

Modelling COVID-19 in Refugee Settlements

Providing a safe environment to explore implications of policies to control the spread of COVID-19 in a refugee settlement

Meyke Nering Bögel

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1. Introduction

As COVID-19 spread across the globe, people were trying to withstand the virus and prevent spread everywhere. Many refugee settlements went in lockdown preventively to protect their inhabitants from the extremely high risk of an outbreak. In refugee settlements, often characterized by a high population density, unsanitary conditions and limited access to healthcare facilities, a single infection was expected to easily lead to an outbreak. To prevent this and protect the inhabitants, many refugee camps went in lockdown preventively. However, the effect of a preventive lockdown or other measures had not been proven yet, while it heavily impacts the lives of the inhabitants of a settlement. For example, before the devastating fire ruined a large part of camp Moria, the inhabitants were in a lockdown already for over 5 months.

This research aims to provide a safe testbed for policy measures in refugee settlements. An agent-based model is developed that captures the daily (inter)actions of refugees within a settlement through which COVID-19 can spread. Besides the impact of policy measures, the model also provides insight in what activities pose the biggest risk for COVID-19 spread, or where most people get infected. The accuracy of the model is unique as the time steps are only 1 minute. Therefore, insight can be obtained in crowd formation, queueing behaviour and the network of infections that is the result of an outbreak. As each settlement has different characteristics, the effect of measures can be different for each settlement and point in time, which is important to understand before copying best practices from one settlement to another.

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1.1 Objectives

Two research objectives are defined that are each split up in respectively three or two sub-objectives. The first goal is drafted to support decision-making in COVID-19 response in refugee settlements. The second goal is to show that agent-based modelling is a useful tool for to gain insight in humanitarian response situations, hence the right means to reach the first objective.

1. *Gain understanding about the spread of COVID-19 through daily activities in refugee settlements.*
 - a. *Understand the mechanisms behind the spread of COVID-19 in refugee settlements.*
 - b. *Understand the impact of preventive and mitigating measures on the spread of COVID-19.*
 - c. *Develop recommendations on the effect of preventive measures in relation to the required COVID-19 treatment capacity in refugee settlements.*
2. *Prove the usability of agent-based modelling as a tool in humanitarian response studies.*
 - a. *Develop an ABM to study the spread of an infectious disease using a bottom-up approach.*
 - b. *Develop recommendations for further use of ABM to understand the results of human (inter)action within a refugee settlement.*

1.2 Methods

In agent-based models (ABMs), a set of behaviour rules defines the actions and interactions of agents in the modelled environment. This makes it possible to study the situation that emerges in refugee settlements during an outbreak of COVID-19, while refugees perform their daily activities. This bottom-up approach enables exploring the resulting effect of policy measures that restrict (inter)actions and movement of people in an environment.

As the input parameters that define the environment can be varied, settlements can be resembled in order to analyse the expected effect of different policy options. The effect is analysed for uncertainty regarding the behaviour and compliance of the refugees in the settlement.

The second research goal, as defined in the previous paragraph, is proving the usability of an agent-based model to serve as a means to an end in determining effective policy measures to prevent COVID-19 spread. Therefore, it is important to first deliver a successful prototype. This prototype is set up on the basis of generic characteristics of major refugee settlements (i.e. Za'atari, Bidi Bidi, Cox's Bazaar, Kakuma and Moria), taking into consideration factors such as topography and demographics. This is described in more detail in paragraph 2.2.

1.3 Report structure

This report provides an overview of the modelling decisions and underlying assumptions in the performed research and reviews the results that are generated with the prototype. Chapter two starts with a description of the model logic with a conceptual model that describes the processes in the model. The

second paragraph of chapter two describes the data collection that underlies the setup of the environment and the epidemiological factors of COVID-19 in the prototypical model. The model implementation, including a model narrative, is provided in paragraph three. Paragraph four describes the verification of the model behaviour. Paragraph five describes the parameters that are altered throughout the experiments in the experiment design. Paragraph six describes how the model reacts to changes in certain parameters and how this reflects in the results. Finally, the results of the prototypical model are validated in paragraph seven, including a sensitivity analysis. Chapter three describes the implications that are obtained from this research, categorized for the two objectives. Chapter four provides a discussion after which recommendations are outlined that are described in chapter five.

2. Simulation model

This chapter describes the model and the results of the model that are obtained from experimentation with the prototype.

2.1 Model logic and concept formalization

The model consists of three conceptual layers. The first layer captures the settlement layout and the inhabitants that perform daily activities. The activities get influenced by the second and third layer that respectively contain the specifics of COVID-19 and policy measures that can both impact the behaviour of the inhabitants.

Figure 1 shows a flow diagram of the model with the three layers in different colours. In black, the steps of an activity routine are shown. Every activity is time-initiated, hence the clock in the top. The risk and impact of COVID-19 that influences the agent behaviour, is shown in red. More information about the epidemiology and how this is modelled, can be found in paragraph 3. In blue, the impact of policy options is shown.

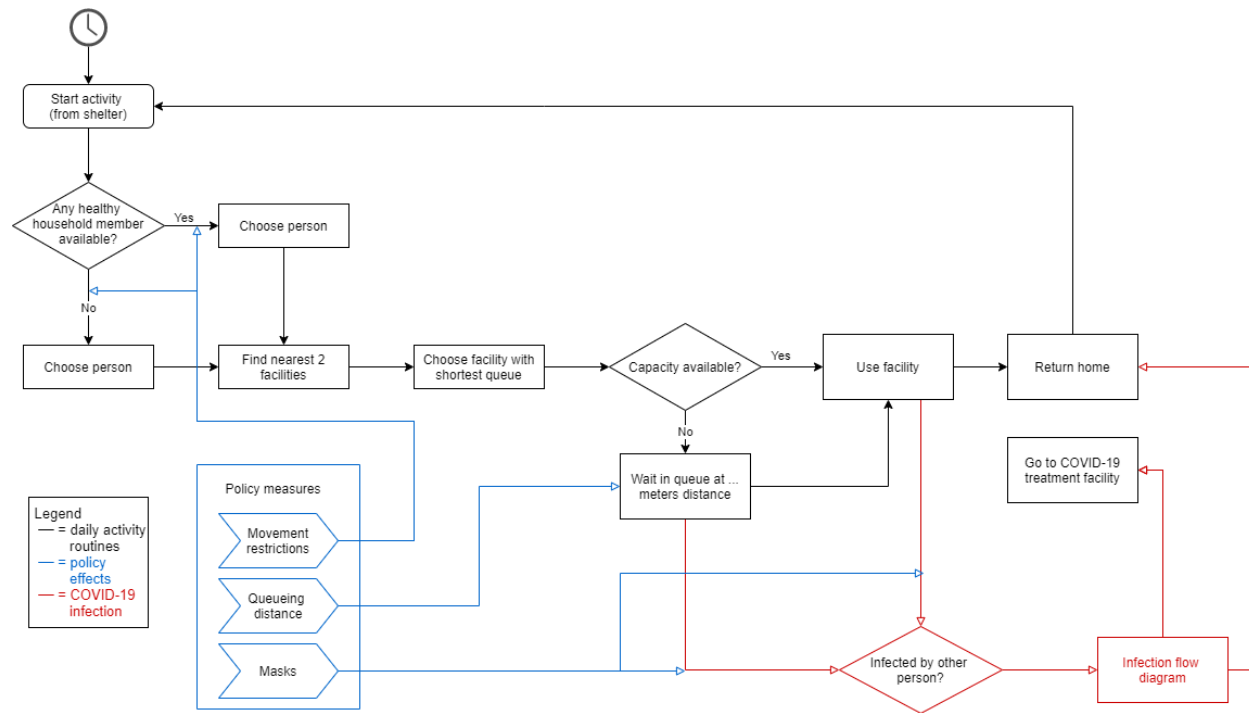


FIGURE 1 FLOW DIAGRAM OF PROCESSES IN SIMULATION MODEL

Concept formalization:

As described above, the model has three layers. Each layer is built to represent key concepts, which are formalized in this subparagraph. The first layer captures the environment, agents and assumptions about core activities. The second layer captures the epidemiology. The last layer are the policy measures that can be imposed. The quantification of the defined parameters and variables is described in 2.2 and appendix A.

Environment (refugee settlement)

One of the goals is to understand how COVID-19 spreads in a refugee settlement. Therefore, it is important to create an environment that allows agents (refugees) to move around in a settlement to perform activities. As COVID-19 infections can occur in a matter of minutes, the time steps should allow this level of detail. Spatially, the modelled environment must approach a refugee settlement, in terms of the shelter and facility locations. Based on interviews, the prototype model captures two blocks of each 120 shelters. The facilities are located along two edges of the settlement to allow scaling up, for example when considering a settlement that is four times this size with facilities in the centre. Although the small-scale boundaries might limit the approach, it is sufficient to capture the dynamics that need to be understood. Interaction across the boundaries of the simulated environment can, for example, be included by adding an infection chance for certain age groups that might travel outside of the boundaries of the settlement on a regular basis. However, to gain insight in the dynamics behind COVID-10 within a settlement, it is important to ensure that all effect can be explained from the model behaviour, hence the limited environment is preferred.

Global variables:

- Time (minutes / hours / days)
- Size of land plots for shelters (m2 per patch)
- Number and location of shelters
- Number and location of facilities

Agents (refugee population, addressed as households)

All entities that can make decisions independently are agents. In this research, the agents represent the refugee population. At the beginning of a simulation, the population is aggregated in households, represented as shelters. Individuals are distinguished during the simulation, as every individual must be able to develop a personal course of the disease.

Agent variables:

- Shelter (location)
- Age group (child/adult/elderly)
- Compliant? (Boolean)
- Infected? (Boolean)
- Occupancy (free / busy / in-hospital / in-queue)
- Infection (susceptible / infected / pre-symptomatic / asymptomatic / symptomatic / severely-symptomatic / critical / recovered)
- Infection perception (healthy / infectious / recovered)
- Time-until-next-stage (the number of days an agent is in a certain stage of COVID-19)
- Next-stage (the next stage of COVID-19 (at setup, this is "infected"))
- Queue-time (time the agent has spent waiting in line for a facility)
- Destination-when-infected (destination and queue-time when agent got infected)

Key activities

One of the goals is to understand how COVID-19 spreads in a refugee settlement. Therefore, an environment should be created that includes the facilities for key daily activities. Currently, four activities are implemented: using latrines, fetching water, obtaining food from a distribution point and consulting healthcare facilities. The first, using latrines, is exemplary for a short activity with a low chance of queue-formation. Contrarily, fetching water takes longer and thus the chance of queue-formation and a risk of getting in contact with other people throughout the activity are higher. Obtaining food has a high chance of causing large queues, which potentially makes it a major spreading event. Lastly, healthcare consultation is of interest to include, because the usage of healthcare is related to the number of people that have COVID-19. To account for specific healthcare that is required to treat people with COVID-19, an extra type of facility is added: a COVID-facility. People who are facing severe or critical COVID-19 symptoms will go there and get a hospital bed or intensive care unit.

Facility variables:

- Location
- Serving-time (number of minutes people spend at the facility)
- Waiting-list (people in queue)

Extra COVID-facility variables:

- Bed-capacity (number of beds available)
- IC-capacity (number of ICU available)
- In-treatment (number of people in hospital beds)
- In-IC (number of people in ICU)

Disease (covid-19)

To measure the risk and impact of an epidemic spread in a refugee settlement, the specification of COVID-19 obtained much attention in this research. The specifications of COVID-19 could be adapted to simulate the spread of other diseases as well. The epidemiology is specified at two levels. First, the different disease stages are defined and the chances of getting the disease and time between consecutive disease stages. Secondly, the refugees obtained a variable that stores their perception of their infection status, which can differ from the actual disease status.

COVID-19 variables: (numbers can differ for disease stage)

- Infection distance (distance in meters in which infection an infector can infect someone)
- Time until next disease stage (hours)
- Next stage (one of disease phases, defined per infected person)
- Time and location of infection (defined per infected person)
- Number of infections (counted per disease stage, distinguishes age groups)
- Multiplication factor for the amount of asymptomatic people (numeric setting to account for uncertainty about the share of asymptomatic people with COVID-19)

Policy measures

Different policy options can be implemented at the beginning of the simulation in order to prevent or mitigate the spread of COVID-19 transmission within the modelled environment. The measures can be combined, or implemented separately and have an impact on:

- Social distancing in queues (define distance in queue)
- Movement restrictions (define when people are restricted to leave their shelters)
- Use of face masks (yes or no)
- Compliance (to account for different behavioural responses to policy measures)

2.2 Data collection and analysis

To make the model useful for real scenarios, the prototype is set up using data about existing settlements and information about the epidemiology of COVID-19. This paragraph describes the data collection that precedes the definition of the parameters that serve as input for the model. First, the setup of the settlement in the model is described. Secondly, the data collection and parametrization of COVID-19 is described.

Data collection on settlements

The prototype is designed to be a proof of concept, so the simulated environment must fit within a range of possible real-life scenarios. Therefore, information about the size, demographics, facilities, shelters and healthcare of five existing settlements is collected and together with the SPHERE standards and UNHCR standards translated into a plausible range of values. From this, an average value is taken. This means that the prototype is not fit to one specific settlement. This approach is chosen for two reasons: firstly, the results of the prototype should be tested further before being applied to a settlement, as further research might be necessary before recommendations can be made. Secondly, every settlement is different and the model must be able to cover for different types, hence exact data should be input when developing recommendations for a specific settlement, whereas the focus is firstly on proving the concept of using ABM to understand the risk of COVID-19 spread in (refugee) settlements.

A summary of the collected data and the sources can be found in annex A. The summary of the findings is shown in table 1 below.

TABLE 1 DEFINING SETTLEMENT PARAMETERS - SUMMARY

Settlement findings summarized	
Average household size:	5 - 7
Population density [people/km ²]	270 - 40.000
Following official designs, a shelter ranges from [m ²]	12 - 25
% children <18:	51 - 69%, mostly around 55%
% adults (19-59):	29 - 49*%, mostly around 40%
% elderly	1.2 – 3.5%, mostly around 2.5%
Male / female:	47 - 53, both ways. Average: 50/50
People sharing 1 latrine:	17 - 23 people per latrine
People sharing 1 water point:	50 - 250
People visiting food supply point	Unclear. Everyone obtains food, but also common to buy extra.
People per healthcare facility	2000 - 10000
Consults per healthcare facility	0.388 - 0.67 / household / week
Queue times at food distribution:	0.5 - 3 hours
Travel time	30 minutes - less than 5 km

Data collection about COVID-19

To analyse the spread of COVID-19 in a settlement, background research has been performed on the epidemiology of the virus and the chance of spreading it. This research focused on two types of numbers: the chance for children / adults / elderly to follow a certain course of the disease and the distribution of time in a certain disease stage.

Course of the disease

Instead of a regular SIR-model, an adapted compartmental model is defined that is tailored to COVID-19. The adapted model not only distinguishes between susceptible, infected and recovered people, but also between different stages between disease onset and recovery or death. Because the disease is modelled using an agent-based model, the number of people in each compartment is not determined mathematically, but determined throughout the simulation as a result of the interactions of agents. The compartments and progression between the stages is shown in the diagram in Figure 2.

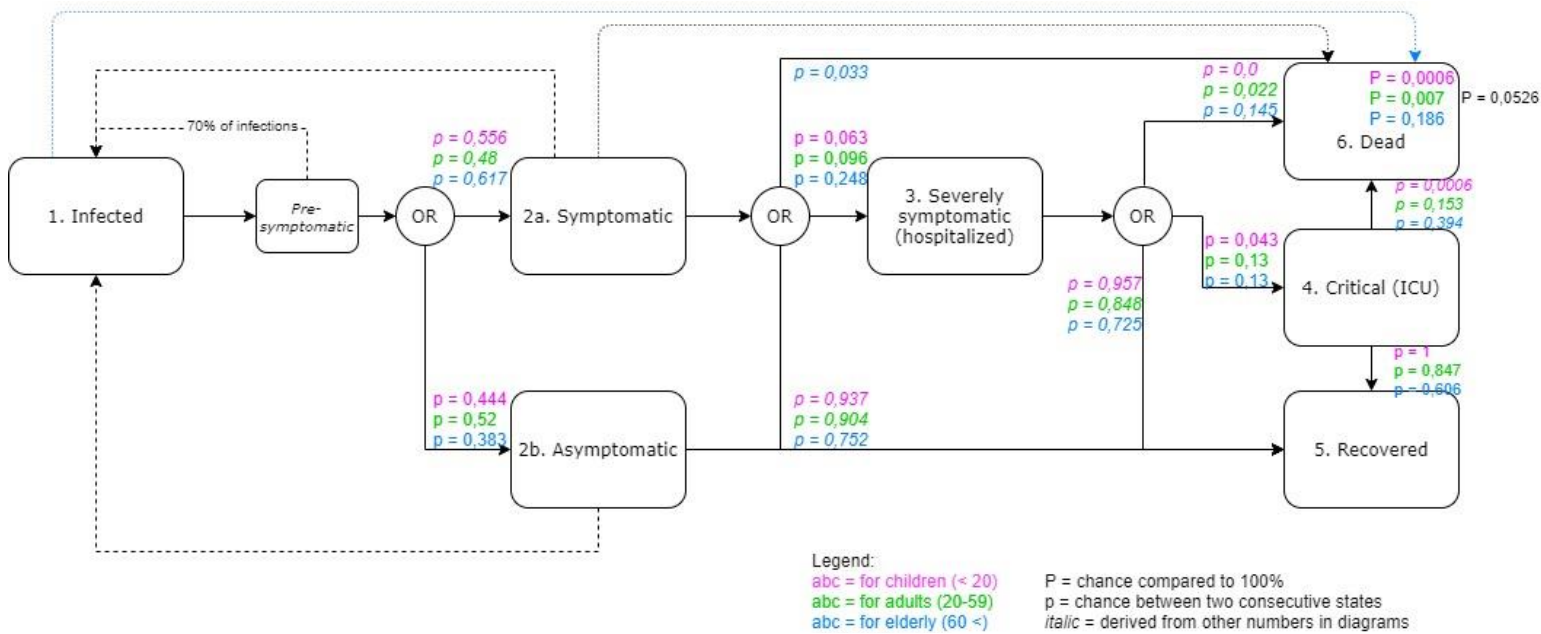


FIGURE 2 INFECTION CHANCES

BASED ON DATA FROM ECDC [1], WHO [11], VERITY ET AL. [6] AND [HTTPS://WWW.STICHTING-NICE.NL/](https://www.stichting-nice.nl/) (ACCESSED ON JUNE 25)

Agents can become *infected* when being within 1.5 meters distance of an infectious person. Infected people become infectious 1 – 2 days before symptom onset [2]. This stage is called the *pre-symptomatic* stage. After incubation, people can show symptoms, or remain *asymptomatic* for the disease. If they are asymptomatic, they will recover without further risk. However, if they are *symptomatic*, they can progress to one of three stages: recovered, *severely symptomatic*, or the symptoms become fatal and lead to *death*. When showing severe symptoms, people usually must be hospitalized. From this stage again, they can either recover, become *critically ill*, or die. When people are critically ill, they are in need of intensive care (ICU). From this stage, they can recover, or die.

Time distribution of disease stages

The time that people remain in a certain disease stage is important to understand, because the disease stage also determines the chance that an infectious person can infect other people. Especially the incubation period and the pre-symptomatic time is important to understand, as infected people will not know they are infected yet during these stages, while already being able to spread the virus further.

The time between disease stages is found to be best described by the distributions shown in Table 2, in which the same disease stages as in Figure 2 are used. For some stages a distribution remains unknown, hence an average is filled in. The used sources can be found in the reference list at the end of this report.

TABLE 2 TIME BETWEEN DIFFERENT STAGES OF COVID-19 PROGRESSION FOR AN INFECTED PERSON

From – to	Mean time (days)	parameters default: SD	distribution
1 – 2 [2] [5]	5.5	2.1	Lognormal
2 – 3 [2]	3.3	$\alpha = 0.617$ $\lambda = 0.187$	Gamma
2a – 5 [7]	7	-	-
2b – 5 [7]	4	-	-
3 – 4 [7]	2	-	-
3 – 5 [7]	14 – (from 2-3)	-	-
3 – 6 [2] [8]	8.8	1.8	Normal
4 – 5 [2] [12]	7	min = 5 max = 12	Triangular
4 – 6 [7] [10]	7.5	3	Normal
2 – 1 [13]	1 - 2 days prior symptom onset	1-2	Uniform

1.	Infected
2.a	Symptomatic
2.b	Asymptomatic
3.	Severely symptomatic
4.	Critical
5.	Recovered
6.	Dead

2.3 Model implementation

The model is setup using the data that is collected as described in the previous paragraph. This paragraph describes the steps in the model setup implementation in bullet-points.

1. Settlement layout

An example of the setup of shelters in the settlement is shown in Figure 3.

- 1) The model is set up as a field of 51 * 26 patches
- 2) Using choosers, one defines the desired shelter plot size and size of shelter blocks:
 - a. The field is divided into 2 or 4 shelter blocks
 - b. Blocks are divided by roads
 - c. Each block consists respectively 120 or 60 households
 - d. Shelter plot sizes are 12.5 / 25 / 50 / 100 m², which determines the scale of the model (table 2)
 - e. Number of black patches / number of household ≈ 4.4 (with 4 blocks it is actually 4.408)
- 3) Shelters are located randomly within the blocks

Household setup:

- 4) Each shelter represents a household of 5 or 7 people, of which the members respectively fit one of the profiles shown in tables 3 and 4
- 5) There is not distinguished between male or female people
- 6) Individuals are modelled separately when they are sick/recovered

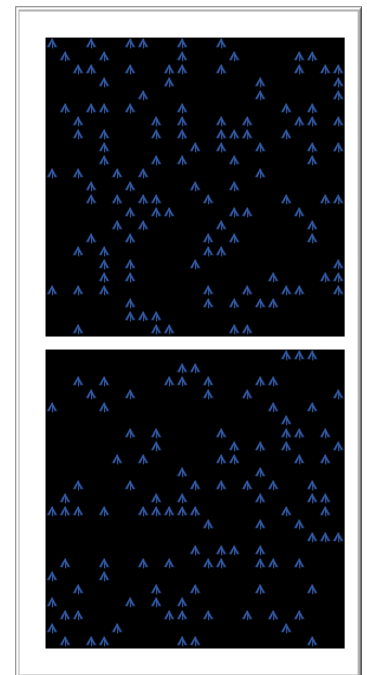


FIGURE 2 SET UP OF SHELTERS IN MODEL ENVIRONMENT

TABLE 3 ASSUMPTIONS ABOUT LAYOUT AND POPULATION OF A GENERIC REFUGEE CAMP

General assumptions	#	metric
No. shelters in camp	240	shelters
Family size	5	people
Shelter plot size	12.5 / 25 / 50 / 100	m2
No. tents in blocks	60 / 120	shelters

TABLE 4 SCALE OF THE MODEL, ACCORDING TO CHOSEN SHELTER PLOT SIZE

Scale of distance and speed				
Surface per household (m2)	12.5	25	50	100
Surface per patch (m2)	2.841	5.682	11.364	22.727
Length 1 patch (m)	1.685	2.384	3.371	4.767

TABLE 5 HOUSEHOLD COMPOSITION PROFILES WITH 5 HOUSEHOLD MEMBERS

	profile 1	profile 2	profile 3	profile 4	profile 5	percentage of population
Elderly (60+)	1	0	1	0	0	8.00%
Adults	2	3	1	2	2	40.00%
Children (<18)	2	2	3	3	3	52.00%

2. Facilities in settlement

- 1) Facilities are located on the edges of the camp
- 2) Facilities have set opening times
- 3) Number of facilities depends on the number of settlement inhabitants
(household * household size)

TABLE 6 – ASSUMPTIONS ABOUT FACILITIES IN GENERAL CAMP SETTLEMENT, BASED ON RESEARCH OF 5 REFUGEE CAMPS: KAKUMA, MORIA, ZA'ATARI, BIDI BIDI AND COX'S BAZAR¹

Facility assumptions for population of 1200 people				
	Latrine block:	Water point:	Food distribution:	Healthcare facility:
No. of modelled instances	5	9	1	1
Time at facility	2 minutes	15 minutes (fill 2x 20 litres)	2 minutes	10 minutes (general consult)
Times per day per household	7	1	Once per 4 weeks (every household)	0.388 / 0.67 * <i>*depends on COVID-19</i>
Opening times	6AM – 11:30PM	6AM – 11:30PM	choice	8AM – 3PM

¹ Sources are listed per camp in the reference list

3. Everyday activities in the settlement

- 1) Activities are:
 - a. Using latrines (up to 2 times per day per family member, average is 7 times per household)
 - b. Fetching water (daily)
 - c. Obtaining food from distribution point (once every four weeks)
 - d. Consult healthcare facility (when sick)
- 2) Inhabitants perform the following key activities throughout the day (from 6AM to 11:30PM), which are initiated at random moments.
- 3) Activities are time-initiated, determined randomly per household
- 4) Every activity is performed by 1 household member
 - a. Food and water are preferably obtained by a household member who perceives to be healthy
 - b. Food cannot be obtained by children
 - c. Food and water are preferably obtained by a household member who believes to be not infected (i.e. perceived infection)
 - d. If no one is available at home:
 - i. Initiated visit to latrines or healthcare facility is not executed
 - ii. Fetching food or water is postponed with one hour (for food, this can result in no new food supply at the end of delivery-day)
- 5) When initiating an activity people arrive at a facility instantly [Note: travel within the refugee settlement has not been taken into consideration, as the risk of COVID-19 transmission thereof has been considered minimal]
- 6) At a facility, people queue when it is already in use
 - a. Within queues people maintain 0.5 / 1.0 / 1.5m distance (policy option)
- 7) The facility manages that people from the queue are served
- 8) After an activity, a person returns to its shelter instantly
- 9) The primary focus lies on transmission of the virus within the camp, travelling in- and out of the camp can be mimicked by creating random new infections.

Latrine-usage visits:

- For household of 7 people: 10 toilet visits per day. For 5 people: 7 visits
- Hours in a day = 17,5 (from 6 to 23:30), but don't start walking after 22:30, so 16,5 hours
- So, for 7 people in a household:
 - 1 toilet visit per 1,65 hours.
 - Chance of using the toilet in this hour is $1/1,65 = 0,606 \rightarrow 61\%$
 - $\frac{60}{61} * 100\% = 98 \rightarrow$ So: set latrine-time (random 98)
- So, for 5 people in a household:
 - 1 toilet visit per $(16,5 / 7 =) 2,35$ hours.
 - Chance of using the toilet in this hour is $1/2,35 = 0,42 \rightarrow 42\%$
 - $\frac{60}{42} * 100\% = 142 \rightarrow$ So: set latrine-time (random 142)

Latrine usage assumptions	Household of 5	Household of 7
Latrine visits per day	7	10
Chance of visit in an hour	42%	61%

Healthcare visits:

- Healthcare facilities are visited between 7AM and 3PM²
- Chance of seeking healthcare depends on chance of getting sick and their COVID-19 status:
 - Chance that a person in a household gets sick is by default 0.0554 per day³
 - When a person has COVID-19, it will not visit a regular healthcare centre
- When mobility is restricted for households where at least one person is known to be infected the chance of seeking healthcare is halved for two reasons. Firstly because people are less tended to leave their shelter during strict mobility limitations, so also for healthcare consultations, secondly because people become suspicious of healthcare facilities when COVID-19 is more widely spread.

Healthcare visit assumptions	
Probability of getting sick in a day	0.0554 per person
Chance of seeking healthcare when sick	100%

Waterpoint visits:

- 1 visit per household per day, preferably a person who believes to be healthy
- Each household fetches water every day at a pre-determined time of day (between 6AM and 6PM)

Water fetching assumptions	
Waterpoint visits per day	1 per household

Food distribution visits:

- Food supply is delivered once every four weeks
- From every household, 1 adult or elderly person goes to collect the food supply, preferably a person who believes to be healthy
- Each household has a pre-determined time at which they collect the food (between 7:15AM and 12:15PM)

Food collection assumptions	
Food is collected once every four weeks (28 days)	
Children cannot collect food	
If food is not obtained in this day, the household must wait 28 days	

² Based on information about healthcare centre opening hours in existing refugee settlements

³ Based on healthcare consults in Cox's Bazar in 2019. The chance of seeking healthcare in a week was equal to 0,388 for every household.

4. Setup COVID-19:

- 1) Initially, one person is at random exposed to COVID-19, initiated with a button-click
- 2) People have one of the following states: healthy / infected / asymptomatic / symptomatic / critical / dead / recovered
- 3) Transmission occurs when a susceptible person is in close distance (1.5m) of an infected person that is at least pre-symptomatic
 - a. Chance of transmission depends on time in proximity and age and disease stage of infector (shown in Table 7)
 - b. When wearing masks, the probability of infection is decreased with a percentage, determined by the effectiveness of the mask (slider)
- 4) People become infectious after an incubation period (this is independent of their health status)
- 5) Health perception can defer from actual status and is: healthy / infected / immune
 - a. Suspecting an infection can occur when household members are symptomatic
- 6) Once a person is sick, it remains a separate agent (also when at home)

TABLE 7 CHANCE OF SPREADING COVID-19

Time spent within 1.5m distance of infected person (symptomatic/asymptomatic)	Chance of infection	
	Adult / Elderly	Child
1 minute (walking by)	5%	2.5%
2 - 15 minutes (increases per minute within infection distance)	$[2 - 15] * 5\%$ $= [10\% - 75\%]$	$[2 - 15] * 2.5\%$ $= [5\% - 37.5\%]$
15+ minutes	100%	100%

6. COVID-19 disease progression

- 1) De disease stages and their chances are shown in Figure 2, where is distinguished between children / adults / elderly
 - a. Chance that a child is asymptomatic is determined using [9], by averaging the measured number of asymptomatic children for consecutive age groups
 - b. The share of asymptomatic people can be adjusted with a factor 1, 2 or 3, as there is uncertainty about the real share among the COVID-19 infections
 - c. According to the stage of the disease, an agent is coloured as follows:
 - i. Infected
Presymptomatic
 - ii. B) Asymptomatic
A) Symptomatic
 - iii. Severely symptomatic
 - iv. Critical

- v. Recovered
- vi. Dead (disappeared)
- vii. In-radius with an infectious tent

- 2) The time between different disease stages is determined using the random distributions shown in Table 2.
- 3) The next disease stage gets determined per person upon transition to a new state

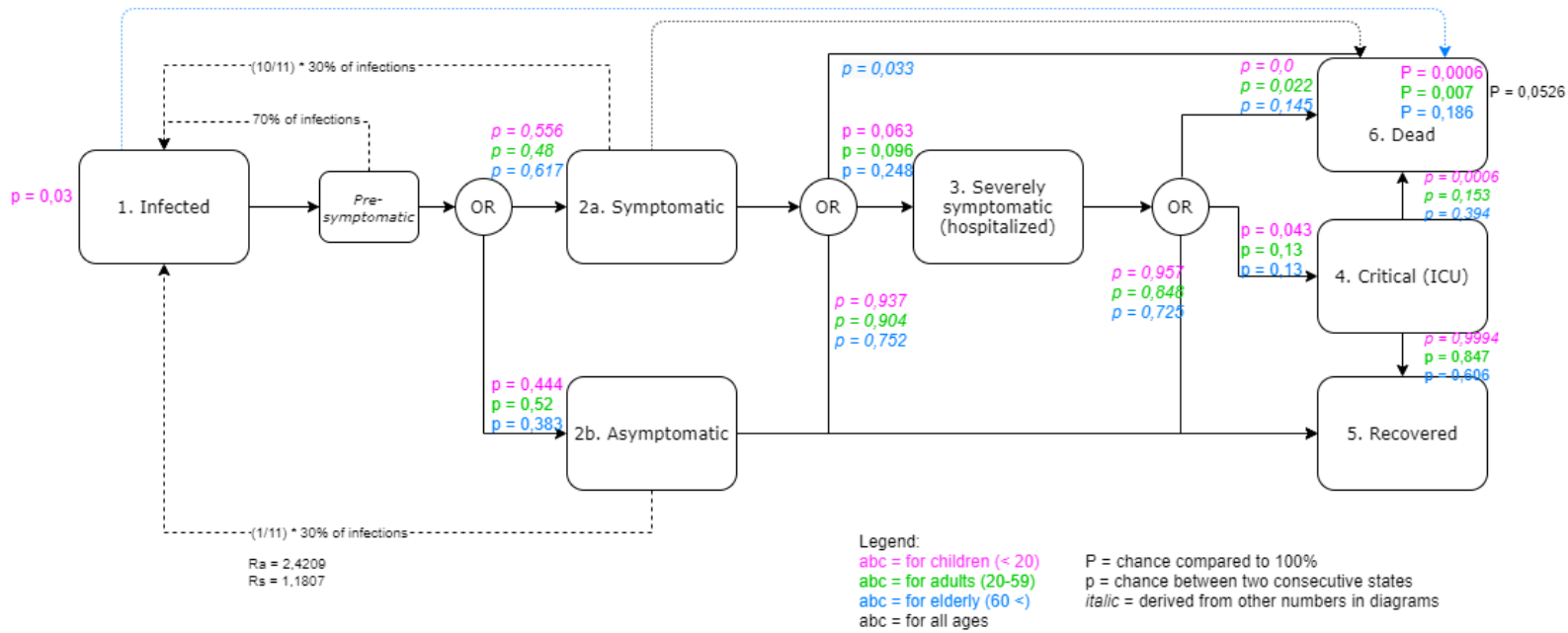


FIGURE 2 INFECTION CHANCES

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TABLE 2 TIME BETWEEN DIFFERENT STAGES OF COVID-19 PROGRESSION FOR AN INFECTED PERSON

From – to	Mean time (days)	parameters default: SD	distribution
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2 – 3 [2]	3.3	$\alpha = 0.617$ $\lambda = 0.187$	Gamma
2a – 5 [7]	7	-	-
2b – 5 [7]	4	-	-
3 – 4 [7]	2	-	-
3 – 5 [7]	14 - from 2-3	-	-
3 – 6 [2] [8]	8.8	1.8	Normal

4 – 5 [2] [12]	7	min = 5 max = 12	Triangular
4 – 6 [7] [10]	7.5	3	Normal
2 – 1 [13]	1 - 2 days prior symptom onset	1-2	Uniform

COVID-19 assumptions
Infection can occur when being within 1.5m distance of an infectious person
Disease progression is determined with randomness, using the numbers from Figure 2 and Table 2
Children have a lower probability of getting infected, but once sick they have a similar chance of infecting others
Elderly are more likely to develop severe symptoms and therefore have a higher CFR
Children are less likely to develop severe symptoms and therefore have a lower CFR
10% of all infected people immediately suspect they are infected (perception = infected) When they become asymptomatic, their perception changes to healthy again
Time between consecutive disease stages is equally distributed among the different age groups
Disease progression only moves from left to right through Figure 2, so people cannot go back to symptomatic anymore once they have become severely or critically ill

7. Using COVID-19 treatment facilities

- 1) A COVID-19 facility has a fixed capacity:
 - a. Treatment capacity (beds for severely symptomatic patients)
 - b. Intensive care capacity (ICU beds for critically symptomatic patients)
- 2) Refugees go to a facility if:
 - a. Refugee is severely symptomatic - it will always go to the COVID-19 facility
 - b. Refugee is critically ill - it will turn to an ICU bed
- 3) Going to the COVID-19 facility is initiated when the refugee is at home and:
 - a. Transitions to a severe/critical disease stage or
 - b. Arrives home in a severe/critical disease stage
- 4) Time spent at the facility depends on the time a refugee remains in a certain disease stage
- 5) When capacity at the required level is full, a refugee will use capacity at a lower level of healthcare if possible (ICU → hospital bed)
 - a. Refugees have full knowledge about the available capacity in facilities at any time
- 6) Using and releasing bed- and IC-capacity at a COVID-19 facility happens by the patients, not by the facilities in the models:
 - a. When going from severely sick to critically sick, release bed capacity and require ICU capacity

COVID-19 facility treatment assumptions	
Opening hours COVID-19 treatment facility	24/7
Hospital beds capacity	100 ⁴
ICU capacity	8 ⁴

8. Policy options

- 1) Multiple policies are possible.
 - Use of face masks
 - Affects the infection risk from infector to infected
 - Effectiveness of masks can be adapted
 - Social distancing in queues
 - People maintain 0.5 / 1.0 / 1.5m distance in queues
 - 100% compliance to this rule
 - Restrict movement
 - Free
 - Quarantine (person stays home when sick)
 - Isolation (entire household stays home when 1 person is sick)
 - Elderly stay at home (no matter infection)⁵
 - *(Future plan) Separate facilities for people with COVID-19*
 - *However: compliance to this measures difficult to estimate*
- 2) Compliance rate determines what percentage of people complies to policies
 - a. A person's compliance is determined at creation of walkers

Movement restrictions:

- Isolation: activities are not initiated for infected households in the 'to go'-command, using the list of shelters
 - When an agent becomes symptomatic, it is removed from the shelters-list. There will be no go-to commands initiated for this household anymore.
 - If an agent in the household is not compliant, this will be skipped, so go-to commands can still be initiated.
 - When an agent recovers or becomes severely ill (goes to the hospital), it will check whether there are any symptomatic agents at home, otherwise (or when the symptomatic agent is not compliant) the home will be added to the shelters-list again.
 - Regular healthcare consults continue normally among people that think they are free from COVID-19, only decreased with 50% during an isolation policy
- Quarantine:
 - Use infection-perception and compliance to determine whether someone can be sent out for an activity
- No-elderly:

⁴ Based on average capacity of two new facilities, according to <https://www.thenewhumanitarian.org/news/2020/05/15/coronavirus-rohingya-camps>

⁵ Sustained by Perrotta et al., 2020: <https://link.springer.com/content/pdf/10.1007/s40520-020-01631-y.pdf>

- Elderly do not leave the shelter, not even for latrine visits
- Elderly comply 100% to this policy

Policy assumptions
Percentage of people that comply is known
Everyone has knowledge about the policy restrictions
When movement for elderly is restricted, they never leave the house and all elderly comply
Compliance for distancing in queues is 100%

Overview adjustable input parameters

The descriptions above gave insight in the model logic and input parameters. Table 8 below provides an overview of the parameters in the model that can be easily adjusted for experimentation.

TABLE 8 OVERVIEW ADJUSTABLE INPUT PARAMETERS

Variable	Effect	Range
Block-size shelters	Number of shelters in one block, divided by roads	60 or 120
Shelter plot size	Scale of the model	12.5 / 25 / 50 / 100 m ² per shelter
Facility conditions	Determines whether number of facilities is limited or good	Limited or Good
Factor asymptomatic	Factor to increase the share of people that are asymptomatic	1 / 2 / 3
Queue distance	Distance maintained by people in queues	0.5 / 1.0 / 1.5 m
Movement restrictions	Policy option determined movement for (infected) people)	Free / quarantine / isolation / no-elderly
Compliance	Chance that a person will comply to movement restrictions	0 - 100%
Food delivery day	No. days until first food distribution happens (repeats every 28 days)	1 - 27
Use of masks - and effect	Policy option to require mask-usage and the effectiveness of masks	Yes or no 0 - 100%

2.4 Verification

The model verification is performed to ensure that the model behaviour is correctly translated into the model, specifying all elements as intended and obtaining the desired behaviour from the defined actions and interactions. The following aspects have been tested and checked to function as desired. The testing process and results are not reported, but confirmed by the researcher.

- Trace agent behaviour
 - o Number of activities performed per household per day (latrines)
 - o Send right person (child/adult)
 - o Send right person (healthy/sick)
 - o Change behaviour when feeling sick
- Interactions tested
 - o Infect susceptible people within 1.5m
 - o Queuing and awaiting turns at facility

The development of model output is inspected on whether it creates logical results without any unexpected fluctuations.

- Number of people (decreases, does not exceed 1440 (240 shelters, 1200 refugees).
- Number of infections does not exceed 1200
- Increase of infections after spreading events and a second peak of infection at home a few days later
- Use of COVID-facility increases and decreases when people recover

By verifying that the behaviour listed above is adequate, the model is ready for experimentation.

2.5 Experiment design

This paragraph describes the parameters for experimentation, the experiment design and the model behaviour when varying the parameters.

Model parameters

Table 9, shown on the following page, provides an overview of the input parameters that can be varied throughout the experiments in the simulation model. The parameters are classified in three groups. The first four variables influence the model setup at the start of the simulation. The second class contains variables that can be adjusted to cover for uncertainty about COVID-19 epidemiology. The third class contains variables that policy measures and their effect.

TABLE 9 MODEL PARAMETERS AND VALUES

	Variable	Effect	Range
Model setup	Block-size shelters	Number of shelters in one block, divided by roads	60 or 120
	Shelter plot size	Scale of the model	12.5 / 25 / 50 / 100 m ² per shelter
	Facility conditions	Determines whether number of facilities is limited or good	Limited or Good
COVID-19 epidemiology	Factor asymptomatic	Factor to increase the share of people that are asymptomatic	1 / 2 / 3
	Transmission probability	Chance of transmitting COVID-19 to someone within 1.5m distance (times minutes in proximity)	[0 – 100%] Default: 5%
Policy options and effect	Queue distance	Distance maintained by people in queues	0.5 / 1.0 / 1.5 m
	Movement restrictions	Policy option, determines movement for (infected) people)	Free / quarantine / isolation / no-elderly
	Mask-usage	Policy option, determines whether people wear masks	Yes / no
	Mask-effect	Effect of wearing masks on the transmission probability	[0 – 100%] Default: 50%
	Compliance	Chance that a person will comply to movement restrictions	[0 - 100%] Default: 100%
	Food-distribution day	Number of days after start of simulation that food distribution occurs (modulo 28 days)	1

Experiment design

Table 10 describes the base case scenario and the values that are used in the initial variations to gain understanding about the model behaviour.

TABLE 10 DESIGN OF EXPERIMENTS TO UNDERSTAND MODEL BEHAVIOUR

Experiment	Variation	Values	Base case scenario
Initial setup effect	Shelter plot size	12.5 or 25 m ² per shelter	12.5 m ²
COVID-19 epidemiology effect	Factor asymptomatic	1 or 2	1
Policy measure effects	Queue-distance	0.5 / 1.0 / 1.5 m	1.0 m
	Mobility restrictions	Free / quarantined / no-elderly / isolation	Free
	Mask usage - with ... % effect	No or Yes with 50% effect	No
	Compliance	80% / 90% / 100%	100%
	Food distribution day	Day 1 or day 8 after start of simulation (modulo 28 days)	Day 1

Policy combination effects

The different policies can be implemented simultaneously. Therefore, there is experimented with a combination of various policies and compliance to see whether policies can reinforce another effect, or diminish the positive effect of each other. As the effect of mobility restrictions has a direct effect on the movement of people, it is interesting to test the impact for different scales of the model as well. The values and combinations thereof in the experiments are shown in tables 11 and 12 below.

TABLE 11 VARIATION OF POLICY PARAMETERS FOR POLICY COMBINATION EXPERIMENTS

Experiment	Variation	Value
Policy combination effects	Shelter plot size	12.5 or 25 m ² per shelter
	Factor asymptomatic	1 or 2
	Queue-distance	0.5 / 1.0 / 1.5 m
	Mobility restrictions	Free / quarantined / no-elderly / isolation
	Mask-usage	Yes or No
	Compliance	100% / 90% / 80%

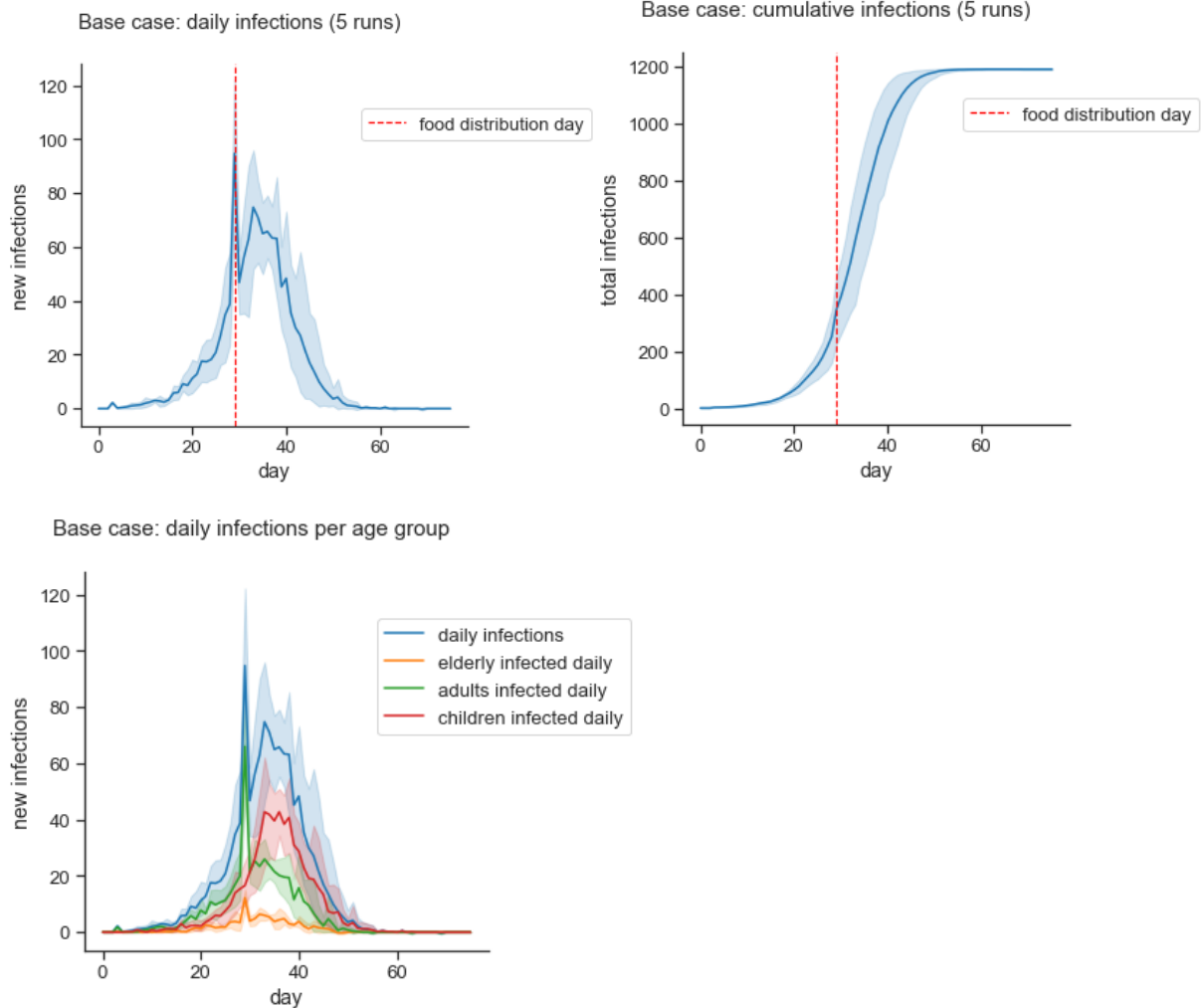
TABLE 12 OVERVIEW OF COMBINED POLICY MEASURES (OTHER COMBINATIONS ARE FOR FUTURE EXPERIMENTATION)

	Mobility restrictions	Queue-distance	Factor asymptomatic	Mask usage	Shelter plot size
Mobility restrictions		X	X	X	X
Queue-distance	X				
Factor asymptomatic	X				
Mask usage	X				
Shelter plot size	X				
Compliance	X			X	

2.6 Model results.

This paragraph presents the results of the experiments as described in 2.5. The base case scenario results are shown first. Then, the effect of individually varying each parameter is studied. Once the effect of all parameters is known, policy measures can be formed that combine various settings to gain understanding about the effect of the policies under varying circumstances.

Base case scenario



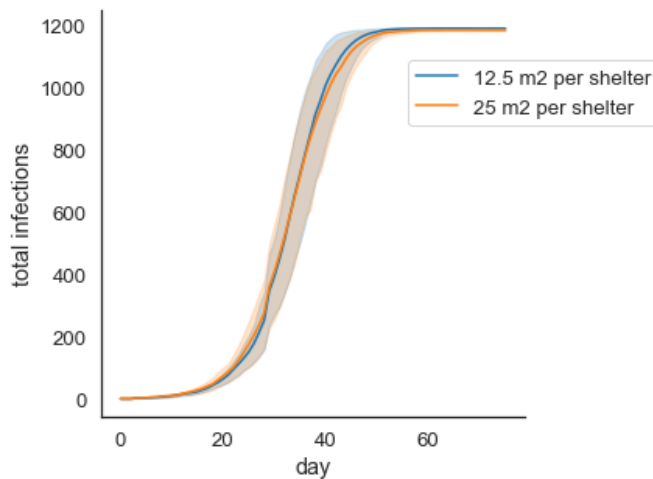
Take-aways from base case scenario:

- Entire population is infected within +/- 50 days
- Food distribution is a mass spreading event (at day 28)
- Starting 3 days after a mass spreading event, COVID-19 spread further (mainly at home)

Effect of individual parameters

Plot-size 25m²

Impact of larger plot sizes per shelter on total infections



Take-aways from larger plot sizes:

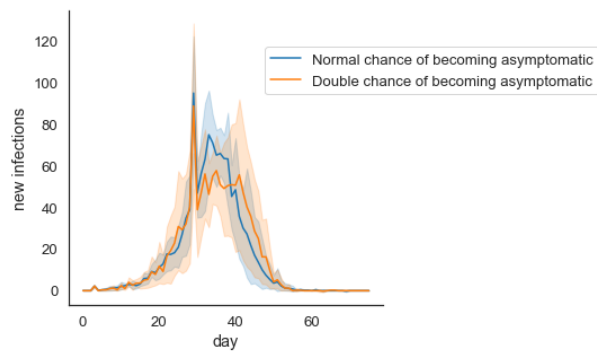
- There is no visible effect of a larger plot size for shelters.

Factor asymptomatic

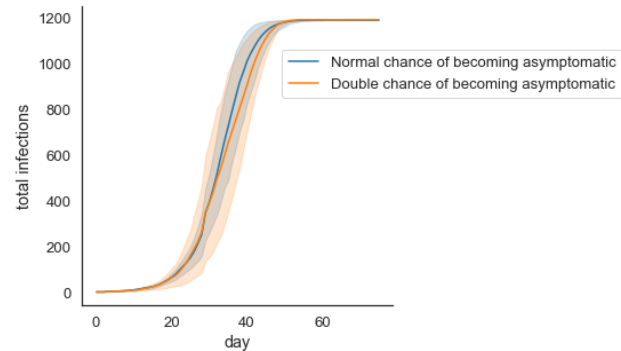
In the base case scenario, the share of asymptomatic people is defined per age group as presented in the epidemiological model in 2.3. This corresponds to a chance of 44.4% for children to become asymptomatic, a chance of 52.0% for adults to become asymptomatic and for elderly a chance of 38.3%. However, this parameter is still very uncertain. Therefore, the option is created to vary the chance of people becoming asymptomatic. In this case, this factor is multiplied by two.

When the share of asymptomatic people is higher, the chance of unknowingly spreading COVID-19 is larger, because people are less aware of the fact that they are infected with COVID-19. Simultaneously, asymptomatic people are less infectious and thus the chance of infecting another person gets smaller. This reflects also in the results of experiment runs where the chance of being asymptomatic is twice as large. The error margins are larger, which means the results show more variation. Eventually, all settlement inhabitants will be infected after more or less the same amount of days.

Effect of double chance of becoming asymptomatic



Effect of double chance of becoming asymptomatic



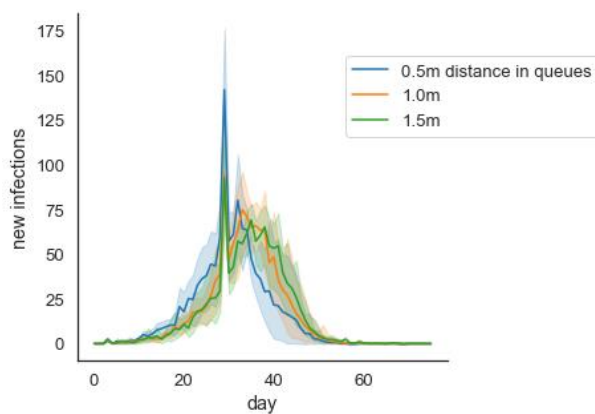
Take-aways from larger amount of asymptomatic people:

- Lower chance of infecting others and higher number of 'unknowingly' infecting others seem to balance each other out (this conclusion should be verified by diving into individual run results)
- The disease spread becomes less predictable (bigger uncertainty) when the share of asymptomatic people is twice as high.
- Within the same time, the whole population is infected.

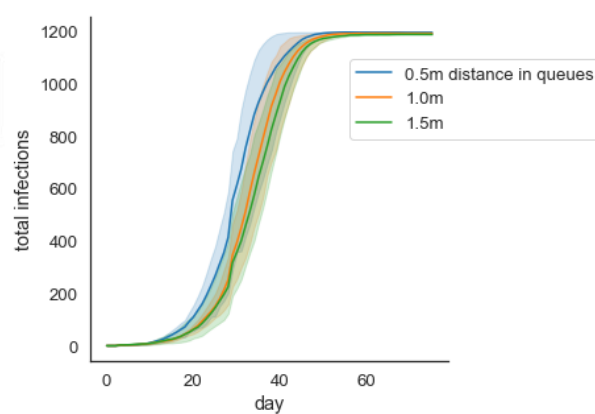
Queue-distance

The impact of distancing in queues is expected to be large, as infecting others is only possible when people are within 1.5m distance of each other. So in case people are standing only 0.5m from each other, one person can therefore infect two people in each direction. This effect is also visible from the results of experiments where the queue-distance is varied from 1.0m to 0.5m and to 1.5m distance.

Impact of distancing in queues



Impact of distancing in queues



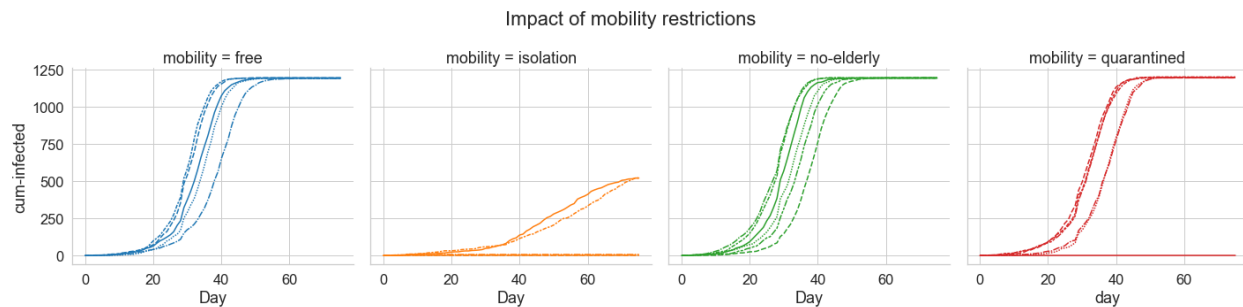
Take-aways from distancing in queues:

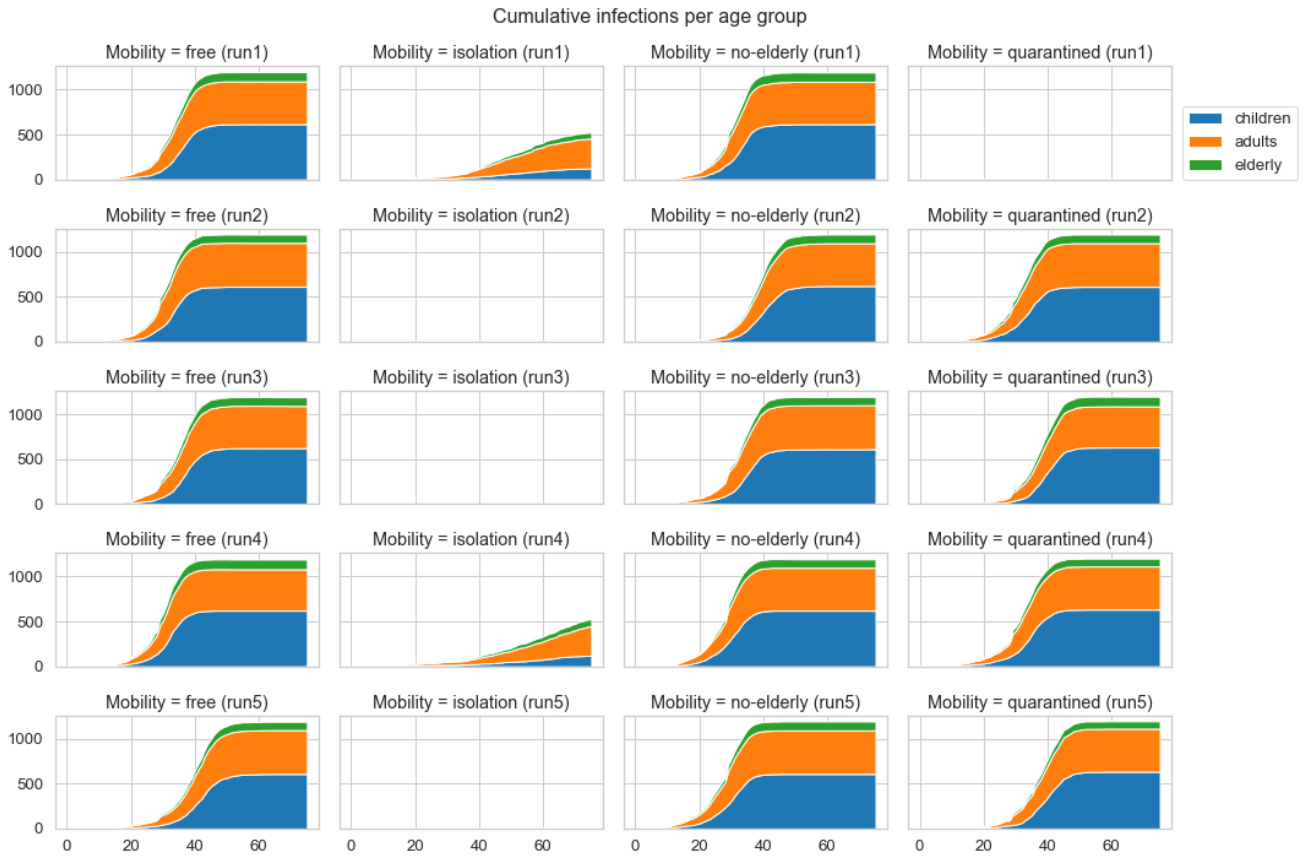
- Distancing in queues seems effective to 'flatten the curve', although all 1200 people were still infected within 60 days.
- The risk of mass spreading events is smaller when people distance in queues (smaller peak).

- When people are standing close to each other in queues (0.5m), the peak infections during a mass spreading event such as food distribution, can be up to 50% higher than when people keep 1.0m distance.
- The difference between maintaining 1.0m or 1.5m distance is not big. Further research is recommended to find what is the most optimal distance to maintain. The possibility to maintain distance might differ between settlements.

Mobility restrictions

Three mobility restrictions have been tested besides the default of free mobility. The first one is 'isolation' which means that people who are sick (or suspect so) must stay at home. The second option restricts movement for elderly, as they are the most vulnerable population group. The third option is 'quarantine', which requires entire households to stay at home if one person in the household is known to be infected (symptomatic, or perceived infection). Below, the total cumulative infections for 6 runs are shown, divided over the different age groups, to explore whether restricting a certain age group to move has an effect on the infections in this group.



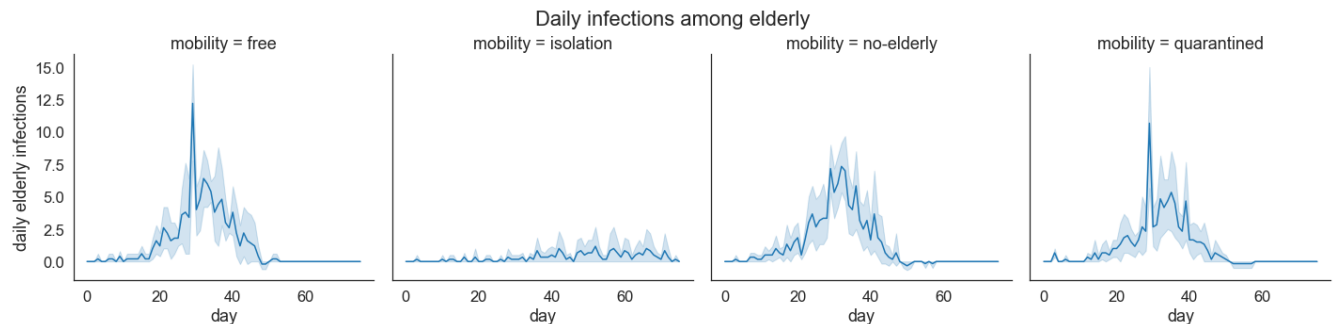


It is evident that there can be major differences between the runs. The differences appear in the moment that the number of infections start to increase and the speed with which COVID-19 spreads through a population. The driving factors behind these differences are dependent on a few factors:

- *The sensitivity of the initially infected person:* The first infected person is chosen randomly and can be either a child, adult or elderly and it is randomly determined whether this person will develop symptoms, or remain asymptomatic and overcome COVID-19 rather quickly. Both these aspects are factors that influence the likeliness of infecting other people. This explains for example why the results of the first run with quarantine restrictions remains almost zero, while the other runs do not succeed in limiting COVID-19 spread, especially during food distribution.
- *Impact on access to aid:* While in isolation no person is allowed to undertake an activity, this is different for a quarantine policy.
- *Random selection of people to undertake activities:* Each time an activity is initiated (obtaining food/water or visiting latrines/healthcare facilities), a random person in the household is selected. Depending on the state of infectiousness of the selected person, this person can or can not infect other people at a facility or while queueing for a facility.

As one of the mobility scenarios is fully focused on restricting mobility for elderly, the daily number of infections among this group is inspected separately. The result is shown below. Restricting movement for elderly has only an effect on the peak in infections among elderly during mass spreading events, as they

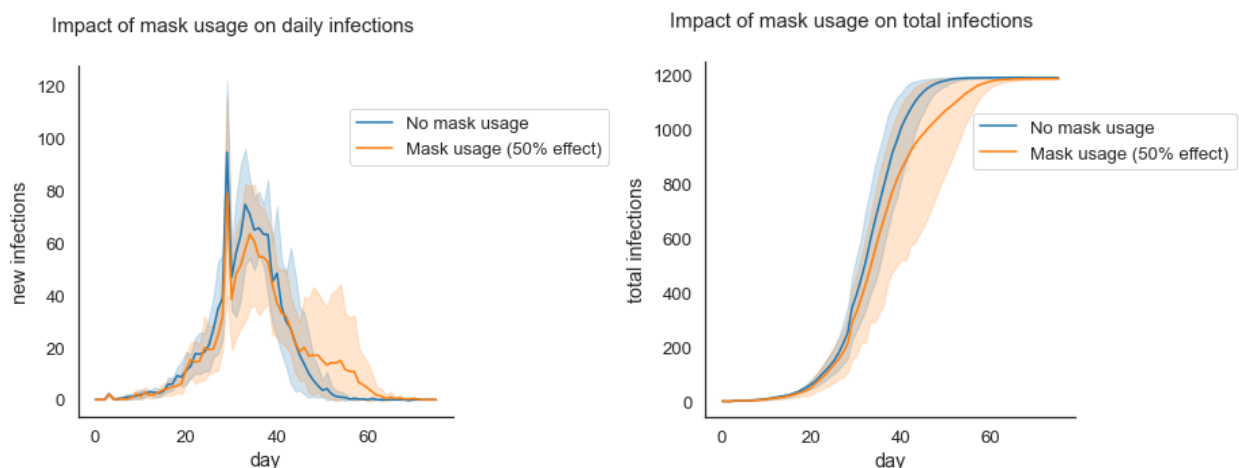
do not participate in these events anymore. Besides that, there is no evident effect of reducing the movement of elderly. This supports the finding that most infections take place at home.



Take-aways mobility restrictions:

- Restricting mobility only seems to slow the number of infections in this group in the first month. Once infections start to spread within households, the elderly quickly get infected as well.
- Isolating entire households when one person is known to be sick appears effective to prevent an outbreak in three out of five cases. This should be tested further to gain certainty about the chance of success with an isolation policy. In other cases, it limits the spread so that not the entire population gets infected with COVID-19.
- Isolating households with at least one infected person appears to be the only mobility measure where not the entire population will get infected.
- Simultaneously, in the cases where isolation is not effective to prevent the epidemic to spread, the disease can stay for a long time within the community, as it spreads slowly through the population. This is interesting to know, as immunity is not a certainty for COVID-19.
- Quarantine of infected people could be successful to prevent the spread of COVID-19. However, in most cases it is not sufficient to prevent a spread of the disease.
- Restricting movement of elderly only reduces the peak of infections in this population group due to mass spreading events. The effect is therefore limited.

Mask usage with 50% effect



Take-aways mask usage:

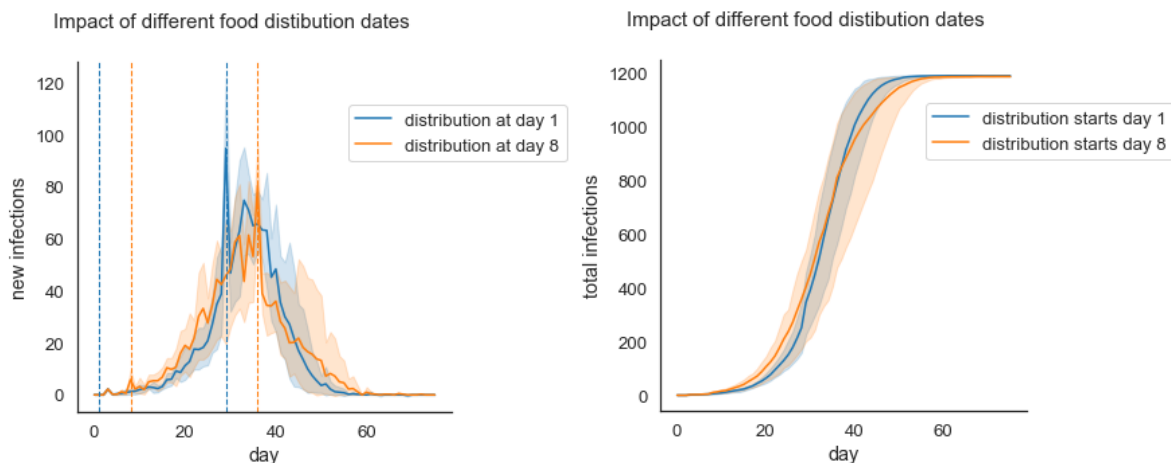
- Could be effective to 'flatten the curve' of infections
- Large error margin for the results with mask usage show that in some cases the infection curve has peaked later, which indicates that mask usage can slow the spread of COVID-19 in the beginning, but cannot prevent that eventually everyone will get infected in the simulation runs.

Compliance

Compliance will only have an effect if there are policies implemented. Further exploration of the results are therefore discussed in the next chapter.

Food distribution day

As the base case results show that food distribution is a major spreading event, it is interesting to find what the impact would be if the food distribution date shifts with 8 days. This means that there will be more infectious people during the first distribution moment already, which might shift the entire peak of infections forward in time. This provides insight in the importance of timing policy measures. The figure on the left contains vertical lines that indicate the days of food distribution where peaks are expected.



Take-aways of shifting food distribution start day with one week:

- Food distribution that requires every household to visit one location during one day (divided in groups), where queues will form, results in many new COVID-19 infections.
- When food distribution starts a week later (or first infection is one week earlier), COVID-19 starts to spread faster earlier on in the simulation. The moment in time that half of the population is infected is therefore reached earlier. However, the impact of the second food distribution moment (day 36) is smaller, as a smaller part of the population is still susceptible. Therefore, it takes longer before the entire population is infected.
- The timing of events that risk to become a mass spreading event is important. When it takes place while already quite some people are infected, it can cause a major upsurge in the number of infections. In other cases, it might cause a smaller spread, after which the epidemic starts to spread through other activities.

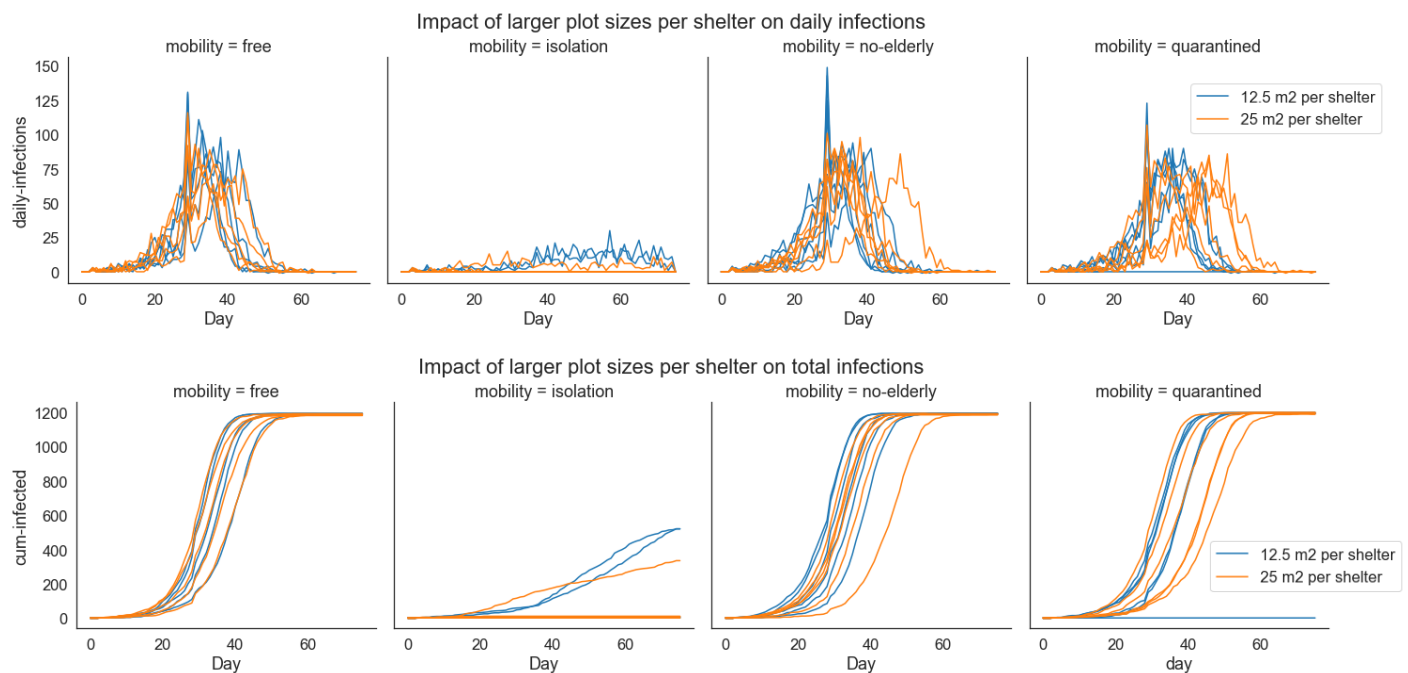
- The orange line in the left figure shows an upsurge every 3-4 days. This is probably related to the fact that people become infectious after 3-4 days but might not be aware of the fact that they are infected yet.

Combining policies with different mobility restrictions and compliance

This section discusses combinations of the factors that are described above. For all mobility restrictions, the same variables are tested.

Plot-size 25m² for different mobility regulations

There was no visible effect of changing the plot-size parameter in the base case scenario. Also when enlarging the size of shelter plots in simulations where mobility-limiting measures are imposed, the effect is small. In some cases, it seems to postpone an increase of the number of infections. As there is no direct explanation for this effect, this would require further investigation. One explanation could be that the location where infected people live plays a role. If infected people live in a shelter that is near to a facility where queues will come to exist often, the chance of spreading it to people hanging around this shelter is present. Similarly, if infected people live far away from facilities, this chance is smaller. This could be investigated by visual reviews of model runs, or by studying the effect of physically moving infected people to a part of the settlement that is further away from facilities.



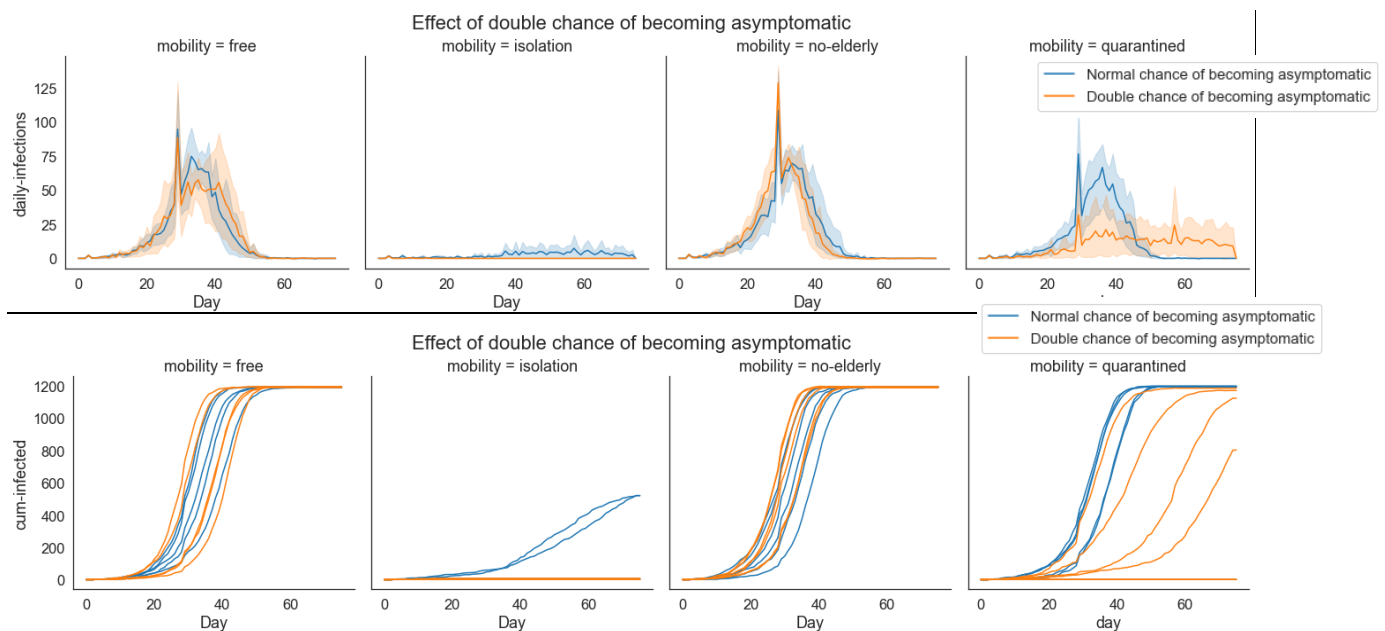
Take-aways larger plot sizes per shelter in combination with different mobility policies

- No major take-aways compared to base-case scenario.
- The impact of plot sizes might become more interesting in combination with other policy options regarding the usage of space, and/or in combination with more detailed information about the

shelter types in a settlement. For example, when shelters have multiple rooms and the size is sufficient, people could isolate from their household-members in a separate room, whereas this is not taken into account in the current model.

Larger share of asymptomatic people for different mobility regulations

In the base case scenario, doubling the number of asymptomatic people slowed the infections over time slightly, but the effect of a lower infection chance seems to be compensated by a higher chance of unconsciously infecting other people. When the mobility of all households where one person is known to be infected is limited, there were no simulations (from 6 runs) where COVID-19 spread. This means that it was successfully maintained within one household. However, in the simulation runs where the mobility is limited only for the infected individuals, a higher share of asymptomatic people benefits will slow the spread of COVID-19 and lower the peak of infections. This is interesting as this suggests that if the share of asymptomatic people is indeed twice as high as anticipated in early summer 2020, the infection curve might be flattened.

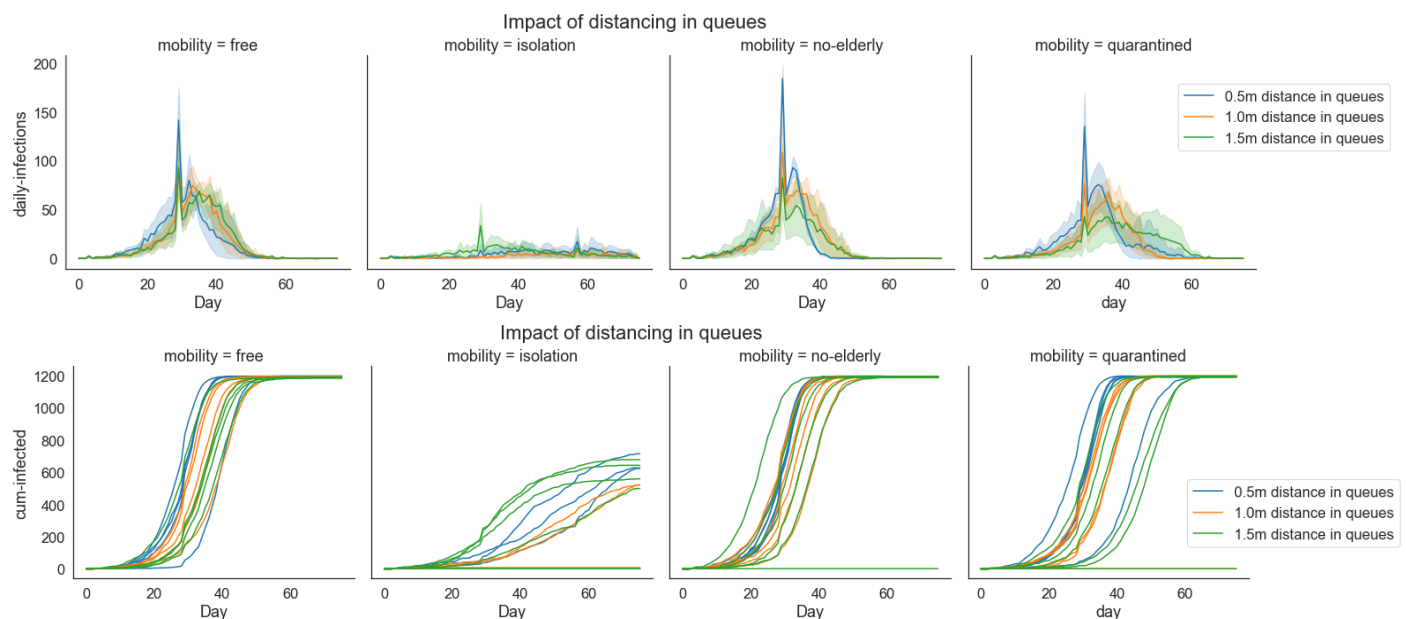


Take-aways from larger share of asymptomatic people for different mobility policies:

- A larger share of asymptomatic people seems to 'flatten the curve'.
- In combination with a policy that restricts movement of people that know they are infected, this gives a more desirable course of the disease spread in a settlement.
- It would be interesting to learn more about this effect and what part is due to 'unknowingly' infecting others and/or a lower chance of spreading the disease with fewer symptoms.

Queue-distance impact for different mobility regulations

In the base case scenario, the impact of maintaining only 0.5m distance in queues showed a significant increase in the number of infections. The difference between keeping 1.0m or 1.5m distance was smaller. It is expected that the impact is smaller for an isolation or quarantine policy, as infected people should stay at home when they know they are infected, which is also when they are most infectious. Interestingly, maintaining 1.5m distance in queues seems to lead to less desirable results when mobility is restricted for households where one person known to be infected. When only the infected person is restricted and the rest of the household can still move around (mobility = quarantined), the effect of distancing in queues is positive, slowing the spread of COVID-19 infections successfully. However, to sustain these findings, more replications of this experiment are needed.



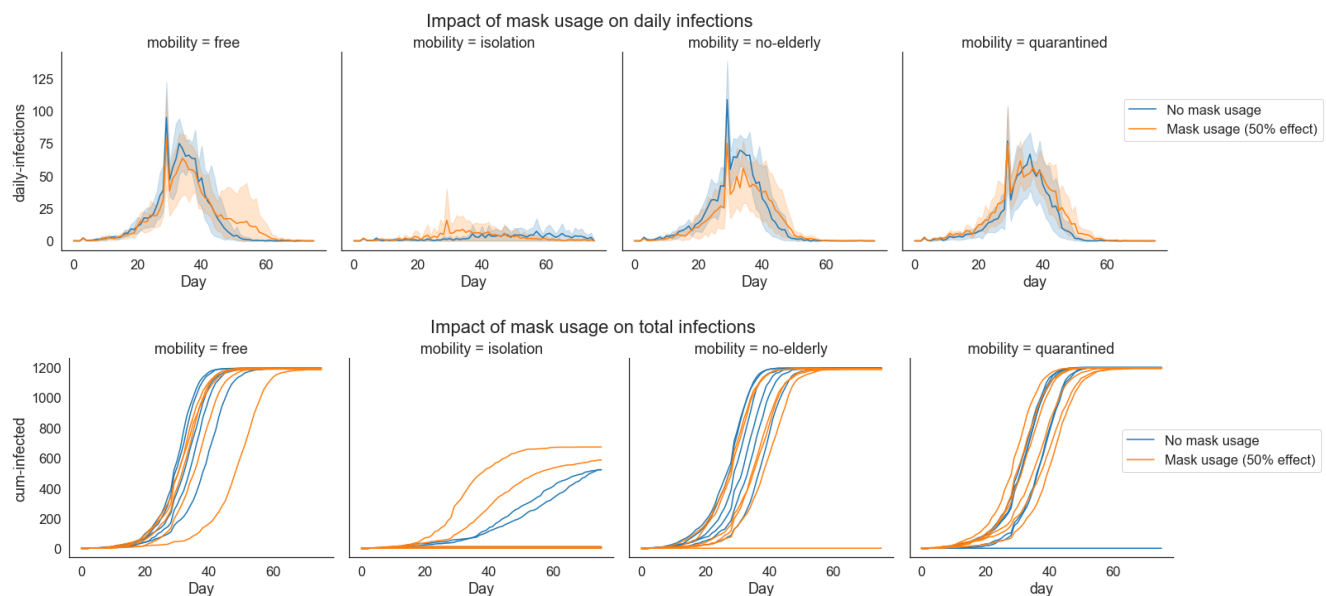
For daily infections; when only sick people quarantine at home, a queue-distance of 1.5m distance seems to lower the number of daily infections strongly during the first 30 days of the simulation. However, the large margin of error area after 40 days shows that the number of infections in a few simulation runs was over 50 infections per day. In these cases, the entire population was infected towards the end of the simulation as well. However, the number of runs where COVID-19 spread was successfully prevented, only occurred in this experiment for the runs where the queue-distance was 1.5m

Take-aways distancing in queues for various mobility policies:

- In combination with isolation of entire households where one person is infected, distancing in queues seems to have an undesired effect (more infections). Further research is needed to understand these results.
- For all other mobility policies; distancing in queues seems effective to slow the spread of COVID-19 among inhabitants.
- The risk of mass gathering events is much lower when people at these events keep sufficient (aim for 1.5m) distance from each other.

Mask usage with 50% effect for different mobility regulations

As mask usage seemed effective to flatten the curve in the base case scenario, it is interesting to know whether it can also flatten the curve in scenarios with mobility restrictions. It appears that this is the case for the situation where mobility for elderly is restricted, but not in simulations where a quarantine or isolation policy is imposed. Moreover, in the scenarios where entire household are refrained from movement around the settlement when one person is sick (isolation) some of the infection results are even less desirable when people are wearing masks. More runs should be performed to verify this counterintuitive effect.

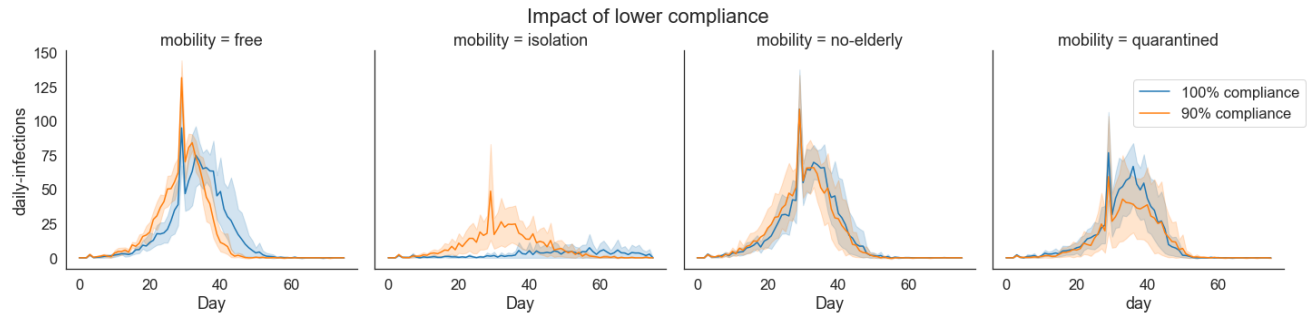


Take-aways mask-usage:

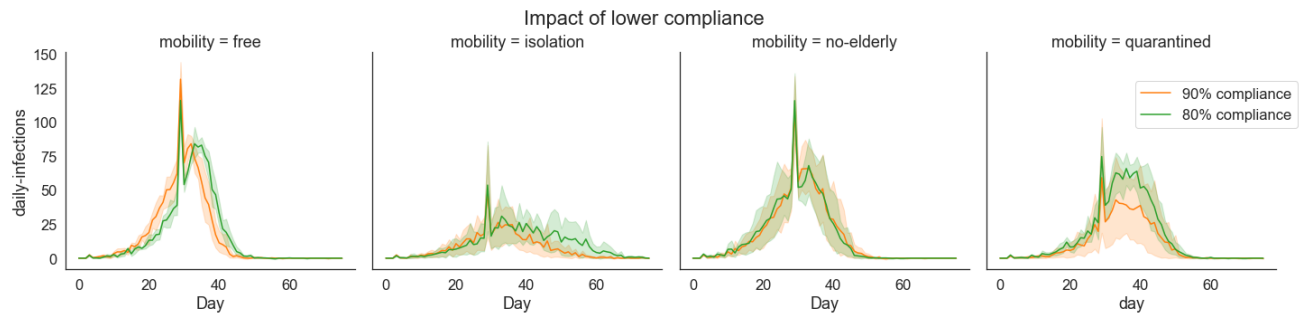
- The effect of wearing masks does not strengthen the effect of an isolation or quarantine policy.
- Requiring masks is most useful in a scenario where movement is unrestricted. However, it is less effective than requiring quarantine or isolation for (household members of) sick people.

Compliance for different mobility regulations

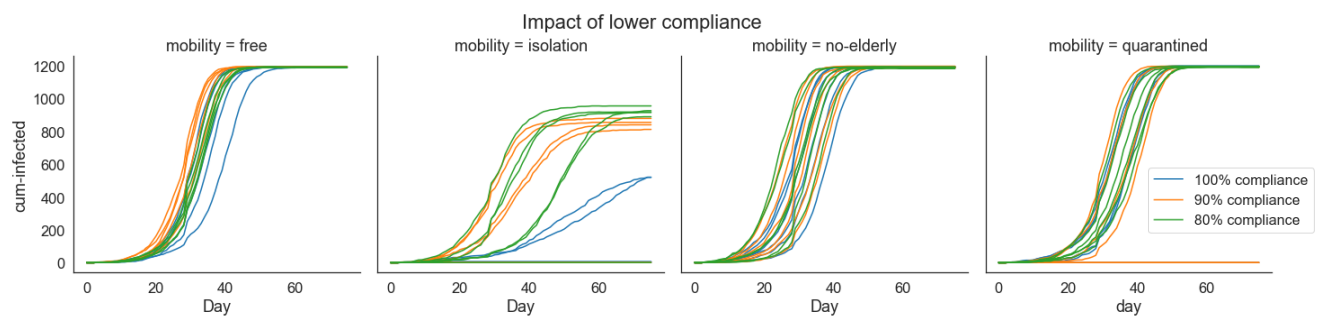
A lower compliance is expected to result in a peak number of infections that is higher and earlier in time, as preventive measures are being ignored by a number of people. Simulations are run where the chance of a person to comply to any policies is either 80% or 90%, compared to 100% compliance in the base case scenario.



Comparing results for 100% compliance with results from experiments with 90% compliance, it is interesting to see that in most cases the results for 100% compliance show a faster increase in the number of infections, with a higher peak during a mass spreading event. Surprisingly, this is not the case when mobility is restricted for people who are feeling sick. This can be explained by the limited number of runs and in this case one single run for 90% in which spread of COVID-19 was successfully prevented from the beginning.



When comparing the results of runs with 90% compliance to the runs with 80% compliance, it is interesting to see that the extra 10% decrease in compliance has a smaller effect on the infections than the first 10% decrease.



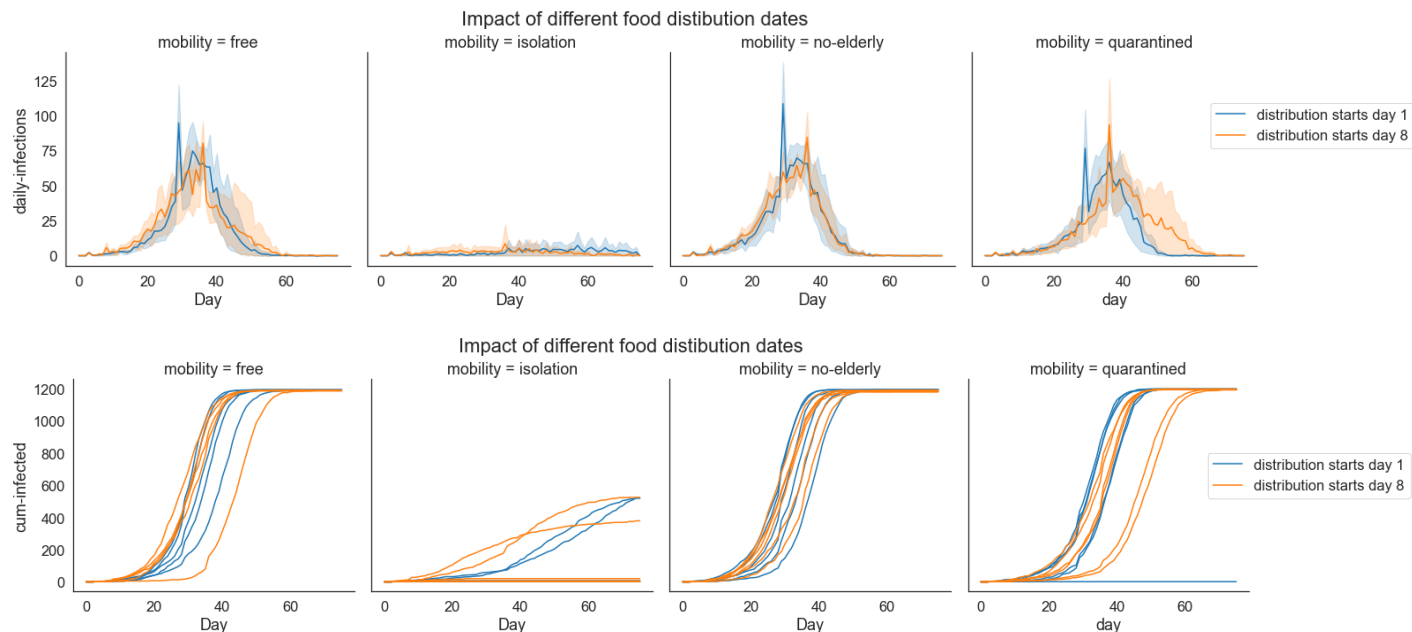
However, when analysing the cumulative results it is not possible to derive a conclusion regarding the effect of lower compliance for the various mobility policies. Only for an isolation policy, where entire households should stay at home when one person is ill a clear impact of lower compliance is found. The orange lines (90% compliance) are ending significantly higher than the blue lines (100% compliance), and the green lines (80% compliance) end even higher. The result is a much larger group of the population that is infected and a much smaller chance of successfully containing COVID-19.

Take-aways compliance and movement restrictions:

- Only for an isolation policy, the effect of lower compliance among the population is clearly visible, leading to a much higher number of people infected before the spread of COVID-19 stops.

Food distribution day

Under different mobility restrictions, the impact of shifting food distribution by one week in time is comparable to the impact when there is free mobility. Again, six runs are compared.



Take-aways of shifting food distribution for each mobility restriction:

- When the mobility restriction is quarantine, the chance of preventing any spread of COVID-19 is decreased when food distribution is shifted with one week in time. This can be the result of people infecting each other within a household, after which the newly infected person can go to a food distribution moment at day 8 while being infectious already without knowing.
- This effect is overcome when the mobility restriction is isolation, which requires entire households to stay inside when one person is known to be infected. This is concluded as still three out of five runs result in contagion of COVID-19.

2.7 Validation

A validation is performed to sustain the confidence in the model and the results. Two different testing methods are used to test the validity of the model. First, an event validity test is performed to test whether the number of fatalities due to COVID-19 is realistic compared to real-world fatalities. Then, a sensitivity analysis is performed for three input parameters: the number of inhabitants, the percentage of elderly and the number of initial infections.

Event validity of fatality ratio

An event validity test is used to test whether the number of occurrences of certain phenomena in the model are comparable to real-life occurrences. To test whether the COVID-19 epidemiology functions adequately, the number of deaths as a result of the disease is examined.

The expected number of deaths can be calculated using the chances as defined in Figure 2 and correspond to a chance of:

$$(0,186\% * 10\% \text{ elderly}) + (0,007\% * 40\% \text{ adults}) + (0,0006\% * 50\% \text{ children}) = 2,17\% \text{ deaths}$$

So for all infected agents, an additional 2,17% should die. If every agent gets infected (1200 agents), the number of deaths should be around 26 deaths.

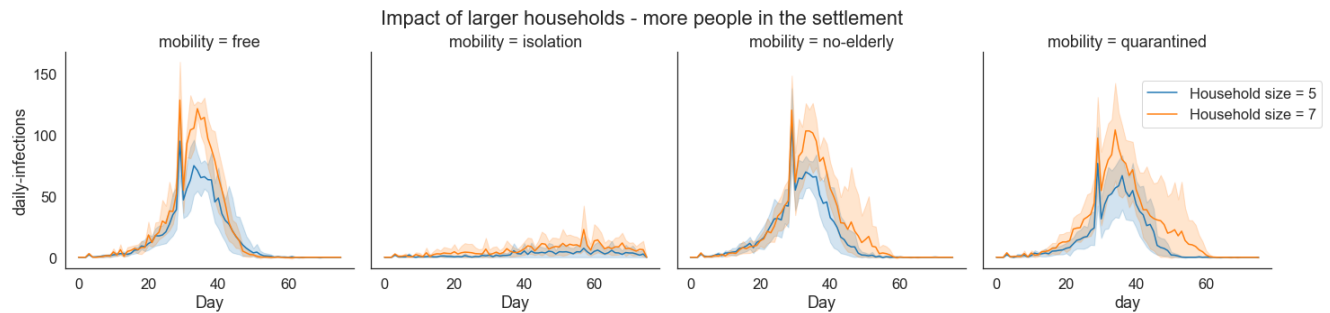
However, at the end of 70 simulation days, many people have not recovered or died yet, but are still in one of the disease stages. Therefore, the formula gets a little more complicated, by adding the number of people that are still sick multiplied by the chance of dying throughout these stages. The results of 4 runs are compared, and found to range between approximately 10 and 20 deaths. This might indicate that the model returns relatively optimistic results on the expected number of deaths, as about 26 deaths were expected. However, to really validate this finding, it is advised to perform more simulation runs with a longer simulation time, to study the result when all people have either fully recovered or died.

Sensitivity analysis for:

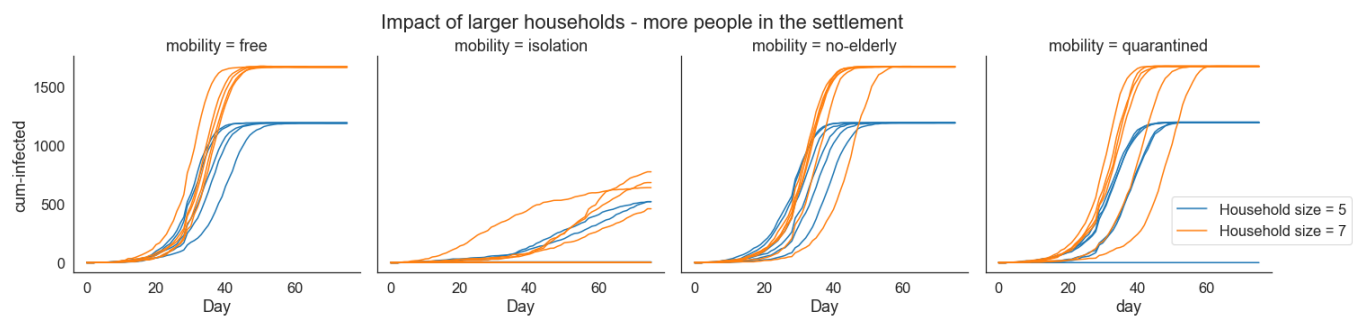
A sensitivity analysis is used to test the validity of parameters that are used as model input. The model input is a simplified representation of reality and must be adapted when running simulations for different applications. Using a sensitivity analysis, the influence of initial parameter settings on the model results gets measured. The bigger the sensitivity, the more important it becomes to specify the numbers correctly. The parameters that are tested are the number of inhabitants in the model (divided over an equal number of households), the percentage of elderly and the number of initial infections.

Number of inhabitants (households of 7)

Increasing the number of people in a household from 5 to 7, while maintaining an equal number of households, means there are 1480 people in the simulation, instead of 1200. Therefore a higher number of infections is expected occur, as there is about 20% more people in the model. As there are more susceptible people in one household, the number of infections is expected to increase faster as well.



The second peak, after food delivery day, is almost as high as the food delivery peak itself. This shows that the model behaviour is adequate. The number of infections during food distribution is higher, because there is a larger number of people. However, the number of people that get infected a few days later is higher, because the infected people have more household-members that they can infect as well. This explains why the second peak is higher, compared to the peak when households contain five people.

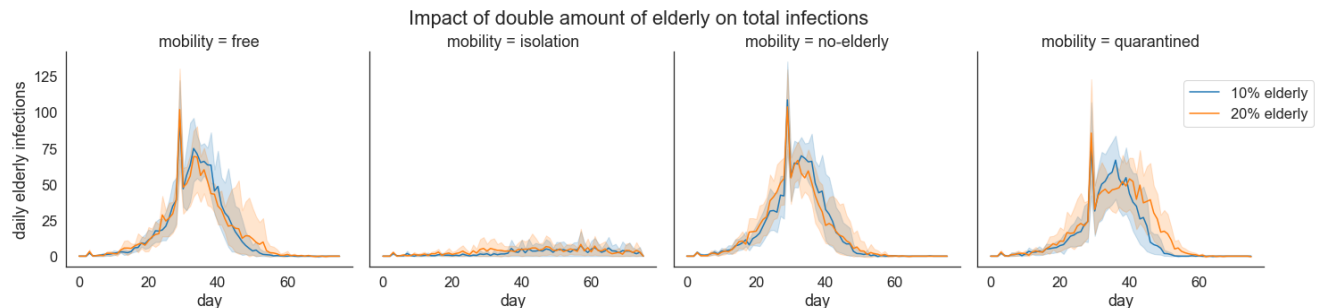


When analysing the cumulative infection numbers, it can be seen that the course of the orange lines is mostly comparable to the course of the blue lines during the first three weeks of the simulations. This is logical, as the effect of the different increase rates of the number of infections for both scenarios only becomes more evident once the numbers are bigger. As expected, a larger population results in a higher infection rate, that stabilizes when almost the entire population is infected. Interestingly, when mobility for sick people or elderly people is restricted, there are also simulation results where the increase in number of infections only starts after a longer period in time. These runs can be compared to the runs where the spread of COVID-19 is prevented in a smaller population. The chance that in a household of seven no-one accidentally spreads COVID-19 is smaller than this chance is in a household of five. This is indeed validated: the number of runs where mobility is restricted for entire households when one person is known to be infected resulted in four runs where COVID-19 spread was prevented successfully in the base case scenario, whereas with an increase in the number of household members there are only two such runs. Similarly, in the experiment where mobility is restricted only for the people who are known to be infected, there is no run where the spread of COVID-19 is prevented successfully when the household size equals seven.

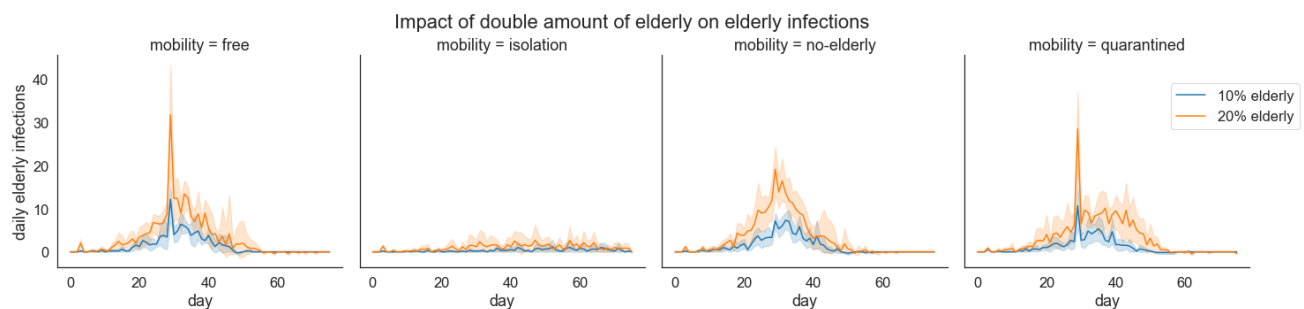
Number of elderly

The percentage elderly in the population is around 8% in the base case scenario. To measure the impact of more vulnerable people, the percentage elderly is increased to around 20%. The percentage of adults

and children is reduced by respectively 5% and 7%. Increasing the percentage elderly in the experiments results in a slightly faster increase of the number of infections, which is justified by their higher vulnerability. Interestingly, the peak of infections that arises a few days after a mass spreading event is lower in most runs.

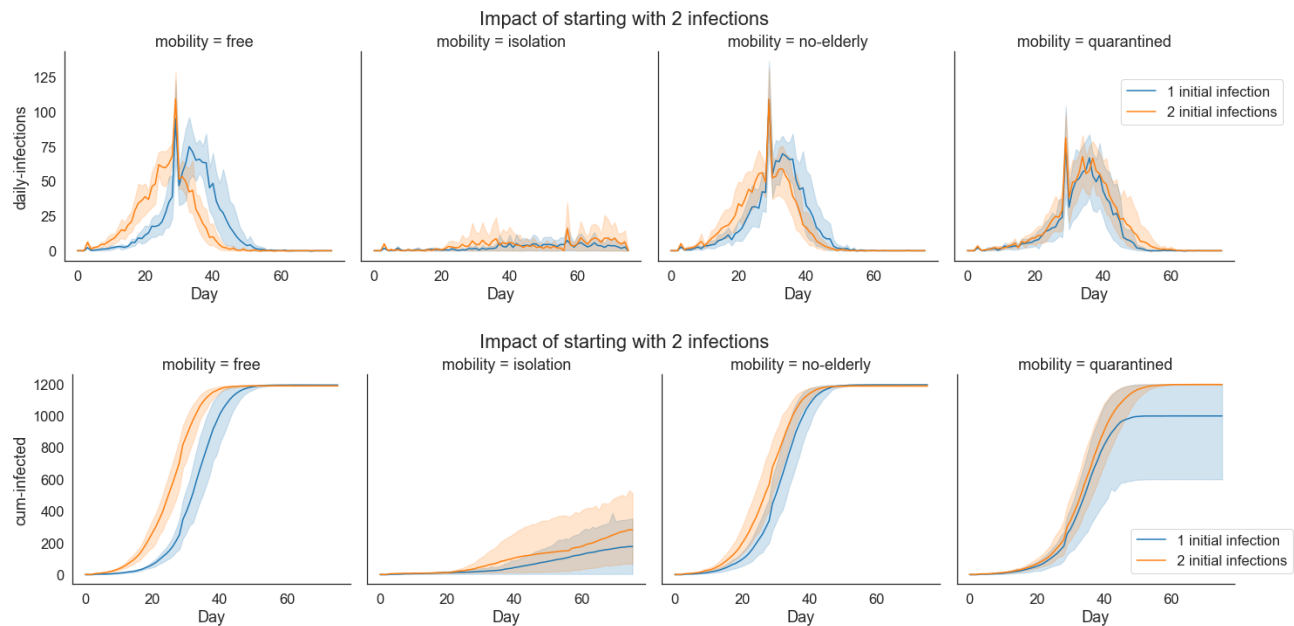


When zooming in on the number of daily infections among elderly, an interesting conclusion can be drawn. As the number of adults and elderly in the households is more equal, the chance that elderly go to food distribution moments is larger, which results in a much larger peak of infections among elderly due to this event. When mobility for elderly is restricted, this peak is much lower, which is the same effect as restricting mobility for elderly in the base case scenario.



Start with 2 infections

When starting simulations with two infections instead of one, the entire infection curve is expected to shift to the left. This is also what is visible from the results. Depending on how many people are already infected, the peak of infections during a mass spreading event can become higher (when more people are infectious, but still a large group is susceptible) or lower (when many people have been infected already, so less people are susceptible). Only when movement is restricted for people who know they are infected, or their entire households, the shift of the curve is less recognizable. The fact that less scenarios result in successfully preventing COVID-19 spread when the initial number of infections is two, contributes to this.



3. Results

The results in chapter 2 show what results the tool can produce and the insights this provides in the impact of various environmental and policy factors. This chapter aims to translate these findings into implications for the two objectives that were determined for this research.

The first objective is to gain understanding about the spread of COVID-19 through daily activities in refugee settlements. The implications of the new understanding for response in settlements during a while facing a COVID-19 epidemic are discussed in 3.1. The second objective is to prove the usability of agent-based modelling as a tool for humanitarian response studies. A reflection on this goal and the implications thereof are discussed in 3.2.

3.1 Implications for COVID-19 response

The objective to gain understanding about the spread of COVID-19 through daily activities in refugee settlements was defined using three sub-goals:

- Understand the mechanisms behind the spread of COVID-19 in refugee settlements.
- Understand the impact of preventive and mitigating measures on the spread of COVID-19.
- Develop recommendations on the effect of preventive measures in relation to the required COVID-19 treatment capacity in refugee settlements.

Mechanisms behind the spread

Of the daily activities, obtaining food and water and visiting health care facilities and latrines, the risk of spreading COVID-19 is highest for the activities where people spend a longer period of time in presence

of other people, mainly in queues. In particular food distribution on a monthly basis resulted in major peaks in the number of infections, and was marked as a mass spreading event. This is due to the large queues that come to exist during this day. The majority of infections, however, takes place at home. As the shelters are considered to be fairly small, there was no option for social distancing between household members.

The epidemiology of COVID-19 as defined in the model is of course a major driver of the spread of the virus in the model. At the beginning of this study, there was still large uncertainty about the share of people that is asymptomatic for COVID-19. Experimenting with the share of asymptomatic people in the simulation showed that if more people are asymptomatic, the spread of COVID-19 slows down, thereby flattens the infection curve. This implies that the epidemiology parameters should be backed by sufficient evidence before estimates of the infection curve can be generated for specific settlements. Moreover, the effect of a larger or smaller share of asymptomatic people may not be mistaken with the effect of policy measures. A more thorough understanding of the epidemiology and the effect on the infection spread is therefore advised.

Understand the impact of preventive and mitigating measures

Once the basics of COVID-19 spread within a settlement were understood, different measures were imposed to understand their impact. It is found that restricting entire households to move, when at least one household member is known to be infected with COVID-19, significantly flattens the infection-curve. The chance that COVID-19 does not spread outside of the initially infected household is realistic and therefore this policy also resulted in some simulation runs where COVID-19 did not spread through the settlement at all. In the other runs with this policy, COVID-19 spread was slowed and not the entire population got infected within the simulated time, but was maximally around 500 infections after 70 days.

Restricting movement of only the infected person has an effect in the same direction, but less effective. This is to be expected, as household members have a big chance of being infected as well, but might not realize this when they do not have symptoms yet. Again, there is a bifurcation between simulation runs where COVID-19 spread through the settlement was prevented and runs where it did spread. In the latter, the curve was significantly less flattened, proving that this measure is less effective to prevent COVID-19 spread.

Distancing in queues proved effective to slightly flatten the curve, however could not prevent that all people got infected. More research and experimentation is advised to gain further understanding of the impact of distancing and in combination with what other policies this could be most effective.

Another policy that is largely debated all over the world is the usage of masks. Wearing masks is found to have a desired effect, flattening the infection curve, when there are no other (movement) restricting measures. However, in combination with other policies, the positive effect almost disappeared.

The timing of food distribution in relation to the number of infections in the population is important to investigate further as well. The results of varying food distribution moments throughout runs implies that the risk of such a mass spreading event depends on the number of infections and the stage of infectiousness in the population. So far, this effect is only tested to a limited extend. Further testing to

understand when and how this risk can be minimized can prevent these distribution moments to become mass spreading events.

Lastly, it is important to understand that compliance to policy measures will never be 100%. The results of simulations where respectively 10-20% of the people did not comply showed to have a severe impact on the effect of mobility limiting policies. For example, the effect of the isolation policy that restricts entire households to move when one person in the household is infected was decreased. When 10% of the people did not comply, the number of infections in the population of 1200 people was already 800 people after 70 days, instead of 500. If a total of 20% of the population did not comply, this increased even further up to 1000 people.

Recommendations on the effect of preventive measures in relation to the required COVID-19 treatment capacity

Due to a lack of time, this effect has not been researched thoroughly yet. The results are available and only need to be analysed to see how much capacity in the COVID-19 treatment facilities was used over time, and how this changed for various levels of infections and policies. Also, it would be interesting to understand how many days are between COVID-19 onset and the demand for treatment capacity. This can be used to prevent too early or too late construction of expensive treatment capacity.

3.2 Proof of concept of ABM for COVID-19 response in humanitarian settings

The objective to prove the usability of agent-based modelling for humanitarian response studies was defined using two sub-goals:

- d. Develop an ABM to study the spread of an infectious disease using a bottom-up approach.
- e. Develop recommendations for further use of ABM to understand the results of human (inter)action within a refugee settlement.

ABM for infectious disease spread in settlements

The simulation model proved to be fit to capture the dynamics of key activities performed by inhabitants of a settlement. The chance that people from different households interact while (waiting for) using facilities is included successfully, thereby creating the risk infection spread among the inhabitants. Validation of the model behaviour showed that the simulations produce proper results. However, the input parameters should be quantified carefully to work towards recommendations for specific settlements.

Recommendations to develop further understanding of human interaction within a refugee settlements

The current model captures four key daily activities. However, these are obviously not the only activities that the population of a settlement is involved in. To gain further understanding of the infection risk in a settlement, other types of (inter)action should be included to. For example, if schools are reopened and children of different households are in a classroom together for multiple hours every day. Or similarly, if

markets and shops are included, the risk of spreading the virus in these places can contribute to a steeper infection curve.

Besides these activities, it would be possible to include social networks. As every agent is modelled separately, an initial network of social relations can be added as an extra layer that incentivizes people to visit each other or perform activities at the same time.

Lastly, an additional feature that is yet ready to use for experimentation, is the inclusion of walking and the risk of infecting others while walking past each other. The dimensions of the settlement in the prototype were too small to derive meaningful implications of this risk. However, it is proven that it is possible to include the walking behaviour of people in settlements in the agent-based model.

4. Discussion

This research and the model have limitations, caused by simplifications and assumptions that needed to be made. This chapter discusses these limitations, starting with limitations that are the result of assumptions. Then, other limiting implications are analysed. Lastly, the limitations due to the research method are discussed.

Critical assumptions

Before the results of the (prototype) experiments can be used to support decision-making on aid planning and policy measures, it is important to review the epidemiology parameters. The epidemiology parameters for this model are determined in June, 2020. More information has become available since then, which is not implemented yet.

Two assumptions that can have a major impact on the dynamics in the model and therefore also on the effect of different measures are the assumption that people become immune, and the simplifying assumption that is made regarding the transmission chance. In the current model the chance of virus transmission increases linearly per minute that two people are within an infection distance of each other. However, it might turn out that an exponential scale is more appropriate here. Moreover, the default chance is set to increase by 5% per minute, but 100% after 15 minutes. This means there is a weird jump in the infection chance as well. It would be advised to perform further research into the transmission chance before further use of the model results.

Many other simplifying assumptions have been made while defining and quantifying the parameters in the model. These assumptions are listed in annex B.

Limited usability of implications

For some disease stages there was no distribution known to estimate the time that people usually stay in this stage. This should be updated for more accurate results. However, the usability of such a tool can still be proven despite these inaccuracies.

Similarly, the effect of wearing masks is not scientifically sustained yet. In the simulations, a reduction of the infection chance of 50% was used, but this might be different in reality. However, this can be easily adjusted in the model, as this is parametrized using a slider that can be changed accordingly.

Before building upon the implications of the results, it is important to perform more experiments with the model to gain understanding about disease progression in the model. As found in the validation, the number of fatalities appears to be low, compared to numbers that are found in literature. Again, it should be taken into consideration that these numbers are obtained in June 2020 and hence might be outdated.

Research method limitations

Choices regarding the research method are unavoidable, as not only simplifications in parameters are needed, but also in the research method. These choices also impact the range of possible outcomes and are therefore important to list as well.

First of all, the decision to include only four key daily activities strongly limits the number of times a household member leaves a shelter in the model and therefore also determines the chance of infecting others or getting infected. Moreover, the agent that performs an activity is randomly chosen, which can result in some agents performing many activities, while others leave the shelter less. This in turn can have an effect on the risk of getting infected, as this is influenced by the age of the agent.

Secondly, only a few combinations of policies have been tested. Combinations of policies can possibly strengthen or diminish each other's effect. It is not always true that the effect of combined policies is simply the sum of separate policies. Therefore, the implications should be tested in the model first to understand the effect of combined policies before this can be used to support decision-making.

5. Recommendations

This chapter discusses the recommendations that follow from this research, based on the discussion in the previous chapter and chances that are identified during this research. The recommendations are divided in two categories. The first category contains recommendations that can be performed by further analysis of the current model results. The second category contains recommendations for extensions of the model and application.

Recommendations for further analysis

First and foremost it is recommended to **tune the model** so that the results correspond with infections that are measured in **existing refugee settlements**. The Rohingya settlements in Cox's Bazar, Bangladesh could be used as an example, as quite some data is available about the measures that are taken and the number of COVID-19 infections over time. Doing this will strengthen the model validation and might highlight important infection-prone activities that have been missed in the current model.

Secondly, there is a **bifurcation in the results** of some experiments that requires further investigation. This bifurcation shows COVID-19 spread is successfully prevented and no new infections have occurred for some runs, whereas other runs in the same experiment show a large number of infections in the

population. By running more experiments, the chance of both scenarios can be approximated and the reason behind the bifurcation can be understood. It is expected to be the result of the age and course of the disease of the first infected person (which is chosen randomly), in combination with the random luck that this person is not performing activities while being infectious. However, this must be analysed more thoroughly before these conclusions can be confirmed.

The results indicated that there is a serious **risk of mass infection spread** during activities where large queues form for a longer period of time. Better understanding about the infection risk for these activities is needed to advise further planning of response activities. **Shifting the food distribution moment** from day 1 to day 8 resulted in a much spikier course of the infection graph. Not only should this effect be further analysed to see when this effect is found, but also more thorough analysis of the interplay between the moment of a mass spreading event and the **number of infections that already exist** in a population should be performed. Insight in this interplay, combined with a serious testing policy, can be used to advise when and how intensive aid distribution should be performed. Secondly, this effect should be further analysed in combination **with other policies**, to see how the number of infections will change accordingly.

Triggered by the results of distancing in queues for food distribution, it is also recommended to experiment more extensively with **different distancing measures**. A significant improvement of the infection numbers was found when maintaining 1.0m distance instead of 0.5m, but the difference between 1.0 and 1.5 was much smaller. Therefore, an optimum can be sought between these two distances, to find when this policy is most effective.

The results of the prototype showed that a larger **share of asymptomatic people** seems to flatten the curve of daily infections. It would be interesting to learn more about this effect and what part is due to 'unknowingly' infecting others and/or a lower chance of spreading the disease with fewer symptoms.

In the executed experiments, all tested policies were applied from the beginning of the simulation, even though there was no outbreak of COVID-19 at that moment yet. In reality, however, policies are often applied only **after a certain threshold** in the number of infections is reached. It would be interesting to understand the effect of policies when they are applied during the outbreak as well, instead of only in prevention of an outbreak.

Lastly, it is important to acknowledge the effect of restricting measures on the **access to aid and supply** for households. For example, when a household is in isolation, they might run out of supplies which can leave them in a critical position. This can be measured by tracking how much supply (such as food and water) households have in stock and how long this stock can last. The current model already allows this to be tracked, however it has not been used in the experiments yet. After implementation, the effect on the access to aid can be extended with researching alternative supply strategies, such as supply delivery at the homes of vulnerable or infected people.

Recommendations for extending the model

As highlighted in the discussion, the model is limited to only four activities that the agents can perform. It would be interesting to **include other activities** where people interact with each other more specifically, such as **shopping in markets and opening schools**. The latter is interesting as it is relatively simple to implement and also impacts at what times children will not undertake other activities. This has an impact

on the spread of COVID-19 from two perspectives. Firstly, the infection spread can increase as children from different households are in the same classroom. From there, they can take COVID-19 home and infect their family. Simultaneously, children will take up a smaller share of other activities, which means that adults and elderly, who are more likely to get infected, have to take up these activities and hence the infection risk increases.

Wearing masks might influence the behaviour of people. For example, people might become less careful in terms of distancing. This is not taken into account in the current simulation model, but might be interesting to include. Especially, as the results showed that wearing masks only seems to have a positive effect in simulations without any mobility restrictions. These are also the runs where distancing had the biggest positive effect.

The results of the prototype simulations showed that the most people got infected at home. Therefore, it would be interesting to research the effect of not isolating infected people at home, but isolating them separately. **Separating groups of people** can be executed in different ways, which are expected to have different effects. One could think of separating elderly from other population groups rather than restricting their movement, as they still get infected at home. Otherwise, one could think about separating infected people, or entire households of infected people. Instead of separating the source (infected people), the destinations can also be separated, by defining facilities that are assigned to affected people. However, in each of these scenarios, it is the question to what extent people will comply. Especially asking infected people to behave differently might be difficult, as diseases are often stigmatised in a settlement.

The impact of plot sizes might become more interesting in combination with other policy options regarding the **usage of space**, and/or in combination with more detailed information about the shelter types in a settlement. For example, when shelters have multiple rooms and the size is sufficient, people could isolate from their household-members in a separate room, whereas this is not taken into account in the current model.

6. References

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- [13] Grasselli et al., 2020. Baseline Characteristics and Outcomes of 1591 Patients Infected With SARS-CoV-2 Admitted to ICUs of the Lombardy Region, Italy. *AMA*, ;323(16), pp. 1574-1581. doi:10.1001/jama.2020.5394 <https://jamanetwork.com/journals/jama/article-abstract/2764365>

List of sources per settlement for environment set up:

Kakuma:

<https://open.sourcemap.com/maps/5e9c38d0344d98be0c8ba221/things/5e9c38d1344d98be0c8ba224>

<https://www.iprjb.org/journals/index.php/JPID/article/view/803/93>

<https://data2.unhcr.org/en/documents/download/71190>

https://www.unhcr.org/ke/wp-content/uploads/sites/2/2019/06/Briefing-Kit_May-2019-approved.pdf

<https://www.agcrsi.org/life-as-a-refugee/life-in-kakuma-refugee-camp-kenya>

Moria:

<https://www.ft.com/content/013d95d6-54d3-11ea-a1ef-da1721a0541e>

<https://www.arcgis.com/home/webmap/viewer.html?webmap=06d12cda57e6481c84d380cc32107374>

<https://reliefweb.int/sites/reliefweb.int/files/resources/75411.pdf>

<https://www.kitrinoshealthcare.org/single-post/2020/03/20/VolunteerDiaries-Dr-Richard>

https://reliefweb.int/sites/reliefweb.int/files/resources/aida_gr_2018update.pdf

<https://www.hrw.org/news/2020/04/22/greece-island-camps-not-prepared-covid-19>

Za'atari:

<https://reliefweb.int/report/jordan/zaatari-refugee-camp-factsheet-march-2020>

<https://data2.unhcr.org/en/documents/download/75407>

<https://www.arcgis.com/home/webmap/viewer.html?useExisting=1>

<https://data2.unhcr.org/en/documents/download/73845>

<https://data2.unhcr.org/en/documents/download/60880>

<https://www.aljazeera.com/indepth/inpictures/syria-war-jordan-zaatari-refugee-camp-180326115809170.html>

https://docs.wfp.org/api/documents/WFP-0000114379/download/?_ga=2.25655805.1316214342.1587469436-769163190.1587469436

Bidi bidi:

https://umap.openstreetmap.fr/it/map/bidibidi-refugee-settlement-base-mapping_245242#14/3.5243/31.3692

https://www.wur.nl/upload_mm/e/d/1/d844351a-2890-47cf-af4a-fb794e2e638b_Factsheets%20UGANDA%20Circular%20refugee%20camps%202019.pdf

<https://www.undp.org/content/dam/uganda/docs/UNDPUG18%20-%20Understanding%20Land%20Dynamics.pdf>

<https://reliefweb.int/sites/reliefweb.int/files/resources/66780.pdf>

<https://www.odi.org/sites/odi.org.uk/files/resource-documents/12595.pdf>

<https://data2.unhcr.org/en/documents/download/73330>

<https://reliefweb.int/sites/reliefweb.int/files/resources/66780.pdf>

<https://data2.unhcr.org/en/documents/download/65900>

<https://data2.unhcr.org/en/documents/download/69674>

Cox's Bazar:

https://www.impact-repository.org/document/reach/c9fac0ed/REACH_BGD_Factsheet_J-MSNA_Refugee_December-2019.pdf

https://reliefweb.int/sites/reliefweb.int/files/resources/final_sitrep_november_2019.pdf

<https://herams.org/project/28>

<https://data.humdata.org/dataset/cba17347-ff3b-4e3f-acca-e084bfca514d>

https://www.humanitarianresponse.info/en/operations/bangladesh/hdx-datasets#table/1?title=title%3A*round*

https://docs.wfp.org/api/documents/WFP-0000113567/download/?_ga=2.97475679.1316214342.1587469436-769163190.1587469436

<https://data2.unhcr.org/en/documents/download/65900>

https://www.impact-repository.org/document/reach/c9fac0ed/REACH_BGD_Factsheet_J-MSNA_Refugee_December-2019.pdf

7. Appendices

Appendix A: Data collection about settlements

The table below shows the data that is collected about five existing settlements in order to establish the synthetic environment in the prototypical model. *(add in PDF 'Model setup - Camps-data (environment)')*

Appendix B: List of additional assumptions

Many assumptions, especially regarding COVID-19 parametrization and the daily activities of refugees are listed in the report in chapter 2.2 and 2.3. Below is a shortlist of assumptions that underlie the model behaviour.

Settlement layout assumptions:

- Settlement has a fixed number of shelters (240)
- Shelters are arranged in blocks
- Agents perform four types of activities: use of latrines, obtaining food and water and visiting healthcare facilities
- Facilities have set opening times and are located on two edges of the settlements

Activity assumptions:

- Activities per household per day:
 - o Visit latrines (7x)
 - o Obtain food (once every 28 days)
 - o Obtain water (1x)
 - o Visit healthcare facility (when sick)
- All households obtain food at the same day and must be done by an adult or elderly
- Food and water are, if possible, obtained by a healthy household member
- People arrive at a facility instantly (no walking)
- People queue with 100% compliance to the defined queueing distance
- After an activity, a person returns to its shelter instantly

COVID-19 assumptions:

- Infection perception can differ from actual infection status
- COVID-19 progression is different for children, adults and elderly
- The next disease stage gets determined randomly per person
- Severely and critically ill people will always go to a COVID-19 treatment facility