Environment And Country Vulnerability To Biological Threats	Environmental risks	What is the risk that the economy will suffer a major disruption owing to a natural disaster?	1, 2, 3, 4	0.400	0.011*
6.2.2a	**6. Risk Environment -** Overall Risk Environment And Country Vulnerability To Biological Threats	Socio-economic resilience	United Nations Development Programme (UNDP) Gender Inequality Index score	0.39–0.96	0.400	0.011*
6.1.1a	**6. Risk Environment -** Overall Risk Environment And Country Vulnerability To Biological Threats	Political and security risk	Government effectiveness (EIU score)	1, 2, 3, 4	0.385	0.014*

3.6.1a	**6. Rapid Response -** Rapid Response To And Mitigation Of The Spread Of An Epidemic	Access to communications infrastructure	Percentage of households with Internet	31–98	0.373	0.018*
6.5.3a	**6. Risk Environment -** Overall Risk Environment And Country Vulnerability To Biological Threats	Public health vulnerabilities	Domestic general government health expenditure per capita (PPP)	56–8078		

Table 10. Ten most positively correlated Global Health Security index (GHSI) sub-indicator items against COVID-19 mortality data for 40 countries with highest mortality data in GHSI.

We found that the health-related outcomes from the first wave (in the northern hemisphere spring of 2020) were primarily negatively correlated with the expected preparedness measured by the existing preparedness indices on a country level. Put another way, the countries with better preparedness did not have better health outcomes in the first wave as measured by the number of COVID-19 deaths. For this pandemic, national level health preparedness rankings were not an indicator of how well a country handled the pandemic.

The results have been published in International Journal of Disaster Risk Reduction:

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