Compound risk: when sudden-onset disasters coincide with COVID-19

Balancing the livelihood and the COVID-19 trajectory of rural communities in developing countries

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COMPOUND RISK: WHEN SUDDEN-ONSET DISASTERS COINCIDE WITH COVID-19

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PREFACE

Before you lies my master thesis, the product of a couple of months of individual work. With its submission, my time at the faculty of TPM and at the University of Delft has come to an end. Even though I had anticipated that this final project would be an individual process, I had not expected it to be quite this isolated. However, as with most plans in 2020, my final months as a student didn't quite happen as I had imagined. Be that as it may, it did provide me with an interesting graduation topic that has given me a new perspective on humanitarian research and compound risk.

Even though I am pretending in the previous paragraph that this has been an individual project, that is of course not the truth. There have been many people that have guided me through the process and have helped me along the way. First and foremost, I want to thank Martijn. His supervision was nothing short of the reputation that Martijn has among students in the faculty: committed, responsive, constructive, and with a talent for creating order in chaos or vice versa, however he sees fit. I also want to thank Tina, my second supervisor, for keeping me sharp, asking critical questions, and providing me with a different perspective on the chosen topic.

Apart from my two TPM supervisors, I also want to thank Marc, who guided me from 510. From the start of my research, Marc was involved in my decisions and helped me by providing relevant literature and hooking me up with contacts that could assist me with my research. Our biweekly meetings were always a source of inspiration and gave me fresh energy to improve my research.

There are some others that I would like to thank for their support in the past couple of months. Firstly, that is Emma, who quite literally ensured that I was able to leave the house during the week by being a highly competent commissioner of Master & Career, and who never missed an opportunity for our daily crossword, contributing to my mental health and overall happiness. Secondly, I want to thank Jens, although some people might know him as Cjoe, for always being up for a debate or in-depth discussion. I still don't understand what convexity is, but I'm glad you took the time to understand agent-based modelling. Lastly, I would like to thank my parents for their unwavering trust in my abilities and for saving every single newspaper article written about natural hazards coinciding with COVID-19 over the past six months.

I hope you'll enjoy reading my thesis.

Fuuk van der Scheer

EXECUTIVE SUMMARY

Good health and well-being is the third Sustainable Development Goal of the UN, which aims to ensure healthy lives and well-being for all at all ages. In many ways, but definitely health-wise, the year 2020 has not been a positive one. With the outbreak of COVID-19, officially declared a global pandemic by the WHO in March 2020, countries worldwide have been faced with unprecedented challenges. The global response has varied from immediate strict lockdown regulations to adopting a wait-and-see strategy until there was no choice but to restrict movements and reduce interpersonal contacts. Lockdown measures have been posed as the best way to control the spread of the highly contagious airborne virus, as these ultimately result in a reduction of interpersonal contacts which reduces the chance of exponential growth of infection cases. "Flattening the curve", referring to the epidemiological trajectory of infection numbers, aims at ensuring that healthcare facilities and hospitals are able to handle the number of COVID-19 patients.

As the months without a vaccine or herd immunity went by, criticism raised due to the devastating economic effects. Especially developing countries without a social security system in place to support those without a stable income, find themselves having to choose between saving lives or livelihood. The pandemic is not an equal opportunity crisis and hits those most vulnerable hardest.

However, the pandemic cannot be seen nor treated as a disaster in isolation: natural and man-made sudden-onset disasters keep happening as well. The coinciding of these independent events may result in a collective impact that is greater than the sum of its parts, which is known as compounding risk. Understanding these risks better is crucial: human suffering can be reduced with well-targeted, early and anticipatory policy interventions, though it is still unclear what these policy interventions should be. Social distancing policies are presented as the best solution for the containment of COVID-19, but are directly counter-productive to some policies in place to save as many lives as possible whilst dealing with a sudden-onset disaster. Evacuating communities to crowded shelters with sometimes questionable hygiene saves lives in the short-term but might result in a drop of livelihood when looking at a longer time window. COVID-19 can spread quickly in those conditions, giving the virus the opportunity of spiraling out of control, resulting in governments deciding for a longer duration and more severe lockdown. In poor rural communities, this may lead to a worse situation overall, as people would no longer have access to basic necessities to provide for themselves and their household. This complex situation leaves decision-makers with a wicked problem: there is no clear and correct solution, proposed measures may have unforeseen effects, and the issue continues evolving in unpredicting ways, as became clear over the past couple of months.

The main research question addressed in this study is formulated as follows: *What robust policy interventions can be identified that balance livelihood of rural communities and the trajectory of COVID-19 during the response phase to a sudden-onset disaster in developing countries?*

This research describes a highly stylistic model that combines three socio-technical systems (livelihood, COVID-19, sudden-onset disasters), their interactions and system behaviour to find general trends and interdependencies. An exploratory ABM model was constructed where these three socio-technical components are integrated to find high-level emergent behaviour over time during the response phase to a sudden-onset disaster. An additional goal is to find under which circumstances policy interventions are most robust. Therefore, it is important to note that the outcomes of the experimentation should be interpreted within the broader context of this issue.

As a first step in answering the main research question, this study began with an extensive literature review to gain insight in three sub systems present at the core of this question: the livelihood (I), the spread of COVID-19 (II), and the sudden-onset disaster (III). Due to the high uncertainties and integration of several model components, an exploratory modelling approach is used. The core concepts of each of these systems are the starting point to create sub models, that are subsequently integrated with each other to identify model behaviour and general trends in both the COVID-19 trajectory and the livelihood of the community.

The livelihood sub system represents a model component that mimics a micro economy. Agents may go to the marketplace, which represents the location for all working activities in the model, to gain livelihood for their household. When access to this market is restricted, their households livelihood will drop. The COVID-19 sub systems entails the spread of COVID-19 and is based on the established SEIR modelling approach. The virus spread depends on both the transmission rate and contact rate: the number of people that an agent has encountered that day. The sudden-onset disaster component entails an evacuation process that might or might not result in overcrowded shelters. This is influenced by the government who can issue an early warning. The three sub systems are integrated with each other and implemented in an agent-based environment using Mesa, an open-source Python based package that was developed in 2014 and has built-in ABM structures. The integration of the model components resulted in a model that gives insight in the trade-offs that exist between shelter choices, lockdown restrictions, and the COVID-19 infection numbers. Without any policy interventions, experimentation with the base model (including both the spread of COVID-19 and the impact of a sudden-onset disaster) resulted inevitably in a drop in average livelihood. This was caused by infection numbers spiraling out of control which left the government with no choice but to impose a lockdown, restricting access to the market.

Based on these initial results and a literature review into possible policy directions, four different policy interventions were implemented. These were either aimed at increasing the average livelihood or controlling the COVID-19 trajectory, but with expected second order effects for the other metrics. Firstly, (A) direct and unconditional cash transfers were implemented. When a households' livelihood dropped below a prespecified livelihood threshold they could receive a non-recurring cash transfer helping them survive for one to three weeks. Secondly, (B) an awareness campaign contributed to an increased level of compliance of the agents, resulting in different behaviour, such as quarantining when infected, wearing protective equipment to public spaces, and a reduction in the number of daily contacts. Thirdly, (C) the shelter capacity was reduced and more shelters were implemented in order to reduce the chance of COVID-19 hubs originating and then spreading through the rest of the community. Lastly, (D) the moment of lockdown was varied by changing the sensitivity of the thresholds. The government enforces a lockdown based on two thresholds: (1) the number of infections and (2) the average livelihood. The goal of this last policy was to find out which lockdown policy would result in the best overall results for both KPIs. In addition, the policy interventions were integrated to study their combined effect on the model.

The model outcomes show several implications for decision-makers facing this situation. Of the policy interventions, the shelter policy (C) shows most promising results regarding both the average livelihood and the COVID-19 trajectory. Due to the reduced number of encountered agents in the shelters, the infection numbers stayed low enough for the government not to impose a lockdown. This policy does ask for creative use of shelter spaces as there are more locations necessary in order to adopt this. The policy with most promising results regarding the average livelihood is implementing direct and unconditional cash transfers (A). A remarkable side-effect is that it also positively influences the COVID-19 trajectory. However, this effect is marginal. The cash transfers remove the need to enter the market and thus reduce the number of interpersonal contacts in the model. This only happens in the scenario that the cash transfers are high enough for the households to survive for the duration of the lockdown restrictions. The awareness campaigns (C) showed significant beneficial results for the COVID-19 trajectory. The infection numbers can be greatly reduced if the agents are aware of the risks and choose to quarantine when they are infected themselves or their housemates. Nonetheless, the circumstances of this policy intervention are crucial in the effectiveness, as it requires regular testing and an early start if the number of infections is to be controlled. Fourthly, the lockdown regulations (D) were varied to find an optimal balance between the COVID-19 trajectory and the average livelihood within the community. Due to the way the lockdown was imposed by the government, the results did not provide much insight in this regard. Combining policies A, B and C showed most promising results regarding both the average livelihood and the COVID-19 trajectory. However, these policy interventions need to be placed into a broader context before being considered by local governments or humanitarian organizations.

The fourth policy intervention regarding the lockdown regulations leads to the first model limitation: the governmental thresholds were modelled as if the government decides to impose a lockdown based on a single threshold number, whereas in reality this is a weighted decision based on more factors, and is thus more nuanced. Another limitation is related to the granularity of the model, both in space and time. The chosen time step represents one day, which limits the possible individual agent behaviour at the shelters, households, and central market. Due to this time step it is not possible to distinguish between encounters that last one hour (at the market) or an entire day (at the shelter). Similarly, no distinction is made between encounters in close proximity or with more distance. Although the advantage of low run times make it possible to run a large amount of experiments, the lack of granularity may result in less specific model findings.

Apart from the limitations, there were several assumptions made in the conceptualization and formalization process of this study. Each of the model systems contains simplifications that reduce the complexity of the model behaviour, such as modelling all sources of income into a single market. Another influential assumption resides in the micro economy, as this is does not include price mechanisms caused by scarcity in products. In addition, the model in this study and its outcomes depend greatly on the parametrisation of the input parameters and uncertainty ranges, which makes it challenging to make the results generalizable. However, even though it is not possible to accurately pinpoint the exact quantitative effect of, for example, cash transfers, it can still be inferred that this policy generally has an immediate positive effect on livelihood, as well as a potential for beneficial second-order effects on the COVID-19 trajectory.

Several recommendations for future research are made, of which two will be highlighted. The first recommendation is to include movements from and to locations. The aim of this study was to examine the effect of, among others, overcrowded shelters on the COVID-19 trajectory, which is why the process of getting to these overcrowded shelters was not considered. However, in poorer communities it is less common to have access to private transport, implying a non-negligible infection risk from moving between certain places. Extending the model with movements could provide more insight in the effectiveness of the implemented policy interventions. For example, the effect of the awareness and thus compliance could be greater than the model outcomes currently suggest. The second recommendation is related to the duration of the model runs and its corresponding focus on the response phase of sudden-onset disasters. In future research, including the recovery phase of the aftermath of sudden-onset disasters could be of great societal value. The lockdown restrictions and impact of the disaster stretch out for longer than the current time period in this study and could provide valuable insights.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVATIONS

ABM	Agent-Based Modelling
EAP	Early Action Protocol
EMA	Exploratory Modelling and Analysis
MUDU	Modelling Under Deep Uncertainty
NRC	Netherlands Red Cross
PRC	Philippine Red Cross
UML	Unified Modelling Language
OOP	Object Oriented Programming
DRR	Disaster Risk Reduction
UN	United Nations
OCHA	Office for the Coordination of Humanitarian Affairs
GHO	Global Humanitarion Overview
RDM	Robust Decision Making
KPI	Key Performanc Indicator

1 INTRODUCTION

1.1 CORONAVIRUS OUTBREAK

The outbreak of the global COVID-19 pandemic has caused countries worldwide to go into lockdown. The Chinese city Wuhan, where the coronavirus was first discovered late 2019, completely closed down upon realization that they could not contain the virus (Lee, 2020). Despite these efforts, the disease continued to spread to the rest of the world in the following weeks and months. As of June 2020, more than 10 million cases of COVID-19 have been reported in more than 188 countries (Worldometer, 2020). Corona is the name of the disease caused by the severe acute respiratory syndrome Corona-2 SARS-CoV-2 (WHO, 2020e).

The World Health Organization (WHO) declared a global pandemic on March 11 and advised to practice social distancing and regular hand washing, due to the disease mostly spreading during close contact (WHO, 2020a). Both measures aim to minimize the spread of the highly infectious disease and therefore reduce the pressure on healthcare systems worldwide. Attempts to not exhaust healthcare capacities and to controllably bridge the period of time until a vaccine is available or until herd immunity is established have coined the concept of "flattening the curve", referring to the epidemiological trajectory of infection numbers (Wiles, 2020).

However, as a vaccine has not been found the choices of governments to impose a strict lockdown are subject to more and more criticism. Small businesses and the self-employed struggle with staying afloat with much less or no income at all, economies around the globe are in severe recession, and the question is raised whether the damage caused by the lockdown outweighs the damages of the virus itself. There is an estimated 5.2% contraction in global GDP, which is the deepest global recession since the Second World War (Calcutt, 2020). Some economists argue that economic and social hardship caused by the restrictions place a heavier burden on society than the death rate caused by the disease (John, 2020).

Some world leaders and government officials also agree that the economic recession and its consequences are worse than the consequences of letting the disease spread and accept more deaths. Illustrative for this debate is a statement from the governor of Texas: "There are more important things than living and that is saving the country" (Samuels, 2020). He continued saying that he would rather die than see the economy destroyed for the next generations. While this represents a strong opinion, the discussion on the trade-off between economic activity and COVID-19 related deaths gains increasing attention.

Apart from economic consequences, the measures taken to contain COVID-19 have a much wider impact. Schools have been closed for several weeks to months, universities have moved their courses online, final exams were cancelled. It is too soon to tell the long-term effects on education and mental health, but it is expected that the consequences will be negative (Burgess & Sievertsen, 2020).

1.2 DEVELOPING COUNTRIES AND COVID-19

The discussion on balancing lives and livelihood (a more in-depth discussion and definition of this concept can be found in chapter 2) changes when the perspective shifts toward developing countries. As aptly described by Malley and Malley (2020) in the American politics platform Foreign Affairs, the COVID-19 outbreak has not been "an equal opportunity pandemic". Infectious diseases have the tendency to strike people with low income hardest, as they cannot afford healthcare costs, are more prone to work jobs without sick leave, and make more use of public services like the public transport. Large low-income communities are mostly prevalent in developing nations. Those who can afford the strict measures, wealthier countries, are forcing them upon those who cannot, pushing developing nations in making a choice between saving lives and livelihood (Malley & Malley, 2020). Large parts of the poorer population in developing countries are dependent on (casual) jobs with frequent human contact and that come without social security. Therefore, imposing a strict lockdown forces them to stay at home and give up their income, resulting in rising malnutrition and an increasing number of homeless people.

In India, the government decided after adopting wait-and-see strategy for a couple of weeks, that a strict lockdown would indeed be most beneficial to contain COVID. Within the span of a couple of hours, they announced a strict lockdown that would last for 21 days. The reasoning was that after those three weeks, the virus would be eradicated from India and life as it was known could continue. However, due to the large proportion of the population being poor and depending on their daily jobs to provide for themselves, the number of malnourished people soared and the government had to recede from their strategy (BBC News, 2020).

The social-distancing advice from the WHO does not consider the different circumstances of countries or populations and has been characterized as 'one-size-fits-all' (Malley & Malley, 2020). This implies that the consequences of the 'one-size-fits-all' regulations in developing countries are more severe, while the usefulness can be less. Loss of work and wages, specifically in the informal economy, is expected to lead to poverty and famine for millions (Anthem, 2020). Most countries seem to agree that at least a partial lockdown is worth suffering some economic loss for, but it is unclear of what magnitude the loss of livelihood will be. This situation becomes more complex the longer it goes on as the pandemic coincides with other disasters.

1.3 COMPOUND RISK: SUDDEN-ONSET DISASTERS

According to Liu and Huang (2015), compound risk considers the multitude of ways that one disaster can cause, or simply worsen, another disaster by severely impairing the resilience and response of affected communities. de Ruiter et al. (2020) use the term *consecutive disasters* instead of compound risk because COVID-19 and the occurrence of a natural sudden-onset disaster are independent events. Compound risk can attribute to a greater potential collective effect of two consecutive disasters than the sum of its parts (Pei et al., 2020). What all papers agree upon is that this risk can no longer be ignored. The collision of two major disasters has happened during hurricane season and will happen again. The COVID-19 crisis leaves households, firms, and governments more vulnerable to other shocks and stresses such as droughts, storms, floods and food insecurity (Calcutt, 2020). This is due to a decreased financial security as governments' fiscal stimulus spending dries up and the capacity to absorb and respond to these other shocks is limited. Higher risk regions, among others defined by seasonal forecasts and financial vulnerability, find themselves in a hard situation. Intersections of climate extremes with the pandemic show that the consequences of consecutive disasters can be lethal, however it remains difficult to accurately quantify the magnitude of this risk (Pei et al., 2020). The Meteorological Department of India reported a 26% rise in frequency of high to very high intensity cyclones (Ober, 2020).

For these higher risk regions, it is important to prepare well in advance (UNDDR, 2020). It is more important for them to monitor risks, revisit plans, and have financial protection in place. With sudden-onset disasters like typhoons and earthquakes, certain questions become important: under what conditions should the COVID-19 restrictions be lifted, for what amount of time, and how will that affect the epidemic? What is known about the virus is still less than what is unknown, but now is the time to plan for a more resilient future (Malley & Malley, 2020). Calcutt (2020) argues that timing is crucial in dealing with compounding risk as preparedness can create large benefits. Specifically relevant in case of consecutive disasters with COVID-19 and sudden-onset disasters is that some of the major response policies in both cases are directly counter-productive toward the other: social distancing to contain COVID-19 versus crowded shelters during an evacuation.

1.4 WICKED PROBLEMS

It is clear that the coinciding of COVID-19 with sudden-onset disasters is a problem. This especially refers to developing countries where a larger part of the population is dependent on their daily income to sustain themselves, as the example of India showed. However, how to deal with this issue is hard to say. There are many interdependencies and multi-causal aspects to consider, where regulations and behaviour to solve one part might cause issues for another. The most effective way of battling a pandemic is to distance yourself from others, whereas seeking shelter in case of a sudden-onset disaster is usually the proposed solution when aiming for saving most lives. In addition, it is not clearly defined whose responsibility it is to deal with these problems and who should be involved for solving which part. In short: there is no clear and correct solution, proposed measures may have unforeseen effects, and the issue continues evolving in unpredicting ways, as became clear over the past couple of months (Hoornbeek & Peters, 2017). This issue can therefore be categorized as a *wicked problem*.

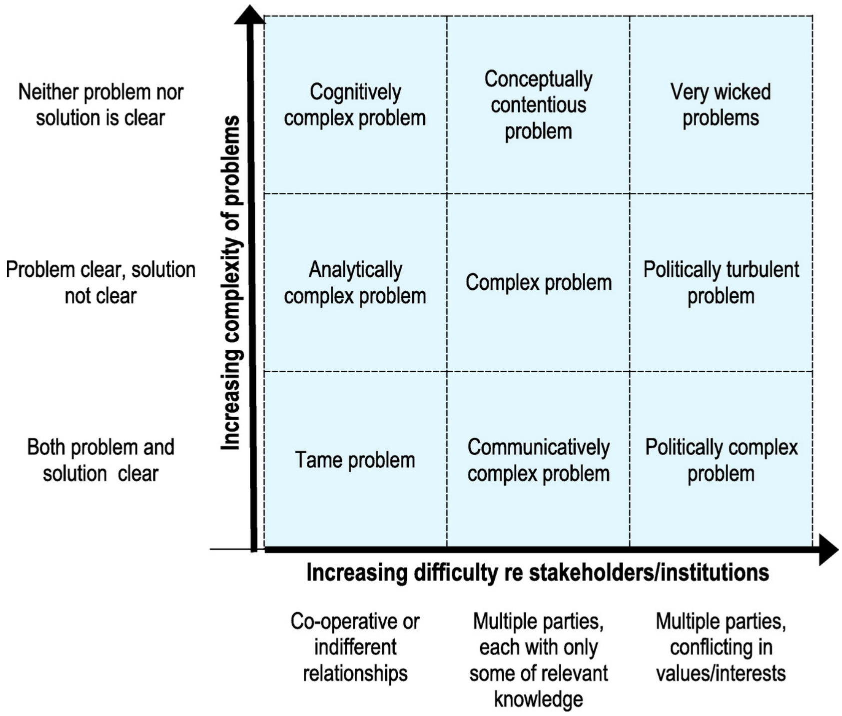


Figure 1.1: Classification problems (Marier & Van Pevenage, 2017)

In figure 1.1 an overview by Marier and Van Pevenage (2017) shows how to classify problems. The problem at hand fits into the upper right box as a wicked problem. This term was first introduced by Rittel and Webber (1973) who showed that there are issues that are not easily solved by engineering solutions, because both the problem and solution are unstructured and unclear. A deeper understanding and structuring of the issue is necessary first, before the first step can be made into solving it. Figure 1.2 displays another framework with wicked problem categorization. As a first step to solve wicked problems, it is suggested to grow from dissensus among stakeholders to consensus among stakeholders, or from uncertain knowledge to certain knowledge (Georgiadou & Reckien, 2018).

Spatial Knowledge	Policy Goals and Values	
	Consensus among Stakeholders	**Dissensus among Stakeholders**
Certain (facts and cause–effects)	**(1) Tame or structured problems** - Debate on technicalities - Geo-information tools as *problem solver*	**(3) Moderately structured problems** - Participation to debate goals and values - Geo-information tools as *mediator*
Uncertain (facts and cause–effects)	**(2) Moderately structured problems** - Participation to debate cause–effects and optimize the collection of facts - Geo-information tools as *analyst* and/or *advocate*	**(4) Wicked or unstructured problems** - Endless debate - Geo-information tools as *problem recognizer*

Figure 1.2: Wicked problem framework (Georgiadou & Reckien, 2018)

1.5 SOCIETAL CONTRIBUTION

This study captures three socio-technical systems in a highly theoretical and stylistic model. Deeper understanding of the interdependencies between COVID-19, sudden-onset disasters, and livelihood enhances insight in the interplay between them and assists policy-makers in making informed decisions. The exploratory character of the research allows for finding robust policies that are consistent for the explored scenarios. These robust policy interventions aim to contribute in the two ways described below.

Contribution to Sustainable Development Goals
Monasterolo et al. (2020) states that 'neglecting compound risk can lead to a massive underestimation of losses' because of the shortsighted focus on short-term repercussions. Interdisciplinary research can address this gap and identify effective policies for improved resilience of socio-economic systems. Developing countries will be hit hardest by COVID-19, with expected income losses exceeding $220 billion and half of all jobs in Africa lost (UN, 2020). The United Nationals Development Programme (UNDP) estimates 55% of the global population being unable to access social protection, resulting in loss of basic food security and nutrition, as many of these people are depending on their day-to-day salary to have access to food and/or resources and are now deprived of their means of livelihood. Their governments have less means to deal with the recession and help business-owners maintain their businesses.

Providing strategies for informed decision-making to developing nations to deal with sudden-onset disasters during the COVID-19 epidemic contributes to *good health and well-being*, which is the third Sustainable Development Goals (SDG) of the UN. The risk of consecutive disasters will increase due to growing exposure, interconnectedness of human society, and the increased frequency and intensity of nontectonic hazard (de Ruiter et al., 2020). Given that the impacts of these disasters are disproportionally distributed and have the largest impact in developing countries, developing a model to support informed decision-making contributes to *reducing inequalities*, which is the tenth SDG.

Policy interventions at 510, Netherlands Red Cross
This research is performed at 510, the data initiative of the Red Cross. The

outcome of this research provides 510 with information on how to advise (local) governments in developing countries that deal with decisions that contain COVID-19 during evacuation whilst keeping the livelihood of their inhabitants on a sustainable level. Even though the model creates insight in systemic behaviour on a rather abstract scale, the model is calibrated in the end on a case study in the Philippines. 510 is active in the Philippines with a COVID-19 response project that includes finance-based forecasting and predictive modelling of the outbreak, the latter of which this research can contribute to. They work closely with the Philippine Red Cross that is providing data for, among others, this research.

1.6 RESEARCH OBJECTIVE

This research describes a highly stylistic model that combines three socio-technical systems, their interactions and system behaviour to find general trends and interdependencies. During the containment of epidemic contagious diseases, sudden-onset disasters keep happening. These two crises are different in nature and some policy interventions are counter-productive for the other. The COVID-19 epidemic asks for social distancing, a reduced number of contacts and highly hygienic conditions. Response to a sudden-onset disaster requires evacuation and, oftentimes, leads to overcrowded shelters with questionable hygiene circumstances and a lack of social distancing. An exploratory ABM-model is constructed where these three socio-technical components are integrated to find high-level emergent behaviour over time during the response phase of a sudden-onset disaster. The goal is to find or understand under which circumstances policy interventions are most robust.

1.7 RESEARCH SCOPE

- This research will be carried out for 510, the Netherlands Red Cross data team. The Red Cross Red Crescent Movement is the largest humanitarian network in the world. The International Federation of the Red Cross and Red Crescent Societies (IFRC) is responsible for preparation and response to disasters in non-conflict situation by coordinating and delivering humanitarian aid in the aftermath of disasters. The aim is to improve the lives of vulnerable people by conducting relief operations in response to a disaster, together with disaster preparedness and capacity building programs.

- Physical, human, natural, financial, and social capital are the five capitals that Quandt (2018) include in their definition of livelihood. In this research, the focus lies on financial capital: the savings and credit of households that they can lose if they lose their source of income.

- Disaster type under consideration will be sudden-onset disaster. Natural sudden-onset disasters are most often given as example. There are four types of disaster as displayed in figure 1.3 (Van Wassenhove, 2006). However, in recent times, the term *natural disaster* has been criticized as there are only natural hazards that can lead to a disaster, but the disastrous consequences are oftentimes caused by inadequate policies and human actions ("Dedicated to spreading the #NoNaturalDisasters campaign", 2019; The World Bank, 2010). Therefore, from this point on, the term disaster will only refer to the situation *caused* by the natural hazard.

	Natural	**Man-made**
Sudden-onset	Earthquake Hurricane Tornadoes	Terrorist Attack Coup d'Etat Chemical leak
Slow-onset	Famine Drought Poverty	Political Crisis Refugee Crisis

Figure 1.3: Disaster types (Van Wassenhove, 2006)

- Response phase: actions taken directly before, during or immediately after a disaster in order to save lives, reduce health impacts, ensure public safety and meet the basic subsistence needs of the people affected (PreventionWeb, 2020). Focus in this research: evacuation procedures and protocols, but including the *early warning* and *early action* as well.

- Humanitarian response: in the model, policy interventions that can be carried out by the Red Cross or the municipality (local government) will be included. The private sector is excluded, the focus lies on humanitarian actors.

- The focus lies on *livelihood*, which is a part of economic activity. Chapter 2 elaborates in more detail about the definition of this concept.

- The focus lies on a rural community with a population that is dependent on their day-to-day income to provide for themselves.

- This study is stylistic and the model itself is not based on a particular case study.

- Compound risk: a multitude of definitions exist regarding compound risk. According to Liu and Huang (2015), compound risk considers the multitude of ways that one disaster can cause, or simply worsen, another disaster by severely impairing the resilience and response of affected communities. This is the definition that is used in this thesis: how the COVID-19 pandemic affects disaster response and vice versa.

1.8 STRUCTURE OF THIS STUDY

This chapter contains the problem introduction, societal contribution, and first outline of the scope. Chapter 2 continues with a literature review that concludes with the academic knowledge gap. Chapter 3 contains the research design, including the main research question, sub questions, and proposed methodologies. Chapter 4 contains the conceptualization of the model, followed by the formalization. Each of the introduced sub systems is conceptualized and formalized separately before being integrated. Chapter 5 introduces the policy interventions, model uncertainties, and KPIs, resulting in a complete overview of the XLRM framework that is used for the experimentation. Chapter 6 continues with the implementation of the model, after which the experimental design is discussed in chapter 7. Chapter 8 contains the results of the experimentation and some first take-aways of those results. Chapter 9 starts with the model validation, after which the model results are discussed, including a discussion of each of the policy interventions on the model behaviour. In chapter 10 critical assumptions and important limitations are discussed, as well as their implications for the model outcomes. Finally, chapter 11 comes back to answering the sub questions and main research question are answered. It also contains the societal and scientific contribution of this study and poses suggestions for future research.

2 LITERATURE REVIEW

In this chapter, the findings of the literature review are presented. First, the method of finding literature is discussed, followed by the most important concepts for this study. The chapter ends with the academic knowledge gap.

2.1 LITERATURE SEARCH

For the literature review, the search started by looking into the definition of livelihood and COVID-19. The trade-off between economic activity and consequences of COVID-19 restrictions came to light early on in the search. Based on the scoping choices for rural areas, and poor and vulnerable communities, the literature search continued to reduce economic activity to livelihood. The search continued looking into sudden-onset disasters and their impact on developing countries, both as a separate system and with respect to epidemics. This led towards a dive into existing SIR COVID-19 models, specifically Agent-Based Models, finally leading to researching the context of deep uncertainty. Key terms were "livelihood", "disaster response", “economic impact COVID-19”, “trade-off livelihood epidemic”, “compounding risk”, “consecutive hazard”, and “deep uncertainty”. Research methods included the snowball method and searching for related publications.

2.2 CORE CONCEPTS OF SUB SYSTEMS

For this study, three different socio-technical (sub) systems are researched. First, core concepts of each individual system are reviewed separately from each other: livelihood(I), disaster response(II), epidemics(III). Second, the combination of two sub systems (I and II, II and III, I and III) are reviewed. Third, existing models are considered that could be used as a starting point for the conceptualization. The three core concepts from the sub systems are reviewed using the same structure:

- A. Definition of core concept from literature
- B. How the core concept will be used in this research
- C. Initial scope and system boundaries of corresponding (sub) system

	Liv (I)	**Dis (II)**	**Epid (III)**	I&III	II&III	I&III
Ellis, 2000	x					
Armah et al., 2010	x					
Chambers and Conway, 1992	x					
Ha et al., 2017	x					
Quandt, 2018	x					
Dobbie et al., 2018	x					
Özdamar and Yi, 2008		x				
Fereiduni and Shahanaghi, 2017		x				
CDCP, 2020		x				
Wang and Chen, 2020		x				
Brown et al., 2020		x				
Browning, 2020		x				
Kermack and Mckendrick, 1927			x			
Ellison, 2019			x			
Hethcote, 1989			x			
Roberts et al., 2015			x			
Martin et al., 2020				x		
Bethune and Korinek, 2020				x		
Piguillem and Shi, 2020				x		
Alvarez et al., 2020				x		
Berger et al., 2020				x		
Hall et al., 2020				x		
Spiegel et al., 2007					x	
Watson et al., 2007					x	
Rogers et al., 2020					x	
-						x

Table 2.1: Overview literature per core concept

Table 2.1 presents an overview of the literature used per section.

2.2.1 Livelihood (I)

Definition from literature

Livelihood is a multi-faceted concept as it both refers to the activities to make a living and the outcome of those activities. In literature, it has most often been defined as a term that comprises the *assets*, *activities* and *access to these* that together determine the living gained by the individual or household (Armah et al., 2010; Ellis, 2000). Chambers and Conway (1992) referred to livelihood as the capabilities, assets, and activities required for a means of living. Ha et al. (2017) found that "women's uttermost need is to raise their income through improved market access", which implies livelihood of a household may depend greatly on access to the market. When harvest suffers under the lockdown restrictions and/or access to the marketplace is blocked, this has negative consequences for the income and food security, and thus negatively influences livelihood.

In 2018, Quandt (2018) introduced the *Household Livelihood Resilience Approach* to provide a tool for measuring livelihood resilience. Until then, they found the definition of both resilience and livelihood ambiguous. In order to reach their goal, they extensively researched the concept of livelihood. In figure 2.1, an overview of their findings is displayed. In Appendix A, a larger version of this table can be found.

The five livelihood capitals as described by various authors.

Type of Capital	Scoones (1998)	Tacoli (1999)	Campbell et al. (2001)	Adato and Meizen-Dick (2002)	Erenstein et al. (2010)
Natural Capital	Environmental services, natural resource stocks such as soil, water, air	Freshwater availability, land management, agricultural space, land	Soil fertility, water resources, forest resources, grazing resources, land quantity and quality	Land, water, forests, marine resources, air quality, erosion protection, and biodiversity	Annual rainfall, soil capability index, farm size, herd size
Financial/Economic Capital	Capital base including cash, credit, savings and basic infrastructure and production equipment and technologies	Infrastructure and tools/equipment	Credit, savings, remittances	Savings, credit, as well as inflows such as state transfers and remittances	Farm size, herd size, bank facilities, credit societies
Human Capital	Skills, knowledge, ability of labor, and good health	Labor including skills, knowledge, ability to work	Knowledge, sills, health, labor availability	Education, skills, knowledge, health, nutrition, and labor power	Female literacy, immunizations, work participation, population density
Social Capital	Social resources including networks, social claims, affiliations, associations	Access to markets, representation and access to the 'state'	Adherence to rules, relationships of trust, mutuality of interest, leadership, kin and ethnic networks, social organizations	Networks that increase trust, ability to work together, access to opportunities, reciprocity; informal safety nets; and membership in organizations	Cooperative societies, self-help groups
Physical Capital	Included in financial capital	Included in financial capital	Households assets, agricultural implements, infrastructure	Transportation, roads, buildings, water supply, sanitation, energy, technology and communication	Irrigated area, farm mechanization, distance to nearest town, access to paved roads

Figure 2.1: Livelihood capital in literature (Quandt, 2018)

On average, farmers constitute 65% of poor rural communities, of which a large part consists of small farmholders that provide for their own household only. Agricultural labourers, not the farm owners, depend also on the availability of casual work (Dobbie et al., 2018). With lockdown restrictions, this availability decreases.

How livelihood will be used in this research

Physical, human, natural, financial, and social capital are the five capitals that Quandt (2018) include in their definition of livelihood. In this research, the focus lies on financial capital: the savings and credit of households that they can lose if they lose their source of income. In this context that leads to being unable to buy food and provide for your household. Livelihood is lost by acquiring food or by buying necessities such as protective equipment. The reason for only including financial capital is this to reduce the complexity and because the financial capital component is the one most affected by the consecutive disasters as seen in the previous months with COVID-19. In addition, other dimensions, such as social capital or infrastructure, are nation-wide livelihood indicators and hence not applicable to the ABM approach, as introduced in chapter 3.

Initial scope and system boundaries

Livelihood is reduced to the daily gathering and spending of livelihood per household. Individuals can contribute to their households' livelihood by trading at the market, which represents their day-to-day jobs. This simplification of the market mechanism is to merely explore when and under which circumstances a negative or positive trend in livelihood can be established. More on the conceptualization and formalization of this concept can be found in chapter 4.

2.2.2 Sudden-onset disaster (II)

Definition from literature

As mentioned in the section 1.7, the four disaster types are characterized by being *man-made* or *natural*, and *sudden-onset* or *slow-onset*. In this study, the focus lies on sudden-onset disasters, where there's no clear distinction made between man-made or natural. The reason for this choice is discussed in the next paragraph. First, it is important to understand what mechanisms are in place in order to deal with disasters. There are four distinct phases: *early action*, *early warning*, *disaster response*, and *disaster recovery*. Early action and early warning both happen before the impact of a disaster whereas the response and recovery phase take place on impact or thereafter. Disaster response refers to the period of time right before, during, and immediately after the impact (PreventionWeb, 2020). This includes seeking safety for the duration of the impact as well as evacuation beforehand or afterwards. This thesis focuses solely on the disaster response phase.

Within disaster response, two major activities are logistics support and evacuation (Özdamar & Yi, 2008). Evacuation policies have been researched in great length to identify evacuation behaviour, chosen routes for evacuation and other decision metrics (Perry, 1979; Yi & Özdamar, 2007). Models have been developed that assist decision makers in opting for the best shelter location, allocation, evacuation procedure, and timing (Dregmans, 2020; Fereiduni & Shahanaghi, 2017). In this broad landscape of disaster response, the focus in this research is limited to evacuation aspects that directly interfere with policies aimed at containment of a contagious disease. Research has shown that COVID-19 can spread quickly in shelters (CDCP, 2020). One of the key findings was that a proactive attitude towards prevention measures is crucial, as well as frequent testing, and reducing movement between shelters. Nevertheless, reports noted that the shelters were often crowded and not conducive of safe distancing.

How disaster response will be used in this research

Disaster response is a transdisciplinary research field with endless factors that can be examined. Actions can be made by (local) governments, NGOs, individuals, or other organizations that impact the outcome. Evacuation decisions such as timing, facility location, hygiene, preparation and more can all be of great influence on the amount of lives that can be saved and influence the well-being of people that need to be evacuated. For this research, the facets of the disaster response are taken into account that are influenced by, or themselves influence, the trajectory of the COVID-19 pandemic because the study focuses on researching disaster response *in combination with* the containment of a highly contagious virus. Optimizing the shelter location can positively influence the evacuation procedure, but is not directly linked to containing or spreading COVID-19. The most important aspect of disaster response in relation to the COVID-19 pandemic is the number of people assigned to a shelter, the possibility to distance households from each other at the shelter, and the general hygienic conditions of the shelter

(Brown et al., 2020; Wang & Chen, 2020).

Initial scope and system boundaries
In this research, disaster response during the occurrence of sudden-onset disaster is reduced in complexity to only represent evacuation to shelters. The travelling to shelters is not expected to lead to a significant increase in infections. However, being at an overcrowded shelter for numerous days *is* expected to have a great influence on the containment. Therefore, agent behaviour that influences their decision to go to a shelter is included, as well as the possibility to distribute agents over shelters and adding more shelters (Browning, 2020; CDCP, 2020).

It is also important to mention that there are different shelter types. There are emergency shelters that are used only for the duration of the natural hazard, but also transitional shelters that are used for longer periods of time when people are unable to return home due to damaged roads or houses (IFRC, 2011a, 2011b). In this study, no distinction will be made for the type of shelter.

2.2.3 COVID-19: the S(E)IR model (III)

In this section, several SIR modelling approaches are discussed, and some are presented that are related to COVID-19. In 1927, Kermack and Mckendrick (1927) published the first mathematical contribution to epidemiological studies that is now known as the SIR model, capturing the trajectory of an infectious disease. It consists of several fairly simple differential equations that calculate how many people in a population move between the 'boxes' of *susceptible*, *infected*, and *recovered*. Ever since it has functioned as a foundation for epidemiology studies (Ellison, 2020). The core of the model is that the population is divided into three compartments: the susceptible (S), infected (I), and recovered (R) population. Based on the transmission and recovery rate, the number of people in each of the compartments changes over time. The logic is often used when dealing with the spread of an infectious disease, either to predict the trajectory or to retroactively find the transmission probability of the disease (Ellison, 2020). Since 1927, many researchers have made adaptations of the SIR model, one of which is the SEIR model and includes a fourth box with an *exposed* part of the population. Adding this to the SIR model includes a latent or incubation period. This results in a delayed effect of infections and allows for more realistic epidemiological models (Kaddar et al., 2011).

In 1989, Hethcote (1989) presented three different basic epidemiological models that were derived from the original one: SIS, SIR without vital dynamics, and SIR with vital dynamics (e.g. either with a constant population, or with births and deaths included). These models built further on the relatively simple mathematical differential equations that calculate how much of the susceptible population (S) moves to the infected population (I) and then either recover (R) or become susceptible (S) again. Benefits of all classes of

SIR models are the well-developed and available numerical methods, which can also be found in appendix A.2. However, there is also criticism. Roberts et al. (2015) describe challenges arising when using this way to model infectious diseases. One of those challenges is for example being unable to implement waning immunity, or embedding more realistic infectivity profiles. How SIR is formalized in this study is described in section 4.2.5 and 4.2.6, more in-depth information about epidemiology modelling can be found in appendix B.

Since the outbreak of COVID, SIR models have been adapted to predict the spread of COVID-19 and to find the best policies to contain it. Ellison (2020) recently published the difference of modelling SIR with a population heterogeneous in their contact rates versus homogeneous. Heterogeneity makes predicting difficult, they conclude, as more parameters need to be calibrated. Those parameters are hard to estimate but equally important. In addition, long runs can be sensitive to factors that are difficult to change early in the epidemic due to a lower number of cases at that point in time. Homogeneous contact rates result in a substantial overestimation of the population that needs to be immune to achieve herd immunity.

Another research that is worth mentioning was performed by Cooper et al. (2020). They modelled the trajectory of COVID-19 using the logic of the SIR model, but did not define the total population nor kept it constant. The underlying assumption of SIR models (i.e. "the probability of contracting the disease is the same for everyone”) is its main limitation and this has been relaxed by Margutti (2020). A variety of SIR models have been developed to predict the trajectory of the spread of COVID-19 and expected hospitalizations, but these models did not include shocks to their system that might happen when a region or country has to deal with a sudden-onset disaster.

How epidemic will be used in this research
Within this research, the SIR model will be expanded to a SEIR model. This includes the *exposed* population (’E’), that is defined as the population that carries a disease and is therefore able to spread it, but not showing symptoms yet (Kaddar et al., 2011). In some SEIR modelling this is not true: the latent period is a period of time where people are unable to spread the disease but are infected. However, with COVID-19, there is evidence that people are able to spread it while not showing the symptoms yet (WHO, 2020b).

In this research, no births or deaths are included, nor the chance that people become susceptible again after recovery (implying that everyone gets temporary immunity).

Initial scope and system boundaries
The epidemic is reduced in complexity to match the same level of abstractness of the other two sub systems and thus only include the core processes. In this case, the movements of people from and to the market place is not incorporated, but only potential infection events while people interact at the

market. The social structure of people is reduced to only people they encounter when they are working and when they are at home. In reality, the social structure is more complex, including the movements of people in the public transport, having social plans in the evening, and practising team sports, among others. Due to a limited timeframe to perform this research, these aspects are not included.

2.2.4 Balancing livelihood and COVID-19 (I and III)

The economic cost of the lock-down is high. Economies around the globe experience a sharp recession due to the severe restrictions imposed by world leaders. A working paper called "The Macroeconomics of Epidemics" models the interaction between economic decisions and epidemics. Cutting back on consumption and work has the desired effect of reducing the severity of the epidemic, measured by total deaths. However, these decisions enlarge the severity of the recession (Martin et al., 2020). In addition, ending the containment measures too early was found to not have the expected effect on the economy. There is an initial surge of 17% in economic activity, but due to the parallel surge in infection rates, the economy plunges into a second and persistent recession (Martin et al., 2020). The paper concludes that ending containment too early is consistent with the evidence for the Spanish flu and it is important to resist the temptation to pursue economic gains associated with abandoning containment measures (Martin et al., 2020).

A study by Bethune and Korinek (2020) does not agree with this approach. The lack of consumption due to the closing of non-essential shops and businesses leads to a sharp decline in aggregate demand and eventually to a sharp drop in GDP. Bethune and Korinek created a model that shows a slow recovery from this drop, taking several years to fully recover. They argue in favour of a milder yet more differentiated approach, focusing the public policy measures on the infected only to contain the disease. By aggressively containing the disease only when confirmed, the total social cost is lower.

Piguillem and Shi (2020) have also tried to find the optimal response to an infectious disease like COVID-19 and found that, despite the criticism of current policies, the extreme measures of stay-at-home orders and social distancing lead towards the best outcome. The overall desire of reducing costs decreases the severity of some of these measures, but extends them for longer. They find that testing can substantially reduce need for indiscriminate quarantines. Even in the most optimal situation, livelihood drops by 40% (Piguillem & Shi, 2020). Livelihood here refers to the means of securing the basic necessities of life and is associated with communities and households, not with the state of the (local) government.

Livelihood in a trade-off with disease transmission was also researched recently with the objective to control fatalities whilst minimizing the cost of the lock-down (Alvarez et al., 2020; Martin et al., 2020). They found that the optimal policy depends on uncertain values, such as the fraction of susceptible and infected people in the population, the fatility rate, and assumed value of statistical life. They stress the influence of uncertainties on the outcome of the best policies and the difficulty to decide in these circumstances.

A different perspective was brought by Berger et al. (2020), who tried to understand the role of testing and case-dependent quarantine. They found that testing at a higher rate in conjunction with targeted quarantine policies can smoothen the economic impact of the pandemic, e.g. flatten the curve in a useful manner. In a study by Stanford University, they found that the maximum amount of consumption that a utilitarian welfare state would be willing to trade off to avoid the deaths associated with the pandemic lies between 41% and 28%, depending on the actual death rate of the disease (Hall et al., 2020).

The literature on the trade-off of livelihood versus COVID-19 consequences displays clearly how important the underlying context is and why the economy is connected to the livelihood as defined in this study. A better economy translates into higher financial capital of individual which translates into higher livelihood. There are many uncertainties that change depending on the policies at place, the response to COVID-19, and the political and financial situation.

2.2.5 Consecutive hazards: epidemics and sudden-onset disasters (II and III)

A study by Spiegel et al. (2007) researched the historical overlap between epidemics, complex emergencies, and natural disasters. They found that, commonly, after the occurrence of a natural disaster the chance for an outbreak of a disease increases significantly. This information is relevant because in the current epidemic, the order is reversed and little is known about the negative impact of a natural sudden-onset disaster. Another study from 2007 focused on the relationship between natural disasters and communicable diseases (Watson et al., 2007). They found that risk factors for outbreaks after disasters are associated primarily with population displacement. Other factors of importance are availability of water, crowding, the underlying health status of the population, and the availability of healthcare services. Typically with some weeks delay there is an increase in infections and potential for disease transmission. More recently, the Global Facility for Disaser Reduction and Recovery (GFDRR) published how to learn from multi-hazard, and stressed one important lesson: the necessity to understand the vulnerability of individuals and communities in order to prepare for a reasonable worst-case scenario based on informed long-term planning (Rogers et al., 2020).

These results illustrate some important findings: firstly, there is not much historic literature on the effects of an epidemic chronologically preceding and coinciding with a natural disaster. There is information missing about the effect of policies that could work to counter the expected negative effects such as a surge in infections or economic plunge. Secondly, current research about multi-hazard stresses the need to understand developments an individual and community level in order to implement adequate policies.

2.2.6 Livelihood and disaster response (I and II)

A deeper dive into the combination of these two sub system is left out of scope. The main purpose of disaster response is to save lives and preserve livelihood of these people as they assist evacuees until they are able to resume their regular lives again. These two sub systems' goals are therefore more or less aligned. This is not a trade-off so this will not be discussed here.

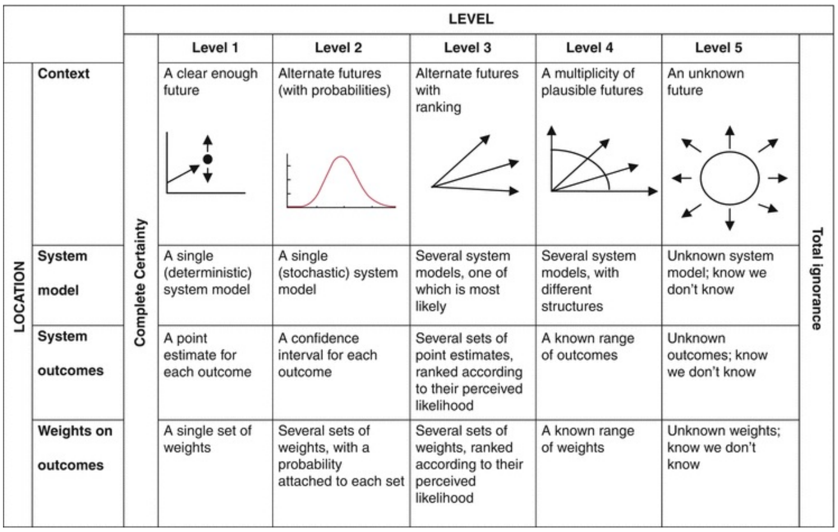
2.3 REVIEW OF EXISTING MODELS

A variety of models have been created since the COVID-19 outbreak, ranging from conceptual models about China and vulnerability in African countries, to macroeconomic models about the global economic impact (Kucharski et al., 2020; Lin et al., 2020; McKibbin & Fernando, 2020). What most of these models have in common is that they cannot predict the future very well and show a wide variety of possible outcomes (Roda et al., 2020).Roda et al. (2020) compare existing COVID-19 models and find that predictions using more complex models are often not more reliable that simpler models, due to the uncertainty that is associated with these complex models.

2.4 DEEP UNCERTAINTY

There are many uncertainties at play. Not only due to information that is unavailable such as the accurate death or transmission rate, but also due to inaccurate information. Inadequate testing leads to inaccurate data. Even countries that are ranking at the top of most tests per capita are assumed to underestimate the total amount of infected cases (Malley & Malley, 2020). Also, the virus seems to behave in localized fashion, with little discernible pattern to date. On top of that, a puzzling finding is that neighbouring countries with similar demographics have vastly different numbers of infections (Malley & Malley, 2020). For example, as measured in August 2020, per 100.000 inhabitants, Dominican Republic counts 184 infections whereas Haiti counts only 30. The extent of these variations and the difficulties in explaining them show just how much about COVID-19 remains unknown. Filling in those gaps is crucial for both people's physical health and their economic security.

A global pandemic with restrictions on freedom of movement is unprecedented and surrounded deep uncertainty, based on the definition displayed in figure 2.2 (W. E. Walker et al., 2013). There are many plausible and unknown future scenarios, there is a wide range of outcomes and a wide range of weights associated with the various parameters that are at play.



			LEVEL				
LOCATION	Complete Certainty	Level 1	Level 2	Level 3	Level 4	Level 5	Total ignorance
Context		A clear enough future	Alternate futures (with probabilities)	Alternate futures with ranking	A multiplicity of plausible futures	An unknown future	
System model		A single (deterministic) system model	A single (stochastic) system model	Several system models, one of which is most likely	Several system models, with different structures	Unknown system model; know we don't know	
System outcomes		A point estimate for each outcome	A confidence interval for each outcome	Several sets of point estimates, ranked according to their perceived likelihood	A known range of outcomes	Unknown outcomes; know we don't know	
Weights on outcomes		A single set of weights	Several sets of weights, with a probability attached to each set	Several sets of weights, ranked according to their perceived likelihood	A known range of weights	Unknown weights; know we don't know	

Figure 2.2: Classification problems (W. E. Walker et al., 2013)

In addition to the uncertainties related to COVID-19, there are also many uncertainties regarding sudden-onset disasters like hurricanes and typhoons. Even though forecasting has improved greatly over the years, predicting the trajectory, location, severity, and impact remains a challenge.

The difference between uncertainty and risk is that probabilities are known when calculating risk, whereas with uncertainty the probabilities for an event nor the impact of said event are unknown. In addition, decision-makers and stakeholders do not know or cannot agree on the outcomes of interest, the system under study, or future developments (J. H. Kwakkel et al., 2015). When modelling in this context, the key is to explore and adapt as well as identify robust strategies. Robust decision-making offers insights into conditions under which problems occur and makes trade-offs transparent. Robust policy interventions are necessary due to deep uncertainty that surrounds both the COVID-19 pandemic and compounding risks.

2.5 SYNTHESIS AND ACADEMIC KNOWLEDGE GAP

Above literature review displays a wide variety of literature available on the relevant socio-technical (sub) systems of livelihood, disaster response, and epidemic modelling, as also displayed in table 2.1. Some research is available on the tradeoff between two of the three systems, where most recent literature covers the tradeoff between *lives* (in this research the epidemic modelling) and *livelihood*. Warnings about compounding risk become more prevalent as the COVID-19 pandemic continues, and creating greater insight in the mechanisms of these three sub systems is both necessary and relevant in order to find robust policies that aid in improving the well-being of people in developing nations.

An integration of these three systems using a exploratory modelling approach has not been done before. It has not been researched what the systemic effects of the occurrence and aftermath of a sudden-onset disaster are on the trajectory of COVID-19 whilst continuously monitoring the livelihood of people. The feedback effect of temporarily lifting restrictions to perform relief efforts is unknown, yet it is highly important to identify strategies that help governments and humanitarian actors make informed decisions. This research aims to find the behavioural and systemic effects of sudden-onset disasters on the severity and duration of the pandemic in order to develop a robust strategy.

The scientific contribution of modelling compounding risk is that these three systems have not been combined before. It is impossible to capture all complexity that goes into either of these systems nor to capture all details of how the systems are integrated with each other, but it is important to identify the main mechanisms of each system and to see what trends can be discovered and what general direction policies should go into in order to maintain or achieve a general level of well-being in areas where people deal with these risks. Using an ABM approach allows for discovering emergent behaviour of the system, which is particularly of interest when it is unclear what types of higher order effects may exist. The complexity of each of the sub models is reduced to the same abstraction level to ensure a valid and useful model.

3 RESEARCH DESIGN

In this chapter, the research approach is discussed and the sub questions derived from the main research question are presented. Afterwards, the methodologies per sub question are discussed and the last section displays a visualization of the research with the Research Flow Diagram.

3.1 MAIN RESEARCH QUESTION

Derived from the academic knowledge gap, the main research question is formulated as follows:

What robust policy interventions can be identified that balance livelihood of rural communities and the trajectory of COVID-19 during the response phase to a sudden-onset disaster in developing countries?

3.2 SUB QUESTIONS

In order to find the answer to the main research question, the following sub questions are posed during this research. The next section will elaborate on the methodologies used to answer these sub questions.

1. What factors during the response phase of sudden-onset disasters affect the COVID-19 trajectory and livelihoods of people?
2. In what way can the balance between livelihood and the trajectory of COVID-19 in the response phase of a sudden-onset disaster be conceptualized and formalized?
3. In what way can the formalized model be implemented in an agent-based model?
4. What is the effect of policy interventions on the interplay between livelihood, sudden-onset disasters, and COVID-19?
5. How can the findings be generalized into policy advice for decision-makers?

3.3 METHODOLOGIES

SQ1: What factors during the response phase of sudden-onset disasters affect the COVID-19 trajectory and livelihoods of people?
This first research question will be answered by doing an extensive literature research to find current literature on each of the individual sub systems as well as by a literature review on the combination of these sub systems. In addition, modelling approaches will be looked into and models that capture either one or more component will be studied to find relevant concepts as a starting point for the conceptualization. Furthermore, the expertise available at 510, the data initiative of the Netherlands Red Cross, will be used. Their network and relations with other Red Cross facilities will be utilized to identify the factors most important to include. The answer to this sub question can be found in chapter 2

SQ2: In what way can the balance between livelihood and the trajectory of COVID-19 in the response phase of a sudden-onset disaster be conceptualized and formalized?
To answer the second sub question, all elements need to be conceptualized. The three sub systems of livelihood, sudden-onset disasters, and COVID-19, are first conceptualized separately, before being integrated with each other. In order to achieve this, the information found while addressing the first sub question will be used as the starting point for the development of Causal Loop Diagrams. These diagrams provide an overview of the most important factors that exist within in a system and display clearly what the causal relations between factors are. Moreover, is also gives insight in existing feedback loops exist within these systems. Afterwards, the Causal Loop Diagrams are translated into flowcharts that support the formalization process. For each of the core processes within the sub systems a flowchart will be constructed, before a flowchart of the aggregate model will be made. Finally, a UML diagram will be made. UML diagrams visualize the design of the integrated systems and presents an overview of all that will be implemented in the agent-based model. Before starting with building the model, the XLRM framework will provide an overview of the entire model. It is a tool that helps structuring the information gathered during the literature review, conceptualization, and formalization into policy levers (L), performance metrics (M), relationships (R), and external factors (X) (Nikolic et al., 2019). This framework aids to defining and finalizing the conceptual and formalized model. The answer to this sub question can be found in chapter 4. The complete XLRM framework can be found in chapter 5.

SQ3: In what way can the formalized model be implemented in an agent-based model?
This step in the research requires building an Agent-Based Model. To achieve this, Mesa will be used. Mesa is a Python based open-source package developed for building agent-based models. It is further discussed in chapter 6, which entails the model implementation. As in the previous steps, the model will be build in a modular fashion. That means that the different sub systems will be implemented as model components that can be run separ-

ately from each other. This contributes both to the verification and validation of each of these models, as to the reusability of the code. An interface will be developed that allows users of the model to experiment themselves with the effect of input parameters. The answer to this sub question can be found in chapter 6.

SQ4: What is the effect of policy interventions on the interplay between livelihood, sudden-onset disasters, and COVID-19?
In this step, an experimental design will be developed that will test the effect of several policy interventions on the base model. Scenarios will be designed that aim to illustrate the range of possible settings implied by the underlying system uncertainties. The policy levers that have previously been identified will be used in the scenario design that address the vulnerabilities and uncertainties in the model. The EMA (Exploratory Modelling and Analysis) workbench will be used for the experimentation, which is further introduced in the next section. The outcomes of the experimentation will be used as input for the data analysis and to draw conclusions from. The answer to this sub question can be found in chapter 8.

SQ5: How can the findings be generalized into policy advice for decision-makers?
The results from running the scenarios will be analysed, after which the objective is to translate the conclusions into policy advice for decision-makers. The purpose of this last sub question is to summarize the findings based on the identified robust policy interventions. This will be translated into an approach that can be used for informed decision-making for local governments that deal with sudden-onset disasters during the COVID-19 pandemic. In this step, there will also be reflected on the research approach and discussed whether this approach would be suitable in other situations, too. The answer to this sub question can be found in chapter 9.

3.4 RESEARCH APPROACH

First, Agent-Based Modelling is discussed, followed by a section about Modelling Under Deep Uncertainty and Exploratory Modelling and Analysis (EMA), and finally about the XLRM framework. EMA provides support for models that are made in various modelling packages, including ABM, and aids in analyzing the uncertainties and findings of the ABM model. The XLRM framework is a tool for robust decision-making and provides an overview of the complete system that will be implemented.

3.4.1 Agent-Based Modelling

One uses a modelling approach when the main goal is to gain a deeper understanding of a system, and when the goal is to explore (the effect of) behaviour or predict possible futures (Nikolic et al., 2019). Models are simplifications of reality. British statistician George E.P Box said: "all models are wrong, some are useful" which is an apt description for those familiar with modelling. There are roughly two types of approaches: bottom-up and top-down. Top-down modelling requires a good understanding of the system in its entirety, and of the interaction of the different components. For more complex matters, such as modelling socio-technical systems, a bottom-up approach is more useful. For this study a bottom-up exploratory modelling approach thus suits best, especially given the many uncertainties regarding compounding risk of COVID-19 and sudden-onset disasters.

Agent-Based Modelling is a modelling approach that enables "disaggregation of systems into individual components" that each have their own rules and characteristics (Crooks & Heppenstall, 2012). It is a bottom-up approach where patterns and combinations of rules are created that together make up recognizable systems. Agent-based modelling simulates the behaviour and interactions of autonomous entities over time. Axtell (2000) defined these so-called agents as objects that have rules and states that they follow each discrete step of the simulation. Advantages of ABM are that spatial and network attributes can be incorporated and that both the path and the solution of the system can be captured, revealing emergent behaviour of the system (Thomalla et al., 2006).

In 2014, Masad and Kazil (2015) developed an open-source package called Mesa. It allows for building agent-based models in an alternative way, using browser-based visualizations and frameworks from other languages such as Netlogo. The results can easily be analyzed using Python's data analysis tools. Since Mesa was developed in 2014, it is continuously enhanced. Some features are still in development and some need further improvement. In 2015, some of the important next steps included servers-side visualizations, the documentation, inter-agent networks, or tools for reading and writing model states to disk. Geospatial simulations are also yet to be launched (Masad & Kazil, 2015). Chapter 6 will discuss more advantages and limitations of Mesa in the context of the model implementation.

3.4.2 Modelling Under Deep Uncertainty

The agent-based model allows for exploration of agent behaviour and to gain insight in emergent behaviour of the socio-technical system. After the conceptual model is formalized in Mesa, experiments will be performed to identify underlying uncertainties that matter. These uncertainties will be used as input for *Exploratory Modelling and Analysis (EMA)*. EMA is based on the assumption that human reasoning alone is incapable of handling complex systems and deeply uncertain contexts. Computer assisted reasoning is needed additionally (J. H. Kwakkel et al., 2015).

The implication of using EMA for designing policy interventions is that these should be flexible: one should be able to dynamically adapt them over time in response to how the future unfolds. It is difficult to predict the timing of the next sudden-onset disaster, nor the precise location, or severity. Therefore, the outcome of this study does not dictate the right solution but facilitates learning about the problem and potential courses of action. Robust decision-making focuses on illuminating vulnerabilities of possible strategies. A prerequisite is that all parties agree that they do not know or agree on the likelihood of alternate futures or how actions are related to consequences (J. H. Kwakkel et al., 2015). To quote Nikolic et al. (2019): "the goal of modelling is insight, not numbers".

3.4.3 XLRM framework

The XLRM framework is a tool for *Robust Decision-Making (RDM)*. RDM is different from conventional sensitivity analysis as the order is the other way around: the objective is to find strategies which perform well regardless of the most significant uncertainties. Figure 3.1 displays the framework, which shows the impact of policy levers (L) on the performance metrics (M) given the relationships in the system (R) and external factors (X). The policy levers are the outcome of the preceding analysis and are actions by decision-makers that can manipulate the outcome. The performance metrics are the KPIs of the model. The external factors form the different scenarios that are to be researched and are outside the control of decision-makers, and finally, the relations of the system will be modelled in the aforementioned agent-based model.

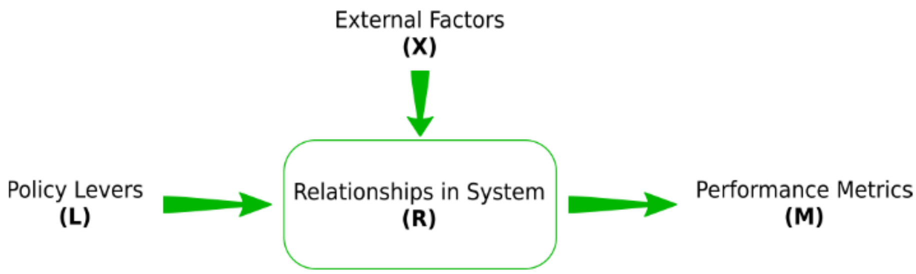


Figure 3.1: XLRM framework from Nikolic et al. (2019)

3.5 RESEARCH FLOW DIAGRAM

In figure 3.2, the Research Flow Diagram is displayed. Every block shows one phase of the study, including the sub questions answered and methodologies used.

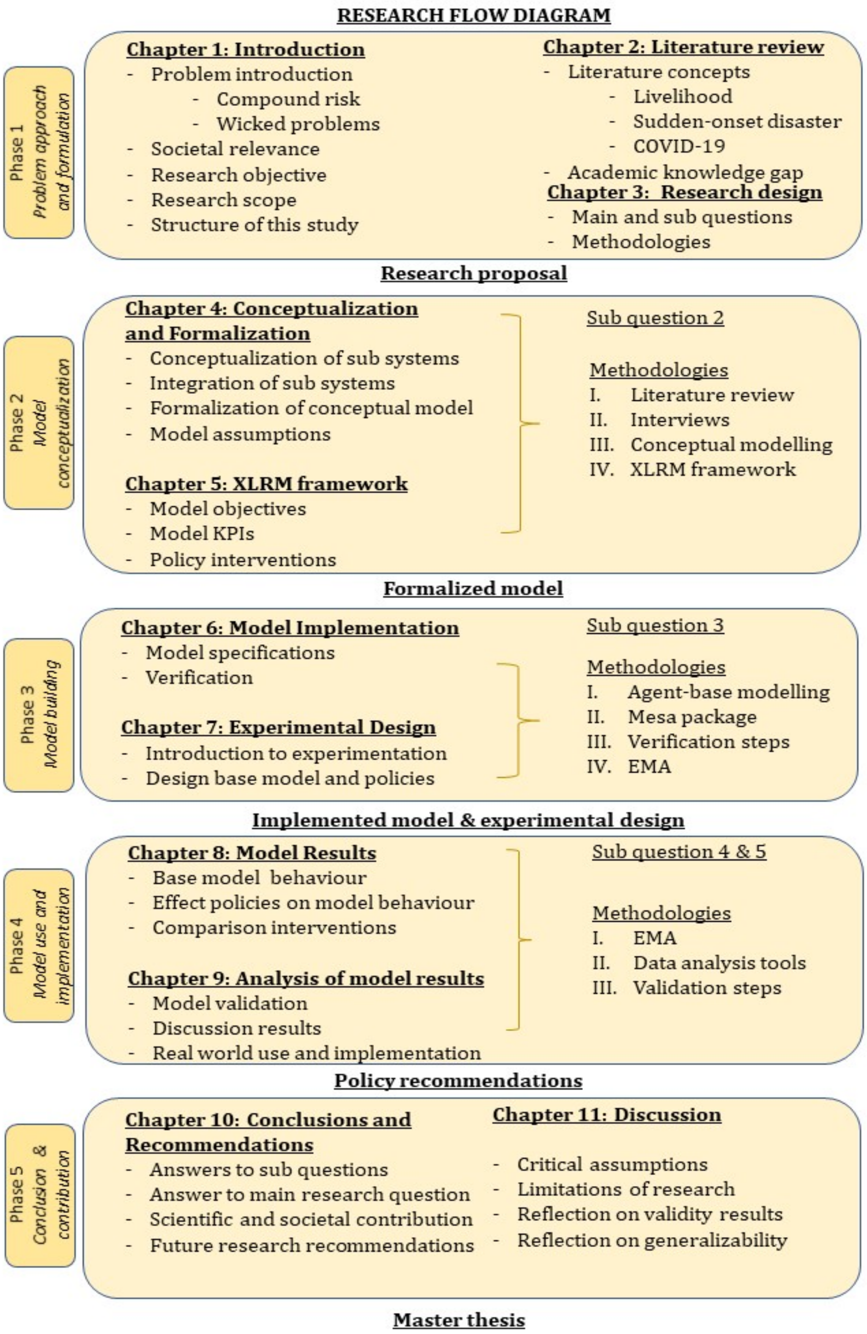


Figure 3.2: Research Flow Diagram

4 CONCEPTUALIZATION AND FORMALIZATION

In this chapter, the following sub question is addressed: *SQ2: In what way can the balance between livelihood and exposure to COVID-19 in the response phase of a sudden-onset disaster be conceptualized and formalized?*

In order to answer this question, this chapter contains a conceptualization of the three sub systems, followed by its formalization. Before discussing the developed causal loop diagrams, the introductory section entails more information about the use of conceptualization and formalization. Afterwards, causal loop diagrams are constructed that are then reframed into flowcharts representing the flow of actions and where the systems interconnect. The formalization of each of these sub systems is presented together with the conceptualization. In reality, the formalization was performed *after* completing the integrated conceptual model, however, to better understand the formalization decisions, it is decided to present these phases in this particular order. Only those formalization processes considered at the core of each of the systems are discussed. The chapter ends with an overview of the assumptions made during both the conceptualization and formalization.

4.1 INTRODUCTION CONCEPTUALIZATION AND FORMALIZATION

Systems thinking is used to tackle wicked policy problems, as it helps policy makers in understanding the system at hand, which can be translated into policy action (Haynes et al., 2020). In the context at hand, there are three different sub systems to analyze and understand before integrating them: (1) the *livelihood* system, where a community is in a "normal" state and a microeconomic marketing mechanism is mimicked where households work to sustain themselves, (2) the *COVID-19* system of how an epidemic spreads, and (3) the *sudden-onset disaster* system, which includes the impact of a hazard and subsequent evacuation. Afterwards, there is also the integration of the three systems where the interaction between components is displayed.

The way of structuring the model is influential for the outcome. Modelling complex systems is inherently subject to so-called observer dependence, describing the fact that a model builder (the observer) "cannot be fully separated from the system" (Nikolic et al., 2019). It is therefore important to understand how the processes are modelled. In this section, five of the core processes are discussed in more detail. These processes are considered essential due to their delay effects or feedback loops with other processes, and are graphically represented in the flowchart (4.9) and causal loop diagram (B.10).

4.2 SUB SYSTEMS CONCEPTUALIZATION AND FORMALIZATION

For each of the three sub systems the conceptualization is discussed first, after which the formalization is presented. For the conceptualization causal loop diagrams were constructed that help providing insight by depicting the complex socio-technical sub system with causal relations between the different components of a sub system. The components can affect each other positively or negatively. The CLDs display how a change in one factor can affect an entire system, also through the use of feedback loops and delays (Kirkwood, n.d.). The causal loop diagrams constructed for the corresponding sub system can be found in appendix B.

4.2.1 Livelihood conceptualization

Armah et al. (2010) studied the effects of floods on livelihoods of farmers in northern Ghana and captured those dynamics in a causal loop diagram that formed the starting point for this conceptualization. Their diagram is displayed in figure 4.1 and can also be found in appendix B with additional explanation. As discussed in chapter 2.2.1, livelihood refers to financial capital in the context of this research and is used to depict whether households are able to provide basic necessities for themselves. This research uses a similar level of abstraction and the component starvation is used in a similar fashion to represent livelihood. Armah et al. (2010) depict several important relations in their CLD, such as the relations between household income and starvation. The most important loop describes the causal relations between profits from trading at the central market and household income, of which the former is dependent on two main factors: food production at farmlands and the *number of people at the market*. The latter will become important when integrating this system with the other two sub systems, the former is left out of scope in this research. The profits influence the household income and livelihood positively.

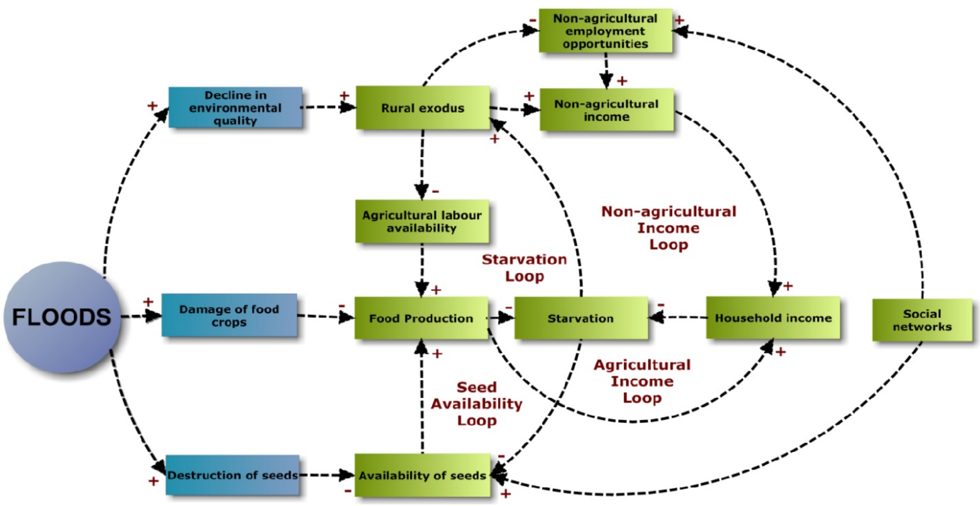


Figure 4.1: CLD floods and starvation (Armah et al., 2010)

The first CLD constructed for this research can be found in figure 4.2 and displays the mechanism where households make a living by producing food on their farmlands and trading goods and services at the central market. Armah et al. (2010) focused on minimizing starvation, which for the CLD for this sub system has been replaced by livelihood. Livelihood is affected by household income, which in turn depends on trading goods and services on the market. The more of those goods available, depending on the food production, the more the inhabitants can trade. Apart from this *livelihood loop*, the effect of a natural hazard is shown by damaging houses and farmlands. Damaging houses starts the evacuation process, where the severity of the hazard determines how many people are displaced and consequently need shelter (Simonovic & Ahmad, 2005). Their conceptual model can be found in B.3.

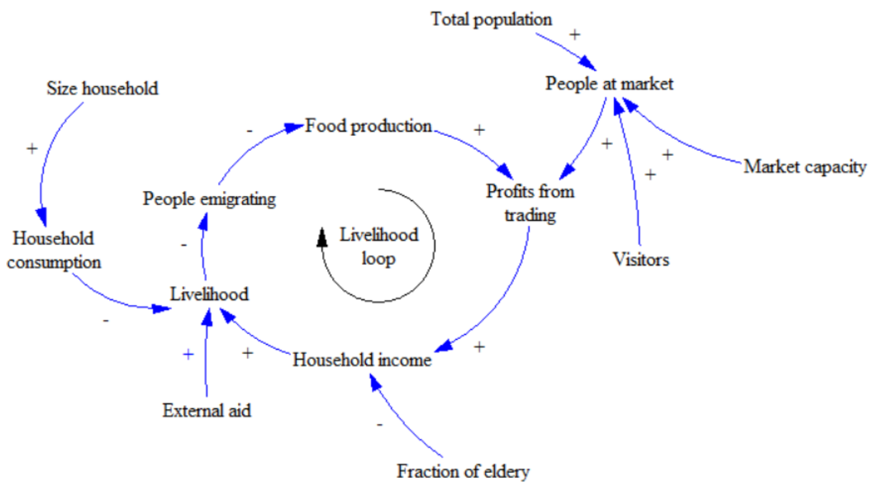


Figure 4.2: Livelihood causal loop diagram

Important scoping decisions regarding livelihood
In order to comprehend the livelihood component, it is important to understand what the central market represents that is at the core of this sub system.

As previously described in chapter 2, livelihood is reduced to the daily gathering and spending of livelihood per household. The central market represents the entirety of jobs and incomes of the community: when agents do not have access to this market, it is not possible for them to acquire livelihood. Livelihood at the central market will never run out of stock, but can drop below the threshold or into negative livelihood, which means that the shortage of livelihood can be traced. The reason behind this conceptualization is to capture the effect on the average livelihood in the community and to what extent external aid or other policy interventions are necessary, without focusing on how this livelihood comes about. From this understanding of the central market, three important assumptions come forth.

Firstly, even though people in shelters have restricted access to the market, they do not suffer from a decline in livelihood due to aid organizations providing basic necessities for those residing in shelters. This is a simplification and does not consider that their livelihood may decrease due to damaged properties and home break-ins while they are away (CDC, 2020b).

Secondly, in reality, the damaged farmlands impact the food production negatively, resulting in less availability of goods and services at the central market. The marketing mechanism in this conceptualization only mimics basic in- and outflow of livelihood and does not account for changes in prices caused by scarcity. The pricing in the model is not influenced by the impact of the sudden-onset disaster, only by the lockdown restrictions. Moreover, the agents residing in shelters are unable to join the workforce and cannot assist any harvesting activities that might be necessary. Both these assumptions simplify the livelihood system and result in more positive average livelihood trends, which should be taken into account during analysis.

Lastly, the supply of food is not included in this part of the conceptual model and livelihood does not run out of stock. When a household drops below the livelihood threshold this is caused by lack of access to the central market and not by issues with the supply side. This allows for identifying negative trends in livelihood due to the lockdown but does not account for the supply side of their necessities. In Bangladesh resources sent by humanitarian organizations have been banned due to fear of it being infected with COVID-19 (Ober, 2020).

4.2.2 Livelihood formalization

The livelihood component of the model consists thus of representing this micro-economic marketing mechanism. This micro economy in the community is brought back to a single central market in the model which represents the location where agents go to gain an income. Their profession, which can either be farmer or non-farmer, does not affect the decision to go to the market or not. The trading mechanism represents how agents and their corresponding households gain livelihood at the marketplace.

Several distinctions influence the degree of livelihood increase. Agents can be either farmers or citizens, where farmers make up for 65% of the community population (Dy, 2017). The profession-specific gains in livelihood are based on current salaries in rural communities in the Philippines (SalaryExplorer, 2020; Sanchez, 2019). Non-farmers earn twice as much as farmers. Table B.1 displays the formalization of livelihood increase. Apart from profession, the gain of livelihood is determined by the severity of the lockdown, which, among others, allow for visitors to the marketplace or not.

To sum it up, the following two characteristics are influential for this process:

- **Profession**: farmer or citizen
- **Visitors**: allowed or not allowed
- **Requirements**
  - Working age (18-65)
  - In need of livelihood
  - Market capacity allows it

The composition of the community is not further specified with regards to the profession. In poor and rural, coastal communities, a significant proportion of these farmers would be fishers or work at aquatic farms (Ober, 2020). The distinction between these different forms of farming is left out of scope. A reflection on this decision can be found in chapter 9.

The trading mechanism is graphically displayed with flowchart that can be found in appendix B.4.1. At each discrete time step agents eligible for the trading process go to the market. The modelling decision to only let agents in need of livelihood go to the market was made to ensure that the livelihood component in "regular" circumstances (without epidemic) would present stable behaviour.

4.2.3 Sudden-onset disaster conceptualization

The causal loop diagram of figure 4.3 depicts the factors at play during the evacuation in the disaster response phase and was based on research from Simonovic and Ahmad (2005). They constructed a causal loop diagram of people evacuating during floods which can be found in B.9. Simonovic and Ahmad (2005) identified three groups in the model: the population under threat, the population in the process of evacuation, and those who reached safety. Factors that contribute to these movements are, among others, the recognition of danger, warnings, evacuation orders, and conditions of the flood.

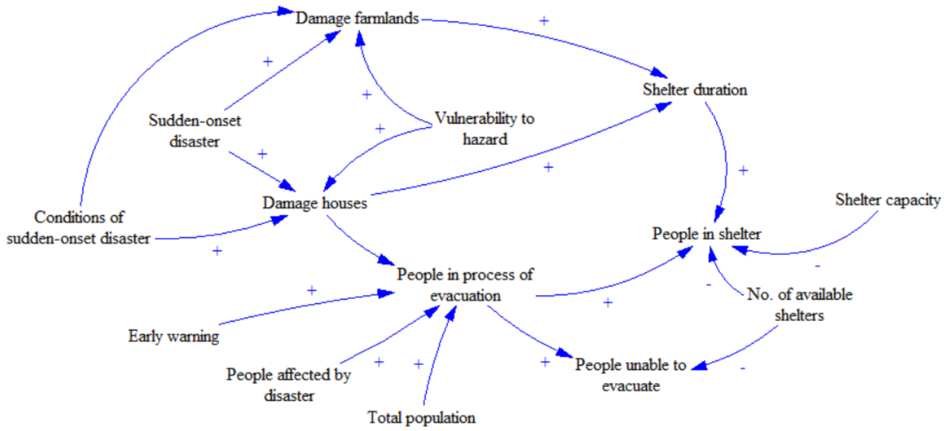


Figure 4.3: Evacuation and livelihood CLD

Based on this research, the causal loop diagram of figure 4.3 was developed. It depicts the factors that influence the evacuation process. The sudden-onset disaster damages houses and farmlands such that evacuation is necessary for people affected by its impact. This does not influence the livelihood loop directly, that was introduced at the start of this section, as it is assumed that the people staying in shelters receive care for the duration of their stay. The number of people in the shelter is dependent on regulations from the (local) government, the number of shelters, and the issuing of an early warning. The latter has been researched by the International Federation of Red Cross and Red Crescent Societies who published extensive research focused on the mechanisms for rapid decision making and the benefits of early warning and early action (Reliefweb, 2014). The actions that are possible due to early warnings reduce the loss of life (IFRC, 2017), at the shortest timescales this is mostly evacuation. With more time, early harvesting (in the right season) is also performed.

Important scoping decisions regarding disaster response
As mentioned briefly in the previous section, there are more early actions possible than early evacuation when a sudden-onset disaster is approaching. Early harvesting is an important one that contributes greatly to reducing the damages as it aims to salvage as much as possible from the yields. This early action is not taken into account in this research, as it is unclear how the protocols have changed in the lockdown situation. The Philippines has restricted farmers from visiting their rice fields in the lockdown, which would prevent early harvesting from happening (Conde, 2020).

Another assumptions regarding the sudden-onset disaster component is the lack of seasonality. The moment of impact matters for farmers as they have a specific moment in the year where they can plant or harvest their crops. If this coincides with the impact of the sudden-onset disaster, the loss of livelihood is way greater at this time as the impact may last a year long. This is not the case for fishers as they depend less on the season for their activities.

Lastly, people are released from their shelters as soon as possible. This is based on the findings of Ober (2020) as people in Bangladesh and India are afraid of staying due to the perceived risk of COVID-19. Whether this is the best approach is questionable, as undetected cases of COVID-19 spread quickly through the rest of the community upon return from the shelters. Testing people and using the shelter as quarantine facility before reintegration with the rest of the community would present a possible solution, but is, due to the aforementioned reason, not included in this research.

4.2.4 Sudden-onset disaster formalization

As it is the goal of this research to better understand the model behaviour when both COVID-19 *and* a sudden-onset disaster occur, the occurrence of the hazard is modelled to happen within the first few days of the model run. The impact of the hazard depends on the model variable *severity* and lies between category 1 and 5, as displayed in table 4.1. The numbers are drawn from natural hazard frequency and severity data of the Philippines provided by the Philippine Red Cross (Philippine Red Cross, 2019).

Hazard category	**Frequency**	**Probability**
1	frequent	0.4
2	frequent	0.3
3	less frequent	0.15
4	rare	0.1
5	extremely rare	0.05

Table 4.1: Impact frequency table hazard (Philippine Red Cross, 2019)

This severity influence the radius of impact and thus the amount of agents affected by this event. In determining this radius there is not accounted for false prediction, meaning that all agents that get the order to evacuate are indeed in need of evacuation.

The model accounts for two different evacuation options, depending on whether the government issues an early warning or not. If there *is* an early warning, the affected agents are all equally distributed over the available shelters in a coordinated fashion. If not, the agents calculate their distance to the nearest shelter and pick the closest shelter as destination. If the shelter is full, they go the next nearest shelter. The pseudo-code for these evacuation strategies can be found in appendix C, as well as the flowchart that graphically displays the flow of actions in this model component. These evacuation strategies are based on the assumption that the evacuation process would be organized with consideration for the pandemic and social distancing, as there are plenty of examples that the capacity of shelters has been reduced and only a handful of families are allowed to stay in one place (UN news, 2020). The Centers for Disease Control and Prevention made a statement regarding different shelter locations during the pandemic, but this is only possible with enough time beforehand (CDC, 2020a).

4.2.5 COVID-19 conceptualization

The third sub system contains the causal relations of the COVID-19 component and is based on the research of Bradley et al. (2020). They found a reinforcing loop in the spread of Ebola that can be generalized to other contagious diseases. The loop consists of the following factors and causalities: *exposure to COVID-19* increases the *number of infectious people*, which increases the *risk of transmission*, again reinforcing the exposure to COVID-19. This loop is depicted in figure 4.4. The CLD developed by Bradley et al. (2020) can be found in appendix B.6 with more information about their research.

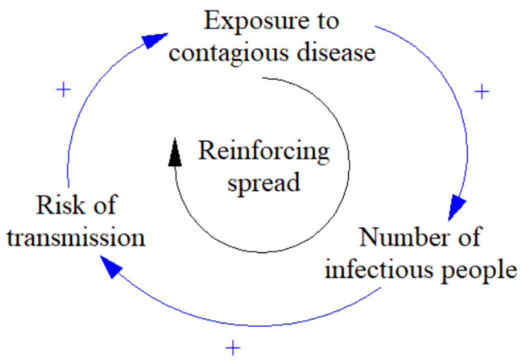


Figure 4.4: Reinforcing spread of contagious disease (Bradley et al., 2020)

The causal loop diagram constructed for this research can be found in B.8 and is simplified compared to the version of Bradley et al. (2020). It does not consider some of the complexity of reality, with concepts such as 'issue fatigue' or protests and outrage from the people. This simplification matches the reduction of complexity of the other two sub systems. Choices are based on including components that are most relevant in combination with livelihood and sudden-onset disasters. Two important policy interventions are included in the causal loop diagram: the awareness campaigns and the social distancing policies. Both will be further introduced and discussed in the chapter 5, section 5.2.3 and 5.2.7.

The reinforcing loop from figure 4.4 is linked to a lockdown loop. The two loops interconnect due to the number of infectious people. This number is monitored by the government and if it exceeds a certain threshold, a lockdown is imposed with varying degrees of severity and duration. The lockdown ensures that the frequency of interpersonal contacts decreases, which leads back to the reinforcing loop as this decreases the exposure to COVID-19.

Important here is that this causal loop diagram differs from the diagram that depicts the SEIR model. The SEIR model conceptualization is depicted in figure 4.5. This figure depicts SEIR with all its features, whereas in this study the reinfection rate is not included. How these two conceptual models are integrated with one another is explained in the next section. A noteworthy distinction to be made here is that the *exposure* to COVID-19 in the SEIR approach refers to people that are carrier of a virus but are not showing any symptoms yet (e.g. during the incubation time). The *exposure* mentioned in the CLDs refers to the time that people are exposed to a number of other people that are carrying a disease, which is in accordance with the definition from Bradley et al. (2020).

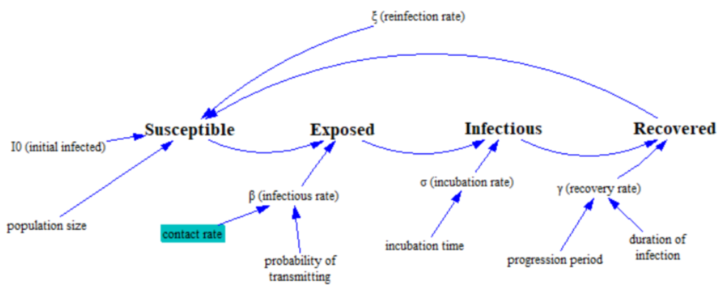


Figure 4.5: SEIR conceptualization (reinfection rate 0)

Important scoping choices regarding COVID-19

Firstly, the reinfection rate is set to zero, meaning that there is no chance for recovered people to become susceptible again, and thus gaining immunity for the remainder of the model run. Even though there is mixed evidence regarding immunity, within the time span of this model this is highly unlikely.

Secondly, the exposed population in this model is also considered to be contagious. There is again mixed evidence regarding this assumption, but based on the publications of the WHO contagiousness from the first moment of infection was included, even though the symptoms appear later (WHO, 2020c).

Lastly, it is important to note that due to the novel character of this study and the relative little information available regarding COVID-19, certain aspects of the spread of the disease have not been included. Silva et al. (2020) published their research on COVID-19 in October 2020, accounting for asymptomatic infected people, the notion of "super spreaders", and different levels of contagiousness during the incubation period. These are all valuable contributions to achieving more accurate infection numbers. However, since the granularity in both space and time for this study is limited, these additions are not included. It is hard to determine the possible effect of these additions, as the asymptomatic infected people would lead to a reduction of the known infection numbers whereas the super spreaders would increase them. However, the aforementioned assumption does account for some asymptomatic infections.

4.2.6 COVID-19 formalization

The formalization for the epidemic was developed in collaboration with 510 and TNO, who built a model to forecast hospitalization for COVID-19 cases in the Philippines (Margutti, 2020), published in July 2020. Their expertise on accurately conceptualizing and formalizing epidemiological modelling contributed to the current formalization in the ABM model.

As introduced in the literature review in chapter 2, section 2.2.3, modelling the spread of COVID-19 was based on the SEIR modelling approach. Figure 4.6 presents an overview of the differential equations that are used in this approach. The differential equations represent the change of population over time from one 'compartment' to another and depend on parameters $\beta = transmission\_rate$, $\sigma = transition\_rate$, and $\gamma = recovery\_rate$. The $transmission\_rate$ β comprises of two factors: the chance of giving the disease to another person and the contact rate. The contact rate is what most social distancing policies aim at decreasing.

$$\frac{dS}{dt} = -\frac{\beta SI}{N}$$

$$\frac{dE}{dt} = \frac{\beta SI}{N} - \sigma E$$

$$\frac{dI}{dt} = \sigma E - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

$$N = S + E + I + R$$

Figure 4.6: SEIR differential equations

This modelling approach is generally used to predict the spread of disease for an entire population. Those are deterministic models because the transmission rate, depending on both the contact rate and the chance of transmission, is the same for the entire population. Stochastic models exist as well. For example, Hunter et al. (2018) researched the spread of an airborne disease using the SEIR approach in an agent-based model. Their approach is similar to what has been used in this study, including factors as population density and varying contact rates.

Formalizing this approach in the agent-based model posed a challenge because using above equations for the entire population would not account for the individual behaviour of agents and emergent behaviour. Twice per day agents encounter others and have the possibility to contract COVID-19. Based on conversations with 510, this is formalized as follows: the probability to contract COVID-19 is based on the number of people that an individual encounters in the span of a day. The health status (S, E, I, or R) of each of the encountered agents is stored and later used for calculating the probability that an agent contracted COVID-19 that day. In these calculations, the number of exposed people is included to the number of infected, because agents are contagious in the incubation time of COVID-19, which is considered an important factor for the spread of the disease (WHO, 2020f). Therefore, the equations presented in figure 4.6 are applied on the level of individual agents. In particular, the infection probability is retrieved only from the set of encountered people of this particular agent.

Equations (I) and (II) showcase the SEIR logic on an individual agent's level. Assume agent i visits the market and encounters a certain number of people, denoted as N_i^{Market}. Those can be further categorized into susceptible (S_i^{Market}), infected (I_i^{Market}), exposed (E_i^{Market}), or recovered (R_i^{Market}). A discretized version of the first differential equation in 4.6 is used to compute the number of susceptible agents ΔS_i^{Market} to move into the 'compartment' of exposed agents. It should be noted that the transmission rate β^{Market} represents the product of the contact rate η^{Market} and the transmission probability p^{Trans}. The individual agent's probability p_i to belong to this group is computed in (II). This calculation is repeated independently for the encounters at home or in the shelters as the second possibility to contract the disease. Consolidating those individual probabilities leads to an aggregate behaviour similar to the population-wide SEIR model introduced above.

$$\text{(I) } \Delta S_i^{Market} = -\beta^{Market} \frac{(I_i^{Market} + E_i^{Market}) S_i^{Market}}{N_i^{Market}} = \eta^{Market} p^{Trans} \frac{(I_i^{Market} + E_i^{Market}) S_i^{Market}}{N_i^{Market}}$$

$$\text{(II) } p_i = -\Delta S_i^{Market} / N_i^{Market}$$

Contact rate

β depends on the contact rate and influences the number of infections. As the resolution within the model is too low to have the agents actually walk around, the number of agents encountered is drawn from an input list that depends on the level of lockdown currently imposed on the model. During one time step, all agents that are eligible to enter the market go to that specific patch in the model. For each agent on that patch, a random number is drawn to determine the number of contacts that this agent will encounter. This random number is drawn from a range that corresponds to the minimum, medium, or maximum amount of contact and formalizes the link between the COVID-19 loop and the lockdown loop as discussed in the previous section.

4.3 INTEGRATION OF SUB SYSTEMS

The three sub systems are integrated. The conceptualization of the components is first discussed, after which a flowchart of the entire model flow is presented. Afterwards, more formalization of processes are discussed that have not been reflected upon in the previous sections.

4.3.1 Conceptualization of integration

Figure 4.7 displays the integration of the three aforementioned CLDs. This is a simplified version that aims to capture the most important mechanisms and system behaviours that influence the livelihoods of households and the exposure of their individuals to COVID-19 during a natural hazard. The systems connect in several areas: (1) process of trading at the central market ensures a higher livelihood for the households, but also increases the contact rate and thus exposure to COVID-19, (2) the number of people per shelter influences the exposure to COVID-19 greatly, and (3), through delayed effects, the number of people in the shelter also influence the livelihood. Another important integration of the two systems is that the livelihood of people is more or less 'protected' by the government or external aid in times of a natural hazard, but not in times of COVID-19. The *livelihood loop* is displayed in orange, the *exposure loop* is displayed in green, and policy interventions are displayed in blue.

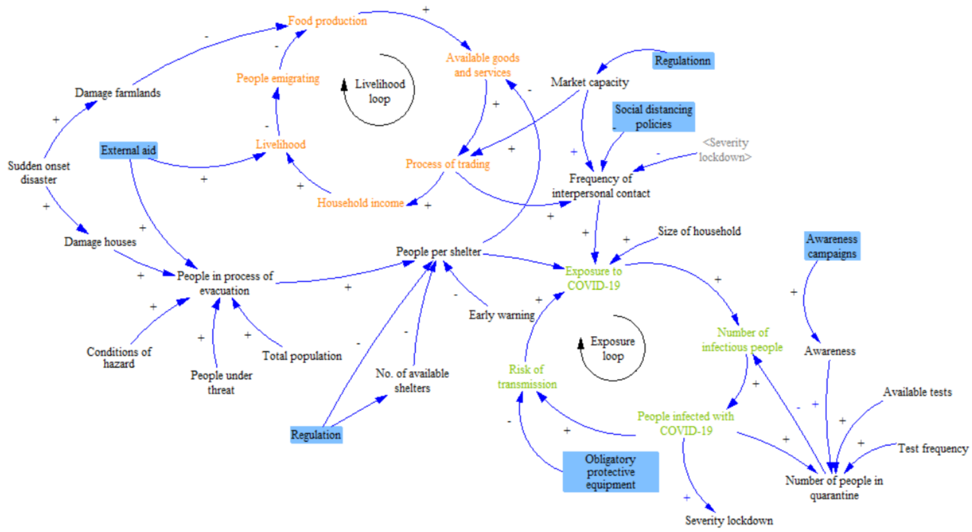


Figure 4.7: CLD of the socio-technical systems combined

The third effect is more clearly presented in figure 4.8 and highlights how the livelihood component is connected with the sudden-onset disaster component. The red factors show how these components are interconnected and the green arrows show the delays for these effects.

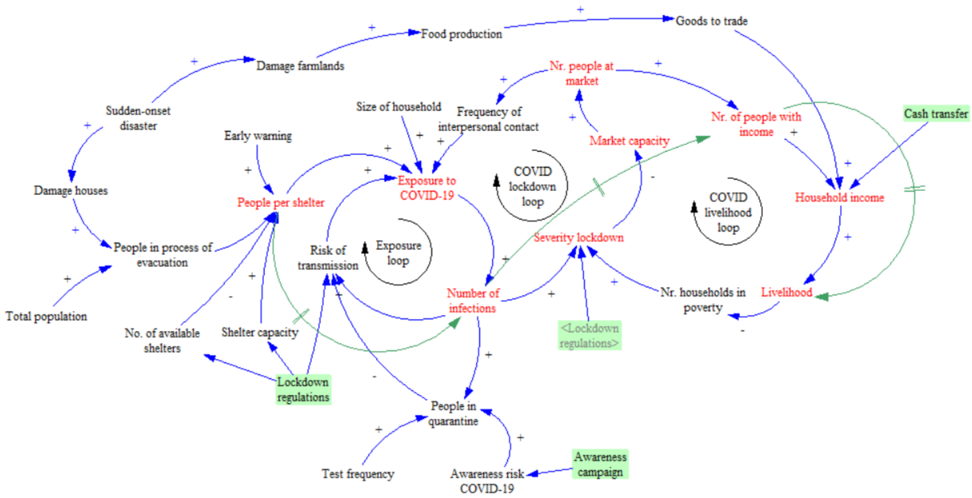


Figure 4.8: CLD with delayed and feedback effects highlighted

Important to note is that the CLD presented in figure 4.7 contains some factors that are left out of the implementation of the agent-based model but are added here for completeness. Emigrating people and food production are both important concepts for the livelihood loop but not included in the model implementation.

4.3.2 Flowchart integrated systems

Flowcharts are diagrams that represent graphical workflows or processes. In the context at hand, the corresponding flowchart for each sub system provides an overview of the different processes undertaken by the population, government, or environment. They are based on the presented previously literature and the constructed causal loop diagrams. The flowcharts can be found in appendix B.

Figure 4.9 displays the flowchart of the decisions made by all actors and in the aggregate environment of the model, combining all sub systems. Appendix B also contains the flowcharts of the predefined processes in figure 4.9: the evacuation process, trading at the market, quarantining when tested positive for COVID-19, and the imposed restrictions by the government.

In figure 4.9, there are three swimming lanes visible: the environment, citizens, and the government. The model starts with opening up the marketplace for trading. The citizens then all check if they meet certain requirements, such as being of working age, being healthy, owning protective equipment etc. If they meet the requirements, they go to the market and start the trading process. After this step, the citizens might get tested, which is dependent on the test frequency of the model (e.g. if the test frequency is every three days, they have a probability of 33% to get tested). Citizens that receive a positive test result go into quarantine for a predefined number of days, but only if they are compliant with the rules imposed by the government. Those who are not compliant will continue with their current activities, which may be either going to the central market or residing in a shelter. Citizens that get tested negative return home. At home, the household "consume" livelihood based on their composition and size.

Subsequently, the government checks two important threshold values: the livelihood threshold and the COVID-19 threshold. A more in-depth discussion on these thresholds can be found in chapter 5. Based on these values the government decides to what extent lockdown restrictions need to be imposed: no lockdown, a moderate lockdown, or a severe lockdown.

At this point in the flowchart, a sudden-onset disaster might occur. In this case there are two parallel developments: (1) there is a chance that the government issues an early warning, and (2) households find out if they live in the affected region and need to evacuate. The warning guarantees an orderly evacuation and thus impacts this sub system. In case no warning can be issued, no orderly evacuation is feasible, and the affected agents aim for the closest shelters in an uncontrolled fashion. Based on the severity of the hazard, citizens stay for a certain amount of days in the shelter, after which they return home.

At the end of each day, the chance to contract COVID-19 is calculated. This probability is discussed in more detail in chapter 5, but is based on the number of agents encountered during the day. The probability determines the chance to contract COVID-19 according to the aforementioned SEIR model. This is process is then repeated from the start for the duration of the model run.

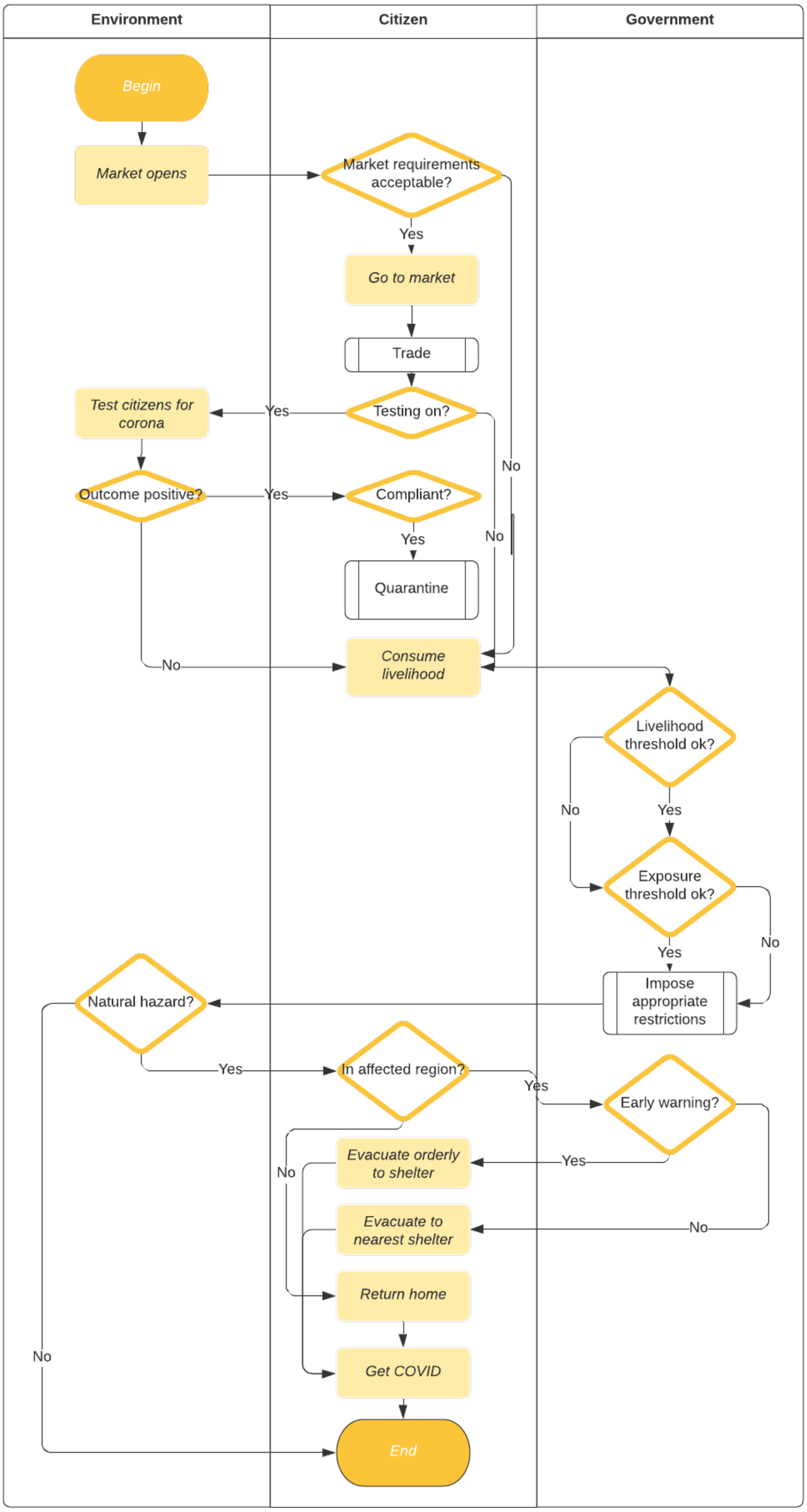


Figure 4.9: Flowchart ABM model

4.3.3 Formalization of integrated sub system

UML stands for Unified Modelling Language and is an approach to modelling and documenting software. To implement all processes in the agent-based model, several classes were constructed. These classes are reusable pieces of code which are used to create individual instances of objects, in this case mostly agents. Classes comprise of attributes and methods. This programming paradigm is better known as *object oriented programming (OOP)*.

A UML diagram was constructed for the ABM and can be found in figure 4.10. It provides an overview of the classes are present in the model, what attributes and methods they have, and how these classes are interrelated. The classes are also listed below:

- Individual
- Government
- Shelter
- Household
- Market
- Sudden-onset disaster

The household consists of individuals and exhibits an initial amount of livelihood, which correspond to the household savings. The households also have a certain exposure to hazards, which is important to determine whether the household needs to evacuate. Residents of the household possess several characteristics affecting their decision-making, for example compliance to the rules imposed by the government. Apart from these characteristics, important attributes are their contact rate and health status. The government has several thresholds to monitor related to the number of COVID-19 infections and the average livelihood. The COVID-19 threshold is reached when two requirements are met: the *growth* threshold (e.g. the R-value) and the absolute number of infections. This is to ensure a lockdown is not imposed when the number of infections goes from 1 to 2 and the growth threshold is met. The livelihood threshold depends solely on the average livelihood of all households in the community.

The environment class contains information for the initial setup of the model.

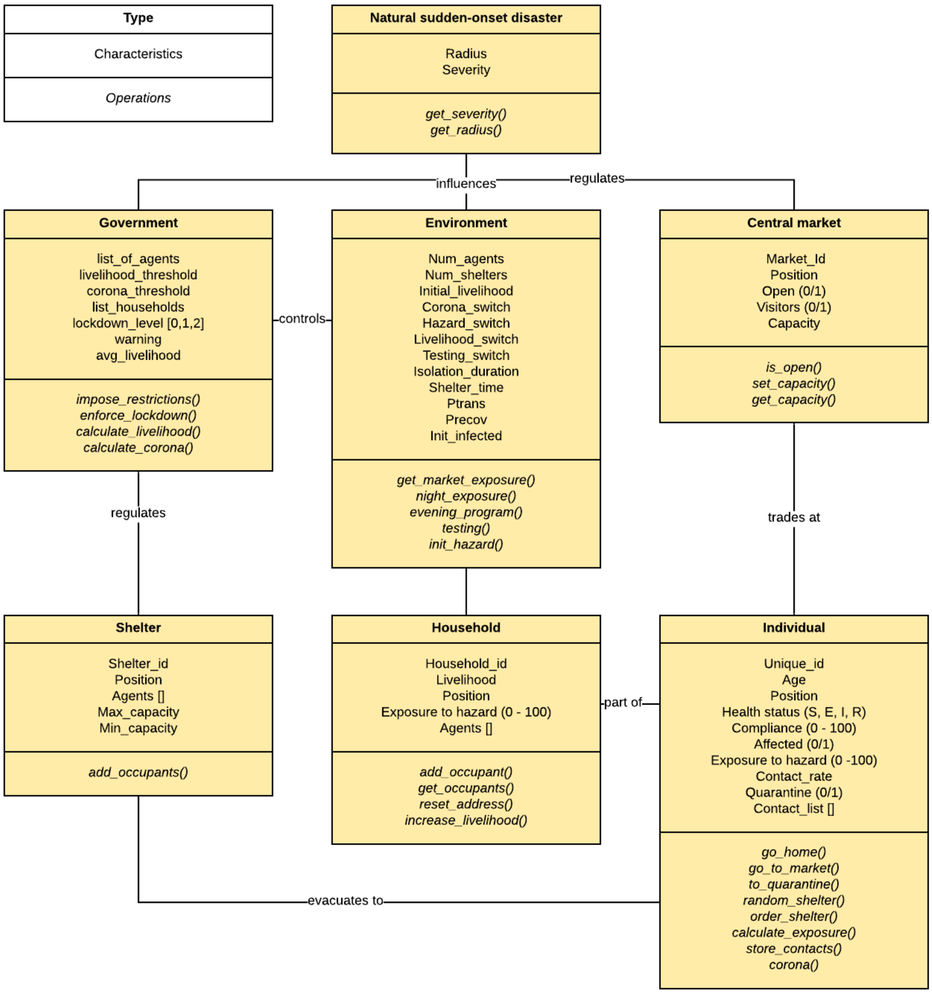


Figure 4.10: UML diagram

4.4 MODEL ASSUMPTIONS

As aptly described in Nikolic et al. (2019), assumptions are 'the bread and butter of modelling'. It is impossible to understand one's model without knowing what assumptions went into modelling relationships and why certain choices were made. In table 4.2 an overview of all core assumptions is given. Appendix C.4 contains a complete list of all assumptions.

Category	Assumption
Livelihood (I)	Livelihood depends entirely on access to the central market or external help
	No other activities than trading are modelled to represent work.
	Only financial capital is included to represent livelihood.
	Agents have the profession farmer or non-farmer.
S.-O. disaster (II)	Infrastructural damage or access is not taken into account
	Natural hazard is initiated in the initial phase of the model as the focus lies on subsequent model behaviour.
	People not affected by sudden-onset disasters do not evacuate.
	People evacuate for several days, based on the impact of the disaster.
	Evacuation costs are not considered in the decision to evacuate.
	Damaged farmlands are not considered in the model.
	The marketplace is never affected by the hazard.
COVID-19 (III)	Agents exposed to COVID-19 are contagious.
	Interpersonal contacts are sufficiently long to enable the (potential) spread of COVID-19
	The social structure consists of the working and home environment
Other	Households consist of working adults or not-working elderly.
	Children do not contribute to livelihood as they do not work and are less likely to catch COVID-19.
	Only a single, isolated community is modelled, therefore, spread between different communities is not modelled.
	No agents die or are born during the model run.
	Movements of agents between locations are not included to reduce complexity.

Table 4.2: Main assumptions made during modelling

4.5 CONCLUSION

This chapter contains the conceptualization and formalization of the model and addressed the second sub question. The most important concepts identified in the literature review were used as starting point for the conceptualization. Three socio-technical sub systems (livelihood, response to sudden-onset disasters, spread of COVID-19) were individually conceptualized before being integrated with each other. After the conceptualization, the core processes of each conceptual sub model were formalized. Afterwards, the complete conceptual model was transformed into a formalized one. A UML diagram was created to provide an overview of all classes included in the model, as well as the most important characteristics of the agents and their methods. Also, an overview of the most important model assumptions was presented.

5 XLRM FRAMEWORK

This chapter contains information regarding the KPIs, policy interventions, and uncertainties for this research. In the previous chapter, the model relations ('R') have been discussed and together with the information presented in this chapter, the XLRM framework is completed. The formalized model of the previous chapter is the starting point for exploring several policy interventions. Before those interventions are discussed, the model metrics are introduced.

5.1 MODEL OBJECTIVE AND KEY PERFORMANCE INDICATORS

The model objective is twofold. Firstly, the aim is to identify the system behaviour when a sudden-onset disaster occurs during the COVID-19 pandemic. Secondly, by establishing the system behaviour, including identifying underlying uncertainties, the chosen policy interventions can be assessed. The policy interventions are developed to either influence the COVID-19 trajectory, or the average livelihood in the model. The KPIs are listed below.

- **Livelihood**: the livelihood of each household is calculated based on the livelihood that its agents bring along. The average livelihood is the average of all households in the model.
  - **Lowest livelihood**: the average livelihood of each model run will fluctuate. Per model run, the lowest point in the average livelihood is one of the metrics to maximize. This is the maximin strategy that seeks out runs that yield the smallest loss.
  - **Cumulative negative livelihood**: the livelihood may drop below the livelihood threshold. This is regarded as "negative" livelihood. The sum of the negative livelihoods for each time step are summed up to assess the total loss in livelihood during an entire model run.
- **COVID-19 trajectory**: the number of infections is calculated based on the individual infection statuses of agents in the model.
  - **Maximum number of infections**: the peak of infections in a model run is one of the metrics. In contrast with the *lowest livelihood* metric, a minimax strategy is used to identify the runs with the lowest peak. This is to reduce the pressure on healthcare facilities.
  - **Cumulative number of infections**: by calculating the area under the graph that represents the total number of infected people per

day, the total number of 'sick days' is calculated. This is a metric that shows how fast the infection curve decreases and the trajectory is better controlled.

Above metrics focus on either the livelihood or the COVID-19 trajectory. The policy interventions, as introduced in the next section, will also focus directly on either the livelihood or the COVID-19 trajectory, but are expected to have second order effects for the livelihood or number of infections as well.

5.2 POLICY LEVERS

The "L" in the XLRM framework represents the policy levers and captures the policy interventions that comprise the variety of strategies that decision-makers want to explore (Bharwani, 2011). These are the levers that the policy makers can influence in order to manipulate the outcome, captured by the metrics of the model. In this research, the decision-makers are either (local) governments in developing countries or humanitarian organizations. The other elements of the framework will be discussed in the next section.

This study focuses on the effect of policy interventions during a sudden-onset disaster whilst dealing with COVID-19. The levers thus aim to reduce the spread of the virus, whilst trying to maintain the livelihoods of people that depend on their daily income. Four levers are considered: cash transfers, awareness campaigns, adjusting shelter capacity of each shelter, and regulating lockdown restrictions. Firstly, the policy levers are introduced including a review of current literature regarding these policies. Secondly, the formalization of each policy is presented, which describes how the policies are used in this research. In appendix C, figure C.1 the flowchart from section 4.3.2 is shown, with in addition the policy interventions and the implementation location. Additionally, table 5.1 displays an overview of selected literature supporting the decision for these policy levers.

	Cash transfer	**Awareness**	**Shelter cap.**	Lockdown
Ståhl and MacEachen, 2020	x			
Delerio, n.d.	x			
Ezeah et al., 2020	x			
Sharma, 2020	x			
Chen et al., 2020		x		
Qazi et al., 2020		x		
Gainforth et al., 2014		x		
UN news (2020)			x	
Nupus (2020)			x	
Drossou, 2020				x

Table 5.1: Overview literature per policy intervention

5.2.1 Policy 1: Cash transfers - introduction

The COVID-19 crisis displays how precarious the position of un- and underemployed people is (Ståhl & MacEachen, 2020). For the aftermath of natural hazards there are policies in place to aid in basic necessities such as food, water, and shelter. However, for the COVID-19 crisis adequate policies are not available and many people suffer from it. In the Philippines, the government is currently issuing subsidy programs that resemble UBI (Universal Basic Income) programs, but this does not seem to have the desired effect: "Only 57 percent of the target 18 million households in vulnerable sectors have received their financial subsidy" (Delerio, n.d.).

Direct and unconditional cash transfers do seem to work well in poor rural communities to improve the quality of life. Handa et al. (2018) and Egger et al. (2019) both showed that direct cash transfers were successful in rural African communities and had a multiplier effect due to being invested wisely. The context in these two studies was different, as the cash transfers were directed at poor communities living without the epidemic circumstances. However, the cash transfers can still have a beneficial effect. In the context of this research, the general goal of the cash transfer would be to stabilize people's livelihoods for the duration of the epidemic or until the government has figured out how to handle the situation best. India is a good example of a country where the government provided stimulus packages because of the COVID-19 situation, that were not meant to increase economic activity, but only to lift people from hunger and extreme poverty (Sharma, 2020). An additional benefit of cash transfers during an epidemic is that it reduces people's exposure, as the need to access the market decreases. People will only need to visit the market for acquiring necessities, which leaves them less time in the proximity of others that need to remain there an entire day to work.

Another reason to implement direct and unconditional cash transfers is that it can be temporarily implemented and is bureaucratically simpler than other policies. Less research is needed as to who is eligible for the cash transfer and there are less transaction costs involved. Cash transfers will be received by households in lockdown that fall below the livelihood threshold. The core idea behind the cash transfers is that the community becomes shock responsive. A shock responsive social protection system is therefore the aim of this policy lever.

In order to find out the kind of assistance that is needed after a sudden-onset disaster, The International Red Cross and Red Crescent Movement conduct so-called *rapid market assessments* (*Rapid Assessment for Markets Guidelines for an initial emergency market assessment International Red Cross and Red Crescent Movement*, 2014). The idea behind this is twofold: identify how people's access to resources has been affected and to identify "market-aligned ways to assist the shock-affected population". The latter means that aid organizations need to be careful that their assistance does not affect the local economy negatively. For this research, the rapid market assessment is not included and this needs to be considered when drawing conclusions from the policy intervention. Another limitation of this policy is that is unclear what the height of the cash transfer should be and that it becomes a costly solution if the circumstances do not change.

5.2.2 Policy 1: Cash transfers - formalization

The cash transfer is a policy lever that enables the government to give out cash transfer to the poorest of households. Whenever a household drops below the livelihood threshold as defined in the model, the government allows a non-recurring cash transfer of a specified amount, that ranges from one to three weeks of livelihood. The "cash" is transferred to the household and multiplied by the number of agents associated with that particular household to guarantee the correct amount. Once a cash transfer has occurred, the household in question is no longer eligible for another one. There are no other requirements to receive the cash transfer other than to drop as a household below the livelihood threshold.

In the pseudo code below the cash transfer policy can be seen. The *household.cash* is the boolean that checks whether households have already received the cash transfer or not.

Algorithm 1: Cash transfer policy

```
Result: Households receive financial aid
for households in list_households do
    if household.livelihood < livelihood.threshold & household.cash != 1 then
        household.livelihood += len(household.agents) * cash_transfer
    end
end
```

Important to understand about the implementation of the cash policy is that agents that receive a cash transfer that is high enough to sustain their household will not visit the central market until their livelihood drops below the threshold again. This does not mean that the agents do not leave their houses to buy food, it only means that they leave their houses for such a short amount of time that it is negligible compared to the agents that need to out all day to gain an income. This is based on the assumption that someone needs to be in the proximity of another person for more than 15 minutes in order contract COVID-19 (WHO, 2020c).

A limitation regarding this policy is that the effect of the cash transfer on the local economy is not accounted for. Humanitarian agencies perform a balancing act when it comes to the cash transfers, as the combination of scarcity due to damaged farmlands and decrease harvest leads to higher prices on the market. If cash transfers are transferred to this community, this would affect the prices of the product. The consequence of this simplification is an overestimation of the beneficial effects of the cash transfer, as there is no inflation of product prices or otherwise an effect on the modelled micro-economy. A second limitation is that the households that receive a cash transfer would be able to provide themselves with more or better protective equipment to lower the chance of contracting COVID-19. This effect has not been included in the policy.

5.2.3 Policy 2: Awareness campaigns - introduction

Rural communities in less developed countries are at more risk contracting diseases (Ezeah et al., 2020). Ezeah et al. (2020) found that this urban-rural health inequality is partly due to a lower level of knowledge and understanding, caused by a lower socio-economic status and higher illiteracy rate. Awareness and knowledge are essential to combat COVID-19, and this can be reached by means of adequate communication. This interpersonal communication works best to spread awareness among rural communities because of the often higher illiteracy rate. Awareness is important because there is a causal link between public health awareness and public health behaviour (Chen et al., 2020). Adoption of social distancing practices is significantly influenced by situational awareness (Qazi et al., 2020). The formalization of awareness can be found in section 5.2.4. The implementation choices are based on research from Gainforth et al. (2014) that found that interpersonal news is most effective within the *core* as opposed to with the *periphery* of someone's interpersonal contacts. It is therefore assumed that interpersonal communication within the households has a greater effect than interpersonal communication at the central market.

The Philippine Red Cross is putting theory into practice and is actively creating awareness about COVID-19 in the Philippines, with the assistance of the Netherlands Red Cross. The awareness campaign is therefore included as policy lever that will be active throughout the duration of the model run. Awareness can be spread when people with low awareness meet people with higher awareness, and get convinced by the gravity of the situation. Awareness influences the agents' decision to abide by the social distancing practices, wearing protective equipment, and deciding whether or not to quarantine.

5.2.4 Policy 2: Awareness campaigns - formalization

Awareness influences decisions of agents in three ways:

1. Quarantining
2. Wearing protective equipment
3. Reducing the number of daily contacts

Based on the awareness, the probability that the agents are compliant to above presented rules is calculated. The government of the local community can introduce an awareness campaign at the start of a model run that targets a certain number of agents. These agents' awareness status is then set to a random number between 0 and 1, with 1 being completely aware and compliant to the rules, and 0 the opposite. The model runs as usual, except that the agents that meet each other at the central market and at home exchange not only the chance to attract COVID-19 but also some awareness around the infection.

- At start model run, all agents' awareness is set to uniform distribution between 0 and 1
- Local government draws random x agents
- Agents set awareness to 1
- Agents with awareness equal to 1 increase the awareness of agents they meet at home or at the market
  - $awareness.self + awareness.other * awareness\_effect$

An important limitation of this policy lever is that neither the effect of fake news is taken into account, nor the effect of news that spreads through digital media. In reality, the awareness can decrease due to these types of news, which is not taken into account in this formalization.

5.2.5 Policy 3: Shelter capacity - introduction

When there is an immediate risk for a sudden-onset disaster, people evacuate to shelters. These shelters are *emergency shelters* and are only used during the impact of the disaster before returning home. If the damage is too large to return home within a couple of days, people are transferred to a transitional shelter (IFRC, 2011a). The number of available shelters is limited and this number has only decreased since some shelters have been put to use as quarantine facilities (UN news, 2020). This has resulted in a decreasing number of options to shelter during and after sudden-onset disasters, especially since the capacity of shelter locations in some places has been reduced by 50% to make sure that social distancing becomes feasible (UN news, 2020). This has triggered the need for creative use of space, as the demand has doubled, while the supply remained equal. Public buildings have offered their space for inhabitants of the Philippines, as there are not enough locations where people infected with COVID-19 can quarantine (UN news, 2020). Schools, churches, and even shopping malls have offered their space, as many of these have been closed due to the lockdown restrictions anyway. Nonetheless, there is not enough room for everyone, as the capacity per building has been reduced due to social distancing regulations.

By introducing additional shelter space, the effect of shelter capacities and number of shelters can be studied. The aim is to find the effect of the number of shelters and shelter capacity on both the trajectory of COVID-19, but also the effect on the average livelihood of the community as a whole. Apart from additional shelter space, there is also the possibility to aim for better distancing within shelters. In the formalization, both of these options are explored.

5.2.6 Policy 3: Shelter capacity - formalization

The shelter capacity depends on the following model settings: (1) the *shelter capacity*, which depends on the fraction of the population that can fit into a single shelter, (2) the *number of shelters*, which is important for the distribution of agents, and (3) the *max contacts per shelter* which is calculated multiplying (a) the population size with (b) the shelter capacity, and (c) the percentage agents are met in the shelter. These variables in the base model had a fixed number but are now varied to see the results of this. As the population size in the model does not change (it is fixed in all model runs), this policy consists of three measures:

1. Varying the number of shelters *(num_shelters)*
2. Varying the percentage of agents met at the shelter *(shelter_perc_met)*
3. Varying the shelter capacity *(shelter_cap)*

The second and third both influence the *max contacts per shelter* variable in the model, which determines how many agents are encountered in the shelter. Including both in the shelter policy makes it possible to investigate which of the two has a larger effect on the model metrics. An important limitation is that no distinction has been made between the emergency and transitional shelter. Agents remain in the same shelter for the entire duration that they need to evacuate. In the next chapter, the experimental design is presented where the exact changes in these variables can be found.

5.2.7 Policy 4: Regulate lockdown - introduction

The government has to decide what lockdown restrictions are required to contain COVID-19, but is also challenged with the task to keep the economy afloat. The discussion regarding the trade-off between lives and livelihood can be found in chapter 2. Many countries, developing countries especially, prioritized economic activity over containing COVID-19. An example can also be found in the Philippines. As the Philippines has only known GDP-growth for more than 20 years, the government is dissatisfied to see the economic loss that is inevitable during a lockdown, particularly president Duterte (Drossou, 2020). The government waited as long as possible with movement restrictions back in March when the number of cases were already growing exponentially. Comparatively late actions were also taken before the second lockdown restrictions imposed in August. This was only done after more than 80 health organizations urged the president to enforce a lockdown as the situation was spiraling out of control (BBC, 2020). Lockdown restrictions are based on the two thresholds, also mentioned in the next section, and result in three options: no lockdown, moderate lockdown, or severe lockdown. Each result in different values for the market capacity, external visitors, and obligated protective equipment. The exact decision rules that the government follows can be found in appendix C.

5.2.8 Policy 4: Regulate lockdown - formalization

The model assumes three discrete levels of lockdown, impacting the following three elements: *market capacity*, *allowing visitors*, and *obligated protective equipment*.

These lockdown levels depend on two important thresholds.

- **Livelihood threshold**: at every model step the average livelihood of the households is calculated. If the average livelihood drops below the threshold, the government is notified.
- **Corona threshold**: this depends on two sub thresholds
  - (1) Growth threshold: this measures the growth in percentage
  - (2) Cases threshold: this measures the absolute number of cases relative to the total number of agents

This policy intervention explores different strategies regarding the thresholds. Imposing lockdown restrictions is not a unique policy intervention, but when this happens varies a lot. Therefore, the following parameters will be changed in order to find changes in model behaviour and investigate whether there are dominant strategies in enforcing the lockdown to be found.

- Vary threshold: R value, cases threshold, livelihood threshold.
- Prioritize COVID-19 over livelihood to see if lockdown effects change

5.2.9 Timeline policy interventions

Figure 5.1 illustrates the policy interventions over the different disaster phases. Some policy interventions are continuous throughout the model run, whereas others are implemented at specific times during the occurrence of the sudden-onset disaster.

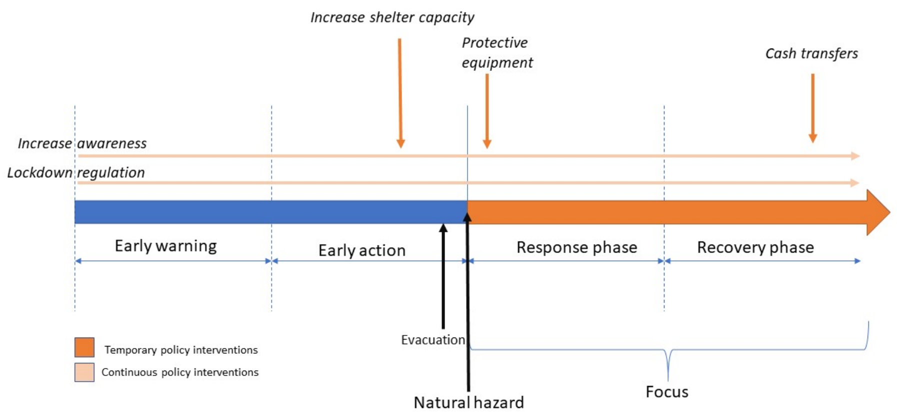


Figure 5.1: Timeline policy interventions

5.3 XLRM FRAMEWORK

In the previous chapter, the conceptualization of the system and its relationships have been described. This forms the 'R' in the XLRM framework, to be complemented with the policy levers ('L') and metrics ('M') as discussed in the previous sections. In this section, the uncertain factors ('X') are discussed, completing the XLRM framework.

5.3.1 Uncertain factors

Natural sudden-onset hazards are inherently uncertain, and can often only be anticipated a few hours before impact. In addition, the situation with COVID-19 is unprecedented and brings uncertainty as well. It is important to identify external *and* internal uncertainties, in order to analyze their impacts on the model relations and the performance metrics. W. Walker et al. (2003) characterize uncertainties along the three dimensions of location, level, and nature. First, the location refers to where in the model the uncertainty is located. For example, the uncertainty could be in the model structure due to lack of sufficient understanding of the system. Second, the level of uncertainty can range from statistical uncertainty to recognized ignorance. For the XLRM framework at hand, the uncertainties refer to the level of *scenario uncertainty*. This results in ranges in outcomes due to varying underlying assumptions, or can be seen as uncertainty in determining which changes and developments are relevant. Third, the nature refers to either epistemic or variability uncertainty. Epistemic uncertainty stems from a lack of knowledge, while variability uncertainty is due to inherent randomness such as non-rational human behaviour.

Table 7.2 displays the uncertainties with an expected moderate or large impact on the metrics, based on the current model results.

Uncertainty	Location	Nature	Level	Range
transmission rate	Parameters	Epistemic	Scenario	[0.05 - 0.2]
recovery rate	Parameters	Epistemic	Scenario	[0.03 - 0.12]
growth threshold	Input (scenario)	Variability	Scenario	[1% - 15%]
initial infected	Parameters	Epistemic	Scenario	[5 - 25]
minimum contact rate	Input (scenario)	Variability	Scenario	[1 - 3]
medium contact rate	Input (scenario)	Variability	Scenario	[3 - 8]
maximum contact rate	Input (scenario)	Variability	Scenario	[8 - 15]
maximum contact shelter	Input (scenario)	Variability	Scenario	[5 - 30]
lockdown level	Parameters	Epistemic	Scenario	[0,1,2]
corona fraction	Parameters	Epistemic	Scenario	[0.01 - 0.15]
livelihood threshold	Model structure	Variability	Scenario	[1 - 10]
shelter capacity	Parameters	Epistemic	Scenario	[0.01 - 0.1]
ratio shelters	Model structure	Variability	Scenario	[0.05 - 0.2]

Table 5.2: Uncertainties considered in the XLRM framework

5.3.2 Performance metrics

The performance metrics are also known as the Key Performance Indicators (KPIs). The main KPIs, stated in section 5.1, are used to evaluate the performance of interventions ('L') over time to see the short and long-term impacts on the livelihood and exposure to COVID-19. In addition, the model keeps track of the total number days of lockdown and the number of days that the average livelihood is too low for households to provide for themselves.

5.3.3 Visualization XLRM framework

Now that all elements of the framework are known, these are graphically represented in figure 5.2.

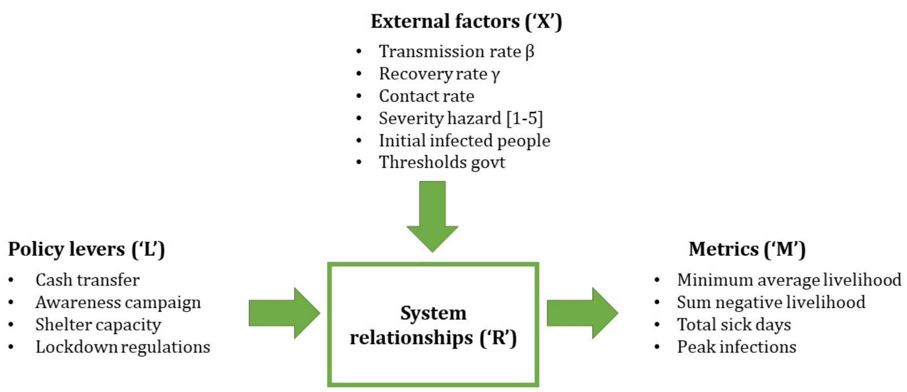


Figure 5.2: Complete XLRM framework

5.4 CONCLUSION

In this chapter, the KPIs, policy interventions, and uncertainties have been discussed. The KPIs focus on the livelihood and COVID-19 trajectory, which were the focus of the policy interventions. Four policies are introduced and formalized: (1) cash tranfers, (2) awareness campaigns, (3), shelter capacity changes, and (4) regulation lockdown restrictions. The uncertainties have been discussed, resulting in completing the XLRM framework.

6 MODEL IMPLEMENTATION

This chapter explains how the model is implemented and is the start of the model exploration. The following sub-question is addressed:

How can the conceptual model be implemented in an agent-based model?

This question is first answered by a section containing a description of the modelling environment, which is elaborated from what was previously mentioned in chapter 3. The second section discusses the time sequence of the agent-based model. The section thereafter dives deeper into the chosen parameters and where they are located in the model, after which some details are shared about the developed user interface. The chapter ends with the verification of the model.

6.1 MODELLING ENVIRONMENT

The agent-based model was built using Mesa, which is a Python-based open-source platform that can be used for ABM analyses. The framework allows creators of agent-based models to use built-in components or customize implementations. Analyses can be performed with data analysis tools that exist within Python.

Mesa poses an alternative to using Netlogo. Netlogo is a programming language and integrated development environment for agent-based modeling and is used by many students and researchers. It has a better developed user interface than Mesa and it makes sense to use it when one has less experience with programming and needs the visualization to inspect if the model behaviour is correct. For this study, a user interface is less important.

Because Mesa is Python-based, it is easier to use approaches such as *object oriented programming* and use data analysis tools that exist within Python. The complete code can be found on the following Github repository: https://github.com/fuukjosephine/thesis_abm_covid_livelihood_hazard

6.2 TIME SEQUENCE

The model runs in discrete time steps. Every time step represents one day. Within that day, there are two sequences that are performed sequentially. The model-steps are executed first. Within these model-steps, there are agent-steps. Figure 6.1 displays how this time sequence works. After the initialization of the model, the first model step is performed. However, when the agents are activated for a specific action, they are all performing that action before the next overarching model-step is executed.

When an agent-step is activated, the agents execute this step sequentially and not simultaneously. This means that it is important to think about the order in which agents perform a step. If agents would always perform steps in the same order, this could significantly influence the spread of the virus or the interpersonal spread of awareness. To make sure that this does not happen, the agents are always randomly activated (Van Dam et al., 2013).

Not all steps are always carried out by all agents, due to their attributes or characteristics. These internal states can furthermore be changed due to their actions or the actions of others, or due to changed regulations from the government. For example, when an agents' *affected* status changes, it means it was in the impact zone of the sudden-onset disaster and should evacuate. Those agents do not have the opportunity to go to the central market until they are relieved of that status. Some of these status changes depend on a probability. When experimenting with the model, a fixed seed is used. This initializes a pseudorandom number generator to ensure that at the start of the model run the same sequence of numbers is used. Model runs are therefore reproducible and can be compared with each other varying only specified parameters.

One complete run consists of 40 steps and thus around 1.5 months. This is considered a reasonable period of time to research the effect of evacuation during a pandemic, because a surge in COVID-19 cases can be seen within this period, as well as that the majority of sheltering durations fit within this time period. Using one day for one time step was deemed appropriate in view of the chosen abstraction level for the different model components. For example, since the travelling to shelters is not included and movements in the model are limited, modelling per hour would not have much added value. What these 40 steps do not consider, is the notion of seasonality. The season could affect the impact of the sudden-onset disaster greatly if it were to be before harvesting or after. As the food production is left out of scope in the livelihood component, it is chosen to also exclude seasonality.

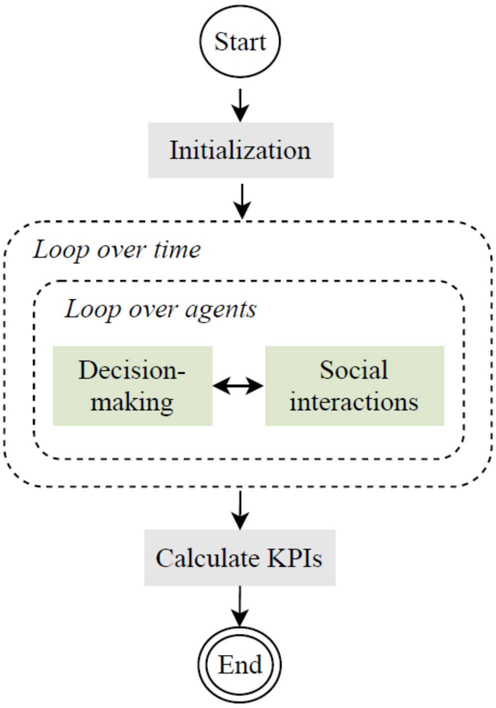


Figure 6.1: Simulation flow of the ABM (Werntges, 2020)

6.3 PARAMETRISATION

Parametrisation consists of finding suitable values for the model variables. The discussion of these parameters is important because the system might be sensitive to initial conditions (Van Dam et al., 2013). For this research, values are based on recent findings in literature regarding COVID-19, evacuation, livelihood, or information provided by 510. The data from 510 came either from discussions with experts, internal documents, or papers published by them. The data provided by 510 was focused on Red Cross organizations they were closely together with, which was often the Philippine Red Cross. Appendix D.1 provides an overview of parameter settings and the respective references. It was not possible to retrieve data for all of the parameters from literature or interviews. Therefore, some parameters are based on assumptions, as also summarized in appendix D.1.

In the parametrisation there is uncertainty for each of the variables. When this uncertainty is large though, this can systemically be explored by experimenting with the input range of this variable. This is discussed more in the next chapter where the experimental design is presented. Table 6.1 presents an overview of the variable categories. More information about each of these variables and their ranges can be found in appendix D. The research is not calibrated for a specific country or region, but most data originates from the Philippines, India, or Bangladesh. These countries have dealt with or are currently dealing with the complex situation described in this study and have data available regarding the parameters present in the agent-based model.

Category	Description
Agent	Agent characteristics: age, profession, household, initial livelihood, but also their compliance and behavioural characteristics
Model	Environment variables: population density, population size
Livelihood	Variables related to livelihood: increase livelihood, market capacity
COVID-19	Variables related to the SEIR approach: isolation time, incubation time, transmission rate, recovery rate, contact rates
Hazard	Variables related to the hazard: severity, radius
Government	Threshold variables: growth threshold, absolute cases. Also early warning

Table 6.1: Overview parametrisation

6.4 USER INTERFACE

The model is visualized by developing a user interface in Mesa. The user interface helps gaining insight regarding the model KPIs and the influence of different model settings. There are several switches in the model that allow for testing the sub systems separate from each other, serving as a method for verification and validation at the same time. Lastly, the user interface helps with communicating model findings with others, such as with the team of 510. Figure 6.2 shows an exemplary depiction of the user interface. Users may choose to adapt the number of agents, the thresholds and several switches to examine sensitivities of the model output. Next to the settings, the grid shows the households, where the grey houses represent houses that are affected by the sudden-onset disaster and will need to evacuate.

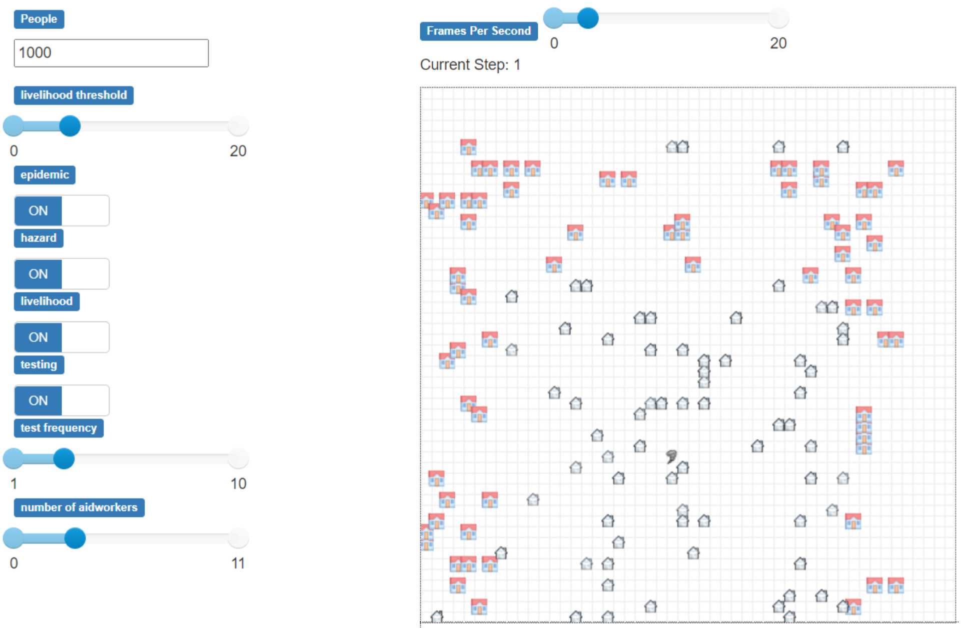


Figure 6.2: User interface

Figure 6.2 depicts a model run where the sudden-onset disaster is visible in the middle of the radius of damaged houses. The houses represent households that are randomly spread across the grid.

6.5 VERIFICATION

An important step in modelling is verifying that the formalized concepts behave as intended, implying a correct translation of model behaviour from conceptualization to formalization. Verification increases the confidence in the model and the output that it delivers (Sargent, 2010). This is important because decision-makers use information obtained from model results and individuals are affected by these decisions.

Verification was performed continuously during the building of the agent-based model to constantly assure that the implemented parts work as expected. Additionally, structured verification steps based on the methods from Van Dam et al. (2013) and Sargent (2010) were performed. These steps are conducted because it is too time consuming to determine whether a model is absolutely valid over the complete domain of its intended applicability. The undertaken steps consist of a structured code walk-through, extreme condition test, face validity, and comparison to other valid models. An elaboration on these steps and their results can be found in appendix D. Before the complete model was verified, the sub components were verified individually as well.

Lastly, the implemented model was checked for consistency with the causal loop diagrams and flowcharts. Based on the verification, it was deemed to be correctly implemented.

6.6 CONCLUSION

This chapter addressed the third sub question: *In what way can the formalized model be implemented in an agent-based model?* The formalized model was implemented in an agent-based model using the Mesa package in Python. The model uses discrete time steps of one day, resulting in a time sequence where agents perform their activities sequentially. The parametrisation consisted of finding suitable values for model variables. Both input and internal variables have gotten their value based on literature or data that was provided by 510. In case literature could not provide an answer, assumptions were made to fill in the gaps. The user interface was developed to create greater insight in the workings of the model as well as to use for experimentation. The complete model as well as the sub components are verified and will be used as input for the experimentation in the next chapter.

7 EXPERIMENTAL DESIGN

This chapter discusses the experimentation. Experimentation is performed to gain insight in the model behaviour, which is achieved through varying the model parameters in a structured fashion. Experimentation consists of three steps: (1) researching the behaviour of the base model, (2) inspecting the behaviour of the model under a large number of scenarios with different policy interventions, and (3) analyzing the impact of changes and combinations of policy interventions on the performance metrics.

This chapter contains the following sections: first, a section that introduces the basic idea behind experimentation and discusses the most important concepts. The second section entails de design of experiments, covering open exploration, scenario discovery, and the experiment settings.

7.1 INTRODUCTION TO EXPERIMENTATION

The experimentation consists of three parts. First, the model behaviour will be investigated by sampling input parameters. Second, the model behaviour will be examined by sampling policies. Third, the model behaviour will be analyzed with sampling *both* the input parameters and policies. Overall, the experiments aim at disclosing the model behaviour under various circumstances and policy interventions as well as providing a quantitative benchmarking and numerical comparisons.

7.2 DESIGN OF EXPERIMENTS

Experimentation aims to create insight in the model itself and the effect of policy interventions on the so-called *base model* where no policy interventions are implemented. However, it is not correct to interpret this as a *base case*, due to the deep uncertainties in both the external factors as the internal model structures. Instead, the base model serves as a benchmark to quantify the effect size of different policies. Due to the large number of uncertain parameters, each simulation run is performed under a large sample of scenarios.

Latin Hypercube Sampling (LHS) is a statistical method used to sample the uncertainty space. It generates near-random parameter values from a multidimensional distribution (J. H. Kwakkel, 2017). In LHS it is key to decide how many sample points will be used in order to generate a meaningful representation of the uncertainty space. Figure 7.1 displays a 2D-representation of the way LHS only has one representation point for each row and column. LHS is the default way of sampling in experimentation in the EMA workbench and thus does not need to be implemented manually.

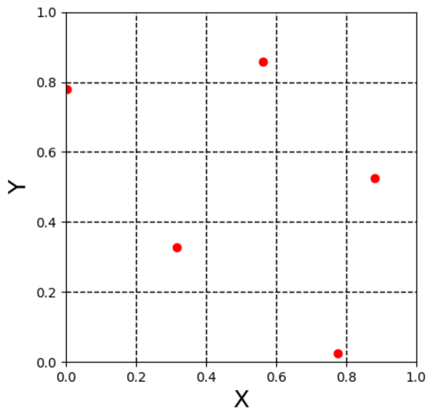


Figure 7.1: LHS 2D example

In figures 7.2 and 7.3 the parameter settings are specified for the simulation runs. In the first step, 2000 scenarios are sampled from the uncertainties listed in section 5.3.1, excluding the policy interventions. Afterwards, more simulation runs were performed including the policy interventions. More simulation runs were necessary due to the larger number of uncertainties involved. Dimensional stacking can be used to determine the minimum required number of scenarios and consists of two steps (J. Kwakkel, n.d.). First, most important uncertainties are identified. Second, a pivot table is created using these identified uncertainties.

7.2.1 Open exploration

As first introduced by Bankes (1993) and pointed out in chapter 3, the Exploratory Modelling and Analysis (EMA) framework is an established research methodology for Modelling Under Deep Uncertainty. J. H. Kwakkel (2017) developed the EMA workbench, an open source toolkit for, among others, open exploration. With the model at hand it is impossible, given the limited available time, to exhaustively sample through the uncertainty space in its entirety. Therefore, open exploration is employed in order to understand "how regions in the uncertainty space and/or decision space map to the outcome space or a partition thereof" (J. Kwakkel, n.d.). Exploration is used to test these mappings under a range of resolutions to various uncertainties. Insight is also gained in the sensitivity of outcomes to the implemented decision levers. As mentioned in the previous section, the workbench uses LHS by default. In the workbench, built-in tools for advanced analysis are available. In particular, for the purpose of this simulation the Scenario Discovery methodology will be used most frequently.

7.2.2 Base model

In figure 7.1 the settings for the base model are shown. Appendix D.1 provides a more extensive elaboration on those parameters. With the base model, 2000 experiments were conducted with all three model components included. Apart from that, the sub models were also run individually with 1000 experiments each. The results of the experimentation with the base model are presented in the next chapter.

Type	Variable	Setting	Meaning
Model	num_agents	1000	number of agents
	lockdown_level	0	no lockdown at initialization
	E0	10	initial number of infected agents
	corona_switch	True	COVID-19 component
	hazard_switch	True	hazard component
	livelihood_switch	True	livelihood component
	testing_switch	True	Testing at specified frequency
	test_frequency	3	test for COVID-19 every 3 days
	population_density	0.15	avg nr. people per household
	min_contacts	5	contact rate
	med_contacts	15	contact rate
	max_contacts	30	contact rate
Livelihood	decrease_mask	-0.5	cost of mask
	initial_live	2	initial livelihood
	increase_livelihood	[0 - 6]	liv. depends on occupation and lockdown
COVID-19	protection	0	agents start without protection
	ptrans	0.1	transmission rate
	precov	1/14	recovery rate
	corona_fraction	0.1	% pop. w. COVID-19 to enforce LD
	isolation_duration	14	days of quarantine
Hazard	shelter_frac	0.05	% pop. that fits in shelter)
	max_cap	pop. * sh.frac	capacity of shelter
	shelter_pop	-	nr. people per shelter
	shelter_time	-	depends on severity
	hazard	False	hazard not happened at initialization
	severity	[1 - 5]	severity determined at initialization
Policies	awareness_policy	False	no policies included
	awareness_effect	0	no policies included
	num_shelters	5	5 shelters at initialization
	cash_transfer_policy	False	no policies included
	height_cash	7	cash transfer starts at 7 days
	corona_prioritization	False	no policies included
	A0	0	targeted agents by awareness campaign

Table 7.1: Parameters for base model

7.2.3 Input parameters

Table 7.2 shows which parameters were used in the experimentation and what the range was over which they were varied. Important to note here is that the severity of the sudden-onset hazard was not always included in the experimentation but sometimes set to a fixed number. This is due to the large effect on the number of agents that need sheltering, leading to large variations in the number of infections that originate in shelters. To better understand the other mechanisms at play in the model, this parameter is was thus sometimes not included.

Parameter	Range	Type	Explanation
Min. nr. contacts	1 - 5	Integer	Number of contacts that people minimally see when going to the market.
Med. nr. contacts	10 - 20	Integer	Number of contacts that people see when going to the market
Max. nr. contacts	25 - 50	Integer	Number of contacts that people maximally see when going to the market
Transmission rate	0.05 - 0.15	Float	Chance to infect someone else
Corona fraction	0.05 - 0.15	Float	Percentage of population infected before threshold is reached
Initial livelihood	1 - 10	Integer	Individual savings that add up to household livelihood
Livelihood threshold	1 - 10	Integer	Average level of livelihood before threshold is reached
Growth threshold	5 - 15	Integer	Represents the percentage growth of COVID-19 cases compare to the day prior
Severity hazard	1 - 5	Integer	Severity of the natural hazard, impacting the radius of affected agents

Table 7.2: Uncertainties

7.2.4 Policy interventions

Apart from the varied input parameters, the policy interventions were also specified. In table 7.3 an overview of the policy interventions and the corresponding settings is displayed. When one of the policy interventions was implemented in the model, the other policies were always excluded. The code implemented in the EMA workbench can be found in Appendix E. With each policy intervention parameter setting 1000 experiments were performed.

Policy	Experimentation	Explanation
Lockdown restrictions	"COVID-19 over liv" "Liv over COVID"	The government can decide to prioritize the livelihood over COVID-19 or the other way around. This determines the length and strictness of the lockdown.
Awareness campaign	"No. target agents" = [0% - 10%] "Effect contact" = [0.01 - 0.1]	With the awareness campaign, there are two parameters to vary: the number of agents that are targeted by the government, and the effect that this interpersonal contact has.
Shelter	"Number of shelters" = [10-20] "Shelter frac" = [0.01 - 0.1] "Shelter perc meeting" = [0.1 - 0.3]	The number of shelters, shelter capacity, and agents you meet are all varied
Cash transfer	"Height" = 1, 2, 3 1 = 7 days 2 = 14 days 3 = 21 days "Switch" = 1, 2 1 = On 2 = Off	Providing the poorest of households with cash transfer that contributes to their livelihood for a specified amount of time

Table 7.3: Policies

The policies presented in table 7.3 are experimented with in isolation. Afterwards, the policies are combined into a fifth and last policy, in order to find out what the interplay of the policy levers is on the model metrics.

7.3 CONCLUSION

This chapter described the design of experiments. After introducing the theory behind experimentation and the decision to use open exploration with the EMA workbench, the input variables for the base model and settings for the policy interventions were presented. The policy interventions are not combined in the model experimentation. The results of the experimentation are presented in the next chapter.

8 MODEL RESULTS

This chapter presents the results from the experimentation. The first section dives deeper into the KPIs and what information is derived from the several experiments. Afterwards, the base model behaviour is presented, with extra focus on some parameters that are influential for the model behaviour. The model with and without the sudden-onset disaster is presented, as well as the effect of the different levels of lockdown, and the influence of the contact rate in the model. After the base model behaviour is discussed, the effect of the four policy interventions is shown whilst the parameters in the base model are kept constant. In this section, the results of the experiments are presented. First, the model results of the base case are shown where no policy interventions are implemented. Specifically the effect of different lockdown levels on the model metrics are displayed and the effect of the hazard component of the model is shown.

This chapter therefore addresses the following sub question: *SQ4: What are the effects of different policy interventions under various scenarios?* Before diving into the model results, the following section discusses the KPIs in more details in order to benchmark the different outcomes.

8.1 KPIS

To answer the main research question, the most meaningful metrics to inspect are the number of infections over time and the progression of average livelihood. Many pre-existing analysis tools of the EMA workbench examine statistics and outcomes at the end of each model run. In the context at hand however, the final outcome is not the most relevant to inspect. Instead, it is more valuable and significant to see the trajectory of the livelihood and COVID-19 metrics. Therefore, there are two metrics that are used to assess the COVID-19 trajectory: (1) the maximum number of infections and (2) the total area under the infections curve. The reason for this first metric is that "flattening the curve" is one of the desired outcomes in order to relief pressure from healthcare facilities. The total area under the curve is checked to see the cumulative amount of sick days in the community. It may also show that, even though the peak might be at a similar height, the recovery from the outbreak is reached sooner.

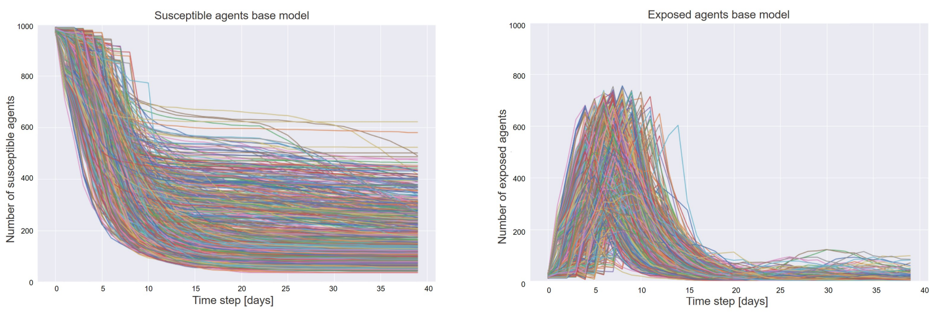
The second main KPI is related to the average livelihood. In this case, it is again not only relevant to see the final average livelihood but to also see how the livelihood develops during the model run. Three metrics from the average livelihood are used for analysis: (1) the minimum average livelihood per run, (2) the variance of livelihood, and (3) the total of the negative livelihood. The reasoning behind the variance metric is that a more stable average livelihood is assumed to be desirable. The total negative livelihood is an indicator for the gravity of the problem that the community is facing when a sudden-onset disaster occurs while dealing with the containment of COVID-19.

8.2 BASE MODEL BEHAVIOUR

For the base case, the chosen parameter settings are displayed in table 7.1. Since an analysis of the entire model behaviour is not feasible and also beyond the scope of this research, the focus lies on the most relevant outcomes with respect to the main research question. Additional outcomes can be found in appendix F.

8.2.1 Base model behaviour on livelihood and COVID-19

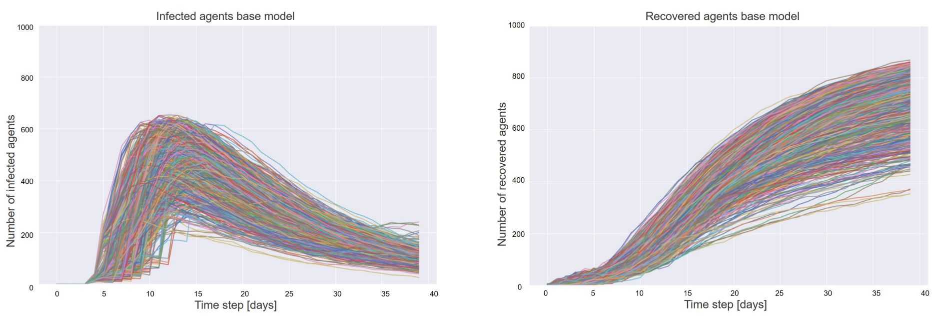
When varying the input parameters within the specified input range, the outcome space for the COVID-19 trajectory looks as presented in figure 8.1 to 8.2. There is a wide range of possible model outcomes and trajectories within these runs. A few drivers for this behaviour are discussed: the effect of the sudden-onset disaster component, the effect of the lockdown restrictions, and the effect of the contact rate both within the shelters and at the market.



(a) Susceptible agents base model

(b) Exposed trajectory base model

Figure 8.1: Susceptible and exposed base model



(a) Infected trajectory base model

(b) Recovered agents base model

Figure 8.2: Infected and recovered base model

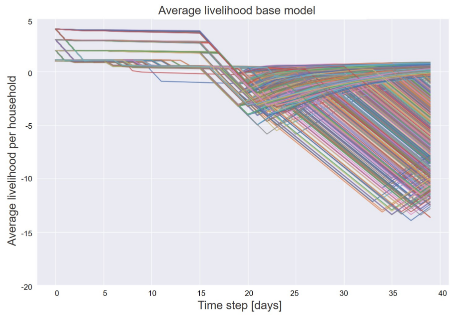


Figure 8.3: Average livelihood base model

The different levels of lockdown during all of these runs are plotted in figure 8.4. Important to note here is that the lockdown level is imposed for *two weeks* and based on the thresholds as discussed before. From figure 8.3 can be derived that most of the time there is a sharp decline in average livelihood, which is associated with the lockdown restrictions. In the base model the government prioritizes livelihood over the infection numbers, but as the infection numbers are increasing without affecting the livelihood at first, this prioritization is not seen back in the model behaviour. This also implies that the *moderate* lockdown setting is not in operation often.

The sharp decline in average livelihood is caused by the lockdown restrictions. The effect of these restrictions is immediately noticeable whereas the effect on the infections has a delay. The reason for this delay in infection numbers is due to the incubation time and the testing frequency in the model. The immediate effect on the average livelihood is because the livelihood also consists of the household savings. This means that even though the livelihood drops directly after the lockdown, this does not mean that the average livelihood immediately falls below the livelihood threshold. If the average livelihood threshold were to be plotted, a more delayed effect of the lockdown restrictions would be displayed, largely based on the initial amount of livelihood of the households and the level of lockdown imposed by the government.

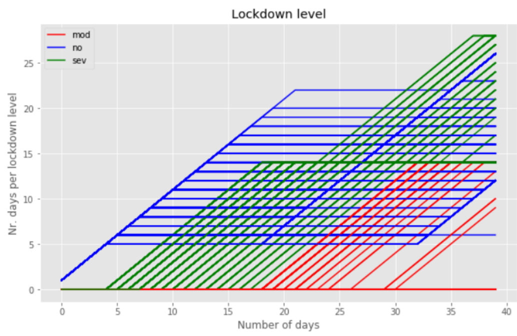
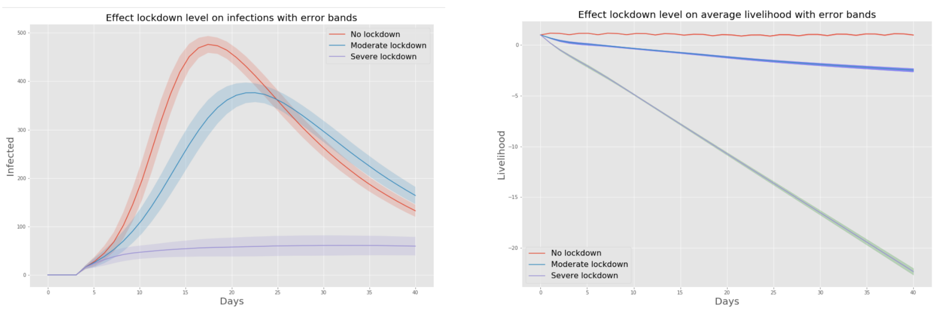


Figure 8.4: Base model: the lockdown levels

8.2.2 Effect lockdown levels

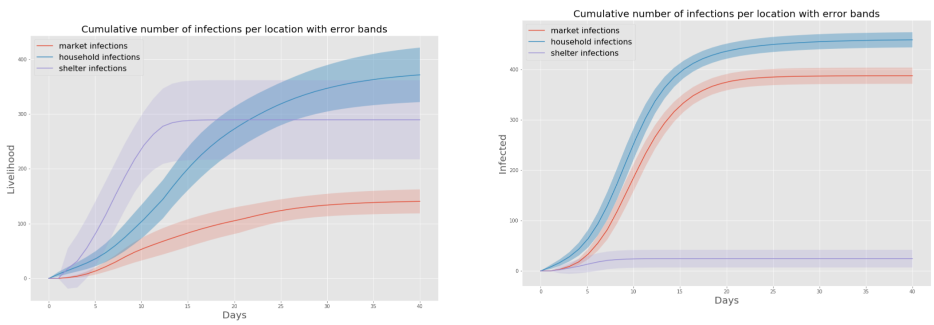
While the effect of different lockdown levels is further examined in the section about the effect of policy interventions, simply fixing the lockdown levels already reveals a trade-off in the base model. The model was run with the lockdown level fixed constantly at *no* lockdown, a *moderate* lockdown, or a *severe* lockdown. The effect on the average livelihood and the infection rate can be seen in figure 8.5. As evident from figure 8.5, the severity of the lockdown is associated with a distinctive trade-off between infection numbers and average livelihood, as the most promising results for the COVID-19 trajectory correspond to a steep downward average livelihood trend.



(a) Fixing lockdown levels: infection numbers **(b)** Fixing lockdown levels: average livelihood

Figure 8.5: Effect lockdown restrictions

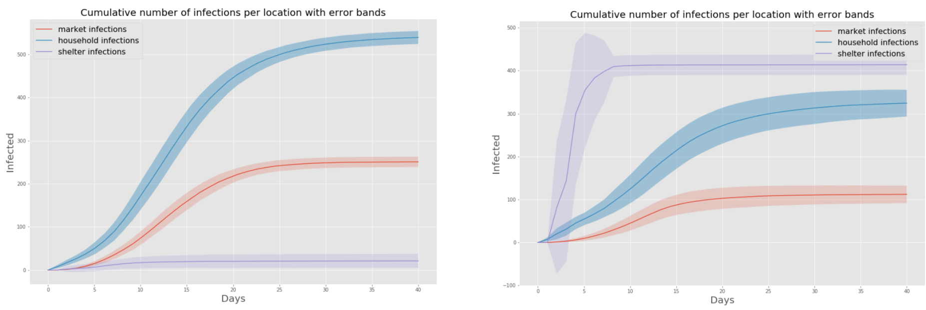
Apart from looking how the lockdown levels affect the KPIs of the model, it is also insightful to see at which of the three locations agents mostly get infected: their households, the shelters, or at the marketplace. Figures 8.6 and 8.7 display the cumulative number of infections grouped per location: at the market (red), at the shelter (purple), or the household (blue). In the base model, the severity of the sudden-onset disaster has been fixed to 1 in order to limit the effect of this model component on the model outcomes. From those results can be concluded that the households are the largest source of infections, closely followed by the shelters, as can be seen in figure 8.6a.



(a) Base model: infection location **(b)** Infection locations distribution: lockdown level 0

Figure 8.6: Infection originating locations base model and lockdown level 0

From inspecting the lockdown levels on the infection locations, the main take away is that, apart from decrease in the overall number of infections when the lockdown level gets more strict, the distribution changes. The share of infections originating in the households increases, as that is where most agents reside during lockdown. The share of infections at the marketplace decreases, which also makes sense as less agents have access to it.



(a) Infection locations distribution: lockdown level 1

(b) Infection locations distribution: lockdown level 0

Figure 8.7: Origination of infections per location in lockdown levels 1 and 2

8.2.3 Effect contact rate on base model

Part of the different outcomes in the COVID-19 graphs can be explained by the contact rate. In the model, the contact rate corresponds to the level of lockdown that is imposed by the government. For example, the contact rate decreases to less than three people per day in case of a severe lockdown. However, the initial contact rate without any lockdown restrictions is most influential as it determines the extent of the outbreak of the virus. It can therefore be concluded that the contact rate is an important driver for the model outcomes and will be included for further experimentation with the policy interventions.

Figure 8.8 illustrates the significant effect of increasing the initial contact rate from three to ten people on the infection numbers. In the figure the different lines represent different iterations of the same configuration with only the contact rates that change. For this analysis, the contact rate was set to a single fixed number instead of an input range from where agents randomly draw the amount of other agents that they will meet.

Figure 8.8: Base model: effect contact rate on infections

Figure 8.9 displays the progression of the average livelihood in the model. The contact rate does not have a significant on these model outcomes, which is to be expected.

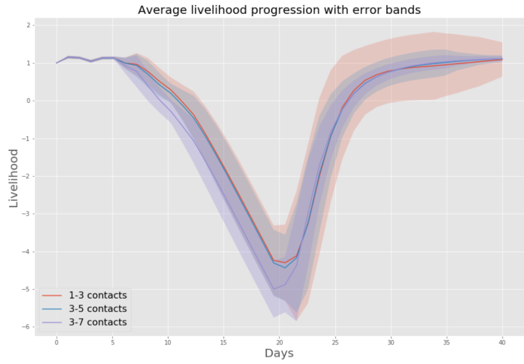
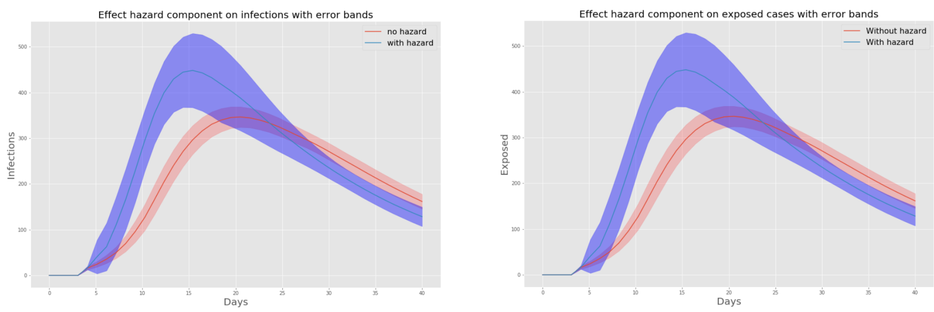


Figure 8.9: Base model: effect contact rate on average livelihood

8.2.4 Effect sudden-onset disaster component on base model

The model behaviour of the base model including the disaster component is vastly different from the model behaviour without it. This difference can be attributed to the origination of so-called *COVID-19 hubs* when, due to large evacuations, people are crowding in shelters for several days.

It is evident from figure 8.10 that the sheltering causes a large upward trend of COVID-19 cases as the contact rate in the shelters is higher than the contact rate at home or at the market. When the agents are released from the shelters and proceed to enter the market for livelihood, the rest of the community gets exposed to these COVID-19 hubs. This leads to an increasing number of infections, resulting in large numbers of people that are in need to stay at home and quarantine.



(a) Infections trajectory with and without hazard component
(b) Exposed trajectory with and without hazard component

Figure 8.10: Effect lockdown restrictions

Another implication of the shelters is that the infection numbers increase so rapidly that a lockdown is imposed on the entire community and also the livelihoods of agents who are *not* affected by the evacuation are decreasing. This effect can be inspected in figure 8.11.

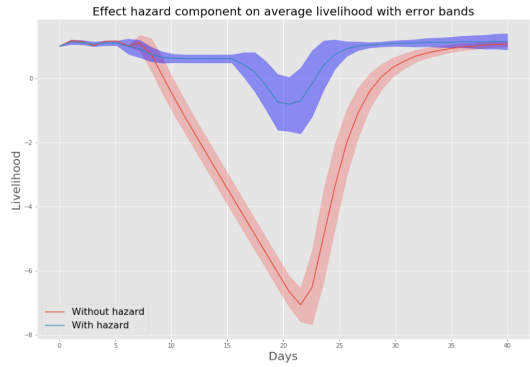


Figure 8.11: Effect max contacts with and without disaster on average livelihood

8.3 INTERVENTIONS ON BASE MODEL

Four different policy interventions were implemented. Each of these was tested in the base model to see what the effect of the intervention on the model behaviour was, while the other input and model parameters were kept constant. The experiments are conducted with each 1000 agents, 1000 runs, and with each model run 40 time steps.

8.3.1 Effect awareness

With this policy intervention, a specified number of agents is targeted that can spread awareness regarding COVID-19 within the community. Before testing this policy intervention, it is important to understand what the possible maximum positive effect can be. Therefore, the base model outcomes are compared to model outcomes where the awareness of *all* agents is set to 100%, meaning that all agents comply with the quarantining regulations and stay at home when they know that they have COVID-19.

Initial results did not show a significant difference in the model outcomes, as depicted in appendix F, figure F.10. This is due the implementation of the quarantining rules, which in these runs only extended to the agents who were infected themselves. Housemates did not quarantine until they were confirmed sick as well, resulting in an ineffective policy. Another difficulty when inspecting the effectiveness of the policy was due to the *incubation time* of five days. After implementing quarantining housemates and experimenting with different incubation times, the same experiment was conducted, of which the results can be found in figure 8.12. It shows the maximum potential of the awareness policy. The legend shows that the purple curve represents the model without any compliance from any of the agents, the red curve represents the model with full compliance from all agents.

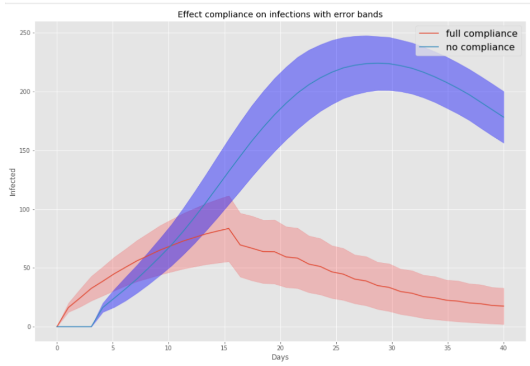


Figure 8.12: Maximum effect awareness policy on infections

After identifying the maximum potential of awareness, experiments were conducted to see how effective the policy was with spreading awareness orally through the community. Experiments were conducted, once with testing on a daily basis, once with testing with a lower frequency. The results can be found in figure F.11a and show that awareness and compliance to quarantine rules have a positive effect on the number of infections with COVID-19. This is only in figure F.11a, because in this scenario the test frequency is set to 1, meaning daily checking of citizens for COVID-19. In figure F.11b the effect of awareness is less fruitful, because due to a lack of testing capacity, the agents are unaware of possibly carrying COVID-19 and thus not quarantining.

There are two important takeaways from this analysis. First, the effect of compliance is limited in case there is a large impact of the sudden-onset disaster. In the model, quarantining in the shelter is not an option due to the limited space and possibilities to isolate. The second takeaway is that awareness is only useful in combination with regular testing.

Though the effect of awareness on the number of infections is positive, the livelihood does suffer from the number of agents not able to go to the market, as depicted in figure 8.13.

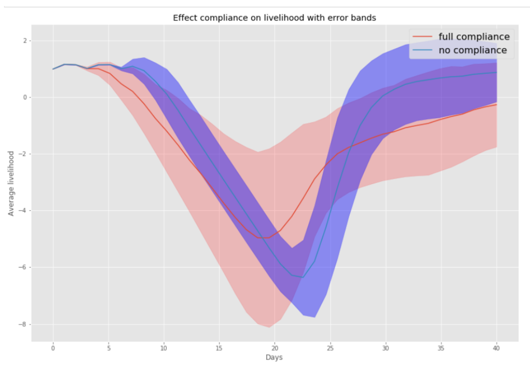
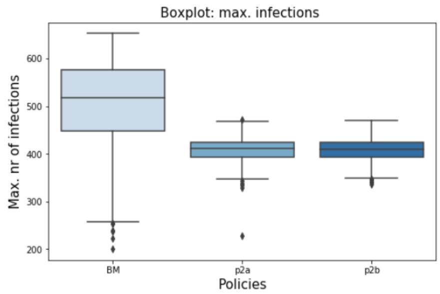
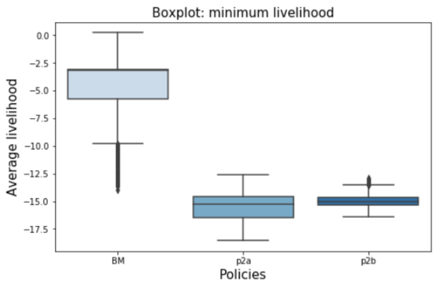


Figure 8.13: Awareness effect on livelihood

As the maximum effect of awareness has been established, it would provide more insight to see what part of the community should be reached by the awareness campaign of either the government or a humanitarian organization to reach a positive effect on the COVID-19 and livelihood prognosis. Figure 8.14a and 8.14b show the model outcomes of 1000 experiments with the awareness policy implemented. Boxplots for two KPIs are plotted: the maximum number of infections is compared to the base model and the average livelihood is compared to the base model. From figure 8.14a can be derived that the awareness policy has a positive effect on the COVID-19 trajectory. It also appears that the policy is robust, as the interquartile range (from 25th percentile to 75th percentile) covers a small range of outcomes. Figure 8.14b shows that the average livelihood does diminish steeply. The reason behind this decline is that the agents that are required to quarantine at home are not visiting the marketplace, hence not acquiring any livelihood for their household.



(a) Infection numbers with awareness policy settings



(b) Average livelihood with awareness policy settings

Figure 8.14: Awareness effect compared to base model

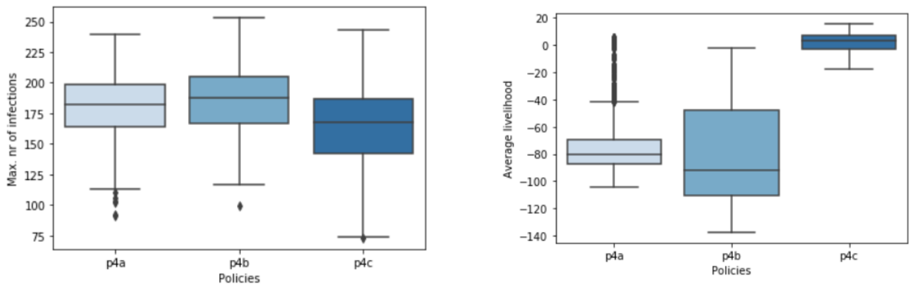
8.3.2 Effect cash transfer

As expected, the cash transfer does not have much influence on the model behaviour except for the average livelihood. The intervention is very straightforward as the cash transfers goal is not to increase economic activity perse, but to lift people from negative livelihood. Appendix F, figure F.9 displays how the different policy interventions were implemented in the EMA workbench. Equations I to III are a representation of this implementation. In figure 8.15 it is clear that this policy intervention has the intended effect. These are results from 1000 model runs. Further discussion on the implementation of this policy can be found in chapter 9, section 9.3.

(I) $p4a = \{awareness\ policy : False, awareness\ effect : 0, num\ shelters : 10, shelter\ frac : 1, corona\ prioritization : False, cash\ transfer\ policy : True, height\ cash\ : 7\}$

(II) $p4b = \{awareness\ policy : False, awareness\ effect : 0, num\ shelters : 10, shelter\ frac : 1, corona\ prioritization : False, cash\ transfer\ policy : True, height\ cash\ : 14\}$

(III) $p4c = \{awareness\ policy : False, awareness\ effect : 0, num\ shelters : 21, shelter\ frac : 1, corona\ prioritization : False, cash\ transfer\ policy : True, height\ cash\ : 21\}$

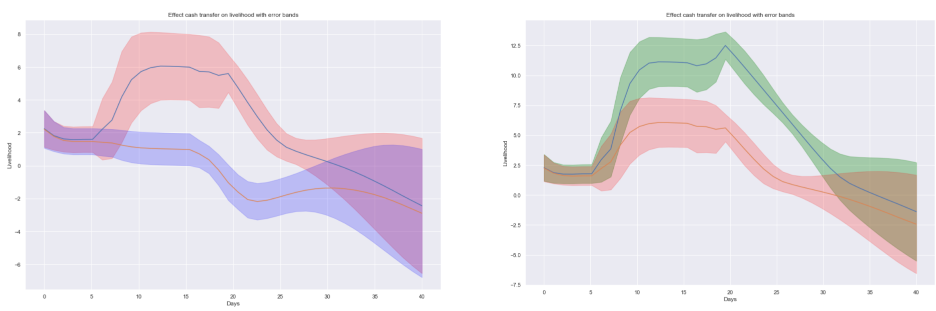


(a) cash transfer on infection

(b) Cash transfer on average livelihood

Figure 8.15: Effect cash transfer

This policy shows that there is quite a difference between the first two and third policy. The explanation is that agents will only go to the market when they are in need of livelihood. In the third policy, the agents have received enough from the cash transfer that many do not go to the market. This leads towards a lower raise of infections and a lockdown is not necessary. As the lockdown is not necessary, the livelihood remains at a stable and healthy level.



(a) Cash transfer (low) compared to base model on livelihood

(b) Cash transfer (low and high) on livelihood trajectory

Figure 8.16: Average livelihood with cash transfer policies

In figure 8.16a the effect of the cash transfer is clearly visible during the model runs. However, the "final" outcome of the cash transfer is not that different from the base model outcomes leaving the average livelihood for households in a similar range. This does not mean that the policy is ineffective as in the base model there are many households whose livelihood dropped below the threshold.

In figure 8.17 the relations between livelihood, cash transfers, and infection peaks are depicted. Each dot in this plot represents an experiment. The darker the dot, the larger the amount of cash in the cash transfer. It is clear that the height of the cash transfer has a positive effect on the minimum average livelihood.

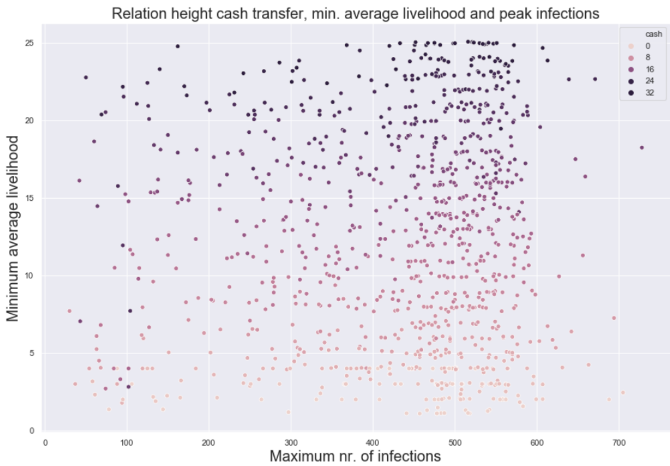
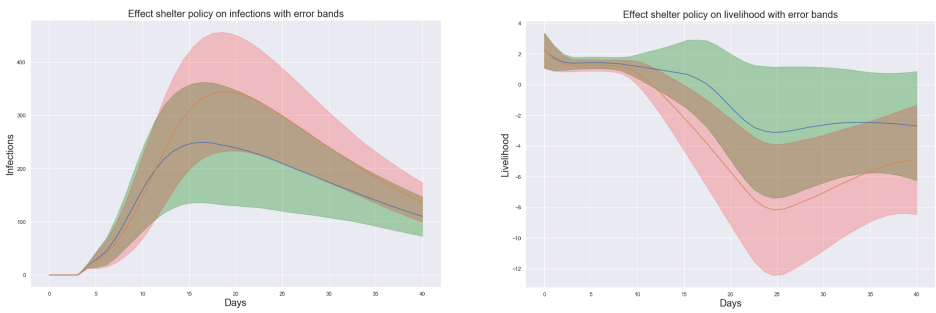


Figure 8.17: Livelihood, cash transfer and maximum infections

8.3.3 Effect shelter choices

This is an influential policy intervention because it deals, among others, with the contact rate within the shelters. Since the severity of the hazard has a large impact, the experiments are run once with the severity fixed to the third level, and once without the severity fixed. The severity is set to a fixed impact in order to isolate the effect of this policy intervention. In these experiments, the number of shelters is increased and the maximum number of encounters per agent is varied by changing either the capacity of a shelter or by restricting the percentage of encountered agents in a shelter. In figure 8.18 the model outcomes are displayed for the shelter policy. Figure 8.18a displays that the infection curve of the model runs *including* the shelter policy is lower on average. Figure 8.18b shows that the shelter policy is also beneficial for the average livelihood of the community.



(a) Shelter policy effect on infections curve base model **(b)** Shelter policy effect on average livelihood base model

Figure 8.18: Effect shelter policy on KPIs

Figure 8.19 depicts the feature scoring of this policy option. Feature scoring involves the calculation of the correlation between individual model variables and the model metrics, using univariate linear regression. It reveals that the *shelter_frac* has the largest impact on the model metrics. This variable determines the capacity of the shelters: the fraction of the population that is able to fit into one shelter.

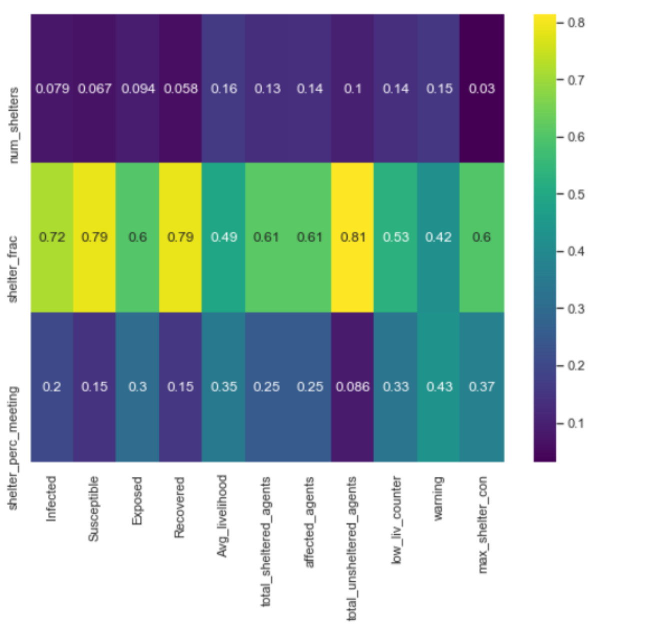


Figure 8.19: Feature scoring shelter policy

This finding is supported by figures 8.20 and 8.21. In 8.20, the relation between the *infection peak*, *sum of negative livelihood*, and the *shelter fraction* is depicted, and shows that a smaller shelter fraction results both in less infections and a higher livelihood.

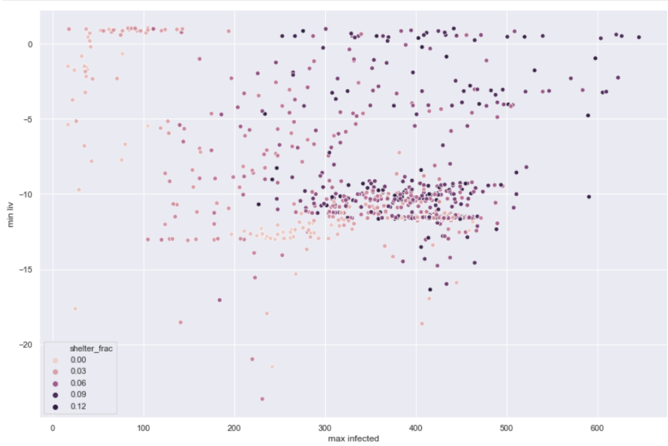


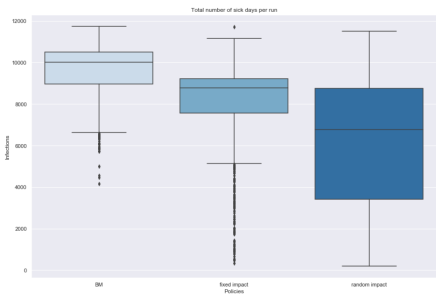
Figure 8.20: Relation infections, livelihood, shelter fraction

The second figure displays the relation between the infection peak, sum of negative livelihood, and the number of available shelters is depicted, and shows that there is not a clear relation between these metrics and model variables.

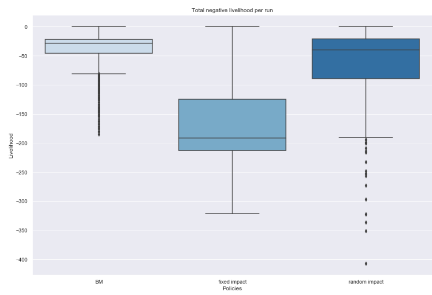
Figure 8.21: Relations infections, livelihood, number of shelters

From these model outcomes can be concluded that increasing the number of shelters has a limited influence on the model metrics. However, the *maximum contacts per shelter*, which depends on the shelter fraction, *is* influential for both of the KPIs.

Another finding from these experiments can be derived from comparing the model outcomes with a *fixed* hazard impact to model outcomes with a *random* hazard impact. The configuration for the model runs with a fixed impact was a relatively large sudden-onset disaster. As depicted in figure 8.22, when a disaster of this size happens, there is little that the shelter policy can do. All agents need to shelter anyway and will be cramped together, resulting in negative results for both KPIs.



(a) Fixed vs. random severity on inf.



(b) Fixed vs.random severity on avg.liv.

Figure 8.22: Fixed - random hazard on KPIs

8.3.4 Effect lockdown policy

There are two alternatives to influence the lockdown in the model. The first is to experiment with the thresholds that determine the type of lockdown that is imposed. The second is to change the prioritization of COVID-19 over livelihood. In the base model, the livelihood is always prioritized over COVID-19 cases, meaning the lockdown level changes to moderate in case the livelihood is under the threshold value, regardless of high infection numbers. This is based on the situation in the Philippines (and more developing countries) where the government is extremely reluctant to impose a lockdown while the economy is suffering (AFP, 2020; BBC, 2020).

The choice of threshold does not significantly alter the progression of infection numbers, which is due to the fact that the government imposes a lockdown when COVID-19 gets out of hand. At that point, a *severe* lockdown is imposed for two weeks. However, the lockdown level does not represent the priority of the government because once a lockdown is imposed, the level of lockdown cannot changed once the livelihood drops below the threshold. This is depicted in appendix F, figure F.12. Relaxing this assumption might provide more insight, as a flexible adjustment of lockdown policies might lead to dominant outcomes. One indication might be figure 8.5, where a moderate lockdown level shows acceptable livelihood levels while infection rates decreased significantly. The next chapter discusses this policy intervention in more detail, as there are some alterations possible that might lead to more insights in the systems at play.

Even though the results do not show promising results in the COVID-19 trajectory, figure 8.23 shows insight in the relation between the *growth threshold* (representing the %-growth needed before a lockdown is imposed) and the total negative livelihood. It is clear that a choosing a larger growth threshold before imposing a lockdown has a positive effect on the total negative livelihood. However, it is remarkable that this does not seem to affect the infection curves.

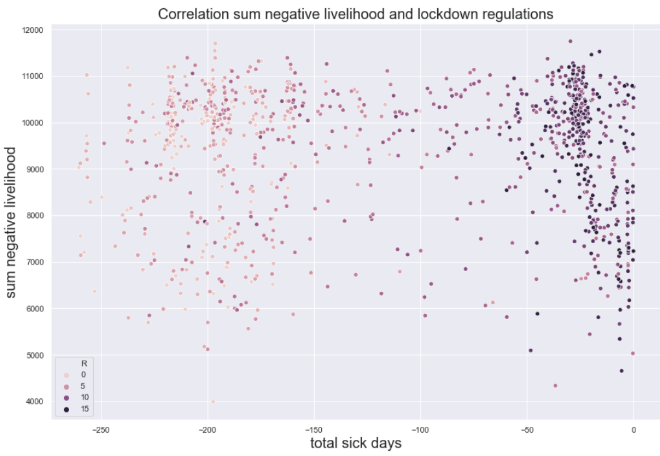


Figure 8.23: Trade-off growth threshold and sum negative livelihood

This input was used for figure 8.24 to create a pairplot where the relations are shown between the *growth threshold*, *total area beneath infections curve*, *total sum of negative livelihood*, and *corona fraction*. It confirms the conclusion from the previous paragraph: the growth threshold does impact the livelihood negatively when it is smaller due to the lockdown restrictions that are imposed, but this does not significantly affect the infections numbers.

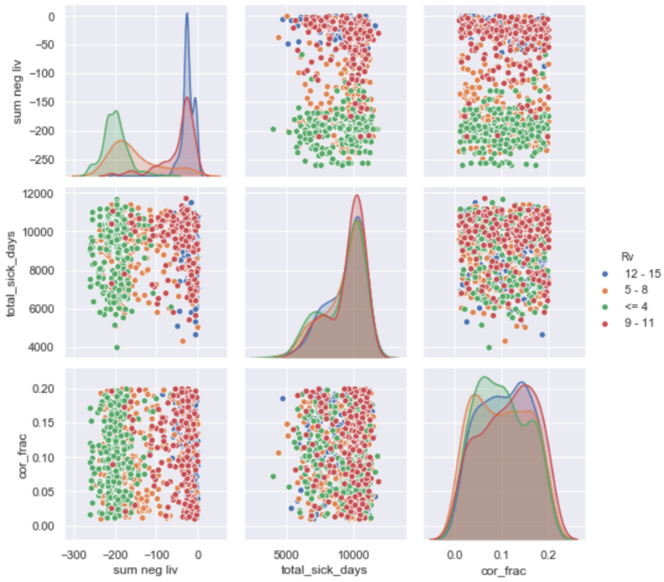


Figure 8.24: Pairplot trade-off growth threshold and negative livelihood (1000 experiments)

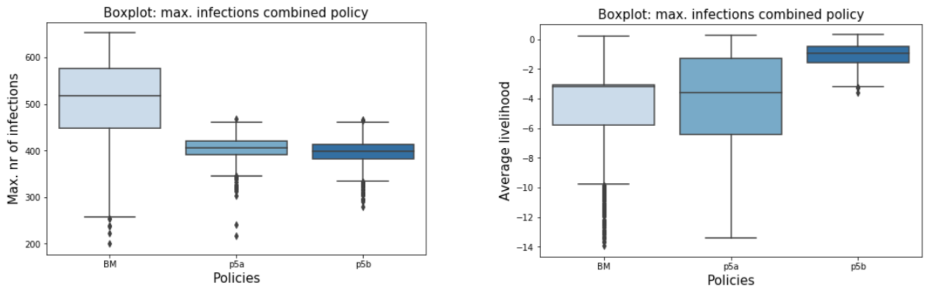
8.3.5 Combining policy interventions

In addition to implementing the policy interventions in isolation, the most promising policy interventions have been combined for the last experimentation. The awareness policy, cash transfers, and shelter policy have been combined in order to see if the beneficial effects would reinforce each other and to find out how they interact. In table 8.1 an overview of the settings for this experiment is depicted.

Policy	Setting 5a	Min	Max	Setting 5b	Min Max	
Awareness	A0	10	100	A0	10	100
	Test frequency	1	10	Test frequency	1	3
	Awareness effect	0.05	1	Awareness effect	0.05	0.1
Cash	Height	7	21	Height	14	21
Shelters	Num shelters	5	15	Num shelters	10	20
	Shelter frac	0.05	0.1	Shelter frac	0.05	0.1

Table 8.1: Settings combined policy experiment

Figure 8.25 displays the boxplots on the model outcomes of combining these three policies. Figure 8.25a displays the maximum number of infections compared to the base model, whereas figure 8.25b displays the minimum livelihood compared to the base model. From these results, several conclusions can be drawn. First of all, the effect on the maximum number of infections is similar to the effect of the awareness policy on the maximum number of infections.



(a) Boxplot maximum infections for combined policy

(b) Boxplot minimum livelihood for combined policy

Figure 8.25: Effect combined policy on KPIs

Figure 8.26 displays the feature scoring of the combined policy. The correlation between the individual model variables and the model metrics is displayed and shows that none of the policies is dominant in achieving the results of the model KPIs. However, when inspecting the average livelihood of policy *5b* in figure 8.25b, this is a significant increase from the results of running the awareness policy in isolation. The combination of the cash transfers in addition to the agents remaining at home to reduce infections proves to be the best overall solution.

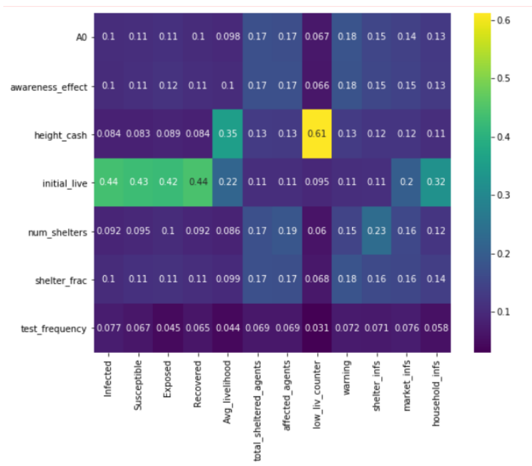


Figure 8.26: Feature scoring - combined policies

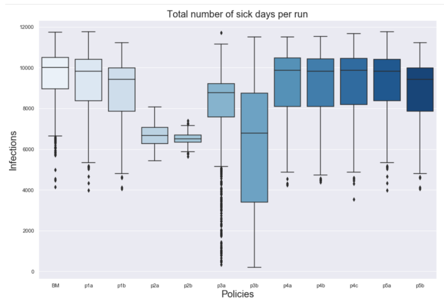
8.3.6 Comparison interventions on KPIs

The policies can be categorized as focusing on either COVID-19 (awareness and shelter capacity) or livelihood (cash transfers and lockdown regulation). However, as the sub systems interconnect, the measures show secondary effects in some cases. In the next sections the effect on the KPIs for each of the policies is discussed.

Impact interventions on infections

An overview of the effects of the policy interventions on the two metrics associated with the COVID-19 trajectory is displayed in 8.27. The largest isolated effect on the COVID-19 trajectory stems from the awareness policy and the shelter policy. The awareness policy focuses on reducing the number of contacts by ensuring that agents quarantine when they are infected or their housemates are infected. This is beneficial for reducing the peak of infections. The shelter policy shows varying results, but overall the outcomes are beneficial compared to the base model outcomes.

(a) Boxplot maximum nr. infections per run per policy



(b) Boxplot total amount of sick days per policy

Figure 8.27: Policy interventions on livelihood metrics

Listed below is shortly summarized what the policy effect is on the COVID-19 trajectory

1. Cash transfer: there is a slight positive effect of the cash transfer on the infections curve, but not significant compared to the base model. The visible effect is due to the decreasing necessity to visit the market when the livelihood is above the livelihood threshold. However, if the height of the cash transfer is not large enough to cover the period of the lockdown restrictions, the infections peak is merely postponed.

2. Awareness: Awareness campaigns have a beneficial effect on the COVID-19 trajectory. This effect is only achieved when regular testing is implemented and it is implemented *before* the epidemic spirals out of control.

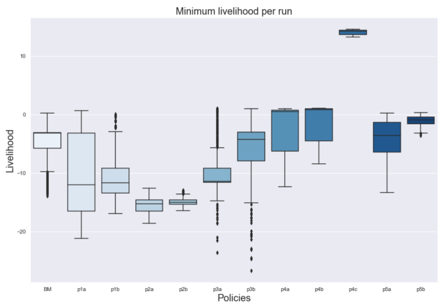
3. Shelter: This has a beneficial impact on the infection curve. This is due to a reduced number of contacts within the shelters and reduced the chance for COVID-19 hubs to originate and spread to the rest of the community. Although only implementing the shelter policy in isolation may lead to a lower number of infections in some cases, the variation is large and this does not pose a robust solution.

4. Combined: combining the cash transfer with both awareness and a better shelter strategy leads to the most robust outcome in terms of infection numbers.

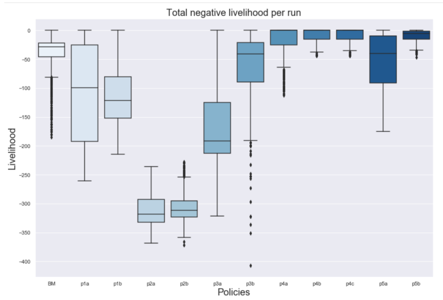
Note: above summary does not consider possible negative effects on the average livelihood.

Impact interventions on livelihood

An overview of the effects of the policy interventions on the two metrics associated with the average livelihood is displayed in 8.28. It is no surprise that the largest positive effect comes from the direct and unconditional cash transfer. However, there is also a beneficial effect that stems from the shelter policy. Livelihood can be preserved by not restricting the market capacity, but also by decreasing the numbers of COVID-19 since infected people must not access the market and thus cannot gain livelihood. A higher awareness magnifies the latter effect, as aware agents comply with quarantine regulations, reducing their livelihood.



(a) Boxplot minimum livelihood per run per policy



(b) Boxplot total negative livelihood per policy

Figure 8.28: Boxplot livelihood metrics per policy

Listed below is shortly summarized what the policy effect is on the average livelihood.

1. Cash transfer: the effect of cash transfers is positive for the average livelihood. There is a significant difference between the different cash transfers policies though. In case the cash transfer is high enough, no negative livelihood is exists in the model runs. This is due to the fact that the cash transfer reaches the point that it supports households for the entire duration of the COVID-19 crisis in the model.

2. Awareness: The awareness campaigns have a negative effect on the average livelihood. This is caused by the large number of agents that are quarantining and therefore unable to gain an income.

3. Shelter: the shelter policy has a positive effect on the average livelihood. This is due to the prevention of COVID-19 hubs in the shelters that later spread through the community. There is a decreased need for lockdown restrictions, allowing all agents to keep visiting the market.

4. Combined: combining the awareness policy with both the cash transfers and the shelter policy may lead to a robust level of average livelihood. This is in large part due to the proportion of the population that is aware of and compliant to the lockdown regulations whilst receiving a cash transfer to sustain themselves in the mean time.

8.3.7 Runtime model

The runtime varied between 1.96 and 4.46 seconds per iteration for the base model. For the policy interventions the runtime varied between 1.03 and 15.43 seconds per iteration. These relatively low runtimes are due to the reduced spatial and temporal granularity of the model and allow for experimentation with many iterations, which would otherwise not have been feasible.

8.4 conclusion

In this chapter the outcomes of the experimentation and base model are discussed in order to answer the fourth sub question: *What is the effect of policy interventions on the interplay between livelihood, sudden-onset disasters, and the COVID-19 trajectory?*, after which the results of the experiments were shown. The model behaviour is analyzed for the base case and different policy interventions. There are several conclusions that can be drawn from the experimentation and base model. First of all, several input parameters are the main drivers for the model behaviour: the contact rate, the lockdown level, and the severity of the sudden-onset disaster. The policy interventions implemented had varying effects on the base model behaviour, with most promising results from combining several policy levers. In the next chapter, the model outcomes are validated and model results are further discussed.

9 ANALYSIS OF MODEL RESULTS

In this chapter, the model results are discussed and data analyses are performed. Both of these steps contribute to answering the last sub question: *How can the findings of this study be generalized into policy advise for decision-makers?*

The chapter starts with a validation of the model results. The model behaviour of the base model is then discussed, after which the results of the policy interventions on the model are examined. The chapter ends with reconnecting the model results to real world application possibilities.

9.1 MODEL VALIDATION

Model validation consists of checking whether the model behaviour is realistic by comparing it to real world behaviour and whether it is able to address the issue posed at the start of this study: developing a model that captures livelihood, sudden-onset disasters, and the spread of COVID-19 to create better insight in the balance between livelihood and the COVID-19 trajectory. Where the verification led to confidence in the model behaviour according to expectations, validation leads to confidence in the model results (Sargent, 2010).

The predictive capacity of the model is limited due to the assumptions and reduced complexity. However, the purpose of the model is not to predict the future nor to reproduce past behaviour, but rather to gain insight into the mechanisms that cause changes in livelihood and the COVID-19 trajectory (Werntges, 2020). The focus of this validation is thus on the general trends that came to light in the model results and the qualitative outcomes rather than the exact quantitative model results. The model validation is performed for the base model as described in section 8.2 and consists of several parts.

9.1.1 Sensitivity analysis

Sensitivity analysis focuses on ceteris paribus changes in model parameters that are not part of the uncertainties and what the effect of theses changes is on the model behaviour. The aim is to gain insight in the model and understand whether certain changes occur due to variations in the aforementioned parameters.

For the sensitivity analysis, the base model is used as reference once again, this time with all the uncertainties as fixed parameters. The chosen configuration for the uncertainties are displayed in table 9.1, as well as the model parameters that are varied for the sensitivity analysis.

Type	Variable	Fixed value / range
Fixed parameter	Min contacts	1
	Med contacts	2
	Max contacts	3
	Max shelter contacts	5
	Initial livelihood	3
	Max shelter contacts	5
Input sensitivity analysis	transmission rate	[0.05 - 0.15]
	recovery rate	[0.035 - 0.105]
	population density	[0.105 - 0.225]
	isolation duration	[7 - 21]

Table 9.1: Fixed and varied parameters for sensitivity analysis

Model input variables are varied by $\pm$ 50% of their base case values, as suggested by J. H. Kwakkel and Pruyt (2013) about dealing with parametric uncertainties in the input values. For the sensitivity analysis 1000 experiments were generated in the scenario space of four external variables. These results can quickly be assessed using feature scoring. Feature scoring involves the calculation of the correlation between individual model variables and the model metrics, using univariate linear regression. Figure 9.1 gives an overview of the results. The metrics are most sensitive to the *transmission rate* that, as expected, mostly influences the values of the SEIR curve. The reason that the *isolation duration* does not impact the model behaviour is due to the fact that this sensitivity analysis was performed on the base model, which means that compliance was not part of this model, therefore, isolation does not happen. These findings correspond to the outcomes of the research from Alvarez et al. (2020), who found that the uncertainties regarding transmission are most influential. They also mention the effect of the fatality rate, but this has been excluded from the study.

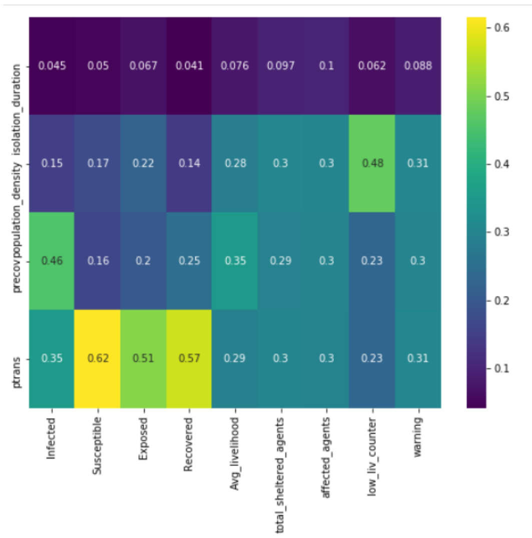
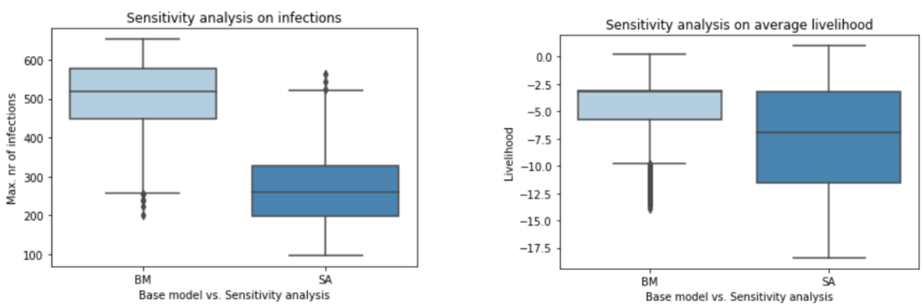


Figure 9.1: Feature scoring sensitivity analysis

To see to what extent the difference in input parameters affect the KPIs, figures 9.2a and 9.2b present boxplots comparing the results of the sensitivity analysis to the base case. It is clear that the result on the infections trajectory is significant, whereas the effect on the average livelihood is less pronounced.



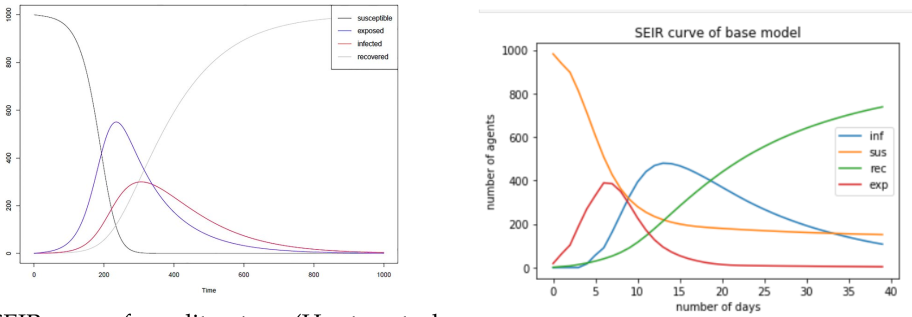
(a) Boxplot sensitivity on infections

(b) Boxplot sensitivity on livelihood

Figure 9.2: Boxplot sensitivity analysis on KPIs

9.1.2 Cross-validation

Due to the novel character of this study, there is no directly comparable study in the literature. However, it is possible to compare the model to other studies within the domain of COVID-19 and evacuation studies.



(a) SEIR curve from literature (Hunter et al., 2018)

(b) Model SEIR curve

Figure 9.3: Comparing model output to validated SEIR curve (Hunter et al., 2018)

In figure 9.3 a SEIR curve from literature is compared with the SEIR curve from the model. The model output is based on 1000 experiments of which the average was calculated. The main difference between the two graphs is the *exposure* curve. The reason that the exposure curve is less high in the model output is due to the modelling decision that exposed agents are already contagious (WHO, 2020b). The figure above thus provides evidence that the formalization of the SEIR model on an agent-level leads to the desired aggregate epidemiological behaviour.

In addition, the outcomes can be compared to current COVID-19 model outcomes from Fang et al. (2020). The curves, as depicted in figure 9.4, are based on data released from the Chinese government and media regarding the COVID-19 outbreak. The curves show a similar trend to the model outcomes of this study.

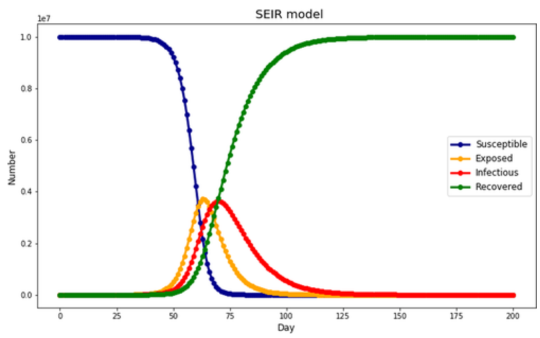


Figure 9.4: COVID-19 SEIR validated outcomes (Fang et al., 2020)

Comparison to literature review

Apart from comparing the COVID-19 infection model outcomes, the model results can also be compared to the literature presented in chapter 2. Two of the three sub systems (livelihood, disaster response, COVID-19) were discussed and the results from those studies display some similarities and differences with this study. The structure of chapter 2 is continued, starting with the literature on both *livelihood (I)* and *COVID-19 (III)*, followed by a section on *Disaster Response (II)* and *COVID-19 (III)*.

Livelihood and COVID-19

Experimenting with the lockdown level in the base model showed that enforcing an aggressive policy regarding containment of COVID-19 resulted in a steep drop in infection numbers. However, it also led to a significant drop in average livelihood of the community, which is a finding that Piguillem and Shi (2020) disagree with. They found that stricter measures lead towards a shorter period of needing them, and is beneficial for the overall level of well-being. Nonetheless, the livelihood numbers in their research corres-pond to the model outcomes. In the most positive scenario of Piguillem and Shi (2020), the livelihood still drops with 40%. That number corresponds to the model outcomes of this study when excluding the sudden-onset disaster component. In that most positive scenario the livelihood drops with 47%, as can be seen in figure 9.5.

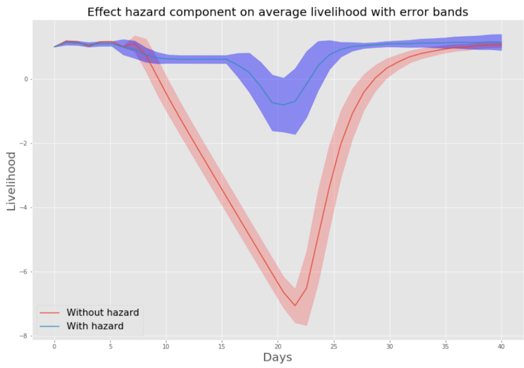


Figure 9.5: Drop in livelihood comparable with Piguillem and Shi (2020)

More qualitative validation can be found in the research from Bethune and Korinek (2020), whose research found that directed quarantining is more useful than a strict lockdown for all. They support strict measures only when COVID-19 has been positively determined, which corresponds to the positive findings of the awareness policy. In addition, Berger et al. (2020) deem testing as highly important. This is also true for the findings of this study. However, asymptomatic infections have been excluded, which makes testing for this scenario effective. When asymptomatic infections would be included, testing would proof a more difficult challenge, resulting in higher infection numbers.

A difference with the found literature regarding COVID-19 and livelihood is related to the chosen time frame. According to both Martin et al. (2020) and Bethune and Korinek (2020) the livelihood drop is persistent and might last for many years to come. They predict a short recovery after the first wave, but suspect that the plunge afterwards is deeper and longer. This thesis only covers a time period of 40 days and can therefore not verify nor falsify this finding.

COVID-19 and Disaster Response

Regarding the literature on COVID-19 and disaster response, there were only a few studies that presented relevant data. According to Spiegel et al. (2007), the chance for outbreak of disease *after* occurrence of natural disaster increases significantly. In the context at hand, the order is reversed as the outbreak was already there. However, the infection numbers did increase significantly after impact of the sudden-onset disaster. In the model outcomes this is due to the crowdedness at shelters, whereas in Spiegel et al. (2007) argue that it is due to poor hygienic conditions. This was not part of the scope and can thus not be validated.

Watson et al. (2007) found that displacement of population is associated with the outbreak of disease, which *can* be confirmed by the model results. The outbreak is primarily due to crowded shelters and can be diminished greatly if people social distance apart from their households. Other factors that Watson et al. (2007) researches are not included, such as the availability of water and healthcare services.

9.1.3 Expert validation

Lastly, the model results are discussed with experts to validate the findings and identify whether the observations comply with practical knowledge and experience. Throughout this research, modelling decisions and scoping choices were discussed with experts in the humanitarian domain at 510. Biweekly meetings and discussions on the findings contribute to the continuous validation of the model input.

In addition to validation on the general direction of research and overall validity of the study, two experts on the SEIR modelling approach reviewed the COVID-19 decisions and modelling choices based on their experience in developing a COVID-19 forecasting model. Their two main points of feedback consisted of ensuring that the 'recovered' population does not become 'susceptible' again, as immunity within the chosen time frame highly unlikely. Their second point is with regards to the decision to model the 'exposed' population as contagious: there is mixed evidence as to what extent that is the case which is important to consider when interpreting the results (Margutti, 2020). The effect of this is a possible overestimation of infection numbers.

9.2 DISCUSSION MODEL RESULTS

The main conclusion drawn from experimentation with the base model is that without interventions, the livelihoods of poor rural communities will inevitably decrease. Policy interventions aiming specifically at increasing the livelihood of households might provide temporary relief, but those efforts are basically lost if no adequate evacuation policy is included at the same time.

An important driver behind the model behaviour is the sudden-onset disaster component and the corresponding decisions affecting the sheltering process. The interplay between the sudden-onset disaster component and livelihood is important but cannot be influenced by the actors in the model, nor by decision-makers in real life. Without the sudden-onset disaster component, no sheltering is needed and no COVID-19 hubs originate there. This leads to less infections, which means less people that are unable to go to the market, but also less need for market restrictions from the government. Overall, the livelihood in this scenario is superior.

When the sudden-onset disaster component *is* included in the model, this leads to a varying number of agents that seek shelter regardless of the associated risk of COVID-19 hubs, as the immediate danger overrules the longer-term risk of contracting the virus and possible lockdown scenarios. In case of a large impact by the sudden-onset disaster, shelters become overcrowded and COVID-19 spreads quickly. These people do not have access to the central market as long as they are sheltering, but when they are able to return home after the shelter time has passed, they mingle with the other agents and increase the infection numbers.

Sheltered agents thus negatively impact the livelihood of agents that were never affected by the sudden-onset disaster. This is an important finding. One of the simplifications for this model was to *not* include loss of livelihood caused by the impact of the sudden-onset disaster (due to damaged or destroyed farmlands and properties). But even under this simplifying assumption, the model demonstrates negative follow-up effects on agents that were not directly affected by the sudden-onset disaster. As infection numbers increase due to overcrowded shelters, a strict lockdown becomes inevitable, reducing market capacity and livelihood over the entire population.

Moreover, when policies solely aim at optimizing sheltering in terms of the spread of COVID-19 (for example by compartmentalizing families, reducing capacity, increasing the number of shelters), the secondary effects on the agents unaffected by the sudden-onset disaster are not accounted for. Disaster response policies should therefore not only focus on infection numbers, but maintain a perspective on population-wide livelihood at the same time.

Similarly, when policies solely aim at sustaining the livelihood of households, the effects of the evacuation are neglected and COVID-19 hubs originate that irrevocably lead to more infections, stricter lockdown, and then a decrease in overall livelihood. Livelihood policies should therefore not only focus on enabling market activities, but maintain a perspective on the epidemiological aspects of disaster response at the same time.

Comparison with Bangladesh and India

In October 2020, a report was published by Ober (2020) regarding the situation in India and Bangladesh caused by COVID-19 in combination with typhoon Amphan. Five months prior, in May 2020, Amphan hit both India and Bangladesh which has been the costliest disaster to ever have impacted these areas, with total damages well over $13 bilion. Over 1.5 million hectares of farmland were destroyed and hundreds of thousands of people had to evacuate to temporary shelters. Ober (2020) describes the complexity of two consecutive disasters happening: migrant workers had to return home due to COVID-19 and had no wages to rebuild after the typhoon hit. Amphan salinized large parts of the damaged farmlands, "rendering them unusable for years to come" (Ober, 2020). They continue stating that rural and poor communities have been hit hardest.

The shelter capacity went down with 60%, with people fleeing shelters as soon as possible due to the perceived COVID-19 threat. Aid deliveries were refused for fear of it being infected, and the number of COVID-19 cases had nearly doubled two weeks after impact of Amphan (Ober, 2020). In Bangladesh almost three times as many shelters were available, but many poor people are unable to afford the test of $1.18 and have low trust in the healthcare sector. Additional floods in the area have resulted in triple disaster, according to Saleemul Huq, director of International Centre for Climate Change and Development. The economic livelihoods of 90% of the unions in these areas was affected, 62% of people reported they are in need of food assistance, and 80% of families skip meals on a daily basis.

These devastating numbers support not only the relevance and necessity of studying consecutive disasters, but also validate the steep drop in livelihood as displayed in the model outcomes. There is a significant change in livelihood levels when multiple disasters are at play and the situation as described in the Bay of Bengal underlines these trends.

9.3 DISCUSSION POLICY INTERVENTIONS

The implemented policy interventions aim at a more favorable COVID-19 trajectory and positive impacts on the average livelihood. In this section, each of the interventions are discussed, focusing on *how* they are implemented in the model. In the next section, the bigger picture is discussed including the feasibility of the interventions.

1. **Prioritization by the government**: This policy intervention focuses on changing the priority of the (local) government and research the result of this change. In the base model, livelihood is prioritized over the number of infections, as real life examples supported (AFP, 2020). In particular, a lockdown would not be imposed if the livelihood ranges below the threshold, despite high infection numbers. This logic would be reversed under the modified prioritization, giving the infection numbers a higher precedence. However, this policy intervention did not show any significant changes in either of the KPIs. This can be ascribed to the fact that once a lockdown is imposed, it is to be maintained for at least 14 days. Instead of rigidly imposing a lockdown when one of the thresholds is met, a more nuanced approach would better describe the decision-making logic of these decision-makers and lead to more realistic model outcomes.

The threshold for a lockdown are changed and experimented with, but the *implication* of the lockdown has not been altered. It would be insightful to examine the impact of changing lockdown restrictions on the model outcomes. For example, the maximum capacity of the market decreases to leaving 20% of all agents able to visit it under a severe lockdown. This has a large effect on the average livelihood in the model and could be experimented with. One approach could involve an assignment of time slots for agents to attend the market, thereby clustering the contacts between agents. However, this is more feasible to implement if the model would have discrete time steps of an hour instead of one day.

2. **Cash transfer**: This policy intervention provides the poorest of households with an immediate, non-recurring, and unconditional cash transfer when their households' average livelihood drops below a certain threshold. As to be expected, this leads to a positive effect on the average livelihood in the model. However, in the model the government does not have a limited budget, which would be the case in reality. Also, it is not included *how* the government establishes which households are below the thresholds and how they can guarantee eligibility for these extra funds. While the distribution of cash certainly has a positive impact on the model metrics, its real world implementation proves to be more complex. A more in-depth discussion on how this policy intervention could and would be implemented can be found in the next section.

3. **Shelter policy**: This policy intervention focuses on increasing the number of shelters and decreasing the capacity of these shelters. The benefit of an extra shelter in the model is negligible compared to the benefit of decreasing the capacity of one shelter, with regards to the number of infected people *and* the average livelihood in the model outcomes. This is due to the effect of a decreasing number of agents encountered in the shelter. The higher average livelihood in the model is caused by these lower infection numbers, as the government in many cases never has the need to impose a lockdown. However, the model does not consider the effect of agents that are unable to find a shelter place for themselves. The feasibility of this solution is discussed in the next section.

4. **Awareness campaigns**: This policy intervention does not consider digital information spreading, nor spreading of fake news that could have counter-productive results. The model further showed that the effect of awareness is only useful when there is adequate and regular testing available for the community. Considering that this research focuses on rural and developing communities, the feasibility of regular testing is questionable. In addition, apart from regular testing, the awareness campaigns should ideally be initiated promptly, as awareness ma not achieve the desired effect once the spread of COVID-19 gets out of hand.

5. **Combined policy**: Combining policies 2, 3, and 4 resulted in the final policy intervention. This resulted in beneficial effects regarding both the overall livelihood and the COVID-19 trajectory. The costs of implementing these policies has not been included, which may be an obstacle given that the focus lies on developing countries that do not have unlimited resources available. Implementing these with the support of humanitarian organizations or international assistance brings organizational challenges along. More on this can be found in chapter 11.

9.4 REAL-WORLD USE AND IMPLEMENTATION

The four policy interventions that have been implemented in this model give an impression of the general positive or negative effect on the identified KPIs. However, the model outcomes cannot directly be translated into policies as they need to be placed in a broader context first. The scope of the research was narrowed down in order to build the agent-based model and to arrive to these results, but important context factors need to be added to conclude generalizable results.

To begin with, awareness policies have not been invented in this pandemic. Governments were faced with the task to inform their inhabitants of possible risks and necessary precautions in previous health crises as well. Also, during the past couple of months, many countries have developed or implemented tools to inform people about the risks of COVID-19 and what precautions people can take to protect themselves and others. The Philippine Red Cross, in collaboration with the Netherlands Red Cross, is also involved in enhancing awareness. The model results do show a beneficial trend for the number of infections. However, there is evidence for a negative side-effect as well if the awareness campaigns are not designed properly. In some African countries people are so afraid of COVID-19 that they no longer dare to visit the hospital in fear of contracting the highly contagious and supposedly dangerous disease (Moscovici, 2020). Patient numbers have dropped with as much as 70%. A survey conducted in 18 African states reveals that this fear originates from negative experience with Ebola, where many hospitals proved to be infection hubs. While the cautious behaviour indeed leads to moderate COVID-19 infection numbers, other types of diseases are rising. More people are currently dying from Malaria than has happened in previous years (Moscovici, 2020). Focusing on increasing the awareness would thus need to be implemented in a different way in developing African countries than in developing Asian countries, where the fear of Ebola did not have an impact on the inhabitants.

Another factor to consider with the awareness policy intervention was first introduced during the literature review. Bradley et al. (2020) found that "risk communication results in increased awareness, which in turn influences people's capability and motivation to perform protective behaviours". However, the context plays once again an important role in the effectiveness of this policy intervention: when alarm is called for a novel hazard but there is low trust in authorities, this may result in public outrage (Sandman, 1993). Bradley et al. (2020) link this public outrage to increased stigma and a reduction in detecting infected people, which leads to a reduction in protective behaviours. The NRC might effectively collaborate with the PRC in creating awareness and launching information tools to communicate about the risk of COVID-19 and achieve the desired result, whereas this might not be the best approach when aiming for the same result in an African country, tormented by Ebola with low trust in authorities.

Moreover, in Bangladesh the risk communication resulted in people turning down food and resources sent by aid organizations in fear of them being infected with COVID-19 (Ober, 2020). All of these examples support the need for carefully designing the strategy regarding campaigns as potential negative (side) effects are prevalent.

The model outcomes also suggest that the awareness enhancement would result in a possible lower average livelihood in the community. The agents that are knowingly infected remain two weeks quarantined, together with their housemates. This causes a drop in livelihood for these households, whereas in a broader context this would not be likely to happen. The WHO found that those with low incomes often continue working despite exposing themselves and their families to COVID-19 (WHO, 2020d).

Second, the direct and unconditional cash transfers gave positive results in addressing decreased average livelihood. To view this policy intervention in a broader context, it is compared to the challenges and opportunities associated with shock-responsive social protection programs. As mentioned earlier, when this policy was introduced in chapter 5, shock-responsive social protection programs aim to extend social protection programs with additional aid in times of sudden crises, be it the aftermath of a natural hazard or an immediate economic crisis. Bastagli (2016) reviewed current literature regarding these programs and summarized most significant findings: when there are finite resources and there is great demand, which is the case in this study, decisions regarding funding priorities are difficult. International government funding tends to be spent on conflict-affected areas dealing with long-lasting crises. With sudden-onset disasters it is generally easier to obtain funding from private sources for natural hazards than it is for economic crises, which implies that obtaining the funding for the cash transfers might prove difficult to people unaffected by the sudden-onset disaster. It supports the modelling decision in this study to provide emergency aid in shelters but not for people that are in quarantine, but also reveals the difficulty of finding enough funds to change this.

A last comment regarding the cash transfers is related to the previously introduced *rapid market assessments*. When aid organizations consider cash transfers (or other forms of assistance such as food), it is important to first assess what effect this will have on the local economy (*Rapid Assessment for Markets Guidelines for an initial emergency market assessment International*

Red Cross and Red Crescent Movement, 2014). The additional money might alter the dynamics of the local market and result in a longer-term negative result. Before considering this policy intervention, it is important to assess the context of the community in question.
Also, this research focuses on developing countries. Bastagli (2016) found that more often than not, the social assistance programs in developing countries continue to depend on donor financing as their main source of funding. If unconditional cash transfers are already in place to some extent, scaling it up due to the COVID-19 crisis might prove difficult as it is likely to require external donor funding which is hard to come by. In addition, it is once again important to also consider the political context of the country or region in question. Bastagli (2016) specifically addresses the considerations with respect to the political economy of social protection. When dealing with a fragile political context or in times of conflict, vulnerability to shocks or lack of social cohesion may negatively influence the effectiveness of unconditional cash transfers.

Regarding the effect of cash transfers on the COVID-19 trajectory, the model outcomes only showed a beneficial effect if the cash transfer enabled people to remain at home for the duration of the infection peak. It decreases the number of agents at public locations and thus also reduces the contact rate, which is crucial in the COVID-19 trajectory. Whether this would translate to the same behaviour in reality is difficult to say, as there is little empirical data available to support this.

Third, the policy regarding sheltering and evacuation showed that one of the most important and effective changes would require to reduce the number of people in the shelters or ensure that people in the shelters are not in close contact with each other. This implies that more shelter locations should be made available. In Japan, local governments have also realized the implications of the consecutive disasters and started preparing for a worst-case scenario. The northeastern Japanse city Kesennuma has increased their number of shelter facilities from 12 to 25 by adding schools and community centers to the list of possible shelter locations (Kyodo News, 2020). The Japanese government has also announced that using hotels for sheltering is an option, although more difficult to guarantee due to fluctuating occupation. Another Japanese city, Amagasaki, has decided to designate shelters specifically to those who have been in close contact with infectious people to prevent COVID-19 hubs from originating in other shelters.

The Japanese approach of dealing with compounding risk provides alternative ways of handling the challenging situation. However, Japan is a developed country with many resources at hand to prevent disasters from happening or manage them. For developing countries, doubling their shelter facilities might be more challenging and implementing shelter policies that filter through people that have and have not been in close contact with COVID-19 requires well organized and collaborating governmental and humanitarian institutions. Increasing the number of shelters may be the more feasible option, as this mostly requires creativity in finding shelter locations.

Fourth, combining the policies might have shown the best overall results for both the average livelihood *and* the COVID-19 trajectory, but this study has left the financial aspects of these policies out of scope. As Bastagli et al. (2016) aptly described in their summary regarding cash transfers, funding is often a challenge, both in acquiring it and the bureaucratic hassle. However, it would be wise to distribute the available budget over a variety of policy interventions rather than to invest all of it in one of them.

9.5 CONCLUSION

In this chapter, the final sub question was addressed and focused on generalizing the model results to advice for decision-makers. First, the model results were validated and a sensitivity analysis was performed. The model results regarding the COVID-19 component are comparable with other research using the SEIR approach, which contributed to confidence in the model behaviour. The sensitivity analysis revealed that the model is sensitive to the transmission and recovery rate. As to generalizing the model results to advice for decision-makers, it is important to put the trends as found in the model outcomes into a fitting context. The positive and negative relations between the policy interventions and the KPIs might change due to variations in the political climate or other context factors at hand.

10 DISCUSSION

This chapter contains the discussion of the model results, its limitations, and validity. The first section presents the critical assumptions and model limitations, including the effect of these on the model behaviour and findings. Subsequently, the validity of the model results is discussed, as well as the generalizability of the results.

10.1 CRITICAL ASSUMPTIONS AND LIMITATIONS OF THE STUDY

Several assumptions were made during the conceptualization, formalization, and implementation of the model. This section reviews several of the critical assumptions that are influential for the model outcomes. The assumptions are first discussed for each sub system and then for the model in its entirety.

The limitations of the model are discussed as well in this section. The limitations are directed at specific model implementation choices, or at the used modelling approach. A graphical overview is presented at the end of this section. Before diving into more specific limitations, it is important to mention that the developed model is highly stylistic and does not fully represent actual interactions and human decision-making. The model outcomes can contribute to identifying general trends of the interacting socio-technical systems, in addition to identifying underlying and influential uncertainties that drive the model behaviour.

10.1.1 Livelihood – assumptions and limitations

Regarding the livelihood component, a critical assumption was to aggregate all sources of income into a single market. This marketplace represents all casual jobs and farmwork, but would in reality be more decentralized and distributed. The implication of this assumption is twofold: first, it does not accurately represent the composition of the community, with only binary occupation statuses (farmer, non-farmer). With more diverse professions a differentiated effect on each of these groups could be identified. Second, it leads to an overestimation of COVID-19 infections as the entire community visits the same place in the model.

A limitation of this model component lies in the scope of the micro economy that was modelled. It was chosen to not extend the trading mechanism with price mechanisms and corresponding supply and demand dynamics. The trading mechanisms have price differences that are related to the lockdown regulations, but do not account for scarcity due to failed harvest or damaged farmlands.

Another assumption is that potential damages to farmlands caused by the sudden-onset disaster are not included in the model, and neither are the corresponding effects on the livelihoods of both the farmers and the citizens that depend on the harvest. The abstractions in this model component merely provide an indication for positive or negative trends regarding community livelihood.

10.1.2 Disaster response - assumptions and limitations

Regarding the sudden-onset disaster component, the assumption was made that all agents in the affected area would and could evacuate, and that the prediction of the affected area itself is accurate. In reality, there are people acting in vain (evacuating when they do not have to) which is not cost-effective (Bischiniotis et al., 2020). Also, agents are not given the choice to evacuate, they all do so by default. Saha and James (2017) researched evacuation behaviour and found reasons for people to not evacuate when they are advised to, for example due to the costs. This behaviour is not represented in the model and might lead to an overestimation of infections and an underestimation of livelihood.

A second assumption in this model component is that an early warning issued by the government results in perfectly distributed agents over all shelter places. Even though this has been announced as desired, it is very well possible that in reality people and households are less optimally distributed. Due to a lack of empirical data this assumption could not be confirmed. This assumption possibly leads to an underestimation of infections.

Lastly, an assumption in this model component was the decision to not further specify the type of shelters. As mentioned before, there are emergency and transitional shelters, which potentially makes a difference for the model outcomes, as the emergency shelters are less equipped for social distancing than the transitional shelters.

10.1.3 COVID-19 - assumptions and limitations

Regarding the COVID-19 component there are several critical assumptions. The first one is related to the social structure. In the model, it only consists of their households and the contacts they meet at either the shelter or market. In reality, the social structure of people is more complex, including interpersonal contacts in social settings, in public transport, during recreational activities, etc. The implication of this assumption is that policies that focus on the reduction of contacts is more complex than reducing the market capacity and leads to an underestimation of the number of infections. Another implication of this assumption is that the model provides limited insight in the whereabouts of the infections. The households and shelters proof to be more important than the marketplace, apart from that there is no further insight. Another limitation is related to the social structure of the agents: agents encounter different agents during every model step, thus each day, at the marketplace. That means that they do not have a stable network. This is only accurate to some extent, as there is usually a certain regularity in daily contacts. The consequence is an overestimation of the infection numbers as agents tend to meet more "new" agents.

Another critical assumption is that agents meet another agent for at least 15 minutes. If contacts are met for a shorter amount of time, this is not registered. Although literature supports the claim that spending at least fifteen minutes in someone's proximity (infected with COVID-19) significantly increases the chance of contracting it, there are also so called *super spreaders* that may infect others in less time. The notion of super spreaders is not included in this research.

Apart from super spreaders, there is more information available about COVID-19 than there was when this study began. This has led to some simplifications in the COVID-19 component that are deemed important for the outcomes. Two of these are (1) the level of contagiousness from start to end, and (2) the effect and existence of asymptomatic infected agents. Both of these assumptions limit the accuracy of the model outcomes with regards to the infection trajectory. Asymptomatic agents would not feel the necessity to test, nor to stay at home and quarantine. This leads to an underestimation of COVID-19 infections in the model outcomes.

In addition, recent events have shown (CDC, 2021) that new mutations of the COVID-19 virus bring additional challenges to the containment of the pandemic. Both in South Africa and in the United Kingdom, a more contagious variant has popped up that impacts the transmission rate in the model. These developments have not been included in this study.

10.1.4 Integrated model - assumptions and limitations

Apart from the sub model specific abstractions, there are also assumptions regarding the integrated model. First, several smaller assumptions and limitations are discussed, then there are a few sections regarding more influential ones, such as the granularity (both in space and time), the policy levers, and the research methodology.

One important simplification is that all agents in the model are assumed to depend on their day-to-day income in order to sustain themselves and their households. Furthermore, the market represents the single source of income for households, with no alternative means of gaining livelihood in case of lockdowns. These two assumptions were made to simplify the marketing mechanism and in order to find the general trend of livelihood when a lockdown was imposed, but may not represent the complexity or real-world microeconomic structures. For instance, people may adopt an increased resourcefulness, or rely on social networks for relief. Furthermore, this simplification increases homogeneity among agents, which is also not reflected by a realistic community. These assumptions lead to a more negative trend in average livelihood than would truly be the case, because the number of poor households is overestimated and their resourcefulness underestimated.

Secondly, one of the validation steps entailed expert validation. In this context, expert input is used to validate model outcomes and modelling choices. While several experts located in the Netherlands were consulted, an inclusion of additional experts in the field would have arguably aided the validity. Due to the ongoing pandemic and crises in the Philippines, some of the scheduled interviews could not take place. Validating choices and outcomes with experts that have a better understanding and local awareness can contribute greatly to the validation of the model and policy interventions.

Granularity in space

Important limitations reside in the level of granularity of the model. Firstly, by adapting the SEIR approach to fit into both the agent-based modelling paradigm *and* the discrete time step of one day, the contact rate abstracts from modelling the detailed movements of agents. Instead, the agents draw a number from a predefined contact rate that corresponds to the currently imposed lockdown level. This means it is abstracted from actually movements at the marketplace, but the number of encounters is predefined according to the random number. However, the main idea of using an agent-based modelling approach is that it enables the possibility for agents to walk around and randomly meet other agents. In the model of this study, the chosen SEIR implementation does not account for this possibility, yet the randomness of market contacts is still preserved.

In addition to the previous limitation, agents do not use transportation to arrive at the central market, shelter, or their household. This limits their number of interactions and might lead to an underestimation of the infection numbers.

Furthermore, the model is a closed model, without interactions with the outside world, apart from the theoretically allowed visitors. The community therefore has no connection with other communities and possible infections caused by travellers is not accounted for. Moreover, mobility within the model is not considered. No agents migrate nor die.

Granularity in time

First of all, the model does not consider the moment of impact with regards to the season. This could impact the livelihood greatly considering that due to the timing a harvest might be lost, impacting the livelihood of the community for the entire year. Secondly, it is assumed that all agents that encounter each other are for the same amount of time in each others proximity. However, the agents residing in shelters are together 24 hours per day, whereas agents at the marketplace could be together for a couple of minutes. The time steps of one day do not account for this possibility and limits the accuracy of the COVID-19 component.

A second limitation regarding the time frame stems from the duration of the model run. The model runs for 40 days, which therefore does not comprehend the long-term results of the impact of these crises. The damages of the sudden-onset disaster can affect a community for many months, similar to the currently predicted effects of the COVID-19 pandemic on the economic recession and thus livelihood.

Policy limitations

Several limitations regarding the policy interventions have been presented in chapter 5. The most important ones are discussed here. Regarding the awareness policy, an important limitation is that the policy does not account for the spread of news through digital channels. This is possibly a large part of where people get their news from. In addition, the possibility of fake news and its influence on people's behaviour is not taken into account. Awareness in the model can therefore only increase, whereas in reality it could also decrease.

Secondly, a limitation can be found in the decision rules for the government. There are two thresholds that the government monitors and based on those thresholds, they do or do not impose a lockdown on the community. In reality there is a less clear prioritization but a more weighted decision-making process resulting in more nuanced behaviour than assumed in this study.

Lastly, the cash transfer policy is limited because there is no repercussion of the added cash on the local economy. In times of scarcity, products on the market would increase in parallel with the increased amount of money available. For humanitarian aid organizations it is a fine balancing act to both support local communities and ensure that their aid does not have negative consequences for the existing economy (*Rapid Assessment for Markets Guidelines for an initial emergency market assessment International Red Cross and Red Crescent Movement*, 2014).

Research method limitations

The chosen research methodology is agent-based modelling. It has been criticized for a lack of validation possibilities (Zhang & Vorobeychik, 2019). D'Souza and Lysenko (2008) support this criticism and argue that emergent behaviour from agent-based models often depends on population size, where scalability restrictions form an issue. Other criticism entail a lack of transparency in generating results, and an insufficient comparability and reproducability, and that the generated results are only moderately comparable and reproducible (Alexander, 2020). Moreover, this study is limited in terms of empirical data and could only be partially validated in quantitative terms.

In table 10.1 an overview of the limitation and their impact on the model outcomes is presented. They are categorized according to the same structure as presented above.

	General characteristics	Effect limitation on KPIs	Spatial characteristics	Effect limitation on KPIs	Temporal characteristics	Effect limitation on KPIs
	Currently implemented		Currently implemented		Currently implemented	
Livelihood (I)	◦Binary occupation status ◦Single marketplace to gain livelihood ◦No detailed microeconomic modelling	◦Effect of cash transfer on local economy precarious ◦Less accurate individual livelihood measure	◦Simplified trading with outside communities	◦Less accurate estimation of livelihood	◦People with cash transfer remain home ◦No seasonality	◦Overestimating effect cash transfer on infections ◦Generalizing effect lockdown on livelihood
Sudden-onset disaster (II)	◦Evacuation as early action for disaster ◦Marketplace, shelters spared by impact	◦Overestimation of livelihood	◦No mobility in shelter ◦No mobility to shelter	◦Less accurate estimation infections ◦Underestimation infections during travel	◦Same shelter (type) for entire aftermath disaster ◦No controlled release from shelters	◦Less accurate estimation infections in shelters
COVID-19 (III)	◦Transmission is simplified ◦No hospitalizations	◦Underestimation of COVID-19 numbers	◦No proximity agents included ◦Purely randmized contacts at market	◦Less accurate estimation infections (both under- and overestimation)	◦Homogenous amount of time in proximity of others day	◦Less accurate estimation infections
Overall model	◦Health status homogeneous ◦No budget restrictions ◦No deaths	◦Better estimation KPIs	◦Closed off community ◦No social interactions	◦Underestimation of COVID	◦No long-term effects of disaster	◦Less accurate estimation of KPIs ◦Only short term impact

Figure 10.1: Model limitations and consequences

10.2 REFLECTION ON THE VALIDITY OF THE MODEL

Validation is used to check whether the developed model is an accurate representation of the system it represents (Van Dam et al., 2013). Validation steps aim at comparing results from the model with real-world data. The validation of agent-based models is more challenging because agent-based models are typically exploratory in nature, implying that the real-world data to compare it to might not be available.

In order to ensure validation, the three model components have been verified and validated separately, to increase confidence in these sub parts. For each of these parts, references in research and literature were available for validation. However, this does not guarantee that the integration of the three sub systems resulted in a valid model, accurately representing the interplay of the three socio-technical sub systems.

Van Dam et al. (2013) describe several validation techniques, of which expert validation, cross validation, and a sensitivity analysis were conducted. Especially the cross validation provided confidence in the validity of the COVID-19 component. The four different epidemiological curves approximate the standard model sufficiently well. Furthermore, the collaboration with TNO and 510 as well as expert assessments of the epidemiological model contribute to validity of this sub system. However, for both the livelihood and the sudden-onset disaster component, cross validation could not be performed.

Another validation technique suggested by Van Dam et al. (2013) is historic replay, but given that the COVID-19 pandemic is unprecedented both in scale and impact, this is not a viable option. Also, as this research is addressing an academic knowledge gap, no literature exists providing valid models that could be used for comparison.

10.3 REFLECTION ON GENERALIZABILITY OF THE RESULTS

In the introduction of this research, the issue at hand was categorized as a wicked problem, meaning that there is no clear and correct solution, proposed measures may have unforeseen effects, and the issue continues to evolve in unpredicted ways. Therefore, by definition a general solution applicable to arbitrary contexts could not be found. The model in this study and its outcomes depend greatly on the parametrisation of the input parameters and uncertainty ranges, which makes it challenging to make the results generalizable. However, even though it is not possible to accurately pinpoint the effect of, for example, cash transfers, it can still be inferred that this policy generally has an immediate positive effect on livelihood, as well as a potential for beneficial second-order effects on the COVID-19 trajectory.

In addition, the characterization as wicked problem, based on the classification principles of (Marier & Van Pevenage, 2017) in section 1.4, implies that the implementation of the proposed policy interventions also forms a challenge. Not only the possible solutions, but also the involved stakeholders are often not aligned. In general, different stakeholders are responsible for different budgets, for different parts of the problem, and in a different moment in the timeline. There are different layers of government to consider, that need to cooperate both together and with humanitarian and other external organizations to achieve a successful implementation. This makes it challenging to coordinate responsibilities and actions.

In section 1.4, a framework was introduced to classify wicked problems. As a first step to solve wicked problems, it is suggested to grow from dissensus among stakeholders to consensus among stakeholders, or from uncertain knowledge to certain knowledge (Georgiadou & Reckien, 2018). This study contributes to the latter, which is important as scientists expect another pandemic at some point in the future, and the frequency and severity of natural sudden-onset disasters is only expected to increase. The COVID-19 pandemic poses a learning opportunity and the model developed for this research is a tool that can be used for this purpose. The model outcomes from this study might not directly translate into generalizable policy interventions. However, the developed model and its model components of livelihood, COVID-19, and sudden-onset disasters are generalizable and can be used in other contexts as well.

Lastly, in spite of the mentioned limitations, the general trends of the model behaviour show how the trade-off between livelihood and COVID-19 unfolds under certain circumstances. Even though there are deep uncertainties at play, there are decisions that the government and humanitarian agencies can make or influence that can steer this complex situation into a more positive direction.

11 CONCLUSIONS AND RECOMMENDATIONS

In this final chapter, the sub questions are revisited and answered based on the findings of this research. The main research question is also answered. The following section discusses what these findings contribute to 510 and other societal causes, after which the scientific contribution is presented. The chapter ends with recommendations for future research, including a graphical overview.

11.1 ANSWERING SUB QUESTIONS

The sub questions posed in chapter 3, section 3.2, are revisited. Each sub question is presented and answered according to the findings in this study.

SQ1: What factors during the response phase of sudden-onset disasters affect the COVID-19 trajectory and livelihoods of people?
The first sub question was answered during the conceptualization and literature review as presented in 2. The aim of this first sub question was to identify what parts of each of the sub systems of livelihood, sudden-onset disasters, and the spread of COVID-19 should be included in this study. The core of each of these sub systems was identified by an extensive literature review, conversations with both 510 (the Dutch data initiative of the Netherlands Red Cross) and the Philippine Red Cross. In the process of scoping these sub systems, the aim was to always include those factors affecting the other sub systems as to find emerging behaviour of the integrated systems, and higher order as well as delayed effects. The focus of the study was to research the interplay of these systems for a rural community in a developing country. Against the backdrop of this context, the livelihood component was included.

The most important factors of each sub system can be summarized as: (1) the ability to access the central market, dependent on the market capacity and eligibility of agents to enter said market, (2) the contact rate that influences the number of people exposed to COVID-19, and (3) the number of shelters available for evacuation and the capacity of these shelters. These factors were considered when the policy interventions were chosen.

SQ2: In what way can the balance between livelihood and the trajectory of COVID-19 in the response phase of a sudden-onset disaster be conceptualized and formalized?
With the most important concepts identified in addressing the first sub question, a starting point was found for the conceptualization. The three socio-

technical sub systems were individually conceptualized before being integrated with each other. Afterwards, the sub systems were formalized.

First, the livelihood sub system conceptualization mimics a micro-economy. An important conceptual choice was to aggregate the entirety of casual jobs and farmwork into this single marketplace. Individual agents go to this market to increase the livelihood of their household, the degree of which this livelihood can be increased depending on their occupation and whether external traders are allowed or not. Access to this market is therefore crucial, which can be obstructed by lockdown regulations from the government.

Second, the sudden-onset disaster sub system was conceptualized. In this conceptualization, the system boundaries were set to only include evacuation to shelters and the possibility to issue an early warning. The reason for this decision was to focus on those aspects of the disaster response that would affect the COVID-19 trajectory most. The severity of the sudden-onset disaster determined the area of the community that is impacted and needs to evacuate. In some cases, the government is in the ability to issue an early warning, which would result in orderly (as opposed to chaotic) sheltering behaviour.

Third, the COVID-19 sub system was conceptualized. This conceptualization showed a reinforcing loop at its core that displays how the COVID-19 trajectory without intervention can easily spiral out of control. The spread of the virus was modelled based on the SEIR modelling approach but altered to fit the agent-based context. In the COVID-19 conceptualization, agents have a chance to contract the virus twice a day: at the market or at home/at the shelter. This infection probability depends on the agents that they have randomly encountered at the market, or the agents that are part of their household/shelter. The transmission rate and recovery rate are both derived from what is currently known in literature.

After the conceptualization, these conceptual models were transformed into a formalized aggregate model. A UML diagram was created to provide an overview of all classes included in the model, as well as the most important characteristics of the agents and methods.

SQ3: In what way can the formalized model be implemented in an agent-based model?
The conceptualized and formalized model was implemented using Mesa, a Python-based open source platform that allows for building agent-based models. It also includes built-in ABM analysis tools as well as access to the Python libraries for data analysis. The implementation involved developing a user interface, finding the suitable input ranges for model variables, and specifying an order of methods and actions within the time sequence of the model.

The model runs in discrete time steps. Every model step represents one day. Within the model, the day is split into two sections. First, all actions that happen during the day are performed, afterwards the actions that happen at night are performed. There are model-steps and agent-steps. The agent-steps are nested in the model-steps. If an agent-step is activated, all agents first perform this step before the next model step is activated. Agents perform their actions sequentially, which is why it is important that the agents are activated at random each action.

The parametrisation consisted of finding suitable values for model variables. The values for both input and internal variables were based on literature or data that was provided by 510. In case neither source could provide an answer, assumptions were made to fill in the gaps. The user interface was developed to create greater insight in the workings of the model. It also allows for experimentation for intuitive experimentation as the interface provides switches and sliders to include or exclude model components and change certain input parameters and policy interventions. It also contributed to the verification of the model, which consisted of several steps to ensure that the conceptual and formalized model were correctly implemented in the agent-based model. The verified model was used as input for the experimentation.

SQ4: What is the effect of policy interventions on the interplay between livelihood, sudden-onset disasters, and COVID-19?
After the model was verified and all input parameters were identified during the parametrisation, the base model was run and its behaviour was examined. The analysis revealed the biggest drivers of the outcome space and the associated uncertainties. The contact rate proved to be most influential for the COVID-19 trajectory, especially the contact rate between agents in the shelters. The average livelihood was mostly affected by the lockdown regulations, as this prohibited agents from going to the market and gain an income.

Policy interventions were implemented to address the factors presented in the main research question of this study. The interventions where either aimed at positively influencing the livelihood or containing the spread of COVID-19. For influencing the COVID-19 trajectory, the number of shelters and shelter capacity were adapted. Increasing the number of available shelters allows for a better distribution of agents in case of an early warning and ensures less infection events between the agents in the shelter. Reducing individual shelter capacities leads to less agents per shelter, a lower number of shelter contacts, and thus less chance of attracting the virus. This policy showed the most promising results for both the COVID-19 trajectory as the average livelihood in the model. The latter is a second-order effect of the reduction in infection numbers, as this removes the necessity of imposing a lockdown by the government. The second policy intervention entailed enhancing the awareness of COVID-19 among the agents in order to increase the compliance with the quarantine rules imposed by the government. The third policy intervention consisted of imposing different types of lockdown restrictions by the government. The government monitors three thresholds: (1) the growth of infections compared to the previous day, (2) the absolute number of COVID-19 cases in the model relative to the size of the population, and (3) the average livelihood compared to the livelihood threshold.

The first two together determine whether the epidemiological situation is deemed acceptable, the second provides the government with information about the livelihood. The third policy intervention set varying threshold values and prioritizations (COVID-19 over livelihood or vice versa) to gain insight into proferable configurations. It turns out that this policy intervention is not as effective, as the lockdown measures have a delayed effect on the livelihood but cannot be reversed. The fourth and last policy intervention was the implementation of direct and unconditional cash transfers to the poorest of households. When a household falls below the livelihood threshold, the government can give them a direct cash transfer, in the context of the model this translates into livelihood. The cash transfer policy was effective if the height of this cash transfer was enough. Due to the fact that agents only go to the central market in case their households livelihood is below the threshold, the cash transfer ensured that the market was always filled well below the maximum capacity and this resulted in both the best results for average livelihood as the best containment of COVID-19. In some scenarios, a lockdown restriction was never necessary. It is important to note here that this also greatly depends on the severity of the sudden-onset disaster as overcrowded shelters are prone to becoming COVID-19 hubs.

SQ5: How can the findings be generalized into policy advise for decision-makers?
To generalize these policy results, it is important to realistically look at the model results and conclusions based on these model results. Due to reduction in complexity and certain scoping choices, the complexity of the real world is not recreated and it is therefore not advisable to generalize the precise quantitative effects of policy interventions as implemented in the model.

That said, the results of the experimentation do provide evidence that some of the policy interventions are more effective than others. From the model results and experimentation, there are several recommendations for decision-makers in governmental agencies or active in the humanitarian branch. Before diving into the recommendations, the main findings are shortly discussed: (1) it is confirmed that the trajectory of COVID-19 largely depends on the contact rate of individuals. The contact rate outside the shelters can more easily be regulated than the contact rate within the shelters. This is due to the fact that lockdown restrictions can be enforced that reduce the market capacity and prohibit people from accessing the market. However, this is impossible when sudden-onset disasters impact the community and people have no choice but to reside in crowded shelters. In addition, (2) the average livelihood of people is affected *even* when they are not directly impacted by a sudden-onset disaster. This is a secondary effect of overcrowded shelters, resulting in increased COVID-19 infections that lead to a lockdown for the entire community. Moreover, (3) there is a trade-off detected during the lockdown in the average livelihood of households and the infection numbers in the community, whilst the location of infections is mostly households or shelter facilities.

A first recommendation drawn from this research is to prepare well for evacuations and ensure that there are enough distributed shelter locations available. Improvised and distributed shelter locations are crucial to reduce the capacity per shelter, meaning that the number of people per shelter decreases. This leads to a lower chance of infection events and ensures that the COVID-19 trajectory does not spiral out of control once the priority shifts to saving people from the impact and aftermath of a sudden-onset disaster. The average livelihood benefits from this intervention as well, since the result of the lower infection numbers removes the necessity of imposing a lockdown.

A second recommendation to tackle issues with livelihood is to implement direct and unconditional cash transfers. This intervention has the most (beneficial) impact on the average livelihood of the community as a whole. That is not only due to the direct effect of the cash transfer, but it also enables people to minimize their movements. There is no direct need of income and therefore their economic activities can be reduced, decreasing the contact rate and the number of infections. However, the effect of the cash transfers on the COVID-19 trajectory is less significant than the effect of reduced shelter contacts or awareness campaign.

Another recommendation can be drawn from the effect of implementing direct cash transfers into the model. A tipping point could be identified after which the trajectory of COVID-19 remained better contained and the average livelihood was also in stable regions. The reason behind this is that people are suddenly presented with a choice: accepting a casual job including the chance of attracting COVID-19, or staying at home while preserving minimum livelihood thanks to cash support. Before, they were not presented with such an option because the short-term consequences of not having an income outweighs the long(er)-term consequences of possibly attracting COVID-19, driving up the infection numbers, and causing a lockdown.

Third, awareness showed promising results but it is important to note that it is only useful in certain contexts. For example, from the model results it became clear that the awareness needs to be in place in combination with an adequate testing protocol. If people in a population are aware that they need to quarantine when they are infected but do not know whether they in fact are infected, the policy is ineffective. Additionally, the housemates of those that are tested positive for COVID-19, need to be compliant to the rules as well. Moreover, the incubation time is an important factor to consider, given that people are contagious but not showing symptoms and thus not testing. This might also happen in the incubation time.
A last recommendation stems from the combined policy results. An integrated and holistic approach results in the overall best results regarding both the average livelihood and the COVID-19 trajectory. The policy interventions are mostly applicable to either livelihood or the infections and therefore not addressing the trade-off between the two appropriately. Therefore, a combination is advised.

11.2 ANSWERING MAIN RESEARCH QUESTION

The main research question posed at the start of this study was:

What robust policy interventions can be identified that balance livelihood of rural communities and the trajectory of COVID-19 during the response phase to a sudden-onset disaster in developing countries?

The focus of this study was finding policy interventions that are beneficial for both the average livelihood and the COVID-19 trajectory of rural communities in developing countries while dealing with both the pandemic and a sudden-onset disaster. It is important to keep in mind that the outcomes of the interventions depend on several factors that are out of the control of decision-makers, such as the severity of the sudden-onset disaster and the number of people affected by this.

This research developed an agent-based model to capture the interplay of three socio-technical systems related to this situation: the livelihood system, the sudden-onset disaster system, and the COVID-19 system. The agent-based model was combined with exploratory modelling, which supports the systematic exploration of deep uncertainties regarding external factors, model parameters, and uncertainties within the model structure itself. Through this exploration it was possible to extract the most influential model uncertainties. These findings could be translated into policy recommendations for governments or humanitarian organizations in order to contribute to finding the best balance when facing two coinciding disasters. From the model results, several conclusions can be drawn.

First of all, the contact rate within the base model has the biggest impact on the trajectory of COVID-19. Reducing the contact rate on the central market proves to be a promising lever to control the spread of the virus, which is to be expected. The effect of the contact rate within the shelters has a more significant effect on the COVID-19 trajectory than the contact rate on the market. Most promising results came from the implementation of the shelter policy, which aimed at increasing the number of shelters and reducing the number of people per shelter at the same time. The latter had the largest effect on the agents encountered in the shelters and on the infection events in the shelters. Abiding by the social distancing regulations is more difficult in those circumstances, which is why a reduction in the number of agents in the shelter is essential. Not only did this decrease the number of infections, it also benefited the overall livelihood as the COVID-19 trajectory no longer caused the need for a lockdown.

A second promising policy intervention is the use of awareness campaigns. However, this measure only pays off in certain circumstances, as regular testing and an early start are both necessary to ensure containment. Also, as discussed in the previous chapter, people globally have a reduced tendency to seek care for other health issues. That phenomenon can be dangerous in countries where the people had a bad previous experience with a contagious disease, for example Ebola, as this might result in unnecessary deaths. Therefore, it is essential to carefully design awareness campaigns in order to convey the desired message and avoid adverse side effects. An important side effect of the awareness campaign is that it resulted in a negative effect on the average livelihood of the community, due to a large fraction of the population quarantining.

Third, one of the most influential factors for the average livelihood stems from the cash transfer policy. Not only does this increase the average livelihood of the community, it also ensure that the minimum livelihood is maximized over all experiments. This policy does not affect the COVID-19 trajectory significantly. Therefore, it is advised to combine the cash transfer policy with the aforementioned policies that aim at regulating the number of COVID-19 cases. The combination of policies showed overall the best results for both KPIs.

11.3 RECOMMENDATIONS FOR 510 AND SOCIETAL CONTRIBUTION

The UN OCHA (Office for Coordination of Humanitarian Affairs) publishes the Global Humanitarian Overview (GHO) which they describe as "the world's most comprehensive, authoritative and evidence-based assessment of humanitarian need" (UN OCHA, 2020). The recently published overview of 2020 confirms the need and urgency to take action regarding compounding risk. The COVID-19 crisis is not a crisis that happens in isolation, but coincides with existing and emerging natural hazards and violent conflicts (Gabraz, 2020). Gabraz (2020) argues that the identification of compounding risk is essential in identifying countries that are prone to "a deteriorating humanitarian situation". Anticipation of these compounding risks by implementing policy interventions before impact can prevent and reduce human suffering. This thesis is a first step in identifying these compounding risks regarding the COVID-19 crisis and sudden-onset disasters. The results contribute to finding general trends without interventions and to assessing the effect of certain policy interventions on these findings.

Minasi (2020) stresses the necessity of looking at the broader context of consecutive disasters and compounding risk in order to provide the best support and respond comprehensively. Understanding and acknowledging the multiple ways in which communities experience shocks is the first step to ensure this. This stylistic research focuses on compounding risk in poor and rural communities in developing countries, but, as was discussed in chapter 9, the effects of the policy interventions may vary greatly between South-East Asian and African countries.

The NRC supports Red Cross societies globally, of which some are currently dealing with the compounding risks of COVID-19 and sudden-onset disasters. The outcomes of this study contribute to support their advice and may be a starting point for more exploration in this area. 510 and other humanitarian agencies can use this study as a decision-support tool when collaborating with (local) governments in developing countries.

Over the last couple of months, it has unfortunately not been difficult to find examples of COVID-19 coinciding with other crises. Not only developing countries are dealing with compounding risk or are dealing with two crises simultaneously. However, this research specifically focuses on developing countries as the COVID-19 pandemic is aggravating existing vulnerabilities and these areas typically have less resources at their disposal to adequately respond to such crises (Gabraz, 2020).

11.4 SCIENTIFIC CONTRIBUTION

This thesis addresses the existing academic knowledge gap regarding a lack of literature and insight on the interplay of livelihood, sudden-onset disasters, and the trajectory of COVID-19. A stylistic and theoretical exploratory agent-based model was developed that is a first step in filling in the gaps in this research area. The necessity to study compounding risk has become more pressing in the past couple of months.

Apart from addressing this knowledge gap, the developed model was built in a modular fashion. Each of aforementioned sub systems can either run individually, with two out of three sub systems, or with all of them together. This implies that the sub systems can also be used and implemented in different contexts. The livelihood component was added due to the focus on developing countries, but there have been plenty of examples of consecutive disasters in developed areas of the world as well, where the livelihood component might be left out or replaced with some other relevant part of the equation.

In their paper regarding the necessity to study consecutive disasters, de Ruiter et al. (2020) argued that little is known about potential adverse effects of policy interventions directed toward one hazard type on other hazard types. This research is addressing this issue: it contributes to identifying second order effects of livelihood policies on the COVID-19 trajectory and vice versa. Adverse effects on the integrated systems can be identified, allowing to derive comprehensive policies aimed at balancing the underlying trade-offs in the desired fashion.

This research contains a first attempt to capture these three systems. Despite certain limitations, the model is generally able to produce valid behaviour and can contribute to discovering trends in consecutive disaster that can be a guideline for decision-makers. The specific results are limited, but the main contribution is the model as decision-support tool.

11.5 RECOMMENDATIONS FOR FUTURE RESEARCH

In this section, several recommendations for future research are pointed out. These are based on insights gained from the model, critical assumptions or model limitations.

The first recommendation stems from the assumption that movements from and to the shelters, marketplaces, and homes are excluded. The decision to include three socio-technical systems made it not possible to incorporate all aspects and as the focus in this study was to examine the effect of overcrowded shelters on the COVID-19 trajectory, the process of getting to these overcrowded shelters was not considered. However, in poorer communities it is less common to have access to private transport, implying a non-negligible infection risk from moving between certain places. Extending the model with movements could provide more insight in the effectiveness of the implemented policy interventions. For example, the effect of the awareness and thus compliance could be greater than the model outcomes currently suggest.

The second recommendation is to include financial incentives in the model. In this study, the cost of evacuation was not taken into account and all agents in the affected area would evacuate. This is not always the case. Some households do not have access to private transport and depend on the use of public transport instead. As a lack of access to private transport typically correlates with less wealth, public transport may not be trivially affordable, and some households may thus not evacuate. Another financial incentive could stem from including hospitalization, the cost of healthcare, and how this influences the effectiveness of the policy interventions.

The focus of the model currently lies on the response phase of sudden-onset disasters. In future research, including the recovery phase of the aftermath of sudden-onset disasters could be of great societal value. The lockdown restrictions and impact of the disaster stretch out for longer than the current time period in this study. This recommendation is related to the *granularity in time*, which is noted as one of the limitations. An additional recommendation related to the granularity in time is to change the time step from one day into a time step with a lower granularity, for example one hour. This would make it possible to distinguish the effect of agents being in someone's proximity for 15 minutes (short market visit) or the entire day (residing in the shelters).

In addition to granularity in time, future research could study the effect of increasing the *granularity in space* as well. The model currently comprises of three types of locations: shelters, households, and the central market. However, movements *within* these locations is not modelled and encounters are simulated by drawing a random number of agents that are present at that location. The advantage of using the granularity of the model is that experimentation is more feasible with a shorter runtime.

Lastly, since the biggest COVID-19 risks originate from the shelters, a suggestion is to research possible strategies to deal with these so-called COVID-19 hubs. It might not be feasible for certain communities, especially poor and rural communities, to come by the resources to increase the number of available shelters. However, it would be insightful to model the effect of different reintegration policies after the sheltering is no longer required, with the aim to compartmentalize the disease in sub communities.

In table 11.1, the table presented in the limitations section of the previous chapter is extended with the recommendations for future research as discussed in this chapter. The recommendations are similarly categorized based on the corresponding model component.

	General characteristics		Effect limitation on KPIs	Spatial characteristics		Effect limitation on KPIs	Temporal characteristics		Effect limitation on KPIs
	Currently implemented	Future research		Currently implemented	Future research		Currently implemented	Future research	
Livelihood (I)	◦Binary occupation status ◦Single marketplace to gain livelihood ◦No detailed microeconomic modelling	◦Extend composition community ◦Extend with market mechanism ◦Include soioeconomic heterogeneity	◦Effect of cash transfer on local economy precarious ◦Less accurate individual livelihood measure	◦Simplified trading with outside communities	◦Include outside connections	◦Less accurate estimation of livelihood	◦People with cash transfer remain home ◦No seasonality	◦People go outside but only for brief moments ◦Timing of lockdown has impact on harvest yield	◦Overestimating effect cash transfer on infections ◦Generalizing effect lockdown on livelihood
Sudden-onset disaster (II)	◦Evacuation as early action for disaster ◦Marketplace, shelters spared by impact	◦Add other early actions such as early harvesting	◦Overestimation of livelihood	◦No mobility in shelter ◦No mobility to shelter	◦Add movements to and within shelter	◦Less accurate estimation infections ◦Underestimation infections during travel	◦Same shelter (type) for entire aftermath disaster ◦No controlled release from shelters	◦Add varying shelter types ◦Controlled transition from shelters to community	◦Less accurate estimation infections in shelters
COVID-19 (III)	◦Transmission is simplified ◦No hospitalizations	◦Add asymptomatic transmission ◦Add infectiousness progression ◦Add hospitalizations	◦Underestimation of COVID-19 numbers	◦No proximity agents included ◦Purely randmized contacts at market	◦Add proximity ◦Regularity patterns in market contacts	◦Less accurate estimation infections (both under- and overestimation)	◦Homogenous amount of time in proximity of others	◦Use time step with higher granularity	◦Less accurate estimation infections
Overall model	◦Health status homogeneous ◦No budget restrictions ◦No deaths	◦Include heterogenous health statuses ◦Include budget constraints	◦Better estimation KPIs	◦Closed off community ◦No social interactions	◦Connect community with others ◦Include more interaction	◦Underestimation of COVID	◦Discrete time step of one day ◦No long-term effects of disaster	◦Discrete time step of higher granularity ◦Include long-term effects	◦Less accurate estimation of KPIs ◦Only short term impact

Figure 11.1: Future research based on model limitations

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A APPENDIX LITERATURE REVIEW

In this appendix additional information and graphics can be found that are related to the literature review.

A.1 DEFINITION OF CONCEPTS

Figure A.1 displays an overview of how livelihood is used in literature. This data was collected by Quandt (2018).

Type of Capital	Scoones (1998)	Tacoli (1999)	Campbell et al. (2001)	Adato and Meizen-Dick (2002)	Erenstein et al. (2010)
Natural Capital	Environmental services, natural resource stocks such as soil, water, air	Freshwater availability, land management, agricultural space, land	Soil fertility, water resources, forest resources, grazing resources, land quantity and quality	Land, water, forests, marine resources, air quality, erosion protection, and biodiversity	Annual rainfall, soil capability index, farm size, herd size
Financial/Economic Capital	Capital base including cash, credit, savings and basic infrastructure and production equipment and technologies	Infrastructure and tools/equipment	Credit, savings, remittances	Savings, credit, as well as inflows such as state transfers and remittances	Farm size, herd size, bank facilities, credit societies
Human Capital	Skills, knowledge, ability of labor, and good health	Labor including skills, knowledge, ability to work	Knowledge, sills, health, labor availability	Education, skills, knowledge, health, nutrition, and labor power	Female literacy, immunizations, work participation, population density
Social Capital	Social resources including networks, social claims, affiliations, associations	Access to markets, representation and access to the 'state'	Adherence to rules, relationships of trust, mutuality of interest, leadership, kin and ethnic networks, social organizations	Networks that increase trust, ability to work together, access to opportunities, reciprocity; informal safety nets; and membership in organizations	Cooperative societies, self-help groups
Physical Capital	Included in financial capital	Included in financial capital	Households assets, agricultural implements, infrastructure	Transportation, roads, buildings, water supply, sanitation, energy, technology and communication	Irrigated area, farm mechanization, distance to nearest town, access to paved roads

Figure A.1: Livelihood capital by (Quandt, 2018)

A.2 SIR EPIDEMIC MODEL

In this section the general theory of SIR epidemic modelling is discussed. The formalization can be found in chapter 5, section 4.2.6.

A.2.1 Mathematical calculations

The SIR model consists of several relatively simple mathematical equations. The basic principle is that a population is divided into three components: the susceptible (S) population, the infected (I) population, and the recovered (R) population. The number of people that change from one component to the next, is dependent on the number of encounters between the compartments in combination with the transmission rate β. For the amount of people that move from *infected* to *recovered* only the recovery rate γ needs to be known as this does not depend on the number of interactions between the groups. The differential equations can be found in figure A.2.

$$\frac{dS}{dt} = -\frac{\beta S I}{N}$$

$$\frac{dE}{dt} = \frac{\beta S I}{N} - \sigma E$$

$$\frac{dI}{dt} = \sigma E - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

$$N = S + E + I + R$$

Figure A.2: SEIR equations

The SIR model can be extended or adapted in several ways. One way is to include the possibility that people move from *infected* to *susceptible* implying that people cannot obtain immunity. For this research, immunity is not taken into account. Another common extension of the SIR model is to include an *exposed* population. The component of the population that is in this box is said to be infected but not able to infect others. It is the so-called latent period or incubation period. For COVID-19, however, scientists are convinced that people are able to infect others while not showing symptoms yet (e.g. in the incubation period). Therefore, the exposed (E) component in this thesis will be agents that are infectious and can infect others, but are unaware of this situation themselves.

B APPENDIX CONCEPTUALIZATION AND FORMALIZATION

B.1 CONCEPTUALIZATION LIVELIHOOD

Figure B.1 displays a CLD where the influence of a flood is seen on farms, seeds, food production, and starvation. This CLD was used to study the system behaviour of natural sudden-onset disasters on livelihood resources.

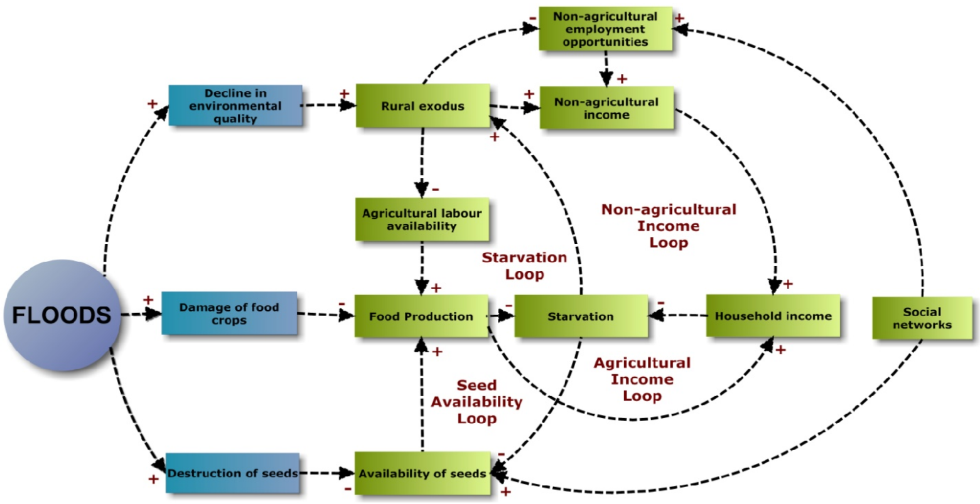


Figure B.1: CLD floods and starvation (Armah et al., 2010)

The first CLD constructed for this research can be found in figure B.2 and displays the mechanism where households make a living by producing food on their farmlands and trading goods and services at the central market. Armah et al. (2010) focused on minimizing starvation, which for the CLD for this sub system has been replaced by livelihood. Livelihood is affected by household income, which in turn depends on trading goods and services on the market. The more of those goods available, depending on the food production, the more the inhabitants can trade. Apart from this *livelihood loop*, the effect of a natural hazard is shown by damaging houses and farmlands. Damaging houses starts the evacuation process, where the severity of the hazard determines largely how many people are displaced and consequently need shelter (Simonovic & Ahmad, 2005). Their conceptual model can be found in B.3. People in shelters suffer from a decline in livelihood as they have less access to the market and participate in trading. At the same time, the damaged farmlands reduce the food production, also resulting in less availability of goods and services. Both these results negatively influence the livelihood of households. External aid during these times is essential.

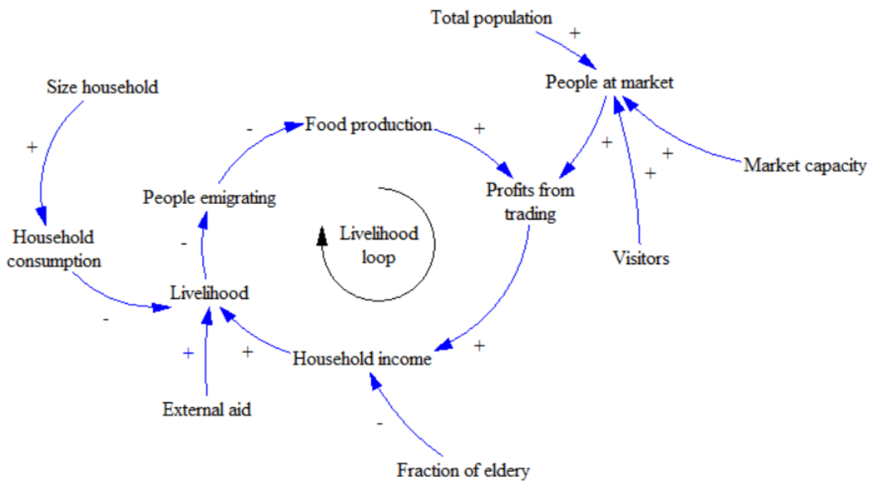


Figure B.2: Livelihood causal loop diagram

B.2 CONCEPTUALIZATON DISASTER RESPONSE

Figure B.3 displays a CLD with system components influencing one another during evacuation (Simonovic & Ahmad, 2005). This research was used to construct an initial causal loop diagram as shown in figure B.4.

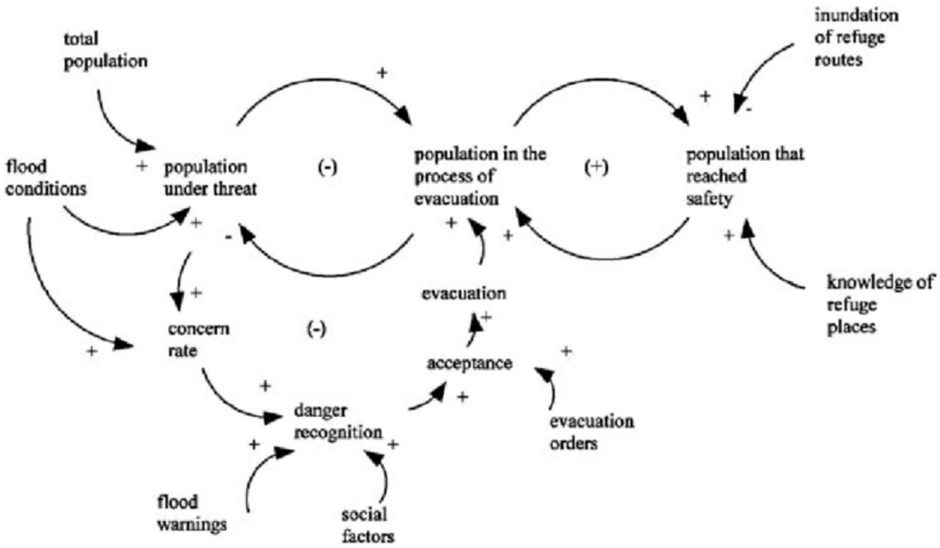


Figure B.3: Disaster response causal loop diagram (Simonovic & Ahmad, 2005)

Based on found relations in the research of Simonovic and Ahmad (2005), the causal loop diagram for this sub system was constructed. The result can be seen in figure B.4. The most important relations in this causal loop diagram are between the number of people that are in the process of evacuation and the number of people in the shelter. It can be seen that the number of available shelters and the shelter capacity influence this.

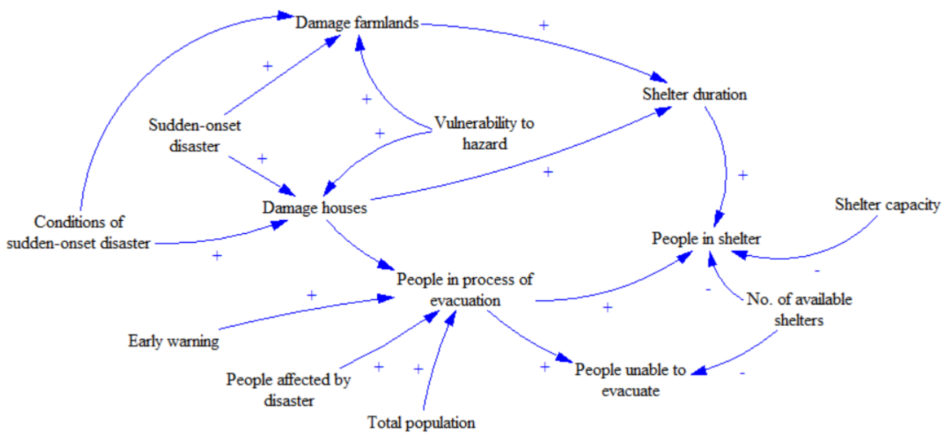


Figure B.4: Evacuation and livelihood cld

B.3 CONCEPTUALIZATION COVID-19

Figure B.5 displays the CLD made for a System Dynamics model created by Bradley et al. (2020). The system components displayed in red is the main loop that shows how infections of COVID-19 spread and how this loop is self-reinforcing. This causal diagram was constructed for the spread of COVID-19 and part of it is used for this research. The other part stems from the diagram displayed in figure B.6, where causal links are displayed for the spread of the disease Ebola. Due to the contagiousness of the disease, some of the links have been reused for this study as well.

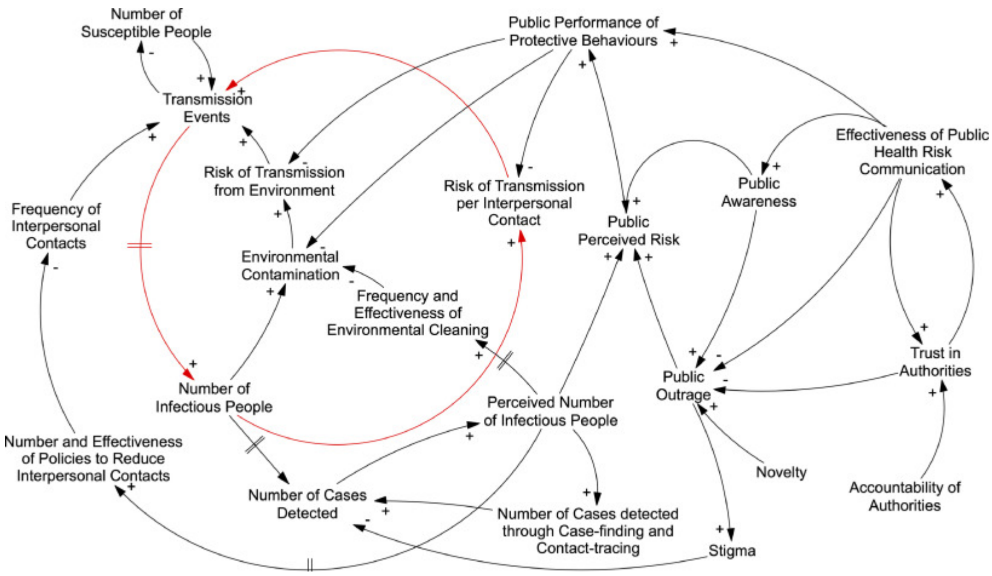


Figure B.5: CLD infections COVID-19 (Bradley et al., 2020)

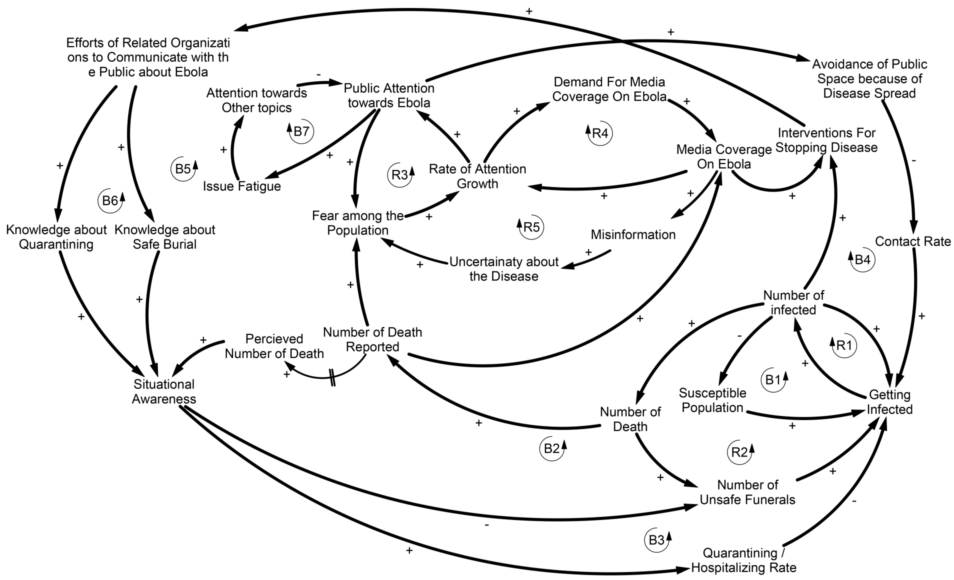


Figure B.6: Ebola causal loop diagram (**Sharareh2016TheApproach**)

In addition, figure B.7 displays the SEIR (susceptible, exposed, infected, recovered) approach in a conceptual way, based on the conceptualization of Amira et al. (2020).

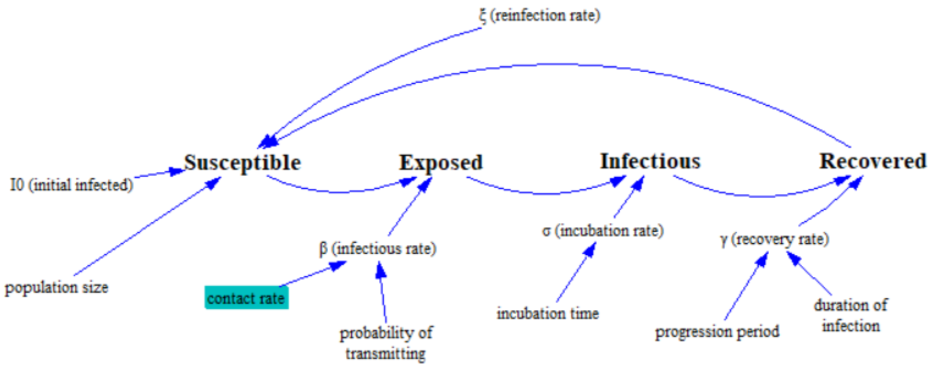


Figure B.7: SEIR diagram (Amira et al., 2020)

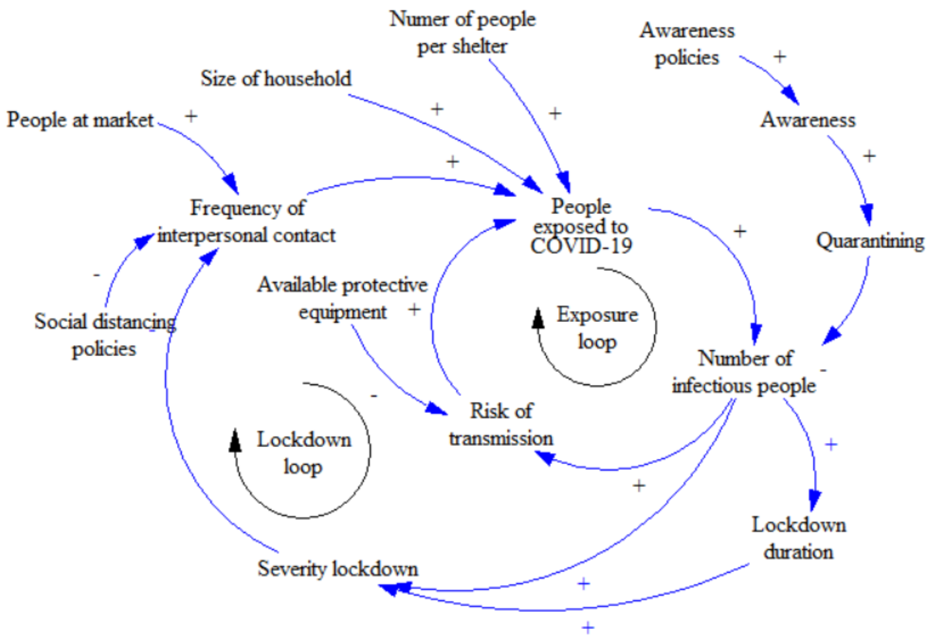


Figure B.8: Exposure and lockdown causal loop diagram

The second CLD can be found in figure B.8 and displays the most important behaviour surrounding exposure to COVID-19. Based on the research of Bradley et al. (2020), the exposure to COVID-19 loop was established, where an reinforcing loop is to be found leading from exposure to COVID, to a higher number of infectious people, increasing the risk of transmission, again reinforcing the exposure to COVID. Bradley et al. (2020) made a CLD for infections of COVID, which can be found in figure B.5. There are more factors influencing the exposure, such as the frequency of interpersonal contact, size of households, and the number of people in shelters. It is worth noting that this is a strongly simplified version and does not take into account the perception of COVID by the local community, the media coverage, nor concepts such as 'issue fatigue', as was included by (Bradley et al., 2020). Most important is to include the main factors contributing to COVID-19 and policy interventions that can influence this such as awareness campaigns and social distancing policies.

B.3.1 Conceptualization integration of CLDs

Figure B.9 displays the interplay between the first two subsystems where evacuation and livelihood come together.

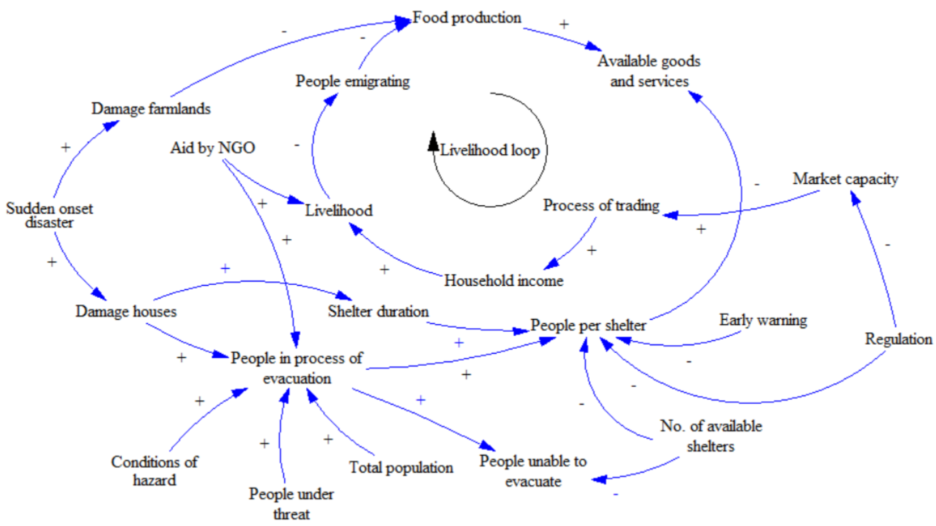


Figure B.9: Evacuation and livelihood cld

The last CLD can be found in figure B.10 and displays the integration of the two aforementioned CLDs. Again, this is a simplified version that aims to capture the most important mechanisms and system behaviours that influence the livelihoods of households and their exposure to COVID-19 during a natural hazard. The systems connect in two main areas: the trading process ensures a higher frequency of interpersonal contact, and the number of people per shelter influences the exposure to COVID-19. The *livelihood loop* is displayed in orange and *exposure loop* in green, the policies that affect these loops are displayed in blue.

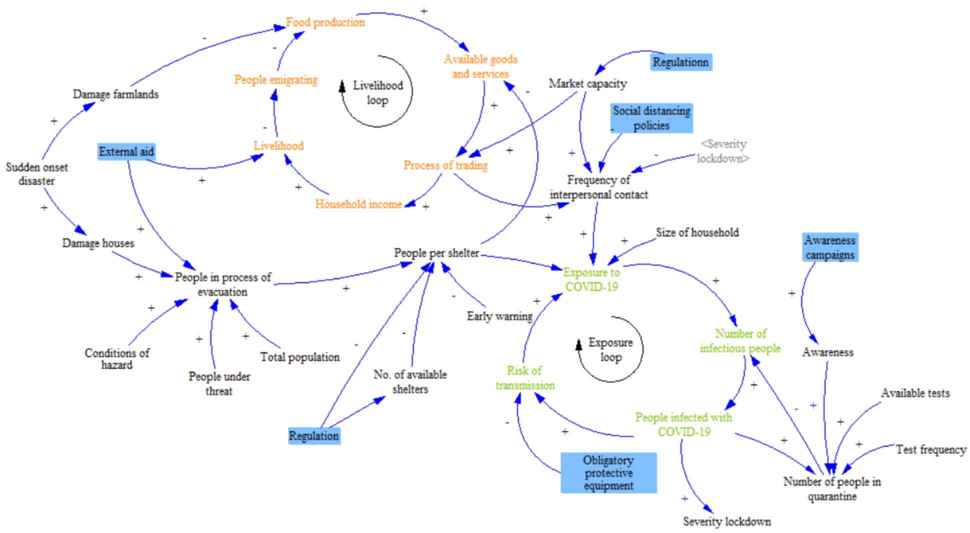


Figure B.10: Integration of three systems - CLD

B.4 FORMALIZATION

B.4.1 Flowcharts

Based on the conceptual models developed for the sub systems, flowcharts were constructed. The flowcharts consist of swimming lanes that consist of the agents, the government, and the environment. From *begin* to *end* the processes, decisions, and actions can be followed. Figure B.11 displays the flowchart of the sub system of livelihood, where the process of going to the market and trading is graphically represented.

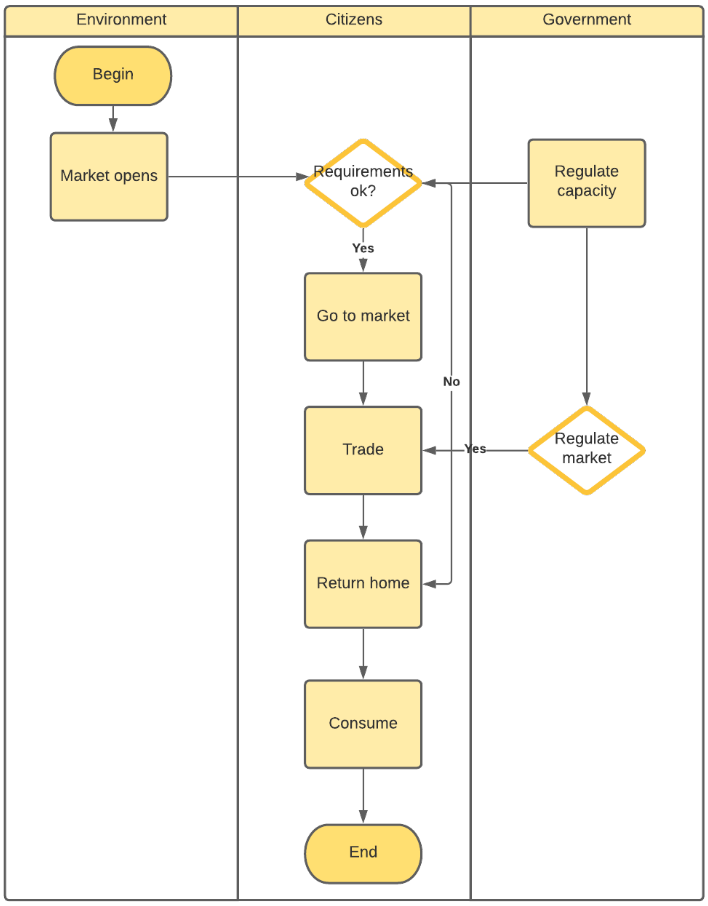


Figure B.11: Livelihood flow chart

Figure B.12 presents the flowchart of the sudden-onset disaster from the moment of hazard initiation to the return from the shelters after evacuation.

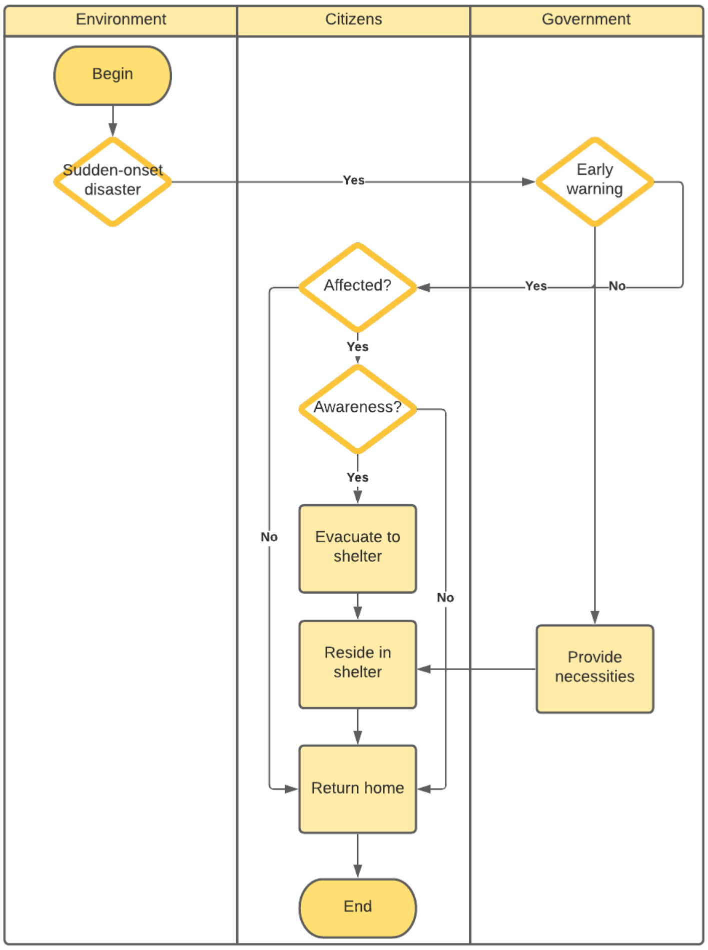


Figure B.12: Disaster response flow chart

The last flowchart in figure B.13 represents the last sub system: the spread of COVID-19. This is interconnected with the other systems as it is related with encounters with other agents. In the main text, the combined flowcharts are depicted into one flowchart of the integrated model.

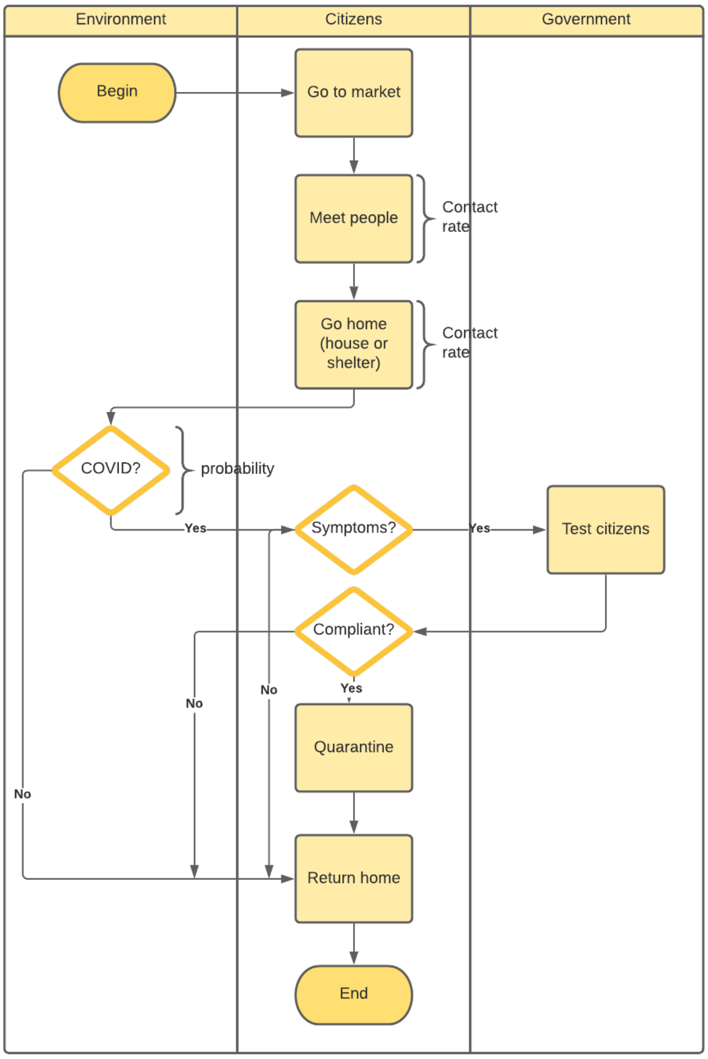


Figure B.13: Epidemic flow chart

B.4.2 Formalization of SEIR modelling

This is a continuation on the literature presented in appendix A on SEIR modelling. To include this in the model, it was implemented as follows.

Model logic SIR

In the model, the SEIR-numbers are calculated using the following model logic and steps. First, the probability to become infected with COVID-19 is computed as follows:

- Agents go to market
- Agents meet random others
  - Minimum amount of others
  - Medium amount of others

- Maximum amount of others

- Agents store the market contacts
- Agents return home (household location or shelter)
- Agents meet household members or shelter mates
  - All household members
  - All shelter mates
  - Subsection of shelter mates
- Agents store the home contacts
- Agents computer their chance to attract COVID twice

Every day, the infected agents have a chance to recover from COVID $dI/dt = recoveryrate * I$

- Agents compute the chance to recover
- If they recover, they change their health status to recovered
- Recovered agents do not become susceptible again

SEIR model equations

Every model step it is stored what the health status of agents is: Susceptible, Exposed, Infected, or Recovered. That information is used later for the calculation of the probability to become infected. The agents each have the following attributes: *Sm*, *Em*, *Im*, *Rm* and *Sh*, *Eh*, *Ih*, *Rh*. The box below clarifies the meaning of these variables. There are two events per day where the agents are able to attract the disease, but it is only calculated once per day whether the agents need to change their health status. This is to ensure that agents to not infect others the same day that they got the disease. The two events are trading at the market place and spending the night at either their own house or the shelter.

Sm = Susceptible people at market
Em = Exposed people at market
Im = Infected people at market
Rm = Recovered people at market
Sh = Susceptible people at home
Eh = Exposed people at home
Ih = Infected people at home
Rh = Recovered people at home

During these two events, the agents encounter a specific number of other agents and store these agents in the corresponding variables. If an agent does not go to the market, for example due to old age, these variables remain zero. At the end of the day, the probability to attract COVID is calculated with the following logic, since the market event and night event are independent from each other, where P(A) represents the market and P(B) the home situation.

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

$$\beta = contact\_rate * transmission\_probability$$
$$P(A) = market\_infection = \beta * S * (I + E)$$
$$P(B) = home\_infection = \beta * S * (I + E)$$

$$P(A) = 1/Sm * (\beta * (Im + Em) * Sm)/(Im + Em + Sm + Rm)$$
$$P(B) = 1/Sh * (\beta * (Ih + Em) * Sh)/(Ih + Eh + Sh + Rh)$$

In short, in above calculations the chance to attract COVID is based on the number of people that someone has encountered that are either exposed or infected.

B.4.3 Predefined processes

In the flowchart presented in chapter 5 there are several processes marked as *predefined*. In this section, these processes are presented in separate flowcharts.

Quarantine

In figure B.14, the flowchart of the quarantine process is visualized.

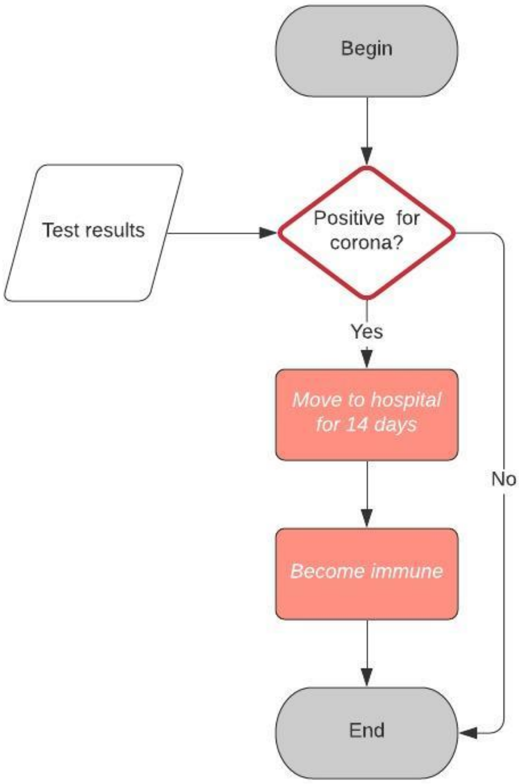


Figure B.14: Quarantine flowchart

Trading

In figure B.15, the flowchart of the trading process is visualized.

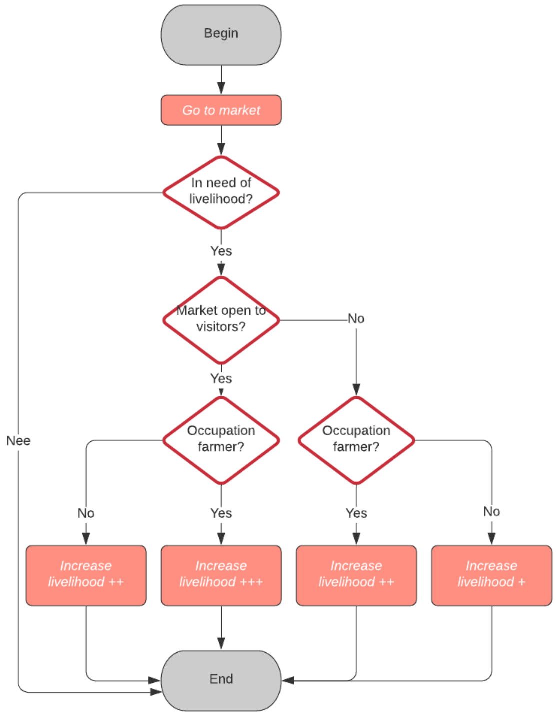


Figure B.15: Trading livelihood flowchart

Government restrictions

In figure B.16, the flowchart of the government

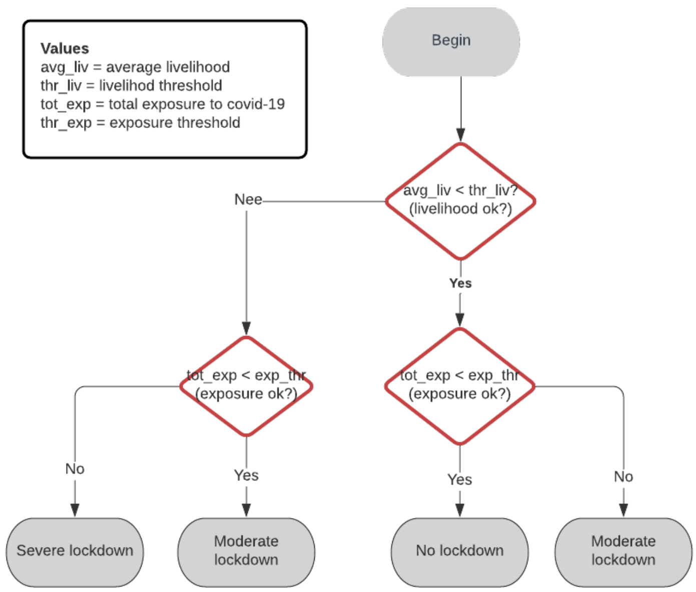


Figure B.16: Government restrictions flow chart

In table B.1 the parameters for livelihood are displayed. In the top part of the table, the wages of farmers and non-farmers are shown (SalaryExplorer, 2020; Sanchez, 2019), including the size of each of those groups (Dy, 2017).

The minimum and maximum have been chosen to represent the wages under different types of lockdown.

	%	No lockdown	Moderate lockdown	Severe lockdown
Wage				
Citizen	35	850	537	140
Farmer	65	425	215	70
Livelihood				
Citizen	35	3	2	1
Farmer	65	1,5	1	0,5

Table B.1: Parametrisation livelihood

C APPENDIX FOR POLICY INTERVENTIONS

This appendix contains additional information regarding the policy interventions. Also, it contains the model narrative, model logic, and the pseudo code that was constructed during the formalization. Figure C.1 represents the flowchart of the aggregate model with the interventions added.

C.1 FLOWCHART POLICY INTERVENTIONS

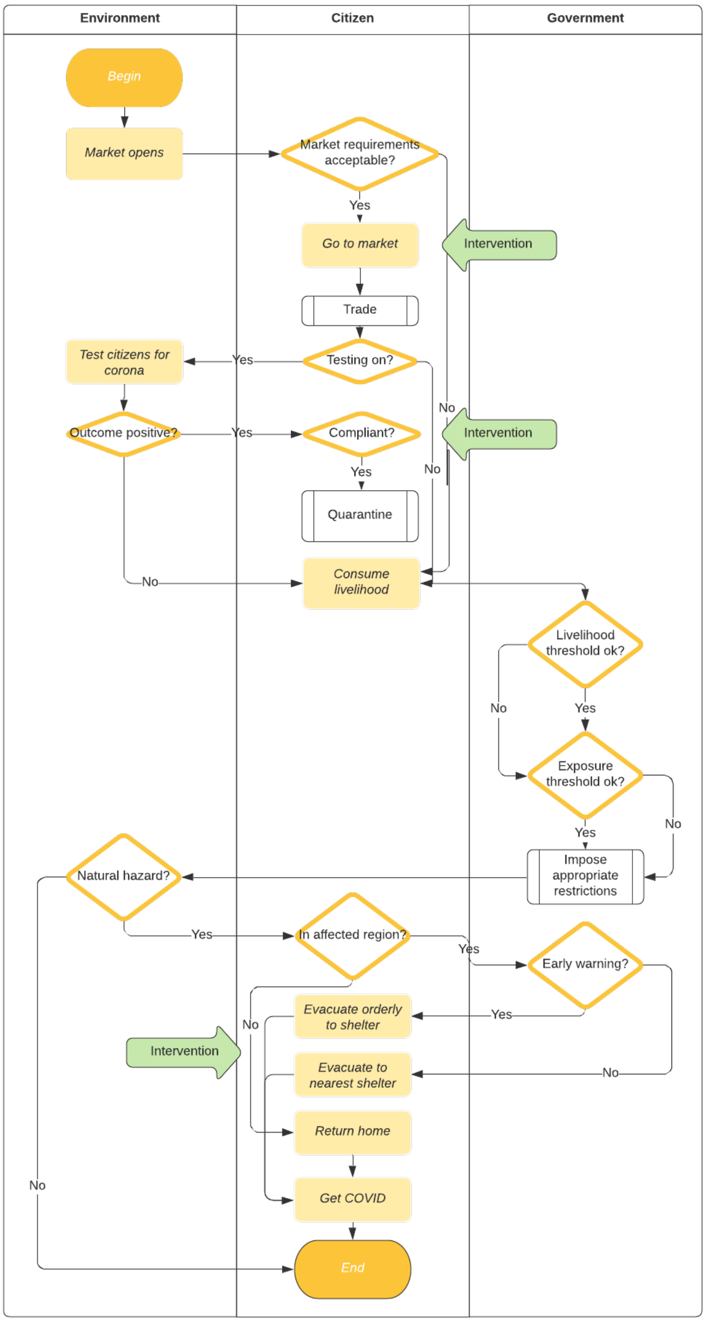


Figure C.1: Flowchart with policy interventions

C.2 MODEL NARRATIVE

In the village, there are several households. The households consist of individuals that are together responsible for the livelihood of their household. The individuals have different characteristics, which are discussed later on. The citizens can increase their households livelihood by selling their products or services on the central market. Access to the central market is therefore crucial. There are two scenarios that will be compared in the model. The first scenario is when the village is hit by a natural sudden-onset disaster. The second scenario is when the village is hit by a natural sudden-onset disaster while also dealing with the containment of COVID-19.

The agents that are part of a household have an age ranging between 18 and 80, they live in a household that has a certain exposure to natural hazards (vulnerability). They are either farmers or citizens, which correlates with the amount of livelihood they gain at the market.

Narrative 1: Natural sudden-onset disaster
A natural hazard has a certain severity and radius that impacts the houses in the village. Households with damaged houses or under threat of losing their house are evacuated to the nearest shelter. They might need external help in reaching the shelter or to provide them with necessities. When the maximum capacity of the shelter is reached, they need to travel to shelters farther away from their homes.

There can be an early warning for the sudden-onset disaster, for example in case of a typhoon, implying that the evacuation happens in an orderly manner. If not, the evacuation happens on impact. The households are always evacuated as a whole and always lose their means of livelihood for the duration of the evacuation, as it is assumed that evacuation means that access to farmlands and its production of food is unreachable, as well as goods and services. For the duration of the evacuation, however, the people are provided with food and essential goods by the government or external organizations in the shelter.

During this scenario, people from other (nearby) villages have access to the central market and contribute to the general livelihood of households living in the village. Based on the severity of the sudden-onset disasters and the vulnerability of the houses, the villagers return home after a certain amount of days.

Narrative 2: Natural sudden-onset disaster during COVID-19 pandemic
The COVID-19 pandemic implies that there are restrictions on the level of freedom of the households. In case of severe restrictions, people from (nearby) villages cannot enter the central market. Agents without protective equipment are banned from the market during the strictest lockdown.

Agents can attract COVID-19 from meeting other agents at the central market or at night, when they are at home or in the shelter. Based on the lockdown restrictions from the government they meet a certain number of other agents at the market. Agents can carry the disease without knowing (health status: exposed) or while knowing (health status: infected) based on the incubation time and whether they show symptoms. Other agents they meet are assumed to be in their proximity for more than 15 minutes. If a certain infection number threshold is met, more severe restrictions will be imposed on the community by the local government. The restrictions either focus on social distancing or on protective equipment. Based on the recovery rate agents will recover from the virus.

When a natural hazard hits, there is again the difference between having an early warning or not. If there is an early warning, households are evacuated as soon as possible as to reduce the exposure to COVID-19 and to distribute the people over the shelters to avoid overcrowding. However, if there is no early warning, the evacuation brings much exposure to COVID-19 as the shelters will be filled with people. In this scenario, the livelihood of people in the shelter is handled the same as the previous scenario.

After trading at the market, all people return to their homes, consume livelihood and have a certain chance that they caught COVID-19 based on the exposure they have had to others. Based on their compliance to the rules and if they are tested positive, they decide if they will quarantine at home. This means that they cannot contribute to the livelihood of their households, but also cannot contribute to spreading COVID-19, except to members of their own household. It is assumed that for the remainder of the model run, the recovered agents will not contract COVID again and are thus temporarily immune.

The government of the community checks at the end of every day what the total amount of corona cases in the village is, in addition to what the average livelihood per household is. Both these KPIs are traced by the local government in order to impose stricter regulations or not. In case the livelihood levels are good enough, a strict lockdown regime is more feasible than if households are already struggling to get by. In the model, there are three lockdown levels implemented: low, medium, and severe. In the lowest level of lockdown (e.g. no lockdown), the capacity of the market is set to the maximum, protective equipment is not necessary, and visitors from other villages are welcome. In the strictest situation, the market capacity is set to the minimum, all agents that go to the market are obliged to wear protective equipment, and visitors are unwelcome.

C.3 MODEL LOGIC

Initialization

- The grid is initialized
- All agents are created and randomly distributed on the grid. They have the following characteristics:
  - Occupation [Farmer or citizen]
  - Initial livelihood
  - Age [between 18-80]
- The agents are added to a list and random schedule of activation

- Patient(s) zero are selected among created agents
- The number of households are created based on the population density
  - All households get a home address
  - All households are assigned one occupant from the list of agents so that no household remains empty
  - The remaining agents are randomly distributed over the households.
  - The address of all agents in the same household becomes the same and they are moved to the correct position on the grid.
  - The vulnerability to natural hazard is assigned to households and based on that vulnerability the chance to need help during an evacuation.
- Shelters are created and appended to a list of shelters
- The government is created with the following parameters to monitor:
  - The corona threshold
  - The livelihood threshold
- The natural hazard location gets set at the beginning of each model run
  - The severity is between level 1 to 5
- The hospitals are created and placed on the grid
- The shelters are assumed to be sturdy enough for the natural hazard and do not close when they are in the affected region.
- The aid workers are created, added to a list of aid workers and added to the schedule of activation.

Step function
Each step in the model run goes the following procedures.

- The market is set to open
- The number of people at the market is reset to 0
- For all agents, their daily routine starts
  - They reset their contacts and contact list to 0
  - They check the market capacity
  - They go to the market to trade in case the capacity has not been reached and if they fit the following requirements:
    * Age lower than 65
    * Livelihood savings of their household does not last a minimum of two days
    * They are not in quarantine
    * The market is open

    * In case of lockdown, they are in possession of a face mask.
  - Trading is based on their occupation and on the allowance of visitors to the market. Visitors are only allowed when there is no lockdown.
  - Livelihood of their corresponding household is adjusted accordingly.
  - If the model runs with the corona switch on True, all agents at the market meet a random sample of other agents and store these agents in their contact list.
  - All agents at the market store the number of susceptible, infected, exposed and recovered agents in their contact list.

- If the model includes testing, agents get tested for corona based on the test frequency. For example, if the test frequency is 3, the agents get tested every three days.

- Agents that are infectious (meaning after the incubation period) and show symptoms are the ones that get tested.

- If testing is not included, it is assumed that all agents know immediately if they are infected.

- For all agents, their nightly routine starts
  - They change their position back to their home address if they are not in quarantine or in the shelter.
  - If they are tested positive for COVID, the agents decide if they will quarantine and set the quarantine time accordingly.
  - After these two weeks of quarantine without recovering, they are immune for COVID for at least 100 days (the rest of the model run) and do not longer contribute to infections in the model.
  - The agents that are currently evacuated increase the number of days in the shelter by one.
  - The agents in the shelter increase their livelihood by one.
  - If the shelter duration is over, they change their status of affected to not-affected and return home.
  - Agents that have endured the incubation time change their health status from exposed to infected.

- The livelihood of households is decreased by the number of people that are part of the household.

- The livelihood per household is computed.

- If the *corona switch* is True, the agents now store the contacts of their night (household members or shelter members) and then compute the chance they have COVID.

- If they are infected, they change their health status from susceptible to exposed and start the incubation period.

- The agents calculate their chance on recovery and potentially recover.
- At the end of the day, the government calculates the livelihood and exposure and compares it with the thresholds. If necessary, the government imposes lockdown restrictions.
  - Corona cases are calculated (infected only)
  - Livelihood is calculated
  - The government chooses an appropriate lockdown level based on these numbers.
  - The government enforces the rules that are associated with the lockdown level
  - The average number of contacts is calculated.
- In each model step, by a certain chance, a natural hazard may occur. This happens only once per model run and during the first few model steps. The government may or may not have issued an early warning.
  - Early warning
    * Three days in advance people get notified that they live in the to-be-affected region.
    * People in the affected region will be evenly distributed over all remaining shelters that are not located in the affected region.
    * After a certain number of days, people return home.
  - No early warning
    * People are immediately affected.
    * People in the affected region will go to the nearest shelter not in the affected region. This leads to full shelters and overcrowding.
    * After 5 days, people return home.
- The datacollector collects all data and the time is increased by one.

C.4 ASSUMPTIONS

This is a list of all assumptions made throughout the modelling.

1. Households consist of adults or elderly, not children
2. Livelihood depends entirely on access to the central market or external help
3. No other activities than trading are modelled
4. Infrastructural damage or access is not taken into account
5. Only one community is modelled, therefore, a spread between different communities is not modelled.

6. No agents die during the model run, nor are born.
7. No agents migrate
8. Sudden-onset disaster is initiated in the first few model steps as the focus lies on what comes afterwards.
9. People living in safe zones (not affected by natural hazard) do not evacuate.
10. People evacuate for a minimum of three days and a maximum of thirty days.
11. Evacuation costs are not considered in the decision-making process to evacuate.
12. Hospital and shelter capacities are not enforced.
13. Hospitals and shelters located in the affected area by the natural hazard are never destroyed.
14. A meeting only contributes to the probability of infection when the encounter lasted more than 15 minutes (CDC, 2020c).

C.5 MODEL FILES

In this table, the files and their contents are displayed.

Model file	**Content**
LivModel.py	The model file, initialization, and main step function
LivAgent.py	The agent file that contains functions for civilians
LivGovt.py	The agent file that contains functions for the local government
LivHazard.py	The agent file that contains the functions for the natural hazard
household.py	File that holds the class Household
shelter.py	File that holds the class Shelter
hospital.py	File that holds the class Hospital
market.py	File that holds the class Market
server.py	File that launches the web server and contains visualization
batch.py	File that holds code to run multiple batches

C.5.1 pseudo code

Pseudo-code for the following pieces can be found in the following figures. In this section, a few of the functions in the code are highlighted. In the first algorithm, the overall model narrative is captured.

Algorithm 2: Global model narrative

```
Result: Step function
set market to open;
set number of people at market to zero;
step-day (agents);
increase market exposure;
step-night (agents);
consume livelihood;
compute livelihood per household;
aid workers help households in need;
government-step;
initiate hazard;
collect data;
```

The second and third dive into the mechanism that enables agents to go to the market and trade with others, increasing the livelihoods of their families.

Algorithm 3: Go to market

```
Result: Agents go to the market to trade
if lockdown_level == severe then
    if posses facemask, not in quarantine, working age, not sick, in need of
      livelihood, capacity is ok then
        move to market;
        trade;
    else
        cannot go to market
    end
    move to market;
    trade;
else
    if lockdown_level != severe then
        if not in quarantine, working age, not sick, in need of livelihood,
          capacity is ok then
            move to market;
            trade;
        else
            cannot go to market
        end
    else
        c
    end
    annot go to market;
end
```

Algorithm 4: Increase livelihood at market

```
Data: Trading at market for livelihood
if visitors == false then
    if occupation == farmer and livelihood < threshold then
        increase_livelihood with 5
    else if occupation == farmer and livelihood > threshold then
        increase_livelihood with 3
    else if occupation == citizen and livelihood < threshold then
        increase_livelihood with 3
    else
        occupation == citizen and livelihood > threshold
    increase_livelihood with 1
else
    if occupation == farmer and livelihood < threshold then
        increase_livelihood with 10
    else if occupation == farmer and livelihood > threshold then
        increase_livelihood with 6
    else if occupation == citizen and livelihood < threshold then
        increase_livelihood with 6
    else
        occupation == citizen and livelihood > threshold
    increase_livelihood with 2
```

The fourth pseudo code is of the algorithm that lets the government impose restrictions on the community.

Algorithm 5: Impose restrictions

```
Data: Setting government regulations
if livelihood < threshold and exposure < threshold then
    lockdown_level = 0                          // no lockdown
    market_capacity = maximum
    visitors = true
    protection = 0
else if livelihood < threshold and exposure > threshold then
    lockdown_level = 1                          // moderate lockdown
    market_capacity = medium
    visitors = false
    protection = 0
else if livelihood > threshold and exposure > threshold then
    lockdown_level = 2                          // severe lockdown
    market_capacity = minimum
    visitors = false
    protection = 1
else
    lockdown_level = 0                          // no lockdown
    market_capacity = maximum
    visitors = true
    protection = 0
```

The fifth pseudo code is of the algorithm that evacuates agents to shelters, either in a random manner or orderly.

```
Def Order shelter(shelter):
    move_agent
    shelter.add_occupant
    in_shelter += 1

Def Random shelter():
    my_shelter = list_shelters[0]
    my_dist = 10000000
    for shelter in shelter_list do
        new_dist = distance self and shelter
        if new_dist < my_dist and shelter.max_cap != 0 then
            go to that shelter
    move to shelter
    shelter.add_occupant
    in_shelter += 1

Def To shelter:
    if warning == True then
        nr_shelters = len(list_shelters) i = 0 for all agents do
            while shelter_cap == 0 do
                i = (i+1) % nr_shelters
            if agent affected == True and not in shelter then
                agent.order_shelter(list_shelters[i]
                i = (i+1) % nr_shelters
    else
        for all agents do
            if agent affected == True and not in shelter then
                agent.random_shelter()
    return shelter location
```

D APPENDIX IMPLEMENTATION

D.1 PARAMETRISATION

Most values are based on literature, or on the information that was made available by 510. However, not all values could be traced this way. For the remaining parameters, suitable values were sought out. It is important to keep in mind that these values are chosen based on certain assumptions, because it was not possible to explore all options. In this section, the assumptions and choices for important parameters are discussed.

D.1.1 Threshold values of government

The government agent in the model keeps track of two threshold: the *corona_threshold* and the *livelihood_threshold*. Each of these are shortly described below.

1. Corona_threshold: this is based on two values. (1) the percentage growth compared to the previous day, what is called the R-value, and (2) the number of absolute cases that is based on a fraction of the total population. The combination is important because in the start of the model run, the number can increase from 1 to 2 infected agents which would lead to a 100% increase but would in reality not lead to a lockdown.

2. Livelihood_threshold: this threshold is hard to determine as it is difficult to find precise information about the height of the livelihood that is necessary for households to sustain themselves. Therefore, his threshold is experimented with to find out the sensitivity of it for the model metrics

D.1.2 Parameter table

In table D.1 the model variables and their initial value or initial range are displayed. For each of the variables, it is specified what the source is or if the variable value is an own specification.

Level	Variable	Initial value/range	Source
Model	Num_agents	100 - 1500 people	own specification
	Ptrans	10%	Tang (2014)
	Precov	1/14	Tang (2014)
	Test_frequency	3	own specification
	Population_density	0.2 (avg hh size = 5)	NDHS (2008)
	Shelter_time	5 - 25 days	Philippine Red Cross (2019)
	Num_days	60 days	own specification
	Min_contacts	5	Elie et al. (2020)
	Med_contacts	15	Tang (2014)
	Max_contacts	25	Elie et al. (2020)
	Corona_fraction	10.00%	own specification
Agent	Initial_livelihood	5	Sanchez (2019)
	Isolation_duration	14	Tang (2014)
	Waiting_time	3	own specification
	Incub_time	5 days	Lauer et al. (2020)
	Symptoms	18% - 82%	Simonovic and Ahmad (2005)
	Compliance	% people compliant	own specification
	Age	18-80	Index Mundi (2018)
	Occupation	0 (citizen), 1 (farmer)	Dy (2017)
Livelihood	max_liv	3	SalaryExplorer (2020)
	med_liv	2	SalaryExplorer (2020)
	min_liv	1	SalaryExplorer (2020)
	liv_mask	-0.2	own specification
Government	Market_capacity	0 - 100 %	own specification
	Lockdown_level	0 (no), 1 (med), 2 (sev)	own specification
	Livelihood_threshold	[1 - 10]	own specification
	Cases_threshold	num_agents * [0.01 - 0.1]	Hellewell et al. (2020)
	Growth_threshold	>1% - >10%	Hellewell et al. (2020)
	Warning	0,1	Philippine Red Cross (2019)
Hazard	Severity	[1-5]	Philippine Red Cross (2019)
	Radius	severity * 8	Philippine Red Cross (2019)

Table D.1: Parametrisation

D.2 VERIFICATION

In this section, the undertaken verification steps are elaborated upon. There are three sub components of the model to verify separately and one model where those are integrated and verified together. Among others, the built-in datacollector provided by Mesa was used to collect output data.

D.2.1 Sub component verification

There are three sub components to the model that need to be verified. Each of the components can be switched on or off based on the following settings: *hazard_switch*, *livelihood_switch*, and *corona_switch*. The switches are responsible for initializing some of the processes. For example, if the corona_switch is turned off, the agents will go to the market but will not track if the agents they meet are infected with COVID and will not be able to attract COVID.

Structured walk-through

Each of the sub components is checked by switching the other two components off and tracking each of the methods in the model. The components were each checked regularly during the development. It was at times challenging to know how to explain some model behaviour as Mesa does not allow for agent inspection as easily as Netlogo does, but with careful code running, print statements, and storing variables for later inspection, the code in its entirety was checked. The interface of the model was also useful for verification. Sargent (2010) describes this as *animation*, when behaviour is displayed graphically as the model moves through time. In figure D.1 one of these animations is displayed.

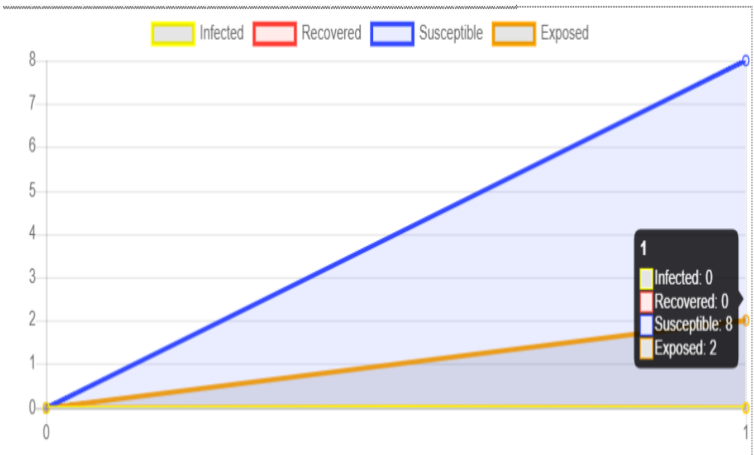
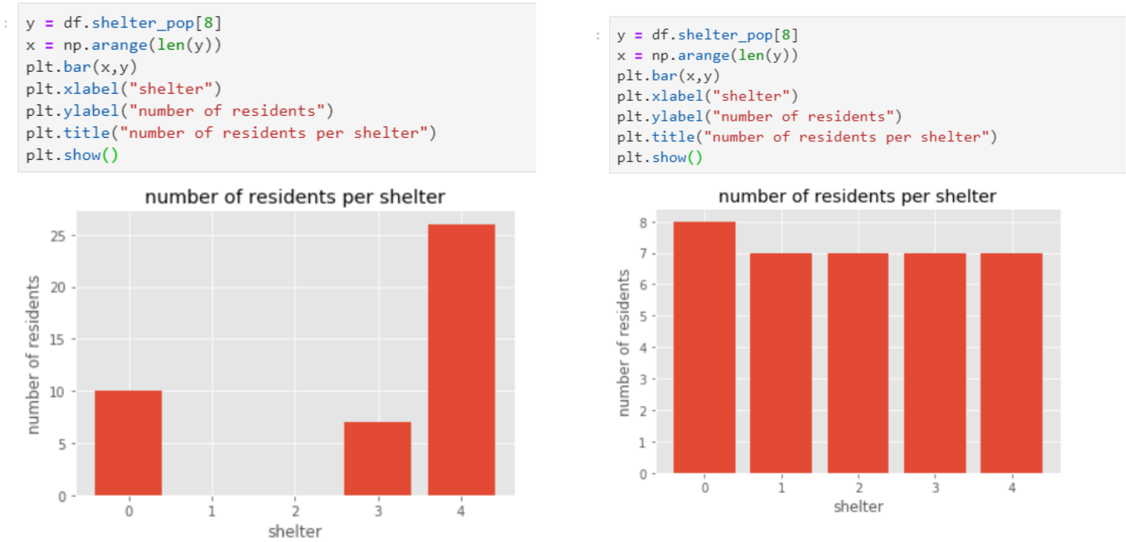


Figure D.1: Increased exposure within one household

When running the model only with the sudden-onset disaster component, this implies that COVID is not spreading and livelihood is not included. This results in behaviour that is mostly interesting when looking at sheltering options. In the graphs below, D.2a shows how the agents are sheltering when there is no early warning and they are forced to go to the nearest shelter. D.2b displays when there is enough time to organize an orderly evacuation process.



(a) Shelters randomized

(b) Shelters orderly

Figure D.2: Difference in sheltering

A last part to mention is what happens to the livelihood component when that sub system is run by itself. Figure D.3 displays the livelihood behaviour. The oscillating behaviour is due to the modelling choice that households only go to the central market to buy or sell their goods when they are in need. They therefore do not build up any savings in "good" times. This modelling choice was made to mimic reality where households in poor communities to not have an increasing livelihood.

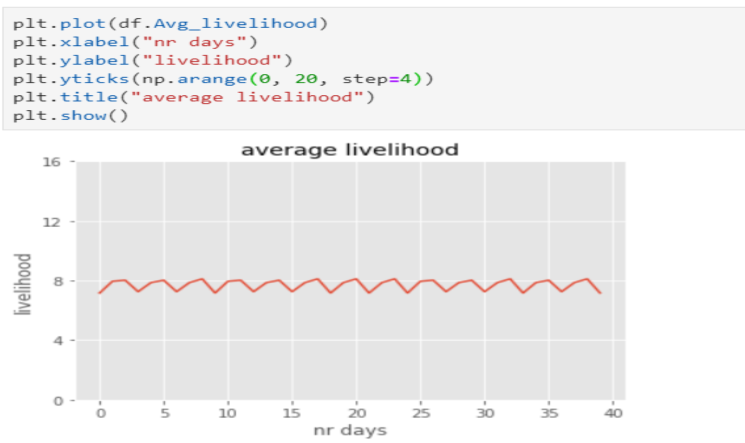


Figure D.3: Livelihood component

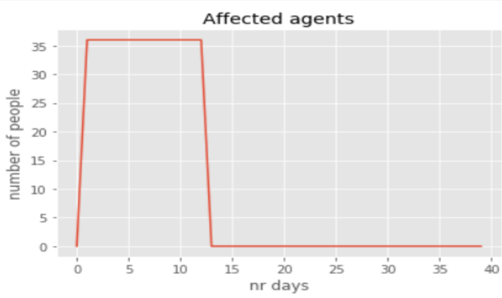
D.3 COMPLETE MODEL VERIFICATION

In this section, the verification steps are performed for the integrated model.

Structured walk-through

From the initialization of the model, every procedure and process was followed and tracked consecutively. This happened during multiple stages of the model development, but in the final stage the code in its entirety was checked. Model runs were performed to see if inactivating methods had the expected effect. As mentioned in the previous section, a switch was implemented for each of the sub components to enable reviewing model behaviour of one or two out of three parts. Inspecting if methods were correctly implemented was also done with graphs like the one in D.4, where it is clear that the agents are affected by the hazard during their time in the shelter. When that status is lifted, they are able to return home.

```
df.affected_agents.plot()
plt.xlabel("nr days")
plt.ylabel("number of people")
plt.title("Affected agents")
plt.show()
print("Agents need to stay in a shelter for ", df.shelter_time[1], " days")
```




```
Agents need to stay in a shelter for  10  days
```

Figure D.4: Check *affected* status and number of days in shelter

The policy interventions were verified as well. In figure D.5 the severity of the sudden-onset disaster was set to the maximum of five, resulting in model runs where all agents are affected and need to evacuate. The model outcomes verify that the infections mostly happen at the shelter, and relatively little infections happen before the impact.

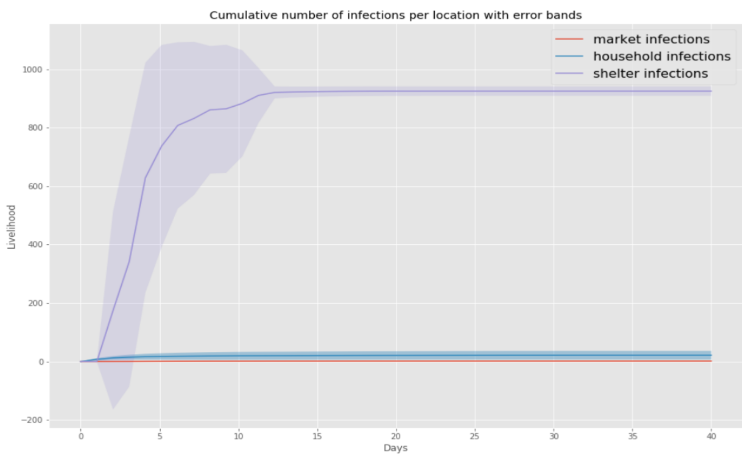


Figure D.5: Check location infections

With the structured walk-through, some minor errors were removed and some redundant code was removed. In a few cases, the code could be more concise, but there were no large errors identified that resulted in errors with the model behaviour. Important to note is that there is a README.doc added to the Github repository (https://github.com/fuukjosephine/thesis_abm_covid_livelihood_hazard) that contains information on how to run the model, as some of Mesas source code was slightly altered to allow for processes during the day and night.

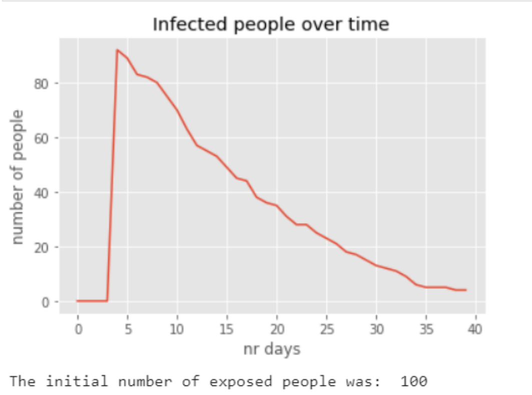
Face validity

With this step, experts about the system or sub components are asked whether the model and its behaviour are reasonable (Sargent, 2010). This step was performed with two individuals knowledge about certain parts: one expert that helped building a SIR epidemic model in collaboration with TNO, that reviewed the conceptual choices and formalized structures of this part in the model. The other expert that checked the model logic and behaviour is knowledgeable in the humanitarian domain.

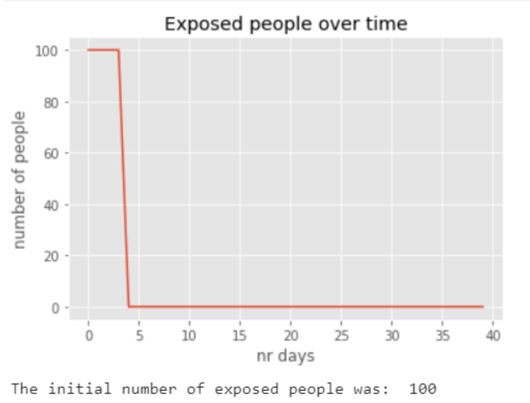
Extreme condition test

The model was also tested under extreme conditions. First, it was predicted what should happen and what model behaviour would come out. Afterwards, this was tested and confirmed. Of extreme conditions, among others, the following were tested:

- Changing the age of all agents to be older than 65. This results in a model where the livelihood drops dramatically as no one is eligible to go to the central market.
- No infected agents and all agents infected. The result of this test can be seen in figure D.6
- Compliance to 0%. This means none of the agents go into quarantine and the exposure goes up quicker than when the compliance is 100%.
- Running the model with 20000 agents. The duration for this test was around 20 minutes, which means that the model is not suitable for testing with large communities as that would take up a lot of computational time.



(a) All agents infected - Infected curve



(b) All agents infected - Exposure curve

Figure D.6: Testing with all agents exposed at start

Minimal environment

In this step, the model is tested with minimal input. For example, it is tested with the minimal number of agents, which is 1. It is also tested with just one household (e.g. with only a handful of agents). In figure D.1 it is visible that the model runs with a single household and that the processes work as they should with this number of agents in the model.

Comparison to other valid models

Specifically the COVID-19 component in this model was compared with other validated models. First, it was compared with SIR-model curves to see if the graphs showed the same behaviour. A more extensive comparison was performed with the model constructed by 510 and TNO. This model can be found on their Github: https://github.com/TNO/Covid-SEIR.

E APPENDIX EXPERIMENTAL DESIGN

This appendix contains additional information about the experimental design as implemented in the EMA workbench. Figure E.1 and E.2 display these settings.

```python
# policy interventions
p0 = {'awareness_policy': False, 'awareness_effect': 0, 'num_shelters': 8, 'shelter_frac': 1,
     'corona_prioritization': False, 'cash_transfer_policy': False, 'height_cash': 0}

# lockdown regulations
p1a = {'awareness_policy': False, 'awareness_effect': 0, 'num_shelters': 10, 'shelter_frac': 1,
     'corona_prioritization': True, 'cash_transfer_policy': False, 'height_cash': 0}

p1b = {'awareness_policy': False, 'awareness_effect': 0, 'num_shelters': 10, 'shelter_frac': 1,
     'corona_prioritization': False, 'cash_transfer_policy': False, 'height_cash': 0}


# awareness + effect awareness
p2a = {'awareness_policy': True, 'awareness_effect': 0.01, 'num_shelters': 10, 'shelter_frac': 1,
     'corona_prioritization': False, 'cash_transfer_policy': False, 'height_cash': 0}
p2b = {'awareness_policy': True, 'awareness_effect': 0.1, 'num_shelters': 10, 'shelter_frac': 1,
     'corona_prioritization': False, 'cash_transfer_policy': False, 'height_cash': 0}

# shelters
p3a = {'awareness_policy': False, 'awareness_effect': 0,
     'corona_prioritization': False, 'cash_transfer_policy': False}
p3b = {'awareness_policy': False, 'awareness_effect': 0,
     'corona_prioritization': False, 'cash_transfer_policy': False}

# cash transfer
p4a = {'awareness_policy': False, 'awareness_effect': 0, 'num_shelters': 10, 'shelter_frac': 1,
     'corona_prioritization': False, 'cash_transfer_policy': True, 'height_cash': 7}

p4b = {'awareness_policy': False, 'awareness_effect': 0, 'num_shelters': 10, 'shelter_frac': 1,
     'corona_prioritization': False, 'cash_transfer_policy': True, 'height_cash': 14}
```

Figure E.1: Code for policy interventions in the EMA workbench

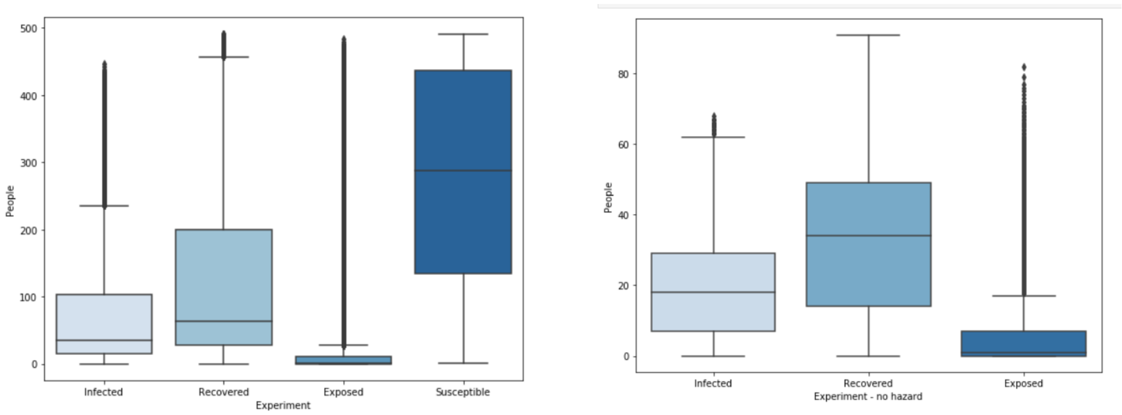
```python
model = Model('livmodel', function = LivModel)

model.uncertainties = [IntegerParameter('min_contacts', 1, 2),
                      IntegerParameter('med_contacts', 2, 5),
                      IntegerParameter('max_contacts', 3, 10),
                      IntegerParameter('max_contacts_shelter', 1, 20),
                      IntegerParameter("initial_live", 1, 5),

                      #POLICY UNCERTAINTIES for LOCKDOWN
                      RealParameter('corona_fraction', 0.01, 0.2), part of policy
                      IntegerParameter('growth_threshold', 1, 15), part of policy
                      IntegerParameter('livelihood_threshold', 1, 10), part of policy

                       #POLICY UNCERTAINTIES FOR AWARENESS
                       IntegerParameter('A0', 10, 100)

                       #POLICY UNCERTAINTIES FOR SHELTERS
                       IntegerParameter('num_shelters', 1, 20),
                       RealParameter('shelter_frac', 0.01, 0.1), #van 10 tot 100 mensen per shelter


                       #POLICY UNCERTAINTIES FOR CASH TRANSFER
                       IntegerParameter('height_cash', 1, 25)
                      ]
```

Figure E.2: Input parameters EMA variations

F APPENDIX MODEL RESULTS

In this appendix, some additional plots and figures are displayed. In the first section, the plots regarding the base model and base runs are depicted. Afterwards, the figures relate to the implemented policy interventions.

F.1 BASE RUN KPIS

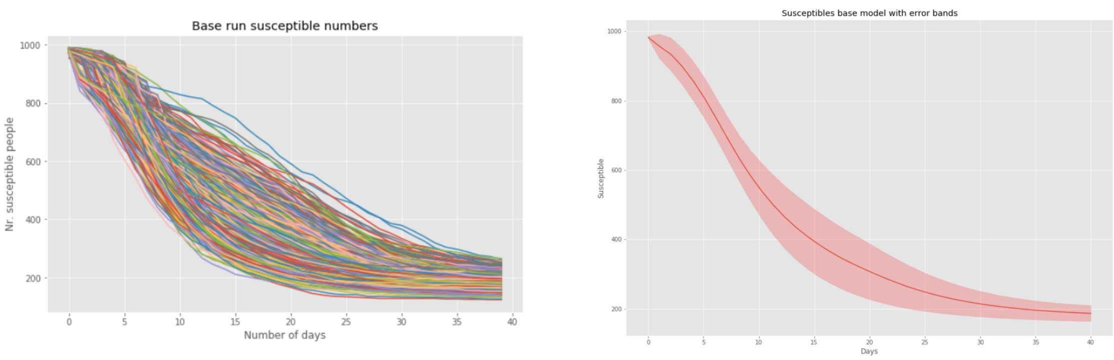


(a) Hazard

(b) No hazard

Figure F.1: Boxplots SIER with and without hazard

Figure F.2 displays the susceptibel trajectory of the base model.

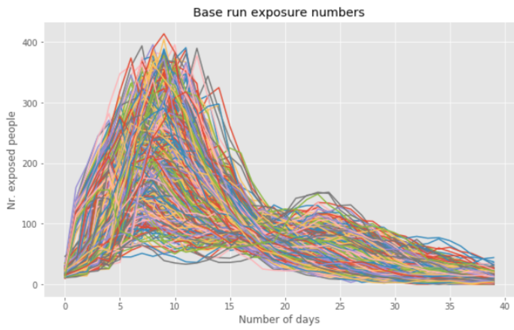


(a) Base model: susceptible

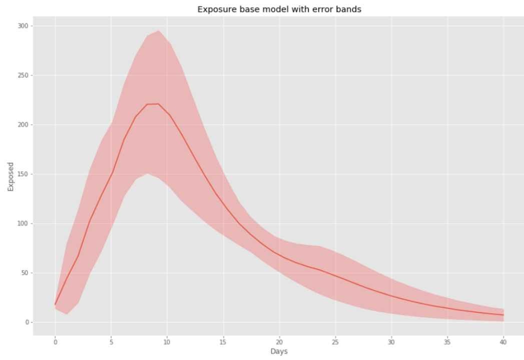
(b) Base model: susceptible with error bands

Figure F.2: Base model: susceptible trajectory

Figure F.3 displays the exposed trajectory of the base model.



(a) Base model: exposed

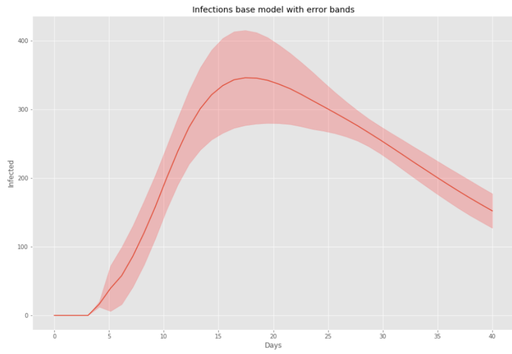


(b) Base model: exposed with error bands

Figure F.3: Base model: exposed trajectory

Figure F.4 displays the infection trajectory of the base model.

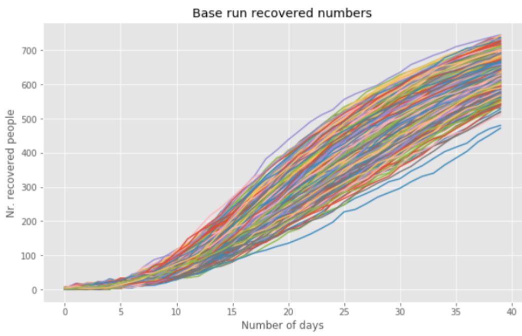
(a) Base model: infected



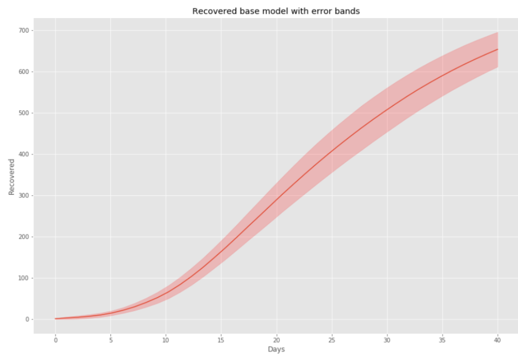
(b) Base model: exposed with error bands

Figure F.4: Base model: infected trajectory

Figure F.5 displays the recovered trajectory of the base model.



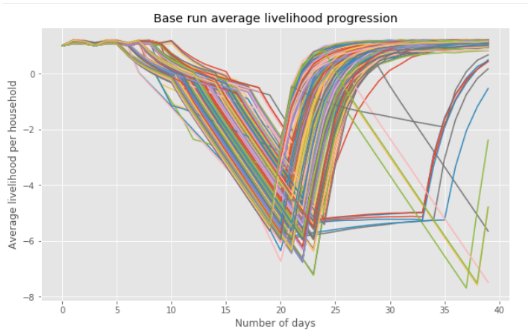
(a) Base model: recovered



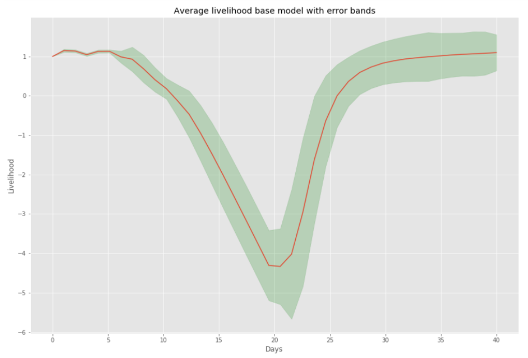
(b) Base model: recovered with error bands

Figure F.5: Base model: recovered trajectory

Figure F.6 displays the livelihood trajectory of the base model.



(a) Base model: livelihood



(b) Base model: livelihood with error bands

Figure F.6: Base model: livelihood trajectory

Figure F.7 displays the lockdown levels imposed during the base model runs.

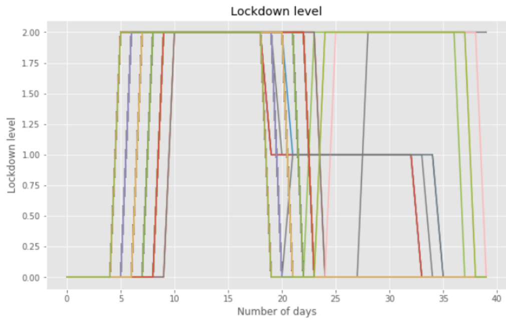


Figure F.7: Lockdown levels of base model

Figure F.8 displays the location of infections during the base model runs.

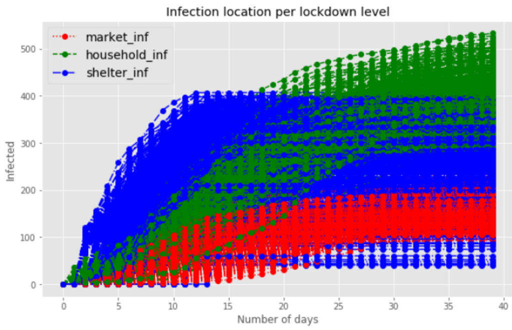


Figure F.8: Location of infections base model

F.2 POLICIES

Figure F.9 displays an overview of the cash transfer policy settings in the EMA workbench.

```
#cash transfer
p4a = {'awareness_policy': False, 'awareness_effect': 0, 'num_shelters': 10, 'shelter_frac': 1,
     'corona_prioritization': False, 'cash_transfer_policy': True, 'height_cash': 14}
p4b = {'awareness_policy': False, 'awareness_effect': 0, 'num_shelters': 10, 'shelter_frac': 1,
     'corona_prioritization': False, 'cash_transfer_policy': True, 'height_cash': 7}
p4c = {'awareness_policy': False, 'awareness_effect': 0, 'num_shelters': 10, 'shelter_frac': 1,
     'corona_prioritization': False, 'cash_transfer_policy': True, 'height_cash': 21}
```

Figure F.9: Cash transfer policies as defined in the EMA workbench

Figure F.10 displays the effect of the initial awareness policy. It is clear that the effect of agents quarantining while their housemates are free to roam wherever they want is not having the desired effect for the infections trajectory.

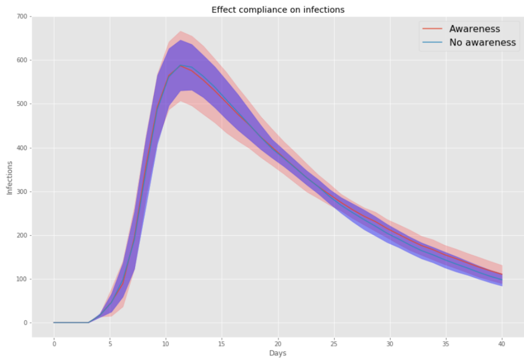
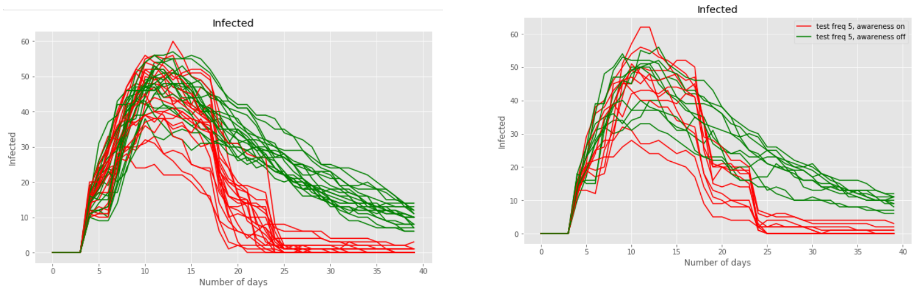


Figure F.10: Effect compliance on infections

Figure F.11 display the initial results from running the awareness policy with regular and without regular testing. Although the peak remains the same (due to the incubation time and the starting period), the infection trajectory is sooner under control with regular testing.



(a) Awareness effect with regular testing

(b) Awareness effect without regular testing (test frequency = 5 days)

Figure F.11: Awareness effect with and without regular testing

Figure F.12 displays that the policy lever regarding the COVID-19 prioritization versus livelihood prioritization does not have any effect on the infection trajectory.

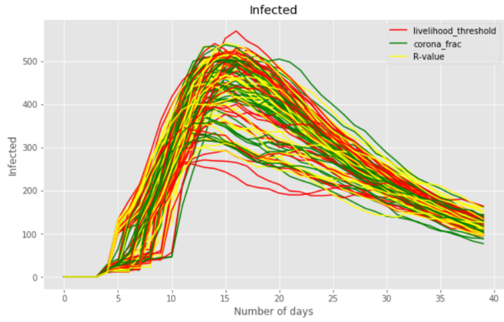


Figure F.12: Varying the liv. threshold, R-value & abs. cases

F.2.1 Feature scoring policy interventions

In this section, the plots of feature scoring of each policy intervention is displayed, as well as for the base model.

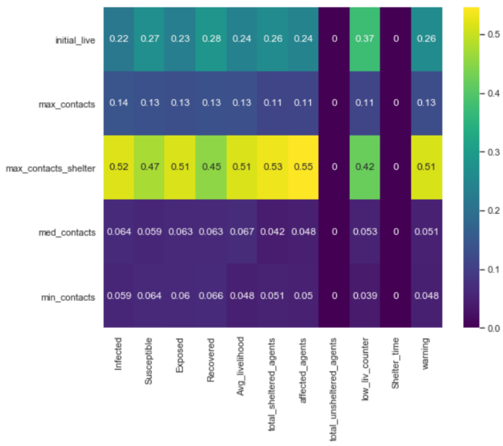
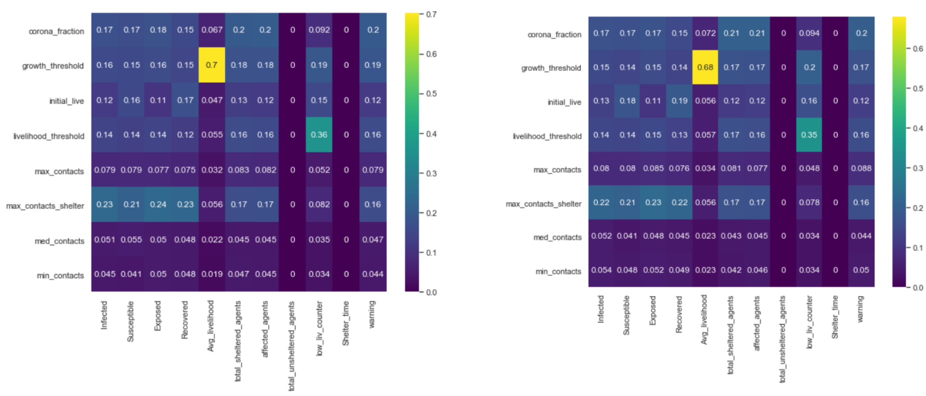


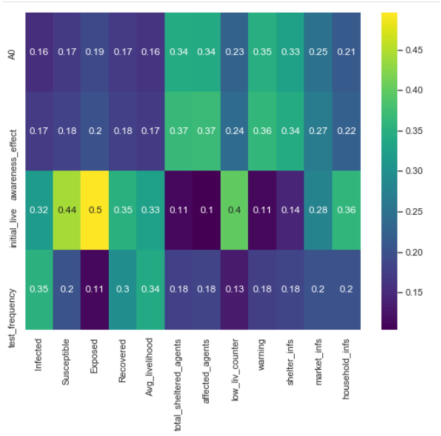
Figure F.13: Feature scoring base model



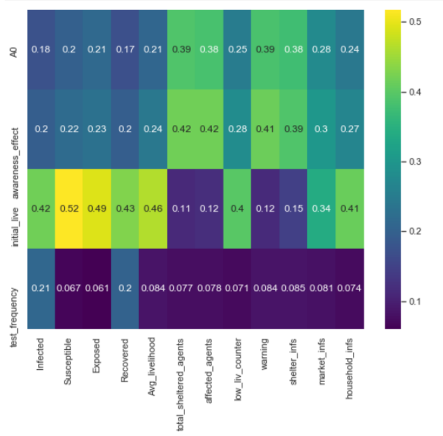
(a) Feature scoring policy 1a

(b) Feature scoring policy 1b

Figure F.14: Feature scoring policy 1

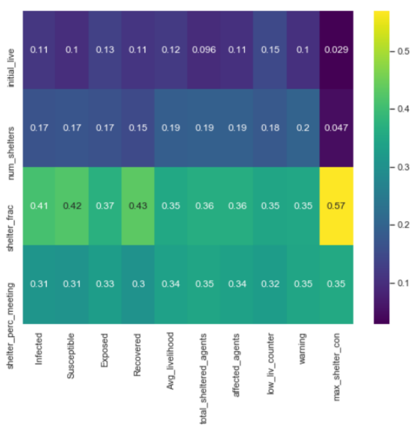


(a) Feature scoring policy 2a

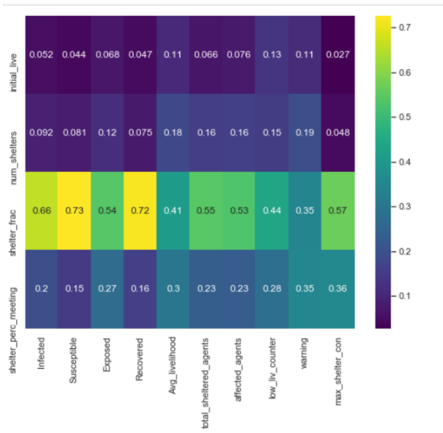


(b) Feature scoring policy 2b

Figure F.15: Feature scoring policy 2

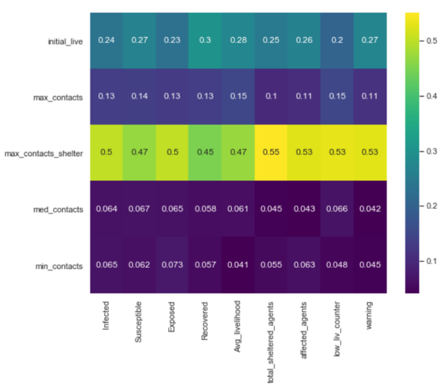


(a) Feature scoring policy 3a

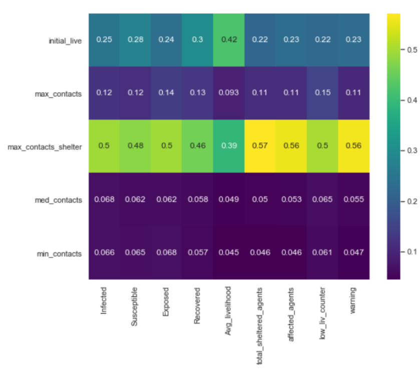


(b) Feature scoring policy 3b

Figure F.16: Feature scoring policy 3



(a) Feature scoring policy 4a



(b) Feature scoring policy 4b

Figure F.17: Feature scoring policy 4a and 4b

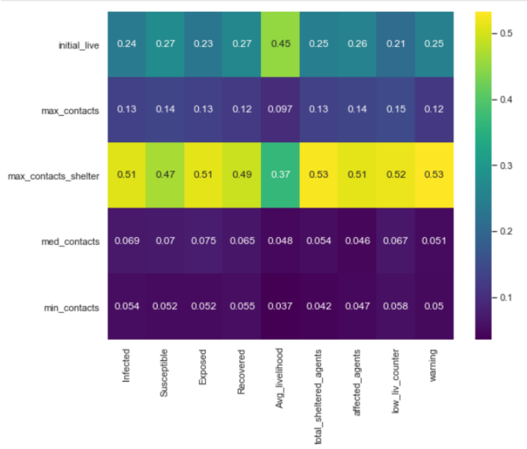
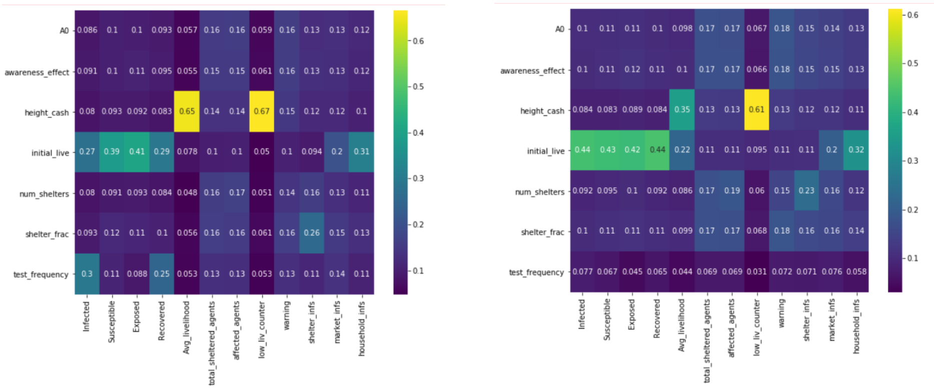


Figure F.18: Feature scoring policy 4c



(a) Feature scoring policy 5a

(b) Feature scoring policy 5b

Figure F.19: Feature scoring policy 5