Informed decision-making on healthcare facility locations in expanding refugee settlements

Researching the interplay between healthcare facility locations and refugee settling choices

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Challenge the future

Informed decision-making on healthcare facility locations in expanding refugee settlements

Researching the interplay between healthcare facility locations and refugee settlement behavior

by

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Associated codes and models are available at https://github.com/meykenb

TU Delft

EXECUTIVE SUMMARY

RESEARCH BACKGROUND AND RESEARCH QUESTION

In 2018, the number of forcibly displaced people all over the world was higher than ever before (United Nations High Commissioner for Refugees, 2019). More than a third of this group are refugees, often living in refugee camps. NGOs try to deliver all necessary aid to these camps, while facing limited access and resources.

Host states are obliged to provide refugees with the needs to meet basic human rights, among which are shelters, food and water, WASH and healthcare. When escaping conflict, violence or disasters, refugees tend to settle in the nearest safe environment, preferably close to people with a similar background. This results in new settlements where refugees are clustered together: refugee camps. Once the primary needs are met in these camps, the expansion of structural facilities such as healthcare and education receives greater attention. For example, in the Rohingya refugee camps in Cox's Bazar, Bangladesh, the percentage of refugees that indicate more attention should primarily be given to healthcare, is increased from less than 6% in 2018 to 44% in 2019 (International Organization for Migration, 2018; Inter Sector Coordination Group, 2019b). However, the structure and layout of a refugee camp cannot simply be adapted, as it has evolved throughout time. This is referred to as the path-dependent nature of the camp expansion. It is difficult to improve the infrastructures and facilities within the camps once they are densely populated. Simultaneously, this population density makes the camps very susceptible for humanitarian disasters.

Aid providers want to optimize the results of the aid they deliver, but are struggling to find the optimal locations for their facilities, as the available spots are very limited. In order to optimize the decisions regarding healthcare facility locations in settlements, facility location models have been studied extensively. Earlier studies have proven their applicability for healthcare facilities within informal settlements, such as refugee camps. However, these optimizations are all designed for application in existing settlements and do not account for the impact of future expansion. Furthermore, humanitarian assistance is mostly a top-down process, despite longstanding recommendations to implement refugees opinions (Rutta et al., 2005).

The research presented in this thesis follows the notion of Augustijn-Beckers et al. (2011) that healthcare facilities should be implemented based on understanding about the development process of the settlement and does this by taking into account the settling choices of refugees upon arrival in refugee camps. The decisions of the many individual refugees result in an emergent camp expansion pattern. Using a model-based approach, the research combines two processes in order to research the interplay between them. The first process consists of the settling choices of refugees, which determines the locations of new shelters in expanding camps. The second process is locating new healthcare facilities using facility location optimization models. Understanding this interplay can assist future decision-making about locations for new healthcare facilities. This is translated into the following research question:

Which facility location approach maximizes the accessibility of healthcare facilities, taking into account the settling preferences of refugees in an expanding refugee camp?

A simulation model of camps Hakimpara, Jamtoli and Potibonia (camps 14, 15 and 16) in Cox's Bazar is made to research the interplay between settling choices of refugees and locating healthcare

facilities by healthcare providers. Subsequently, this interplay is used to develop an approach for future decision-making on healthcare facility locations in expanding refugee camps.

THE OPTIMIZATION MODEL

The refugee decisions on shelter locations and healthcare provider decisions on healthcare facility locations are implemented in an agent-based model, to study the emergent camp expansion. The location decision approaches for healthcare providers are defined by two optimization algorithms. The first algorithm aims to minimize the average demand-weighted travel distance between shelters and healthcare facilities. The second algorithm aims to maximize the number of shelters that is covered by the capacity of a healthcare facility, within a maximum distance of 400 meters as the crow flies. By using predictions about future camp expansion based on the settling preferences of refugees, the healthcare providers can adapt their locating decisions to the settling preferences of refugees. Simultaneously, the placement of new facilities designed for expected camp expansion can affect the settling choices of refugees. This interplay is analyzed in this research and applied in an approach for decision-making on healthcare facility locations.

The effect of location decisions of both actors is measured in the accessibility of healthcare facilities. This accessibility is determined using four indicators. The first indicator is the travel distance between shelters and healthcare facilities. The second indicator measures the ratio of refugees that is allocated to a healthcare facility that has sufficient capacity to cover for all allocated demand. These two indicators are the most important indicators for the accessibility of healthcare in the modeled system. The third indicator measures the capacity shortage within all facilities. Lastly, the fourth indicator measures the ratio of patients that are waiting for a treatment over the unused capacity. The latter two parameters provide an insight in the spread of healthcare facilities over the camp site.

THE INTERPLAY BETWEEN REFUGEE BEHAVIOR AND LOCATION DECISIONS OF HEALTHCARE PROVIDERS

This research has shown that agent-based simulation is capable of resembling the emergence of a refugee camp and the interplay between settling preferences of refugees and different approaches to locate healthcare facilities. Regarding the location decisions of healthcare providers, both location optimization methods are found to be effective in realizing accessible healthcare for the camp inhabitants, complying to the SPHERE standards (Sphere Association, 2018).

In case healthcare providers use an optimization algorithm that minimizes the average distance between shelters and healthcare facilities, refugees are mostly not adapting their settling choices successfully. This means that their adapting their settling choice to the located healthcare facilities does not not improve the overall accessibility of healthcare facilities in the refugee camp. On the other hand, when healthcare providers use an optimization algorithm that maximizes the coverage of shelters, adapting settling choices by refugees increases the accessibility of healthcare facilities in the refugee camp.

Healthcare providers can adapt their locating decisions to expected camp expansion by taking into account the settling preferences of refugees during the locating optimizations. In case the used algorithm minimizes the average travel distance, this adaptation leads to an increase of the accessibility of healthcare facilities. However, in case the optimization algorithm maximizes the coverage of shelters, including expected camp expansion in the optimization does not improve the locating decisions of healthcare providers.

RECOMMENDED APPROACH TO MAXIMIZE THE ACCESSIBILITY OF HEALTHCARE FACILITIES

The recommended approach to locate healthcare facilities that maximizes the accessibility of healthcare facilities in expanding refugee camps depends on two aspects.

First, in case refugees can choose a location to settle upon arrival in a refugee camp, facility location optimizations improve when taking expected camp expansion into account. The expected camp expansion should be determined, based on the settling preferences of refugees. However, if refugees can not choose a their settling location, the inclusion of expected camp expansion in the facility location optimization does not improve the resulting accessibility of healthcare facilities.

Second, in case a space restriction of 45m^2 surface area per person is maintained in a refugee camp, it is recommended to locate healthcare facilities using an algorithm that minimizes the travel distance between refugees and healthcare facilities. However, if the available surface area per person is significantly lower than 45m^2, it is recommended to locate healthcare facilities in a refugee camp using an algorithm that maximizes the coverage ratio of shelters in the camp.

Finally, the accessibility of healthcare facilities in a refugee camp strongly improves when a space restriction of 45m^2 surface area per person is maintained in the camp. This results in a camp where shelters and healthcare facilities are spread evenly over the area. This enhances the possibility to locate healthcare facilities in strategic places, maximizing the accessibility of healthcare facilities for all refugees.

Preface

Delft, December 2019

Before you lies the result of the research I have conducted in my final year as a master student at the TU Delft. The choice to research a topic that is connected to the Rohingya minority is inspired by a lingering interest in Myanmar, which started once I visited this country in 2017. I wanted to approach the situation from the perspective of the refugees, as news about this minority is often written from a political point of stance.

Fortunately, Tina and Martijn were enthusiastic about this topic and helped me narrowing it down to a research that is suitable for a master thesis project. I would thank both of them for encouraging me throughout the process and to help me focus on the most interesting findings. Also, they challenged me with some time pressure, but were also very patient when extra time was needed. Then, I haven't even mentioned the fun conversations we had at the ends of meeting. All this made me walk out of every meeting with renewed energy and enthusiasm.

Most of all, I owe Martijn a major thank you, for the effort you put in to make my model run on the cluster. Also, for the many many errors we surpassed, emailing back and forth. In the end, number 42 did appear to be the answer to everything. Only one model did not really agree on this. However, even this final error, we solved in the end.

Then, I would like to thank everyone who helped me throughout the entire process. The people who were willing to help me with information gathering by taking the time to share their experiences, or providing their feedback on my work. Also, I want to thank Pieter, my family and my friends for their endless support, cheering along with every small victory and every errors that was solved, the good advises and their patient help when I got stuck.

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INTRODUCTION

1.1. RESEARCH PROBLEM

1.1.1. WORLDWIDE REFUGEE PROBLEM

In 2018 a world record has been reached in the number of forcibly displaced people worldwide (United Nations High Commissioner for Refugees, 2019). Over the last ten years, this number has increased from 43,3 million to over 70,8 million people, which is more than 9% of the world population (United Nations High Commissioner for Refugees, 2019). 25,9 million people from this group are refugees, often living in refugee camps. NGOs provide aid to improve the living conditions, but have to divide their resources over multiple aid demanding situations over the world and cannot guarantee a constant aid flow. This affects refugees' decisions, as the presence of NGOs makes a location more attractive, but the extent to which supplies are available is more important.

Host states are obliged to safeguard human rights for refugees, including shelter, food, water, WASH, healthcare and education (Bakewell, 2014; Sphere Association, 2018). However, neighbouring host states are often developing countries that simply do not have the resources to host any more residents (United Nations High Commissioner for Refugees, 2018; Collier, 2007). In search for supplies for primary needs, the refugees contribute to deforestation and pollution of water in the surroundings of their new settlements (Abedin, 2019; Datta, 2015). Especially around rapidly expanding camps, the environment suffers a lot due to the rapidly increasing need for supplies. This has long-term impacts on the environment (Abedin, 2019; Datta, 2015).

The whole of events and decisions make the development of the refugee camps a path-dependent process, in which camps expand based on previous development decisions (Ligmann-Zielinska & Sun, 2010). Therefore, refugee camps can be regarded as complex adaptive systems with many agents, that react to their environment and each other (Suleimenova et al., 2017; Miller & Page, 2007).

1.1.2. FACILITIES IN EXPANDING CAMPS

Refugees are mostly "escaping conflict, generalized violence, violations of human rights, or natural or man-made disasters" (United Nations High Commissioner for Refugees, 2019, p. 63). Once they have escaped this situation, they prefer to settle close to people with a similar background, which often results in new settlements where they are clustered together (Augustijn-Beckers et al., 2011; Interview B, 2019). In these new settlements, refugee camps, there is a great need for basic facilities that cover the primary needs such as shelters, clean drinking water, food and first-aid. Surveys among refugees show that NGOs aim to cover these primary needs first, after which the focus shifts to other needs (International Organization for Migration, 2018). Secondary needs that come forward in refugee settlements are education and expanded healthcare infrastructure with specialized healthcare facilities (Demusz, 1998).

1.1.3. THE ROHINGYA MINORITY IN BANGLADESH

Bangladesh is the country with the biggest number of refugees living in refugee camps, hosting over 900.000 Rohingya refugees that fled the violence in Rhakine state in Myanmar, where this muslim minority is continuously threatened (United Nations High Commissioner for Refugees, 2019). The first Rohingya fled to Bangladesh in 1978 (Tay et al., 2018). Refugees built an existence in the camps, based on the circumstances formed by environmental and political impacts in Myanmar and Bangladesh. At the time the first Rohingya arrived in Bangladesh, there were no guidelines for refugee camps yet. Ever since, the camps evolved during various waves of refugee arrivals and are subjected to many different impacts, such as natural hazards and regulations. Currently, the refugee camps are overfull and very susceptible for humanitarian disasters (Inter Sector Coordination Group, 2019a). Bangladesh is already facing overpopulation and the government simply does not have the resources to host any more residents (United Nations High Commissioner for Refugees, 2018). During rapid expansion of the camps, the high number of refugees contribute to deforestation and pollution of water in the surroundings, causing a long-term impact (Abedin, 2019; Datta, 2015). Therefore, the Government of Bangladesh is hesitant to allow development of long-term structures for the refugee population (Interview A, 2019).

NEED FOR HEALTHCARE

The above-mentioned shift in needs for facilities among refugee populations also comes forward when comparing needs assessments among the Rohingya population in Cox's Bazar over time, as conducted by International Organization for Migration (2018; 2019b). For example, the severity of the need for education for children has strongly increased from 7,6% in 2018 to 36,7% in 2019, whereas the severity of need for cooking fuel during that time decreased from 74,4% to 52,5%. Another strong increase can be found in the severity of the need for health facilities, which has increased from 5,8% to 44% over the same time. Simultaneously, the percentage of people that indicate to have no access to a static healthcare facility has doubled. There is a strong need for specialized mental health and psycho-social support to help the refugees cope with the violence they have witnessed (Lacroix & Sabbah, 2011; Riley et al., 2017). Essential health services for survivors of gender-based violence are lacking in 56% of the sites (Inter Sector Coordination Group, 2019a). Within Bangladeshi host communities, even 85% of the area has limited access to service for gender-based violence victims (Inter Sector Coordination Group, 2019a). The need for healthcare is also getting more recognition from organizations outside of the camps. Healthcare facilities are being developed to ensure total coverage for all refugees living in the camps. However, due to the high population density and limited space in the camps, accessible places are often already occupied.

IMPROVING THE ROHINGYA SITUATION IN BANGLADESH

In literature, only three solutions are mentioned for the Rohingya in Bangladesh: repatriation, local integration and resettlement of refugees (Azad & Jasmin, 2013; United Nations High Commissioner for Refugees, 2013; Kuhlman, 1990). None of these consider a long-term stay of the refugees in the camps. Moreover, the reports of the UNHCR and Government of Bangladesh do not mention any durable solutions to improve the conditions and structure within the camps. This implies that the durability of the camps to uncertain impacts such as floods or a new big influx of refugees is not being increased and the situation of the refugees therefore remains vulnerable. Improving the conditions within the camps is difficult, because the high population density and limited space limit the remaining number of available locations for healthcare facilities. The limited number of locations are often far from optimal. This makes one wonder what efficiency could have been gained if the healthcare facilities had been established during the expansion phase of the camps. To answer this question, this research explores the usage and development of healthcare facilities in an expanding refugee camp and the experienced accessibility of these facilities for refugees.

1.2. RESEARCH GAP

Much research has been done in exploring the motives and patterns for refugees to migrate. Especially when huge migration streams resulted in humanitarian crises, situations are extensively researched. During these researches, agent-based simulation models are often put to practice, as they can be used to interpret location decisions of separate agents that result in emergent societies (Johnson et al., 2009; Anderson et al., 2007). However, these researches all tend to look at a broad picture, such as migration streams and the locations of camp settlements (Collins & Frydenlund, 2016; Groen, 2016; Suleimenova et al., 2017). No researches were found that use agent-based simulation to explain how camps are expanding.

Simultaneously, a lot of research is performed in humanitarian logistics and demand determination to optimize the distribution of aid in refugee camps (Kovács & Spens, 2007; Day et al., 2012; Gupta et al., 2017; Dubey & Gunasekaran, 2016). NGOs depend on funding and try to use these funds as efficient as possible, which makes optimization of aid distribution desirable (United Nations High Commissioner for refugees, 2019). Most of these researches aim to optimize the locations of facilities in existing settlements, leaving approaches to improve the conditions in expanding camps unmentioned (Rahman & Smith, 2000; Goodchild, 1979; Owen & Daskin, 1998; Vallim & Mota, 2012). As Augustijn-Beckers et al. (2011) explain, health facilities should be implemented based on understanding about the development process of the settlement. Understanding how refugees maximize their access to healthcare facilities when settling in a camp, would make it possible to optimize the effectiveness of healthcare facilities when using this knowledge to optimally locate facilities. This research aims to find an approach to make informed decisions on healthcare facility locations in expanding refugee camps. Therefore, this research studies the impact of different approaches to locate healthcare facilities on the accessibility of healthcare facilities in an expanding refugee camp. This is studied for various refugee preferences regarding their shelter locations. The impact of the various approaches and different refugee preferences are explained in the following chapters.

1.3. RESEARCH QUESTIONS

The knowledge gap, as explained in section 1.2, indicates that there is insufficient knowledge about the emergence of healthcare facility locations in expanding refugee camps and how this affects refugees settling choices. To gain understanding about these patterns, this research aims to explain the interplay between two concepts: a) settling choices of refugees and b) locations of healthcare facilities in spontaneous settlements. Assessment of the resulting interplay is done using the resulting accessibility of healthcare facilities, as regarded by refugees. This research goal is summarized in the following research question:

Which facility location approach maximizes the accessibility of healthcare facilities, taking into account the settling preferences of refugees in an expanding refugee camp?

The accessibility of healthcare facilities is measured in four indicators. Firstly, the average travel distance between refugee shelters and healthcare facilities. Secondly, the ratio of shelters that is covered by sufficient capacity of healthcare facilities. Thirdly, the capacity shortage within healthcare facilities. Fourthly, the ratio of patients that are waiting for a consult over the unused capacity. The first three indicators provide information about the ease of accessing healthcare for refugees. The last indicator provides information about the division of healthcare facilities over the refugee camp.

The research question is based on two hypotheses. The first hypothesis is that refugees take the accessibility of healthcare facilities into consideration when choosing a location to settle in an expanding refugee camp. The second hypothesis is that healthcare providers can adapt their locating decisions for healthcare facilities to the settling preferences of refugees. They can do this by predicting future camp expansion and optimizing the location of a new healthcare facility for this future scenario. When both hypotheses hold, and the settling choices of refugees and healthcare facility location decisions of healthcare providers are understood, an approach can be designed for locating healthcare facilities in expanding refugee camps.

1.3.1. SUBQUESTIONS

The study leading to an answer to the main research question is divided in six sub questions, that are presented in table 1.1. The first sub question seeks to explain the settling choices of refugees upon arrival in a refugee camp. The second sub question aims to explain the location decisions of healthcare providers. The third and fourth sub questions aim to translate the emergence of a refugee camp, the refugee shelters and the healthcare facilities within, into a simulation model. The fifth question aims to define the interplay between different approaches in locating healthcare facilities and refugee settling preferences. The gained understanding about this interplay is then used to answer the last sub question. This final sub question aims to design approach that can be used during future decision-making on healthcare facility locations. Answering these sub questions will provide the conclusions to answer the main research question. The six sub questions are described in more detail below.

Table1.1: Subquestions

	Subquestions
1.	What factors affect the settling choices of refugees and their healthcare-seeking behavior, from the moment of arrival in a refugee camp?
2.	How can a location optimization model for healthcare facilities in refugee camps be defined?
3.	How can a conceptual model of refugee behavior when settling and using healthcare in an expanding refugee camp be made?
4.	How can the emergence of a refugee camp, and the facilities within, be explained with an agent-based model?
5.	How do settling choices of refugees affect, or are affected by, the locations of healthcare facilities?
6.	How can the outcomes of this study be generalized into an approach for decision-making on healthcare facility locations in expanding refugee camps?

SQ 1 What factors affect the settling choices of refugees, and their healthcare-seeking behavior from the moment of arrival in a refugee camp?
To explain the decision to settle in a certain location in a refugee camp upon arrival, the drivers that affect these settling choices must be understood. The hypothesis is that the settling choices are related to the healthcare-seeking behavior, so the healthcare-seeking behavior must be researched as well.

SQ 2 How can a location optimization model for healthcare facilities in refugee camps be defined?
The situation of a refugee camp requires a specific facility location model, that ensures access to healthcare for as many refugees as possible. What optimization is suitable?

SQ 3 How can a conceptual model of refugees behavior when settling and using healthcare in an expanding refugee camp be made?
The factors that are found to affect the healthcare-seeking behavior in sub question 1, are conceptualized for implementation in an agent-based model.

SQ 4 How can the emergence of a refugee camp, and the facilities within, be explained with an agent-based model?
Various scholars acknowledge that the emergence of camps should be regarded as a process (Ligmann-Zielinska & Sun, 2010; Augustijn-Beckers et al., 2011). As Kennedy (2008) states, the design of a camp should therefore also be viewed as a process. Okyere et al. (2017) add that this process can be understood in terms of refugee settling choices. Besides the refugees, healthcare providers and governmental actors are agents that also contribute to this process. Hence, the emergence of the camp, resulting from collective behavior of all agents, can be researched through experiments in an agent-based model (Anderson et al., 2007). The collective behavior that emerges, is the result from individual agents decisions in the model (Johnson et al., 2009; Anderson et al., 2007).

SQ 5 How do settling choices of refugees affect, or are affected by, the locations of healthcare facilities?
This sub question aims to define the interplay that explains how refugee settling choices are affected by the accessibility of healthcare facilities. The impact of decisions on healthcare facility locations can be examined using experiments (Anderson et al., 2007). Experimenting with the settling preferences for agents, different camp development patterns will emerge. Analyzing the impacts of the different settling preferences leads to several hypotheses about the impact on camp expansion, which can be verified in an iterative round of experiments. Simultaneously, the impact of decisions on new healthcare facility locations on the settling choices of refugees is tested for different settling preferences of refugees. How these two behaviors are found to affect each other, defines the interplay that can be used to develop an approach for locating healthcare facilities.

SQ 6 How can the outcomes of this study be generalized into an approach for decision-making on healthcare facility locations in expanding refugee camps?
Using the hypotheses from sub question 5, the emerging patterns are translated into an approach that can be used for informed decision-making on the need of new healthcare facilities and where they should be located to maximize the accessibility of healthcare facilities for refugees during camp expansion.

1.4. STRUCTURE OF THE REPORT

This report provides the results that are found while answering the sub questions, seeking to answer the main research question. In chapter 2, the findings of the literature review are discussed. Hereby the first two sub questions are answered and a suitable facility location model is presented for this research. Chapter 3 illustrates the system to which the facility location models will be tailored, and discusses its components. The case study that is used in this research is described in this chapter as well. Chapter 4 provides a review of previous models, to identify the best practices that can be used in this research. Together, chapter 3 and 4 provide an answer to sub question 3. The fourth sub question is answered in chapters 5 and 6, that describe the model design and the usage of the model to obtain results. Chapter 7 analyzes the model behavior, thereby answering sub question 5. Then, the outcomes are generalized and formulated into an approach in chapter 8. Chapter 9 discusses the research method and its limitations, before the main research question is answered in chapter 10. Besides the conclusion, this final chapter also presents suggestions for further research.

2

LITERATURE RESEARCH

This chapter is used to explore the existing field of research in the topics that are addressed in chapter 1: emerging refugee camps, healthcare needs and usage among refugees and facility location choices. It thereby provides an answer to the first two sub questions about the healthcare-seeking behavior of refugees and a suitable facility location model. First, characteristics of refugee camps are discussed, after which the refugee perspective and the healthcare provider perspective are researched. This is complemented with information from interviews about the Rohingya camps in Cox's Bazar.

2.1. PROTRACTED REFUGEE CAMPS

Protracted refugees are refugees that live in exile for at least five years, in groups of over 25.000 people of the same nationality (Executive Committee of the High Commissioner's Programme, 2004). The average time in refuge for these so-called protracted refugees is over twenty years (Devictor, 2016). The refugee camps provide shelter and save the lives of many, but they "progressively waste these same lives" while time passes, as the chance of a bright future declines (Azad & Jasmin, 2013, p. 27).

2.1.1. LONG-TERM CHARACTER

A refugee crisis is a situation in which large groups of people are forcibly displaced (United Nations High Commissioner for Refugees, 2019). The severity of a crisis gets measured by the crude mortality rate and the under-five crude mortality rate (Sphere Association, 2018). Refugee crises are characterized by suffering for many different groups. Besides the refugees who are suffering, host countries and communities are suffering from heavily constrained physical and financial resources. The constraints get heavier when the situation remains for a longer period of time, increasing the pressure on involved parties and the international community for support (Azad & Jasmin, 2013).

When building up refugee camps, there is an overarching focus on short-term solutions (Rooij et al., 2016; Wali et al., 2018). This influences the structural design of refugee camps and facility locations within these camps (Kennedy, 2008). Kennedy (2008) describes four conclusions regarding refugee camps. Firstly, the camps are built with the idea to close after a certain period, despite the fact that a longer time span is more probable than a shorter one (Herz, 2008). Secondly, in current camp designs there is insufficient attention for the long-term effects of (lacking) resources for refugees, such as a lack of education or chronic malnutrition. Thirdly, the environmental conditions for each camp site are different, making it impossible to define optimal numerical guidelines for universal use. Lastly, designing a camp is an incremental process, subject to the unpredictability of the use and impacts it is subject to. To conclude, Kennedy stresses the need for assessing the design of a refugee camp as a process, rather than a tool.

2.1.2. STRUCTURED VERSUS SPONTANEOUS CAMPS

The Sphere Handbook describes minimum standards that should be maintained when setting up camps (Sphere Association, 2018). The UNHCR developed a Handbook for Emergencies (2016), that implements these standards in the description of proper site planning for refugee camps. These guidelines describe an ideal design for refugee camps, ensuring efficient delivery of goods and services and health and well-being of the community. The differences between camp locations trouble the implementation of this design. Also, it is acknowledged that in spontaneous settlements these requirements cannot always be regarded (United Nations High Commissioner for Refugees, 2015; Moore, 2017). Moreover, spontaneous settlements are characterized by a lack of essential infrastructures such as water, electricity, education and health care (Ekandem et al., 2014).

The concepts camps and settlements are used interchangeable. It is therefore important to define these concepts for use throughout this study. The Dutch development bank (FMO) defines camps as places where refugees have no degree of self-reliance (Schmidt, 2003). UNHCR differentiates between permanent camps and camps, whereas the Refugees Studies Program in Oxford distinguishes organized settlements, camps, and assisted self-settlements (Schmidt, 2003). Multiple studies distinguish between spontaneous and organized settlements, with camps being part of the latter category (Kuhlman, 1990). Spontaneous settlements are overall characterized by self-settling of refugees, having some sort of choice regarding their accommodation (Schmidt, 2003). Augustijn-Beckers et al. (2011) categorize informal settlements as established without a planning and not following regulations. Dovey (2013) adds to this transgression with the condition that informal settlements arise from an immediate need for shelter and a community. This definition can be closely linked to the definition of spontaneous settlements. The concepts of spontaneous and informal settlements are also often found in literature about slum formations (Fawaz, 2017; Beardsley & Werthmann, 2008; Hofmann et al., 2015). Fawaz (2017) even argues that slum-like neighborhoods can be approached as refugee camps.

To conclude, when refugee camps are developed without planning or compliance to regulations, they can be referred to as informal settlements. When refugees are choosing their preferred settling location without any formal accordance to regulations, or overarching planning, the result can be referred to as a spontaneous settlement. When the settlement expansion is planned and regulated by another party, the settlement can be referred to as an organized settlement, or “refugee camp”. Refugee camps can initially start as an informal settlement and become regulated and organized in a later stadium.

PREFERENCE OF ACTORS

In this study, the emphasis lies on the difference between the spontaneous character of camps, formed by the emergent refugees’ settling choices, and the organized character, imposed from the actors. Interestingly, the UNHCR prefers the spontaneous settlements over the establishment of camps, because they indicate that refugees merge in host communities. The focus then lies at building up an existence in this new community rather than depending on aid (Crisp & Jacobsen, 1998). On the contrary, many any aid agencies prefer the camps, because this concentrates the needs geographically, which makes it easier to deliver aid to a bigger group (Crisp & Jacobsen, 1998). Important is the opinion of host governments, who prefer camps to structure registration of refugees, center the need for aid and limit local integration (Crisp & Jacobsen, 1998). Another reason for governments to prefer this type of organized settlements is to keep repatriation of the entire group a possible solution, as everyone is concentrated in one place (Kuhlman, 1990).

2.2. THE REFUGEES’ PERSPECTIVE

Humanitarian assistance is mostly a top-down process, despite recommendations that came up in the eighties that strive for implementation of refugees’ opinions (Ruffa et al., 2005). Informal camps are characterized by a process of expansion that does not follow formal laws and regulations and is hence not appropriate for top-down planning (Vahidi & Yan, 2016). It is therefore of significant use to approach the growth of an informal refugee camp from the refugees point of view before turning it into an organized camp, as the refugees know best what their needs are and how urgent these are (Rutta et al., 2005). Some NGOs use participatory data in assessments of the needs, but often they summarize the results and do not document the respondents views transparently (Rutta et al., 2005).

2.2.1. HEALTHCARE NEEDS OF REFUGEES AFTER ARRIVAL

When refugees arrive in a refugee camp, their physical condition is often deteriorated. They might have fled to escape a violent situation, or due to a natural disaster that destroyed their belongings. It is not uncommon for refugees to have been travelling multiple days before arriving in a refugee settlement. Many refugees are suffering from direct injuries caused by violent behavior, such as gunshot wounds, rape or burn wounds (Inter Sector Coordination Group, 2017; Drennan & Joseph, 2005). Besides these injuries, they often endured a lack of food and clean water while fleeing. During their trek to the new place of refuge, refugees can come across diseases for which they have little to no resistance (Collier, 2007). They can carry these along to their new settlement, possibly infecting the host community with these diseases as well (Collier, 2007). Thirdly, their mental health status is impacted by the horrific situations that refugees have witnessed (Khanlou, 2010). The stress of living in a refugee camp also negatively affects the mental health condition of refugees (Lonn & Dantzler, 2011; Drennan & Joseph, 2005). These mental health issues are most often addressed at primary healthcare facilities, because they express in physical complaints such as headaches, fatigue or other disturbances (Vasilevska & Simich, 2010). Lastly, refugees can carry communicable diseases that are prevalent in their home country (Drennan & Joseph, 2005).

Once healthcare in the refugee camps is organized according to standards, it is often better fit to the needs than what the refugees are used to in their previous living conditions (Rutta et al., 2005). For example, Rohingya in Myanmar are used to face discrimination, lack of respect and racism when seeking healthcare. It can take months to obtain the expensive permit needed to leave IDP camps (Internally Displaced People) (Ripoll, 2017). Moreover, health information is often not understandable for Rohingya, for instance due to language barriers (Ripoll, 2017). Therefore, they need to be informed and get used to the availability of healthcare in the camps, preferably by people they trust (Ripoll, 2017). Especially for female Rohingya that fled Myanmar, healthcare is urgent. The two-child policy by the government, limiting the number of children Rohingya couples may have, leads to unregistered and unsafe abortions (Ripoll, 2017). One out of seven Rohingya women have had an abortion, often performed by unskilled staff in unhygienic circumstances. Released from the child-limitation, a huge number of births is seen in the Rohingya camps in Bangladesh (Ripoll, 2017).

The main barriers to healthcare that are identified by Rohingya refugees within the camps have to do with accessibility, cost and lack of staff (Ripoll, 2017).

2.2.2. SHELTER LOCATION CHOICE

"The growth of a settlement is clearly not a random process and is likely to be influenced by a number of physical, cultural, and economic factors," Augustijn-Beckers et al. (2011) cite Sliuzar (1988, p. 27). Understanding these factors that influence the expansion of settlements can be used to improve the design of facilities (Augustijn-Beckers et al., 2011). In spontaneous camps, as defined in the previous chapter, refugees decide where to settle with their family. The emergent settlement is the result of all these decisions together (Johnson et al., 2009). Therefore, spontaneous camps can be regarded as the result of many separate refugee settling decisions. Which factors influence these decisions, is researched widely. It is stated that people prefer to settle close to people with a similar background,

preferably close to friends (Augustijn-Beckers et al., 2011; Interview B, 2019). Proximity to roads and footpaths is another important factor (Okyere et al., 2017). In slums this can be recognized in the preference to settle in places with close access to public transport, because transport makes it possible to travel to a job outside the settlement (Dovey, 2013). This also goes for refugees in camps, who often hope to earn some money (Interview B, 2019). Fawaz (2017) emphasizes the preference to settle in neighborhoods with widespread solidarity to secure opportunities for employment, health care and with high visibility towards relief agencies. This can be found in areas that have a high density of refugees, such as camps (Fawaz, 2017). Refugees prefer to settle on the edge of the densest camps, since this is likely to guarantee presence of facilities (Interview D, 2019; Interview E, 2019).

Considering the camps as the result of a system of changing human decisions practices helps to understand local needs and spatial developments (Okyere et al., 2017). While analyzing the decisions, it is important to bear in mind that every individual can have a different view on importance of factors, which reflects on their decisions (Van Dam et al., 2013). Sufficient sources must be reviewed to overcome this so-called observer-dependency (Van Dam et al., 2013).

2.3. THE HEALTHCARE PROVIDERS' PERSPECTIVE

Refugees are attracted by the availability of aid in certain locations (Wali et al., 2018). Actors can act differently upon this. NGOs can act proactively, preparing before an influx of refugees in this region occurs, or reactively, by stepping in once the needs increase (Wali et al., 2018). On the contrary, host governments can restrict the distribution of aid to prevent attraction of a great influx of refugees (Wali et al., 2018).

2.3.1. ACCESSIBILITY DEFINED

From the healthcare providers' perspectives, it is the aim to make healthcare accessible to all inhabitants of a refugee camp, also when the camp is expanding (Inter Sector Coordination Group, 2018b). To ensure that accessibility can be measured, it must be defined. The most straightforward definition of accessibility is given by Daskin & Dean (2004), who define accessibility as the ability of clients or patients to reach the healthcare facility, or vice versa when it concerns a mobile facility or doctor. However, this definition neglects the actual performance of healthcare at the facility, which is about being able to receive the right services at the right moment.

Penchansky & Thomas (1981) use five a's to describe the fit of a healthcare system: availability, accessibility, accommodation, affordability and acceptability. Availability and accessibility are most important in refugee camps (Interview A, 2019). McPake et al. (1999) relate to the availability by addressing that a healthcare facility is only meaningful when there are enough supplies: drugs and qualified staff. In academic literature, the accessibility of healthcare facilities is often regarded in terms of travel time to reach the facilities (Tanser et al., 2006). Aid providers consider more factors when measuring accessibility of healthcare facilities. They consider the number of people a facility serves, the waiting times in combination with the time it takes for people to reach the facility, the opening hours of the facilities, the physical accessibility, affordability of health care and access to male and female staff at the facilities (Guzek et al., 2017; International Organization for Migration, 2018; Inter Sector Coordination Group, 2019a). Accessibility of healthcare for people with special needs or disabilities is often regarded separately (International Organization for Migration, 2018; Inter Sector Coordination Group, 2019a). A special kind of healthcare facilities are mobile facilities. Their accessibility depends on their operations which are often part of emergency response such as natural disasters (Inter Sector Coordination Group, 2019a).

Improving the accessibility of facilities is difficult. Akhmat & Khan (2011) states that facilities can best be developed or upgraded during the process of setting up a settlement, because it only becomes more expensive and impractical to intervene once a settlement is established. Moreover, existing (social) structures in settlements can be valuable and should not be disrupted (Beardsley &

Werthmann, 2008).

In this research, the interplay between the presence of healthcare facilities and the settling choices of refugees is researched. Therefore, the indicators related to travel distance and time are used to define accessibility. Factors that are not included are waiting times, expensiveness, the capability of the staff, discrimination and availability of medicines. Capacity is included as a separate factor, which is described in the following section. To simplify the accessibility measurement, it is assumed that all healthcare facilities share the same hours of operation.

SPHERE performance indicators

Besides accessibility, targets for acceptability of healthcare in emergency settings are defined in the SPHERE Handbook. The SPHERE standards set minimum requirements to secure “life with dignity and security” (Sphere Association, 2018, p. 32). This includes access to water, sanitation, food, nutrition, shelter and healthcare. According to the SPHERE handbook, at least 80 percent of the population must be able to reach primary healthcare within one hour of walking (Sphere Association, 2018). The number of inpatient beds per 10.000 people must be at least 18. Moreover, the ratio of healthcare facilities per number of people should be 1:10.000, and for hospitals this should be 1:250.000 (Sphere Association, 2018). In terms of staffing, the key indicators require 1-2 community health workers per 1000 people, and at least 23 skilled birth attendants per 10.000 people (Sphere Association, 2018). About the availability of supplies, the standards determine that healthcare facilities may be maximal 4 out of 30 days out of medicines.

2.3.2. Facility location decision-making

Facility Location Problems (FLPs) are used to strategically determine the desired location for a facility. Often, facilities are constructed for a long time-span and require an investment of money (Owen & Daskin, 1998). The facility location problems can be assessed by various facility location models, that serve different objectives. These models can focus on travel times or distances, uncertainties, costs, coverage, or a combination of these objectives (Ahmadi-Javid et al., 2017). This section provides insight in the various objectives that are served with facility location approaches.

Facility Location Problems (FLPs) are optimization problems that involve a location decision for a facility that serves a number of demand centers with each a certain demand level, for the lowest possible cost (Estrada et al., 2017; Harkness & ReVelle, 2003). During a refugee crisis, resources are limited, so a high efficiency in terms of cost and supplies is desired. Also, decision-making must be swift, because every second counts in saving lives. Facility location decisions can be used to assess the location of a camp, but also the specific location of separate facilities within a camp, such as medical or educational facilities (Rooij et al., 2016). Choosing facility locations can impact the landscape, which in turn must be considered as a factor that, over time, can contribute to possible facility failure (Estrada et al., 2017). Overpopulation of refugee camps asks for expansion of the FLPs of the camp. Yet it is difficult to estimate the amount of people in need, because there is a continuous influx of people in expanding camps and not all new-born children are registered. Furthermore, a lack of decision-making tools and IT-applications sustaining humanitarian logistics trouble the assessment of FLPs (Seifert et al., 2018; Kovács & Spens, 2011).

Optimizing a facility location is strongly dependent on the aspects that must be considered, the users of the facilities and the criteria used to define the accessibility of the facility (Leonardi, 2006). Examples of aspects are the number of people it serves, proximity of a road network, accessibility for vehicles, but also the risk of floods and the possibility to clear waste (Inter Sector Coordination Group, 2019a). Especially medical waste must be handled with extra care to prevent spread of diseases or environmental impacts (Inter Sector Coordination Group, 2019a). In current refugee settlements, barriers to healthcare are assessed by surveying inhabitants of the camps.

FACILITY LOCATION PROBLEMS IN LITERATURE

A great number of articles describe, summarize and apply various facility location problems. Each situation asks for its own objectives and constraints. Table 2.1 shows a brief overview of objectives and properties that are addressed in facility location models for healthcare facilities by various authors, in comparison with the objectives and properties in this research. When a cell contains "both", this means the article explains applications with and without this objective.

Table2.1: Objectives and properties of facility location models in literature

	Objectives					**Model properties**					
Author (year)	Fixed number of facilities to locate	Demand coverage (coverage-based problems)	Robustness	Cost of facility construction	Time/distance to facility	Continuous location problems (facilities can be located anywhere)	Discrete location problems (facilities can be located at candidate locations)	Dynamic environment	Capacitated	Emergency situation	Different types of health facilities
Ahmadi-Javid et al. (2017)	(both)	X			X		X			(both)	X
Boonmee et al. (2017)	(both)	X	(both)	X	X		X	X		X	
Daskin & Dean (2004)		X	X		X		X		X	X	
Owen & Daskin (1998)		X	X					X			
Rahman & Smith (2000)	(both)	X			X		X		X		X
Vallim & Mota (2012)	(both)	X			X		X		X		
Farahani et al. (2010)		X		X	X	X	X	X	X		
My contribution		X	X		X		X	X	X	X	

Table 2.1 shows that every article describes how to cover all demand. However, robustness of the facilities is in most of the literature not included. Costs mostly consist of travel costs, leaving the cost of construction and usage out. Estrada et al. (2017) even argue that it is not possible to formulate a cost function that accounts for all costs in such complex situations, as monetary costs of facilities in refugee camps are just one facet of the complex problems that must be dealt with (Estrada et al., 2017). This research also leaves out construction costs, as it includes the perspective of refugees, who are not affected by these costs.

Most articles are in favor of simplifying the computation, by using discrete location decisions. Discrete location problems consider a set of possible locations, whereas in continuous problems all locations are possible (Ahmadi-Javid et al., 2017). Few scholars apply dynamicity, which means accounting for the change of the environment over time. This includes stochastic problems, focusing on the uncertainty in input parameters. Uncertainty can be implemented through probability distributions, or through scenario planning (Ahmadi-Javid et al., 2017; Daskin & Dean, 2004). In refugee crises, the number of affected people, and thereby also the required aid, is time-dependent. Therefore, the problem is preferably modeled as a dynamic instance of the FLP (Estrada et al., 2017). The capacity of healthcare facilities is mostly left out of scope when dividing the demand over the facilities. However, the number of people that need healthcare during a refugee crisis is increasing over time with the number of refugees, so it is important to use a dynamic approach (Estrada et al., 2017). When articles report of emergency situations, this resembles sudden impacts such as a flood (Boonmee et al., 2017). Taking these emergencies into account, it is important to locate the facilities in safe areas (Boonmee et al., 2017). The last property is only considered by Ahmadi-Javid et al. (2017), who distinguish between different types of healthcare facilities, using hierarchical modeling.

2.3.3. CHOICE OF FACILITY LOCATION MODEL

TAILORING THE FACILITY LOCATION PROBLEM

When formalizing the facility location problem in this research, the objectives must be specified. The aim is to find the impact of considering the future expansion of a refugee camp when choosing facility locations. This difference will be measured by the accessibility of healthcare facilities for refugees in two scenarios: the first scenario does not consider the future camp expansion while assessing accessibility of healthcare, whereas the second scenario does take future expansion into account. The difference between these two scenarios will be analyzed to find the interplay between settling choices of refugees and location decisions by healthcare providers, resulting in the accessibility of healthcare.

In each scenario, the accessibility gets maximized. This will be measured by the demand-weighted travel distance between refugee shelters and healthcare facilities, taking into account the capacity of the facilities to help these patients. The capacity of a healthcare facility is the constraint, as it should not be exceeded. Ensuring a minimum level of coverage is a determinant for the robustness of the system. This is a major challenge in vulnerable locations, such as Cox's Bazar where the monsoon season poses a serious threat every year. In the model, shelters get allocated to a healthcare facility, based on minimization of the distance to a facility. Every facility has a capacity and when the capacity of the nearest facility for a shelter is already fully allocated to other shelters, this new shelter gets recorded as over-capacity, which indicates a capacity shortage in this facility. However, unused capacity of facilities is also undesired, so equal division of the shelters of the facilities is desired.

In this research, all facilities are assumed equal, so hierarchical modeling is not necessary. Demand gets re-allocated once a new healthcare facility is taken in use. First, demand points (refugee shelters) must be allocated to a healthcare facility. Then, shelters can seek for a second facility, which has free capacity. Having a second facility within a bigger range allocated as well, is referred to as applying a Double Standard (Li et al., 2011). It is desirable to have a second facility within a bigger range allocated as well, in case the first facility falls out (Li et al., 2011). However, this research does not apply a double standard, but instead assumes that refugees have full information of all other facilities and can turn to these facilities if necessary.

CHOOSING A MODEL

The objectives and properties that are covered by scholars and shown in table 2.1 are applied in different facility location models. An overview of these models and the objectives and properties they capture is shown in table 2.2 below, complemented with an additional row for the objectives and properties in this research. It can be seen that this research shows most resemblance with the P-median model, that aims to locate a number of facilities such that all demand points are covered and the demand-weighted travel distance is minimized. It uses discrete location choices, using the demand points as a set of feasible locations. In P-median optimization models, every demand point gets assigned to one facility.

In this research, the P-median problem will be extended by including the capacity of the facilities and the robustness of the coverage over time. Robustness measures have not been included in P-median models, but multiple researches have suggested this as an interesting future research direction for dynamic healthcare center selection methods (Ahmadi-Javid et al., 2017; Daskin & Dean, 2004). Increasing robustness equals hedging against worst case scenarios (Owen & Daskin, 1998).

The robustness can be measured according to the SPHERE standards, as described in 2.3.1. The robustness will be tested by measuring the performance of the system under future circumstances. As this research aims to clarify the difference between taking into account the future expansion of the refugee settlements or not, it is expected that the first scenario will show lower robustness in comparison to the second scenario. However, future growth can be different than expected. Using scenario planning, possible future parameters can be specified and applied (Owen & Daskin, 1998). Scenario planning can serve three different approaches: 1) optimizing performance over all scenarios, 2) optimizing worst-case performance, and 3) minimizing the worst-case regret across all scenarios (Owen & Daskin, 1998; Daskin & Dean, 2004). The latter aims to minimize the difference between the compromise solution and the scenario-specific preferred solutions (Daskin & Dean, 2004).

Table2.2: Objectives and properties of different facility location models

	Objectives							Properties			
FLP	Locate p facilities	Minimize average demand-weighted travel distance	Minimize establishing cost	Minimize separation distance between facilities	Robustness	Cover demand points	Minimize maximum travel distance	Continuous location problems (facilities can be located anywhere)	Discrete location problems (facilities can be located at candidate locations)	Demand is assigned to one facility	Capacitated
P-median (minisum)	X	X				X			(X)	X	/[1]
P-center (minimax)						X	X			X	
P-dispersion	X			Max distance X							
Fixed charge		X[2]	X						X	X	
Hierarchical	X	X				X		X	X		
Scenario-based	X	X			X	X				X	
Set Covering	/		X			X			X	X	
Maximal covering	X				X	X			X	X	
My research	X	X			X	X			X	X	X

[1]Multiplied by a constant to convert demand-at-distance into cost units

[2]/ indicates mostly not, but examples exist where this objective or property is met. Most P-median models are uncapacitated, however Rahman shows it is possible to add a capacity restriction for health facilities in P-median models.

COMPARING TO MAXIMUM COVERAGE: A SECOND MODEL

As the P-median model does not ensure maximum coverage of the shelters with the available amount of facilities, it is interesting to measure the difference with results of a model that focuses on maximizing coverage instead of minimizing average travel time. Therefore, a second model is created in which the maximal covering model is applied to the same scenarios as the P-median model. Again, the first scenario will give results in which the number of shelters that is covered by healthcare facilities is maximized for the assessment of needs in the current camps. The second scenario will take into account expected future camp expansion in the assessment, to ensure maximum coverage also during this expansion. The difference between these results will be compared to the results of the first model.

THE P-MEDIAN FACILITY LOCATION MODEL

The P-median facility location model (also known as "minisum facility location problem") shows most overlap with the objectives and properties that are desired in this research, focusing on reduction of the average travel times. It is widely used and adapted to own preferences (Rahman & Smith, 2000). This is exemplified by Tien and El-Tell (1984), who adapted their P-median model to address both accessibility and availability, or by Oppong (1996), who used a P-median model in various scenarios to open the way to multi-criteria decision analysis (Rahman & Smith, 2000). The P-median model is very often used for disaster situations, also in a multi-objective context (Boonmee et al., 2017). Examples are the application of the P-median model to find optimal shelter locations combined with optimal evacuation routes for flood evacuation plans, or combined with a geographic information system to minimize travel costs to relief facilities during hurricane disasters (Boonmee et al., 2017). The choice for the P-median model for locating healthcare facilities is also supported by the results of research in location optimization of healthcare facilities in Brazil by Vallim & Mota (2012). Vallim & Mota showed that the P-median model was most successful in reducing the average weighted travel time to reach healthcare facilities for city inhabitants. The maximal covering model scored lowest in reducing the average weighted travel times, but prove successful in reducing the maximal travel distance, especially in comparison to the P-median model (Vallim & Mota, 2012).

Optimization under uncertainty can be done using stochastic models, that can be developed from deterministic models, such as the maximal covering model (Boonmee et al., 2017). The uncertainty can stem from (limited) time or resources, while maximizing the number of people serviced in a healthcare model optimization (Boonmee et al., 2017). Robust optimization is another approach under uncertainty, but knows very few applications in emergency humanitarian logistics so far (Boonmee et al., 2017).

The P-median optimization function

Simplicity is key when building the model. Extra constraints bring extra restrictions to possible solutions, thereby sometimes increasing the cost and increasing the number of facilities needed (Rahman & Smith, 2000). The formulas that are concerned with the P-median optimization model are shown below. The objective function of the P-median model (2.1) is to minimize the sum of demand-weighted distance from the demand point to the facility. A fixed number of facilities gets located (2.2). Every demand point will be assigned to one facility (2.3). Constraint (2.4) ensures that demand is only assigned to points where a facility is located. Finally, (2.5) and (2.6) are binary requirements for the decision variables. The P-median model can be extended to a pq-median problem, which finds an efficient location for two or more levels of facilities (Rahman & Smith, 2000).

$$Min \sum_i \sum_j D_i d_{ij} Y_{ij} \tag{2.1}$$

$$\sum_j X_j = \mathrm{P} \tag{2.2}$$

$$\sum_j Y_{ij} = 1 \quad \forall i \tag{2.3}$$

$$Y_{ij} - X_j \leq 0 \quad \forall i, j \tag{2.4}$$

$$X_j \in 0,1 \quad \forall j \tag{2.5}$$

$$Y_{ij} \in 0,1 \quad \forall i, j \tag{2.6}$$

Variables:
i = demand location
j = potential facility location
D_i = demand at point i
d_{ij} = distance between demand point i and potential facility site j
P = number of facilities to locate

Decision variables:

$$Y_{ij} = \begin{cases} 1, & \text{if demand } i \text{ is served by facility } j \\ 0, & \text{if not} \end{cases}$$

$$X_j = \begin{cases} 1, & \text{if facility } j \text{ is located at location } i \\ 0, & \text{if not} \end{cases}$$

THE MAXIMAL COVERING FACILITY LOCATION MODEL

The maximal covering facility location model aims to maximize the covered demand with a fixed number of facilities p. As explained before, this optimization model has been found very effective in not only maximizing the average coverage when allocating the capacity of facilities, but also in minimizing the average demand weighted travel distance (Vallim & Mota, 2012). As travel times in some areas are not known, or available, they can be estimated using a distance measure. Therefore, the maximal covering optimization model is interesting to compare to the P-median model.

The maximal covering optimization function

The formulas for the maximal covering location model are shown below. The objective function of the maximal covering facility location model (2.7) is to maximize the number of demand points that is covered. Constraint (2.8) determines that demand can only be covered, if there is at least one facility to cover for it. A maximum number of p facilities gets located (2.9). Finally, (2.10) and (2.11) are binary requirements for the decision variables.

$$Max \sum_i D_i Z_i \tag{2.7}$$

$$Z_i \leq \sum_{j \in N_i} X_j \quad , \forall i \tag{2.8}$$

$$\sum_j X_j \leq p \tag{2.9}$$

$$X_j \in 0,1 \quad \forall j \tag{2.10}$$

$$Z_i \in 0,1 \quad \forall i \tag{2.11}$$

Variables:
i = demand location
j = potential facility location
D_i = demand at point i
p = maximum number of facilities to locate
Decision variables:

$$Z_i = \begin{cases} 1, & \text{if demand-point } i \text{ is covered} \\ 0, & \text{if not} \end{cases}$$

$$X_j = \begin{cases} 1, & \text{if facility } j \text{ is located at location } i \\ 0, & \text{if not} \end{cases}$$

CREATING A SCENARIO WITH FUTURE EXPANSION

Multiple researchers have tried to embed environmental factors, disruptions or future demand in location-allocation models, showing how the robustness of the system can benefit from including these aspects (Oppong, 1996; Sasaki et al., 2010). An example using the P-median optimization model is provided by Oppong (1996), who shows how the rainy season can affect the usage of roads and how this affects the performance of the P-median optimizations. In order to do this, Oppong defined three scenarios for his research. The first scenario represents the dry season in which all roads are accessible. The second scenario shows what happens with the access to healthcare facilities when the rainy season starts and parts of the area become impassable. The third scenario takes into account which areas are likely to become impassable during the rainy season and get excluded from the set of possible locations in the model. Oppong finds that the second scenario can decrease the performance of the system with 76% and returns much less predictable results, while the third scenario is found to improve the model performance with 5% (Oppong, 1996). Oppong concludes that "failure to identify and accommodate relevant variables could lead to empty, unfounded claims of improvements in accessibility, and possibly produce less accessible systems" (Oppong, 1996, p. 135). When including these variables correctly, Oppong finds that the system can be improved, possibly leading to a system with a higher accessibility with less facilities. As Oppong shows, the accessibility of healthcare in different future scenarios can be significantly improved when accounting for these scenarios while locating the facilities.

2.4. CONCLUSION

There are two important perspectives that must be embedded in a system that researches the expansion of refugee camps and the accessibility of healthcare facilities during this camp expansion. First, the perspective of the refugees. Their settling choices shape the camp expansion and their healthcare seeking behavior shapes the need for healthcare. The perspective of healthcare providers is important, as the healthcare providers make the final decision about the facility location. Based on needs assessments among refugees, the healthcare providers define when accessibility is sufficient or when new healthcare facilities should be constructed. The P-median location-allocation model can be used to locate a fixed number (p) of facilities with the objective to minimize the average demand weighted travel time for refugees. The maximal covering location-allocation model can be used to meet the objective of covering a maximum number of refugees with a fixed number of facilities. It is expected that proper inclusion of expected future camp expansion can improve the accessibility in the assessed system.

3

THE BEHAVIOR AND COMPONENTS OF A REFUGEE CAMP SYSTEM

This chapter describes the system that represents a refugee camp, that is used to apply the location-allocation models from chapter 2 and analyze the results. Section 3.1, describes how a refugee camp can be regarded as a system that can be used for analyses. In section 3.2, this system is described in terms of its components and boundaries. From there, the actions and state changes are defined in the conceptual model, after which the necessary simplifications in the system are described. The chapter is concluded in section 3.3

3.1. THE REFUGEE CAMP CASE

The interplay between healthcare facility location decisions and settlement preferences of refugees during camp expansion is researched using a case study. A case study is a very suitable method for studies that focus on communities and plans (Yin, 1994).

Specifying a case study is useful to draw a context, which is important as results are strongly context-dependent. This context-dependency can be illustrated by the difference between needs in two types of refugee camps. First, imagine a camp that is emerged after a natural disaster. The camp hosts many people who have lost their homes and belongings and the area is heavily affected by the disaster. In this situation, the biggest need could be the need for food and proper infrastructure to deliver supplies. Now, consider a camp that hosts people who have fled violent areas. These people also had to leave their homes and belongings, but the surrounding area and communities of the camp might still have intact infrastructure and supplies for food. In this camp, there will be a greater need for immediate healthcare for wounds. As the different contexts bring forward different needs, a case study can be used to define the context.

For the case study, it is desirable to analyze the settling choices of refugees and facility location decisions of healthcare providers in a clearly demarcated area, because every individual settlement has unique structures (Hofmann et al., 2015). This research focuses on the effect of refugee settling choices on facility location decisions by healthcare providers, and vice versa, during camp expansion. Therefore, data must be available about the camp under study during the expansion phase of the camp. This data should contain the locations of healthcare facilities, the usage of healthcare and the assessment of accessibility of healthcare by refugees in the camps. Choosing a camp with a homogeneous group of refugees, makes it more easy to understand their preferences and translate this to behavioral rules that determine the choices for agents. If the expansion phase of the case study is clearly demarcated in time, the time span can be used in the analysis as well.

3.1.1. THE CASE STUDY: CAMPS 14, 15 AND 16 IN COX'S BAZAR, BANGLADESH

A case study that lives up to the described aspects is found in the refugee camps in Cox's Bazar, Bangladesh. Already for forty years, Rohingya refugees have been arriving here, crossing the border from Myanmar. The Rohingya are a Muslim minority from Myanmar. They share a homogeneous set of beliefs, resulting in a rather homogeneous population in the camps. Within Cox's Bazar, three camps are geographically separated from the main camps Kutupalong and Balukhali. These three camps are Hakimpara, Jamtoli and Potibonia (also knows as camps 14, 15 and 16) and came to exist after the outbreak of the Rohingya crisis in August 2017, when the Government of Bangladesh allocated undeveloped forest land for these camps in September 2017 (Inter Sector Coordination Group, 2017). Camps 14 and 15 were first mentioned in site assessments in September 2017, followed by camp 16 in October the same year (International Organization for Migration, 2017a,b). The two main camps (Kutupalong and Balukhali) already exist for a longer time, and many NGOs have been providing healthcare in these camps for years before 2017. Therefore, by the time the situation became an emergency 3 level, the necessary infrastructure was there to perform monthly needs assessments among the population in all camps. This also happened in the new camps 14, 15 and 16, resulting in regular situation reports. As camps 14 and 15 were first assessed in September 2017, this research uses data from September 2017 until June 2019.

3.1.2. THE BEHAVIOR OF INTEREST

The system is modelled in order to research the interplay between settling preferences of refugees upon arrival in a refugee camp and locating healthcare facility. In other words, the relation and interaction between two patterns is researched. The first pattern is the emergence of shelters in an expanding refugee camp and the second pattern is the development of new healthcare facilities in the camp and the usage rate of these facilities. A comparison will be made between scenarios that take future camp expansion into account during the allocation of health facilities, and scenarios where this is not taken into account. The hypothesis is that a pattern will emerge, in which facilities are placed nearby groups of shelters and, similarly, new shelters get placed close to existing facilities. It is also expected that taking future camp expansion into consideration while locating new facilities, will reinforce this pattern. If this hypothesis holds, the obtained understanding about the interplay between the two initial patterns can be used during future decision-making about allocating new healthcare facilities in an expanding refugee camp. This is mainly of interest for healthcare providers, who often have a limited budget and therefore want to maximize the effect of their facilities. The obtained understanding can also be used to convince political stakeholders. As described in chapter 2.1 Political stakeholders sometimes want to prevent a refugee camp from obtaining a long-term character, and therefore want to put a stop to the development of new facilities. For this reason, plans that are tailored to expected future expansion are not always accepted.

3.2. SYSTEM IDENTIFICATION AND DECOMPOSITION

Before clarifying what actions are taking place in the system and creating the emergent behavior, the elements in the system are defined. The elements are the agents and the environment, which both have specific properties. It is important to note that assumptions have to be made while setting the definition of the elements and their attributes, in order to limit the complexity of the system. Figure 3.1 shows a diagram in which the important elements of the healthcare usage system in refugee camps are represented. The camp is considered as an expanding system in which healthcare providers and refugees are making decisions, resulting in the overall accessibility of healthcare facilities in the system. Section 3.2.1 describes the agents in the system, and 3.2.2 describes the components of the modeled environment. Section 3.2.3 describes how the system is simplified before translating it to a model.

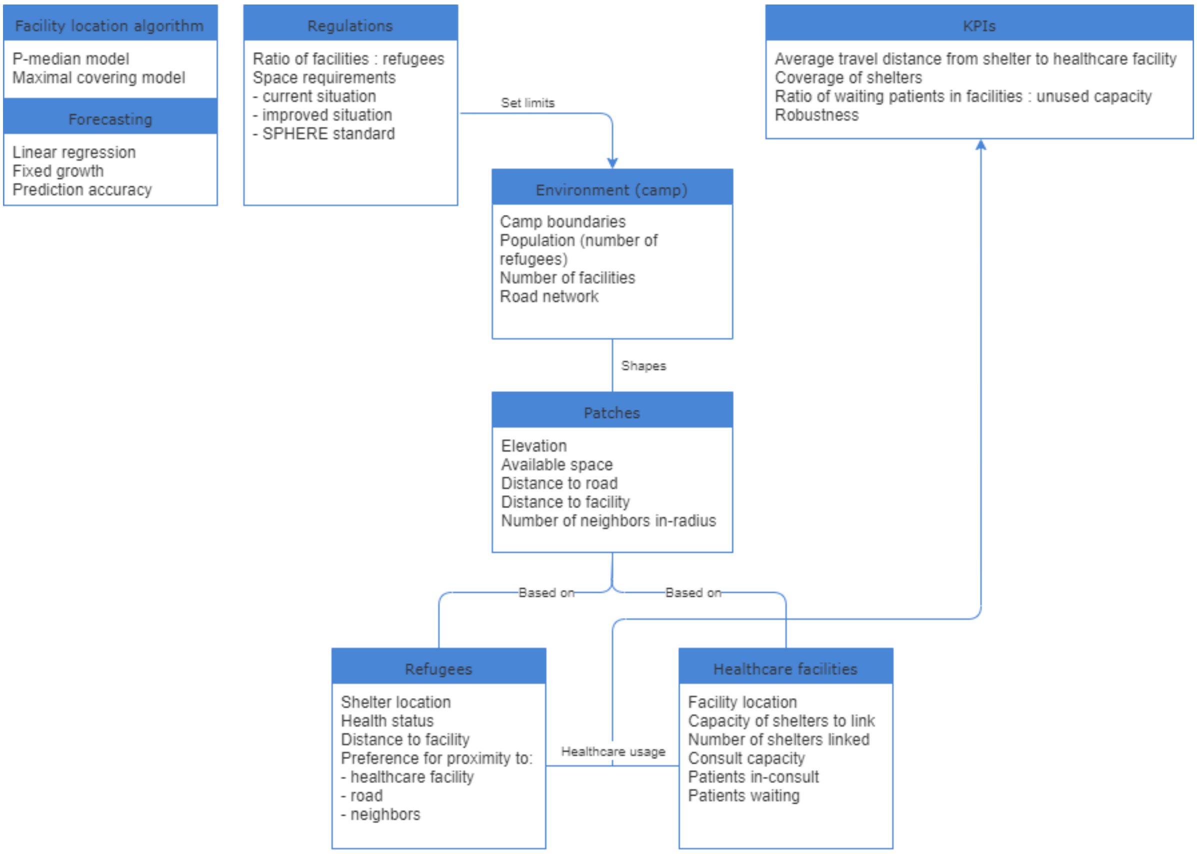

Figure3.1: Overview of camp system in UML inspired diagram

3.2.1. THE AGENTS

The agents in the system are refugees and healthcare providers (often NGOs). **Refugees** have preferences regarding the proximity of their shelter to other places and a health status, which shapes their need for healthcare. Refugees make settlement decisions based on the available space and elevation of the patches. According to their preferences, weights are assigned to three aspects. These aspects are the number of neighbors of a certain patch, the distance from this patch to the nearest road and the distance to the nearest healthcare facility. Based on the weights and the distances, the refugee chooses a patch to settle on. Their health status defines whether they will consult a healthcare facility.

The presence of NGOs in the system is represented by the **healthcare facilities**. Every healthcare facility has the same characteristics. Different approaches from NGOs are applied through the experiments, as explained in section 6.2. Healthcare facilities are located based on other healthcare facilities that are already present and the shelter locations, which form demand points. Every facility has an initial number of shelters it can cover and a capacity for consults, which is measured per week. The extent to which these capacities are used is measured by the number of shelters that link to the facilities and the number of patients in consult, or waiting for a consult.

3.2.2. THE ENVIRONMENT

The refugees and NGOs are operating within the boundaries of the **camp environment**. The camp environment is characterized by the elevation, the literal boundaries of the camps, the agents inside the camp, and the roads within and leading to and from the camp. The environment is spatially divided into a raster of patches. Each patch has attributes that store information about five aspects. The first aspect is the elevation of this specific piece of land. The second aspect is the space that is available at this patch, which makes it possible for shelters or facilities to be developed at this patch. The last three aspects are the distance to roads and facilities and the number of shelters around it. Both type of agents are based at patches in the system and base their decisions on patch-attributes in the environment.

Lastly, there are **regulations** regarding the minimal space required per person and the minimal number of facilities per person. These are based on international guidelines, such as the SPHERE standards (Interview A, 2019; Sphere Association, 2018). These requirements are applied in the model, as will be explained in section 6.2. The system behavior that emerges is measured in Key Performance Indicators (KPIs) that measure the average distance traveled to obtain healthcare, the total coverage of healthcare facilities (measured as the number of refugees per facility) and the available capacity within the facilities, compared to the requested capacity. Further elaboration upon these indicators is given in section 6.3.

3.2.3. ADAPTATIONS FOR THE CASE STUDY

To make the model operable for the case study, a few simplifications are applied to the components in the model and the way attributes are used in agent behavior.

First, it is assumed that refugees have full information about the locations of facilities when choosing a location to settle. For example, when visiting a healthcare facility, the refugee agent knows which facilities have capacity available at that moment for a patient consult. It is also assumed that healthcare providers have full knowledge of the number of refugees in the system and where they are located. The new facilities are placed accordingly, their locations calculated through a facility location optimization algorithm.

Secondly, the agents are distributed over the patches, by giving the patches an attribute that represents their availability and decreases for every shelter or facility in the surroundings. The effect of a shelter or facility on the availability of the surrounding patches is linked to the space-regulations that can be varied throughout the experiments, as explained in 6.2.

A third simplification regards the preferences of refugees that determine the weight each of them gives to the proximity of roads, healthcare facilities and neighbors. It is assumed that these preferences do not change throughout the simulation. Moreover, once a refugee has chosen a shelter location, it will not move anymore. There is not distinguished between genders or age of the refugees, although this might cause deviating healthcare usage patterns in reality. For example, Rohingya women who escaped Myanmar have a very high pregnancy rate (Ripoll, 2017). This is because of the regulations that limit them from getting children in Myanmar, which is not the case in Bangaladesh (Ripoll, 2017).

Lastly, there will be experimented with the impact of taking future camp expansion into account while placing new facilities. In order to do this, the model can advance a few steps, and the information of the newly placed shelters will be used to locate the future facilities. Since the parameter settings are constant during one model run, it is likely that the prediction is rather accurate. In half of the experiments that use predictions, the prediction accuracy will be set to 100%, which indicates even full knowledge about the future shelter locations.

3.3. CONCLUSION

This chapter explained the choice for camps Hakimpara, Jamtoli and Potibonia in Cox's Bazar for the case study. The homogeneous population, geographical demarcation and data availability from the start of these camps, makes it a suitable case study. The modeled system consists of refugee agents and healthcare providers, and are located in the environment. Four important simplifications are made regarding the agent behavior and impact of decisions, which make it easier to create a model that simulates the studied behavior. The next chapter discusses best practices from comparable models.

4

BEHAVIOR IN OTHER MODELS

“*The best adaptations are those that use the tools at hand the best, not those that can identify what the best of all tools would be*” (Van Dam et al., 2013, p. 30). In other words, using best practices from previous models can strengthen a new model, leaving room for development of parts that have not been modeled before. It is important to set-up the modeled environment carefully. Therefore, models in previous researches are regarded before the new model is built, to take along their best practices.

As Day et al. (2012) emphasize, the most important attribute of the environment is its dynamic behavior, which must be consistent with dynamic demand of agents in the environment. This is complicated by the inter-stage conflict: actions that are taken at one stage, will affect the abilities to achieve objectives during a following stage (Day et al., 2012). This goes for decisions regarding the model development, but also for the behavior of agents within the model. For example, the preferences of refugees during settlement, influence the distance to healthcare facilities once they get sick. The assessment of past research is divided in two sections. First, section 4.1 focuses on modeling expanding refugee camps. Then, section 4.2 explains how the facility location optimization can be applied in agent-based models. Section 4.3 follows with a description of modeling practices for healthcare usage. The chapter is concluded in section 4.4 by summarizing the findings that will be applied in the newly created model for this research.

4.1. EXPANSION OF SPONTANEOUS SETTLEMENTS

Refugee camps can be regarded as spontaneous settlements, as they are the result of self-settling refugees in informal camps (Augustijn-Beckers et al., 2011). The expansion of informal settlements is the result of individuals that choose a location to settle, according to their own preferences (Augustijn-Beckers et al., 2011). Governments can have an influence on the expansion direction by developing infrastructure which makes the area more attractive, or by defining formal outlines for a settlement (Augustijn-Beckers et al., 2011).

The field of research in refugee movements has been studied extensively. However, the majority of these researches is focused on predicting the number of refugees and to which region they flee (Sokolowski et al., 2014). Only a few researches can be found that study the exact location choices of refugees within a settlement. In these researches, agent-based modeling is a popular simulation method for studies in population and migration and the formation of informal settlements (Suleimenova et al., 2017; Hofmann et al., 2015; Collins & Frydenlund, 2016; Epstein, 2006). The models proved very effective in imitating refugees’ settlement behavior, but neglected how the settlement choices were affected by the presence or lack of healthcare facilities (Hofmann et al., 2015).

DETERMINING THE NUMBER OF ARRIVALS

A method for determining the number of refugees is developed by Suleimenova et al. (2017). Suleimenova et al. state that the number of refugees can be predicted based on risk factors such as civil violence, economic conditions and external interventions forcing people to migrate. In their research, they used linear extrapolation to determine the number of refugees between data points from two real-world counts and used this in their model to simulate the number of newly arriving refugees. This can be done for the total number of refugees in a camp, or for separate regions within a bigger camp, to allow some deviations between the regions (Suleimenova et al., 2017). Every tick, the number of refugees in the simulation was corrected by multiplying the camp population with the real-world data number divided by the simulation data number (Suleimenova et al., 2017). A decrease in the total number of refugees was processed in the next time instant where the population increases again (Suleimenova et al., 2017). In other words, agents were not deleted, so the population could only increase. However, it is acknowledged that, in reality, refugee communities do not show linear behavior (Anderson et al., 2007). Therefore, not all scholars agree with the method to use few data points and obtain the other numbers with linear extrapolation.

DETERMINING THE LOCATION ASSESSMENT BY AGENTS

Where refugees decide to settle, is often modeled as a variable that depends on the travel distance. Suleimenova et al. (2017) created a model that could predict refugee destinations from the location they escape to the place of refuge with an accuracy of more than 75% after 12 simulation days. They used the assumption that refugees go to the nearest camps (Suleimenova et al., 2017). If these camps are full, the refugees can get forwarded to other locations (Suleimenova et al., 2017). The routes that refugees use, are implemented by adding a network graph with links, of which the weight (the distance in kilometers) was based on routes found in Bing Maps, which is a method that is applied by multiple scholars (Groen, 2016; Suleimenova et al., 2017). Many models first neglect the spatial elevation and obstacles in an area. Examples of assumptions in this regard are assuming a flat environment and that agents in the model can see their end goal from any point. However, research by Hofmann et al. (2015) on the exchange-ability of slum expansion models and informal settlement expansion models, found the terrain situation to be very important in agent-based simulation models. According to Fawaz (2017), slum-like neighborhoods can be regarded as refugee camps. Therefore, the finding by Hofmann et al. (2015) should not be ignored and the environment should be embedded in the modeled environment. This environmental complexity can be added by considering elevation changes and obstacles on the route (Vahidi & Yan, 2016).

As the decisions of agents in the model are affected by the environment, so is the environment affected by the actions of agents. Agents are goal-oriented, and this is often combined with economic activities. Many scholars take economic activity into account while modeling settlement decisions of agents. Augustijn-Beckers et al. (2011) created a model in which the attractiveness for an agent to live in a location can be regarded from two points of stance: 1) an agent who chooses a place to live, or 2) an agent who will own a house, but not live in the house. In their model, Augustijn-Beckers et al. make the assumption that agents have the freedom to settle on a place of their choice and that agents have the possibility to sense all possible locations before making a decision. They also give their agents the choice between extending an existing house, by filling empty space between existing houses, or extending the settlement by building on empty land (Augustijn-Beckers et al., 2011). These methods were made alternately dominant throughout the simulation. Once an agent made a choice, the house got aligned with the environment. The assumption that agents can sense the possible locations is also applied in other models, for example in the assumption that refugees have full information about local facilities (Wozny, 2018). If full information availability is not assumed, knowledge can be modeled to spread via agents when they are located in the same area, or within a specified radius (Crooks & Wise, 2013).

4.2. AGENT-BASED PERSPECTIVE IN DISASTER RESPONSE MODELS

A lot of simulation techniques have been applied for disaster situations, but most of them only during the preparation phase before the actual disaster (Kovács & Spens, 2011). Only a few simulation models are applied to the immediate response phase, assuming particular scenarios and assuming that demand data is known (Kovács & Spens, 2007). In disaster response, various actors are involved in the supply network of humanitarian aid (Kovács & Spens, 2011). As Augustijn-Beckers et al. distinguish between two different points of stance when making decisions, the perspectives for actors in the supply network should be separated for NGOs, governments, military and logistics providers in the response phase (Kovács & Spens, 2011). In a disaster response phase, information is limited, so assumptions must be made about the kind and quality and amount of supplies needed (Kovács & Spens, 2007; Day et al., 2012).

4.3. HEALTHCARE USAGE

Vasilevska & Simich (2010) distinguish three important aspects for accessing healthcare services. Firstly, refugees should feel entitled to use the healthcare services and is it intended for the refugees to uses. Secondly, the ease of accessing the facility. Thirdly, the level of trust in the service at the facility. Research among refugees in the United States showed healthcare-seeking behavior is held back by a lack of time or access to affordable healthcare, or because of other health concerns (Barnes et al., 2007). Anderson et al. (2007) created an elaborate agent-based model of healthcare usage in a refugee camp. In their model, Anderson et al. (2007) let refugees adjust their weights for certain needs according to the conditions in the environment and the needs they are most deprived of. This behavior can be influenced by other agent types in the model. In the same model, Anderson et al. simulate sickness using a nonlinear function, based on basic needs, such as food, water and sanitation. If agents get sick, they will always seek to consult a healthcare facility, which has a limited capacity. In contrast to the model of Suleimenova et al. (2017), agents can die in the model of Anderson et al., if healthcare comes too late. The effectiveness of the healthcare facility is determined using a nonlinear function, based on the presence of medical resources, personnel and security. Input parameters for the nonlinear functions get a value between 1 and 10 (Anderson et al., 2007).

4.4. IMPLICATIONS FOR MODEL DESIGN

The field of research that combines healthcare facility location models with a changing problem setting, such as a changing patient population, still needs attention (Ahmadi-Javid et al., 2017). From various researches in this field, a selection of assumptions is chosen to be applied in the new model.

First, the determination of the number of refugees in the camps in the model. As this research focuses on the location decisions of refugees, it is not necessary that the number of refugees represent reality accurately. Therefore, this number is determined using the linear extrapolation based on Suleimenova et al. (2017). The modeled population will be based on a linear extrapolation between nine data points, over a time period of 94 time steps. Random factors will be added to create variation, so the simulation numbers might deviate from these linearly obtained numbers. This deviation is then corrected, using the difference between the simulated population and the initial data points. The correction is processed in the next time step where new refugees are added to the model. The random factor and the correction balance each other in order to create a variety of scenarios, with a comparable amount of agents throughout the scenarios.

Secondly, for the simulation of location decisions for both shelters and healthcare facilities, the assumptions from Wozny (2018), Augustijn-Beckers et al. (2011) and Suleimenova et al. (2017) are combined. It is assumed that agents have full knowledge of the modeled environment and use this to identify the distance between possible shelter locations and possible healthcare facility locations. When using healthcare, the agents that represent refugees always go to the nearest healthcare facility, or get forwarded to another facility when the nearest one is full.

Thirdly, the healthcare demand will be simplified according to the advice of Kovács & Spens (2007) and Day et al. (2012). Data about the average usage of healthcare facilities, in terms of consultations and the ratio of patients that have to stay in the facilities a longer time or not, is used to simulate the healthcare demand from the refugees. This simplification eliminates the possibility to simulate a possible epidemic outbreak, unless this gets specified in the experiments.

Lastly, following the advice from Vahidi & Yan (2016), Fawaz (2017) and Hofmann et al. (2015), terrain specifications will not be ignored. Elevation data will be used to setup the modeled environment to make sure that refugee agents take this into account while choosing a shelter location. Since proximity to roads is found important for refugees, as this increases the possibilities for refugees to leave the camp, they are also important to include in the environment. Hence, the main roads in the environment are included in the model as well.

How these implications are embedded in the model design is explained in chapter 5, which describes the model formalization and conceptualization of the model, followed by key indicators that can measure the system behavior.

5

MODEL DESIGN

The model in this research is the formalization of the researcher's interpretation of refugees' perceptions of the availability of facilities, which means it is three steps away from reality. Therefore, a clear conceptualization is important to define the concepts and relations of the system that are represented in the model.

This chapter formalizes the model design, building on the components and boundaries that are described in chapter 3. Thereby, it gives an answer to sub question 3: *How can a conceptual model of refugees behavior when settling and using healthcare in an expanding refugee camp be made?* It is key to identify the main components and actions in the system, which can be done by finding the most straightforward behavioral rules for the system components (Vahidi & Yan, 2016). Some other behaviors and actions can be left out of scope, as not all are needed or applicable when researching the emergent patterns (Vahidi & Yan, 2016). Section 5.1 describes the formalization of the main concepts and components in the model. Section 5.2 continues with a description of the processes in the model. How the model performance gets measured, is explained in section 5.3. Lastly, the model verification is discussed in section 5.4. A recap of the chapter is given in the conclusion in section 5.5.

5.1. CONCEPT FORMALIZATION

In the model, several concepts are used. This research aims to explain the interplay between settlement decisions of refugees and locations of health facilities. The main concepts are the agents that make decisions, being the refugees and the healthcare providers, and the environment. The hypothesis is that refugees use the concept of accessibility of health facilities to choose their shelter location upon arrival in a refugee camp. This hypothesis uses the assumption that refugees and actors share the same definition of accessibility. What this exact definition is, is explored and defined in subsection 5.1.1. The environment is explained using global variables, which mainly determine the setup of the research environment. Agent-specific variables are determined for the agents, which are different for refugees and healthcare providers. All global and agent variables are described in subsection 5.1.2.

5.1.1. CONCEPTUALIZATION OF ACCESSIBILITY

In section 2.3.1, the definition of accessibility as described in literature is discussed. Travel time and distance came forward as the most important aspects of the accessibility of healthcare facilities. The model that is explained in this chapter, is tailored to a case study about the Rohingya refugee camps in Cox's Bazar, Bangladesh. The definition of accessibility is therefore verified by the results of questionnaires among the Rohingya, regarding their assessment of facilities within the camps. Every two months, the International Organization for Migration randomly distributes an extensive questionnaire among people in the camps and publishes this as the Needs and Population Monitoring (NPM). One of the topics in this questionnaire is the availability and accessibility of healthcare. The respondents answer questions regarding the physical access, distance, travel time, waiting times, operational hours, staff and availability of supplies to obtain healthcare. By combining results of these assessments with data about the present healthcare facilities, the definition of accessibility for refugees can be verified.

To have the most up-to-date definition, the latest data set about the presence of healthcare facilities is connected to a NPM that was assessed in the same time period. The latest list of healthcare facilities dates from November 13, 2018 (Inter Sector Coordination Group, 2018a). NPM 13 is conducted in the same time period, namely between November 4 and 20, 2018 (International Organization for Migration, 2018). From these two data sets, the exact geographical location of the facilities and the respondents can be obtained, as well as the travel time to the facilities. Figure 5.1 shows links between the geographical locations of respondents and their closest healthcare facility. The link color represents the travel time, ranging from less than 15 minutes to over an hour. It is assumed that every respondent has knowledge of every healthcare facility and visits the nearest facility to minimize distance.

While distance and travel time were concluded to be most important factors when assessing the accessibility to healthcare, figure 5.1 shows that the length of the connections does not seem to explain the difference in travel times. Many links of similar length are either green or yellow, and some of the shorter links are orange or even red. What does seem to be related, is the proximity to a road. Facilities that are located on a road have many green links, whereas the ones further from the main road seem to have a higher amount of links with longer travel times. Moreover, there are more healthcare facilities located in the Eastern part of the camps, which are closer to the main road. This results in shorter links in this part of the camps. The Western part of the camps does not hold many facilities and, correspondingly, travel times are longer there. This also comes forward in the heat map presented in figure 5.2, which summarizes the travel times for areas within camps 14, 15 and 16. Despite a ten month time difference between the assessments, the respondents in the Western parts again report longer travel times to reach healthcare facilities, compared to inhabitants of the Eastern parts. Lastly, when comparing the obtained figure with the elevation of the area, it appears that most facilities are located in elevated areas. Some facilities are close to lower lying areas, which also reflects in longer travel times. An important assumption is that accessibility is only useful, when the healthcare facility also has capacity to help patients.

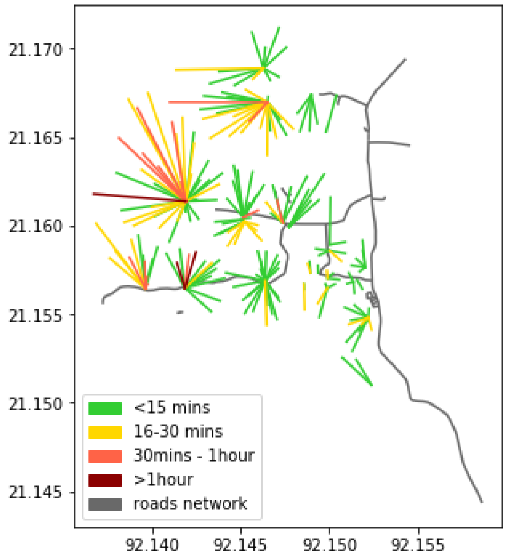

Figure5.1: Geographical representation of travel times to closest healthcare facilities. Road network retrieved from Team Humanitarian OpenStreetMap (2019)

In the assessments, the respondents were also asked to explain what troubles their access to a healthcare facility, since many different explanations are possible. Here, it is found that neither the long waiting times at facilities, nor the number of refugees that is connected to a facility can be

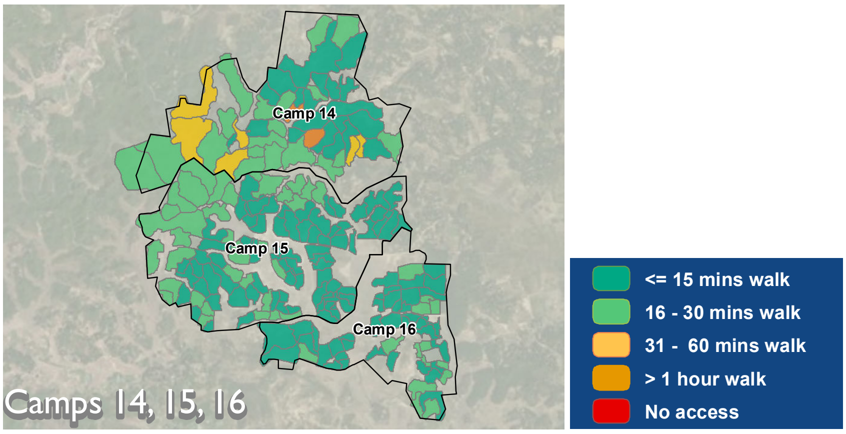

Figure5.2: Heat map of access to health facilities in camps 14, 15 and 16.
Based on data from June, 2019. (International Organization for Migration, 2019a)

related to the accessibility, as shown in figure 5.1.

To conclude, when assessing the accessibility, the travel times between healthcare facilities and refugee shelters are not directly correlated with the travel distance, while assuming the shortest distance. Proximity to roads can be influential for travel times, increasing the ease of access. But it is found most important, that capacity within the facilities is sufficient to serve the refugees, regardless of preceding waiting times.

In the model, shelters that represent the refugees, make a choice for a healthcare facility, based on the distance that is measured as a straight line. Simultaneously, facility locations are chosen, regardless of proximity to roads. This makes it unexpected that the preference for refugees to settle close to roads positively influences their access to healthcare facilities. The maximum acceptable distance between a shelter and a facility is determined to be 40 patches, which implies a relative distance as shown by the links between a shelter and a facility in figure 5.3. In reality, this resembles a mere 400 meters [1]. One must imagine, that in a very densely populated area with many slopes, it is definitely not possible to cross in a straight line. Therefore, 400 meters is already difficult to cross. The aim is to minimize this distance.

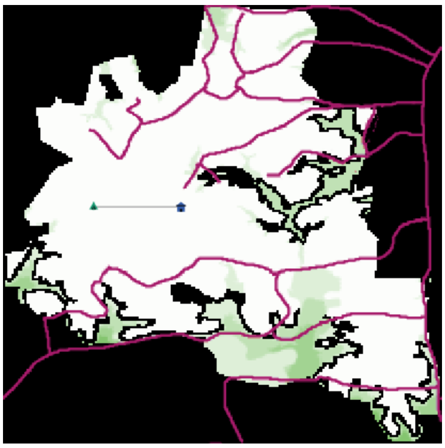

Figure5.3: Visual representation of 40 patches distance between
a shelter (left) and a healthcare facility (right) in the model.
Road network retrieved from the online map developed by IOM.

[1]Measured using the open online map from IOM through http://iom.maps.arcgis.com/

5.1.2. FORMALIZATION OF AGENTS AND VARIABLES

All system components that are described in section 3.2 are formalized for implementation in the model in this chapter. Formulating the components as formalized concepts overcomes ambiguous meanings of the concepts for computers (Van Dam et al., 2013). Dependency on context factors must be clearly demarcated. This is done by formulating the variables as concepts that are understandable for the computer. The initial settings are described in appendix B.

GLOBAL VARIABLES

The camp environment, that can be seen in figure 5.3, is set up using patch variables that are saved after creation and loaded into the NetLogo environment before a specific model run is initiated. An explanation of this initial model setup is given in appendix B. These first settings are the elevation of the area and the road network. Additional settings for the NetLogo environment are captured in global parameters, which are given below, followed by the global variables and reporters.

Environment settings

- Elevation [meters] (float)
- Color (float)
  - Roads (color code 125)
  - Camp boundaries (color code 0)

Global parameters

- Maximum population (integer)
- Road-proximity preference (integer, [1-10])
- Neighbour-proximity preference (integer, [1-10])
- Healthcare-proximity preference (integer, [1-10])
- Space-usage (string, ["22m^2 per person" / "35m^2 per person" / "45m^2 per person"])
- Future-modus (boolean)
- Prediction-accuracy (string ["0", "100"]
- Linear regression for prediction of camp expansion, based on last four weeks (boolean)
- Initial capacity of healthcare facility (integer)

Global variables

- Counter (integer)
- Number of shelters to create (integer)
- Number of facilities to create (integer)
- Number of consultations (integer)
- Radius of patches affected by a building (integer)

Global reporters

- Count shelters (integer)
- Count facilities (integer)
- Average travel distance between shelters and facilities (float)
- Amount of shelters covered by healthcare facilities (integer)
- Amount of refugees waiting in line for healthcare (integer)
- Amount of refugees that are linked to a facility, exceeding the maximum capacity (integer)
- Unused capacity of healthcare facilities (integer)

PATCH VARIABLES
These are the variables that can differ for every patch.

- Available space of this patch and surroundings (integer)
- Distance to nearest road (float)
- Distance to nearest healthcare facility (float)
- Number of neighboring shelters in the defined radius (integer)

AGENT VARIABLES
All entities that can make decisions independently are the agents (Miller & Page, 2007). The most important agents are the refugees. In this research, the refugees are represented in aggregated form, as hundred complete households in the shape of one shelter. The second type of agents in the model, is the healthcare facility type. The healthcare facilities represent the physical presence of healthcare providers.

Shelter variables

- Preference for proximity to healthcare facilities (float)
- Preference for proximity to roads (float)
- Preference for proximity to neighbors (float)
- Covered by facility within available capacity (boolean)
- Available space at the current patch (float)
- Sick? (boolean)
- Distance to healthcare facility of consultations (float)
- Prediction? (boolean)

Facility variables

- Capacity available for shelter coverage (integer)
- Capacity shortage for shelter coverage (integer)

- Number of patients in-consult (integer)
- Number of patients waiting for consult (integer)

Link variables

- Length of link from shelter to facility (float)
- Color representing current usage (string)

5.2. SCHEMATIC OVERVIEW OF FORMALIZATION

Knowing what is in the model and how this is defined, it is time to define what is happening in the model to find how emergent patterns arise from actions and interactions (Van Dam et al., 2013).

Three main processes take place in the simulation. How these three processes take place and are linked, is shown in figure 5.4. The first process is the arrival of new refugees in the camps and their search for a suitable location to locate their shelter. Once settled, the refugees can become sick and consult healthcare facilities, which is the second process. Thirdly, the healthcare providers asses the presence of all shelters and healthcare facilities and the capacity usage of healthcare facilities, to decide whether new facilities are needed and where these should be located. The decision upon a new facility location is made using either an algorithm that minimizes the average travel distance, or an algorithm that maximizes the coverage ratio, as described in chapter 2.3.3. The three processes are described in more detail in the subsections below. The complete model narrative can be found in appendix B.1.

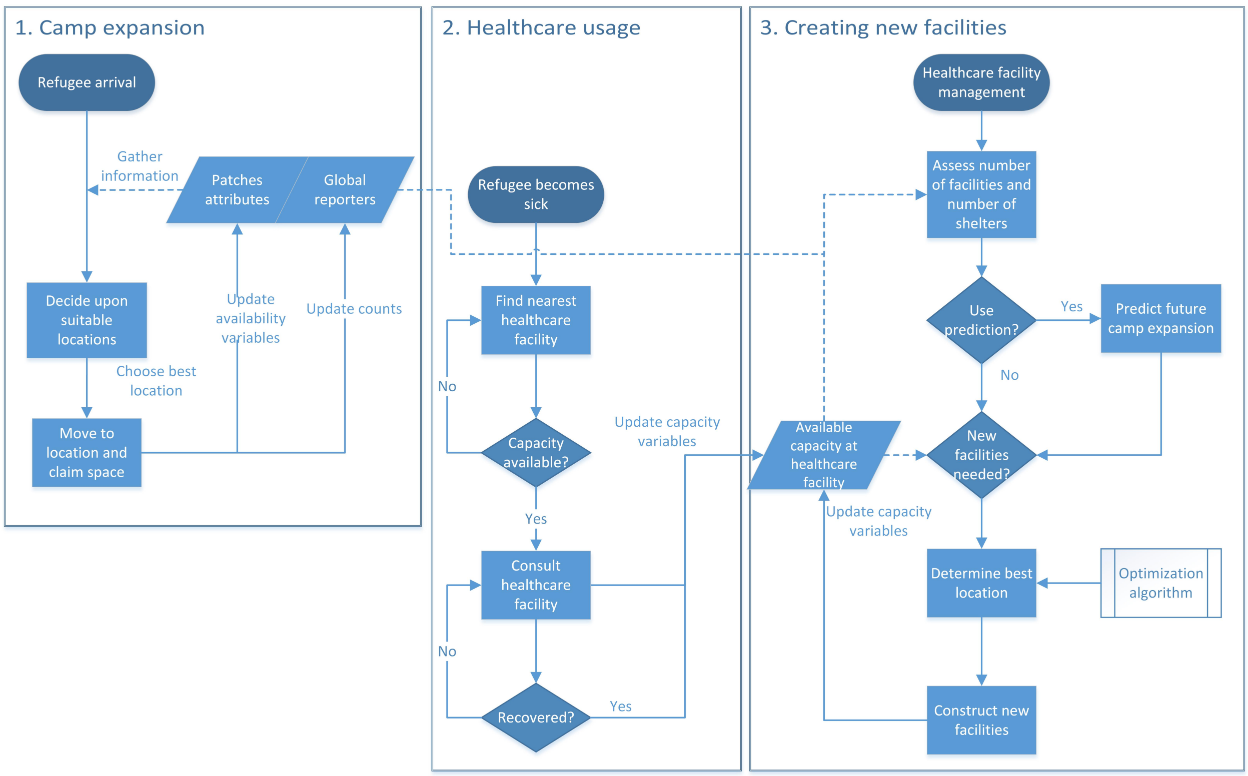

Figure5.4: Flow diagram of the three main processes: camp expansion, healthcare usage and creation of new healthcare facilities

5.2.1. CAMP EXPANSION

Camp expansion is simulated by the creation of new shelters, based on real numbers from regular population monitoring reports by International Organization for Migration, as represented in table 5.1. Shelters represent the refugee population in the model. 1 shelter in the model resembles 100 households in reality. Over time, the average household size was 4,574 people, so 1 shelter represents 457 refugees. The number of new shelters to be created is determined by choosing a random number between the maximum population at that time, from table 5.1, and the current number of shelters in the model. Upon creation, shelters choose a location with a high elevation, which is desirable in the flood prone region of Cox's Bazar. Every refugee agent (a shelter) has its own preferences regarding the proximity to healthcare facilities, roads and to other shelters. Using these preferences, a location is chosen that minimizes the product of the distance to healthcare facilities, roads or neighbors with the corresponding preference. While doing this, it interacts with the patches in the model, as these have information about the available space at this location and the respective distances. When a location is chosen, the patch at the new shelter location updates its attributes. Then, the global reporters that count the number of facilities get updated as well. The shelters are created one by one, because of the path-dependent character of this process. When a shelter has chosen a new location, a second shelter can decide to settle in the neighborhood of this shelter, and so on.

Table5.1: Camp expansion in number of households and refugees in camps 14, 15 and 16, Cox's Bazar
Derived from Needs and Population Monitoring reports by International Organization for Migration

Date	Households	People	Household-size
2017-10-01	20479	106362	5.1937
2017-11-01	18028	81753	4.5347
2018-03-01	22488	99552	4.4268
2018-05-01	22203	98493	4.4360
2018-07-01	22112	98016	4.4327
2018-09-01	23605	104355	4.4208
2018-11-01	22084	107114	4.8502
2018-12-01	24088	107706	4.4713
2019-02-01	23116	103156	4.4625
2019-06-01	24169	109107	4.5143

5.2.2. HEALTHCARE USAGE

In Cox's Bazar, the tendency to visit healthcare facilities has increased over time (Health Sector, 2017a). In the simulation model, it is assumed that agents will always consult a healthcare facility when they get sick. The chance of getting sick is determined by combining the average number of consultations per week in 2019 as reported by the World Health Organisation (2019), and the corresponding counts of camp inhabitants that is reported in biweekly health sector bulletins. The exact derivation and increasing number of consultations that are are described in B.2.2. The average amount of consults per refugee per week in 2019 is multiplied by the number of people in one household in the modelled system, to obtain the chance that a shelter will use consultation capacity of a healthcare facility. This is found to be approximately 0,346 healthcare consults per shelter per week. The shelter will always try to go to the nearest facility, but if there is no possibility for an immediate consult here, the shelter will choose the nearest facility with available capacity. If all capacity is taken, it will get into a fictitious queue.

The simulation runs in ticks of 1 week. The chance of being recovered after one week is derived by the ratio of in-patients and out-patients in Cox's Bazar. In-patients must stay at least one night under supervision and require a bed, whereas out-patients leave after the consult (Médecins sans Frontières - USA, 2018). This ratio is found to be about 0,021 (see appendix B.2.2), and is applied to weeks instead of days in the simulation model. When agents are recovered, they release the capacity of the facility, or leave the queue.

5.2.3. CREATING NEW FACILITIES

The process of creating new facilities takes place partly within and partly outside the agent-based simulation model. The ratio of the healthcare facility capacity in the system and the number of shelters is measured within the simulation model and should comply to the standard of 1 facility per 10.000 refugees. If this requirement is not satisfied, new facilities are created. Their location is determined outside the simulation model, using one of the optimization algorithms formulated in a Python script, which is described in appendix B.1.2. Actors in Cox's Bazar have not considered future camp expansion while planning new facilities (Interview D, 2019; Interview A, 2019). The hypothesis in this research is that taking future expansion into account will increase the effectiveness of the facility location optimizations. The predicted number of shelters can be quantified by linear regression of the camp growth in the past, or with a fixed number of shelters, after which their probable locations are determined. If the (expected) number of shelters requires an increased number of healthcare facilities, two new facilities will be created. The exact locations for these facilities are determined using one of the two optimization algorithms.

APPLICATION OF THE TWO OPTIMIZATION ALGORITHMS

The first optimization algorithm aims to minimize the demand-weighted average travel distance. The second optimization algorithm aims to ensure that every shelter is covered by capacity of a shelter within the acceptable distance, as determined in 5.1.1.

In the model, the first algorithm is applied by first minimizing the distances of all shelters to the existing facilities and potential new facilities. Then, the capacity of the facilities gets distributed over the nearest shelters, after which the combination of new locations is determined that minimizes the average distance for all shelters. The second algorithm is applied in the model by calculating the distances between all possible facility locations and all shelters that are currently not covered by a facility's capacity. It locates a healthcare facility such that the number of currently uncovered shelters within a maximum distance of forty patches to this new facility is maximized. Where the first optimization algorithm places two facilities simultaneously, this is not possible when using the second optimization algorithm, because it then chooses two locations that are very close to each other. Therefore, the optimization algorithm that maximizes the coverage of shelters places only one facility at a time, but does this twice during one assessment round. The optimization algorithm that minimizes the average travel distance between shelters and healthcare facilities places two facilities at once. Both the algorithms perform their optimizations in Python and send the outcomes to the agent-based modeling environment, where the results become visible.

The potential locations for the new healthcare facilities are determined by the available space of a discrete set of patches. This set is derived from all existing shelter locations. Patches where no shelter is located are thus excluded. This assumption is the result of a trade-off between the run time and the accuracy level of the simulations. Including all possible patches would lengthen the simulation time and is not required, as long as both optimizations use the same way of retrieving the discrete set of possible locations. As the locations of the facilities are determined based on the location of shelters, so will new shelters take these new facility locations into account while choosing a place to settle, since refugees have a preference to settle close to a healthcare facility.

5.3. KEY PERFORMANCE INDICATORS

The system behavior that emerges during the simulations is captured in Key Performance Indicators (KPIs). In this research, four indicators are identified that measure the system performance throughout the simulation. The first indicator measures the average distance traveled by refugees. The second indicator measures the coverage ratio of shelters by healthcare facilities. The third indicator is the total capacity shortage within facilities and the fourth indicator is the ratio of unused capacity over the amount of waiting patients. The robustness of the system is measured after the simulation, by inspecting whether the system behavior can be sustained in case facilities fail. This can be regarded as the fifth KPI.

The **coverage** is measured by the share of refugees that is covered by a nearby facility. A shelter is considered covered, when it is connected to the nearest facility and this facility has sufficient capacity to cover for this shelter. Only when this condition is satisfied, the shelter gets the status "covered". Preferably, the coverage ratio of all shelters is as high as possible. According to the SPHERE standards, at least 80% of the camp population must be able to reach a facility within an hour walk (Sphere Association, 2018). Based on this standard, this study considers a coverage ratio of 80% as a minimum acceptable ratio. When shelters are linking to a facility that has no capacity for them any more, this gets reported as a capacity shortage in the facility.

Where the coverage should be maximized, the **average traveled distance** between refugees and healthcare facilities should be minimized. This indicator resembles the lengths of the links that shelters make with a healthcare facility in the model. Preferably, the shelters make a link with the healthcare facility that is closest to themselves. When a shelter gets a status of being sick, it will consult a healthcare facility. If the facility they are linked to has no free capacity, they will link to another facility that still has free capacity. With this behavior, the average travel distance increases, as the second facility will by definition be further away. If the average travel distance becomes very high, this is either because the nearest facility is far away, or because the nearest facility has no free capacity while other facilities do still have free capacity. In both cases, this indicates that the distribution of facilities over the system is very poor. The maximum acceptable distance for refugees to travel in the model equals a link-length of 40 patches. This resembles 400 meters as the crow flies in reality, as explained in 2.3.1. A very high coverage ratio in combination with a short average travel distance can be reached by placing many facilities. However, this is not desired, because resources are limited during humanitarian crises.

The **number of waiting patients** gives an indication of the consultation capacity shortage in the system. If the capacity of all facilities is fully utilized, the sick agents will become waiting patients. In the results, a trade-off is expected between the average distance traveled by refugees and the number of waiting patients. If the capacity of every facility is used by the shelters that are closest to the facilities, there is no point in going to a second facility further away, as this facility cannot help the refugee either. In this case, the refugee will remain linked to the first shelter and become a waiting patient, while the average travel distance does not increase.

However, it could also happen that facility A is overfull, so if shelters that are connected to facility A get a status of being sick, they will visit facility B. Because of these extra patients, facility B has no capacity anymore for the shelters nearby that get sick, but facility A is also still full. If the shelters around facility B then get a status of being sick, they will have to wait until capacity is free. In this case, the results will show a high average link-length and a high number of waiting patients. Therefore, an additional indicator is needed to measure the system performance.

The **unused capacity of facilities** will be compared with the number of waiting patients. As the first logic explained, a short average travel distance in combination with a low number of waiting patients can be explained by unused capacity in facilities up until this moment. Similarly, if the average traveled distance is large, and the number of waiting patients is low, this could indicate a high unused capacity as well. However, if simultaneously the unused capacity has a low value, this indicates that the distribution of facilities over the camp was very successful. If the unused capacity is very low and the number of waiting patients is high, this indicates a shortage of healthcare facilities in the system, regardless of the travel distance. However, this would also result in a very low value for the total coverage ratio in the system.

The **capacity shortage in facilities** is also measured. This represents the number of shelters that cannot be covered by a certain facility anymore, but do have this desire in order to minimize the link length. The facility of their choice, which is closest by, has no capacity anymore and this gets measured as capacity shortage. This indicator shows strong coherence with the coverage, but provides an additional insight in the dispersion of facilities over the camp environment when compared to the unused capacity. When the capacity shortage and unused capacity are both very high, this indicates that the locations of the facilities are far from optimal.

The **robustness** of the system is interesting to review, as it gives an indication of the extent to which the system will be able to cope with possible future scenarios. The robustness of a system can be measured along many aspects. In this research, the robustness is mainly measured as the extent to which the results of an optimization hold in future scenarios. These future scenario can focus on specific risks, such as floods. When refugees settle in higher elevated areas in order to safeguard their shelter for floods, this results in limited space availability for facilities in these elevated areas. However, it is of great importance that healthcare facilities remain robust in times of heavy rainfall. In other words, their location is desirably elevated, to assure its accessibility throughout the seasons. Another aspect of robustness is the ability of the system to continue providing healthcare, even when a facility falls out. This aspect of robustness can be estimated in combination with the unused capacity. This research uses the latter notion of robustness, by determining the capacity of the system to cover for increased demand or a failing facility.

5.4. VERIFICATION

Before the model is used to execute experiments and analyze results, the model is verified to ensure that the model behavior is correctly translated from the conceptualization to a modeling language. In other words, through verification it is ensured that all elements in the model are specified as intended and the actions and interactions result in desired behavior. This increases the confidence in the model and the output it delivers (Sargent, 2010). After successful verification, the emergent model behavior can be analyzed, which is discussed in chapters 7 and 8.

Verification of the model ensures that the simulation language is correct and that the components and their behavior and interactions are specified in the right way (Sargent, 2010). Fairley (1978) distinguishes between static and dynamic verification. The static verification tests the correctness of the code without actually executing it. The dynamic verification tests the programming logic by execution and analysis of the results.

In order to execute the static verification, a structured code walk-through is executed. The dynamic verification is done in three steps. First, the agent behavior is traced and analyzed. Then, the interactions between the agents are tested, to check whether the path-dependency as described in the previous chapter takes place. Lastly, the development of model output during the simulated time is inspected, to see whether it behaves logically. A more elaborate description of the verification is given in appendix C.

5.5. CONCLUSION

This chapter described the conceptualisation of a refugee camp that is expanding in terms of the number of shelters and healthcare facilities and the usage of these facilities. The most important concept, which is used to measure the results of simulations, is the accessibility of healthcare facilities. This is defined as the ability to reach a healthcare facility, which has the right supplies and capacity, within a maximum of 400 meters as the crow flies. The conceptualization describes three key processes: camp expansion, healthcare usage and placement of new facilities. These three processes develop the path of the camp expansion and together shape the emergent camp and the usage of healthcare facilities within. The model performance is measured in four KPIs that measure the average traveled distance between shelters and healthcare facilities, the coverage, the capacity shortage in facilities and the ratio of waiting patients over the unused capacity of facilities. The model is verified, to ensure its suitability for experimentation. The next chapter will continue with an explanation of the experiment setup.

6

EXPERIMENT SETUP

The experiments are set up to create results that can be used to compare two scenarios for two algorithms, as shown in table 6.1. Each algorithm serves a different aim, resembling different aims of healthcare providers. If the aim is to place a facility that maximizes the coverage of uncovered demand, the maximal covering algorithm should be applied. Alternatively, if the aim is to minimize the average demand-weighted travel time for all demand, the P-median algorithm should be used. A set of experiments is executed for each model to study the emergent behavior of the model over a range of parameter settings. The experiment setup is similar for every model. Section 6.1 explains the variation of the parameters for the experiments. Section 6.2 explains the experiment design.

Table6.1: Two scenarios and two algorithms result in four models

	P-median algorithm	Maximal covering algorithm
Current scenario	Model 1: Minimizes average travel distance	Model 3: Maximizes the coverage ratio
Future scenario	Model 2: Minimizes average travel distance includes predictions about camp expansion	Model 4: Maximizes the coverage ratio includes predictions about camp expansion

6.1. PARAMETERS FOR EXPERIMENTATION

The parameters that are varied throughout the experiments are the parameters that define the preferences of refugees regarding their shelter location and the space standard that is applied in the camp, determining the minimum amount of square meters per refugee. This space standard variation refers to the different guideline requirements that can be used. The current space usage in the camp is found to be 22 m^2 per person. The SPHERE standards requires 45 m^2 per person (Sphere Association, 2018). To find the influence of an intermediate improvement, a third option with 35 m^2 per person is also used. How these parameters affect the internal variables in the model, is explained in appendix B. The preferences of refugees concern the proximity to healthcare facilities, roads and neighbors.

In the optimizations that include expected future camp expansion, the method for determining the future expansion is varied. The number of predicted shelters is either a fixed number (20), or gets determined by linear regression of the camp growth since the previous assessment, which happens every four weeks. The prediction-accuracy can either be 0%, or 100%. When this is 100%, the locations of new shelters are predicted correctly. However, the number of predicted shelters may be inaccurate, as this is specified separately and can deviate from the realized number after four weeks.

6.2. EXPERIMENT DESIGN

Tables 6.2 and 6.3 show the design of the experiments. The experiment results are discussed in respectively chapters 7 and 8. Chapter 7 starts with an exploration of the model behavior by discussing the results of the experiments from table 6.2. The results of a base case model with initial parameter settings is compared with the results for model runs with different parameter settings. The parameters that are varied at this point, are the ones that influence the settlement decisions of refugees. This decision process applies to process 1, as described in section 5.2. When the influence of the preferences for proximity to roads, healthcare facilities and neighbors is understood, the influence of the three space requirements is researched. Then, the influence of the different optimization algorithms is researched. This is done by first comparing the columns of table G.2, so models 1 and 2 are compared with models 3 and 4. Then, the rows of table G.2 are compared, to find the influence of taking future expansion into account. This means comparison of model 1 with model 2 and, similarly, comparison of model 3 with model 4. There are four different prediction methods, so the next experiment zooms in on the effect of varying the prediction parameters on the model behavior. The last analysis to explore the model behavior is the sensitivity analysis, in which variables that are determined in the model set-up are varied with 20%. After exploring the effect of parameter changes, a large set of experiments is run, as shown in table 6.3. In this set, the variables are varied simultaneously throughout every model. These experiments provided the results that are analyzed and discussed in chapter 8.

Throughout all the experiments, the random-seed is kept constant to make sure that the effect is solely due to the parameter variation. Therefore, for every combination of parameters there is one set of results from every model. Only the experiments about the preference influence, space requirement influence, algorithm effectiveness and prediction methods are performed a second time with another seed. Performing the experiments multiple times while varying the seeds would increase the validity of the model results.

Table6.2: Experiment design to understand model behavior

Experiment	Variation	Value
Preference influence	Proximity to roads	1 or 10
	Proximity to neighbors	1 or 10
	Proximity to healthcare facilities	1 or 10
Space requirement influence	Space requirement [1]	22 / 35 / 45
Algorithm effectiveness	Model choice	1 / 2 / 3 / 4
Prediction method	Prediction accuracy	0 or 100
	Linear prediction method	True / False
Sensitivity analysis	Probability of getting sick[2]	0.277 / 0.346 / 0.416
	Probability of remaining sick[2]	0.017 / 0.021 / 0.025
	Maximum population increase	0.8 / 1 / 1.2 / 1.5 / 2
	Initial capacity of facilities[2]	18 / 22 / 26

[1] Value determination is explained in appendix B.2.3

[2] Value determination is explained in appendix B.2.2

Table6.3: Experiment design for research

Experiment	Variation	Value
	Refugee settling preferences	1 / 5 / 10
	Space requirement	22 or 45
Research experiments	Model choice	1 / 2 / 3 / 4
	Prediction accuracy	0 or 100
	Linear prediction	True / False

7
Model results

This chapter discusses the results that are produced with the simulation models, following the experiment design that is described in section 6.2. In the model, the number of refugees is aggregated to shelters that each represent 100 households that hold an average of 4,57 people. The data that is presented in this chapter is scaled to the real numbers. 1 shelter therefore represents 457 refugees. It should be noted that the average distance is still measured in distance as the crow flies, therefore presenting the result optimistically.

Section 7.1 discusses the model behavior in two subsections. First, the base case scenario is described and its results are discussed, followed by the effect of various parameter settings that influence the settling choices of refugees. Section 7.2 then continues with the results for the two different algorithms used throughout the models. Section 7.3 zooms in on the model results that include future predictions. The validation of the model results is discussed in section 7.4, including a test for the validity of internal parameters, sensitivity analyses to the input parameters and an extreme conditions test. A conclusion on the model behavior for various input parameters is given in section 7.5.

7.1. General model behavior

This section first discusses the model behavior in a base case scenario. Then, the model results for the first two experiments from table 6.2 are discussed. These experiments aim to clarify the influence of varying the preferences for refugees and the space requirement. These parameters are all linked to the first process that is identified in 6.2: the settlement decision of refugees steering the camp expansion.

The base case scenario

The base case scenario is the scenario in which all the preference parameters and the space parameter are set to one, which minimizes their impact on the model behavior. For the space requirement, this translates to 22 m^2 per person. In this case, the size of the future expansion is not predicted by linear regression, but with a fixed amount of shelters equal to 20 and there is no predetermined prediction accuracy for the shelter locations. This is the most simple version of the model and therefore defined as the base case scenario. Setting the prediction accuracy equal to zero leaves most space for the settlement choices of refugees to be affected by the locations of healthcare facilities.

Figure 7.1 shows the results of the base case scenario across all models, measured every ten ticks (weeks). The color moves from red to green as time progresses. At time step zero, no results are measured yet, hence the red line in the bottom of the graph. The figure shows the results for four of the five key performance indicators. Firstly, the ratio of shelters that is covered by capacity of a healthcare facility. Secondly, the average distance between shelters and the nearest healthcare facility, or second facility when the first's capacity was full. Thirdly, the shortage of capacity within facilities (arises when too many shelters are linked to the same facility). Lastly, the ratio of waiting patients over the unused capacity, which is used to find whether a short or long average travel distance can be linked to abundant capacity or not. The last KPI, the robustness, is not shown in the figure, as the robustness is determined qualitatively afterwards. Except for the coverage, it is desirable to have low values for all key performance indicators. In general, it can be remarked that the optimization algorithms perform well. In most cases, the average coverage quickly increases to values between 80 and 100% and the average distance is for the majority below the maximum of 400 meters. The capacity shortage is mostly below 15.000 refugees, which means that maximally 32 shelters in the model are linked to a facility which has too much capacity. However, these shelters are not necessarily sick yet, so are not posing a problem yet. The ratio of waiting patients over the unused capacity is mostly below one, which means that there is no large shortage of facilities.

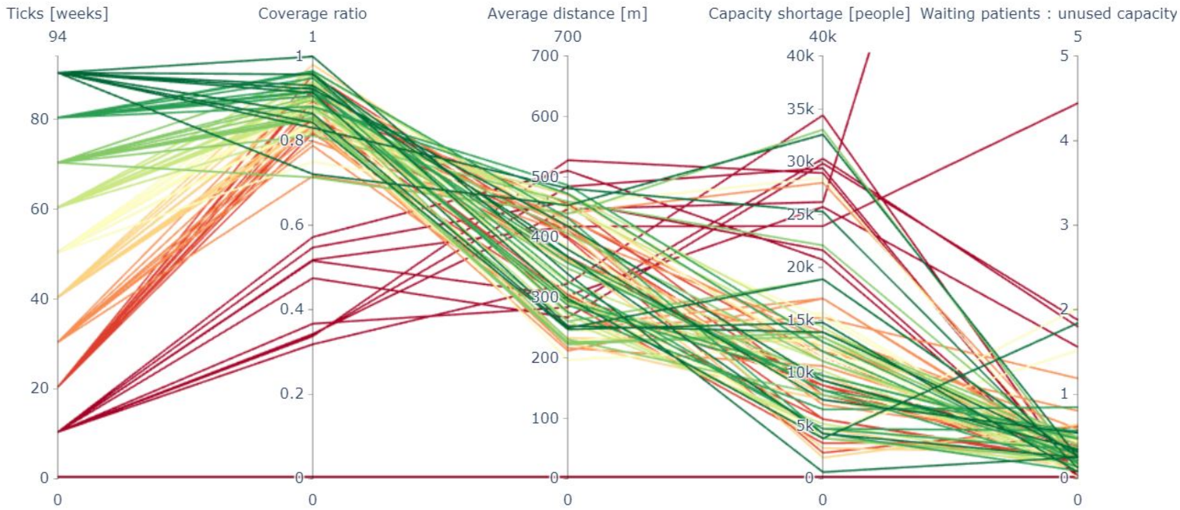

Figure7.1: The results in the base case scenario, measured in time steps of ten weeks

Moving through the figure from left to right, it first becomes evident that the average coverage ratio increases fast, to stabilize between values 0,8 and 1. This indicates that between 80% and 100% of the shelters in the model is linked to a healthcare facility that has sufficient capacity to cover this shelter. Only two facilities can be created at one time step, therefore this fast increase in the average coverage in the beginning of the simulation is expected. This can be seen as only the dark red lines indicate a low coverage value. Simultaneously, this logically corresponds to a high capacity shortage and some outliers with a very high value for the ratio of waiting patients over the unused capacity. There is no convergence to be found in the average distance over time. The variance in these results can stem from the different algorithms, which will be explored in section 7.2. Some model runs return values above the posed threshold of 400 meters, but the majority remains below this value. The ratio of waiting patients over unused capacity gives an idea of the division of facilities over the camp site, when combined with the average distance. If this ratio returns relatively low values in combination with a very high travel distance, this indicates that there is sufficient capacity in all the healthcare facilities in the camp, but that needed capacity is not always close to the people who need it. Similarly, when the ratio returns low values in combination with a low average distance, this indicates that all refugee agents are able to reach a healthcare facility within acceptable distance, which is desired. By definition, this situation also corresponds to low capacity shortages.

SMALL FLUCTUATIONS OVER TIME

When inspecting the results over time, it is found that the results fluctuate continuously throughout the simulation. Whereas big fluctuations are due to placement of new facilities, the small fluctuations are the result of the healthcare seeking behavior of the refugee agents. When the agents get sick and their nearest facility (A) has no free consultation space, the agent will turn to a second facility (B), thereby increasing the average distance. For this time, the refugee agent releases the capacity of facility A, and require capacity from facility B. Often, the free consultation capacity a facility B can be explained by a lower amount of shelters that is linked to this facility. This means that the agent, which is now connected to the facility B, can obtain a status of being "covered" while connected to facility B. Meanwhile, the released capacity at facility A can be allocated to another refugee agent, therefore this can simultaneously realize an increase in the average coverage. Simultaneously, this reduces the capacity shortage in facility A and the unused capacity in facility B. The result is shown in figure 7.2.

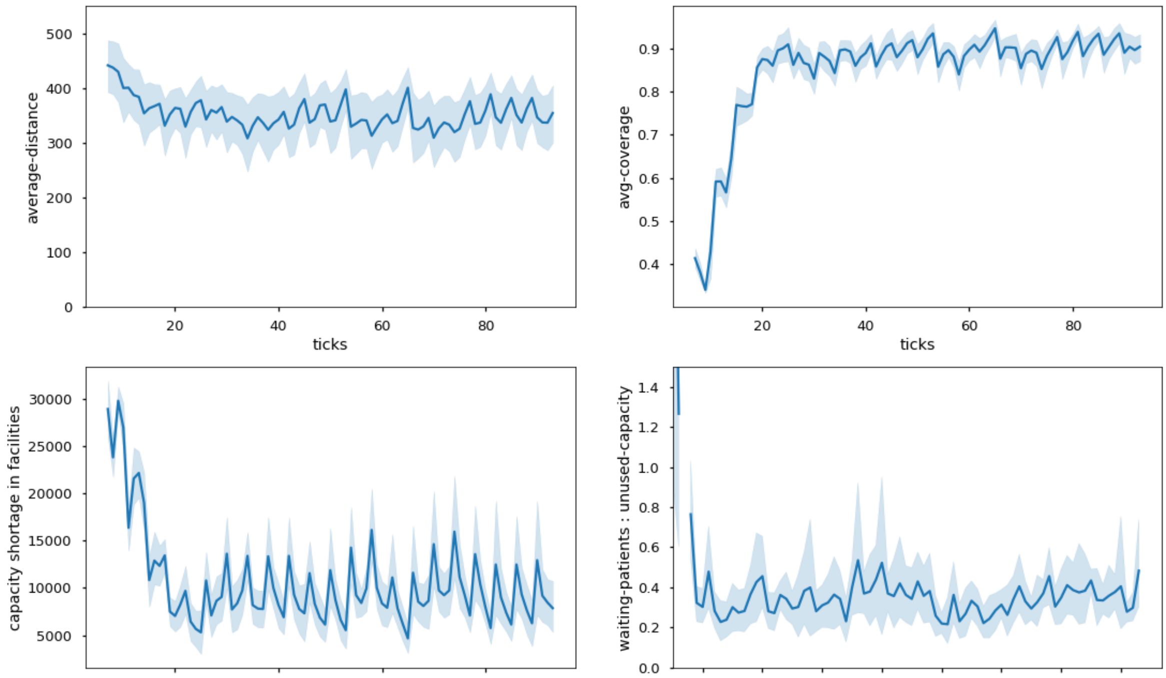

Figure7.2: Base case behavior throughout all models over time

PARAMETER INFLUENCE

The influence of the preference and space variables is tested by consecutively varying their values, while keeping the other parameters equal to the base case scenario value. The preference parameters alternately get a value of ten and the space variable will be raised from 22m^2 per person to 35m^2 or 45m^2. The effect is measured and compared for the same KPIs as the base case scenario.

High preference for proximity to roads

Raising the preference for proximity to roads to 10 instead of 1 in the model, shows an overall decrease of the average travel distance of approximately 50 metres, as can be seen in the left graph of figure 7.3. The average coverage returns values that remain a little higher with a higher preference for proximity to roads, as shown in the graph on the right side. Also, the fluctuation of the results does not reach the low values that are reached without this higher preference value. It is also found that the average coverage increases faster in the beginning of the simulated time when the preference for proximity to roads is higher. These findings are interesting, because the roads have no further function in the model, so besides being a point of attraction during the settlement of refugees there is nothing about roads that affects the travel distance or coverage. Moreover, healthcare providers indicate that it is attractive for them to be located close to roads, as this increases the ease of reaching the facilities and supplying them. However, this interest has not been in included in the model yet, but would be interesting to research further. Another impact that was found of raising the preference for proximity to roads, is a structural decrease in the occurrences of too many shelters being linked to one facility, measured as the overcapacity. However, this effect is limited and does not reflect in the ratio of waiting patients over the unused capacity.

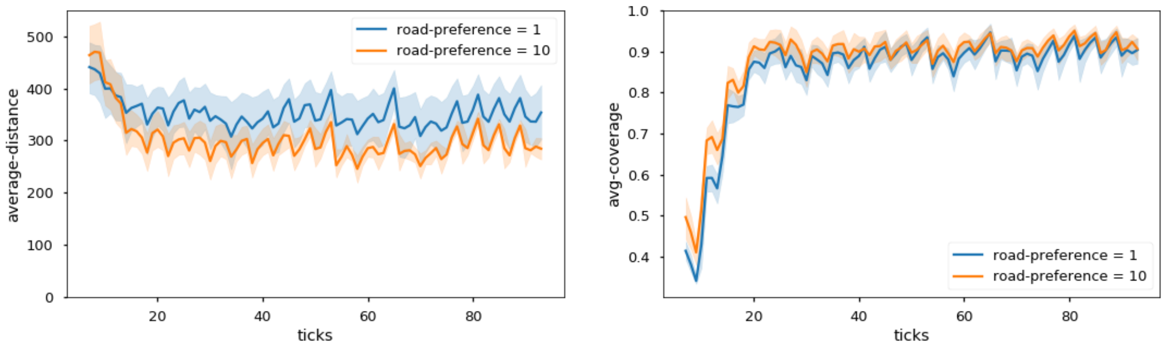

Figure7.3: Results average travel distance and coverage with high preference for proximity to roads

High preference for proximity to neighbors

The preference for proximity to neighbors shows an even bigger decrease of the average travel distance compared to the base case scenario. As shown in figure 7.4, raising this preference from 1 to 10 seems to be able to decrease the average traveled distance with 25% to almost 50%. Besides a decrease in the average distance value, the fluctuation of the results decreases as well. This can be explained by recalling the first and the third process in the model. The first process explains the settlement process in which refugees assess their environment and then choose a place to settle. The third process is the placement of new healthcare facilities, using the optimization algorithms. If many refugees decide to settle close to each other, the best location for a facility will be in this group of refugees. The ratio of waiting patients over the unused capacity shows no significant differences compared to the base case scenario, which implies that the capacity in the system is simply spread more successfully throughout the model environment and therefore increases the overall performance. If the decline in average distance would go hand in hand with an increase in the capacity shortage, this means most refugees are turning to a selected number of facilities that are very nearby, leaving facilities in other areas unused. As this is not happening in this scenario, it can be concluded that a higher preference for proximity to neighbors increases the model performance.

High preference for proximity to healthcare facilities

Interestingly, it is found that a high preference for proximity to healthcare facilities does not have a clear influence on any of the KPIs. This could be explained by the fact that healthcare facilities are often placed in, or around, groups of existing shelters, leaving little space around the facilities for new shelters. Figure 7.5 shows the average traveled distance in the base case scenario and in a scenario with a higher preference for proximity to healthcare facilities among refugees. In the latter scenario, the positive effect of a new facility on the average traveled distance keeps increasing throughout the simulation. This can be seen in figure 7.5 from the increasing difference between the orange and the blue line and the smaller shaded area, which represents the variance of the results. However, this effect nearly completely disappears when refugees have to turn to a second facility. This can be seen in the small peaks in the figure.

An explanation for the bigger influence of the high preference for proximity to neighbors com-

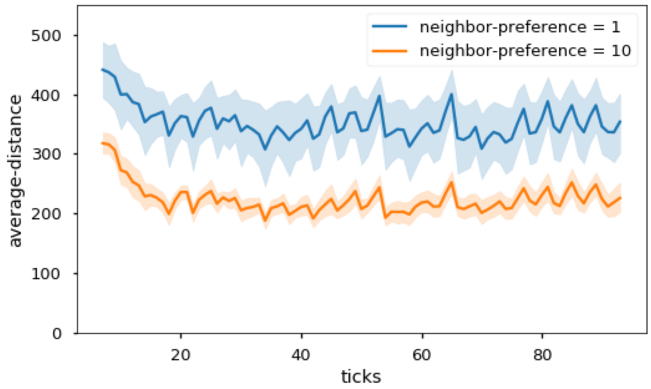

Figure7.4: Results average travel distance with high preference for proximity to neighbors

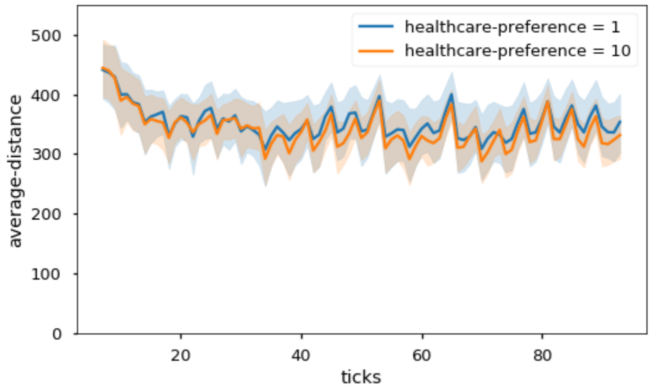

Figure7.5: Results average travel distance with high preference for proximity to healthcare facilities

pared to the influence of the high preference for proximity to healthcare facilities is found in the camp expansion process. In the beginning, the growth of the number of refugees is still very big. At this point, the preference for proximity to healthcare can steer the first settlers to locations close to facilities. However, the placement of new facilities will be fit to the refugee population as well. Moreover, when refugees that arrive later prefer to settle close to the first settlers, their proximity to healthcare facilities is thereby somewhat guaranteed as well. This questions to what extent it is useful for a refugee to focus on the existing healthcare facilities while choosing a place to settle. This gets researched in chapter 8. Based on the results of varying only the preference for proximity to healthcare facilities, the location decisions of healthcare providers are expected to have a stronger effect than the effect of the settling choices of refugees.

Varying the space requirement

Varying the space requirements shows an interesting result. As shown in figure 7.6, the higher space requirements tend to lower the average travel distance. This can be explained by the fact that more space between shelters remains free, leaving this space for necessary facilities in between the shelters. However, there is still limited space for new shelters to settle close to these facilities. The effect of refugees taking healthcare facility locations into account while choosing a place to settle is therefore limited. Further exploration of this effect is described in section 8.1. By applying a variation of the space requirements in simulations that include future expansion, the facility locations are optimized while room for new shelters is taken into account. Varying the space requirements shows no clear effect on the average coverage rate or the capacity shortage at facilities. However, it is found that the ratio of waiting patients over the unused capacity of facilities becomes more unsure. Some outliers with a very high value can be found when the requirements are more strict, which implies that in some cases this has no positive effect on the division of facilities over the model.

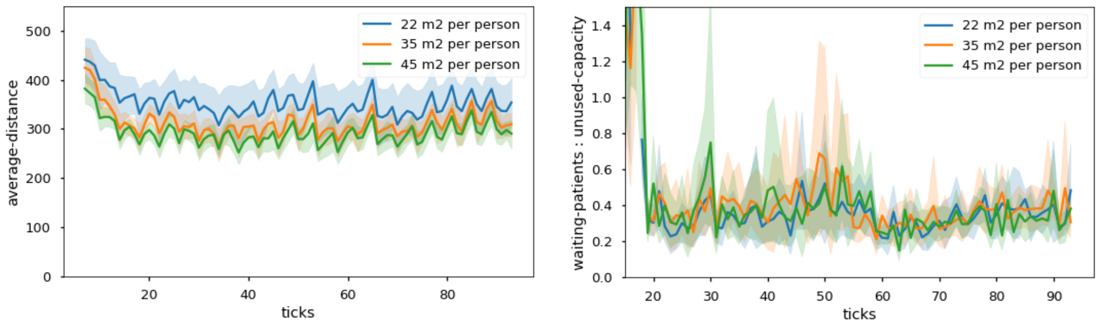

Figure7.6: Effects of varying the space requirements compared to the base case scenario

7.2. COMPARISON OF THE FACILITY LOCATION OPTIMIZATION ALGORITHMS

After the analysis of the influence of the general parameters, the different algorithms will be discussed. Figure 7.7 shows the results for the KPIs when distinguishing between the two different algorithms that are used throughout the models. The first algorithm, the P-median algorithm, aims to minimize the average distance between shelters and healthcare facilities and is applied in models 1 and 2. The second algorithm, the maximal covering algorithm, aims to maximize the coverage ratio among shelters and is applied in models 3 and 4.

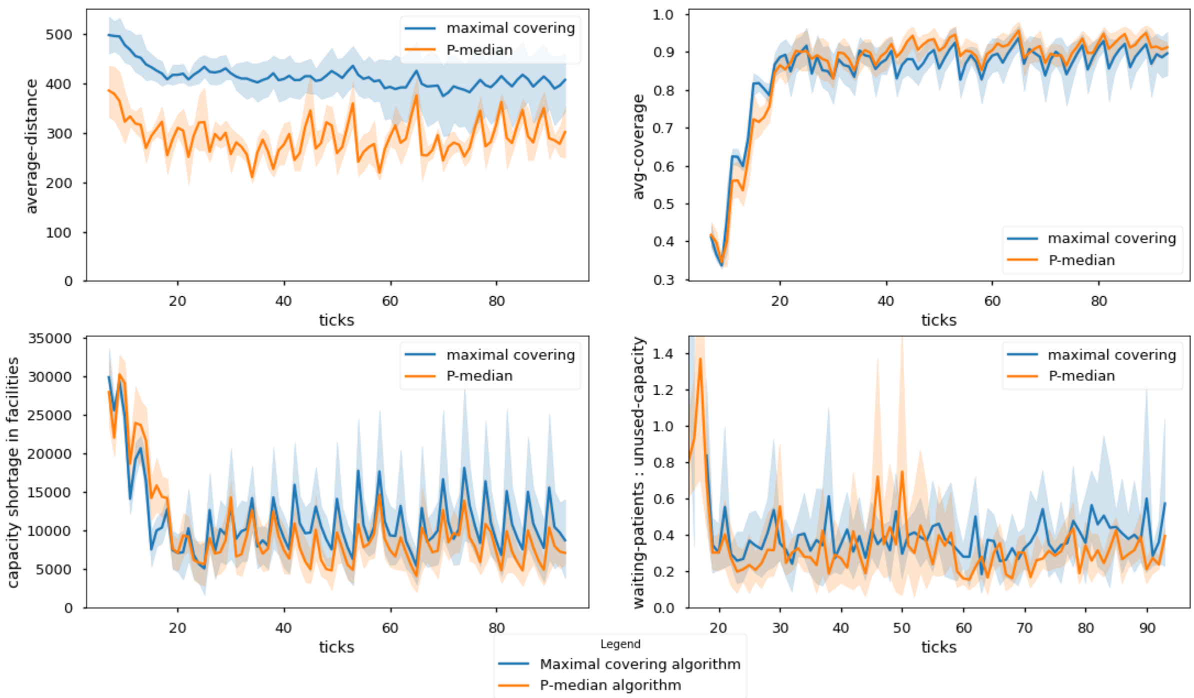

Figure7.7: Comparison of KPI results in the base case scenario for both algorithms

A few things occur when comparing the algorithms. First, it appears that the P-median algorithm, that aims to minimize the average distance between shelters and facilities, successfully realizes this goal. Throughout the simulation the threshold of 400 meters is exceeded only a few times. On the other hand, the algorithm that aims to maximize coverage has an average distance that is mostly above the threshold of 400 meters. This is remarkable, as this algorithm does take this threshold into account while maximizing the coverage. This difference arises because the algorithm focuses on all uncovered shelters, including the ones that are further away from clusters of shelters, and aims to maximize their coverage. The fluctuations due to the healthcare seeking behavior are smaller when this second algorithm is applied. The heavy fluctuations of the average distance results in the models that apply the algorithm that maximizes coverage, represented by the shaded area in figure 7.7, are found to be explainable by the future prediction, as will be discussed in 7.3. Secondly, it is found that second algorithm successfully realizes its aim of maximizing coverage of shelters, as the placement of new facilities with this algorithm more effectively increases the average coverage. This can be seen in the beginning of the simulation, when this algorithm returns a steep increase of the average coverage, which indicates that the algorithm is successfully reaching its goal of maximizing coverage prior to minimizing travel distance. This also leads to a lower overcapacity of the facilities in the first 16 weeks of the simulation. However, this advantage does not last throughout the simulation, as the average distance minimizing algorithm returns more desirable results on all indicators after about 35 weeks. According to expectations, this will go hand in hand with a lower capacity shortage in facilities. The fluctuations of this indicator are also much smaller when the algorithm that minimizes the average distance between shelters and healthcare facilities is applied. The ratio of waiting patients over the unused capacity shows some heavy fluctuations in both models, but also here minimizing the average travel distance leads to more stable results after 60 ticks. Lastly, it is found that towards the end of the simulation runs, the results of the models that apply an algorithm that minimizes the average travel distance are much more converged for all KPIs than the models that apply an algorithm that maximizes coverage. This implies a higher reliability of the first optimization algorithm. Based on these results, an algorithm that minimizes the average travel distance between shelters and healthcare facilities seems to create more desirable results throughout the simulation. However, the impact of refugees turning to a second facility is bigger when using this algorithm, as can be seen from the small fluctuations throughout the simulation.

7.3. EFFECT OF FUTURE PREDICTIONS

The previous section highlighted the difference between the results of the two algorithms, as represented in the columns in G.2. The optimization algorithm that is applied in models 1 and 2 realizes a minimization of the average distance between healthcare facilities and shelters. In models 3 and 4, an optimization algorithm is applied that realizes a fast increase of the coverage of shelters. This section distinguishes the difference between the models on each row for both columns in table G.2, the even and odd numbered models. Each algorithm is applied in two models. The odd-numbered models apply the optimization algorithm on the situation as-is and the even-numbered models use predictions about future camp expansion in its optimizations. First, the base case results of the models without predictions (models 1 and 3) are compared to the base case results of the models that include predictions (models 2 and 4). Then, the impact of different prediction methods will be discussed.

7.3.1. IMPACT OF FUTURE PREDICTIONS ON ALGORITHMS

Figures 7.8 and 7.9 show the difference between the results when distinguishing between the models that take future camp expansion into account while placing facilities (orange lines), or the models that do not consider future expansion (blue lines). Figure 7.8 shows the results when focusing on minimizing the average travel distance. Figure 7.9 shows the results when the focus lies at maximizing equal allocation of capacity of healthcare facilities, measured as the coverage ratio. Comparing the two models, it is found that for each algorithm, the indicator that is subject of the optimization shows bigger fluctuations when future predictions are included. In figure 7.8 this can be seen in the average distance results and in figure 7.9 this can be seen in the average coverage results. Logically, the latter also reflects in the capacity shortage in facilities.

Interestingly, including future predictions does not seem to lead to a significant improvement of the results. Moreover, the average distance between facilities and shelters is much higher in the model 4, compared to model 3. The distance stabilizes between 400 and 500 meters, while the model without future predictions returns results between 250 and 400 meters. In the comparison of the models 1 and 2, where the focus lies at minimizing this distance, there is no such significant difference found.

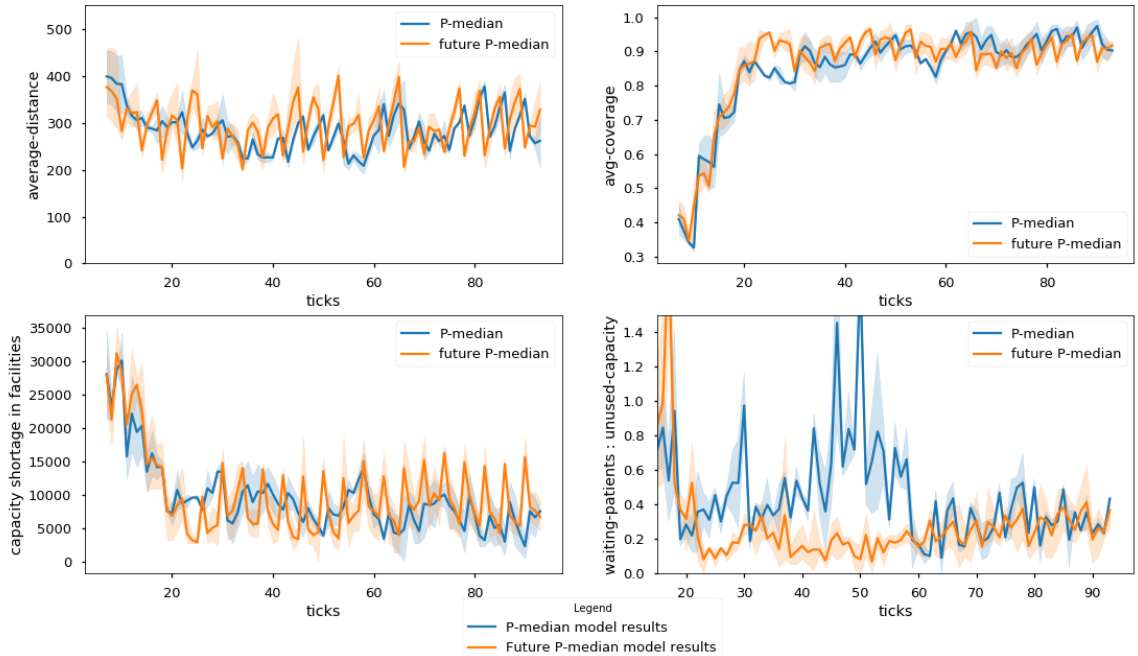

Figure7.8: Impact of future predictions on KPIs when the focus lies at minimizing the average travel distance to healthcare facilities

What can be found for both algorithms, is that the models that include future expansion in their optimizations return lower values for the ratio of waiting patients over the unused capacity. Simultaneously, the fluctuation of this ratio over time is decreased. The ratio remains mainly below a value of 1.0. This is according to expectations, as the placement of a new facility will occur earlier in the simulation when needs of predicted shelters are taken into account during the assessments. Simultaneously, the predicted shelters cannot get sick, so the number of waiting patients will not increase. Inspection of the high values for the ratio of waiting patients over the unused capacity in the models without future predictions are found to result from limited free capacity and a relatively high number of waiting patients. As the coverage ratio remains high, a possible explanation is that a shortage of capacity is neared, but the threshold of one facility per ten thousand camp inhabitants has not been exceeded yet.

In both future models, the fluctuation of the overcapacity is bigger. This is due to the modeling choice to let predicted shelters also link to facilities, as if demanding capacity, which ensures that locations of new facilities are in accordance with the needs of predicted shelters. It is therefore interesting to compare the troughs of the overcapacity graph. Over time, the non-future models show troughs that indicate a lower capacity shortage in the facilities, compared to the future models.

In section 7.2 it was found that the average travel distance is much higher when applying an algorithm that aims to maximize the coverage of shelters by healthcare facilities. However, when distinguishing between the model that include predictions about future camp expansion and the

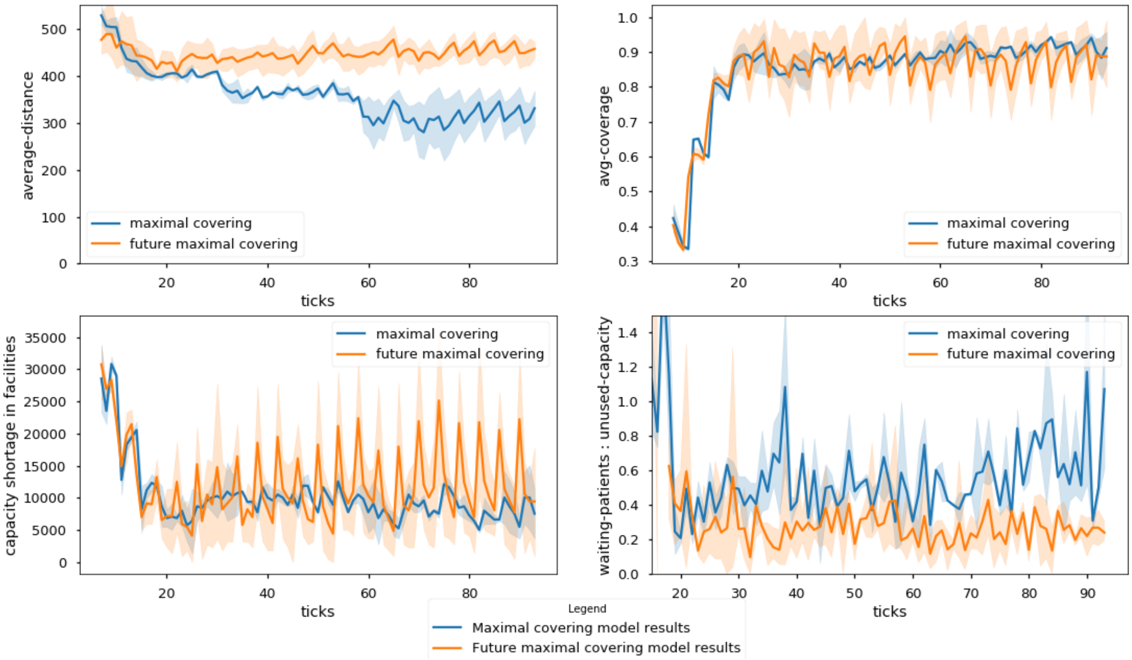

Figure7.9: Impact of future predictions on KPIs when the focus lies at maximizing equal allocation of healthcare for all shelters (maximizing the coverage ratio)

model that does not, this higher average distance only occurs in the model that includes future predictions (model 4). Model 3, that aims to maximize the coverage of shelters, without using future predictions in its optimizations returns an average distance that is comparable to the results that are obtained with the algorithm that aims to minimize the average distance. After about 60 weeks, the results of both algorithms in models without future prediction (models 1 and 3) produce results around 350 meters.

7.3.2. VARYING THE PREDICTION PARAMETERS

The method of the predictions in both future models depends on two variables, which were kept constant thus far. The first variable influences the number of predicted shelters and the second variable influences the prediction accuracy of the predicted shelters. The number of shelters is either fixed on twenty shelters, or determined using linear regression over the camp expansion in the past four time steps (weeks). In the base case scenario, this is fixed to 20 shelters every time step (this corresponds to 2000 households in reality). The prediction accuracy for the shelter locations is 0% in the base case scenario, but can be set to 100%, which means that the predicted shelter locations will all be correct. However, the number of predicted shelters can still deviate from the real number of shelters. Both prediction variables are varied throughout the experiments. This section explores the influence of these variables, and therefore only future models are used in this section.

VARYING THE NUMBER OF PREDICTED SHELTERS

The results of varying the method to determine the number of predicted shelters is shown in figure 7.10 for both optimization algorithms. Applying the linear regression lowers the number of predicted refugees in comparison to predicting 20 shelters. 20 shelters account for almost 10 percent of the final number of refugees. Such a big influx in the real number of shelters is only found in the first few time steps.

When the number of predicted shelters is determined by linear regression over the past four ticks instead of with a fixed number of twenty shelters, this mainly affects the results of the algorithm that focuses on maximizing coverage. Using this algorithm, the results for the average traveled distance are consequently lower when linear regression is included. Furthermore, the behavior of the results over time remains more or less the same throughout the comparison. The fact that the algorithm that focuses on coverage is more strongly impacted by the number of predicted shelters, implies that location decisions regarding healthcare facility by healthcare providers have a bigger impact than the impact of settling decisions of refugees.

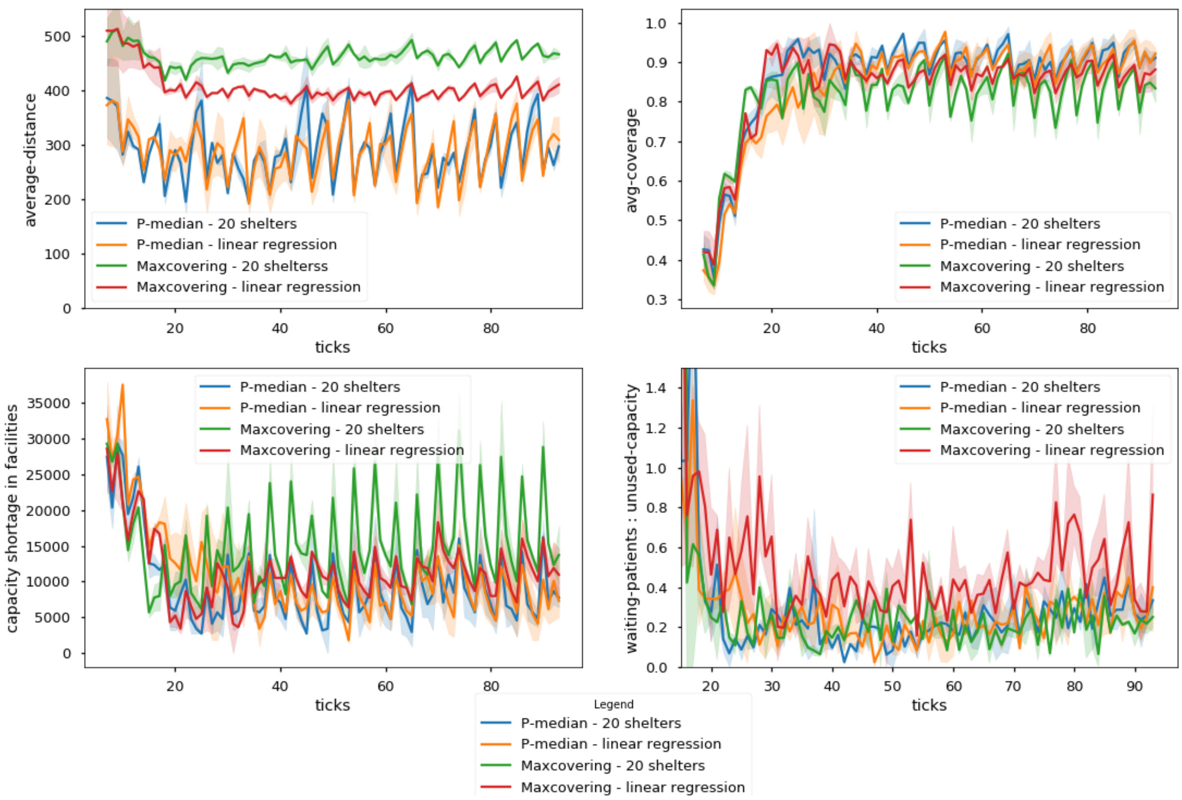

Figure7.10: Effect of varying the number of predicted shelters during facility location optimization

The coverage ratio seems to benefit from a fixed number of predicted shelters in the beginning of the simulation, regardless of the optimization algorithm. Towards the end of the simulation, this benefit turns into a disadvantage in the model that where the optimization aims to maximize coverage, resulting in a lower coverage ratio and a 15% higher average travel distance. The impact of the number of predicted shelters becomes insignificant for the algorithm that focuses on minimizing the average distance. This implies that the optimization algorithm that is focused on maximizing coverage performs better when the number of predicted shelters decreases. Comparing these to the results of section 7.3.1, model 3 still overtakes the model 4, which includes predictions about camp expansion, on average coverage from 60 ticks onward. So a bigger number of predicted shelters makes the results less precise, thereby decreasing the success of realizing a high coverage ratio.

The effect of a higher number of predicted refugees on the capacity shortage at facilities, is comparable to the result of including future predictions in the model. A higher capacity shortage occurs when a bigger number of refugees is predicted, so when this is fixed to 20 shelters.

The effect on the ratio of waiting patients over the unused capacity is very chaotic. The two lines representing the models that aim to minimize the average distance (models 1 and 2), show no clear difference. On the other hand, the results of the models that aim to maximize coverage (models 3 and 4) diverge slightly. When using linear regression to predict the number of shelters, the ratio values are higher and the variance of the results is larger, which indicates less secure results. This suggests that the unused capacity is lower in most cases, which corresponds to the higher values for the coverage ratio. When more shelters are covered, the facilities are more equally distributed over the model environment and hence the unused capacity is lower. However, the difference due to the number of predicted shelters can also be due to the fact that the threshold to build a new facility gets exceeded earlier in the model with a fixed number of predicted shelters and therefore the (unused) capacity is higher and the number of waiting patients is lower.

VARYING THE PREDICTION ACCURACY

Figure 7.11 shows the impact of predictions about future camp expansion with a high or low prediction accuracy. The number of predicted shelters always equals 20 in these runs, so the green and blue lines are equal to the ones in figure 7.10.

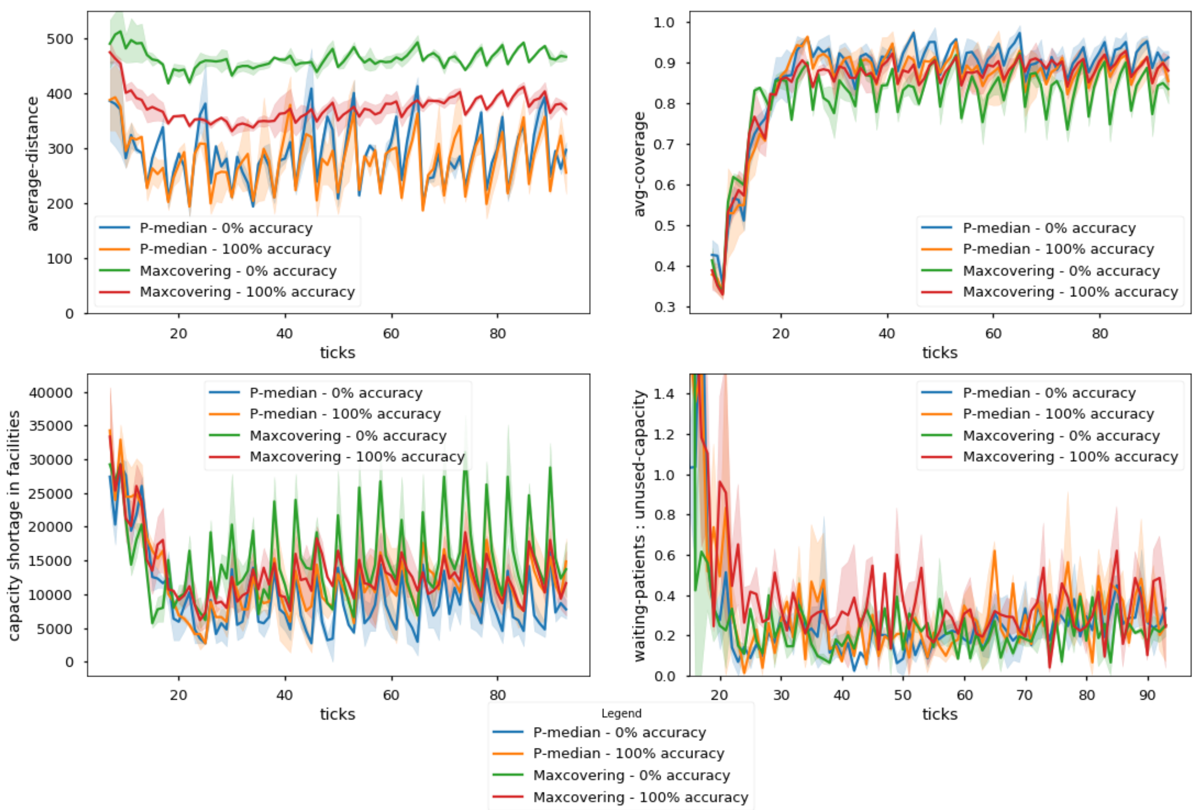

Figure7.11: Effect of varying the prediction accuracy of new shelters while optimizing facility locations

Interestingly, it appears that a higher prediction accuracy can decrease the average distance in both algorithms. This effect is very small for the models that aim to minimize this distance, but is very significant (around 10%) when the optimization algorithm is focused on maximizing coverage. The effect is even bigger than the effect of using linear regression, as shown in figure 7.10.

Simultaneously, the ratio of waiting patients over the unused capacity is slightly higher in the models with 100% prediction accuracy. This can either mean that the number of waiting patients is slightly higher, or the unused capacity is lower in these models. The second would be expected, as the facilities can be placed more strategically when the location of new shelters is already known.

However, further inspection shows that both factors are showing a slight decrease, together strengthening the effect in the ratio.

The capacity shortage is found to be higher for the models that have 100% prediction accuracy, while the average distance is slightly lower. This is an interesting result, as it is expected that the chance for a refugee that it cannot get a consult at the nearest healthcare facility is larger when the capacity shortage is larger. This would lead to an increase of the average travel distance, as they will seek a facility further away that has free capacity. However, the results from this experiment imply that the prediction accuracy can overcome this effect. This can be explained by the fact that new facilities are placed while taking into account the locations of the predicted shelters, which are in this case 100% accurate. This means that, until these predicted shelters become real, the facilities are located to serve a demand that does not exist yet. Therefore the chance decreases that a patient has to wait for a consult. This still does not explain why the average distance does not increase. Because the same reasoning would imply longer travel distances for the shelters that already existed, as the facility is less optimal placed for them. However, this effect is smaller than the benefit of optimizing for future expansion, because the past facilities have already taken the shelters that already exist into account during previous optimizations. This effect becomes stronger as the real camp growth has a decreasing growth rate, while the predictions use the same (larger) number of predicted shelters.

In general, it is expected that a high prediction accuracy will accelerate improvements on the accessibility of healthcare. However, this effect is only found for the average travel distance in the model with an algorithm that is focused on reaching equal allocation of healthcare throughout the model. Interestingly, this goal is not accelerated by a 100% prediction accuracy.

7.4. VALIDATION

Model validation is the second step, after verification, to increase the confidence in the model and its results (Sargent, 2010). It is used to compare the model behavior and results to the real world behavior. In the verification, it is shown that the behaves according to expectations. For example, the number of shelters increases over time, the average distance between shelters and healthcare facilities decreases as new facilities are created and simultaneously, the coverage of shelters increases.

This section describes the validation of the results along three tests. First, an event validity test is performed, to test whether the internally generated numbers are realistic (Sargent, 2010). Then, a sensitivity analysis is performed, to test the sensitivity of the results to a variation of fixed input parameters (Xiang et al., 2005; Sargent, 2010). How these input parameters are quantified initially, is described in appendix B. After the sensitivity analysis, an extreme conditions test is performed, to confirm that the model also holds under extreme conditions (Sargent, 2010). If the model behavior remains valid under all these tests, the confidence in the model results is sustained and increases the possibility to generalize the model results. The validation is performed using the base case scenario, as described in 7.1.

7.4.1. EVENT VALIDITY TEST

An event validity test is used to test whether occurrences in the model are comparable to real-life occurrences. As described in section 5.2, there are three main processes in the model. The first and the third process are initiated by fixed parameters, but the second process is completely based on model variables. The event validity test is performed to test the results that are produced in this second process, that imitates healthcare seeking behavior of refugees based on the chance of getting sick. The number of consultations that comes forward from this process, is an occurrence that should be validated. The number of shelters and number of healthcare facilities is also validated, using the same approach.

The data to determine the number of consultations in the model is described in B.2.2, resulting in an average of 0,346 consultations per household per week. This is applied in the model using a random uniform probability that determines whether a refugee agent gets sick and a consultation will be requested. The last 24 ticks of the model runs represent the 24 first weeks of 2019, spanning the months January until July. The number of consultations that is requested in the model is compared to real input data of this time and found to give comparable results. This is tested for models 1 and 3, that do not include future predictions. The results are measured throughout four replications of the base case scenario with different random-seeds.

VALIDATING THE NUMBER OF CONSULTATIONS IN THE MODEL

In the first model, that focuses on minimizing the average travel distance, the average number of consultations per shelter is found to range between 0,255 and 0,265. This is lower than the real 0,346 consultations per shelter that is found in the data. This can be explained by the fact that if agents are not directly helped in the model, but become a waiting patient, their consult request is not counted as a consultation yet. Only when capacity is released and the waiting patient will use this, the consult is counted. In the meantime, it can happen that waiting patient already changed its status back to 'healthy' again, as it is not realistic that refugees will keep waiting even if the waiting time is over a week. Therefore, the chance of getting sick and the number of consultations are not 100% correlated. Following this reasoning, the number of consultations + the number of waiting patients should give a better representation. Indeed, the number of consultations plus the number of waiting patients, divided by the number of shelters in the model ranges between 0,320 and 0,367. Therefore, this model behavior is acting exactly as requested in the syntax. This also stresses the importance of assessing the number of waiting patients in the KPIs.

The same check is performed in the third model, which focuses on maximizing the coverage ratio. Again, the number of consultations per shelter was lower than in reality, giving results between 0,253 and 0,258. With the number of waiting patients added to this, it results in values between 0,328 and 0,337. Therefore, it is concluded that the behavior of the second process is valid.

VALIDATING THE NUMBER OF SHELTERS AND FACILITIES IN THE MODEL

For the first and the third process, similar tests are performed. For the first process this is simply done by comparing the number of shelters with the intended number of shelters. As the intended number of shelters is a direct input for the number of shelters to be created in the model, it is not a surprise that the modeled number is a correct resemblance of reality. In the third process, the necessary number of healthcare facilities is determined. With the same runs that are used to validate the number of consultations, the number of healthcare facilities is checked, to validate whether not too many or too little facilities are created. The number of facilities over the number of shelters in the model should not be lower than 1:22, which equals 0,0455. Nevertheless, it is also not desirable to have a value much higher than this number, because this requires extra resources. In the results of model 1, values between 0,0467 and 0,05 are found. The latter is remarkably high, but can be expected as facilities are located with two at a time. Inspection of this specific scenario shows indeed that in this case (12 facilities for 240 shelters), removing two facilities would result in a shortage. The runs in model 3 result in values between 0,0462 and 0,0466. The small interval is explained by the accuracy of the ratio because here only one facility at a time is placed.

7.4.2. VALIDATION OF SHELTER LOCATIONS

The simulation model is made, using parameters and information from the case study: camps 14, 15 and 16 in Cox's Bazar, Bangladesh. This research aims to understand the impact of different settling preferences of refugees. To understand the implications of the findings for real refugee camps, it is interesting to know which preferences lead to a camp layout that is most similar to the real camp layout in Cox's Bazar. Therefore, the model result is for the various preferences compared to the real camp layout in camps 14, 15 and 16.

Figure 7.13 shows the locations of shelters and healthcare facilities in camps 14, 15 and 16 in Cox's Bazar. It is found that the simulation model approaches this camp layout best, when the refugee preference to settle close to roads is large. Figure 7.13 shows the result of the simulation for the two different scenarios. Two things can be concluded. First, in case refugees have a strong preference to settle close to roads, the resulting shelter locations mimic reality quite well. Appendix D shows the resulting camp layout for other refugee settling preferences in the simulation model as well. The second conclusion regards the facility locations. In the simulation that applies an optimization algorithm that aims to minimize the average travel distance (left figure in 7.13) the healthcare facilities are more centered in the camp area. When the simulation applies an optimization algorithm that aims to maximize the average coverage (right figure in 7.13), the healthcare facilities are located closer to roads. When comparing this to the healthcare facility locations in figure 7.12, the real situation seems to combine a bit of both aspects: the healthcare facilities are all located at roads, but not necessarily close to clusters of shelters. However, it must be noted that the healthcare facilities in figure 7.12 are all different types of healthcare facilities. This means that if two facilities are located next to each other, this is not necessarily creating an abundance of capacity in this place. It might be all different types of healthcare facilities.

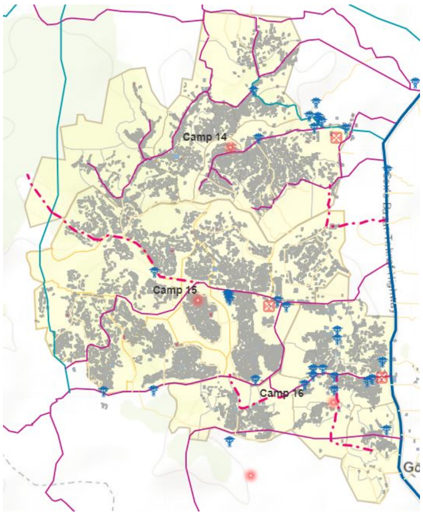

Figure7.12: Camp layout of camps 14, 15, 16 in Cox's Bazar and healthcare facilities within

[1]Retrieved from the online map developed by IOM, through http://iom.maps.arcgis.com/

7.4.3. SENSITIVITY ANALYSIS

The previous section discussed the validity of the parameters that get quantified within the model. This section discusses the validity of parameters that are used as model input. Although these input numbers are quantified using literature and reports on the case-study, they cannot yet be determined as correct with confidence. The numbers typically depend on the time of assessment, the reporting party and other case-specific circumstances. With a sensitivity analysis, the influence of initial parameter settings on the model results gets measured (Xiang et al., 2005). The bigger the sensitivity, the more important it becomes to specify the numbers correctly.

The experiments for the sensitivity analysis are executed to test the influence of the fixed parameters in the model. These parameters are the probability that agents get sick, the probability that they remain sick and the growth of the population. Their values are determined based on data from camps 14, 15, and 16 in Cox's Bazar. If the model results correspond logically to a variance in

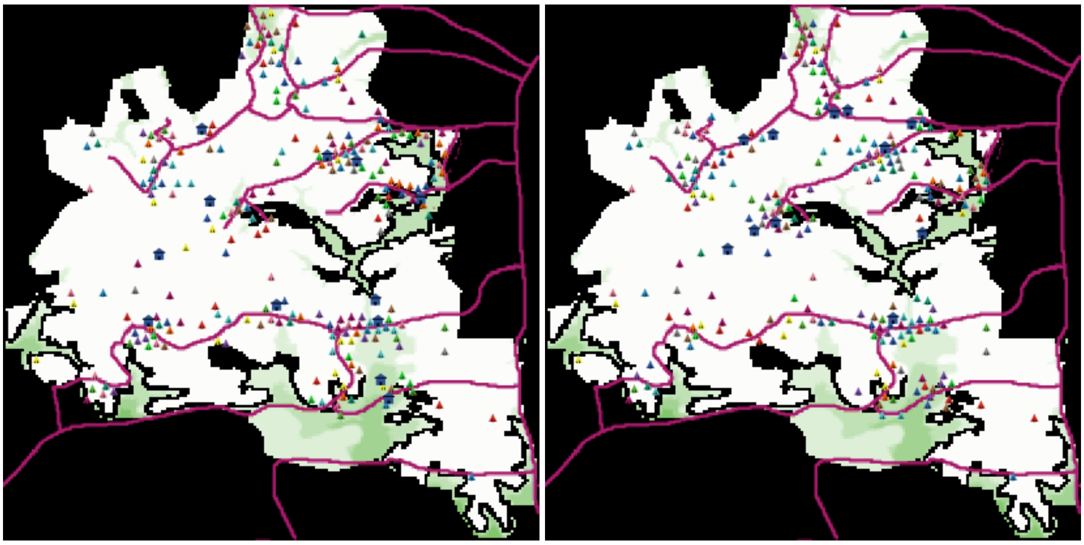

Figure7.13: Simulation model result when the refugee preference for settling close to roads is strong and the space requirements equal 22m^2 per person.
Applied optimization algorithm:
Left) minimizing average distance Right) maximizing coverage

these parameters, it is known to what extent the results are camp and scenario specific, or whether the models can be generalised and adapted to be used for other situations as well. The sensitivity analysis is performed by increasing or decreasing the value of the input parameters with 20%.

Initial capacity of healthcare facilities
Varying the initial capacity of healthcare facilities impacts the number of patients that can consult one facility at the same time. It is found that varying the initial capacity with 20% does not have a big impact on the average coverage. When increasing the initial capacity, most results show a minor increase in the average coverage over time. Especially in the first 22 ticks of the simulation the positive result is big, as more shelters can be covered by the limited number of healthcare facilities. For the impact on the average travel distance, a lower capacity in healthcare facilities is expected to increase the number of sick agents that will try to turn to a second facility when the first facility is full, which can lead to higher travel distances. However, the travel distance does not increase, because sick agents will not be triggered to travel to a second facility because the second facility is more probable to be full as well. Therefore, no clear difference is found in the average traveled distance when decreasing the initial capacity of healthcare facilities. On the contrary, when the initial capacity increases with 20%, the average distance decreases with about 20% as well, as can be seen in figure 7.14. This figure also represents the variance of the results. The big variety originates from the four different models that give different results. Inspecting the algorithms separately reveals that the decrease in average distance for a higher capacity does not occur when the optimization model is focused on optimizing the coverage without taking future camp expansion into account (model 3), but is very strong when it does take future expansion into account (model 4). Moreover, in the first case, the average distance seems to be more constant at a higher value. Both model results are shown in figure 7.15. When the optimization is focused on decreasing the average travel distance, there is no significant difference between the results for the normal model or the model that uses future expansion predictions.

Interestingly, the impact on the ratio of waiting-patients over the unused capacity shows a positive correlation with the initial capacity of healthcare facilities. This implies that an increase of the

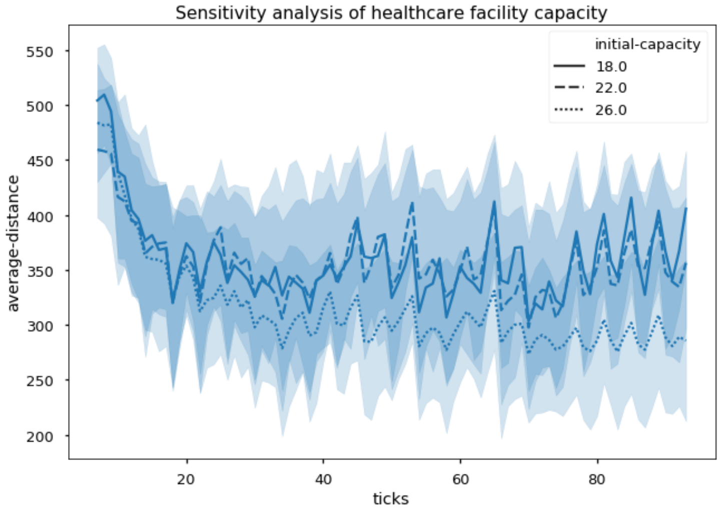

Figure7.14: Effect of varying initial capacity of healthcare facilities on average travel distance

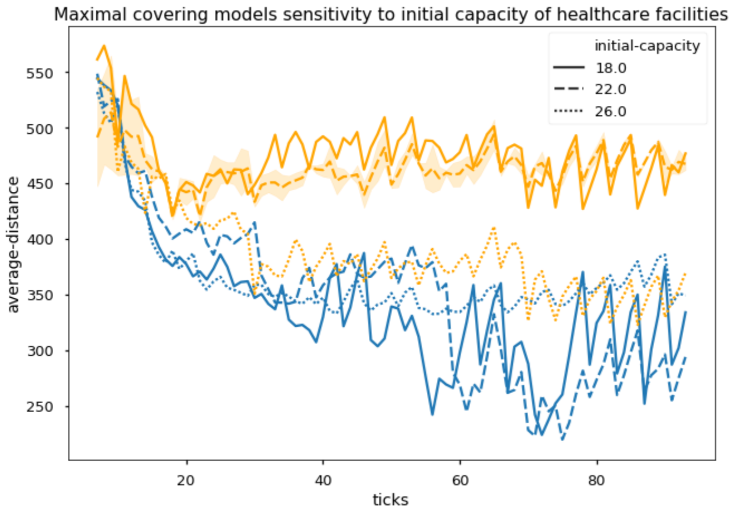

Figure7.15: Effect of varying initial capacity of healthcare facilities on average travel distance in models 3 and 4, where focus lies at maximizing the coverage ratio Orange lines are with future expansion taken into consideration, blue lines are without future.

initial capacity at facilities leads to a higher number of waiting patients and/or lower unused capacity. In the models that take future expansion into account, this ratio even reaches values that are over three times higher than in the initial situation. At first, this might not seem logical, as the free capacity is expected to return a higher value. However, the number of required facilities gets determined by securing a certain capacity over the number of refugees in the model, instead of simply securing 1 facility per 10.000 refugees. Therefore, when the initial capacity increases or decreases with 20%, the ratio of facilities per refugee will also increase or decrease accordingly, with 20%. The higher outcomes of the ratio are due to a higher number of waiting patients. This is shown in figure 7.16, which shows the box plots of the number of waiting patients throughout the models for the different initial capacities.

When the initial capacity is higher, it takes longer before a new facility is created, because the threshold is raised. Until that time, the number of waiting patients is higher. However, further inspection shows that, as the initial capacity is raised with 20% in comparison to the base case sce-

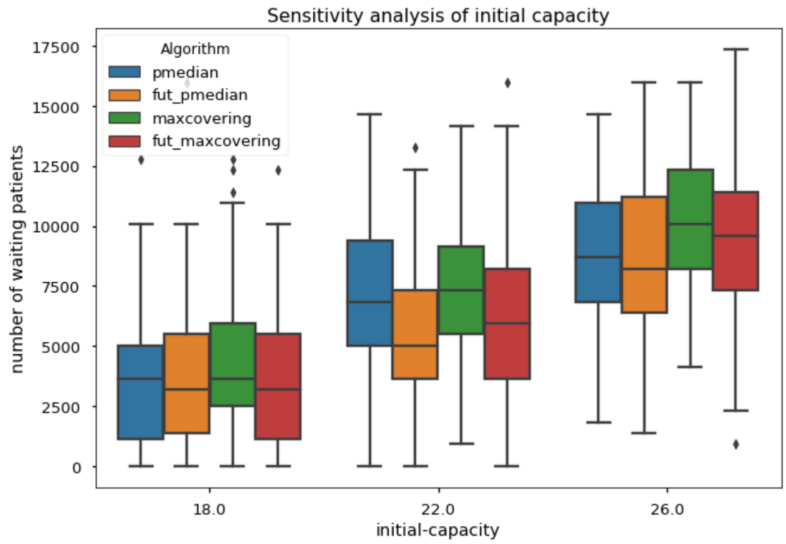

Figure7.16: Higher initial capacities result in higher number of waiting patients in all models

nario, the capacity shortage does decrease. This corresponds to the higher average coverage ratio that is obtained in this scenario. Conversely, a decrease of the initial capacity shows results more similar to the base case scenario, but slightly lowers the amount of waiting patients. These findings are interesting, as it implies that a larger number of smaller facilities could improve the system behavior. It is concluded that the effect of this parameter is therefore dependent on the optimization algorithm and can be researched more thoroughly to find the impact on the number of facilities and the total available capacity in the system. A higher initial capacity seems to increase the average coverage, but it is expected that this depends on the percentage increase and therefore it is expected that it can also occur for certain lower initial capacity values.

Chance of getting sick

The chance of getting sick determines at every time instance the probability that an agent will become sick. Since it is assumed that every refugee will always seek healthcare, the biggest effect is expected to be found on the number of (waiting) patients at a facility.

It is found that the average travel distance between shelters and facilities is not much affected by a higher or lower probability of getting sick. With a higher probability of getting sick, the average distance seems to decrease slightly, which is explained by the fact that the patients will become waiting patients at their closest facility instead of travelling to a facility further away.

The average coverage ratio is also not much affected by the probability of getting sick. The results of the model runs with a higher probability of getting sick, seem to return a lower average coverage result, but before a conclusion can be tied to this, more replications should be run to sustain the results.

The ratio of waiting patients over the unused capacity is higher throughout the entire model simulation if the chance of getting sick is higher as well. This is especially the case in the models that take future expansion into account while optimizing facility locations. Interestingly, the effect is even larger than 20% (see figure 7.17), which makes it interesting to research further. Overall, the future models return lower values when compared to the normal models.

Chance of remaining sick

If the chance to remain sick increases or decreases with 20%, the number of refugees that are at a facility and will stay here for another tick is expected to increase. Again, it is found that model 4

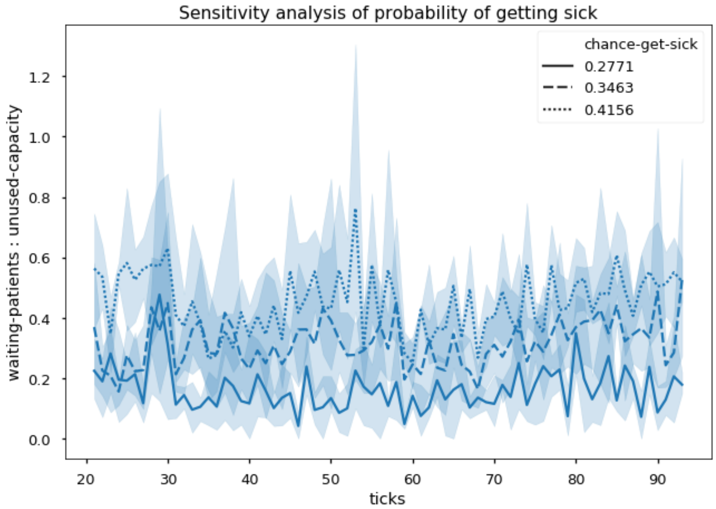

Figure7.17: Effect on ratio of waiting patients over the unused capacity of healthcare facilities when varying the probability of getting sick

(the optimization model that aims to maximize the coverage ratio and includes future predictions) shows remarkable behavior, where both sensitivity analysis runs return a 20% lower average distance than the base case run. A reduced average distance can be explained because capacity is expected to fill faster, so refugees become waiting patients at the nearest facility. However, this does not explain why this solely happens in the fourth model. Moreover, for the model that applies the same algorithm, but without future expansion, it is the other way around. This is shown in figure 7.18. Further inspection of the behavior in the fourth model shows the capacity shortage is much higher, while number of waiting patients is lower and free capacity is high. This means that the division of facilities over the model is far from optimal in this scenario. A higher or lower probability of remaining sick does not cause clear fluctuations in the average coverage of shelters, or the ratio of waiting patients over the unused capacity. This follows logically, as the impact is rather low.

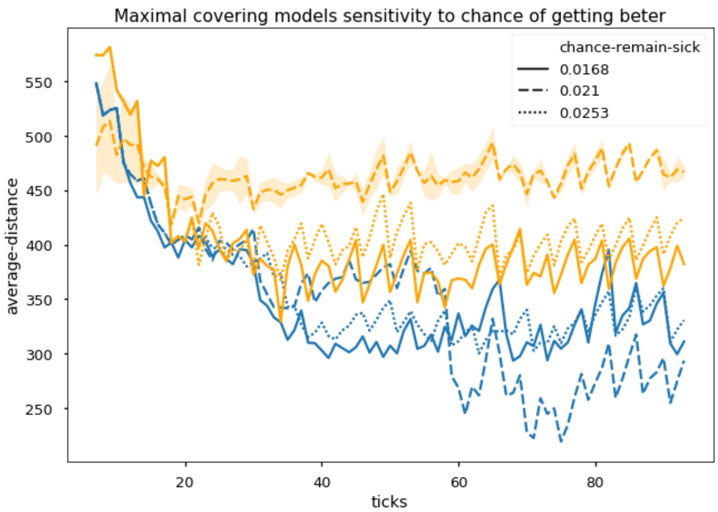

Figure7.18: Effect of varying the chance that refugees remain sick on average travel distance in models where coverage is maximized
Orange lines are with future expansion taken into consideration, blue lines are without future.

Maximum population
Deviations in the maximum total population should not impact the model results severely, as the optimizations are fit to the number of agents to the system. When varying the population with 20%, this can be seen when viewing the average traveled distance, which sustains the model validation. Sometimes the average distance seems to decrease a little bit when the population size is 20% larger. This can stem from the fact that extra facilities will be created when the population increases. Interestingly, again model four is the only model that shows a clear deviation between the results for the average distance between the base case run and the run with a smaller population, compared to the run with a population increase of 20% as can be seen in figure 7.19.

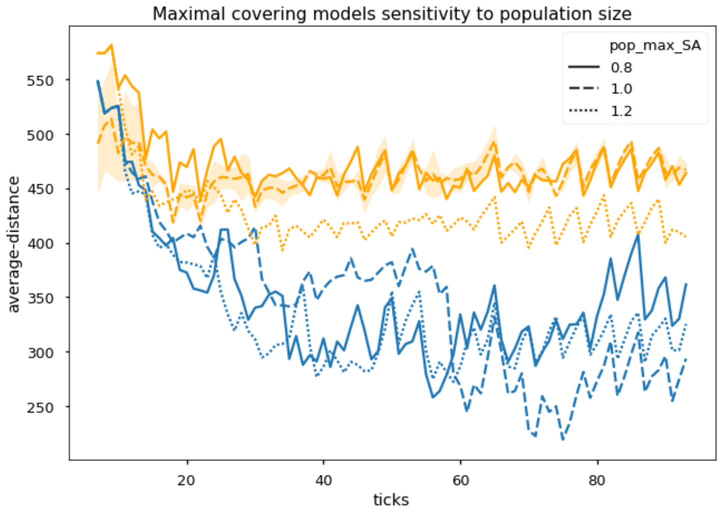

Figure7.19: Effect on average travel distance when varying the population size with 20%. Orange lines are with future expansion taken into consideration, blue lines are without future.

The average coverage ratio is not affected much by a varying population size. On the contrary, the ratio of waiting patients over the unused capacity shows interesting behavior when the population size fluctuates. For example, in model 3, where the aim is to maximize the coverage ratio without taking future camp expansion into account, this ratio fluctuates more heavily for smaller population sizes. It even reaches values up to 2,4 in the first half of the simulation. For bigger population sizes, the ratio returns lower values. When future camp expansion predictions are taken into account (model 4), this effect is the other way around. Then, a bigger population size increases the ratio of waiting patients over the unused capacity. However, all results remain below a value of 0,7. Both results are shown in the left graph of figure 7.20. When applying the algorithm that aims to minimize the travel distance (models 1 and 2), the same difference is found for the ratio of waiting patients over the unused capacity, although less extreme (see the right graph in figure 7.20).

7.4.4. EXTREME CONDITIONS
Refugee crises are characterized by large insecurity about the future. The created model uses real numbers about the population size in the Rohingya camps in Cox's Bazar, starting from the massive refugee influx in August 2017. To sustain the validity of the models for future use when the estimated population growth is subject to bigger insecurity, a few model runs have been performed with a larger population size. The population size is increased with 50% and combined with the various space requirements. The extreme situation of a doubled population size is tested as well.

As the population size increases and the space limitations become more severe, the average travel distance seems to decrease, as shown in figure 7.21. This has two reasons. First, the stricter space requirements have a beneficial effect, as found in section 7.1. This explains the difference be-

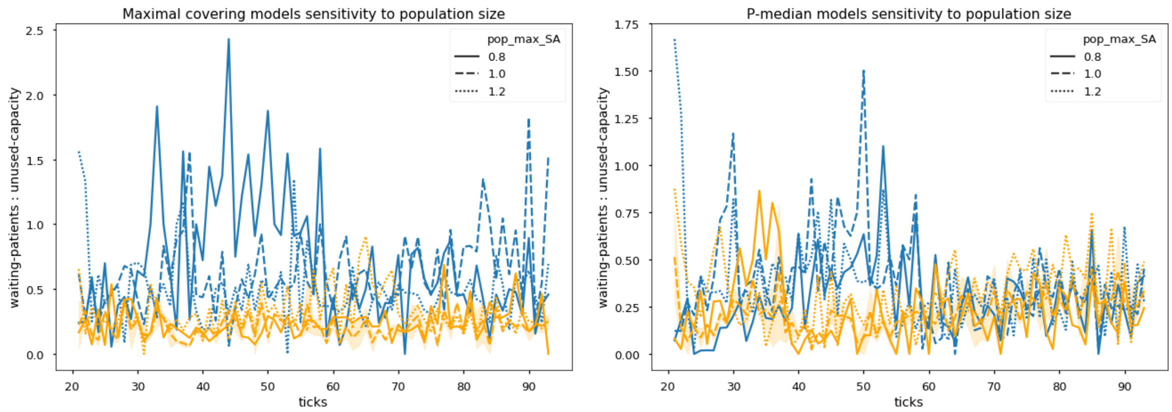

Figure7.20: Effect on the ratio of waiting patients over the unused capacity when varying the population size with 20%.
Orange lines are with future expansion taken into consideration, blue lines are without future.

tween the yellow, green and red lines in figures 7.21 and 7.22. Secondly, the high number of refugees increases the chance that facilities will be full and sick agents become waiting patients instead of turning to a second facility. This explains the difference between the yellow and purple lines. Again, these positive effects are strongest in the models that apply an optimization algorithm that does not focus on minimizing the average distance. The optimization algorithm that maximizes coverage thus benefits most of these changes.

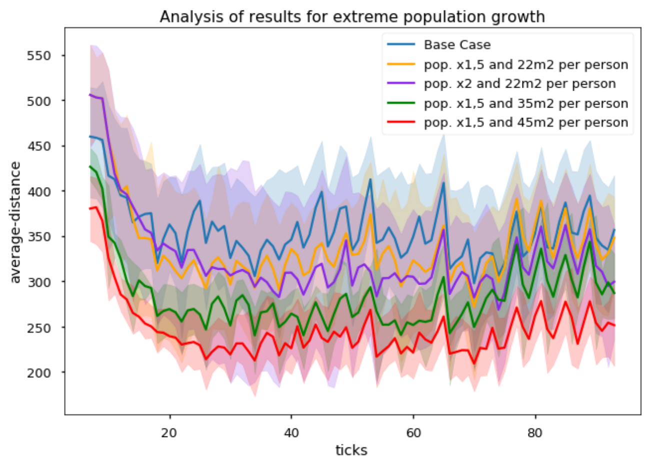

Figure7.21: Effect on average travel distance in meters across all models for a strongly increased population size

Increasing the population size slows the process of securing capacity of healthcare facilities for all shelters, as the coverage increases significantly slower. This is shown in the left graph of figure 7.23, where the yellow and purple lines show an increase of the population size, in comparison to the base case scenario in blue. This is explained by the limited number of facilities that can be placed after every assessment. When the population growth is combined with stronger space requirements, the coverage ratio seems to restore slightly. Both effects are shown in figure 7.23. Further inspection of the effect on the separate models gives no outstanding differences between the models. The effect on the ratio of waiting patients over the unused capacity shows an expected result. As it takes longer before the number of facilities covers for the number of refugees, there is a

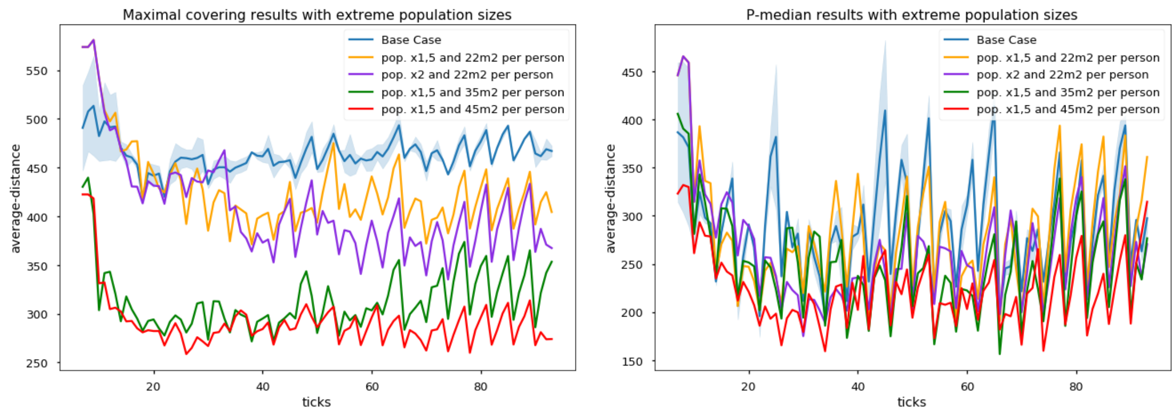

Figure7.22: Effect on the average travel distance in meters for a strongly increased population size. Both figures represent the model results that take into account future camp expansion

higher number of waiting patients in the beginning of the simulations. Once this is stabilized, there is no clear difference between the different experiments. This is shown in figure 7.23.

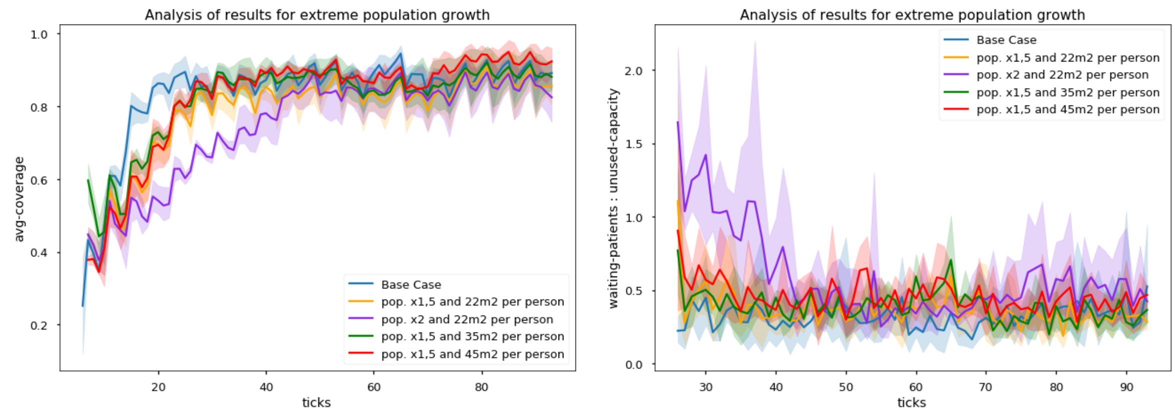

Figure7.23: Effect on coverage ratio of shelters and ratio of waiting patients over the unused capacity of healthcare facilities across all models for a strongly increased population size

7.5. CONCLUSION

This chapter explored the base case behavior of the simulation runs in this research and the impact of the various input parameters on the results. Then, the validity of the model was confirmed. This makes it possible to draw some hypothesis that can be tested by combining experiments in the following chapter.

In section 7.1 it was found that when refugees have a higher preference for proximity to roads or to neighbors, the average distance between shelters and healthcare facilities decreases significantly. The preference for proximity to healthcare facilities appeared less influential and even has a negative effect on the average coverage rate. Increasing the space requirements appears to positively affect the average traveled distance, without affecting the other indicators much. This is interesting to research more closely by combining parameter settings.

Section 7.2 compared the results of two different optimization algorithms. The P-median algorithm aims to minimize the average travel distance and is applied in models 1 and 2. The maximal covering algorithm aims to maximize the average coverage, and is applied in models 3 and 4. It was found that both algorithms are successful at realizing their predefined goal. However, when the simulation lasts for longer than 60 time steps, the optimization of the average distance also returns more desirable results on the coverage ratio.

These findings hold when distinguishing between models that include predictions about future camp expansion or do not include this. As discussed in section 7.3, optimizing for coverage while taking future camp expansion into account results in structurally higher travel distances. Overall, including future expansion enlarges the variance of the model results, except for the number of waiting patients. This is due to the number of predicted shelters, that demand coverage, but can not get sick. While varying the method of determining the number of predicted shelters, it seems that a larger number of predicted shelters decreases the success of healthcare facility locations when applying an algorithm that maximizes coverage. There are no signs that indicate the same effect for the algorithm that minimizes the average travel distance. Concerning the prediction accuracy, an acceleration in reaching desirable results for the KPIs was expected, but could not be confirmed. However, the higher prediction accuracy is found to decrease both the number of waiting patients and the unused capacity and is therefore interesting to apply.

Finally, from section 7.4 it can be concluded that the model shows valid behavior. This is shown in two consecutive steps. First, by ensuring that the parameters that are determined within the model reflect reality correctly. Secondly, by inspecting the impact of varying the input parameters on the various output parameters. Therefore, there is confidence that the model results will be usable and the model can be adapted for usage in other situations as well.

8
ANALYSIS OF RESULTS

This chapter discusses the results of the experiments, in order to define the two-way relationship between the settlement preferences of refugees that steer their settling decisions and the decision-making about healthcare facility locations in expanding refugee camps. This interplay is represented schematically in figure 8.1.

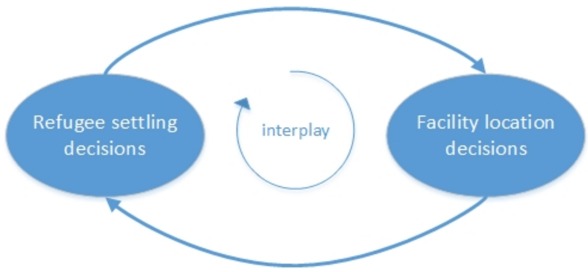

Figure8.1: The interplay between settling decisions of refugees and facility location decisions

The hypothesis in this research is that refugees take the accessibility of healthcare facilities into account while choosing a location to settle upon arrival in a refugee camp. Their location choices are subject to preferences that are defined in the input parameters in experiments. The proposition is that healthcare providers should proactively take these refugee preferences into account during the decision-making about new facility locations. It is assumed that healthcare providers and refugees use the same definition of accessibility. Healthcare providers aim to maximize the accessibility of healthcare facilities for refugees. The behavior of both actors is simulated in an agent-based model, in order to determine whether the behavior of both agents influence each other. This influence can be used in the decision-making on new healthcare facility locations in expanding refugee camps. Analyzing the simulation results for various preferences and locating strategies leads to key findings, that are used to design an approach for locating healthcare facilities.

POSITIVE OR NEGATIVE EFFECT OF BEHAVIOR ADAPTION

When refugees adapt their settling choice due the presence of healthcare facilities, this adaption can cause an increase of the overall accessibility, or to a decrease. When it leads to an increase, the behavior adaption is considered 'successful'. Similarly, if healthcare providers understand the preferences of refugees, they can predict future camp expansion and locate new healthcare facilities to cover for future camp expansion. These two behaviors can reinforce each other, leading to a positive interplay effect. Six different combinations of behavior impact can occur, resulting in either a positive or a negative interplay effect. The six combinations are shown in table 8.1. When an agent successfully adapts its behavior, it has a positive influence on the accessibility of healthcare facilities. If not, it has a negative influence on the accessibility of healthcare facilities. When both agents can positively adapt their behavior, this can reinforce each other, leading to a positive interplay. They can also both be unsuccessful in their behavior adaption, resulting in a negative interplay. It is also possible that only one of the two agent types can adapt its behavior successfully. This can lead to either a positive or negative impact loop. The behavior adaptions and the impact they have, are studied by comparison of model results when healthcare providers use expectations about camp expansion to inform their decisions. When these expectations about future camp expansion are 100% accurate, refugees can not deviate from these expectations. If these expectations are not 100% accurate, the realized camp can be different from the expectations. The different model results are analyzed and discussed in this chapter.

Table8.1: Possible impact and interplay relationships

Refugee choices adapt to healthcare facility locations $\longrightarrow$	Healthcare providers adapt facility locations to refugee preferences $\longleftarrow$	Positive or negative effect of interplay on accessibility $\Longleftrightarrow$
+	+	+
+	-	+
+	-	-
-	+	+
-	+	-
-	-	-

Results from the simulation models that allow predictions about future camp expansion are different from the results of models that do not allow these predictions. There are two reasons for this difference. Firstly, when using predictions about future camp expansion, the locations of new healthcare facilities will deviate from the chosen locations in the models without prediction. As a result, the settling decisions of refugees will be affected as well. The fact that every decision affects future decisions, is referred to as path-dependency, and is the second reason for different results. A further explanation about this path-dependency is provided in chapter 9 and in appendix D. Consequently, comparing the effect of varying the preference parameters in normal models and in models that account for future camp expansion does not measure solely the impact of settling choices of refugees on locating healthcare facilities by healthcare providers, but also how these located facilities impacts refugee settling choices in its turn. This is the interplay that is researched in order to develop an approach for healthcare providers in decision-making on facility locations. To attribute the right impact on the results to the right agent, the results of a model where healthcare providers can 100% accurately predict camp expansion are compared to the results of a model where these prediction are inaccurate. The difference between the results of these models, is solely due to different settling choices of refugees, because healthcare providers use the same method to predict the camp expansion. When the impact of the changing settling choices of refugees is known, the next step is analyzing how healthcare providers adapt facility location decisions to settling preferences of refugees. This is analyzed by comparing models that allow healthcare providers to include predictions about future camp expansion in their location decisions and models that do not allow this.

STRUCTURE OF THE CHAPTER

Section 8.1 will reflect on the influence of healthcare facility locations on settlement decisions of refugees. Section 8.2 will continue with analyzing how healthcare providers adapt the location decisions for new healthcare facilities to the settling preferences of refugees. Together, these two sections will provide the answer to sub question five: How do settlement decisions of refugees affect, or are affected by, the locations of healthcare facilities? The resulting interplay is discussed in section 8.3. Section 8.4 discusses the robustness of the model results and the system resilience during possible future events. Finally, the findings about the researched influences are translated into an approach for healthcare providers. This is discussed in section 8.6. All the model results of the experiments that are discussed in this chapter, are described in more detail in Appendix G.2.

8.1. DECISION BEHAVIOR OF REFUGEES

Refugees make a choice for a location to settle, based on their preferences for proximity to roads, other shelters and healthcare facilities. This section seeks to answer the question how refugees adapt their settling choices to different facility location decisions, made by healthcare providers. An answer to this question is sought by comparing two scenarios. Firstly, the results of model runs in which healthcare providers make a 100% accurate prediction of camp expansion are compared to the results of model runs in which these predictions are not 100% accurate. The difference is due to adapted settling choices of refugees. This is analyzed for different combinations of settling preferences.

WHERE TO EXPECT BEHAVIOR INFLUENCES

If refugees would adapt their settling choice to the accessibility of healthcare facilities, one would expect this to reflect in results of simulation runs where facilities are placed based on expected future camp expansion, but this prediction is not 100% accurate. When healthcare providers take future camp expansion into account, they will place the facilities such that part of the capacity is intended for future shelters. If refugees adapt their settling choice to increase their access to healthcare facilities, it is likely that they will settle close to these facilities. This will result in better results on the accessibility indicators. When the prediction accuracy equals 100%, there is no chance for refugees to adapt their settling choice. Therefore, comparison of the results of these simulations can be compared to find how the changes in settling choices of refugees affect the accessibility of healthcare facilities. As the settling choices of refugees are initially determined by their preferences, this comparison will return different results for different preferences. Comparing the results of the models with and without future predictions also provides information about the impact of facility locations on refugees' settling choices. However, the difference between these models is only partly due to adapted settling choices of refugees, as it is also due to different location decisions by healthcare providers.

In section 7.3.2 it was found that a higher prediction accuracy in the base case simulation results in a lower average travel distance, but also a lower coverage ratio. Throughout the other scenarios the impact of the prediction accuracy varies, depending on the optimization algorithm that the healthcare providers use and the location preferences of refugees.

A FIRST INDICATION OF BEHAVIOR INFLUENCE

A first indication that settling decisions of refugees are affected by the locations of healthcare facilities, is found when comparing the models without and the models with future prediction for different refugee preferences regarding healthcare proximity. When healthcare providers do not use predictions about future camp expansion in their decisions, there is no impact of different refugee preferences regarding proximity to healthcare facilities. On the contrary, when healthcare providers account for future camp expansion, a strong or weak refugee preference for proximity to healthcare facilities makes a difference. This difference is partly due to the fact that healthcare providers take future camp expansion into account, but gets enlarged by the different refugee preferences. In other words, when future expansion is not taken into account, the effect of varying the preference for proximity to healthcare facilities does not influence the settling choices of refugees. When future camp expansion is considered while placing the new facilities, this preference does have an influence. For the refugee preferences to settle close to roads and neighbors there is also an effect in the models that do not take future expansion into account. What the effect of different refugee preferences is when healthcare providers do or do not optimize for future camp expansion, is discussed in section 8.2 on healthcare provider decisions.

It should be noted that the predictions about future camp expansion do not take into account the effect of the new facilities on future settling decisions of newly arriving refugees. In other words, the healthcare providers are not considering the change of refugee settling choices due to the realization of new facilities while locating the new facilities. This is a shortcoming that is expected to cause flaws in the placement of facilities. Also, the impact of this shortcoming is expected to increase as the number of predicted shelters deviates more from the real number of shelters. Interestingly, a larger number of predicted shelters seems to lead to a higher coverage ratio. This is shown in figure 8.2 for the model results when healthcare facilities are located using an algorithm that aims to maximize the coverage. The blue line shows accessibility results in the base case scenario with the number of predicted shelters determined by linear regression. The orange line shows the different results, due to a higher refugee preference for proximity to healthcare facilities. The green line shows the difference between using linear regression for the prediction of camp expansion, or a fixed number of 20 shelters. Linear regression mostly results in numbers smaller than 20 shelters. The red line shows what happens if this larger prediction number is combined with a high refugee preference for settling close to healthcare facilities. The difference between the blue and the green lines and between the orange and red lines shows the impact of increasing the number of predicted shelters. It appears that increasing the number of predicted shelters has a minor negative impact on the average travel distance. However. the average coverage benefits from larger predictions, despite a slower increase in the first twenty time steps. The capacity shortage within facilities becomes smaller, as well as the ratio of waiting patients at facilities over the unused capacity of facilities.

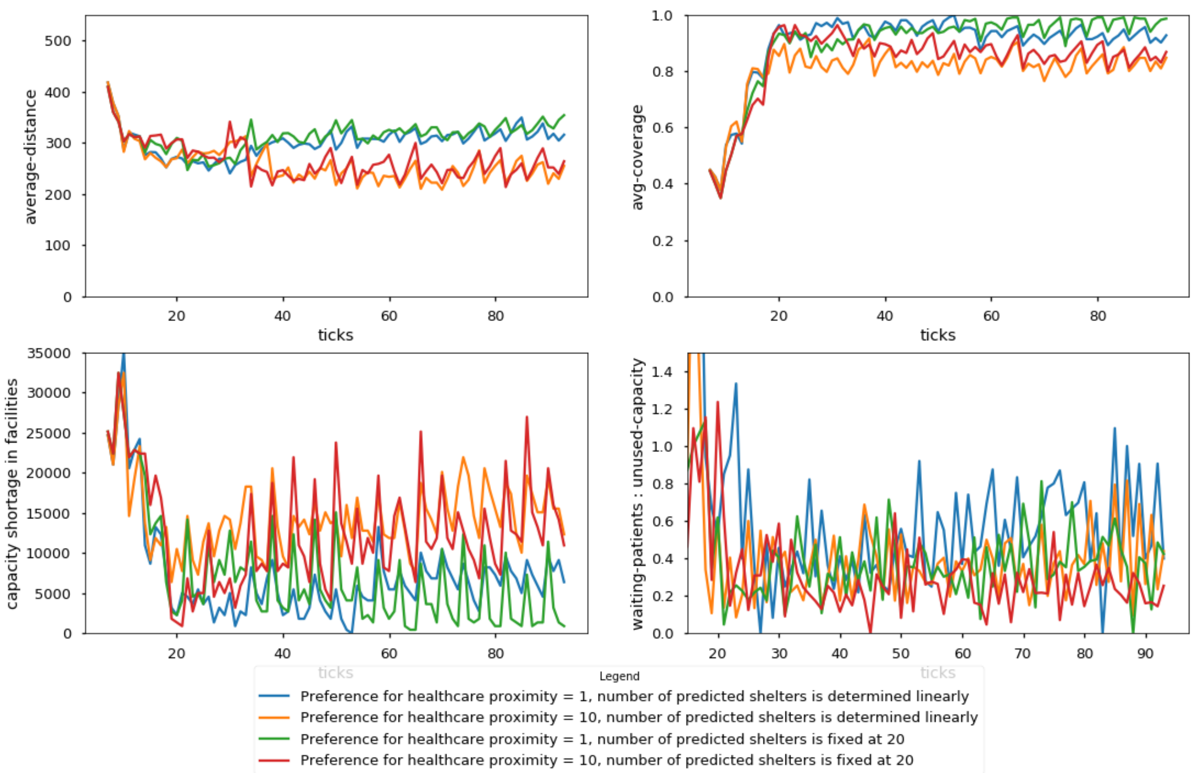

Figure8.2: Impact of number of predicted shelters while maximizing coverage of shelters for different refugee preferences regarding proximity to healthcare facilities.

8.1.1. UNDERSTANDING ADAPTATION OF REFUGEE SETTLING CHOICES IN FUTURE MODELS

Refugee settling choices are inspected in the models that use future predictions (models 2 and 4, as explained in chapter 6) to understand how refugees adapt their settling decisions to the locations of healthcare facilities. Therefore, experiments are run where the predictions of healthcare providers about future camp expansion are 100% accurate, and also without this prediction accuracy. In both cases, the healthcare providers use the same logic to predict and the same optimization algorithm to determine facility locations, so their locating decisions do not differ. Therefore, the differences in the results over time are fully due to a change in settling choices of refugees. Throughout this round of experiments, the number of predicted shelters is kept constant at twenty shelters. Of course, it should be noted that the model behavior is still path dependent. This means that the same behavior of healthcare providers does lead to different location decisions, when the shelter locations are different.

From section 7.3.2 it is known that having a prediction accuracy of 100% reduces the average traveled distance with over 10% when using an algorithm that aims to maximize coverage, but only has a marginal effect when using an algorithm that aims to minimize the travel distance. The effect on the average coverage is negative, regardless of the optimization algorithm. Again, the effect is only marginal when the focus lies at minimizing the average distance, while it is 5 to 10% when aiming to maximize the coverage. Given this information, the impact of different refugee preferences on the model results is studied. It is determined whether the changes in the refugee preferences improve the model results when predictions are 100% accurate. Then, it is determined whether this positive effect is reinforced in the model without the prediction accuracy, as the refugee agents then have the opportunity to adapt their decisions to the new facilities. These analyses are performed separately for model 2 and model 4. In model 2, healthcare providers combine future predictions with an optimization algorithm that aims to minimize the average distance between shelters and healthcare facilities (P-median algorithm). In model 4, the healthcare providers combine future predictions with an optimization algorithm that aims to maximize the coverage (maximal covering algorithm). The results of these analyses are quantified to provide insight in the size of the impact. This is presented in table G.4, in the columns 'Refugee behavior impact', for the average distance and the coverage ratio throughout the variations. The percentages show the deviation of the results in the scenario where future predictions are not accurate, compared to the scenario where these predictions are 100% accurate. Row 0 gives the average distance and the coverage ratio in the base case scenario with 100% accurate predictions. Row 1 shows the impact of letting refugees adapt their decisions to new facility locations in the base case scenario. In other words, row 1 shows the deviation of the model results in a scenario with 0% prediction accuracy, compared to the model results in a scenario where healthcare providers have a prediction accuracy of 100%.

IMPACT OF REFUGEE SETTLING PREFERENCES IN MODEL 2

In model 2, healthcare providers use an optimization algorithm that minimizes the average distance between shelters and healthcare facilities.

Impact of a strong refugee preference to settle close to healthcare facilities

In this model, it is found that the model results do not increase when refugees have a higher preference for settling close to healthcare facilities. When this preference is increased while healthcare providers cannot predict camp expansion accurately, the accessibility in the model results decreases. Interestingly, there is an improvement noticeable between the simulation results for a high preference for proximity to healthcare facilities, when changing the prediction accuracy from 0% to 100%. The latter gives better results. This implies that if refugees are more focused on settling close to healthcare facilities, they are less successful in contributing to a higher accessibility when adapting their settling choices to new facilities. When refugees are only focusing on old facilities and the healthcare providers optimize the locations of facilities to the refugee locations, using predictions about the camp expansion, the accessibility still decreases, but the impact is smaller.

Impact of a strong refugee preference to settle close to other shelters
The same is found for the preference of refugees to settle close to other shelters. In simulations without prediction accuracy, the accessibility of healthcare decreases when refugees grant more importance to a high number of neighbors. The average traveled distance becomes approximately 12,5% higher, while the average coverage ratio decreases very slightly. However, if the prediction accuracy of healthcare providers is 100%, a higher preference of refugees to settle close to neighbors increases the model behavior. This big increase exceeds the summation of the effects of increasing the prediction accuracy and increasing the preference parameter. Therefore, it is again concluded that healthcare providers can correctly anticipate to this preference of refugees and increase the effectiveness of healthcare facilities. However, if it is up to the refugees to adapt their settling decisions to the presence of new healthcare facilities, the model behavior does not improve when the refugees have a strong preference to settle close to other shelters.

Impact of a strong refugee preference to settle close to roads
When refugees focus strongly on settling close to roads, this has a positive influence on the resulting coverage ratio of shelters. However, the effect on the average travel distance is negative. When healthcare providers can accurately predict the settling choices of refugees with this preference, the model performance shows opposite results (when raising the prediction accuracy from 0% to 100%). This means a lower average travel distance, but a lower coverage ratio. The effect on the average traveled distance and the average coverage are shown in figure 8.3 and are quantified in row 4 of table G.4. The orange lines represent the simulations where refugees have a high preference for settling close to roads and have the possibility to adapt their settling choices to new healthcare facility locations. The red lines show the results when refugees have a high preference to settle close to roads, but cannot adapt their settling choices to the decisions of healthcare providers. The graph on the left side shows the average travel distance over time, and shows that the red and orange lines largely overlap. The red line is slightly more desirable. The graph on the right side clearly shows the benefit of the refugee choice adaptation on the coverage ratio, as the orange line is more than 7% higher than the red line. This is interesting as there are no further benefits on settling close to roads in the model. However, the improved results can be due to the more spatial camp layout that arises when refugees focus on settling close to roads.

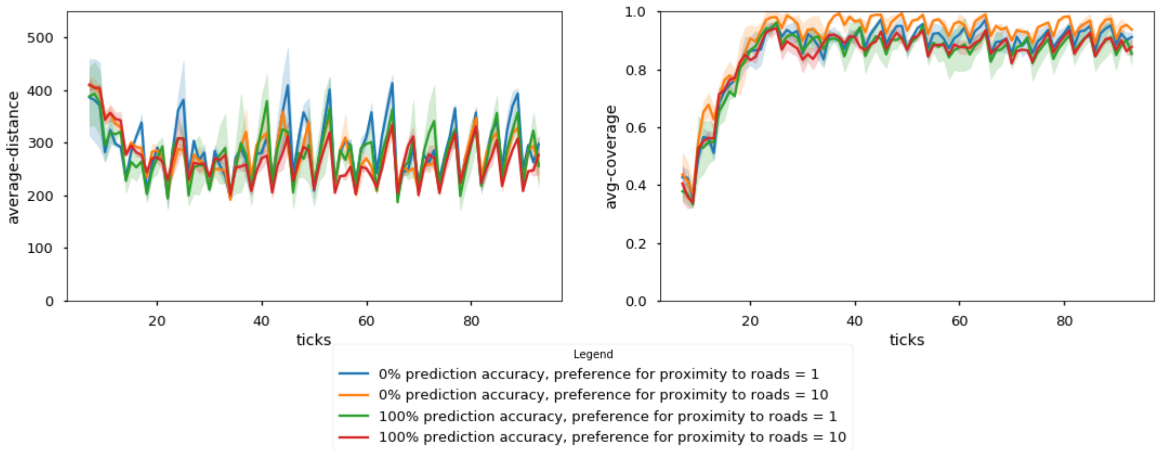

Figure8.3: In model 2, the positive influence of a strong refugee preference for settling close to roads is bigger on the average coverage when refugees can adapt their settling choices (orange line)

While a strong preference for settling close to roads leads to improved model results when refugees get the chance to adapt their settling choices to new facilities, a small increase of the initial preference for settling close to roads shows the opposite. If the preference for settling close to roads is increased from 1 to 5 instead of from 1 to 10, the results are better when the prediction accuracy of healthcare providers is 100%. This means that in this case the effect of new facilities on the settling choices of refugees is less beneficial for the overall accessibility of healthcare, than the decisions of healthcare providers. Nevertheless, this only goes if the prediction accuracy is 100%. As represented in row 7 of table G.4, a preference for to settle close to roads equal to 5 instead of 10, leads to an additional 15% increase of the average traveled distance and a decrease of over 11% of the average coverage ratio.

Impact of stricter space requirements

From these findings, a new hypothesis arises. This hypothesis is that a stronger focus to settle close to facilities or close to other shelters, who are probably located close to these facilities, has a negative effect on the accessibility of healthcare facilities. On the contrary, if refugees seek locations close to roads, the camp layout will be more spatially divided, which improves the impact of their settling choices on the accessibility of healthcare facilities.

This hypothesis is sustained when studying the effect of stricter space requirements, which forces the refugees to locate their shelters more spatially divided over the camp area. As it was found in section 7.1, increasing the spatial requirements benefits the average traveled distance, without affecting the average coverage. In model 2, where the optimization algorithm for facility locations aims to minimize the average travel distance, the impact of more strict spatial requirements slightly improves the model performance. The average distance shows a marginal decrease, but the average coverage improves slightly as well. Also, no high peaks in the ratio of number of waiting patients over the unused capacity arise. However, when healthcare providers can predict future camp expansion 100% accurately, these benefits seem to disappear. No impact can be defined in this case, which implies that the benefits arise from the choice adaptations by refugees. When varying the preference parameters and studying the difference their impact has for the different space requirements, it is found that for almost all preferences, stricter space requirements (from 22 to 45m^2 per person) clearly improve the model performance. An exception is found for a combination of a high preference for proximity to roads combined with the high space requirements. However, when the preference for settling close to roads equals 5, the results are strongly improved with more strict space requirements. Figure 8.4 shows the results of this specific scenario on the average travel distance and coverage ratio for this specific scenario in red. It can be seen that the coverage ratio almost equals one throughout this simulation.

Finding 1:
Increased attention for spatial dispersion of shelters over the camp environment improves the ability of refugees to adapt their settling decisions successfully. Thereby, they have a positive impact on the accessibility of healthcare facilities.

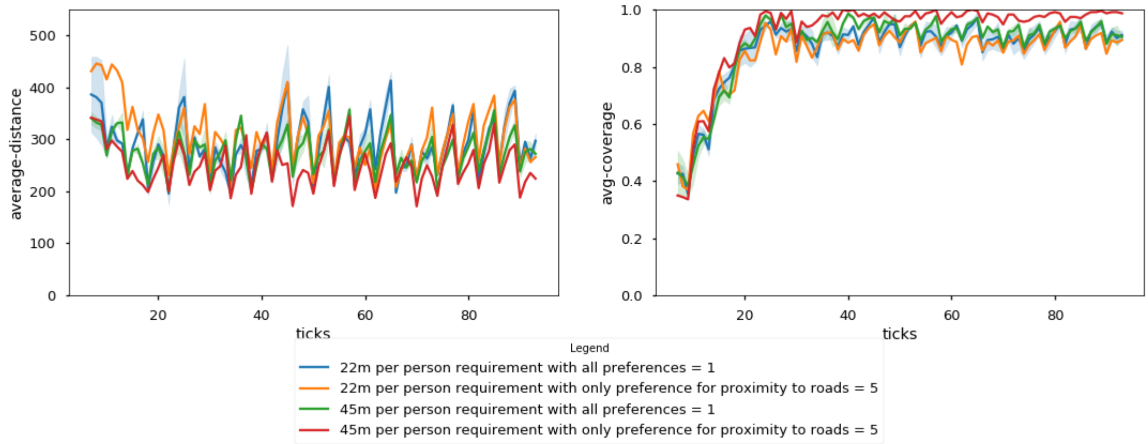

Figure8.4: In model 2, high space requirements and a preference of refugees to settle close to roads equal to 5, lead to a very high coverage ratio throughout the simulation (red line)

Combined preferences in model 2

So far, only extreme preferences are discussed. As only the preference for proximity to roads is found to improve the model results, it is interesting to study whether this can mitigate the negative effects of a preference for proximity to healthcare facilities or to other shelters. Also, the combination of a preference for proximity to other shelters and to healthcare facilities might lead to a different effect as well. The different combinations are discussed in appendix G and summarized in table G.4.

Three conclusions can be drawn from the model results. First, when a high preference for proximity to roads is combined with an increased preference for proximity to neighbors, refugees adapt their settling choices successfully to the presence of new healthcare facilities. This is regardless of the value for the preference to settle close to healthcare facilities. These results can be found in table G.4 at rows 20, 22, 23 and 24[1]. However, when combining a high preference to settle close to roads with a higher preference to settle close to healthcare facilities, while the preference for proximity to neighbors equals 1, the positive impact of the refugee preference to settle close to roads disappears. Thirdly, when the preference to settle close to roads equals 1, but the other two preferences are bigger than 1, the settling choices of refugees also reinforces positive model outcomes.

IMPACT OF REFUGEE SETTLING PREFERENCES IN MODEL 4

In model 4, healthcare providers use an optimization algorithm that maximizes the coverage ratio of shelters to determine facility locations.

Impact of a strong refugee preference to settle close to healthcare facilities

In this model, the overall accessibility of healthcare facilities improves when refugees with a strong preference to settle close to healthcare facilities can adapt their settling choices to the locations of healthcare facilities. As both a high prediction accuracy and a high preference for settling close to healthcare facilities improve the accessibility, it is expected that a combination of these two settings improves the simulation results. However, the opposite happens. Combining these settings returns a smaller improvement than only increasing the refugee preference for settling close to healthcare facilities. In other words, if refugees can not adapt their settling choice to the presence of new healthcare facilities, the accessibility is lower in comparison to the situation where they can

[1]At rows 23 and 24 an increase of the average distance is found in comparison to the scenario where refugees cannot adapt their settling choices, due to 100% prediction accuracy of healthcare providers. However, this increase is smaller than the increase in the base case scenario, shown in row 1. Therefore, the effect is positive.

adapt their settling choice. Therefore, it is concluded that for a high preference to settle close to healthcare facilities, refugee settling choices are clearly influenced by the locations of healthcare facilities. Moreover, when the prediction accuracy is 100%, an increase of the preference to settle close to healthcare facilities leads to a minor deterioration of the model results compared to 100% prediction accuracy while all preferences equally low. This is represented by the orange boxes in figure 8.5. Comparing the blue boxes in the figure, it can be seen that refugees adapt their settling choices more successfully when they have a high preference for settling close to healthcare facilities. However, the blue boxes mainly show less desirable results than the orange boxes. This means that the accessibility increases when refugees cannot adapt their settling choices to healthcare facility locations.

Impact of a strong refugee preference to settle close to other shelters
Figure 8.6 shows the different model results when the refugee preference to settle close to other shelters is high or low and healthcare providers can predict 100% accurately or not. It is visible that the orange line in the graph on the right side, shows more desirable results than the other lines. The orange lines represent the simulation run where refugees get the chance to adapt their settling choice to new facilities. The red lines represent the runs where this is not possible, as healthcare providers have predicted their locations 100% accurately. This means that the coverage ratio throughout the simulation is improved by the settling choices of refugees, that is adapted to new healthcare facilities. Moreover, when refugees cannot adapt their settling choices to new facilities, this positive effect of the preference for settling close to neighbors is completely disappeared (shift from green to red line in figure 8.6.

However, the graph on the left shows that this positive effect does not apply to the average distance indicator. A higher refugee preference for proximity to neighbors does improve the average travel distance, but on average the results for this indicator become 5% less desirable when refugees can adapt their settling choices to newly located healthcare facilities. Healthcare providers can most effectively adapt the locating of healthcare facilities to the settling preferences of refugees, when refugees have a strong preference to settle close to neighbors.

Impact of a strong refugee preference to settle close to roads
Varying the refugee preference to settle close to roads also shows that refugee settling choices is impacted by the location decisions of healthcare providers. When healthcare providers do not predict 100% accurately, the positive effect of this preference gets bigger, which is due to refugees that adapt their settling decisions. Interestingly, it appears that healthcare providers can not successfully adapt their location decisions to this refugee preference. When their predictions are 100% correct, knowing that refugees prefer to settle close to roads, their location decisions decrease the coverage ratio. The average travel distance becomes higher as well, compared to the

Studying the impact of increasing the preference to settle close to roads among refugees also shows that refugee settling choices are impacted by the location decisions of healthcare providers, as the positive effect of a large value for this preference is increased in the simulation runs with no prediction accuracy. While increasing the preference has a positive effect, and separately raising the prediction accuracy to 100% also has a positive effect, the combined effect is negative for the average coverage and also decreases the benefits of the increased preference on the average travel distance. Therefore, it is found that refugees can positively adapt their settling choices to healthcare provider decisions, while healthcare providers can not positively adapt their decisions to the high preference of refugees to settle close to roads.

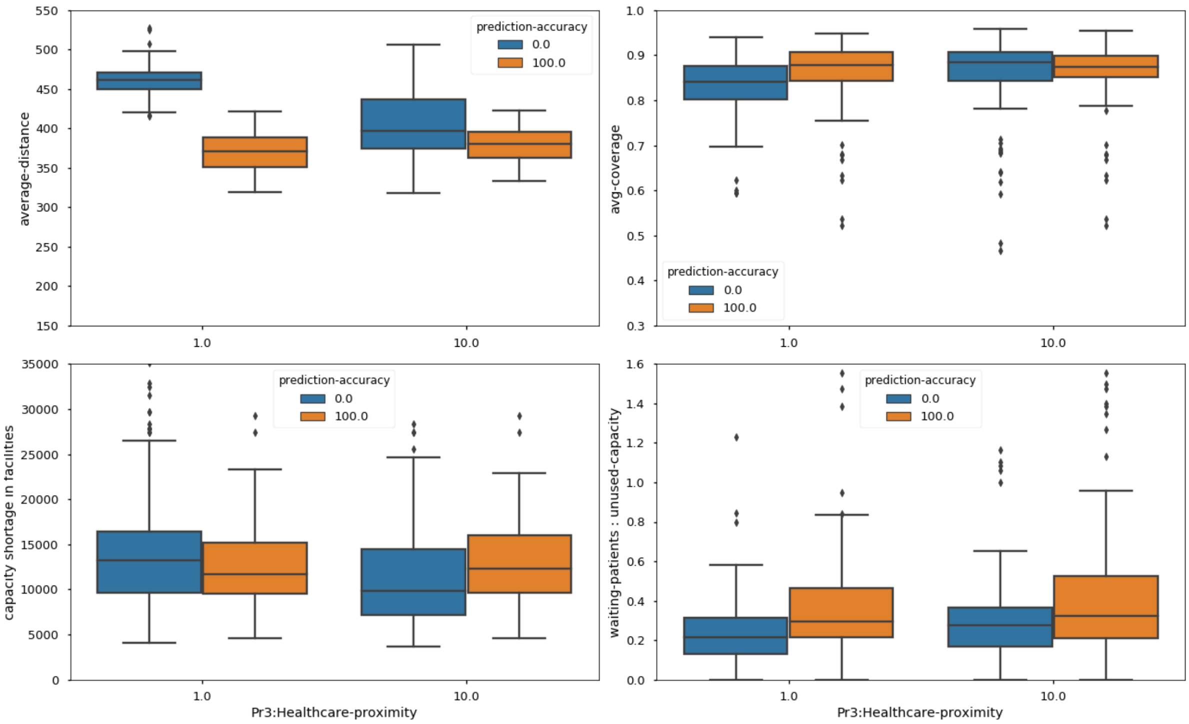

Figure8.5: In model 4, a high preference for proximity to healthcare is effective to increase accessibility of healthcare, unless the prediction accuracy of healthcare providers is 100%

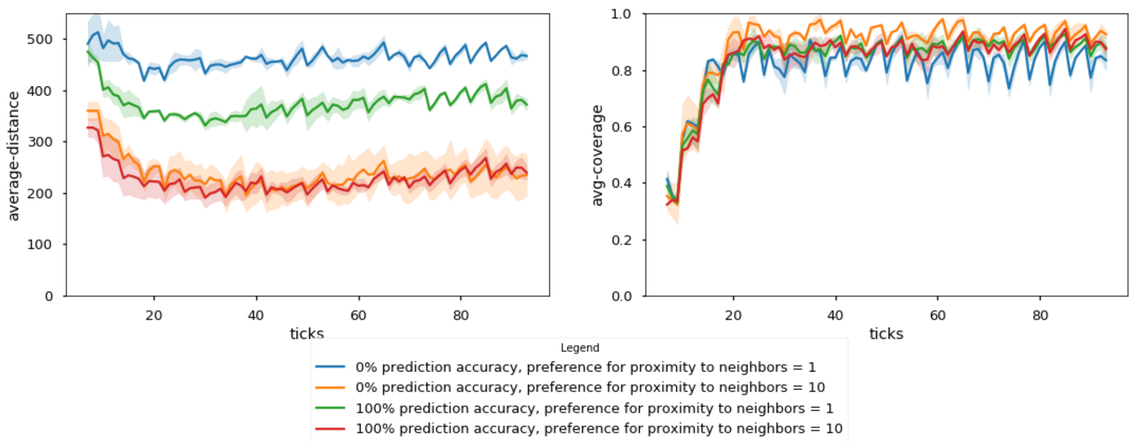

Figure8.6: Boxplot of accessibility indicators in model 4 when refugees have a strong preference to settle close to neighbors. The accessibility results improve when the refugees can adapt their settling choices (orange boxes show more desirable results than blue boxes).

Impact of stricter space requirements

The positive effect of more strict space requirements also appears in this model. Therefore, the first finding about the positive effect of spatial dispersion of shelters over the camp environment is sustained by the results in model 4. is found to hold when healthcare providers use an algorithm that aims to maximize the coverage as well. Another conclusion can be drawn from the results in this model. Healthcare providers optimize the facility locations to maximize the coverage, hence the average distance is significantly higher in comparison to results of model 2. However, when refugees have a strong preference to settle close to healthcare facilities or neighbors, they are able to successfully adapt their decisions to the presence of new healthcare facilities. Thereby, they can compensate for the lack of focus on minimizing travel distance by healthcare providers.

Finding 2:
When healthcare facilities are located with the aim to maximize coverage of all shelters, refugees that prefer to settle close to neighbors can successfully adapt their settling choices. Thereby, refugees can positively influence the accessibility of healthcare facilities.

Combined preferences in model 4

Throughout the experiments in model 4, it appeared that when healthcare providers aim to maximize coverage of shelters when locating healthcare facilities, refugees can increase the accessibility when they can adapt their settling decision to the presence of the new facilities. This positive effect of refugee settling choices is found for all strong preferences. It is found that the positive impact of refugee settling choices hold throughout different combinations of settling preferences. There are only two sets of preference combinations for which the effect of refugees adapting their settling choices is not positive for all KPIs. Firstly, when the refugee preference to settle close to roads equals 1, while the other preferences are both larger than 1, refugees are not success at adapt their settling decisions to the presence of new facilities. This results in an increase of 12 to 14% of the average travel distance, compared to the situation where the refugees cannot adapt their settling choices (this is shown in rows 15 and 17 in table G.4). However, when this preference combination includes a very high preference for proximity to settle close to other shelters, the refugees can successfully contribute to a higher average coverage. Secondly, there is one combination of preferences that makes settling choices of refugees only successful in decreasing the average travel distance, but does not improve the other KPIs. This combination consists of a preference for proximity to other shelters equals to 5, while the preference for proximity to healthcare facilities equals 10.

CONCLUSION ON REFUGEE SETTLING CHOICES

The results in this section showed that the settling choices of refugees is sensitive to the decisions of healthcare providers. How this sensitivity impacts the accessibility of healthcare for all refugees depends on their locations preferences. The method that healthcare providers use to determine optimal locations for new facilities, also impacts this sensitivity. When healthcare providers determine the facility location to optimize for the coverage of all shelters, the access to healthcare is mostly improved when refugees get the chance to adapt their settling choice to the presence of new facilities. This is different when healthcare providers determine optimal locations for facilities by minimizing the average distance between shelters and facilities. In this case, refugees are capable of increasing the overall accessibility of healthcare facilities only when having certain preferences. The next section discusses how healthcare providers adapt their location decisions to the settling preferences of refugees. This is done by comparing the effect of different methods in locating healthcare facilities between the models that include predictions about future camp expansion and the models that do not include these predictions.

8.2. BEHAVIOR OF HEALTHCARE PROVIDERS WHEN LOCATING FACILITIES

This section seeks to understand how healthcare providers adapt the locating decisions regarding healthcare facilities to the emergent settling patterns of refugee shelters. These patterns are shaped by preferences of refugees, regarding their shelter location. Healthcare providers can take these settling preferences into account while making location decisions for new facilities and adapt these location decisions accordingly. How healthcare providers do this, is studied in two ways. Firstly, by understanding the difference between the optimization methods that are used to define location decisions of healthcare providers, as these shape the model behavior. Secondly, it is studied how healthcare providers adapt their decisions when taking future camp expansion into account, given the settling preferences of refugees. When healthcare providers use predictions about future camp expansion in their decision-making on new facility locations, the measured accessibility can improve. However, this improvement must be corrected for the impact of refugees that adapt their decisions, as found in the previous section. Then, it is known whether healthcare providers can successfully adapt their location decisions to the expected settling choices of refugees. This is researched for all combinations of refugee preferences for shelter locations.

8.2.1. HOW THE OPTIMIZATION ALGORITHMS USE SHELTER LOCATIONS AS INPUT FOR OPTIMIZATION OF FACILITY LOCATIONS

Two algorithms are applied throughout the models. The first algorithm is the P-median algorithm, which aims to minimize the average distance between shelters and their nearest healthcare facility. In order to do this, the best locations for new facilities are determined, based on all shelters and all existing healthcare facilities. The second algorithm aims to maximize coverage of all shelters. Therefore, it searches a facility location that maximizes the number of uncovered shelters that will be covered by the new facility within maximal 40 patches distance (this equals approximately 400 meters as the crow flies).

So both algorithms take a different group of shelters into consideration when determining a new facility location. The algorithm that aims to minimize the average travel distance between shelters and healthcare facilities takes all shelters into account. On the other hand, the algorithm that aims to maximize the coverage of shelters takes only the uncovered shelters into account. Consequently, when shelters are distributed evenly over the camp environment, the second algorithm might be better at realizing a high coverage, as the healthcare facilities will be distributed more equally as well. Similarly, while the shelters all settle close to each other, the average distance can be minimized easily. However, this might be at the expense of the coverage ratio, as too many refugees might prefer to connect to the same facility in this case, while the facility's capacity is limited.

Clearly, the healthcare provider's decisions depend on the shelter locations within the camp. In other words, the healthcare provider's decisions depend on the settling choices of refugees. These settling choices of refugees are steered by their settling preferences. Therefore, the next section researches how healthcare providers can improve their location decisions, given the settling preferences of refugees.

8.2.2. HOW INCLUDING FUTURE PREDICTIONS AFFECTS HEALTHCARE PROVIDERS DECISIONS

Healthcare providers can make an assessment of a current camp settlement and determine what would be an optimal location for a new healthcare facility, to optimize the accessibility of healthcare for all camp inhabitants. However, when the camp expands, the newly arrived refugees need proper access to healthcare as well. Therefore, healthcare providers can adapt their location decision, by including expectations of future camp expansion. In this way, they can ensure that future refugees can have proper access to healthcare facilities as well. The shelter locations that refugees choose, depends on their settling preferences. Therefore, healthcare providers should take these preferences into account in their predictions. When this leads to better results on the accessibility indicators, healthcare providers have adapted their decisions successfully to the settling preferences of refugees.

For example, consider that a simulation run that does not allow predictions about camp expansion return a coverage ratio of 0,8 at time step 40, given that the refugee preference for proximity to healthcare facilities equals 10, while the other preferences are equal to 1. If the same refugee preferences are applied in a simulation run that allows predictions about future camp expansion, and return a coverage ratio of 0,9 at the same time step, the placement of facilities was clearly more successful. This improvement is due to the adaptation of the healthcare providers' location decision, to the settling preferences of refugees. To what extent healthcare providers can adapt their decisions successfully, is tested by comparing all the results of simulation runs with the normal models (models 1 and 3) with the models that allow predictions about camp expansion (models 2 and 4). This comparison is made for all different combinations of refugee preferences. However, these findings should not be fully attributed to the decisions of healthcare providers, as the decisions of the healthcare providers in turn affect the settling choices of refugees. Therefore, the results that are presented in this section are corrected for the adaptation of refugee settling choices, as found in 8.1.

HOW TO DETECT DECISION ADAPTATIONS BY HEALTHCARE PROVIDERS

The impact of healthcare provider behavior adaptation is first researched by comparison of results in model 1, that neglects future predictions, and model 2, that includes future predictions. For various refugee preferences, the differences between these models are analyzed. In models 1 and 2, the healthcare providers determine facility locations that minimize the average travel distance. Then, the same comparison is analyzed for models 3 and 4. In models 3 and 4, the healthcare providers determine facility locations that maximize the coverage ratio of shelters.

The results of these comparative analyses is quantified to provide insight in the size of the impact. This is presented in table G.4, in the columns 'HP behavior impact', for the average distance and the coverage ratio throughout the experiments. The percentages show the deviation of the results in the scenario that allows future predictions, compared to the scenario where future predictions are used. These predictions are not 100% accurate. Row 0 gives the average distance and the coverage ratio in the base case scenario with 100% accurate predictions. Row 1 shows the impact of using predictions about camp expansion in the location optimizations by healthcare providers in the base case scenario. In other words, row 1 shows the deviation of the model where healthcare providers take expected future camp expansion into account, compared to the model where they do not take future camp expansion into account.

In section 7.3 it was found that using future predictions does not necessarily improve the model performance. Comparing the results of model 1 and model 2, the average distance and capacity shortage measures shows bigger fluctuations over time when healthcare providers use predictions about camp expansion in their optimizations. Comparing models 3 and 4, bigger fluctuations are found for the coverage ratio and capacity shortage when including predictions about future camp expansion. Also, the average distance is much higher throughout the base case simulation in model 4, compared to model 3. For both models, the ratio of waiting patients over the unused capacity returned structurally lower results, because the unused capacity is bigger when covering for future camp expansion.

IMPACT OF HEALTHCARE PROVIDER BEHAVIOR IN MODELS 1 AND 2

In models 1 and 2, healthcare providers use an algorithm that aims to minimize the average distance between shelters and healthcare facilities. In model 1, this algorithm is applied on the current camp situation. In model 2, predictions about future camp expansion are included in the location optimization.

Impact when refugees have a strong preference to settle close to healthcare facilities

When healthcare providers do not use predictions about future camp expansion in their optimizations, there is no difference between the simulation results where refugees have a high preference to settle close to healthcare facilities or a low preference. However, when healthcare providers do include predictions about future camp expansion, the higher refugee preference for settling close to healthcare facilities leads to less desirable simulation results. This is in line with the findings in the previous section, that concluded that refugees cannot successfully adapt their settling decisions to new healthcare facilities when having a higher preference to settle close to facilities. In the base case scenario, where all refugee preferences are low, the model results improve when healthcare providers include future predictions in their decisions. This indicates that decisions of healthcare providers change, when they are adapting to the preferences of refugees. However, the negative impact of the refugee settling choices is partly mitigated when healthcare providers take this preference in future camp expansion into account. Therefore, the results suggest that healthcare providers can successfully adapt their decisions to the (expected) settling choices of refugees.

Impact when refugees have a strong preference to settle close to other shelters

When healthcare providers adapt their location decisions to expected future camp expansion where refugees focus on settling close to other shelters, the accessibility of healthcare increases. The average traveled distance decreases with 1,5% and the coverage ratio increases with an average of 4,5%. This can be seen in row 3 of table G.4, in the columns 'HP behavior impact' in models 1 and 2. In the previous section, it was found that refugees are not capable of successfully adapting their settling choice to the presence of new healthcare facilities, when having a strong preference to settle close to other shelters. But, when refugees settle according to these preferences, this results in clusters of shelters. This enables healthcare providers to locate facilities in or nearby this group of shelters, thereby decreasing the average distance. Healthcare providers can thus successfully adapt for the settling choices of refugees when they have a strong preference to settle close to other shelters. The negative influence of the higher refugee preference to settle close to each other is much smaller in the model that allows future predictions, than in the model that does not allow predictions. This is in line with the findings in the previous section, where the effect of predictions with a 100% accuracy was found to increase the overall accessibility of healthcare facilities.

Impact when refugees have a strong preference to settle close to roads

In the model simulations where healthcare providers do not use future predictions while determining optimal facility locations to minimize the average travel distance, an increase of refugee preferences to settle close to roads decreases the resulting accessibility of healthcare facilities. This is shown in figure 8.7, by the shift from the blue line to the orange line. This goes for both an increase of this preference from 1 to 5 and from 5 to 10. However, when healthcare providers include future predictions about camp expansion, given these preferences, the negative influence is mitigated. This can be seen from figure 8.7, where the red lines shows that model behavior is improved when refugees have a high preference to settle close to roads while healthcare providers use future predictions when locating their facilities.

In the previous section it was found that refugees with a strong preference for settling close to roads, will adapt their settling choices when healthcare providers take future camp expansion into account. This was found to have a negative impact on the average travel distance, but a positive impact on the average coverage ratio. Given this adaptation of settling choices of refugees, it can be concluded that the location decisions of healthcare providers become more successful when they include predictions about future camp expansion, knowing the preference of refugees to settle close to roads. The negative impact of the adapted settling decision of refugees on the travel distance is fully compensated, and the positive effect on the coverage ratio is maintained.

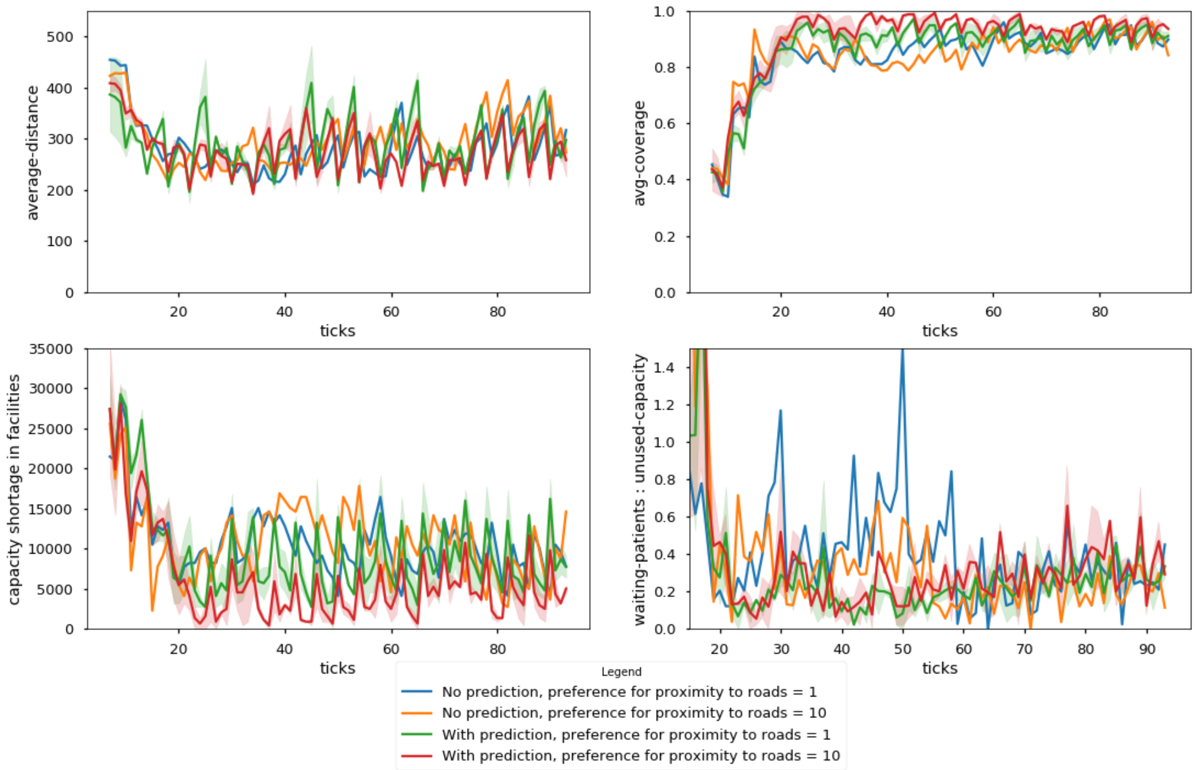

Figure8.7: In model 2, the decisions of healthcare providers and refugees successfully adapts to each other, leading to the results shown in red.

Impact of stricter space requirements

Just as in the previous section, the impact of higher space requirements are studied as well. This time, combined with the effect of healthcare providers that adapt their location decisions to the preferences of refugees. Again, this confirmed the suggestion that more strict space requirements always lead to more desirable model results. An exception is found for a combination of a high preference for proximity to roads combined with the high space requirements. Apparently, the improvement does not help when refugees are already showing a tendency to settle more separated. The first finding from the previous section can therefore also be applied to location decisions regarding healthcare facilities by healthcare providers.

> **Finding 3:**
> Healthcare providers can adapt their facility location decisions that are designed to minimize the distance between shelters and facilities to settling choices of refugees.
> When refugees focus on spatial dispersion of shelters over the camp, healthcare providers adapt location decisions most successfully, increasing the accessibility of healthcare facilities.

Combined preferences in model 2

So far, the impact of healthcare facility locations is discussed for scenarios in which refugees have a strong preference for a shelter location that is either close to healthcare facilities, to shelters, or to roads. It is found that the positive impact of decisions on healthcare facility locations can positively increase, when healthcare providers take predictions about future camp expansion into account. It is interesting to know whether this positive impacts holds when the refugee preferences are combined. It is expected that combinations of preferences for refugees that contain a high preference for proximity to neighbors or roads, will bring forth more desirable results when healthcare providers use predictions about future camp expansion.

Analyzing the impact of decision adaptations from healthcare providers when taking into account future camp expansion during optimizations that aim to minimize the average travel distance, an interesting finding occurs. When refugees combine a preference to settle close to roads equal to 5 with a preference to settle close to other shelters that is larger than 1, the positive impact of healthcare provider decisions adaptations disappears. However, when the refugee preference to settle close to roads is very strong, this effect disappears. Then, a combination with an increased preference to settle close to neighbors leads to even better accessibility of healthcare facilities. In other words, healthcare providers can not adapt their decisions successfully by taking into account predictions about future camp expansion, given refugee preferences to settle close to roads equal to 5, in combination with a strong preference to settle close to neighbors. On the contrary, healthcare providers can very successfully adapt their decisions by taking into account predictions about future camp expansion, given a strong preference of refugees to settle close to roads. For all other combinations of refugee preferences, healthcare providers can successfully adapt their decisions and improve the accessibility of healthcare facilities.

IMPACT OF HEALTHCARE PROVIDER BEHAVIOR IN MODELS 3 AND 4

In model 3, healthcare providers apply a location optimization algorithm that aims to maximize the coverage of all shelters. The same algorithm is applied in model 4, but then healthcare providers include predictions about future camp expansion in the optimizations. In section 7.3 it was found that model 3 shows an interesting decline in the average traveled distance, which does not occur in model 4. Therefore, the average result of the travel distance is much higher in model 4, where future camp expansion is not included in the location optimizations. Furthermore, this model shows much bigger fluctuations for the coverage ratio, with mostly lower values than the normal model results. This reflects in the capacity shortage within facilities as well with bigger fluctuations and higher values than model 3. Lastly, the ratio of waiting patients over the unused capacity returns lower values when future camp expansion is included in the optimizations, which is due to a higher unused capacity.

Impact when refugees have a strong preference to settle close to healthcare facilities or other shelters

It is found that healthcare providers can not successfully adapt their decisions to future settling choices of refugees that prefer to settle close to healthcare facilities or close to other shelters. For both refugee preferences, a lower accessibility is obtained in the model that allows healthcare providers to use predictions about future camp expansion when determining facility locations that maximize the coverage.

However, in line with the findings from the previous section, increasing the preferences has a positive influence on the model outcomes. Figure 8.8 shows the model results when refugees have a high or low preference for settling close to other shelters, while healthcare providers take future camp expansion into account, or not. The shifts from the blue line to the green line and from the orange to the red line show the impact of healthcare providers adapting the locating of healthcare facilities to the settling choices of refugees. Especially the graph on the left, shows that the future predictions do not improve the model results. This graph shows the average traveled distance between refugee agents and healthcare facilities in the model. The shift from the blue line to the orange line and from the green to the red line, shows that the effect of the preference increase itself, is positive. Therefore, it is concluded that healthcare providers are not able to adapt their facility location decisions successfully to the expected future settling choices of refugees.

Shifting the preference for proximity to healthcare facilities between the non-future and future model does not affect the number of waiting patients or the unused capacity specifically besides

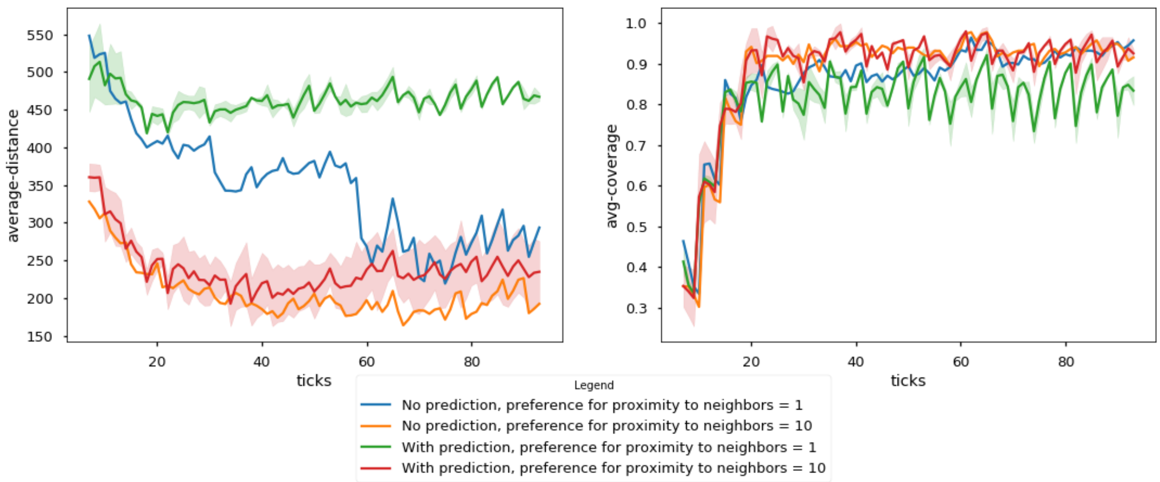

Figure8.8: Model behavior decreases when healthcare providers adapt their decisions to refugee settling preferences. When refugee have a higher preference to settle close to proximity neighbors, model performance increases.

the known influence of a bigger capacity due to future predictions. However, when the preference for proximity to neighbors is high, it is found that the number of waiting patients throughout the simulation is higher. This happens in both the models where healthcare providers use predictions about future camp expansion and the models where they do not use these predictions. As expected, the unused capacity increases when the model allows predictions about future camp expansion in its optimizations.

Impact when refugees have a strong preference to settle close to roads
Comparing the impact of changing the refugee preference to settle close to roads in model 3 and model 4 returns interesting results. In model 3, during rapid camp expansion in the beginning of the simulation run, the coverage ratio is higher for a high refugee preference to settle close to roads. Simultaneously, the average travel distance is lower. This can be seen in figure 8.9 from the orange lines. However, once the rapid expansion decreases, both the coverage ratio and the average travel distance decrease and keep fluctuating around one value for the rest of the simulation. Without the higher refugee preference for proximity to roads, the average coverage in model 3 keeps increasing slowly and the average distance mainly decreases until the end of the simulation. In other words, the accessibility keeps increasing. This is shown with the blue lines in figure 8.9.

Comparing these results to the results of model 4, where healthcare providers use predictions about future camp expansion in their location decisions, a different impact is found. The average distance between shelters and healthcare facilities is much higher when refugees have no strong preference to settle close to roads, as shown by the green lines in figure 8.9. On the contrary, when refugees do have this strong preference, the predictions tend to increase the overall model behavior. This can be seen when comparing the red lines to the orange lines. Furthermore, a higher refugee preference for proximity to roads in model 4 seems to lower the number of waiting patients. Interestingly, when in this model the refugee preference for proximity to roads is only raised to 5 instead of raising it to 10, the results are different. The number of waiting patients becomes much lower, while the unused capacity remains approximately equal. In model 3, this difference does not exist. A refugee preference to settle close to roads equal to 5 produces very similar results to a simulation where this preference equals 10. However, the smaller fluctuations in the ratio of waiting patients over the unused capacity in this model, are due to a small increase in the unused capacity when the preference for proximity to roads is increased.

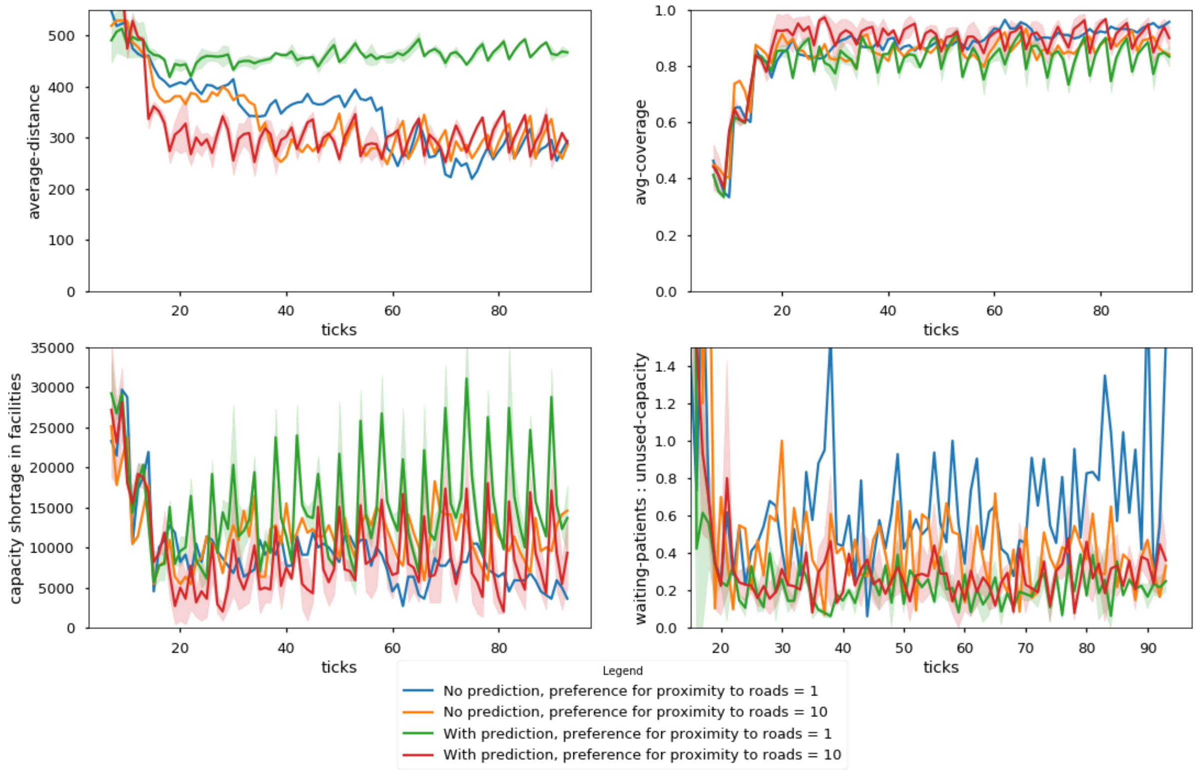

Figure8.9: A higher preference for proximity to roads in models without predictions decreases performance, whereas it leads to improved results when predictions are used by healthcare providers when locating facilities.

Overall, it can be concluded that healthcare providers can successfully adapt the facility location decisions to the settling preferences of refugees, when refugees have a strong preference to settle close to roads. In this case, using the optimization algorithm that aims to maximize coverage of all shelters leads to better results, compared to the situation where this algorithm is applied without including future predictions.

However, when refugees have a strong preference for settling close to other shelters, or close to healthcare facilities, this positive effect of healthcare providers that adapt their decisions disappears. However, as found in the previous section, the refugees can adapt their settling choices to the decisions of healthcare providers rather well, thereby even completely compensating for the negative influence of the future predictions sometimes.

> **Finding 4:**
> When using an algorithm that aims to maximize coverage of shelters, healthcare providers can not successfully adapt their location decisions to refugee preferences, given a strong refugee preference for either settling close to other shelters or close to healthcare facilities.

Combined preferences in model 4

From section 8.1, it is known that refugees can always adapt their settling choices successfully to the location decisions of healthcare providers. However, it is found that healthcare providers are mostly not capable of successfully adapting their decisions to the expected future settling choices of refugees. This counts for almost all combinations of refugee preferences. Only when a higher preference for proximity to roads (5 or 10) is combined with no increase of the preference for proximity to neighbors, do future predictions in the optimization improve the accessibility of healthcare facilities in the simulations. Interestingly, these specific combinations of preferences are causing different results of a comparison between the models that allow and the models that do not allow future predictions. In the models that do not allow future predictions, these preferences lead to a decrease of the model results. In the models that allow healthcare providers to use future predictions, these preferences lead to strong improvements of the capability of refugees to adapt their settling choices successfully.

It is therefore concluded that healthcare providers are mostly better off when not using future predictions during their location decisions with an algorithm that aims to maximize coverage. Only when it is known that refugees have a preference to settle close to roads but not close to neighbors, it can be beneficial for healthcare providers to use future predictions.

However, when healthcare providers do not use predictions about future camp expansion while locating healthcare facilities, the refugees have less opportunity to adapt their settling choice to the decisions of healthcare providers. This becomes evident when comparing the positive effect of refugee preferences in the models that allow future predictions (models 2 and 4) with the effect of these preferences in the models without future predictions (model 1 and 3). An example is the following: in models 1 and 3, without an increased preference to settle close to neighbors, an increase in the preference to settle close to roads leads to less desirable model results. On the contrary, in models 2 and 4, a higher preference for proximity to roads always makes the adaption of refugee settling choices successful. An exception to this rule is when both the preference for proximity to roads and to healthcare facilities equal 10 while the preference for proximity to neighbors equals 5. In this scenario, the average distance does decrease successfully, but the average coverage decreases.

CONCLUSION ON FACILITY LOCATION DECISIONS BY HEALTHCARE PROVIDERS

The influence of locating healthcare facilities is found to be sensitive to the preferences of refugees. First of all, the location decisions of healthcare providers are based on the refugee settlements that emerge from all separate refugee decisions. Therefore, the decisions are certainly impacted by different refugee preferences. However, the answer to the question to what extent healthcare providers can successfully adapt their locating decisions to changing settling choices of refugees is found to depend on the optimization algorithm that healthcare providers use when determining facility locations.

When using an algorithm that minimizes the average distance between shelters and facilities, healthcare providers can mostly successful adapt their location decisions to the settling preferences of refugees. Using predictions with knowledge about the settling preferences of refugees improves the model performance, when applying this algorithm. The adapted locating decisions of healthcare providers sometimes even overcomes the negative impact of the settling choices of refugees, that was found in section 8.1.

> **Finding 5:**
> When using an algorithm that aims to minimize the average distance between shelters and facilities, healthcare providers can mostly successful adapt their location decisions to the settling preferences of refugees.

On the contrary, when using an algorithm that maximizes the coverage ratio of shelters, healthcare providers are mostly unsuccessful in adapting their location decisions to the settling preferences of refugees. Only with a high preference among refugees to settle close to roads, healthcare providers increase the accessibility of healthcare facilities in the simulations results by using future predictions.

Finding 6:
When using an algorithm that aims to maximize coverage of shelters, healthcare providers are mostly not able to adapt their location decisions successfully to the settling preferences of refugees. An exception arises when refugees strongly prefer to settle close to roads.

8.3. INTERPLAY BETWEEN SETTLING CHOICES OF REFUGEES AND FACILITY LOCATION DECISIONS BY HEALTHCARE PROVIDERS

Section 8.1 discussed how the settling choices of refugees get influenced by the location decisions of healthcare providers. Then, section 8.2 discussed how the decisions of healthcare providers are affected by the settling preferences of refugees. Combining these findings, gives insight in the interplay between the settling preferences of refugees and location decisions by healthcare providers.

Healthcare providers are given two different methods to determine optimal facility locations. In the first method, healthcare providers use an optimization algorithm that maximizes the coverage of shelters. It is found that refugees are most effective in adapting their settling choices when healthcare providers use this method. However, healthcare providers are not improving the model performance when they are adapting their decisions to settling preferences of refugees, by using predictions about future expansion in this algorithm. The opposite happens with the second method, when healthcare providers use an optimization algorithm that minimizes the average distance between refugees and healthcare facilities. It is found that refugees are less successful at realizing a greater accessibility of healthcare facilities by adapting their settling choices to the locations decisions of healthcare providers that use this second method. In contrast, healthcare providers can improve the accessibility of healthcare facilities when using predictions about future camp expansion in their location decisions.

8.3.1. DETERMINING THE INTERPLAY BETWEEN CHOICE ADAPTATIONS BY BOTH ACTORS

The effect of choice adaptations by the actors differs for each optimization method of healthcare providers, which makes it difficult to predict what the result will be of the interplay between the decisions of both actors. This result of the interplay is researched, by comparing the key performance indicators for different scenarios to the key performance indicators in the base case scenario for each optimization method. The different scenarios consist of different combinations of refugee preferences. In every scenario, healthcare providers include predictions about future camp expansion in their optimizations. The results are subject to the interplay between the choice adaptations by both actors. From the comparisons with the base case scenarios, it is found that most scenarios show an increase in the accessibility of healthcare facilities. In other words, the effect of the interplay is positive. In some scenarios, positive effects of the choice adaptations by one actor are reduced by the choice adaptations of the other actor. In other scenarios, the positive and negative choice adaptations mitigate each other.

The interplay effects are determined separately for the two KPIs that measure the average traveled distance and the average coverage ratio. Each interplay is determined by comparing the results with the base case simulation in the normal model, in which no future predictions are used by healthcare providers. An overview of the analyzed effect of the choice adaptations by both actors and the resulting interplay is shown in table G.4 for both optimization methods. For some combinations, the interplay results in a trade-off between a higher average distance with a higher coverage, or a lower average distance with a lower coverage. This is found to have two causes. The first reason lies in the choice of location optimization algorithm, which focuses on only one of the KPIs. The second reason is that refugees can let the distance to a facility play a role in their settling choice, but neglect whether this facility has free capacity. Healthcare providers, on the other hand, are more focused on reaching a high coverage. This trade-off is often found when refugees can successfully adapt their settling choices to the locations of healthcare facilities, but healthcare providers cannot successfully adapt their choices to expected future camp expansion. This combination often leads to a lower average traveled distance, with a slightly lower coverage ratio. In some cases, the negative influences of the decision adaptations by both actors cancel each other out.

An example of negative influences that cancel each other out is found when the optimal facility locations are determined with an optimization algorithm that minimizes the average distance between shelters and healthcare facilities. The example comes from the scenario where the refugee preference to settle close to roads and to settle close to other shelters are both equal to five. This can be found in row 5 of table G.4. This combination of preferences does not improve the accessibility of healthcare facilities, compared to the scenario where all preferences are equal to 1. Neither do future predictions seem to improve the model results. However, combining the future predictions with these preferences does improve the travel distance between shelters and healthcare facilities with more than 11%.

8.3.2. EXPLORING THE SCENARIOS THAT MAXIMIZE ACCESSIBILITY

It is desired to maximize the accessibility of healthcare facilities for all refugees in a refugee camp. Healthcare providers aim to locate their facilities such that this improves the accessibility. This research has simulated camp expansion and the development of healthcare facilities within for many different scenarios. In every scenario, the settling preferences of refugees were different, or the approach of healthcare providers in locating healthcare facilities was different. It is interesting to determine which scenario is found most successful in maximizing the accessibility of healthcare facilities for refugees.

From the previous sections, it is derived that the scenario that maximizes the accessibility of healthcare is expected to appear in model 2 or model 3. Three important findings lead to this conclusion. Firstly, when facilities are located using an algorithm that maximizes the coverage of shelters, the chance of a negative interplay is smaller compared to when facilities are located using an algorithm that minimizes the average travel distance. This is due to the very positive effect of refugees adapting their settling choice to the decisions of healthcare providers. However, the resulting average traveled distance in the model that applies this optimization algorithm is generally much higher. Moreover, the benefit of a much higher coverage due to the objective of this optimization is only found in a few scenarios. Secondly, a positive effect of healthcare providers' decisions when using the optimization that is focused on coverage is only found in a few cases. Therefore, the best performing scenario is not expected to be found in model 4, but rather in model 3. In model 3, healthcare providers apply the algorithm that aims to maximize coverage, without using future predictions. Thirdly, when healthcare providers use an algorithm that minimizes the average distance when locating facilities, the optimizations improve when they include predictions about future camp expansion. Therefore, the best performing scenario is expected to be found in model 2, rather than in model 1.

The best performing scenario is sought by systematic comparison of scenarios with different settling preferences of refugees and different space requirements in models 2 and 3. As model 2 allows predictions about future camp expansion, the best performing scenario in this model is sought for two possible prediction outcomes. First, when the prediction outcomes are 100% accurate. Secondly, when the prediction outcomes have no assurance about the prediction accuracy. The second scenario assumes a 100% prediction accuracy of locations of new shelters. In model 3, healthcare providers do not use predictions. Then, a comparison is made of the best performing scenarios for different space requirements. As it was found that a spatial distribution of shelters over the camp environment improves the accessibility of healthcare facilities, it is expected that the scenarios will improve when the space requirement increases.

Best performing scenario in model 2
In model 2, the scenario that maximizes accessibility is found when refugee preferences to settle close to roads and to neighbors are equal to ten, while the preference to settle close to healthcare facilities equals one. In this scenario, healthcare providers locate healthcare facilities, using an algorithm that aims to minimize the distance between shelters and healthcare facilities. Hereby, they take predictions about future camp expansion into account, but without a fixed prediction accuracy. The resulting average traveled distance is 219,0 meters and the average coverage ratio equals 0,84.

When the prediction accuracy is 100%, the accessibility is maximized when refugees preferences are only increased for the preference to settle close to neighbors. The resulting average traveled distance in this scenario equals 200,5 meters and the average coverage ratio equals 0,84.

When higher space requirements are maintained in the camp layout, the accessibility of healthcare facilities is maximized with a different scenario. When the space requirements equal $45m^2$ per person, the best performing scenario is found when refugees have a preference to settle close to roads and neighbors equal to 10, while the preference for proximity to healthcare facilities equals 5. The average traveled distance equals 163,6 meters and the average coverage ratio equals 0,92.

Combining the higher space restrictions with a 100% prediction accuracy about future camp expansion, the accessibility is maximized with the first scenario again: when refugees have a preference to settle close to roads and neighbors equal to ten, while the preference to settle close to healthcare facilities equals one. A small trade-off is found between a scenario where the preference to settle close to healthcare facilities equals five and a scenario where this preference equals 1. The first scenario results in an average traveled distance of 148,5 meters with an average coverage ratio of 0,91. The second scenario results in a slightly lower average traveled distance of 145,7 meters with a slightly lower average ratio ratio of 0,9.

The latter two scenarios perform better than the first two scenarios, which is due to the higher space requirements. In other words, the accessibility of healthcare facilities is highest when space requirements are equal to $45m^2$ per person. Also, the accessibility is maximized when refugees have a strong preference for settling close to roads and close to other shelters. Whether healthcare providers are able to predict the camp expansion accurately or not, results in a minor trade-off between a slightly higher coverage ratio, or a slightly lower average distance.

Best performing scenarios in model 3
In model 3, the healthcare facility locations are determined using an algorithm that maximizes the coverage of shelters. The scenario that maximizes the accessibility of healthcare facilities in this model, is found when the refugee preferences for settling close to roads and healthcare facilities are both equal to 1, while the refugee preference to settle close to neighbors equals ten. In this model, healthcare providers do not use predictions about expected camp expansion in their optimizations. The resulting average traveled distance is 207,1 meters and the average coverage ratio equals 0,88.

When higher space requirements are applicable to the camp, a trade-off between the average coverage ratio and the average travel distance arises throughout different scenarios. For the same settling preferences of refugees (a value of ten for the preference to settle close to neighbors, both other preferences equal to one), the average traveled distance equals 163 meters and the coverage ratio equals 0,81. When the refugee preference to settle close to roads also equals ten, the average traveled distance increases slightly to 167,7 meters. This also leads to an increase in the average coverage ratio, which then equals 0,84. However, both scenarios have a coverage ratio that is close to the posed threshold of 0,8. Throughout the simulation, they can vary with more than 0,1. This means that the threshold is not always met. Interestingly, when healthcare providers are using future predictions in their optimizations, this low coverage ratio is overcome. In a scenario where a) space requirements equal 45m^2 per person, b) refugees strongly prefer to settle close to roads and other shelters, and c) healthcare providers use predictions about camp expansion, the resulting average coverage ratio is 0,9. Simultaneously, the average traveled distance in this scenario equals 169,2 meters.

Two best scenarios are now identified. The first scenario occurs when space requirements equal 22m^2 per person, the best performance is found when refugees strongly prefer to settle close to neighbors and healthcare providers optimize facility locations for already existing shelters. The second scenario occurs when space requirements equal 45m^2 per person, the best performance is found when refugees strongly prefer to settle close to neighbors and roads, and healthcare providers optimize facility locations for all shelters in the future. Comparing these two scenarios, the last one is found most effective in maximizing the accessibility of healthcare facilities for all refugees.

8.3.3. IMPLICATIONS FOR DECISION-MAKING BY HEALTHCARE PROVIDERS

The previous subsection explored in which scenarios the accessibility of healthcare facilities is maximized, because it is interesting for healthcare providers to know how they can increase the effectiveness of their facilities. This section explains how they can use these optimal scenarios in their approach for locating healthcare facilities.

In order to do this, it is first needed to take a step back from theoretical thinking, and understand how refugee camps come to exist. Some camps are fully planned by aid providers. In these camps, shelters are placed by the aid providers and assigned to refugees. This means that the choice adaptations that are found in this research, do not apply. Other camps are not planned by aid providers. Then, the settling choices of refugees will have an impact on the resulting accessibility of healthcare.

When healthcare providers want to maximize the effectiveness of a new healthcare facility in the first type of camps, they should answer two questions regarding the camp layout, as shown in figure 8.10. First, it must be known what space restriction is applicable to this camp. Then, it must be determined whether refugees are able to choose their own shelter locations, or whether they are assigned to shelters. Then, according to the scenarios that are found in the previous section, healthcare providers determine the optimization algorithm that is best fit. However, this approach is fit to the optimal scenarios that are found in the previous section. The general implications for healthcare providers are discussed in section 8.6. First, the robustness of the results is discussed in section 8.4.

THE BEST PERFORMING SCENARIOS FOR VARIOUS SPACE REQUIREMENTS

As can be seen from figure 8.10, the recommended algorithm seems to cohere with the space requirements. This is interesting, as this implies that aid providers could agree on a space requirement and thereby also know which approach is most effective.

Figures 8.11 and 8.12 illustrate the differences between the best performing scenarios in models 2, 3 and 4 for the different space requirements. Figure 8.12 also shows that, against the expectations, model 4 results in a higher average coverage than model 3, when the space requirements are high. However, the results of model 2, where the algorithm aims to minimize the average travel distance, are better.

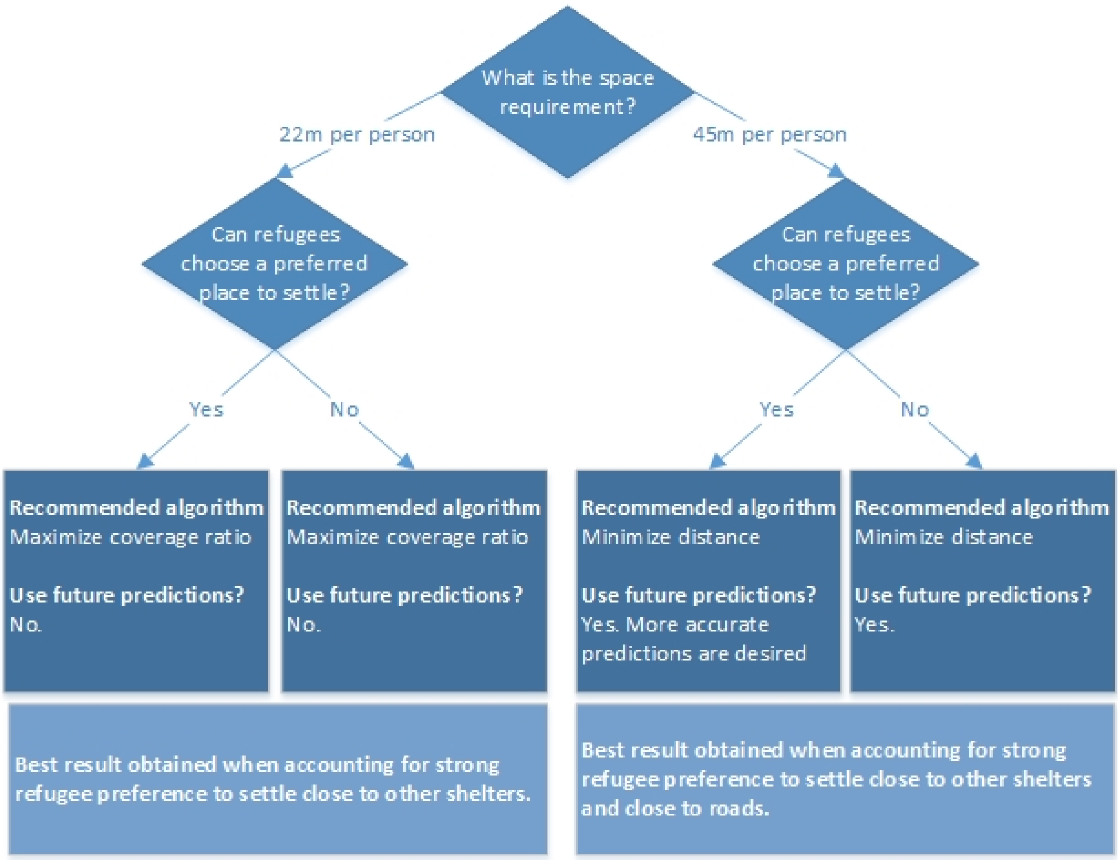

Figure8.10: Most effective approach for healthcare providers, according to the scenarios that maximize accessibility of healthcare facilities

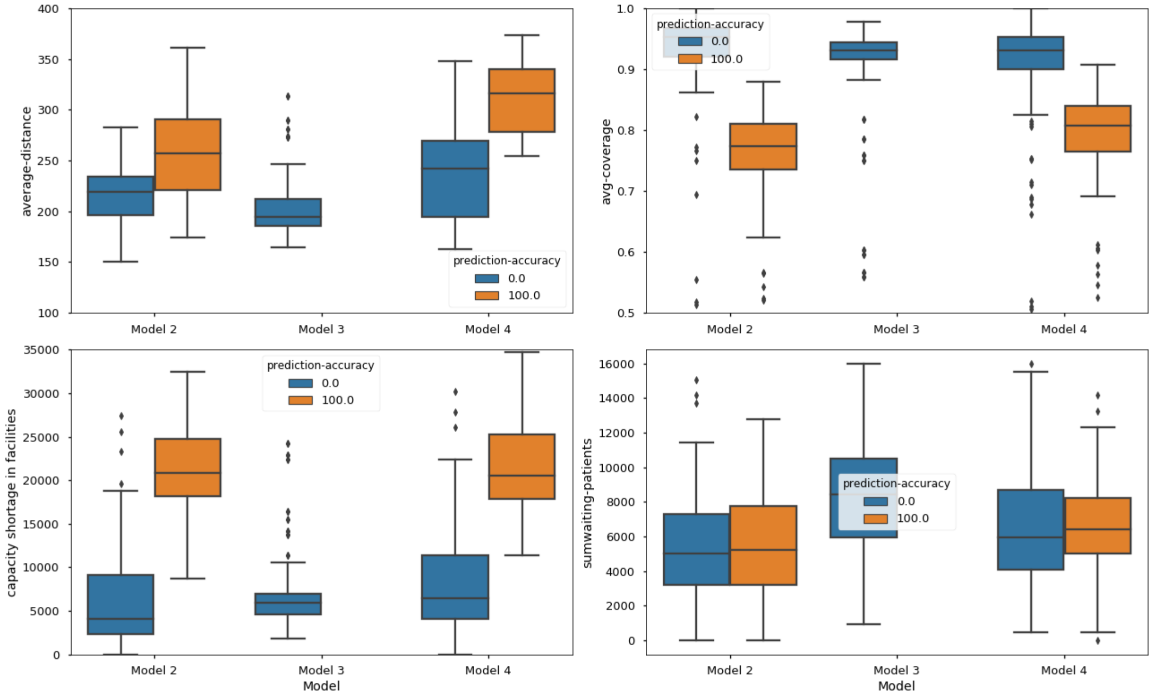

Figure8.11: The best model results when the spatial requirement is $22m^2$ per person, is obtained in model 2. In this scenario, refugees have a strong preference to settle close to other shelters.

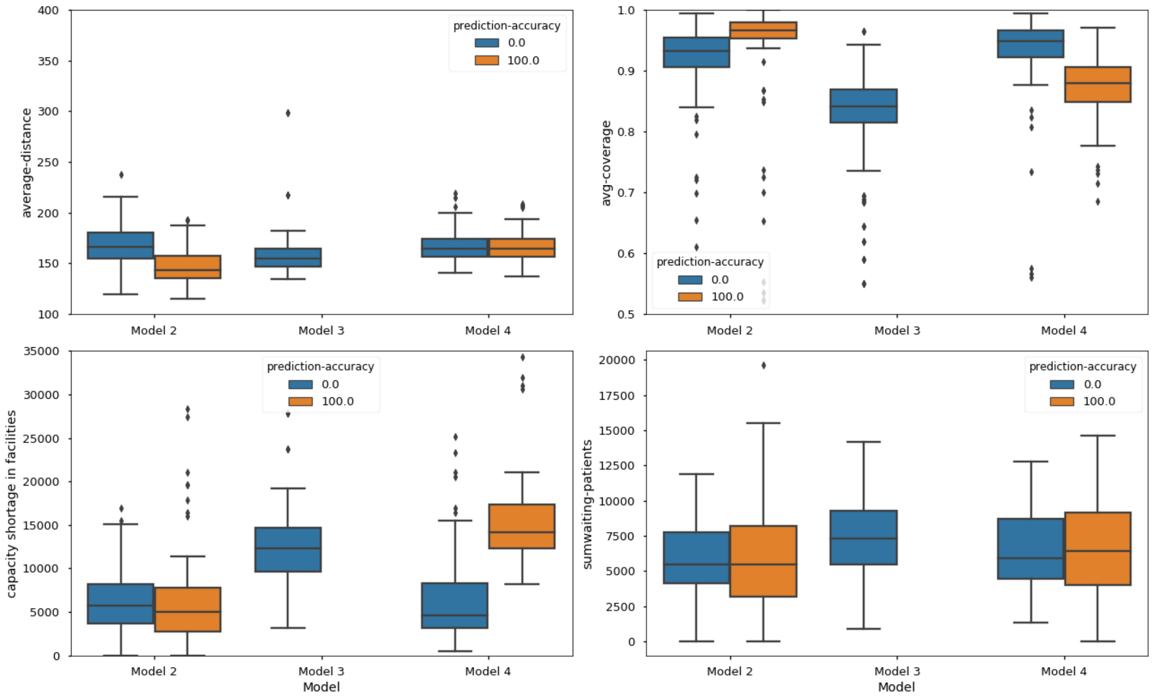

Figure8.12: The best model results when the spatial requirement is $45m^2$ per person, are obtained in model 2, when healthcare providers can predict future camp expansion 100% correctly. In this scenario, refugees have a strong preference to settle close to roads and close to other shelters.

8.4. ROBUSTNESS OF THE RESULTS

Having researched the influence of agent behavior on the effectiveness of healthcare facilities, it is important to assess the resilience of the resulting system during possible future events. The possible future events and their impact are strongly context dependent (Van Dam et al., 2013). If results of certain scenarios are structurally more robust, these scenarios can be favorable over other scenarios. Even when these robust scenarios produce less desirable results on the accessibility indicators, they can play a role in the final approach for location-decisions that is developed.

The area of Cox's Bazar in Bangladesh, subject of the case study in this research, is prone to floods. Floods can cause facilities to be destroyed, or roads to become unusable. Floods are only one of the many reasons why a healthcare facility can get affected. The facility can become unreachable, get destroyed, become unsafe for healthcare workers to access, or impossible to supply. For this reason, the robustness of the system is researched. Throughout the experiments, the unused capacity is measured. This is the capacity of facilities that is not allocated to shelters. When combining this with the capacity shortage within facilities, an estimation can be made of the division of facilities over the camp. Also, the impact of a failing facility can be determined. When the unused capacity is very small, the system is not robust to cover for any malfunctioning facilities. Another indication for a low robustness is when the capacity shortage within facilities is high. This is a bad sign for two reasons. Firstly, because a high capacity shortage within facilities implies that many shelters prefer to turn to this facility. If this facility fails, the distance to the nearest facility will increase for all these shelters, which will reflect on the average travel distance. Secondly, if a communicable disease spreads among the group of refugees that are allocated to this facility, there will be insufficient capacity to treat all of them.

It is important to realize that the simulation model is a simplification of the real world, which changes the way in which the modeled environment is sensitive to impacts. The simplifying assumptions in this research therefore influence the extent to which the robustness of the model can be tested. For example, it is assumed that healthcare providers always have the ability to place new facilities in the model, regardless of limiting funds or government decisions. The only two limiting factors throughout the simulations are the availability of space and the fixed number of facilities that is placed simultaneously. If a flood would occur during the simulation, the model would correct itself by realizing two new facilities at the next assessment round. However, it is possible to get an idea of the resilience of the system.

Two methods are used to determine the resilience of the system. The first method is inspecting the model behavior when the usage of healthcare increases. The second method is comparison of the unused capacity and the capacity shortage in healthcare facilities throughout the simulations. The first method provides insight in how much the healthcare usage can increase, before the system can not handle the consultations anymore. The second method provides insight in the redundant capacity that could cover for a possible malfunctioning healthcare facility.

8.4.1. MODEL ROBUSTNESS FOR INCREASED HEALTHCARE USAGE

As described in section 7.4.3, increasing the chance of getting sick leads to a higher number of consultations at healthcare facilities. It should be noted that these results are based on only one replication of each run and therefore the implications should be checked with multiple replications before being taken for granted.

The only effect due to an increased chance of getting sick is found in the number of waiting patients. Figure 8.13 summarizes the number of waiting patients throughout the simulation from time step 10 onward in a box plot. The numbers on the x-axis are the chance for a shelter in the model to become sick, which is scaled to the number of consultations per 100 households as explained in appendix B.2.2. The first time steps are excluded, because the restriction on the number of facilities that can be placed simultaneously results in very high numbers of waiting patients in the beginning of the simulation. Three findings can be derived from this plot. The first thing that occurs, is that a lower chance of getting sick also results in a lower number of waiting patients, which indicates that there is sufficient capacity among all healthcare facilities in the model. The second finding applies to the situation where the chance of getting sick equals 0,4156. The capacity in the healthcare facilities is then insufficient, which leads to an increase of the number of waiting patients of more than 20% and is thereby larger than the initial increase in the chance of getting sick. The third observation that can be retrieved from this plot, is that the future models have a lower average number of waiting patients which is due to the larger number of facilities throughout the simulations, as it is suitable for a larger population.

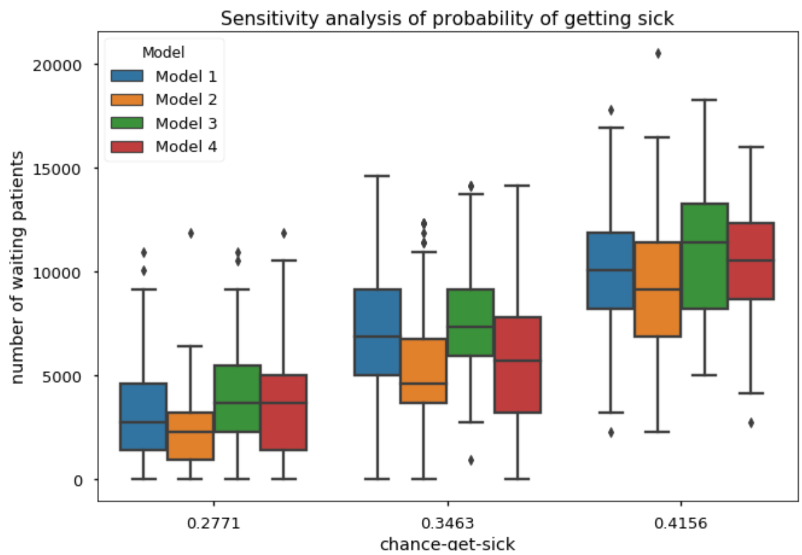

Figure8.13: Higher chance of getting sick results in higher number of waiting patients

These numbers indicate that the robustness of the model is very limited. For example, consider an epidemic spreading through the camp environment. An epidemic might increase the number of people who require healthcare with more than 20%, whereas it appears that an increase of only 20% is already more than the system can cover for. The healthcare system would fail to treat all refugees in need in that case. When future predictions are used to determine the need for healthcare facilities, the system is more robust for future situations. This is simply due to the fact that a larger number of facilities is realized. In some cases this results in an extra facility and therefore also a higher redundancy of capacity.

8.4.2. HEALTHCARE ROBUSTNESS IN TERMS OF OVERCAPACITY

When the unused capacity is high, this indicates that there is capacity within the existing facilities, that is not allocated to refugees. Ideally, this is low, as this indicates that the spread of facilities over the camp is equal, and most capacity is allocated to refugees. Surprisingly, in both the models that allow predictions about future camp expansion (models 2 and 4), a low unused capacity occurs for almost all refugee preference combinations. In model 3, the unused capacity is never low, as long as the preference for proximity to roads equals 1. In model 1, the unused capacity is never low when the preference for proximity to healthcare facilities equals ten. These findings for models 1 and 3 have no implication on the findings from the previous section, as both these preferences are not found to lead to high accessibility.

In the models that do include future predictions, combinations are found where the unused capacity is very high (over 30.000, which corresponds to capacity for 65 shelters in the model), while the coverage ratio is also low (below 0,7). This means, that there is capacity in facilities to cover for minimally 26% of the population[2], which is not used. This indicates that the spread of the healthcare facilities over the camp is very unsuccessful. In model 4 this is found for every combination of refugee preferences, except when the preference to settle close to neighbors equals ten. In model 2, there is not a particular preference that excludes this situation. In models 1 and 3, that do not take future camp expansion into consideration, this combination of high unused capacity with a low coverage does not occur. Moreover, throughout the simulations in model 3, the unused capacity never exceeds 25.000.

Together with the findings in the previous subsection, these findings imply that the robustness of the modeled healthcare system is limited. However, the conclusions regarding the robustness should first be sustained by running multiple replications. Thereafter, the possibilities to expand the capacity within existing facilities should be researched, which can be applied as a measure to increase the resilience of the system.

8.4.3. UNSUCCESSFUL SPATIAL DIVISION OF HEALTHCARE FACILITIES IN MODEL 4

Another example of unsuccessful division of healthcare facilities over the camp is found during particular simulation runs in model 4. Model 4 applies an optimization algorithm that aims to maximize the coverage ratio, and includes predictions about future camp expansion in the optimization. In some simulation runs with this model, the simulation stopped because the optimization algorithm returned an error. Inspection of the runs for which this occurred, shows that these experiments return an error because all shelters are covered by a facility. Hence, no new optimal location for a facility can be determined. This means that 100% coverage is reached. Figure 8.14 shows an example of the NetLogo environment at the moment such an error occurred. It can be seen that the locations of the healthcare facilities are not optimal, as for many shelters the distance is still very far. Moreover, the average distance between shelters and healthcare facilities at this moment equals more than 330 meters. Although this is below the threshold of 400 meters, this is very high in comparison to the results in other simulations. However, every shelter is connected to a healthcare facility, and the capacity is divided equally, assuring coverage for all shelters.

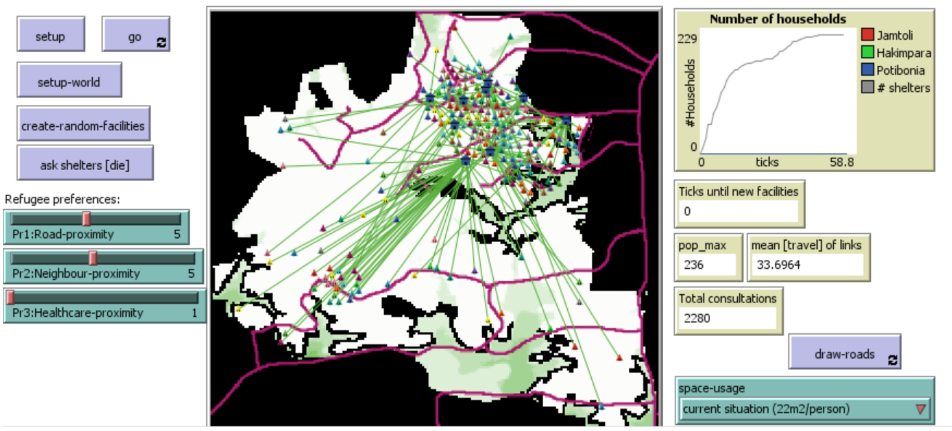

Figure8.14: NetLogo interface at the moment 100% coverage is reached, showing a non-optimal division of facilities over the camp environment

[2]The maximum population in the model is 242 shelters. 65 shelters is 26,6% of this maximum number. Since the occurrences are found throughout the simulation, this percentage of the population that could be covered by this unused capacity is even higher.

8.5. OVERALL COMPARISON OF FACILITY LOCATION ALGORITHMS

From the robustness, the findings about the best scenarios are supported. Also, there is a slight preference for models 3 and 4. They are very successful at reaching coverage. However, model 4 also leads to bad average distance results.

The previous sections have analyzed how refugees adapt their settling choices, how healthcare providers can adapt facility location decisions to the settling preferences of refugees, and what the resulting accessibility of healthcare facilities is. Moreover, in section 8.3 it was found that two combinations of refugee preferences are most successful in realizing a maximal accessibility of healthcare facilities for all refugees. These combinations contain either a refugee preference for settling close to shelters equal to 10, or a preference for settling close to shelters and close to roads equal to ten. In both combinations, the preference for settling close to healthcare facilities equals 1.
These preferences shape the best performing scenarios in respectively model 3 and model 2. However, in a real refugee camp situation, it can be difficult to assess the settling preferences of refugees exactly. Therefore, the effect of small adaptations in the above-mentioned scenarios are tested throughout the four models. Four different comparisons are mode across the models. The first comparison shows the results for all models, when the space requirement equals 22m^2 per person, and a high refugee preference to settle close to other shelters is known, while the other preferences are unknown. Figure 8.15 shows the results. Figure 8.16 shows the results across the four models with the same refugee preferences, but with a space requirement equal to 45m^2 per person. Then, figures 8.17 and 8.18 show the comparison among the four models when the refugee preferences for settling close to other shelters and for settling close to roads both equal 10, while the preference to settle close to healthcare facilities is undefined. Figure 8.17 applies a space restriction of 22m^2 per person, while figure 8.18 applies a space restriction of 45m^2 per person.

DETERMINING THE PREFERRED OPTIMIZATION ALGORITHM

Models 1 and 2 apply an algorithm that minimizes the average travel distance, while models 3 and 4 apply an algorithm that maximizes the coverage ratio. Models 2 and 4 allow healthcare providers to use predictions about future camp expansion in their optimizations.

Interestingly, it is found that in most scenarios, the results across models 1 and 3 and across models 2 and 4 are rather comparable. Also, an average distance below 400 meters is guaranteed in every model. A coverage ratio above 0,8 is not secured in every scenario.

When a space restriction of 45m^2 per person is applied, the accessibility indicators improve significantly in all four models. Surprisingly, models 1 and 2 generate higher results for the average coverage ratio with this restriction than models 3 and 4. This is interesting, because models 1 and 2 apply an optimization algorithm that is not focused on maximizing coverage, but is focused on minimizing the average distance. On the contrary, the optimization algorithm in models 3 and 4 is focused on minimizing the average coverage ratio, but this does not reflect on the results. Also the indicator for the capacity shortage in facilities shows bigger improvements in models 1 and 2, when space requirements are raised.

Combining all the findings, two conclusions are drawn. These conclusions are used to determine the approach for locating healthcare facilities, which is explained in the next section. The conclusions are as follows:

> **Conclusion 1:**
> An optimization algorithm that aims to minimize the average distance between shelters and healthcare facilities can most effectively maximize the accessibility of healthcare facilities.

> **Conclusion 2:**
> Applying a space restriction of 45m^2 improves the accessibility of healthcare facilities.

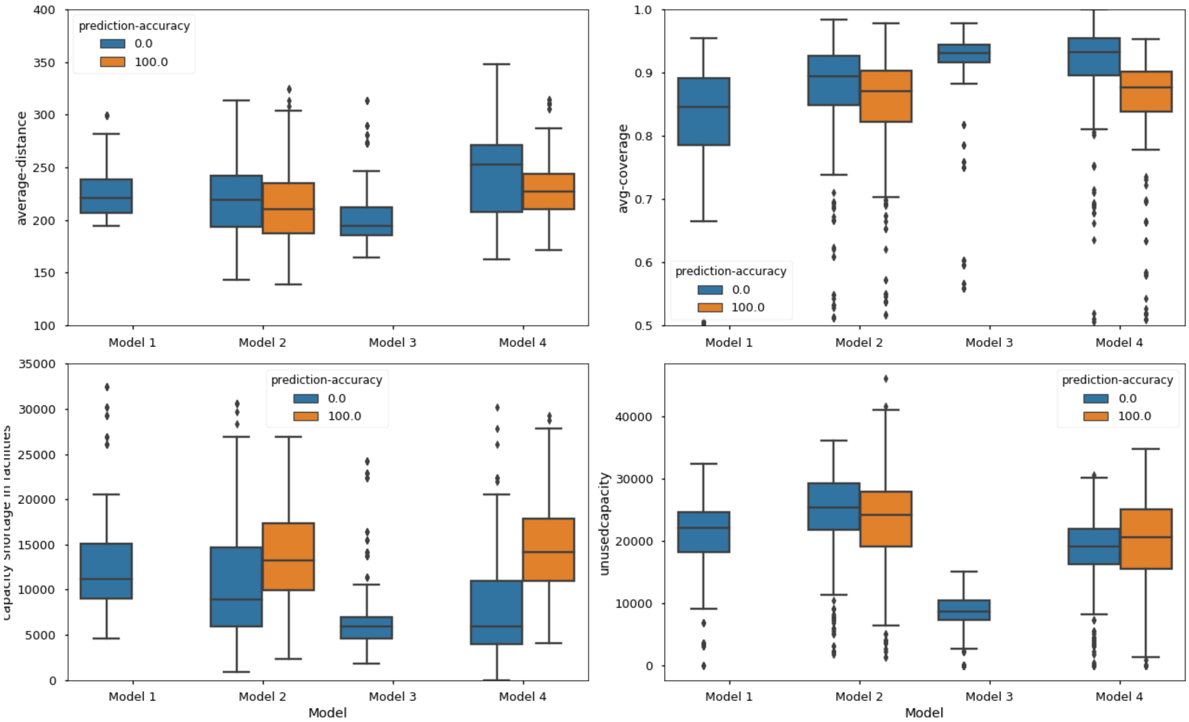

Figure8.15: Results across all four models when the space restriction equals 22m^2 and refugee preference to settle close to other shelters is fixed at 10

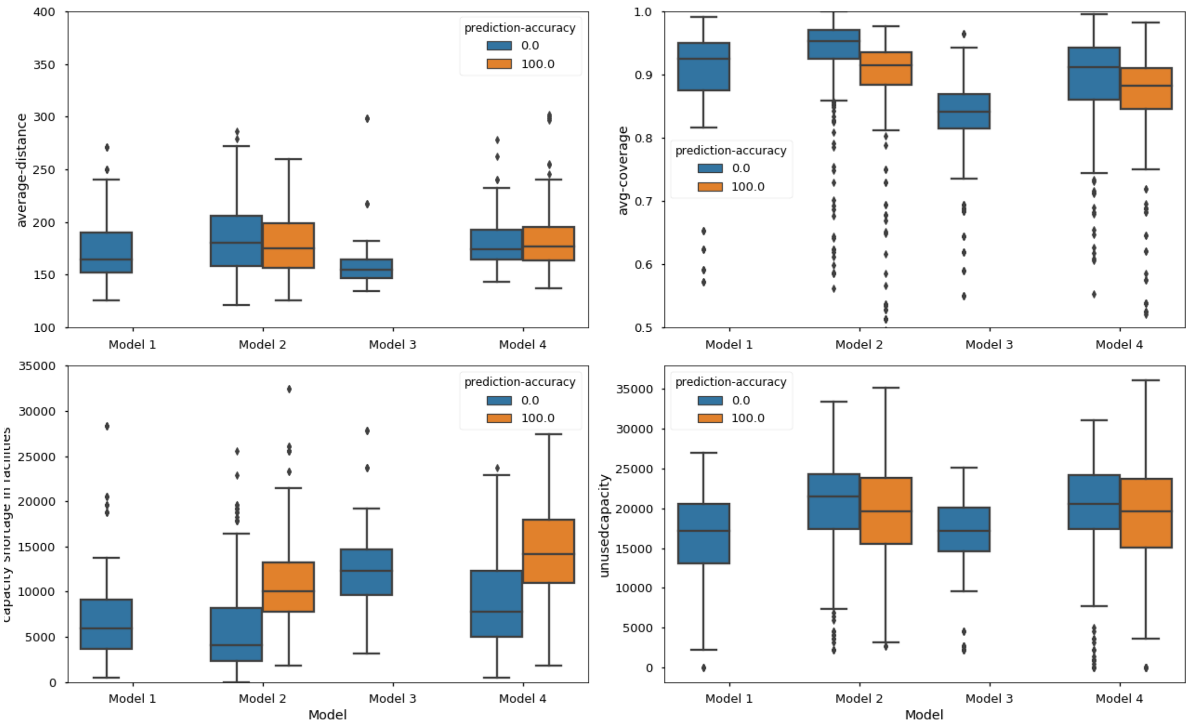

Figure8.16: A higher space restriction (45m^2) improves the results of most indicators across all models, while the refugee preference to settle close to other shelters is fixed at 10

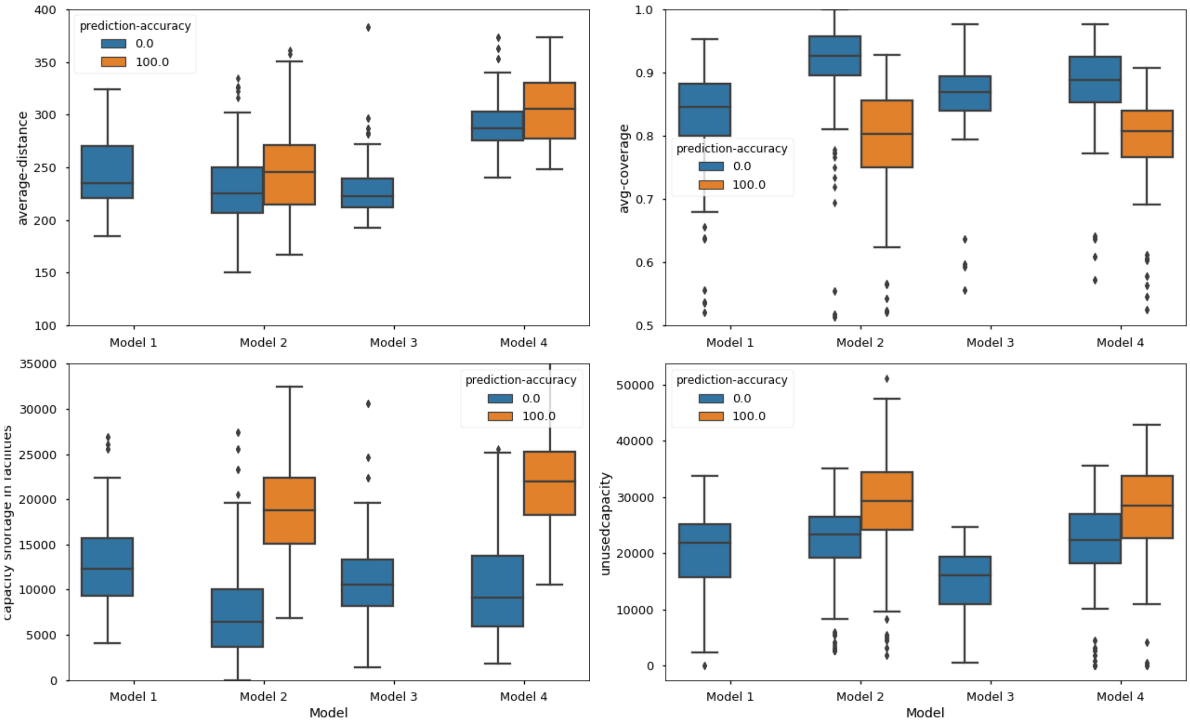

Figure8.17: Results across all four models when the space restriction equals 22m^2 and refugee preference to settle close to roads and to other shelters are fixed at 10

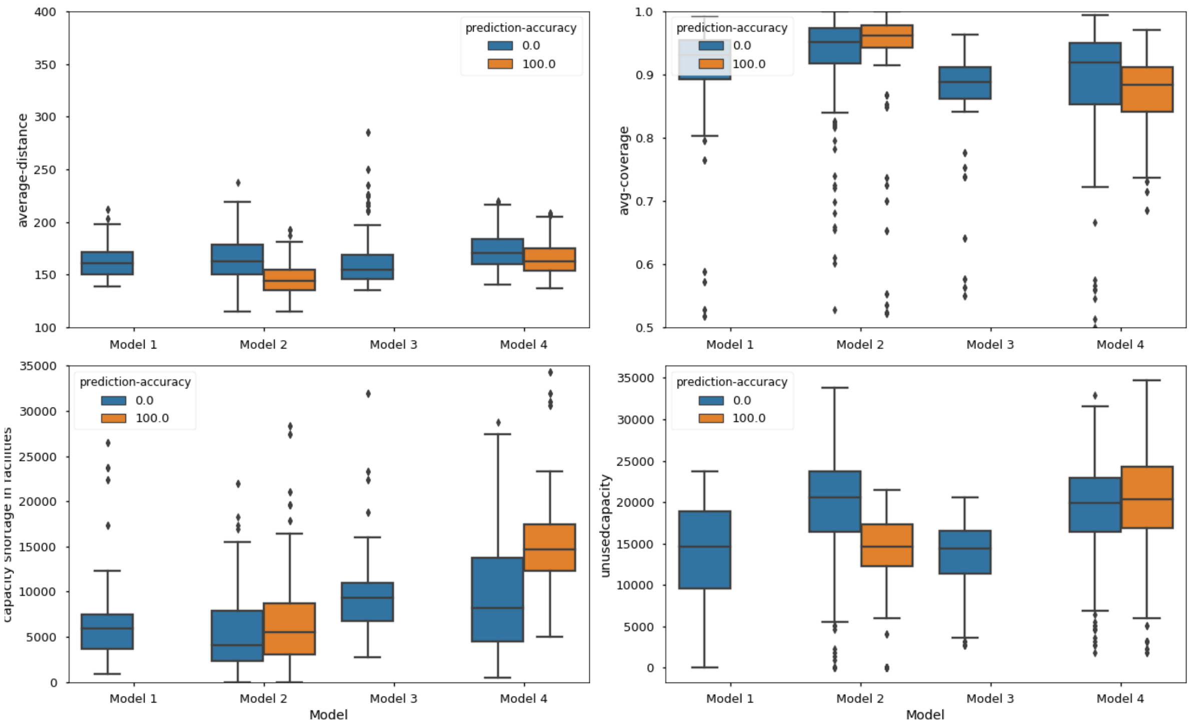

Figure8.18: A higher space restriction (45m^2) improves the results of most indicators across all models, while the refugee preference to settle close to roads and to other shelters are fixed at 10

8.6. TRANSLATING THE FINDINGS INTO AN APPROACH FOR HEALTHCARE PROVIDERS

The previous sections discussed the emergence of new shelters and healthcare facilities in expanding refugee camps. Section 8.1 discussed how refugees adapt their settling choices to the locations of healthcare facilities, which are determined by healthcare providers. In section 8.2, the effect of refugee preferences on the location decisions of healthcare providers is researched. Hereby, it came forward that the impact of settling choices by refugees, as defined in section 8.1, can be recognized in the effectiveness of locations decisions by healthcare providers. These two identified impacts can reinforce each other or mitigate each other's effect. In most cases however, the accessibility of healthcare in the camp is found to improve when refugees and healthcare providers have the possibility to adapt their decisions to each other. This is discussed in section 8.3. The robustness of the model outcomes is discussed in section 8.4. The question remains how these findings can be captured in an approach that can assist healthcare providers in future decision-making on healthcare facility locations. As Anderson et al. state "The purpose of the analysis is to determine leverage points in complex systems on which to base policy decisions," (Anderson et al., 2007, p. 333). Therefore, this section discusses how the results from the previous sections can be generalized into an approach.

8.6.1. KEY FINDINGS FOR IN THE APPROACH

The most important findings in this chapter, were highlighted in special boxes. These boxes contained the following findings:

1. Increased attention for spatial dispersion of shelters over the camp environment improves the ability of refugees to adapt their settling decisions successfully.

2. When healthcare facilities are located with the aim to maximize coverage of all shelters, refugees that prefer to settle close to neighbors can successfully adapt their settling choices.

3. Healthcare providers can adapt their facility location decisions that are designed to minimize the distance between shelters and facilities to settling choices of refugees. When refugees are focused on spatial dispersion of shelters over the camp, this adaptation most successfully increases the accessibility of healthcare facilities.

4. When using an algorithm to maximize coverage of shelters, healthcare providers can not successfully adapt their location decisions to refugee preferences, given a strong refugee preference for either settling close to other shelters or close to healthcare facilities.

5. When using an algorithm that aims to minimize the average distance between shelters and facilities, healthcare providers can mostly successful adapt their location decisions to the settling preferences of refugees.

6. When using an algorithm that aims to maximize coverage of shelters, healthcare providers are mostly not able to adapt their location decisions successfully to the settling preferences of refugees. An exception arises when refugees strongly prefer to settle close to roads.

Besides these key findings, two conclusions are drawn from the comparison between the four models. These conclusions are the following:

1. Applying a space restriction of 45m^2 improves the accessibility of healthcare facilities.

2. An optimization algorithm that aims to minimize the average distance between shelters can most effectively maximize the accessibility of healthcare facilities.

Combining these findings has led to an approach which consists of two main steps. First, a proper assessment of the camp situation is needed. This is explained in section 8.6.2. Then, the optimal location can be determined, for which the steps are explained in section 8.6.2.

8.6.2. DEVELOPED APPROACH FOR DECISION-MAKING ON HEALTHCARE FACILITY LOCATIONS

This section describes the approach that is developed, applying the knowledge that is gained through this research. The approach is developed for healthcare providers, who need to locate new healthcare facilities. Following this approach, they can optimize the locations of healthcare facilities. This means that on average:

- Every refugee is located within 400 meters of a healthcare facility.
- At least 80% of the refugees is allocated to a healthcare facility with sufficient capacity.
- Capacity shortage in facilities is minimized.
- Unused capacity of facilities is minimized.

Before the optimal locations of healthcare facilities can be determined, an assessment of the camp and the refugees within the camp is needed. This is explained in section 8.6.2. Section 8.6.2 continues with elaborating upon the location optimization. This is visualized in figure 8.19, which schematically shows the approach that is found most optimal for healthcare providers when locating new healthcare facilities.

1. ASSESSING THE SITUATION

First, the situation must be assessed, which comprises of gaining information about four aspects. First, the extent to which refugees can choose their own location. Secondly, determine the accessibility aspect that requires improvement the most. Thirdly, the refugee preferences regarding a location to settle. Fourth, understand the way information about facilities is spread through the camp.

Starting off, it must be determined whether refugees are choosing shelter locations, or whether they are getting assigned to a location. If a reception centre is set up, the refugees register at the reception centre, receive an identification card and get allocated to specific sites within the camp (Interview D, 2019). Usually, it takes a couple of weeks or months before a reception centre is set up in an emerging camp. Until that time, the preferences of refugees will determine the location where they settle. To what extent they can live up to their preferences, of course strongly depends on the information that the refugees have. For example, without knowing where all healthcare facilities are, they cannot make a proper consideration of where to settle close to these facilities. Typically, a reception centre is where refugees obtain information.

When space requirements are strict (according to SPHERE standards), it is found most desirable when refugees also focus on settling close to roads. This is interesting, as both conditions enlarge the spatial dispersion of refugee shelters over the camp. This implies that the accessibility of healthcare facilities can be enlarged when there remains space between shelters for healthcare facilities. If a reception centre is operating, it is up to the reception centre to ensure a proper spread of refugees when allocating them to sites in the camp.

When refugees are not allocated, but choose a location themselves, they choose a location depending on their preferences. The moment the refugees arrive in a refugee camp, they have mostly endured a difficult travel of multiple days and are mostly looking for comfort. They can find this comfort with people who have a similar background, share the same values and understand what they have experienced. Therefore, the preference for refugees to settle close to other refugees is usually strong. It became evident from the model results in this research that this preference results in settling choices that are usually beneficial for the accessibility of healthcare throughout the camp.

Refugees mostly rely on each other for information, as the diffusion of information via other channels can be limited due to language barriers. It is therefore important to deduce how much information refugees obtain and to what extent they are aware of healthcare facilities when they are choosing a location to settle. Only with full knowledge about the present facilities will they be able to take this into consideration while choosing a location to settle. Therefore, the second question is to what extent the refugees have information about the presence of healthcare facilities.

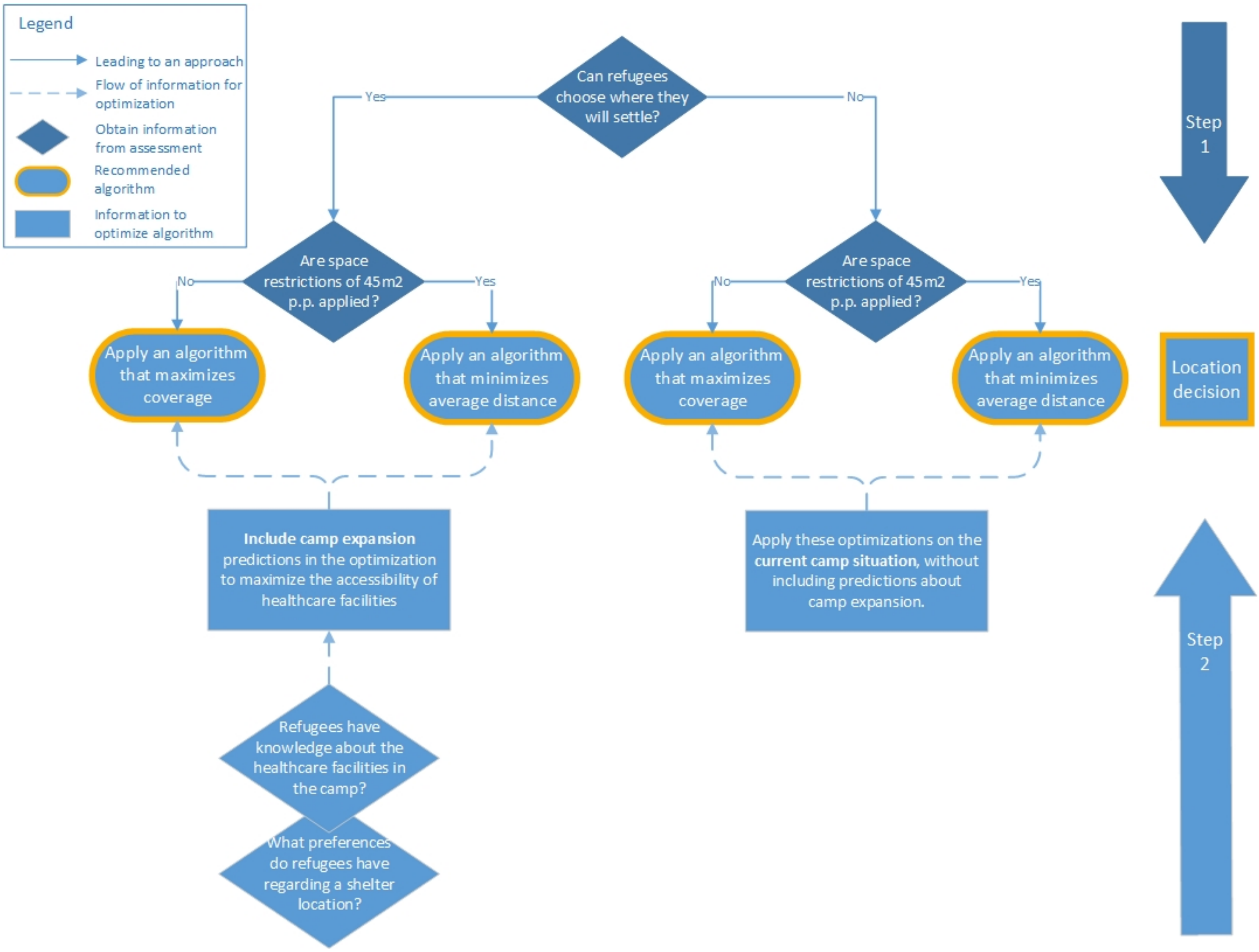

Figure8.19: Recommended approach for locating healthcare facilities.

2. DETERMINING THE OPTIMAL LOCATIONS

According to the information that is gathered in the first step, an algorithm is recommended. This can be found by walking through the dark blue diamonds in figure 8.19, starting from the top. This effectiveness of the algorithm can be optimized, using information about the settling preferences of refugees and how much information the refugees have. This is shown in light blue in figure 8.19.

When refugees are not able to choose their own settling location, there is no benefit in including predictions about future camp expansion in the optimization. When refugees can choose their own settling location, there is a benefit in using predictions about future camp expansion. Refugees can often successfully adapt their settling choices to the presence of healthcare facilities. To make the predictions as realistic as possible, it is necessary to know the preferences of the refugees regarding shelter locations. Secondly, it is necessary to know whether they have full knowledge about the healthcare facilities in the camp. Without this knowledge, their settling choices will differ and their ability to adapt their settling choices to the presence of healthcare facilities will also decrease. It is therefore important to ensure that knowledge about all healthcare facilities and the services provided in the facilities are communicated well, so that the usage will be optimal. This communication does not only concern the refugees in the camp, but also other healthcare providers or aid organizations to prevent that redundant facilities are getting created.

Again, it should be stressed that the accessibility of healthcare facilities is maximized when space restrictions of $45m^2$ per person are applied. The most desirable path in figure 8.19, is the path that leads to the middle left algorithm. This means that refugees can choose where they can settle, and space restrictions of $45m^2$ per person are applied. When these conditions are met and a location optimization algorithm is applied that aims to minimize the average travel distance between shelters and healthcare facilities, the accessibility of healthcare facilities is maximized.

An essential challenge lies at convincing the host government of plans for new healthcare facilities. Host governments must consent with plans for any type of facilities, before these can be realized. It is therefore important to convince this party of the benefits of the usefulness of the approach and, in some cases, the use of accounting for future camp expansion. This is something that governments not always approve of (Interview A, 2019).

9
Discussion

This chapter discusses the model and the results shown in previous chapters. In this research, the expansion of a refugee camp and the facilities within is researched using a combination of an agent-based simulation model and an optimization algorithm in Python. The model is developed based on a case study of three Rohingya refugee camps in Cox's Bazar, Bangladesh. The study and the model have limitations, which are caused by the simplifications and assumptions that had to be made. These limitations are important to discuss.

Section 9.1 describes the limitations of the research, divided into the most critical assumptions underlying the model, followed by other limiting implications. The last part of this section discusses further limitations of the research method, that affect the results. Section 9.2 then discusses the implications of these limitations for use of the model results. This is split up into implications for researchers and implications for policy makers regarding healthcare facilities in refugee camps.

9.1. Model discussion

A model can be used to study a particular phenomenon or process, as it can recreate a simplified version of reality, that can be run multiple times under varying parameter settings. To research a phenomenon, a researcher must focus on the core processes and components, and make simplifying assumptions to implement these in a model. Taking every detail into consideration is simply too broad, turning a research into a lifelong project. Besides a lifetime to build such a detailed model, it would also take a long time to run the model, which undermines its usefulness. The critical assumptions that are made in this research are discussed in the following section.

9.1.1. Critical assumptions

A number of assumptions has been made throughout this research. The most critical assumptions get discussed here. A full list of assumptions can be found in appendix E. It should be noted that also during the parameter setting process, assumptions have been made, which are described in appendix B.

The first critical assumption is that refugees in the model are assumed to be a homogeneous group. As Goodchild (1979) states, the usage of aggregated data can influence the results heavily, but is necessary to save server capacity. This is applied to the refugee group by not distinguishing between genders or age groups. This is an important limitation, as the type of healthcare that people need can be strongly gender-related. Moreover, for the Rohingya refugee population, this has proven to be a big issue, especially when considering antenatal care, as explained in section 2.2. Since the refugees are modeled as shelters, representing one hundred households, the healthcare usage is heavily influenced by the average numbers that are used as input for the chance of needing healthcare. It is important to bear this in mind, as this means that the results are more aggregated as well and show less variation in the results. Especially the robustness of the model behavior can be influenced negatively when more variation in the usage of healthcare is included. There is also no distinction made between different types of healthcare facilities in the model. In reality, there are many different types of facilities, starting with primary and secondary healthcare facilities, smaller health posts, or more specialized care. Since all facilities are assumed to be equal, the healthcare consultations have been piled and averaged as well, leaving out the specialized care. This means that the number of consultations per facility in reality may show stronger deviations.

A second important assumption is made in the definition of accessibility in the model. It is assumed that a distance of 40 patches in the model is the maximum acceptable distance between shelters and healthcare facilities, as this corresponds to approximately 400 meters. However, this distance is rather unrealistic, because it is measured as the crow flies and ignores any elevation differences or objects on its way. Although it is based on real assessments, the relative distances will be very different in reality.

Thirdly, it is assumed that all actors have full knowledge about the environment and all other actors in the environment. This is a strong assumption, as in reality refugees have very limited knowledge about the camp and all other people and facilities in the camps upon arrival. Moreover, even after assessments in the camps, healthcare providers will never have full knowledge about the camps. This already becomes evident from the numerous deviations between similar assessments performed by NGOs in Cox's Bazar during the same time period. Optimizations are more effective when the input is complete, rather than incomplete. Therefore, the efficiency that is obtained in this model might be unrealistic to obtain in reality.

The fourth important assumption lies in the structure of the algorithms. The way the algorithms are designed, determines largely what their result will be. The algorithms and their limitations are discussed in the model narrative B.1. An important part of the structure is the placement of two facilities simultaneously in models 1 and 2, when applying the algorithm that minimizes the average distance between shelters and healthcare facilities. This may lead to less efficient locating decisions than placing one facility at a time when demand has increased. However, it can be argued that this inefficiency is closer to reality. It has appeared that the construction and placement of facilities by various healthcare providers in Cox's Bazar was not coordinated well. Especially during the early expansion phase of the camps, many facilities were created simultaneously as the need was very high. This resulted in a chaotic placement of too many facilities. Therefore, the rationalization of healthcare facilities was started in 2018, during which the number of healthcare facilities was reduced (Interview B, 2019). In the model, most facilities are placed in the beginning of the run time as well, this can be said to resemble the real expansion.

9.1.2. MODEL LIMITATIONS

The model is constructed in NetLogo, a tool that can create agent-based models. The model is set up by loading in geographical data about camps 14, 15 and 16. The NetLogo environment divides the modeled area in patches. Therefore, the geographical data is simplified to a field of 200*200 patches. The road network is drafted in the environment, but is only used by refugees while choosing a location to settle. It is acknowledged that roads are expected to increase the travel speed, but this is not implemented in the model. The NetLogo environment is not designed for usage of optimization algorithms. Therefore, the model is connected to the Python environment for executing the optimizations. However, this connection increases the computational time, as Python has to read the

NetLogo variables, optimize and push the results back to NetLogo every four ticks. It was not possible to run multiple experiments on a single computer, so the experiments are run on a cluster. This brought new challenges, because there was no example of this type of experiments on the cluster yet. Once the experiments could be set up successfully, it was chosen to run many experiments at once. The number of iterations in experiments and analyzing results is limited because of this.

The model creates a visual representation of the camps, which is very useful for validating the model behavior and communicating the model logic. However, this also slows the run time down a lot. Using a more abstract representation of the camp and the actions and interactions within the camp could improve the run-time while still researching the same behavior.

Limitations in optimization algorithms

Another limitation is the choice of the algorithms. The choice for the algorithms is made after thorough desk research, and the choice to use two different algorithms makes it possible to compare the results of the different algorithms. The results showed that the choice of the algorithm indeed has an important impact on the results, sometimes with surprising results. This makes one wonder what effect the implementation of different optimization algorithms would have on the results. The use of patches in the NetLogo environment make it impossible to use continuous optimizations. Furthermore, the algorithms are drafted such that the set of possible locations consists only of certain shelter locations. The design of the optimization algorithm that maximizes the coverage ratio of shelters also contains a limitation. It aims at maximizing the coverage for all uncovered shelters and thereby ignores the locations of shelters that are already covered, although these might switch to a new facility once it is located. The decision for this simplification is made because of the aim to maximize the number of uncovered shelters within the maximum acceptable radius. Lastly, the optimizations in the future scenarios where the prediction accuracy is not 100% are a bit off compared to the other optimizations. This lies in the fact that also in these optimizations the possible facility locations are determined by the set of shelter locations where availability of the location is bigger than 0. However, this fails to exclude the shelters that are a mere prediction and will disappear after the optimization step.

The optimization algorithms resemble the locating decisions of healthcare providers. In the current model, their locating decisions are shaped by the settling preferences of refugees. In reality, healthcare providers also have preferences regarding their facility locations. For example, they have a strong preference to locate a facility close to roads, to make it easier for staff and supplies to reach facilities, but also for refugees who might be limited in their movement to reach the facilities safely. When this preference is taken into account as well, the locating decisions of the healthcare providers might change, leading to a different interplay effect.

Limited prediction ability

The implementation of future predictions in the model is also limited. In the agent-based model, the prediction is implemented by pausing the tick-counter, and proceeding the placement of shelters, using the same logic as usual. It is, however, unable to include the emergent pattern of the refugee settling choices in the predicted future expansion, corrected for the placement of new facilities. Instead of looking at the pattern of camp expansion over the last time period, it predicts the camp expansion according to agents' behavioral rules for settling in the model. It is found that the emergent behavior is not just a sum of its components and interactions, but rather a product of the components and interactions. Therefore, the prediction is limited. Also, in experiments where the prediction accuracy equals 100%, this only refers to the locations of the number of predicted shelters. The number is not predicted, so when the actual number of new shelters becomes larger than the number of predicted shelters, the prediction accuracy becomes 0% for these shelters.

9.1.3. REFLECTION ON RESEARCH APPROACH

The choice for usage of a simulation model is part of the research design. The research design contains several limitations as well, which are often the result of trade-offs between more realistic research results and time. The choice for an agent-based approach is made for two reasons. The first reason is the gap that was identified in the literature review. This gap identified a lack of attention for the settling preferences of refugees in expanding refugee camps, in combination with the presence of healthcare facilities. The second reason to use an agent-based approach, is the desire to contribute to a humanitarian crisis, by focusing on the humans within and the interest in human behavior. However, translating human behavior into behavioral rules and quantifying these is very difficult, especially when studying the choices of a population that lives in such different conditions from the researcher. Moreover, one of the first people that was approached for this research, a person with experience in refugee camps, stated that he did not expect this research approach to be successful at all. However, many other people did support it and were interested to know whether an agent-based approach could be successful or not. Interviews are included in the research design, to obtain information from people that have seen the settling process of refugees. However, the interviewed people are all aid workers, not refugees themselves, and also their understanding of the drivers of specific decisions of refugees is limited. Unfortunately, it was not possible to go to Bangladesh and talk to refugees in person, or distribute a questionnaire among a group of refugees. However, the interviews were found to be very inspiring and encouraged the researcher to continue with this research.

This research focused on the interaction between healthcare facility locations and settling choices and healthcare usage of refugees in expanding refugee camps. Focusing only on one type of facilities is a fundamental limitation. This excludes all settling preferences that are linked to other types of facilities or environmental aspects. However, if similar research would be performed for other types of facilities within refugee camps, the results could possibly be combined into a larger model in which the interplays between all types of facilities and refugee settling choices could be combined.

9.2. IMPLICATIONS OF THE RESULTS

The simplifications and assumptions that are made in this research can lead to model results that deviate from results that would be obtained in reality. It is therefore important to reflect on the value of the results from this research. The practical implication of the findings are discussed for two different stakeholders. In section 9.2.1, the implications for policy makers are discussed. Section 9.2.2 discusses the implications for researchers. Each section describes the practical implications, but also highlights findings that are interesting, but require additional research before they can be applied.

9.2.1. IMPLICATIONS FOR POLICY MAKERS

Facility location optimizations are known to be successful for increasing the accessibility of the facilities for the intended users. This research confirmed that the usage of facility location optimizations for healthcare facilities can be successfully applied in refugee camps. Moreover, this research found that it is possible to apply facility location optimizations in refugee camps that are still expanding.

Also, it is found that taking future camp expansion into account in these optimizations can improve the effectiveness of the facility location decisions. This is an important finding for healthcare providers, as they have limited funds and therefore want to reach a maximum effect with their aid. This finding can also be helpful to convince other stakeholders of the need to develop a new healthcare facility, even though the current number of healthcare facilities is sufficient to cover for all shelters.

Another important implication, is the positive effect on the accessibility of healthcare facilities, when refugee shelters are not clustered densely together, but are spread over the refugee camp. If refugee shelters are densely clustered together, the possibility to place facilities in optimal locations disappears. This research sustains the importance of following the SPHERE guidelines, that require $45m^2$ per person. This significantly improves the accessibility of healthcare facilities for all refugees. The focus on spatial dispersion of shelters of the camps is found to improve the accessibility of healthcare facilities, regardless of the settling preferences of refugees.

A combination of three findings implies that location optimization approach that is developed in this research can also be used to locate other types of facilities. The first reason is that a strong preference among refugees to settle close to healthcare facilities does not improve the accessibility of healthcare facilities. This indicates that the positive results of the simulations in this research are due to preferences that are not specific for any type of facility. The second reason is that the spatial dispersion of shelters over the camp is found to have the most significant impact on the accessibility of healthcare facilities. This is also not linked to a specific characteristic of a healthcare facility, showing that the methods used in this research are also valid for other types of facilities. Finally, preferences of healthcare providers were not included in this model. Therefore, the optimizations might as well have been performed by another type of aid provider.

However, the conclusion that the location optimizations can be applied to other types of facilities needs to be verified by additional studies, before it can be applied. Characteristics of other types of facilities will be different as well, such as the number of refugees it should serve. Also, some facilities need to be placed in a certain environment. For example, a water point might require certain conditions from a location. However, it is plausible that also the locations of water points can be optimized using an optimization algorithm, if the specific conditions are added to the optimization algorithms as constraints.

Lastly, it is expected that the developed approach can be applied in other refugee camps as well. This research used three Rohingya refugee camps in Cox's Bazar as a case study, so the findings are tailored to this case study. However, there are only three characteristics of these camps that could have an important impact on the model outcomes. These are the environment of the camps, the population size, and the homogeneous character of the Rohingya. The characteristics of the camp environment were limited to elevation differences and the main road network, both in simplified form. Therefore, it is expected that this specific combination had little influence on the results. The population size in the model mimics the population size in the Rohingya camps over time. However, the population in the model is strongly aggregated. Therefore, it is not expected that this exact number influences the results. Moreover, simulations with a bigger population size showed that similar or even more preferable results can be obtained when the population size is much higher. The assumption that the refugees have the same preferences is derived from the homogeneous character of the Rohingya population. However, the preferences that are used are not specific for the Rohingya, and are mentioned in literature for many other refugee populations. Finally, this research determined an approach to determine locations for healthcare facilities in camps that are expanding. However, the results imply that this approach is also suitable for camps that are not expanding anymore. This is concluded from the finding that facility locations can best be determined without taking future camp expansion into account, when refugees do not choose a place to settle. In other words, when refugees cannot adapt their settling choices to the presence of new healthcare facilities. This strongly resembles the characteristics of a refugee camp that is not expanding anymore. For these reasons, it is expected that the facility location approach to maximize accessibility of healthcare facilities can also be applied in other refugee camps.

IMPLICATIONS FOR POLICY MAKERS THAT REQUIRE ADDITIONAL RESEARCH

Another few findings occurred, which might lead to interesting implications. However, it is not possible to draw any conclusions about these findings yet. These findings are discussed briefly below.

From a robustness point of view it might be more interesting to place multiple smaller healthcare facilities instead of fewer larger facilities. The model results show that decreasing the initial capacity of healthcare facilities leads to a lower number of waiting patients. Moreover, if one facility then fails, the impact will be smaller. A downside of a larger number of facilities is that it requires more movements to supply all facilities. However, this downside can be mitigated when combining the supply of multiple facilities in supply operation. The implications for the supply of the facilities could be studied using routing problems, for example. Furthermore, a larger number of smaller facilities might be more expensive, or bring along more administrative burdens, as for every facility a permission by the national government is required.

Besides, from the robustness tests, it was found that the ratio of 1 facility per 10.000 refugees is very sensitive to increasing demand for healthcare. This implies that a lowering this threshold would make the healthcare system in a refugee camp more robust. However, before this threshold is adapted, it is advised to perform robustness experiments to define what would be a desired threshold.

In this research, facility locations were determined using optimization algorithms. Preferences of healthcare providers regarding facility locations were not included. In real refugee camps, it is very likely that healthcare providers will have preferences regarding locations and might follow these preferences when determining optimal locations. As this research neglected the preferences of healthcare providers, it is unknown how this will affect the accessibility of healthcare facilities. It can not be assumed that refugees will adapt their settling choices successfully when facility locations are determined differently. There was already a difference between the effectiveness of refugees' choice adaptations in combination with the two optimization algorithms of healthcare providers. Therefore, the impact of healthcare preferences should be researched before using these preferences in the approach that is developed in this research.

This research has not distinguished between different types of healthcare facilities. However, in reality, there are many different types, with each different requirements regarding the amount of refugees they should cover. Also, when different types of healthcare facilities are distinguished, this can cause large deviations in the number of consultations per facility. Therefore, it is advised to first research the impact of distinguishing between types of healthcare facilities, before using the approach from this research on different types of healthcare facilities simultaneously. Nevertheless, the robustness tests in this research showed that it is possible to apply the optimization algorithms for healthcare facilities with different requirements. For example, simulations were successfully run with a higher or lower capacity of healthcare facilities and a higher or lower number of consultations. However, the approach is not developed to optimize locations for different types of healthcare facilities simultaneously.

Lastly, this research did not include changes to the environment. Examples of changes to the environment are the development of new roads or a natural impact, such as heavy rainfall that makes part of the camp unusable. It is found that a strong refugee preference to settle close to roads can lead to a higher accessibility of healthcare facilities. Typically, the road network in a refugee camp develops as the camp expands. Therefore, it would be interesting to research the impact of a developing road network, as this might impact the settling choices of refugees.

9.2.2. IMPLICATIONS FOR RESEARCHERS

This research aimed to approach the placement of facilities and expansion of a refugee camp from the perspective of refugees and their accessibility to healthcare. It remains difficult to translate the behavior of people into a model, and maybe even more difficult to verify these behavioral rules. However, this should not be a reason to simply leave out refugee behavior from the optimizations and use a top-down approach, as is often done. Moreover, this research showed that it is possible to use an agent-based approach to simulate the expansion of a refugee camp.

Also, it is shown that facility location optimizations can not only be applied to existing camps, but also to expanding camps. Furthermore, it is found that taking this expansion into account during the location optimizations, can be very useful to increase the accessibility of healthcare facilities for refugees.

Thereby, this research proves that it is possible to combine facility location planning with agent-based modeling. Moreover, this approach is found to be suitable to simulate locating healthcare facilities and how refugees adapt their settling choices to these healthcare facilities. It is also expected that this approach will be suitable to apply on other types of facilities in refugee camps as well.

IMPLICATIONS FOR RESEARCHERS THAT REQUIRE ADDITIONAL RESEARCH

A few other implications are found, that could lead to interesting findings, but first require more thorough research. These implications are discussed below.

This study used data in aggregated form. Before similar researches will be conducted, it is advised to determine the impact of using aggregated data. This can be done by repeating some experiments with a smaller aggregation level. One shelter in the simulation model of this research corresponds to 457 refugees in reality, which means that if there is one healthcare facility per 10.000 refugees, almost 5% of a facility's capacity is allocated to one shelter. Moreover, in terms of the number of patients a healthcare facility can help in one time step, one shelter occupies almost 25% of the total capacity. When a lower aggregation level is used, this percentage will be much lower. This is expected to decrease the fluctuations in the usage of healthcare facilities.

It would be interesting to extend the simulation model, by including the chance that an infectious disease develops and spreads through the camp. However, then it is even more important to know what the impact is of using aggregated data. The risk of getting infected for an agent increases when the number of agents increases that could possibly carry and transfer the disease. The impact of infection waves might therefore be bigger when the population is less aggregated. However, this effect should be researched before conclusions can be tied to this. Another aspect that might be affected strongly when the aggregation of the number of refugees is decreased, is found in the tipping points of when a new healthcare facility is needed. In the current model, one extra shelter can make the difference between sufficient healthcare capacity, or a shortage for 457 refugees. In reality, one more refugee will not cause such a big capacity shortage. It might be more difficult to convince governments of the need to realize an additional healthcare facility. However, the method for including expected future camp expansion might overcome this issue, as exceeding the threshold can be somewhat foreseen and acted upon beforehand.

The consequences of aggregating the healthcare facility types should also be researched before any of the models in this research is applied in real settlements. It will be key to divide the healthcare facilities such that the accessibility of different types of facilities is maximized for the refugees. This can be done using hierarchical modeling in the optimization models.

Furthermore, as this research showed that it is possible to account for refugee preferences while optimizing facility locations, it would be interesting to research the possibility of including preferences of healthcare providers as well. This might affect the outcomes of the facility location algorithms. As a result, the locations of healthcare facilities might be different. The refugees might react differently to this as well, since it is found that they adapt their settling choices differently in various situations. Therefore, it would be interesting to study two aspects regarding the preferences of healthcare providers. First, how these preferences influence the effectiveness of healthcare facility locations on the accessibility of healthcare facilities for refugees. Secondly, how refugees adapt their settling choices to these facility locations. Moreover, it would be very interesting to include the preference of healthcare providers to locate a facility closer to roads. This might lead to an increase of the accessibility of healthcare facilities, as it is found that this preference among refugees also has a positive effect.

Lastly, it would be interesting to dive one step further into the path-dependency of the emergent refugee camps. This research showed that refugees adapt their settling choices to the presence of healthcare facilities. Simultaneously, the facility locations were determined, based on the locations of refugee shelters. Therefore, the future location choices for both the shelters and the healthcare facilities depend on the preceding location choices. This is referred to as the path-dependent character of the emerging refugee camp. In this research, a shelter or healthcare facility can not be moved to another location anymore once it is located. This makes the path-dependent character of the simulation model even stronger. The analysis of the path-dependent character in this research is limited. Letting healthcare providers take future camp expansion into account while locating healthcare facilities, creates the opportunity for refugees to adapt their settling choices. This is something that the algorithms in this research do not take into account. In other words, they do not account for the consequences of the locating decisions made by healthcare providers. Therefore, the healthcare providers have a limited view on the results of their locating decisions regarding healthcare facilities. If the location optimization algorithms would account for the adapted settling choices of refugees, they will probably locate the healthcare facilities differently. Again, the refugees will adapt their settling choices to the locations of the healthcare facilities. This process of choice adaptations continues over time, so is difficult to capture fully in an optimization algorithm. However, it is expected that the effect of the choice adaptations become smaller as the number of reciprocal adaptations increases. Therefore, it would be interesting to research to what extent this reciprocal effect should be included in the optimization algorithms.

10

Conclusion

This chapter presents the conclusions and recommendations, based on the findings in this report. First, the research questions from chapter 1 are answered. Section 10.1 answers the main research question as presented in the first chapter. Section 10.2 presents the answers to the sub questions. Sections 10.3 and 10.4 reflect on the scientific and societal contribution of this research. This is followed by the relevance of this research through the lens of the EPA masters program in section 10.5. The chapter is concluded with suggestions for further research in section 10.6.

10.1. Answering the main research question

This research focused on answering the following main research question:

Which facility location approach maximizes the accessibility of healthcare facilities, taking into account the settling preferences of refugees in an expanding refugee camp?

This question was draft to address the knowledge gap that was found in researches regarding the expansion of refugee camps. So far, no research has been performed that studies the process of camp expansion from the perspective of the camp inhabitants: the refugees. The answer to the research question, based on the findings in this research, is formulated as follows:

In order to maximize the accessibility of healthcare facilities in expanding refugee camps, decision-makers should use an optimization algorithm to determine facility locations. The facility location optimization should take expected future camp expansion into account, in case refugees can choose their settling location upon arrival in a refugee camp. These camp expansion predictions must consider the settling preferences of refugees. However, in case the camp expansion is planned and refugees cannot choose their settling location, the inclusion of predictions is not recommended.

In case the camp is built up spatially, offering 45m^2 surface area per person[1], this optimization algorithm should aim to minimize the average distance between shelters and healthcare facilities. On the contrary, in case the surface area per person in the camp is limited, the optimization should aim to maximize coverage of shelters.

The accessibility of healthcare facilities is measured along four indicators. First, the average travel distance between shelters and healthcare facilities. Secondly, the ratio of shelters that is allocated to healthcare facilities with sufficient capacity to cover for this shelter. Thirdly, the capacity shortage in healthcare facilities in the refugee camp. Lastly, the ratio of waiting patients over the unused capacity, which provides insight about the equal spread of healthcare facilities over the refugee camp.

[1]According to SPHERE guidelines, 45m^2 of surface area is desired for each person in a refugee camp.

10.2. ANSWERING THE SUB QUESTIONS

Before the main research question was answered, several sub questions needed to be answered. The answers to these sub questions are discussed in this section.

1. What factors affect the settling choices of refugees and their healthcare-seeking behavior, from the moment of arrival in a refugee camp?
The settlement choices of refugees are mainly determined by their own preferences regarding a shelter location and the available terrain. The refugee preference to settle close to people with a similar background is found very important. Other important settling preferences are proximity to roads, which makes it easier to perform activities outside the camps, and proximity to facilities. Standards regarding the required space per person in a camp will influence the settling choices of refugees, although this depends on the enforcement of these standards throughout the camp.

Regarding the healthcare-seeking behavior, there is no reason for refugees not to use healthcare once they have knowledge of the availability thereof. However, getting accustomed to the availability of healthcare and developing trust in aid workers takes time for refugees who had no access to healthcare in the situation they fled. In case refugees require healthcare, they will visit the nearest facility.

2. How can a location optimization model for healthcare facilities in refugee camps be defined?
Two facility location models are proven to be suitable to maximize the accessibility of healthcare facilities in refugee camps. The accessibility of healthcare facilities is maximized when the average distance between shelters and healthcare facilities is minimized and the allocation of shelters to healthcare facilities maximizes the usage of each facility's capacity.

The first optimization model applies an algorithm that minimizes the average distance between shelters and healthcare facilities in a refugee camp. The second optimization model applies an algorithm that maximizes the share of shelters that is allocated to a facility with sufficient capacity to cover for this shelter. The optimizations use information from regular assessments about the number of shelters and their location in the refugee camp. Including predictions about camp expansion in the algorithms can improve the optimization results.

3. How can a conceptual model of refugee behavior when settling and using healthcare in an expanding refugee camp be made?
The modeled system must be suitable for researching the settling choices of refugees and location decisions for healthcare facilities in a refugee camp. The model should also capture the impact of these location decisions on the settling choices of refugees, and vice versa.

Key components of the system are the camp environment, specific characteristics of sites in the camp and the agents. The agents are the refugees and the healthcare providers. The system is subject to regulations regarding the required surface area per person.

Location optimization algorithms must be applicable in the model. The system performance is determined using the resulting accessibility of healthcare facilities. This is measured with four key performance indicators. Firstly, the average distance between healthcare facilities and shelters. Secondly, the coverage ratio of shelters. Thirdly, the capacity shortage within facilities. Fourthly, the ratio of waiting patients over the unused capacity of facilities. Finally, the system performance should be robust in future scenarios and in extreme scenarios, such as extreme camp expansion, the spread of an infectious disease or heavy rainfall during monsoon season.

4. How can the emergence of a refugee camp, and the facilities within, be explained with an agent-based model?
To explain the emergence of a refugee camp and the facilities within, the model must simulate three

processes. These processes are linked due to information exchange between them. The first process resembles the camp expansion that stems from refugee settling choices upon arrival in the refugee camps. The second process is the usage of capacity of the healthcare facilities, when refugees get sick. This is linked to the first process, as refugees prefer to visit the healthcare facility that is closest to their shelter location. The third process is locating new healthcare facilities in the camp. The last process uses information about the number of refugees and healthcare facilities in the camp, to determine whether new healthcare facilities are needed. This connects the third and the first process.

The number of agents in the model can be approximated using linear extrapolation between data points about the population size over time. The number of facilities is determined using the SPHERE standards that set the target at 1 facility per 10.000 refugees. The chance that a refugee gets sick is quantified by the number of consultations at healthcare facilities in the case-study over time. The locations of healthcare facilities are determined using optimization algorithms outside the agent-based simulation model, but are immediately applied in the simulation model.

5. How do settling choices of refugees affect, or are affected by, the locations of healthcare facilities?

This questions seeks an explanation for two different effects. First, the extent to which refugees adapt their settling choices to the locations of healthcare facilities in a refugee camp. Simultaneously it seeks to explain for the effect of the refugee settling choices on facility location decisions from healthcare providers. The settling choice of a refugee is based on its preference for proximity to healthcare facilities, roads and other shelters and the availability of elevated areas in the camp. Healthcare providers use an optimization algorithm to locate new healthcare facilities. This algorithm can be focused on minimizes the average distance between shelters and healthcare facilities, or on maximizing the coverage of shelters by healthcare facilities within maximal 400 meters as the crow flies.

For both agents, the success of their choice adaptations depends on the location optimization algorithm that the healthcare providers use. A choice adaptation is successful when it improves the accessibility of healthcare facilities for refugees in the refugee camp.

CHOICE ADAPTATIONS IN CASE FACILITIES ARE LOCATED TO MINIMIZE THE AVERAGE TRAVEL DISTANCE

In case healthcare providers locate facilities using an optimization algorithm that minimizes the average travel distance between shelters and healthcare facilities, refugees are not always capable of adapting their settling choices successfully. On the contrary healthcare providers can adapt their location decisions successfully to the settling preferences of refugees when using this algorithm.

Refugees are most successful in adapting their settling choices, when having a strong preference to settle close to roads and close to other shelters. This is explained by the resulting camp layout, where shelters are located along roads and neighboring each other. This leaves space to locate facilities in optimal locations. This finding also reflects in the positive impact on the accessibility of healthcare facilities when maintaining a standard of $45m^2$ of surface area per person.

Healthcare providers can adapt the healthcare facility location decisions by taking expected camp expansion into account when determining the optimal location for a healthcare facility. It is found that this leads to an increase of the accessibility of healthcare facilities, in case the optimization algorithm aims to minimize the average travel distance between shelters and healthcare facilities. This adaptation of the location decision leads to an increase of the accessibility of healthcare facilities in the refugee camp.

Interestingly, it is found that healthcare providers can not successfully adapt their locating decisions to the refugee preferences, when the refugee preference to settle close to roads is equals 5, while the preference to settle close to other shelters equals 1 (both preferences measured on a scale from 1 to 10). So except for these refugee preferences, can healthcare providers improve the accessibility of healthcare facilities in the refugee camp by adapting the location decisions to the expected settling choices of refugees.

CHOICE ADAPTATIONS IN CASE FACILITIES ARE LOCATED TO MAXIMIZE COVERAGE
In case healthcare providers use a location optimization algorithm that maximizes the coverage of shelters, it is found that refugees are mostly able to adapt their settling choices successfully. On the contrary, it is found that healthcare providers can mostly not successfully adapt their decisions to the settling choices of refugees when using such an optimization algorithm. Only when refugees have a strong preference to settle close to neighbors, can healthcare providers successfully adapt the location decisions for healthcare facilities. This corresponds to the finding that the application of this algorithm is more desirable than the other optimization algorithm, when there is no high standard for the required surface area per person in the camps.

CONCLUSIONS REGARDING REFUGEE SETTLING PREFERENCES AND FACILITY LOCATION OPTIMIZATIONS
Interestingly, the refugee preference to find a shelter location that is close to a healthcare facilities is found to have little to no influence on the average travel distance between shelters and healthcare facilities. This might stem from the fact that refugees have knowledge about all facility locations, but not about the available capacity at these facilities. In case a refugee gets sick, this might result in the need to turn to another healthcare facility that is further away.

It should be noted that healthcare providers have more knowledge than refugee agents throughout the simulation. Besides the locations of other facilities and shelters, they also know the coverage ratio of all shelters. Therefore, the decisions of healthcare providers have a stronger influence on the overall accessibility. However, they are also strongly influenced by the emergent settling choices of the refugees, as the healthcare facility locating decisions are solely based on the refugee settlements.

It is found that an optimization algorithm that aims to minimize the average distance between shelters and healthcare facilities, can most effectively maximize the accessibility of healthcare facilities in a refugee camp.

Lastly, it is found that maintaining a higher surface space requirement per person improves the accessibility of healthcare facilities.

6. How can the outcomes of this study be generalized into an approach for decision-making on healthcare facility locations in expanding refugee camps?
For future decision-making on healthcare facility locations in expanding refugee camp, an approach is developed to maximize the accessibility of healthcare facilities for refugees. This approach consists of three parts, which are visualized in figure 8.19 in chapter 8.

The first step is an assessment of the camp situation. This should provide an answer to two questions. The first question is whether refugees can choose their settling location. The second question is what space restrictions are applicable to the refugee camp. The answer to these questions determines which optimization algorithm is suitable to maximize the accessibility of healthcare facilities.

The second step is developing expectations about future camp expansion, to take into account during the location optimization. In order to develop these expectations, information about the settling preferences of refugees is required. In addition, it is important to know whether refugees have full knowledge about the locations of healthcare facilities and the shelters of other refugees in the camp. This determines to what extent they can follow their preferences when choosing a location to settle.

The third step is to apply the location optimization algorithm and locate the healthcare facilities. It is important to ensure that information about healthcare facilities is sufficiently available for all refugees. This enables refugees to turn to the nearest facility that has free capacity to treat them, in case they get sick.

An important implication that is found in this research, is the need for spatial division of shelters over the refugee camp. This is found to benefit the accessibility of healthcare facilities in all scenarios. Therefore, it is key to educate aid workers about this need. Subsequently, they can guide refugees in their settling choices, to improve the division of shelters over the camp. Other decision makers in the refugee camp should also support the spatial division of shelters and facilities over the camp. For example, by making various parts of the camp equally accessible by realizing a proper road network, as this encourages an equal spread of shelters over the refugee camp. A final important advice is to ensure that information is available for all agents, as much as possible.

10.3. SCIENTIFIC CONTRIBUTION

This thesis started by addressing the gap in existing literature regarding the usage of agent-based simulation techniques to explain the expansion of refugee camps. As described in section 1.2, much research has been done in exploring the motives and patterns of refugee migration, using agent-based simulation models. These researches describe the first part of the refugee problem, namely the reason behind migration and the macro migration patterns. This research showed that it is also possible to use agent-based simulation models to simulate the following step in the migration of refugees, being the settling process in refugee camps. It is shown that it is possible to simulate the expansion of refugee camps, based on the settling preferences of refugees. If this gets applied on a large scale for multiple refugee camps, this could be added to the former migration predictions. Together, this will not only predict migration patterns of refugees, but also how refugee camps will emerge. This would be useful for informing policy makers on how to anticipate for the emerging refugee camps.

It is found that the effectiveness of located facilities can be improved when optimizing their locations while taking future camp expansion into account. As this makes it possible to prepare the healthcare system in a refugee camp for future demand, it increases the robustness of the healthcare infrastructure. It is thereby proven that it is possible to apply facility location optimizations combine multiple objectives and properties, that have not been combined before. As shown in table 2.1, this research combined the objective of robustness with the objective of demand coverage and demand-weighted distance in a dynamic environment with facilities that have restricted capacities.

Also, this research combined the field of agent-based modeling with the field of facility location optimizations. This combination has not been found in existing literature yet. By combining the field of agent-based modeling with the field of facility location optimizations, it is found that the settling preferences of refugees affect the success of facility location optimizations. Similarly, it is found that facility locations affect the settling choices of refugees. This interplay between the refugee settling preferences and the facility location decisions can improve the effectiveness of healthcare facilities. However, it can also decrease the effectiveness of healthcare facilities. The successful combination of the field of agent-based modeling and facility location optimizations opens the door for research into the interplay between refugee settling choices and decision making about other types of facilities as well. Moreover, it is expected that this combined research method is also interesting in other fields of research where an emergent pattern can be linked to a facility location optimization.

10.4. SOCIETAL CONTRIBUTION

Refugee crises are challenges that span across multiple societies. The different aims and behaviors of all actors in and around the camp environment make the refugee camps complex systems. This makes it difficult to make an informed decision, that oversees the consequences. This research developed an approach for locating healthcare facilities in expanding refugee camps, while taking the effect on settling choices of refugees into account. This approach is developed to assist healthcare providers to make an informed decision about healthcare facility locations.

One of the main conclusions from this research is that the accessibility of healthcare facilities is significantly improved when strict space requirements are applied from the moment the camp started to develop. This space requirement corresponds to the guideline that is provided by the SPHERE handbook Sphere Association (2018). Therefore, this research sustains the importance of this guideline. This is especially interesting for refugee camps where the expansion is led by an organization. This organization can take the importance of this spatial restriction into account and thereby contribute to accessible facilities in the camp.

This research also concludes that the accessibility of healthcare can be improved effectively when healthcare providers include expectations about future camp expansion in their decision-making about locations for new healthcare facilities. This is very relevant, as this does not happen nowadays. As explained in 2.3, healthcare providers are often limited by the host country's government, who does not want to encourage the expansion of the refugee camps by providing good facilities. However, as this research shows, the effectiveness of the facilities can be significantly improved, which might lessen the number of needed facilities. This could be an argument to convince host governments to allow these predictions about future camp expansion. Moreover, in section 1.2 the need to use funds as efficient as possible is described. Therefore, if the effectiveness of healthcare facilities can be increased, this might decrease the overall number of healthcare facilities that is placed, thereby saving funds for other types of facilities or aid.

Lastly, if it is possible to perform this research that is specialized on healthcare facilities, it will also be possible to perform this research for other types of facilities. These researches might also succeed in developing an approach for locating other types of facilities. The different approaches could then be combined, to find implications that can be used in decision-making about future refugee camps to maximize the accessibility of all types of facilities.

10.5. RELEVANCE TO THE EPA MASTERS PROGRAM

In the EPA masters program a lot of attention is given to grand societal challenges. Performing analytical research that improves or support the quality of decision-making in the complex environment of these grand challenges is encouraged. It is thereby key to take the interests of all involved stakeholders into account, besides the interests of the decision-maker. This makes it a multi-actor system approach.

Refugees are an example of a vulnerable group of people, who have very little to no decision-making power. However, by their number, they have become a substantial group that requires attention from many different groups. For example, the government of the region they fled, the government of the host area, host communities and aid providers are all stakeholders that are involved in refugee crises. By applying simulation techniques, this research has combined the interests of the healthcare providers and the refugees to find an approach for decision-making that can systematically increase the effectiveness of facility location decisions in refugee camps. It thereby aims to contribute to the grand challenge of refugees worldwide. This is a challenge that concerns many societies. This research acknowledges the value of the ' way of thinking that is taught in the EPA masters program, by proving once again that simulation tools can be applied successfully to inform decision-making on societal challenges. Also, this research emphasizes the value including the interests of other actors, besides the policy makers. Moreover, it showed the importance of taking the preferences of the most vulnerable stakeholder in this grand challenge into account.

10.6. SUGGESTIONS FOR FURTHER RESEARCH

The fact that agent-based simulation has proven to be a suitable technique to study refugee camps, opens the path for more research using this approach, diving into other factors that might influence camp expansion, or could improve the accessibility to other types of facilities. Some suggestions for future research are discussed in this section. First, suggestions for improvement of this research are given. Then, some suggestions for research in related fields are given.

SUGGESTIONS FOR IMPROVEMENT

This research looked at the high-level emergence of the refugee camps, and used aggregate data about healthcare usage, assuming the refugee population to be a homogeneous group, not distinguishing between age or gender. It would be interesting to add these physical differences between people and zoom in on the healthcare-seeking behavior of refugees within the camps. For example, there are big differences between men and women regarding the healthcare usage. Female refuges are found to depend heavily on their male relatives. Therefore, access to female healthcare facilities does not always get the same attention as access for males (Khanlou, 2010). A higher rate of illiteracy and a bigger language barrier makes women less confident in seeking help regarding their health (Floyd & Sakellariou, 2017). When it comes to childcare, women take up a bigger role. Research among Burundian and Rwandese refugees in Tanzania by Rutta et al. (2005) indicated that for child illness parents will visit a healthcare immediately, instead of waiting a day or two. Related to this, is that women need labor rooms, which could be distinguished when a difference is made between different types of healthcare facilities. The number of women that give birth at home is astonishing, especially in informal settlements where women do not even get a home delivery kit (gloves, sheets and soap) (Ripoll, 2017). This indicates a need for more trust in, and availability of, labor rooms. There are more than a dozen different types of healthcare facilities in Cox's Bazar. However, a first differentiation between primary healthcare facilities that provide professional healthcare and have capacity to keep in-patients and secondary healthcare facilities that include hospitals and specialized care, would be an interesting start (Inter Sector Coordination Group, 2018a).

Secondly, different zones could be included in the model that represent spatial areas. The created simulation model studies three camps as being one, and optimizes for that. In reality, NGOs might consider one camp at a time while placing facilities. This would lead to different optimization results. In the same way, it would be interesting to apply the optimizations to a larger region, containing even more camps. This would make the simulation computationally more heavy, which means that the computational speed of the model should be improved first.

Because the average travel distance seems to increase the more importance refugees give to proximity to neighbors, it would be interesting to study the impact of increasing the number of agents in the model. If the effect is empowered when considering larger populations, this would be very positive, as in reality the number of 'agents' is much larger.

To make the results more realistic, an error margin could be applied to the accuracy of the assessments of the number of refugees and their coverage. While analyzing the assessment data of various actors, it was found that their results differ quite a lot, even during the same time period. However, it is desired to perform the optimizations based on proper assessments.

Furthermore, experimentation with the robustness of the system can easily be extended. For example, researching the system behavior in case an epidemic breaks out. Also, in the current model the chance of getting sick for a refugee is applied using a random normal distribution. This could be extended with a more comprehensive function, that increases the chance of getting sick when a neighbor or household member is sick. As mentioned in chapter 6, part of the robustness is the availability of supplies at the healthcare facilities. In this research, it is assumed that there is always a fixed amount of supplies available. However, in reality this might not be the case, as the process of supplying facilities in refugee camps is a whole other field of research on its own.

Lastly, it would be interesting to extend the locating decisions of the healthcare providers by including their preferences as well. Healthcare providers have a preference for setting up a facility close to roads, as this increases the ease of supplying the facility and improve access for staff and patients. Moreover, in an emergency situation this would make it easier to evacuate the patients and staff. Since it is found that a preference for proximity to roads among refugees is beneficial for the model outcomes in many simulations, it is interesting whether this gets strengthened or weakened when healthcare providers share this preference.

SUGGESTIONS FOR RELATED RESEARCH

It would be interesting to repeat this research for other types of facilities. By small adaptations to the model, this could be researched. If this results in clear patterns, these could be combined to make a more advanced simulation model of emerging refugee camps. Besides other types of facilities, distinguishing between different types of healthcare facilities could also be added. As identified in the literature review in chapter 2, it is possible to apply facility location optimizations for different types of healthcare facilities. There are different standards for different types of healthcare facilities. Not every type of facility has to satisfy a ratio of 1 facility per 10.000 refugees. Distinguishing between the healthcare facility types, would create a more realistic picture of the camp environment. When different types of facilities are included, the model can be extended by including referrals to other types of facilities. During interviews it came forward that the referral system in the refugee camps can be rather well organized and is therefore interesting to include in the model.

Other related research could be in the prediction methods. In this research, it was found that a larger number of shelters in the prediction leads to better results, compared to the results when using linear prediction. However, it is expected that this does not always hold, and that there will be an optimum. By slight modifications in the model, this optimum could be sought by varying the prediction method and the number of predicted shelters strategically.

Lastly, the travel distances in the simulation model are not realistic. It would be interesting to research whether a factor can be determined with which the obtained distances can be multiplied to approximate the real travel distances.

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Note: Check the reference list (some have both URL and doi, this might be too much!)

A

SUMMARY OF INTERVIEW FINDINGS

Following the request of several interviewees, their names are anonymized. A summary of the interviews is made, but not included for the same reason. For more information about the background of the interviewees, please refer to the author of this thesis.

B

MODEL SETUP AND PARAMETER SETTINGS

This appendix describes the model that is built to perform experiments to research the interplay between settling behavior of refugees upon arrival in a refugee camp and the decision-making of healthcare providers upon locations for new healthcare facilities within the camp. Three processes are simulated within the model. These are the process of camp expansion through settlement of new refugees, the healthcare usage by refugees that get sick, and the creation of new facilities in the camp. The processes are described in detail in chapter 5.2. Section B.1 describes the model build-up, after which section B.2 describes the determination of variables that are inserted in the model and not changed throughout the simulation, such as the number of consultations per refugee and the chance of getting sick.

B.1. MODEL NARRATIVE

The model is build-up in two major components. The first component is the agent-based model, that simulates the camp and the agents within. Here, the first two processes are defined. This component is built in NetLogo. The second component contains the optimization algorithms for allocation of new healthcare facilities and is used to direct the experiments. This component is built in Python. Subsection B.1.1 describes the first component, after which the optimization and the manner of experimentation is described in subsection B.1.2. A model narrative is used to explain the order of actions and processes. This narrative is only one step away from the programming language, which defines the model.

B.1.1. AGENT-BASED MODEL

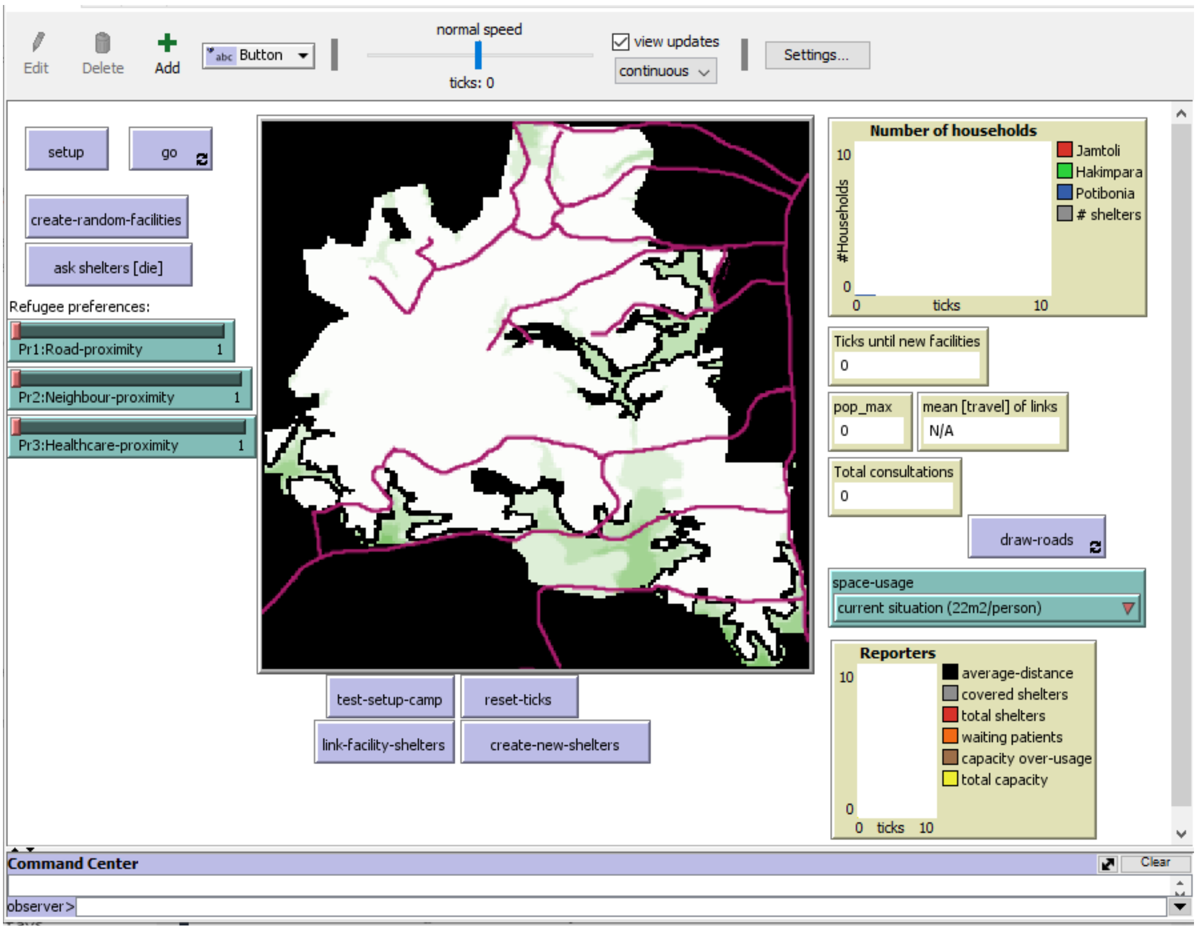
The agent-based model generates a visual outline of the refugee camps Hakimpara, Jamtoli and Potibonia in Cox's Bazar. The refugees behavior is defined within this model. Below, all processes are described in order of performance. First, the setup is described, followed by the refugees actions. When specific data is prepared before being used in the model, this is described in section B.2.

CREATING THE CAMP ENVIRONMENT

Figure B.1 shows the NetLogo interface with camp environment being loaded in. This is loaded in to the NetLogo model once in separate steps, after which the resulting NetLogo world is exported to be loaded in every time a new model run is initiated. The steps in creating the world are loading and reading the elevation data and drawing the roads. The road network is based on the network from the dashboard map that is maintained by the International Organization for Migration[1]. The steps are as follows:

[1] http://iom.maps.arcgis.com/apps/webappviewer/index.html?id=f5eef41ef81b4ee183c96085cbf60801

- Create the elevation:
  - Load the coordinate system in NetLogo, using a projection dataset.
  - Load the dataset that contains the elevation data about camps Hakimpara, Jamtoli and Potibonia in Cox's Bazar (data is retrieved from HDX[2]).
  - Color the **patches** accordingly to the range of values in the dataset.
- Draw the road network:
  - If the mouse is down, and there is no drawer yet, a drawer is created as a pen.
  - The drawer follows the mouse.
  - When the mouse is lifted, the drawer becomes a tracer and raises the pen.
  - The tracer is removed.
- Export the world to a .png file and a file containing all information.



FigureB.1: NetLogo interface after world-setup

[2] https://data.humdata.org/dataset/bangladesh-contour-lines

SETUP THE MODEL

The model setup consists of two steps. First, the camp environment is read in with the command *setup-world*, after which the camp is initiated by creating the first shelters. This number is based on the number refugees that lived in the camp in September 2017, as the simulation aims to mimic the camp growth from September 2017 until June 2019.

- Set up the world by importing the world that is created before.
- Set up the world variables:
  - Ensure the counter equals zero.
  - Ensure the future-modus is off.
  - Determine the *space-usage* requirement, based on the space-variable that is determined in the experiment. In default this is 1, which corresponds. 22m^2 per person. The space-usage requirement determines the *radius* of patches that gets a lower availability when a shelter is located.
  - Let patches determine their availability through “patches-availability”.
  - Define the set *kansje*, which holds all patches that are not a road or black and have an elevation higher than 8,5m.
  - Let all patches in *kansje* determine the distance to a road and store this is in *distRoad*.
  - Initially, about 187 **shelters** are created.
  - The *initial-capacity* of facilities is determined at 22 (see B.2.2).
- Set up the camp population:
  - Create shelters using a random-normal distribution, based on the maximum population that is defined and a standard deviation of approximatly 10%.
  - Give them a shape, size, mark them as uncovered and healthy and “set-preferences” about their desired shelter location.
  - The first 60 shelters choose a random location that is available with the highest possible elevation.
  - Then, the shelters move to a location that minimizes their *location-utility* function and has at least one shelter in a distance of twice the defined radius.
  - Ask patches within 3 patches distance to set their availability to 0, set the availability of the patch at which the shelter is located equal to 0,5 (this makes it still a possible location for a facility).
- Patches-availability:
  - Initial availability is equal to *radius*.
  - The initial availability decreases when there is an elevation difference with a neighboring patch.
  - If there are shelters at this patch, decrease the availability accordingly.
- “Set-preferences” determines the importance shelter agents give to proximity to roads, neighbors and healthcare facilities on a scale from one to ten:
  - Determine the shelters-own variables: *distRoad-pref*, *distneighb-pref* and *distHF-pref*, using a random-normal distribution based on the variables determined in the experiment.

- Determine *location-utility* by minimizing the following formula:
  (distHF-pref∗distance to nearest healthcare facility)+(distRoad-pref∗distance to nearest road)−(distneighb-pref ∗ number of neighbors in 1,5 times the radius distance)

REALIZING HEALTHCARE FACILITIES IN NETLOGO

The location of **healthcare facilities** is determined using Python and described in section B.1.2, but the realization of this is done in NetLogo.

- Determine the need for facilities based on the number of shelters and facilities.
- Create facilities if needed and set their size, color and initial-capacity.
- All shelters that are not currently at a consult, or waiting for a consult, will determine again what their nearest facility is and "link-facility-shelters"
- Link-facility-shelters creates links between shelters and nearest healthcare facilities in order to determine the average distance and the coverage of shelters.
  - If shelters are *sick*, they maintain their existing link and give it a violet color.
  - Else, they remove the link and create a new one with the healthcare facility that is closest.
  - The link-length is determined and reported as *dist-HF*.
- Then, the coverage is determined:
  - The healthcare facilities are asked to determine the number of shelters that is linked to them.
  - The 22 closest shelters get a green link and gets the status of being *covered*, the rest is counted as *overcapacity*.

RUNNING THE MODEL

The "go" command can only be run when there is at least one healthcare facility in the model. Running the model initiates three core processes: creating new shelters, establishing links between shelters and facilities and consulting healthcare facilities when agents get sick.

- First, the number of shelters that should be created is determined, based on the maximum population (*pop_max*).
- "create-new-shelters"
- "link-facility-shelters"
- "use-health-facilities by shelters that are not a prediction"
  - If they are sick, they determine whether they remain sick, or get better. When they remain sick, nothing changes. If they get better:
    - ◇ If they were in consult, they release the capacity of the facility by subtracting one from the count of *in-consult* agents.
    - ◇ If they were a waiting-patient, they subtract one from the number of *waiting-patients* and pretend to have had a consult in the meantime, so add one to the number of consultations.
  - If they are not sick, they might become sick:
    - ◇ When becoming sick, the agent will visit a healthcare facility, using consultation space by adding one to the in-consult parameter and the total consultations count.

· If the facility they are already linked to has a free place for a consultation, the agent will go here and will add one to the in-consult number and the total count of consultations.

· If the facility has no place for a consultation, the agent will seek the nearest other facility with free consultation space and link to this facility and update the consultation variables here. Re-linking to another facility will initiate an update of the indicators about average distance and coverage.

· If all healthcare facilities are already fully using their consultation space, the sick agent will stay with its nearest healthcare facility and add one to the count of waiting patients.

- Return performance indicators: the *average-distance*, the number of shelters, the number of *waiting-patients*, the number of shelters in *overcapacity* at healthcare facilities, the *unused capacity* of facilities.

- Define the maximum population of the next time instance. This follows table B.1.

CREATING NEW SHELTERS

The manner of creating new shelters depends on the model settings. If future camp expansion gets predicted, this process deviates from the normal process.

- "Create-new-shelters"

- If future-modus is switched on:

  – First, remove all shelters from the past prediction (four ticks earlier) that are still present.

  – Count the number of shelters and if the *future-regression* switch is on, determine the number of shelters that will be predicted at this time instance by linear regression over the past four weeks. Else, set the number of *shelters_to_create* equal to 20.

  – Create the shelters, just like when setting up the camp population. Define *prediction* to 'true'.

- If future-modus is switched off:

  – If the current model uses future prediction, then check whether the prediction accuracy is 100%.

    ◇ If the prediction-accuracy is 100%, and there are still predicted shelters, ask these shelters to set their prediction status to 'False'.

    ◇ Else, create new shelters with the prediction status 'False'.

    ◇ If the number of shelters that should be created is smaller than one, all the predicted shelters will be removed.

  – If the current model does not use future prediction, create new shelters as while setting up the initial camp population.

Limitations:

- NetLogo goes from one shelter to the next, so if one shelter still has to determine its health status and become healthy, another shelter might already experience a lack of consult space.

B.1.2. OPTIMIZATION SCRIPTS IN PYTHON

The Python models are designed to completely control the experiments. The scripts can activate the NetLogo model, request information from the NetLogo model, perform the optimization algorithm, and send the optimization outcomes back to the NetLogo model. A separate algorithm is written for the P-median optimization and for the maximal covering optimization. To include the predictions about future camp expansion, these blocks are altered. First will be explained how the experiments are initiated. Then the optimization logic will be explained for each algorithm, after which the adaptions for the future models is explained.

STARTING UP THE NETLOGO MODEL AND DEFINING THE EXPERIMENTS

The NetLogo file must be in a predefined folder and the experiment setup is defined in an Excel file with a separate row containing each parameter setting for that particular experiment.

- Import the necessary packages to setup a connection with NetLogo (see appendix B)
  - Start NetLogo and load the model
  - Read the Excel file with the experiments
  - Define the random seed (throughout all experiments in this research, the random seed 42 is used. The second round of experiments to explore the model behavior, the random seed 8 is used).

RUNNING THE NORMAL MODELS (WITHOUT FUTURE PREDICTION)

Every four ticks an optimization is performed with one of the two algorithms. In between, the model results are recorded and saved. When the model has run 94 ticks, the results are exported to a .csv file. This gets initiated from a standard "run_simulation" command.

- Set the input parameters:
  - Command NetLogo to "setup-world"
  - Send the experiment settings to NetLogo, including the random-seed
  - Command NetLogo to "setup", which creates the initial camp
- Run the simulation once for every row in the experiments file
- Export the results to a .csv file

P-MEDIAN OPTIMIZATION

The P-median optimization is designed to minimize the demand-weighted average distance between shelters and healthcare facilities. Every 4 ticks, the optimization is performed. In between, the model results are recorded and saved.

- Read information from the NetLogo model:
  - Read the coordinates of shelters, whether their location is 'full' or still has available space and whether the shelter is allocated to a healthcare facility's capacity
  - Read the coordinates of facilities in the model
  - Store all this information in five dataframes:
    1. All shelters
    2. All uncovered shelters
    3. All facilities

4. All shelters with available space
5. All shelters and all facilities

- Determine the best facility location:
  - For every shelter in the model:
    - ◇ Calculate the distance to all possible facility locations by summing the squares of the horizontal and the vertical distances
    - ◇ Store this in a new data frame X
  - For every existing facility, determine the demand that gets allocated to this facilities in the following steps:
    - ◇ Sort the distances in X in ascending order
    - ◇ Select maximal 22 shelters are within a radius of 40 patches that will be allocated to this facility
    - ◇ Remove these shelters from X
  - Remove all facilities from X
  - Create a new data frame ('Y')
  - For every combination of two possible new facility locations:
    - ◇ For every shelter in X:
      - · Determine which of the two facilities minimizes the distance between this shelter and a healthcare facility
    - ◇ Determine the average distance across all shelters
    - ◇ Store this in Y
  - Sort the values in Y in ascending order
- If there is a shortage of facilities in the model (the threshold of 1 facility per 10.000 refugees is reached):
  - Command NetLogo to create 2 facilities
  - Retrieve the identities of the 2 newest facilities from NetLogo
  - Send these facilities to the locations in the top row of Y
- Update the availability of the patches where the facilities are located.
- Command NetLogo to 'link-facility-shelters'
- Proceed the model simulation for four time steps, while reporting the parameter settings and the model results at every time step.

MAXIMAL COVERING OPTIMIZATION

The maximal covering algorithm is designed to determine the best location for a new facility to maximize the coverage of all shelters that are not allocated to a healthcare facility yet. This optimizations is performed every 4 ticks. In between, the model results are recorded and saved.

- If the number of ticks is smaller than 7:
  - Set the number of facilities to create equal to 2
  - Perform the optimization once

- If the number of ticks is larger than 7, but smaller than 94:
  - Set the number of facilities to create equal to 1
  - Perform the optimization twice (the locations of shelters and facilities are read once more in between, to ensure that new facilities will not be located to close to each other or in the same location)

The optimization:

- Read information from the NetLogo model:
- Read the coordinates of shelters, whether their location is 'full' or still has available space and whether the shelter is allocated to a healthcare facility's capacity
- Read the coordinates of facilities in the model
- Store all this information in four dataframes:
  1. All shelters
  2. All uncovered shelters
  3. All shelters with available space
  4. All facilities
- Determine the best facility location:
  - For every uncovered shelter in the model,
    - ◇ Calculate the distance to all possible facility locations by summing the squares of the horizontal and the vertical distances
    - ◇ Store this in a new data frame 'X' with the possible facility locations as columns and the uncovered shelters in the rows.
  - Remove all the data rows that have a distance larger than 40 patches
  - Create a new data frame 'BestLocation'
  - For every column of X:
    - ◇ Sort the rows in X in ascending order
    - ◇ Count the number of rows that have a value below 1600 (the distances are still squared to save one computational step)
    - ◇ Store this number in 'BestLocation' for this particular facility location
  - Choose the facility location that has the largest number in 'BestLocation' (this can return more than one location):
    - ◇ If this number is larger than the number of facilities to create:
      - · Determine the distance between each of these facilities and the existing facilities
      - · Calculate the average of all these distances
      - · Choose the location that maximizes the average distance
- If there is a shortage of facilities in the model (the threshold of 1 facility per 10.000 refugees is reached):
  - Command NetLogo to create 1 or 2 facilities

  - Retrieve the identities of the 1 or 2 newest facilities from NetLogo
  - Send these facilities to the locations in the top row of Y

- Update the availability of the patches where the facilities are located.
- Command NetLogo to 'link-facility-shelters'
- Proceed the model simulation for four time steps, while reporting the parameter settings and the model results at every time step.

RUNNING A MODEL INCLUDING FUTURE EXPANSION

This model adds a few steps before and after the actual facility location optimization models, so is an extended version of the normal P-median optimization model or maximal covering model. This model uses a boolean 'future-modus' to determine when shelters are getting predicted. The narrative includes the main bullet points of the normal optimization and only explains the additional actions.

- Set 'future-modus' to True
- Create new shelters (NetLogo now creates predicted shelters, which will also affect the availability at locations)
- Perform the *P-median optimization* / *maximal covering optimization* and place new facility / facilities
- Ask the predicted shelters to reset the availability of their locations
- If prediction-accuracy is 100%, the predicted shelters must only remove their links
- If prediction accuracy is 0%, the predicted shelters are removed
- Set 'future-modus' to False
- Command NetLogo to 'link-facility-shelters'
- Proceed the model simulation for four time steps, while reporting the parameter settings and the model results at every time step.
- Set 'future-modus' to True
- Create new shelters (NetLogo now creates predicted shelters, which will also affect the availability at locations)
- *Perform the P-median optimization* and place two new facilities
- Ask the predicted shelters to reset the availability of their locations
- If prediction-accuracy is 100%, the predicted shelters must only remove their links
- If prediction accuracy is 0%, the predicted shelters are removed
- Set 'future-modus' to False
- Command NetLogo to 'link-facility-shelters'
- Proceed the model simulation for four time steps, while reporting the parameter settings and the model results at every time step.

B.2. QUANTIFICATION OF INPUT VARIABLES

B.2.1. THE NUMBER OF SHELTERS

The number of shelters in the model is derived from table 5.1 and translates to a maximum population in the model at fixed times, as shown in table B.1 below.

TableB.1: Maximum shelter population in the NetLogo model

Ticks	Maximum population
6	180
10	225
27	222
35	221
44	236
53	221
61	241
65	231
74	242
91	242

B.2.2. DETERMINING THE NUMBER OF HEALTHCARE CONSULTATIONS

USAGE OF HEALTHCARE SYSTEM

As described in 2.2 the Rohingya mostly faced very limited access to healthcare in Rakhine state and therefore had to get accustomed to healthcare in the camps in Cox's Bazar. Table B.2 shows the growth of the number of refugees and the number of healthcare facilities and consultations as reported by the health sector in Cox's Bazar (Health Sector, 2017a,b, 2018a,b,c,d,e, 2019a,b). It shows that the tendency to use healthcare has increased over time. This is visible in table B.2 which shows the cumulative number of healthcare consultations per 1000 refugees in Cox's Bazar over time. From this is derived, how much the tendency to use healthcare has grown over time. This growth is particularly strong towards the end of 2017, which can be explained by the fact that refugees get used to the healthcare availability and get more comfortable with it. Throughout 2018, a more steady increase is found, between 1,5 and 2. Towards 2019, the increase seems to stabilize around 1,2. However, this still indicates a significant growth in the number of consultations. Since the system should be able to cover for all demand, even in extreme situations, there is chosen to zoom in on the healthcare usage in 2019 (see table B.3). In 2019 we see a declining number of facilities. It is desirable that the modeled system can serve all refugees, also with the number of 2019. Therefore, there is zoomed in on the consultations in 2019, and an average tendency of healthcare usage is derived. This is done by dividing the average amount of consultations per week in 2019 by the total amount of refugees reported in the corresponding week. This results in an average of approximately 0.076 consultations per refugee per week. This number is then multiplied by 4,57, as this is the approximate number of people in one household in the model. This results in approximately 0,346 consults per household per week.

After these linkages are made and the results are recorded, the shelters that are not covered yet, get linked to a facility nearby, after which the over-capacity of these facilities gets recorded as well.

[3] This number is obtained from NPM 15 (International Organization for Migration, 2019c), which is counted differently and hence explains the deviating number.

TableB.2: Healthcare consultations over time
Data retrieved from Health Sector bulletins (Health Sector, 2017a,b, 2018a,b,c,d,e, 2019a,b)

Bulletin No.	Year	Months	No. Refugees (x1000)	No. Consultations (x1000)	Consultations per refugee	Growth of usage	No. Facilities
1	2017	oct-nov	830	653,755	0,787657		200
2	2017	nov-dec	867,5	1916,262	2,208948	2,804455	169
3	2018	jan-feb	900	1949,508	2,16612	0,980612	185
4	2018	feb-apr	883,5	NaN	NaN	NaN	192
5	2018	apr-jun	914,16	1876,908	2,05315	0,947847	203
6	2018	jun-sep	937	3387,92	3,61571	1,761054	262
7	2018	sep-dec	933	5702,467	6,111969	1,690393	212
8	2019	jan-mar	952,993	6417,31	6,733848	1,101748	212
9	2019	mar-may	942,517 [3]	7713,283	8,183707	1,215309	196

TableB.3: Healthcare consultations in 2019
Data retrieved from Bi-weekly situation reports by World Health Organisation (2019)

Date	Cumulative amount of consultations in 2019	New consultations	People	Number of reporting facilities
17/01/2019	130318	130318	908000	166
31/01/2019	316456	186138	909000	166
NaN	NaN	153212	910000	168
23/02/2019	622880	153212	911000	170
14/03/2019	776059	153179	911000	171
29/03/2019	922066	146007	911149	156
11/04/2019	984240	62174	911149	152
25/04/2019	1109719	125479	911149	153
09/05/2019	1251615	141896	911149	152
23/05/2019	1377554	125939	911359	152
09/06/2019	1571285	193731	911359	153
20/06/2019	1606669	35384	911359	153
04/07/2019	1756613	149944	912485	153
18/07/2019	1961816	205203	912485	149
01/08/2019	2117702	155886	912485	144
15/08/2019	2235428	117726	912485	149
29/08/2019	2317853	82425	911566	148
12/09/2019	2468035	150182	911566	154
26/09/2019	2621581	153546	911566	159

RATIO OF IN- AND OUT-PATIENTS AND HEALTHCARE FACILITY CAPACITY

The number ratio of in- and out-patients is 0,02104 (Médecins sans Frontières - USA, 2018). The capacity of facilities is determined at 22 shelters in the model, as the SPHERE standard requires 1 facility per 10.000 refugees. In the model, 1 shelter represents 457 refugees, hence 1 facility is required per 22 shelters.

B.2.3. SPACE REQUIREMENTS FOR SHELTERS IN SETTLEMENTS

According to SPHERE standards (Use sphere handbook, from page 237 onwards). Camps 14, 15 and 16 are located in Ukhia. The landscape of this area is far from ideal to host a refugee camp. In and around the camps, the soil is eroding and deteriorating and the possibilities to produce food are limited, even as access to sources of energy (UNHCR, 2019). The slopes in the surroundings are unstable, forcing people to live close to each other between the slopes (UNHCR, 2019). The refugees live in average densities of 21.72m^2 per person[3], although the international standard is 45m^2 per person (The Sphere Project, 2011; UNHCR, 2019). Camps 14, 15 and 16 are not the most densely populated camps in this region. Throughout Cox's Bazar, the average space is 18,76m^2 per person. UNHCR set a target for entire Coxs Bazar of 20m^2 per person (UNHCR, 2019).

Combining data about the surface of camps 14, 15 and 16 with the number of people that are living in the camps currently, the space per shelter in the model is determined as shown below:

$$\sum_s \mathrm{S} = s_{14} + s_{15} + s_{16} = 857.000 + 984.000 + 528.000 = 2370.000 \tag{B.1}$$

$$S_{hh} = \frac{S}{N} = \frac{2370.000}{24169} * 100 = 9804m^2 / \text{ household in the model} \tag{B.2}$$

$$\text{One patch resembles:} \frac{S}{x} = \frac{2370.000}{21801} = 108,69m^2 \tag{B.3}$$

$$x_h h \frac{9804}{108,69} = 90,2 \tag{B.4}$$

$$r = \frac{\sqrt{x_{hh}}}{\pi} = \frac{\sqrt{90,2}}{3,14} = 14,3 \text{patches} \tag{B.5}$$

Variables:
S = total camp surface
s_{14} =surface camp 14: 857.000 m^2
s_{15} =surface camp 15: 984.000 m^2
s_{16} =surface camp 16: 528.000 m^2
S_{hh} = area per household
N = number of households: 24169 households
x = number of patches that is within camp outline: 21801
$x_h h$ = number of patches per household
r = radius around 1 household in the model

[3]Derived from http://iom.maps.arcgis.com/

C

MODEL VERIFICATION

Verification of the model is done iteratively while creating the model. Following (Fairley, 1978), the verification is divided in two types: static verification and dynamic verification. The static verification is best performed using a structured code walk-through (Fairley, 1978; Xiang et al., 2005; Sargent, 2010). This is performed for both the NetLogo model and the Python model. The dynamic verification is performed using three basic techniques. First, the agent behavior is traced, followed by an inspection of the interactions between agents and the environment (Xiang et al., 2005; Sargent, 2010). Thirdly, the behavior of model output during the simulation is inspected graphically, which is called animation (Sargent, 2010). Finally, special attention is given to the validation of interactions between the NetLogo model and the Python model.

C.1. STATIC VERIFICATION

STRUCTURED CODE WALK-THROUGH

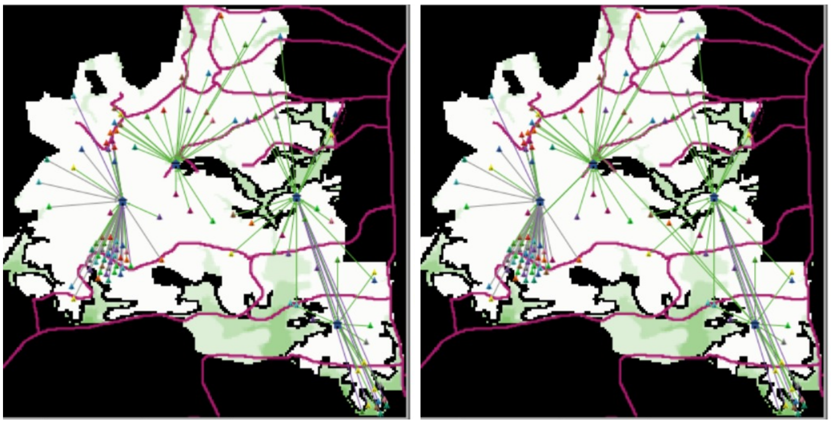
Throughout the NetLogo model development, new parts of code have been checked. Once the small parts behaved correctly, they were implemented in the entire code and made sure to function well. Commands that request information from attributes of different model components, or must adopt these attributes, were found to be prone for errors. This is partly due to the NetLogo environment, which limits the possibilities to read and adapt attributes of other components in the model. Implementing prediction in the NetLogo model resulted in the addition of many commands that should only be executed if parameter settings related to prediction have a certain value. Especially when the prediction accuracy is set to equal 100%, NetLogo must distinguish between shelters that are already settled and shelters that are only predictions. This resulted in many comparison statements, which are sensitive to mistakes. Once the model was finished, it is confirmed that all components and attributes from the formalization in section 5.1 are present in the model. Then, the attributes in the model were checked to confirm that there are no redundant attributes in the model. Then, all commands were checked and when multiple commands were initiated from another command, the order was checked to ensure that every reporter gets measured only when all other commands are executed.

C.2. DYNAMIC VERIFICATION

TRACING AGENT BEHAVIOR

The behavior of agents in the system is traced to verify that they show the right behavior, according to the behavioral rules. Upon creation, the shelters settle in the elevated areas. They link to the nearest healthcare facility. The links are green if the shelters fits within the initial capacity of the facility, or grey if this capacity is already full. When the health-status of a shelter changes to being sick, their link will get a purple color and if their current facility does not have patient capacity, the shelter links to another facility that does have a place at that moment C.1. In the next tick, depending on their updated health-status, they will re-assess which facility is closest by, or maintain their connection with the former facility if they are an in-patient. In-patient must stay overnight in the facility and therefore will not switch to another healthcare facility C.2.

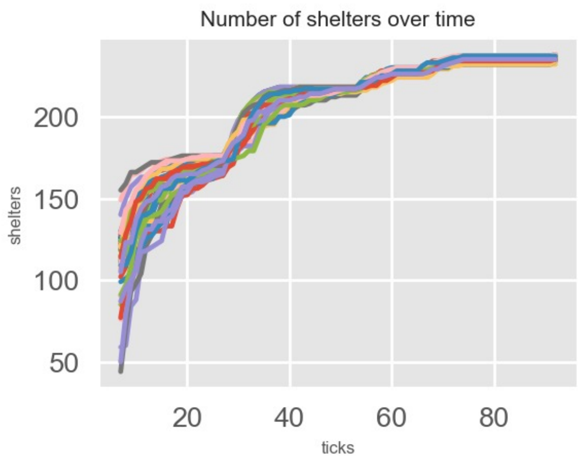
FigureC.1: Verifying agent behavior:
1) Shelters settle on elevated areas
2) Shelters link to closest facilities and color links correctly, they switch to available capacity if necessary



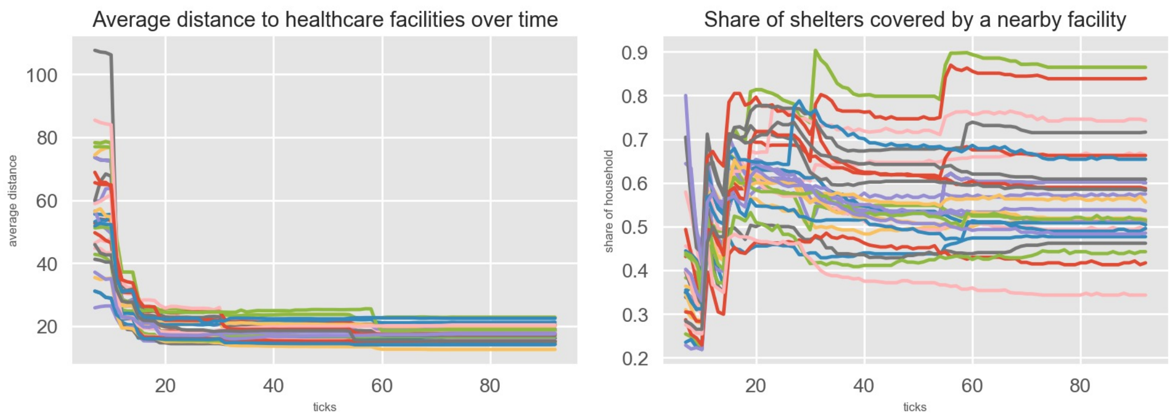
FigureC.2: Verifying agent behavior:
3) Shelters reconnect to nearest facility, but stay when they are currently helped.
4) Again, they switch to facilities with capacity if needed

ANIMATION

By visualizing the results of various model runs, it becomes evident that the model behaves as expected. Figures C.3 and C.4 show respectively the number of shelters in the model over time, the average length of the links between shelters and healthcare facilities over time and the share of shelters that is covered by facilities over time. The number of shelters converges to the maximum defines population, as predefined in the parameter settings. The average distance between healthcare facilities and shelters decreases fast with the creation of the first few facilities. It then shows slow increases, which can stem from the choice of refugees to go to another healthcare facility that has free capacity when the nearest facility is full. The share of shelters that is covered by healthcare facilities shows a peak every time new facilities are created and then slowly decreases as more shelters are created, but the threshold to build new facilities has not been exceeded yet.

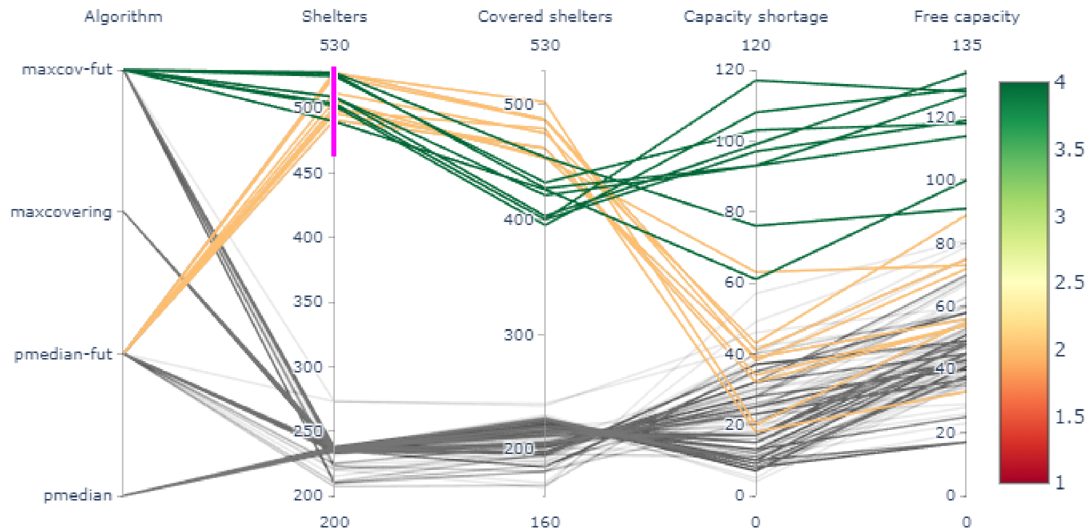


FigureC.3: Number of shelters throughout multiple simulations

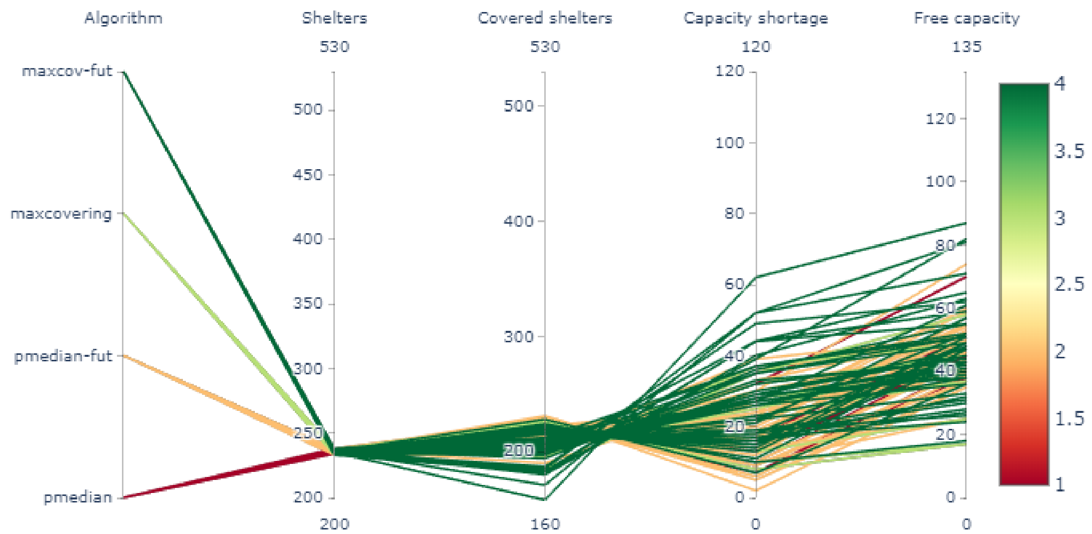


FigureC.4: (left) Average distance between shelters and facilities and (right) the coverage throughout multiple simulations

After running the first round of experiments. It was found that some experiments created way too many shelters. This can be seen in figure C.5 which shows that the number of shelters at the end of the first round of experiments went up to over 500 shelters. These high numbers come from algorithms that take into account the future camp expansion. By visual inspection of the data for the experiments that give these high results, it is found that it only happens in scenarios where the future-regression is off and the prediction-accuracy is 100. The mistake was found in the code and the new results look as shown in figure C.6.



FigureC.5: Results showing too many shelters



FigureC.6: Results showing normal numbers of shelters

VALIDATING PYTHON-NETLOGO INTERACTION

In the Python script, it was key to define all dataframes that store attribute values at the right moment. In iterative rounds, the correct way of setting up the optimizations was found. An example of such an iteration is given for setting up the P-median optimization. The P-median optimization reviews the distances for each shelter to the established and the to-be established healthcare facilities. To save computational time, it was first decided to optimize only for the so-called uncovered shelters (shelters that do not fit within the capacity of a healthcare facility within the maximum distance of 400 meters as the crow flies). In this optimization, the distance between these uncovered shelters and the new optional facility locations was minimized. The discrete set of possible facility locations was limited to a set of these uncovered shelters, since that would minimize the distance as a resulting distance equal to 0 for one shelters. However, this created unrealistic results, since the new facility could be closer to another shelter, which was already covered in the previous situation, but will now switch to using the new facility instead. Therefore, it was necessary to optimize for all shelters. However, this optimization would be incomplete, as it ignores the existing facilities. Finally, the optimization is set to include all shelters and all facilities, determine the shortest distance for each, and then remove all shelters that would be preferred to be covered within the capacity of one of the existing facilities. The resulting optimization is more realistic in a simulation that assumes full-knowledge of agents and does what it should: aiming to minimize the average demand-weighted travel distance.

D

RESULTING CAMP LAYOUT FOR DIFFERENT REFUGEE SETTLING PREFERENCES

The different refugee settling preferences that are used in the simulation model, result in different camp layouts. This appendix briefly discusses these different layouts according to two aspects. First, the settling choices of refugees. Second, the effect of the different location optimization approaches for healthcare facility locations. The simulations that are discussed in this appendix all applied a space requirement equal to 22m^2 per person. In the simulations, the optimization algorithms included predictions about future camp expansion in these simulations, without a predefined prediction accuracy. This means that both the healthcare providers and the refugees had the possibility to adapt their choices in these simulations.

STRONG PREFERENCE FOR SETTLING CLOSE TO OTHER SHELTERS

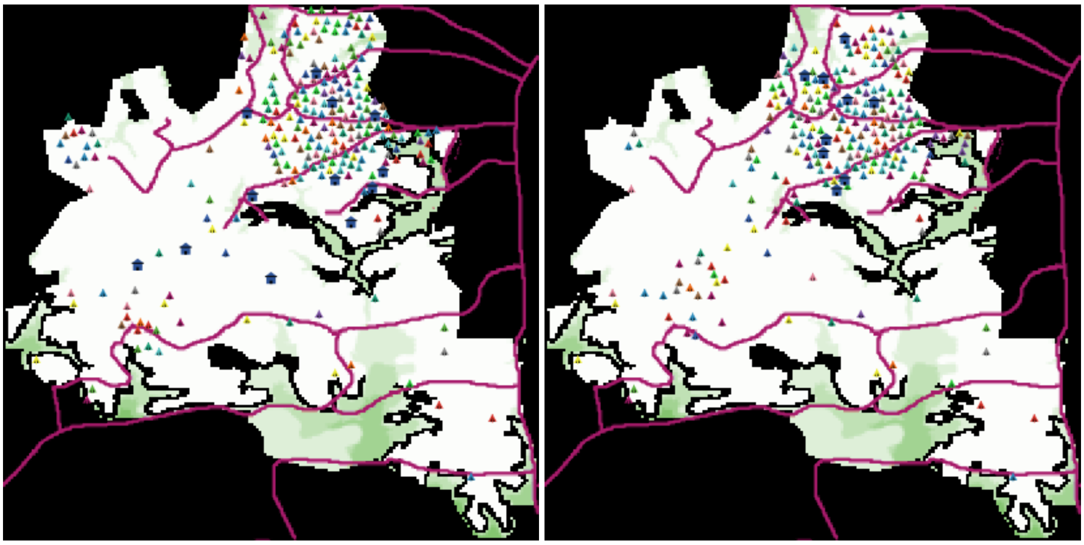
Figure D.1 shows the camp layout that results when refugees have a preference to settle close to other shelters equal to 10, while the preferences for settling close to roads and healthcare facilities are both equal to 1. Following these preferences, the refugees settle very densely together.

The figure on the right shows the end situation of the simulation that applied an algorithm that maximizes the coverage of shelters. It can be seen that the healthcare facilities are located in or on the edge of the cluster of shelters. As the number of facilities is sufficient to cover all shelters, the resulting coverage ratio can be high. However, it is also seen that the travel distance to healthcare facilities will be very long for the shelters that are located outside the cluster of shelters. The logic behind this model behavior is explained in section 8.4.3.

The figure on the left shows the camp layout at the end of the simulations that applied an algorithm that minimizes the average travel distance between shelters and healthcare facilities. Here, the healthcare facilities are more divided over the camp area. Therefore, they are easier to reach for shelters that are further away from the cluster of shelters.

STRONG PREFERENCE FOR SETTLING CLOSE TO HEALTHCARE FACILITIES

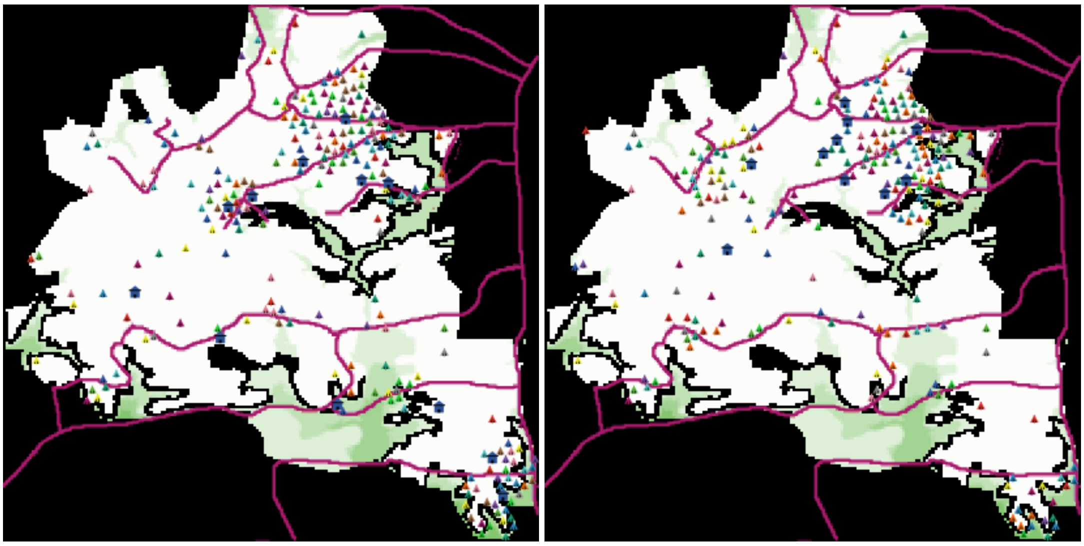
Figure D.2 shows the camp layout that results when refugees have a preference for settling close to healthcare facilities that equals 10, while the preferences for settling close to roads and other shelters are both equal to 1. The figure on the left shows the end situation of a simulation in model 2, that applies an algorithm that minimizes the average travel distance between shelters and healthcare facilities. The figure on the right the end situation of a simulation in model 4, that applies an optimization algorithm that maximizes the coverage ratio of shelters. Both simulation runs started with an identical camp layout. The first 60 shelters were located exactly the same. Because of the different algorithms, the healthcare facilities were located differently. While having the same settling preferences, this leads to different settling choices of refugees. This becomes evident when



FigureD.1: Simulation model result when the refugee preference to settle close to other shelters is strong and the space requirements equal 22m^2 per person.
Optimization algorithm:
Left) minimizing average distance Right) maximizing coverage

comparing the different locations of small clusters of shelters between the figure on the left and the figure on the right in D.2.

The location optimization algorithm that aims to maximize the coverage of shelters located the healthcare facilities mainly around the largest cluster of shelters. The location optimization algorithm that aims to minimize the average distance between shelters and healthcare facilities located the healthcare facilities differently, as can be seen in the left figure in D.2. Here, healthcare facilities are located more spread over the camp.



FigureD.2: Simulation model result when the refugee preference to settle close to healthcare facilities is strong and the space requirements equal 22m^2 per person.
Optimization algorithm:
Left) minimizing average distance Right) maximizing coverage

E

ASSUMPTIONS

Throughout this research, a number of assumptions is made, which have a possible impact on the research outcomes. These assumptions are listed below, and their impact is discussed in the discussion.

Assumptions regarding accessibility

- All agents use the same definition for accessibility.
- While choosing a location to settle, accessibility is defined by the travel time to and from a health facility. This definition is extended with the capacity of facilities during the simulation. This means that in the analyses, accessibility is defined by the travel time to and from a health facilities with available resources.

Assumptions regarding settlement behavior

- Refugees have full knowledge of the camp layout and the capacity of healthcare facilities in the camp.
- Refugees take into account the accessibility of healthcare facilities when choosing a location to settle within a refugee camp.
- Refugees settle once, and stay in that place, unless visiting a healthcare facility.
- The first 40 shelters choose their location only based on elevation.

Assumptions regarding facility location problems

- Healthcare providers have full knowledge of all other agents in the model and the availability of locations.
- Facilities can only be located at a shelter.
- Healthcare facilities in the model are assumed to be always fully functioning, so always having sufficient supplies.

- There is one week between facility allocation and facility usage, which can be seen as the construction time.

Assumptions regarding healthcare consultations

- When refugees get sick, the will always seek healthcare.
- Waiting patients have the same probability of being healthy in the next step as other patients. The probability of getting healthy is therefore dependent on time and not on consultations.
- All refugees have the same probability of getting sick and the same probability of remaining sick, regardless of how long they have been sick or visited a healthcare facility.
- All shelters with the notion of being sick weigh equally, they cannot count double to model a very infectious disease.
- There is no difference between different types of illnesses in the model.

Assumptions regarding prediction

- When prediction accuracy is set to 100%, this only regards the location of settlements, but it does not guarantee a 100% accuracy of the number of predicted shelters.

F

SOFTWARE AND PACKAGES

Throughout this study, several modeling and simulation tools have been used, which made it possible to create the model and analyze the results. Since the correspondence between the different packages and software's often depends on the versions, the used versions are listed below.

Program	**Version**
NetLogo	6.0.4
Anaconda Navigator	4.7.12
Jupyter Notebook	5.7.8
Spyder	3.3.6

Package	**Version**
PyNetLogo[1]	0.3

Associated codes and models are available at `https://github.com/meykenb`.

To enable Netlogo to load the elevation data, it is necessary to enlarge the Java heap space that Netlogo can use. Therefore, make sure to be have administrator ownership over all Netlogo files. Then, find the Netlogo app folder in Program Files and adapt the file with .cfg extension, where the heap limit of the files is determined by -Xmx1024m. Alter this to -Xmx2048m.

[1]The PyNetLogo extension is implemented with help of (Jaxa-Rozen & Kwakkel, 2018).

G

MODEL RESULT ANALYSES

G.1. IMPACT OF REFUGEE PREFERENCES ON MODEL BEHAVIOR

First, it is tested whether there is an impact of varying the healthcare proximity preference. It is found that in models 1 and 3, there is no impact of varying the healthcare preference at all in both algorithms. For all KPIs the results are exactly the same when the preference for proximity to healthcare is raised. However, in models 2 and 4, there is a difference in the results.
As discussed in chapter 7, model 3 shows a surprising decline in the average distance after about 58 time steps. This should be taken into account while comparing the impact of varying the parameters in the model 4 with model 3. Again, the impact of varying the preference for proximity to healthcare facilities is found to be nonexistent in the model 3.

In this appendix, the model results for all combinations of preferences are analyzed. The refugee preferences are abbreviated. These abbreviations are shown in table G.1. Also, there is referred to models 1 to 4. What these models entail is shown in table G.2. The result analysis is performed systematically. First, the impact of an increased refugee preference to settle close to healthcare facilities is analyzed. Then, the impact of an increased refugee preference to settle close to other shelters is analyzed. Lastly, the impact of an increased refugee preference to settle close to roads is analyzed. The round bullet points indicate the combination of preferences that is analyzed. The dashed bullet points indicate for which location optimization algorithm the model behavior is analyzed. First, the results are analyzed when facilities are located using the P-median optimization algorithm, that aims to minimize the average distance between shelters and facilities. Then, the results are analyzed when facility locations are determined using the maximal covering algorithm, that maximizes coverage of shelters by facility capacity.

TableG.1: Abbreviations for refugee preferences

Preference:	**Name in model:**	**Abbreviation:**
Preference to settle close to roads	Pref1:Road-proximity	Pref1
Preference to settle close to other shelters	Pref2:Neighbor-proximity	Pref2
Preference to settle close to healthcare facilities	Pref3:Healthcare-proximity	Pref3

TableG.2: Two scenarios and two algorithms result in four models

	P-median algorithm	Maximal covering algorithm
Current scenario	Model 1: Minimizes average travel distance	Model 3: Maximizes the coverage ratio
Future scenario	Model 2: Minimizes average travel distance includes predictions about camp expansion	Model 4: Maximizes the coverage ratio includes predictions about camp expansion

Impact of Pref3:Healthcare-proximity:

- Pref1 and Pref2 equal to 1 and Pref3 varied from 1 to 10:
  - Performance in model 2 is slightly less desirable when Pref3 is raised to 10 and also less desirable than the results of model 1, that excludes future predictions. Model 1 returns very high values for the ratio of waiting patients over the unused capacity. Values larger than one are obtained twice. This is found to be due to a combination of a very low unused capacity and a high number of waiting patients. This signals there is a nearing shortage of capacity in the model. It follows logically that this ratio is lower in model 2, as the prediction enlarges the population and therefore the threshold to realize new facilities is crossed earlier.
  - In model 4 the average traveled distance improves strongly when increasing Pref3 from 1 to 10. The average coverage ratio also improves. However, when comparing this with the results in model 3, all results of model 4 are less desirable on average distance, coverage, capacity shortage and constancy of the ratio of waiting patients over the unused capacity.
- Pref1 and Pref2 equal to 5 and Pref3 varied from 1 to 10:
  - Performance in model 2 is slightly more desirable when Pref3 is raised to 10. The following effects are found: the coverage ratio is higher, average distance is slightly lower, capacity shortage in facilities is lower, ratio of waiting patients over the unused capacity is more or less equal. However, it would be interesting to inspect the underlying behavior of the ratio for these settings towards the end of the run.
  - Performance in maximal covering model responds differently to an increase of Pref3. The average distance becomes much better after about 35 ticks for a higher preference for proximity to healthcare facilities. However, at the same time the average coverage ratio dips below the average coverage results of Pref3 equals 1. This effect is regardless of the number of predicted shelters and is therefore totally dependent on the way the algorithm adopts to new shelters.
- Pref 1 equal to 5, Pref2 equal to 1 and Pref3 varied from 1 to 10:
  - Performance in model 2 does not change much. The only result that is significant, is the faster decrease in average distance, when the preference for healthcare proximity is raised. This also reflects in the average coverage in the beginning of the simulation, which remains higher between assessments. Compared to the results from model 1, the average coverage is also much higher, which logically results in a lower total capacity shortage in facilities.

  - Performance in model 4 increases slightly when the preference for proximity to healthcare facilities is raised from 1 to 10 while the preference for proximity to roads equals 5 and the preference for proximity to neighbors equals 1. Although the coverage ratio increases more slowly, it then remains structurally higher. There is no difference between Pref3 at 5 or at 10.

- Pref1 equal to 1, Pref2 equal to 5, exists only for Pref3 equal to 10, and is more desirable than Pref1 equal to 5 and Pref2 equal to 1 for model 2.
  Comparing the results from models 3 and 4, 1-5-10 is a little better in model 3. However, in model 4 the results are comparable on average distance, but 5-1-10 returns an average distance that is about 10% higher.

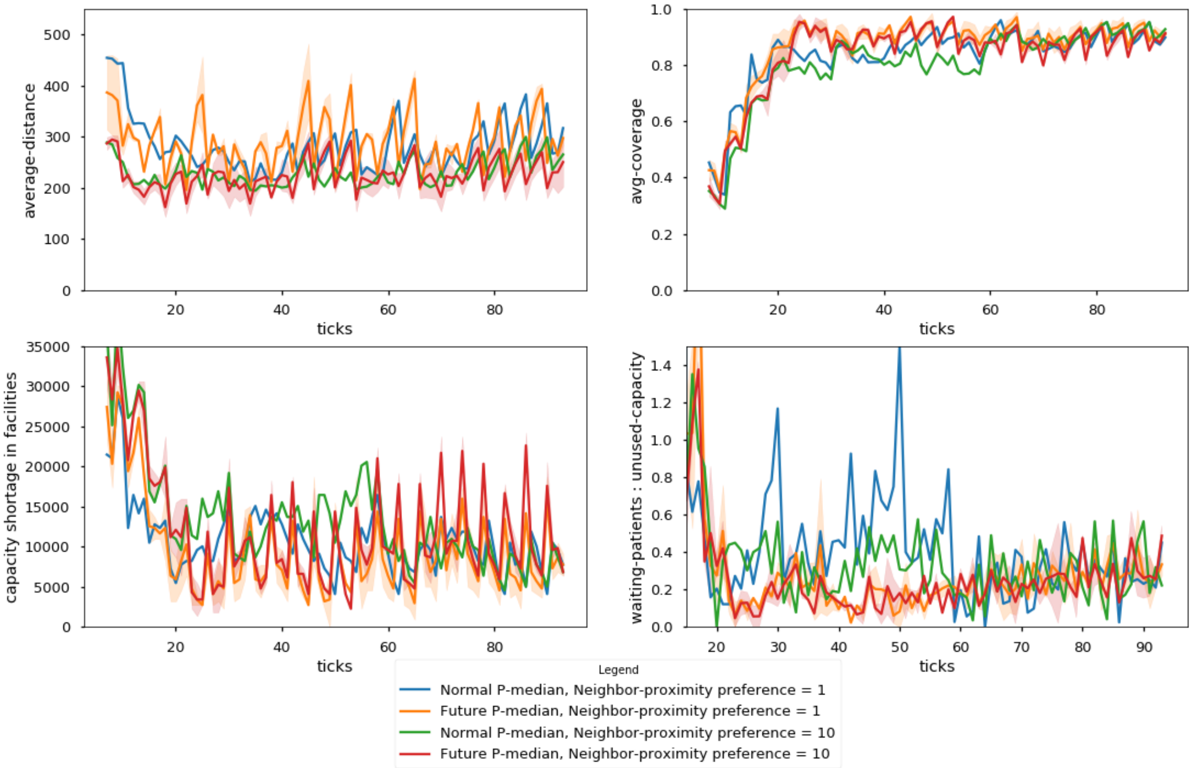
Combination of high preference for healthcare facility proximity (5 or 10) with Pref2 equal to 1 and Pref1 equal to 5 provides best results.
Impact of Pref2:Neighbor-proximity:

- Pref1 and Pref3 equal to 1 and Pref2 varied from 1 (to 5) to 10:

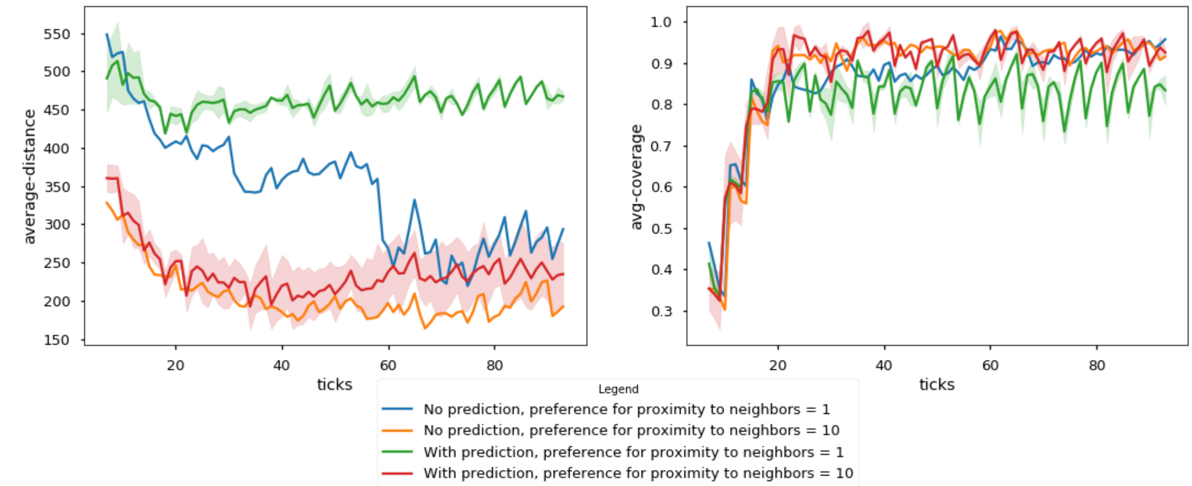
  - Performance in model 2 shows that when facility locations are optimized for future camp expansion, the impact of varying the preference for proximity to neighbors on the average traveled distance is about the same in model 2 as in model 1. For the other performance indicators, the negative effect of this preference seems to be mitigated. This suggests that healthcare providers' behavior is affected by the behavior of refugees. Comparing the impact of the preference variation in model 1 with the impact of the preference variation in model 2, the negative impact of the preference on the average coverage and capacity shortage is removed and the overall performance is increased. This can be seen when comparing the blue and green line with the orange and red line in figure G.1 below.
  - It was already concluded that in model 3, the average traveled distance returns much better results than in the model 4. However it is found that raising the preference for proximity to neighbors overcomes this negative effect of future predictions. However, the non-model 4 with a high preference for proximity to neighbors does give the best results, when comparing the four outcomes, as can be seen in figure G.2. It can also be seen that the impact of a higher neighbor-preference is not much reinforced in model 4. The difference between the orange and the red line in figure G.2 is approximately 45%, whereas the decrease in model 3 is first relatively even higher than this, and then becomes about around 40% after 60 ticks.

- Pref1 and Pref3 equal to 5 and Pref2 varied from 1 to 10:

  - Performance in model 2 The effect in model 2 is more or less the same as when Pref1 and Pref3 are equal to 1, except that the average distance is a bit lower, while the average coverage and capacity shortage is always a bit lower as well. However, when comparing this impact to the impact in model 1, the results are different. In model 1, the impact of increasing the preference for neighbor-proximity has a positive impact on all performance indicators, whereas this positive effect is decreased in model 2.



FigureG.1: Negative impact of higher neighbor preference is mitigated in model 2



FigureG.2: Impact of raising the preference for proximity to neighbors in models 3 and 4

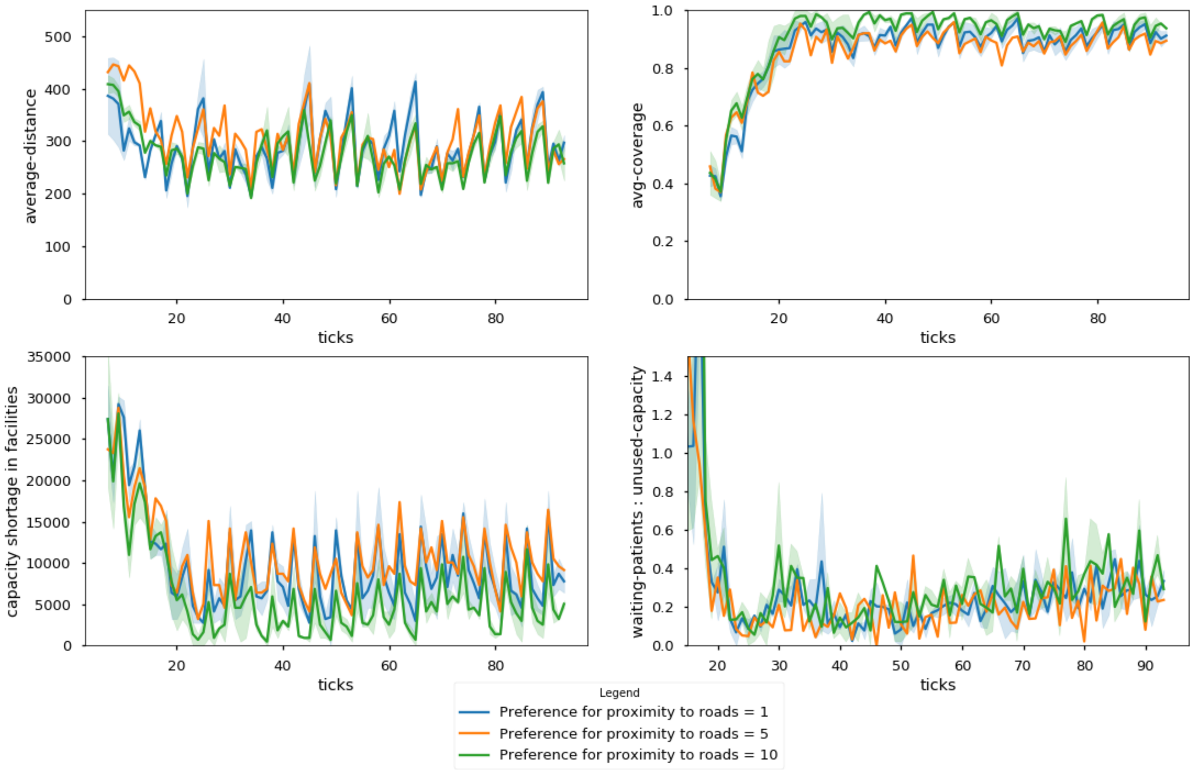
– Varying the preference parameter for proximity to neighbors while setting the other preferences for proximity to roads and healthcare facilities equal to 5, the impact of changing the neighbor-preference becomes much smaller in the model 4. This is due to the positive impact that is already imposed by the other two variables, and which do not just add up, but together create an effect. With these settings, the model outcomes for a high preference to settle close to neighbors gives very comparable results to the model outcomes with the other preferences equal to 1.

- Pref1 equal to 5, Pref3 equal to 1 and Pref2 varied from 1 to 10:
  - Performance in model 2 shows that increasing the preference for proximity to neighbors has a very small positive effect on the average distance, but no positive effect on the average coverage and capacity shortage. This is interesting, as in model 1 this preference change clearly affects the results positively for the average traveled distance, coverage and unused capacity. This implies that the healthcare providers do not effectively respond to this behavior. This can be explained, as for these settings the refugees do not take into account the locations of healthcare facilities, but only the locations of road and other refugees, while the healthcare providers only take into account the locations of refugees.
  - Raising the value for the preference for proximity to neighbors from 1 to 5 to 10, the performance i the model 4 shows an increase in both the average traveled distance and the average coverage ratio when the preference is raised to 5. When raising the preference to 10, this is mitigated again and is very close to the behavior while the preference parameter equals 1. Interestingly, in model 3, the average distance never increases when the preference for proximity to neighbors is increased in steps of 5. The coverage however shows similar results.
- Pref1 equal to 1, Pref3 equal to 5 and Pref2 varied from 1 to 10:
  - This scenario cannot be compared to a scenario where Pref2 equals 1, because this is not tested. But when comparing the results for these preferences in model 1 with the results for these preferences in model 2, the latter clearly produces better results. This sustains/explains the findings in the bullet point for 1-10-1.
  - Comparing the simulations in models 3 and 4, the results in model 4 return a higher average distance, while the coverage remains approximately equal, despite a more rapid increase in the beginning.

Impact of Pref1:Road-proximity: Lastly, the impact of varying the road proximity preference is tested. In models 1 and 3, it is found that the impact of varying this preference does create different results, but it is not clear in what direction. However, in the models that allow future predictions, there is an impact of varying the preference for settling in proximity of roads.

- Pref2 and Pref3 equal to 1 and Pref1 varied from 1 to 5 to 10:
  - Performance in model 2 shows that increasing the preference for proximity to roads from 1 to 10 in steps of 5, while maintaining the preferences for proximity to neighbors and healthcare facilities equal to 1, the overall performance might increase. The average distance shows less high results, while the troughs do not become deeper either. When increased to 5, the preference for proximity to roads does not positively affect the average coverage yet. When changed to ten, the average coverage becomes clearly higher, often nearing a value of 1 which means 100% coverage. The ratio of waiting patients over the unused capacity shows bigger fluctuations when increasing the preference for road-proximity. It is found that raising the preference for road-proximity lowers the unused capacity throughout the simulation. The number of waiting patients becomes slightly

lower but also shows bigger fluctuations in these cases, hence the bigger fluctuations in the ratio. The difference between the results when varying the preference are showed in figure G.3. When comparing these effects of raising the preference for proximity to roads in refugee' choice behavior with the effect in model 1 that does not take future camp expansion into account while optimizing healthcare facility locations, the normal model shows no clear effect of varying the preference. The results are different, which indicates an impact, but the variation due to the preference change seems quite random.



FigureG.3: Changing impact of raising the preference for proximity to roads in model 2

- Performance in model 4 shows a big improvement in the average travel distance when raising the preference for proximity to roads to 5. Raising it further to 10 does not have a big impact on the average distance traveled, but the impact on the average coverage is bigger. All key performance indicators are positively influenced when raising this preference. In model 3, the impacts are different. Showing a rapid decrease in the average distance, which then stabilizes. Also the average coverage turns out highest in the base case experiment.

- Pref2 and Pref3 equal to 5 and Pref1 varied from 1 to 10 does not exist, but 5-1-1 does:
  - Performance in model 2 improves slightly when comparing the impact of increasing the preference for proximity to roads from 1 to 5.
  - Performance in model 4 improves better when the preference for road-proximity increases.

- Pref2 equal to 1, Pref3 equal to 5 and Pref1 varied from 5 to 10:

  - Interestingly, a combination of a high preference for proximity to roads leads to less positive results when combined with a higher preference for proximity to healthcare facilities in model 2. This might be due to the varied effects of both parameters. It is found that Pref1 mostly has a positive effect on the average coverage, while Pref3 mostly has a positive effect on the average distance traveled. Again, when comparing the results of model 2 with the results of model 1, the effects can not be recognized in model 1.
  - Performance in model 4 shows a deterioration in the model results when the preference for proximity to roads is increased from 5 to 10 while the preference for proximity to neighbors and healthcare facilities are respectively 1 and 5. The effect of increasing Pref1 is smaller in the model 3, which implies that the negative impact of the preference for proximity to roads gets reinforced when adapting for future camp expansion.

- Pref2 equal to 5, Pref3 equal to 1 and Pref1 varied from 5 to 10:
  - Increasing the preference for proximity to roads in model 2 from 5 to 10 while Pref2 is 5 and Pref3 is 1, shows an improvement of the key performance indicators. Especially the average coverage becomes much higher, reaching values that are above 0,9 on average. This behavior is strongest in the beginning of the simulation. Up until 22 ticks, the average coverage is much higher. The average traveled distance is in the beginning a bit higher, but before 20 ticks have passed, it is lower for higher preference for proximity to roads. Interestingly, the positive effect of raising the preference for proximity to roads in model 2 does not exist in model 1. Both the coverage ratio and the average traveled distance are returning less desirable results. When comparing this to the experiments with Pref2 also equal to 1, model 1 shows better performance when Pref2, the preference for proximity to neighbors has a value equal to 5. However, model 2 shows less desirable results when the preference for proximity to neighbors is increased. Including future expansion increases the positive effect of a higher preference for road-proximity, but decreases the positive effect of a higher preference for neighbor preferences.
  - Performance in model 4 shows that when the preference for proximity to roads is increased, while the preference for proximity to neighbors equals 5 and the preference for proximity to healthcare facilities equals 1, the average distance decreases after about 35 ticks, but the coverage ratio also decreases.

Results when healthcare providers aim to minimize travel distance

When the space-requirement gets higher, the positive influence of the higher Pref3 gets slightly reinforced. The average coverage becomes slightly higher with a higher preference for proximity to healthcare facilities compared to the situation with high space requirements and low preference for healthcare facilities. The average travel distance also becomes slightly lower. For Pref2, the positive effect or raising the preference from 1 to 10 becomes much larger for the average coverage when the space requirement is bigger in both models 1 and 2, while this effect is negligible when the space requirement is set to the current situation. Only for a high Pref1, the higher space requirements slightly decrease the effect of a higher preference in model 2. In model 1, the positive effect is present. The positive effect of Pref1 seems to get reinforced by a higher space requirement, leading to almost 100% coverage in both models 1 and 2 except when the preference for roads is raised to 10 while all other preferences are equal to 10. More strict space requirements then lead to a decrease of the average coverage throughout the simulation.

Overall: Models that allow healthcare providers to use predictions about future camp expansion, reinforce the positive effect of the preference for proximity to healthcare facilities. However, these predictions nullify the positive impact of a higher preference for neighbor-proximity. As there is no clear influence of varying the preference for road-proximity in the models that do not allow future predictions, it is difficult to say whether the usage of future predictions reinforces the impact or diminishes it.

Results when healthcare providers aim to maximize coverage of shelters

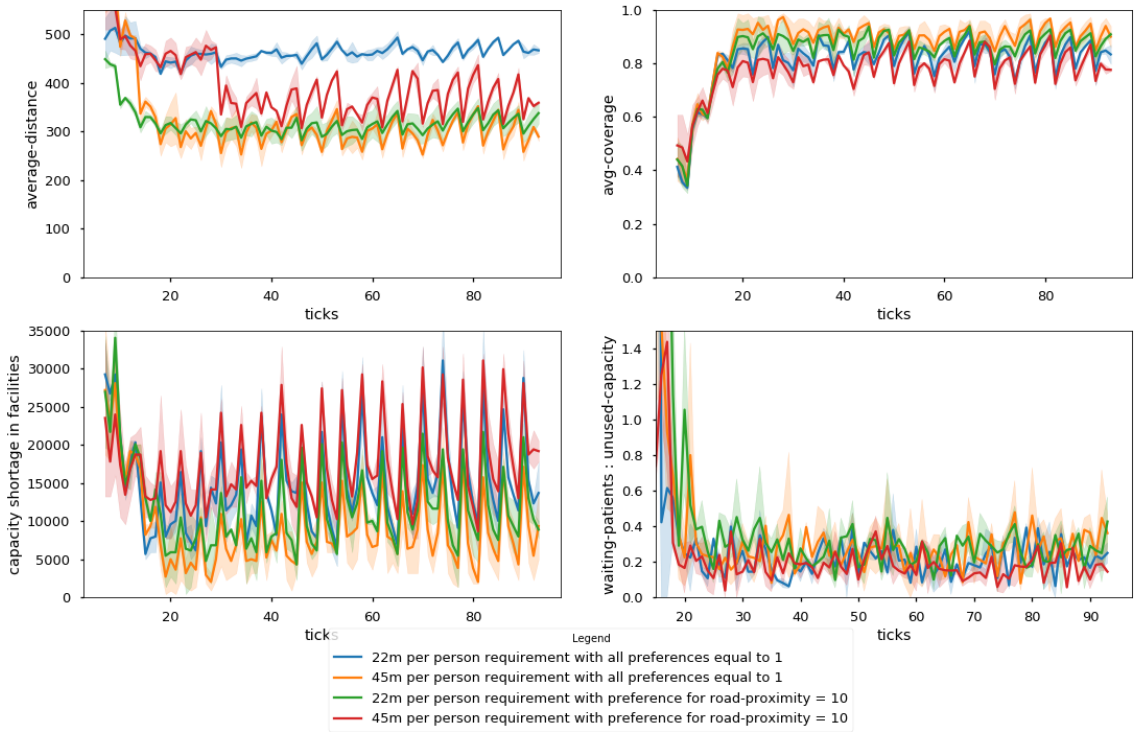
While all preferences are kept to one and varying only the healthcare preference, a higher space requirement leads to significant improvement of the simulation outcomes for average distance traveled, and to slight improvement of the average coverage ratio. This is the case for Pref2 and Pref3. However, when studying the impact of stricter space requirements on the impact of raising only the preference for proximity to roads, an interesting finding occurs. While the stricter space requirements have a very positive influence on the base case scenario in the model 4, the effect is the opposite in the simulations where the preference for proximity to roads equals 10. This is shown in figure G.4.

Interesting behavior is found in the following situation: When the space requirement gets higher, while the preferences are 1-5-10, the average traveled distance becomes much shorter, decreasing with about 30%. The effect on the average coverage ratio is smaller, and only becomes a positive effect after a while. the space requirement is varied from 22m^2 per person to 45m^2 per person while the preferences for proximity to roads, neighbors and healthcare facilities are respectively 1, 5 and 10. An improvement of the average distance traveled can be seen, while the average coverage remains more or less the same with a slight improvement towards the end for the performance with more strict space requirements. The green and red lines show the same comparison, but then for preference values that are respectively 5, 1 and 10. Now, the opposite result appears. Stricter space requirements increase the average distance traveled with about 50% and decrease the average coverage with more than 20%. This same type of behavior is found for the experiments where the preferences for road and healthcare facility proximity equal 5 and the neighbor-preference is varied from 1 to 10. Also, when 5-1-1 or 5-1-10, the average coverage decreases for higher space requirements, while the average coverage decreases a lot as well.

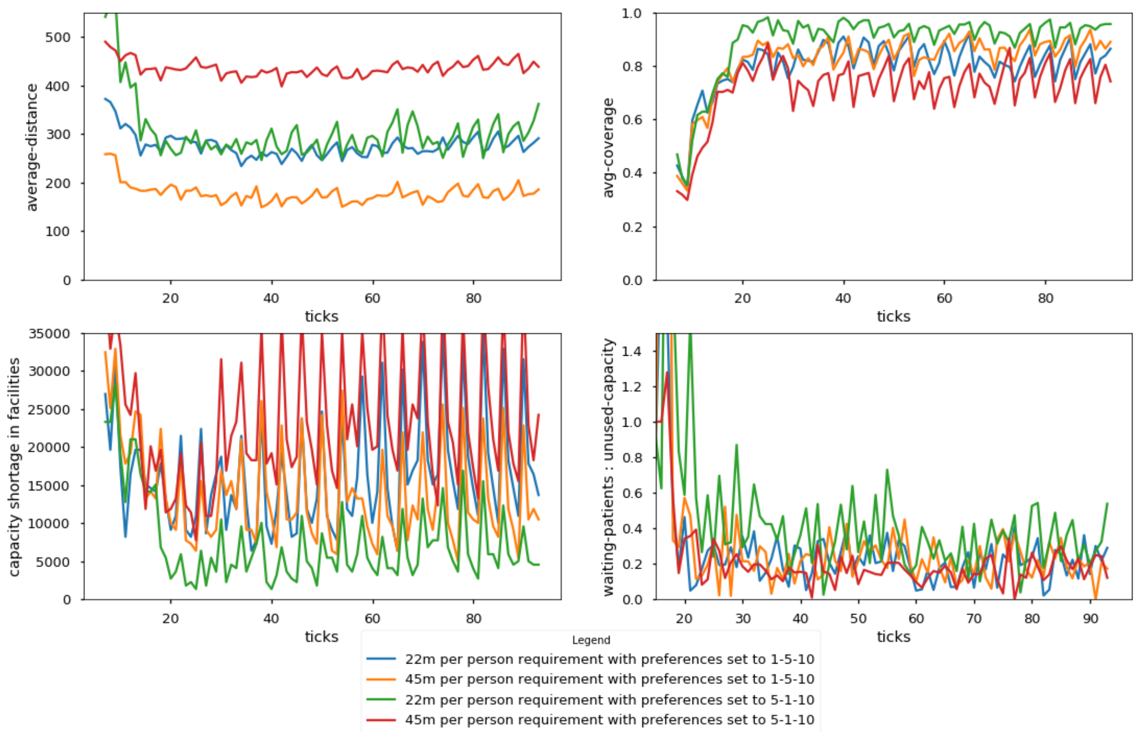
Overall: Including expected future camp expansion in the maximal covering optimizations It became evident that increasing parameters in model 4 sometimes decreases the effectiveness of this model. This is an interesting finding, as the future-modus should increase the effectiveness. However, it is also known that refugees only take into account the presence of healthcare facilities as the distance, not as capacity. So this finding could support the thought that in fact refugee decisions and healthcare provider decisions can reinforce each other. Only the preference for healthcare proximity is found to increase the effectiveness of the model 4. Although, it is still less effective than model 3.

G.2. IMPACT OF REFUGEE PREFERENCES WHEN VARYING THE PREDICTION ACCURACY.

When comparing the results of the simulation runs with 100% prediction accuracy with the runs with 0% prediction accuracy, while keeping all parameter settings equal, the deviating results are due to different agent behavior, adapted to the presence of the new facilities.



FigureG.4: Diverting results for parameter settings with high preference for road proximity while varying the space requirements.



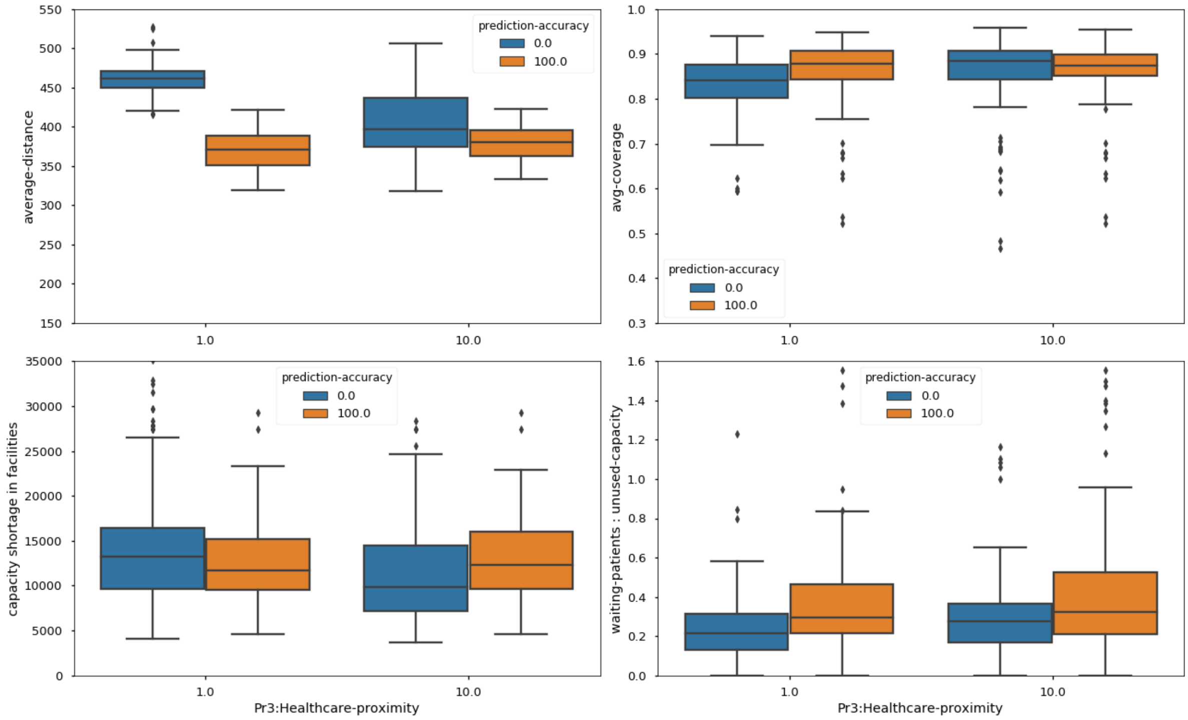
FigureG.5: Diverting results for parameter settings with high preference for healthcare proximity while varying the space requirements.

The behavioral changes are compared step-wise by varying the input variables one by one. The question is what the effect is of a parameter change in the simulation with 100% prediction accuracy (where the refugees cannot adopt their behavior to the new healthcare facility anymore) and the simulation with 0% prediction accuracy (where refugees can adopt their behavior to the new healthcare facility). It would be expected that the differences due to parameter settings that affect refugee behavior are biggest in the 0% prediction accuracy simulations, as these reflect refugee behavior changes. In section 7.3 it was found that increasing the prediction accuracy decreased the average distance traveled in all models, but had a negative effect on the average coverage ratio. This also reflected in the capacity shortage within facilities. Also in the ratio of waiting patients over the unused capacity, the increase of prediction accuracy increased the variety in the results.

Impact of Pref3:Healthcare-proximity:

- Pref1 and Pref2 equal to 1 and Pref3 varied from 1 to 10:
  - With no prediction accuracy, the impact of increasing the preference for proximity to healthcare facilities is slightly negative in the model that applies the algorithm that aims to minimize the average distance between shelters and healthcare facilities. The average distance increases slightly, while the average coverage returns lower values throughout the simulation. In the simulations with a 100% prediction accuracy this negative effect becomes slightly less negative and the results of varying the preference parameter becomes very small, which makes sense as the optimization from the healthcare providers is much more effective and leading in the simulations with 100% prediction accuracy. The other capacity shortage follows the trend in the average coverage and the ratio of waiting patients over the unused capacity only gets larger fluctuations when the preference parameter is increased. Together, these results imply that refugee behavior is ineffective in reaching better accessibility for themselves.
  - The results of model 4 show somewhat more desirable results. Whereas increasing the preference for proximity to healthcare facilities in the model with 100% prediction accuracy leads to a minor decrease of the model performance, the behavioral change in the 0% prediction accuracy model leads to a clear improvement of the model behavior throughout the simulation. This is shown in figure G.6 below. Although the coverage increases more slowly, it then remains higher throughout the simulation, while the average distance decreases structurally with approximately 10%. The ratio of waiting patients over the unused capacity remains comparable while changing the preference parameter. In general, increasing the prediction accuracy in the model 4 leads to better results for the average coverage.

- Pref1 and Pref2 equal to 5 and Pref3 varied from 1 to 10:
  - Performance in model 2 increases very slightly when the preference for proximity to healthcare facilities is increased from 1 to 10, while the other preferences are equal to 5 in the 100% prediction accuracy simulations. In the simulations with 0% prediction accuracy, this positive effect of changing the preferences becomes larger. This is interesting, as only increasing this preference lead to a slight



FigureG.6: In model 4, a high preference for proximity to healthcare is effective to increase accessibility of healthcare, unless prediction accuracy of healthcare providers is 100%

deterioration of the model outcomes. Now, the average travel distance becomes slightly lower, while the average coverage is slightly higher. The fluctuation of waiting patients over the unused capacity does not show different behavior.

– Performance in model 4 with 100% prediction accuracy shows no clear improvement or decrease in the model outcomes for this parameter change. However, without the prediction accuracy, the increase of the preference for proximity to healthcare shows an increasing decrease of the average distance traveled, but also an increasing decrease in the average coverage. This implies that the positive effect of a higher preference for proximity to healthcare facilities is empowered by one of the other parameters, while the average coverage is strongly decreased by this.

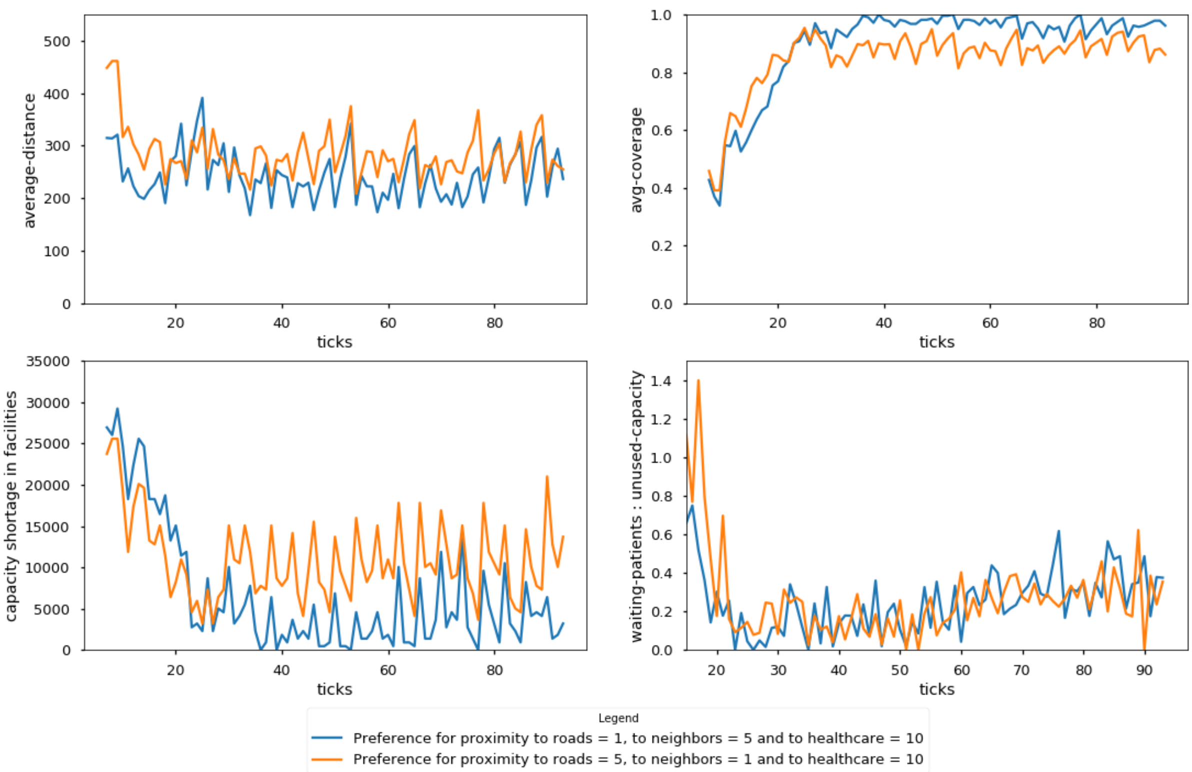
- Pref1 equal to 5, Pref2 equal to 1 and Pref3 varied from 1 to 5 to 10:

  – When varying the preference for proximity to healthcare facilities from 1 to 5, a variance of the model results only comes to exist after 40 ticks in the simulation with 100% prediction accuracy. Increasing the preference to 10 has no additional influence at all. After minor fluctuations, the lower value for Pref3 returns slightly better results towards the end of the simulation. When the prediction accuracy is not determined, the effect of increasing the preference for proximity to healthcare facilities from 1 to 5 slightly improves the average travel distance, while very slightly decreasing the total coverage. However, raising the preference up to 10 returns values for the average coverage that are structurally higher from 30 ticks on-wards, while the average distance is also decreased. This implies that these preferences are effective in improving the key performance indicators.

– Performance in model 4 with 100% prediction accuracy shows a slight decrease when the preference for proximity to healthcare is increased from 1 to 5, after which it again remains the same. The 0% prediction accuracy model returns interesting results, as an increase of Pref3 from 1 to 5 increases the model performance, after a slow start for the average coverage ratio. However, when the preference for proximity to healthcare facilities is raised from 5 to 10, the performance decreases much more than this positive effect.. The average distance increases with approximately 25% and the average coverage decreases from values mainly above 0,9 to values that fluctuate around 0,8.

- Pref1 equal to 1, Pref2 equal to 5 and Pref3 varied from 1 to 10 does not exist.

  – For model 2 with 0% prediction accuracy 1-5-10 performs much better compared to 5-1-10, reaching values of maximum coverage almost equal to 1, as shown in figure G.7. With 100% prediction accuracy, 1-5-10 is only in the beginning more attractive for the average travel distance, but then becomes performs much lesser on the average coverage.



FigureG.7: A high preference for proximity to healthcare in combination with other preferences without future prediction has very different results.

  – For model 4 with 0% prediction accuracy, 1-5-10 returns better results for the average coverage, but slightly less good results for the average distance traveled. With 100% prediction accuracy, 1-5-10 performs much better. Especially on average distance traveled.

Impact on Pref2:Neighbor-proximity:
The impact of a higher preference for proximity to neighbors is found to be very positive for

the model performance in section 7.1. Here, the impact of varying the preference for settling in proximity to neighbors for refugees is analyzed by comparing scenarios with 100% prediction accuracy of refugee behavior by healthcare providers to scenarios with no prediction accuracy. It is expected that the positive effect can empower model performance in the 0% prediction accuracy scenario.

- Pref1 and Pref3 equal to 1, Pref2 varied from 1 to 10:
  - Performance in model 2 becomes better when the preference for proximity to neighbors for refugees is increased from 1 to 10 in the model runs with 100% prediction accuracy. The average distance decreases significantly and from 40 ticks onward the average coverage is also higher. The fluctuations in the ratio of waiting patients over the unused capacity seem to decrease slightly as well. However, without the prediction accuracy, these improvements become less, disappearing completely for all but the average distance indicator. Comparing not the effect of the parameter shift, but purely the results of both simulations with a high preference for proximity to neighbors, it is found that fluctuations of the model results are smaller for all KPIs in the 100% prediction accuracy simulations, and improvements on the average travel distance are found, as well as marginal improvement for the average coverage.
  - Performance in model 4 returns an opposite effect when comparing the preference change in the simulation with 100% prediction accuracy with the simulation without prediction accuracy. With no prediction accuracy, the effect of the parameter change results in a bigger decrease of the average distance indicator and also the average coverage increases more in comparison to the 100% accuracy simulations. The ratio of waiting patients over the unused capacity increases slightly, which is found to be due to a higher number of waiting patients, while also the unused capacity increases. This difference is slightly smaller in the 100% prediction accuracy scenario. Also, in the 100% prediction accuracy scenario, both the number of waiting patients and the unused capacity are structurally lower. These findings are interesting, as they suggest that the behavior of the refugees can increase the effectiveness of the algorithm that aims to maximize coverage of all shelters with the healthcare facilities, when refugees are focused on settling close to other refugee shelters.

- Pref1 and Pref3 equal to 5, Pref2 varied from 1 to 10:
  - Performance in model 2 shows the exact opposite performance of 1-10-1. This time, the simulations without prediction accuracy return a desired shift in model results when the preference for proximity to neighbors is increased and this effect is lessened when the prediction accuracy is 100%.
  - Performance in model 4 is less affected by the changing the preference for proximity to neighbors in the simulation without prediction accuracy, than in the simulation with prediction accuracy. However, the simulation without prediction accuracy and a higher preference for proximity to neighbors returns the highest coverage, the lowest average distance, lowest capacity shortage within facilities and a lower number of waiting patients, compared to the three other

simulations. However, the effect of raising the preference is smaller in the runs without the prediction accuracy.

- Pref1 equal to 5, Pref3 equal to 1 and Pref2 varied from 1 to 5 to 10:
  - Performance in model 2 with 100% prediction accuracy decreases significantly when the preference for proximity to neighbors is raised to 5, while the preference for proximity to roads equals 5 and the preference for proximity to healthcare facilities equals 1. Increasing the preference for proximity to neighbors to 10, improves the performance slightly, but not yet up to the original level. When comparing this behavior to the behavior in model 2 with 0% prediction accuracy, raising the preference from 1 to 5 slightly improves the performance on average traveled distance for most of the simulation, especially in the first 40 ticks, but decreases the coverage throughout the entire simulation. Also, these preferences result in a high unused capacity. This combination of performance indicators suggests that the distribution of the healthcare facilities over the modeled population is not very well. Raising the preference to 10 again slightly improves the behavior on average traveled distance, and also mitigates part of the decrease in the average coverage, reaching even higher values than with the initial preference at some points in time.
  - Performance in model 4 with 100% prediction accuracy shows a major improvement of the average traveled distance when the preference for proximity to neighbors is increased from 1 to 5. This improvement is about 35% in the beginning of the simulation, and decreases to about 10% towards the end of the simulation. The average coverage also increases with approximately 10%. Increasing the preference for proximity to neighbors to 10 decreases the average traveled distance a bit further, but partly cancels out the positive effect on the average coverage. The effects of increasing the preference for proximity to neighbors are much different without a 100% prediction accuracy. An increase to 5 leads to much less variation in the average distance, but for a higher average value, while the average coverage improves significantly after 20 ticks. Interestingly, the unused capacity is very low in this run. Raising the preference to 10 does improve the average traveled distance with 10-20%, but nullifies the positive effect on the average coverage again. An interesting difference between the simulations is that for higher values of Pref3, the average distance gradually increases from 50 ticks onward if the prediction accuracy is 100%, whereas in the simulation without prediction accuracy, it remains at the same value. This implies that the effect of refugee decisions can be more effective than only optimization by the healthcare providers.
- Pref1 equal to 1, Pref3 equal to 5 and Pref2 varied from 1 to 10, compared to 5-10-1:
  - When comparing the 1-10-5 to 5-10-1 in model 2s with and without prediction accuracy, an adverse effect is found. In the 100% accuracy simulation, the model performance is less desirable for 1-10-5, whereas in the 0% accuracy simulation, the model performance this is vice versa. Here, 1-10-5 returns more desirable results.
  - Performance in model 4 shows the exact opposite results as the P-median comparison for these settings. The 100% predication accuracy simulation results are

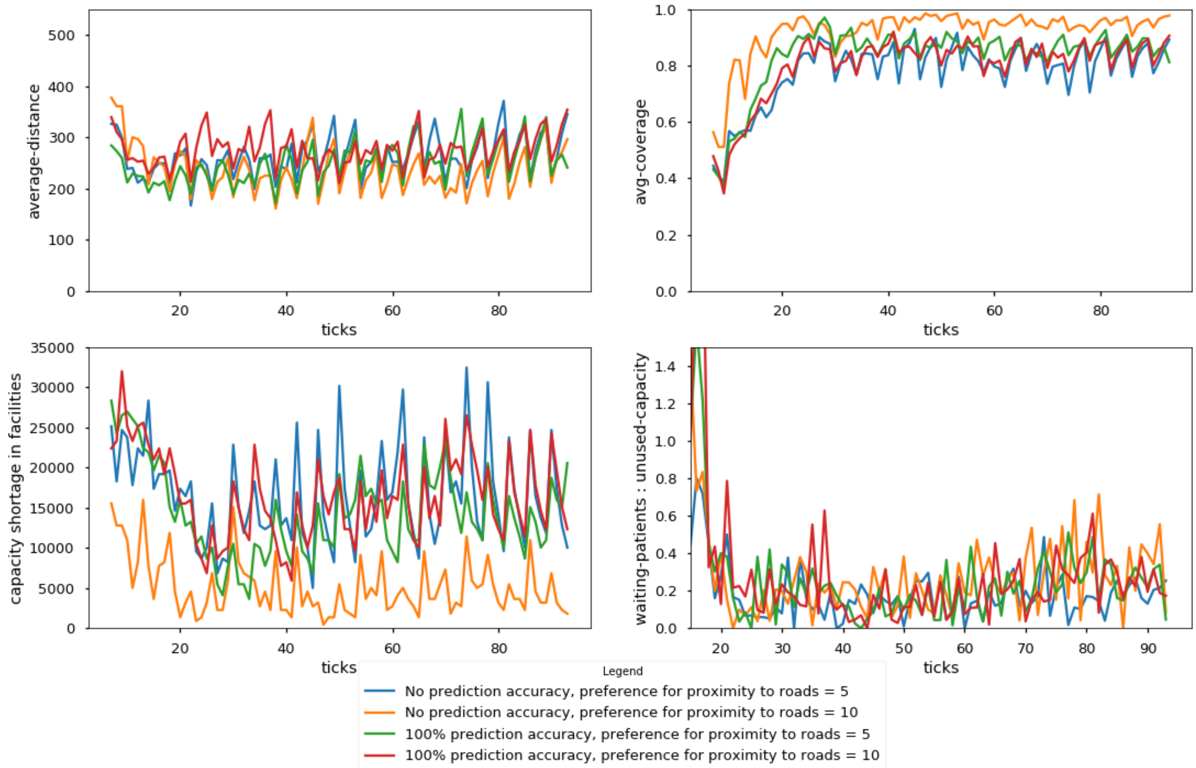
less desirable for 5-10-1, while in the 0% accuracy simulation, the model performance if more desirable for 5-10-1.

Impact on Pref1:Road-proximity: In section 7.1, a higher preference for proximity to roads was found to improve model performance.

- Pref2 and Pref3 equal to 1 and Pref1 varied from 1 to 5 to 10:
  - Performance in model 2 with 100% prediction accuracy increases when the preference for proximity to roads is raised from 1 to 5. The unused capacity decreases slightly, but the number of waiting patients decreases more strongly, therefore this ratio deviates while the parameter is changed. Increasing the preference to a value of 10 only seems to lower the peaks in the average traveled distance, but has no further impact on the model results. In the 0% prediction accuracy simulation, there is no improvement for Pref equal to 5 but rather causes a minor decrease of the model performance. Increasing the preference to a value of 10 increases the model performance, also causing a lower number of waiting patients and unused capacity.
  - When the preference for proximity to roads is increased from 1 to 5 in the simulations with 100% prediction accuracy, this first improves the average coverage while also increasing the average traveled distance. After 25 time steps, both indicators show a big dip, after which they remain structurally lower. When raising the preference to 10, the changes in average traveled distance are lessened, while the average coverage is structurally lowered further. Both increases of the preference parameter return a higher unused capacity. In the simulations without prediction accuracy, the parameter increases lead to a better model performance on every indicator.

    Performance in model 4 with 100% prediction accuracy improves the average coverage the first 25 time steps in the simulation, after which the performance becomes structurally less desirable, as the preference parameter increases to a value of 10.
- Pref2 and Pref3 equal to 5 and Pref1 varied from 1 to 10 does not exist, but 5-1-1 does:
  - model 2 returns less desirable model results when the prediction accuracy is 0% and the preference for proximity to roads is increased from 1 to 5.
  - model 4 returns more desirable model results when the prediction accuracy is 0% and the preference for proximity to roads is increased from 1 to 5.
- Pref2 equal to 5, Pref3 equal to 1 and Pref1 varied from 5 to 10:
  - Performance in model 2 does not improve in the simulations with 100% prediction accuracy when increasing the preference for proximity to roads while settling for refugees. When the prediction accuracy is not set, the increase of the preference however does lead to significant improvements of the model behavior. Especially the coverage shows a sharp increase in the first 20 time steps, in which the population growth is steep and new healthcare facilities are placed every 4 ticks. The unused capacity decreases as well, causing a small increase in the ratio of waiting patients over the unused capacity. The same increase in the ratio seems to appear in the 100% prediction accuracy simulations as well,

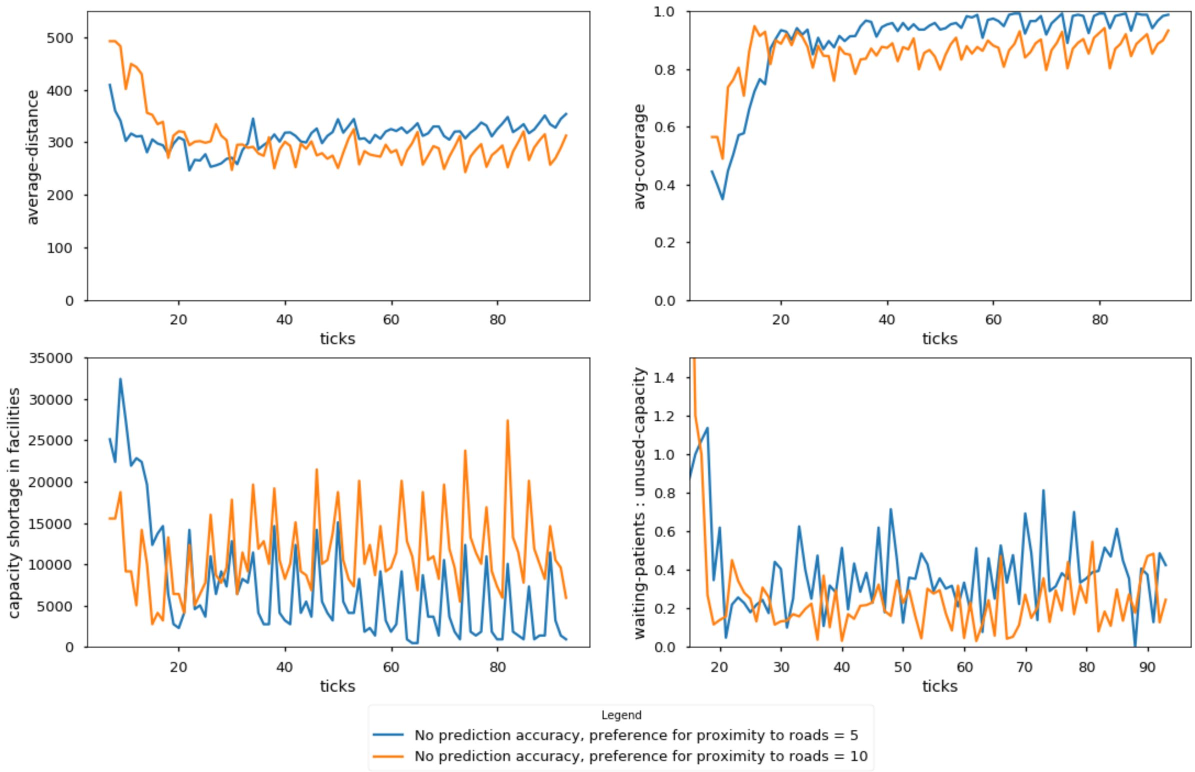
but is found to be due to a rising number of waiting patients in these cases instead. Therefore, the effect of increasing the preference for proximity to roads has a much more positive effect in the simulations without prediction accuracy. The results are shown in figure G.8.



FigureG.8: Without a 100% prediction accuracy, a high preference for proximity to roads (orange line) leads to significant better model results in model 2

- Comparing the influence of varying the preference for proximity to roads in model 4 with and without the 100% prediction accuracy returns interesting results. If the prediction accuracy equals 100%, the model performance significantly decreases when the preference for proximity to roads is increased. However, without the prediction accuracy, the results for average traveled distance are opposite, decreasing the average distance when the preference for proximity to roads is higher. However, it starts with a higher average distance, which corresponds to the earlier seen trade-off with the average coverage, as can be seen in figure G.9. The ratio of waiting patients over the unused capacity returns lower values, which appears due to a higher unused capacity throughout the model, while the number of waiting patients remains equal.

- Pref2 equal to 1, Pref3 equal to 5 and Pref1 varied from 5 to 10:
  - The effect of raising the preference for proximity to roads in model 2 with 100% prediction accuracy, decreases the desirability of the model results very slightly. In the 0% prediction accuracy simulation results, they increase a slight improvement instead.
  - Performance in model 4 returns the exact same outcomes as for 10-5-1.



FigureG.9: Impact of increased preference for proximity to roads when facility locations are located to maximize coverage model.

Results when healthcare providers aim to minimize travel distance
Impact of space-variable on 1-1-10 makes the behavior of the 0% simulation better compared to the 100% accuracy simulation. But makes the behavior of 5-5-10 less desirable. Where the improvement of the average coverage is higher for 5-5-10 in the 0% simulation, it became a decrease when the space-variable is increased. However, overall the results of the higher space requirement are much better. On 1-10-1 it has a positive effect in both variations of prediction accuracy. On 5-10-5 it has a similar effect, both leading to higher outcomes. For the 0% it leads to a much higher coverage, but not in the 100% prediction accuracy simulations. For 10-1-1, the 0% was increasing more for an increase of the preference, but with the higher space variable, it is the other way around and the 100% simulation shows a bigger improvement. However, if not considering the size of the impact, but purely the result, the 0% simulation performs better. For 5-1-1, the 100% was reacting much better, but with the space variable the effect in the 0% prediction model is bigger.

Overall: the 0% scenario is model 1 is more sensitive for variables that increase the spatial distance between shelters.

Results when healthcare providers aim to maximize the coverage ratio
In 1-1-10, increasing the space requirement lowers the effect of raising the preference parameter, but still improves the model outcomes. Same for 5-5-10, but then the 5-5-1 for 0% gives highest average coverage. 1-10-1 same as 1-1-10. Increasing the space requirement in 5-10-5 increases the impact of varying the preference parameter in both simulations. Interestingly, here the results of the 0% simulation become less desirable by increasing the space requirement. 10-1-1 shows interesting behavior when increasing the space require-

ment. The model performance becomes much less desirable when combined with a higher preference for the proximity to roads. For 5-1-1 the same happens in the 100% simulation, but in the 0% simulation it does improve the results.

Overall: the effect of more strict space requirements is largest and mostly positive in the simulation runs where healthcare providers have 0% prediction accuracy.

TableG.3: Results of the base case scenarios without future predictions and with future predictions

	P-median algorithm: minimizing average distance		Maximal covering algorithm: maximizing coverage	
Base case scenario results:	average distance: (meter)	average coverage: ratio	average distance: (meter)	average coverage: ratio
including future predictions (0% accuracy)	284	0,838	347	0,857
including future predictions (100% accuracy)	279	0,841	374	0,841
without future predictions	291	0,865	464	0,809

TableG.4: Synthesis of the interplay throughout the different approaches and refugee preferences

		Models 1 and 2: P-median optimization						Models 3 and 4: Maximal covering					
Index:	Preference settings	Refugee behavior impact (from 100% to 0% accuracy)		HP behavior impact (from non-future to future)		Interplay effect		Refugee behavior impact (from 100% to 0% accuracy)		HP behavior impact (from non-future to future)		Interplay effect	
0.	Base case values	average distance: 279 m	coverage ratio: 0,841	average distance: 284 m	coverage ratio: 0,838	on average distance:	on coverage ratio:	average distance: 374 m	coverage ratio: 0,841	average distance: 347 m	coverage ratio: 0,857	on average distance:	on coverage ratio:
1.	1-1-1[1]	+ 3,97 %	+ 2,64 %	+ 2,30 %	+ 3,26 %	+ 2,30 %	+ 3,26 %	+ 23,92 %	- 3,85 %	+ 33,67 %	- 5,67 %	+ 33,67 %	- 5,67 %
2.	1-1-10	+ 12,91 %	- 1,68 %	+ 7,30 %	- 0,87 %	+ 7,30 %	- 0,87 %	+ 6,47 %	- 0,06 %	+ 17,51 %	- 2,21 %	+ 17,51 %	- 2,21 %
3.	1-10-1	+ 12,5 %	- 0,31 %	- 1,50 %	+ 4,46 %	- 20,57 %	+ 0,23 %	+ 4,97 %	+ 5,71 %	+ 15,31 %	+ 0,51 %	- 31,18 %	+ 3,4 %
4.	10-1-1	+ 3,20 %	+ 7,09 %	- 5,76 %	+ 7,26 %	- 1,98 %	+ 7,96 %	- 12,41 %	+ 15,85 %	- 3,04 %	+ 4,65 %	- 7,59 %	+ 1,98 %
5.	5-5-10	+ 7,54 %	- 3,00 %	+ 16,73 %	- 4,92 %	- 11,04 %	- 1,85 %	- 3,88 %	- 3,20 %	+ 6,94 %	+ 0,58 %	- 23,33 %	- 2,27 %
6.	5-10-5	+ 3,90 %	+ 1,20 %	+ 10,42 %	- 0,94 %	- 18,19 %	+ 0,08 %	- 3,22 %	+ 8,37 %	+ 6,74 %	+ 5,77 %	- 28,87 %	+ 4,89 %
7.	5-1-1	+ 18,17 %	- 4,47 %	+ 7,86 %	+ 4,43 %	+ 8,29 %	+ 1,48 %	- 10,11 %	+ 5,24 %	- 3,75 %	+ 0,88 %	- 7,64 %	- 0,71 %
8.	5-1-5	+ 6,25 %	- 4,40 %	- 0,16 %	+ 4,34 %	+ 0,24 %	+ 1,38 %	- 18,25 %	+ 14,82 %	- 8,80 %	+ 5,95 %	- 12,48 %	+ 4,28 %
9.	5-1-10	+ 6,25 %	- 4,40 %	- 0,16 %	+ 4,34 %	+ 0,24 %	+ 1,38 %	- 18,25 %	+ 14,82 %	- 8,80 %	+ 5,95 %	- 12,48 %	+ 4,28 %
10.	5-10-1	+ 18,22 %	+ 0,17 %	+ 22,73 %	- 1,52 %	- 9,07 %	- 0,51 %	- 6,65	+ 3,27 %	+ 7,83 %	+ 0,49 %	- 28,14 %	- 0,35 %
11.	1-10-5	- 10,25 %	+ 7,69 %	- 4,19 %	+ 6,99 %	- 22,74 %	+ 2,66 %	+ 11,99 %	+ 9,55 %	+ 29,97 %	+ 1,91 %	- 22,43 %	+ 4,84 %
12.	1-5-10	+ 4,19 %	+ 9,28 %	- 5,18 %	+ 6,43 %	- 14,07 %	+ 6, 97 %	+ 14,13 %	- 4,42 %	+ 17,57 %	- 5,75 %	- 20,39 %	- 6,36 %
13.	10-1-5	+ 2,11 %	- 1,73 %	- 3,13 %	+ 2,17 %	+ 0,75 %	+ 2,84 %	- 11,31 %	+ 17,85 %	+ 5,8 %	+ 3,76 %	+ 0,84 %	+ 1,12 %
14.	10-5-1	- 13,33 %	+ 14,54 %	- 11,02 %	+ 8,44 %	- 15,65 %	+ 9,93 %	- 20,13 %	+ 11,4 %	+ 5,53 %	+ 2,74 %	- 12,66 %	- 0,40 %
15.	10-1-10	+ 2,11 %	- 1,73 %	- 3,13 %	+ 2,17 %	+ 0,75 %	+ 2,84 %	- 11,31 %	+ 17,85 %	+ 5,8 %	+ 3,76 %	+ 0,84 %	+ 1,12 %
16.	10-10-1	- 16,12 %	+ 20,29 %	- 10,50 %	+ 11,41 %	- 22,89 %	+ 7,14 %	- 5,94 %	+ 10,30 %	+ 21,35 %	+ 1,44 %	- 14,44 %	- 0,64 %
17.	10-5-10	- 16,76 %	+ 9,44 %	- 12,31 %	+ 4,89 %	- 16,88 %	+ 6,33 %	- 8,74 %	+ 2,45 %	+ 15,63 %	- 4,15 %	- 4,31 %	- 7, 08 %
18.	10-10-5	+ 3,53 %	+ 8,45 %	+ 0,53 %	+ 7,56 %	- 13,39 %	+ 3,45 %	- 2,93 %	+ 12,13 %	+ 19,63 %	+ 2, 95 %	- 15,65 %	+ 0,85 %

[1] These three numbers represent the values that are given to the refugee preferences. The first number is the preference for proximity to roads, the second number the preference for proximity to neighbors and the third number is the preference for proximity to healthcare facilities.