Decision-making on pre-disaster evacuation strategies in danger of cyclone induced floods

Two case studies in Mozambique showing how to balance timeliness and uncertainty reduction in making shelter location decisions

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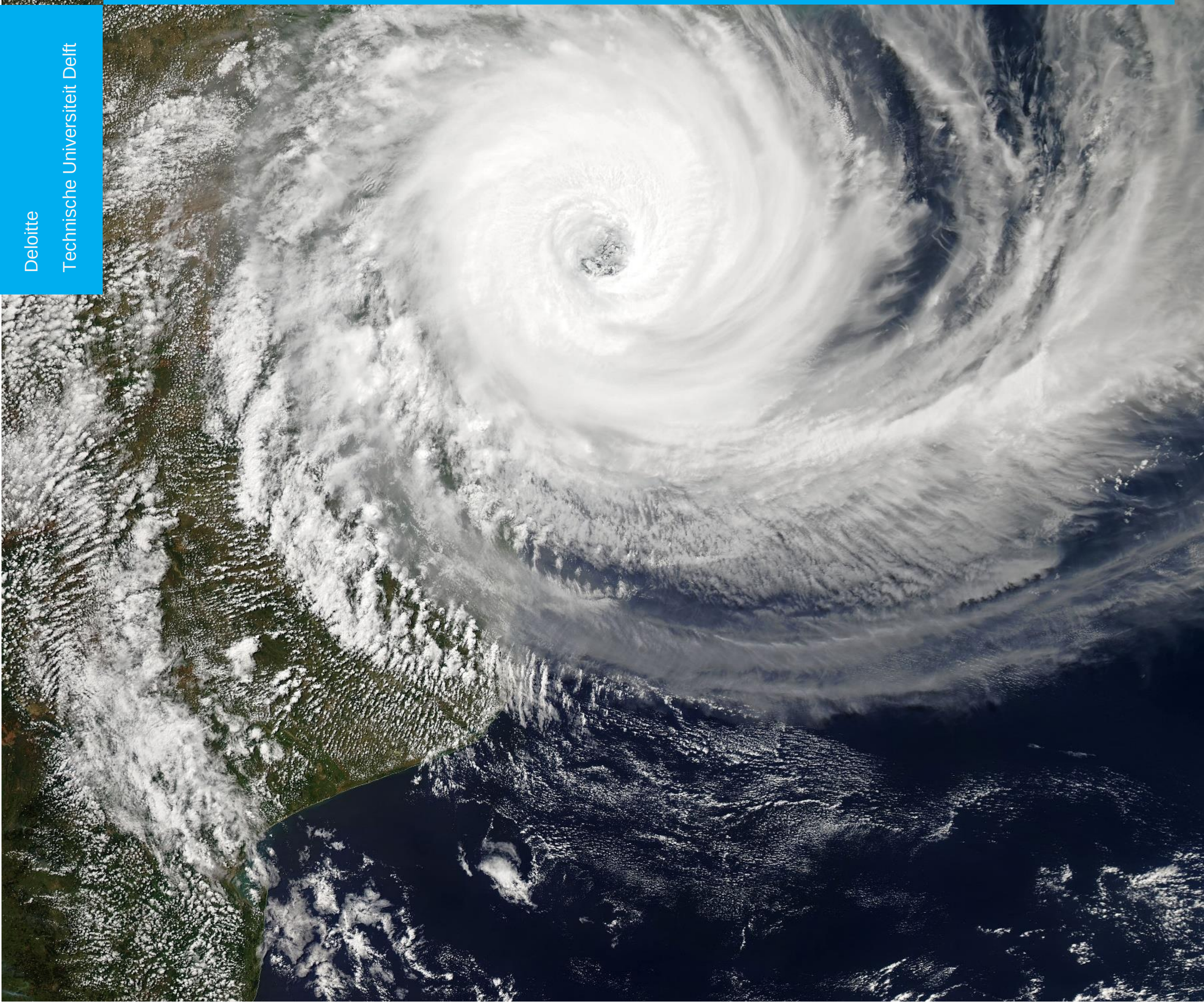
Deloitte

Technische Universiteit Delft



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Two case studies in Mozambique showing how to balance timeliness and uncertainty reduction in making shelter location decisions

by

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An electronic version of this thesis is available at http://repository.tudelft.nl/.
A repository with the scripts and data files is available at
https://github.com/RobDregmans/Master-thesis/.

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Executive summary

As Needham et al. (2015) concluded based on researching 700 storm surge events: "tropical cyclone induced floods are among the world's deadliest and destructive natural hazards". Due to this growing threat, there is a growing need for evacuation policies in case of an impending cyclone, in order to reduce the negative effects of a cyclone. The literature review in this research points out that there are many pre-disaster evacuation models, which focus mostly on either small scale evacuation of a city, or large scale evacuation with the use of motorized vehicles. However, in stretched out rural and developing areas, where access to motorized vehicles is limited or non-existent, residents need ample time to leave the area that is in danger of cyclone induced floods. This means that there should be enough time between the issue of the evacuation order and the moment the cyclone is forecasted to make landfall. However, the sooner the evacuation order is issued, the more uncertainty there is regarding the area that may be subject to the devastating consequences of the cyclone. That means that many residents would be unnecessarily evacuated. This is why the moment of the evacuation order should be at a point where the timeliness of the evacuation order and the uncertainty of the cyclone are optimally balanced. Currently, there does not exist a pre-disaster evacuation model for cyclone-induced floods that accounts for this trade-off.
This research uses concepts of existing evacuation models and extends them with the trade-off between timeliness and uncertainty reduction in order to research the added value and applicability of this trade-off. This leads to the following research question:

How to balance the trade-off between timeliness and uncertainty reduction in making shelter location decisions in rural and developing areas, under impending cyclone induced floods, while accounting for behavioral aspects of the vulnerable residents?

The computer model that is developed to answer the research question consists out of three parts, which are called the *building blocks* of the model. The first building block translates discrete forecast reports about a cyclone into an area that is vulnerable and should be evacuated, because it will possibly be affected by the cyclone. These forecast reports form the decision points for an **evacuation moment**. Based on this vulnerable area, possible shelter locations are found in the surroundings of (horizontal evacuation), or on higher grounds within (vertical evacuation), the vulnerable area using a shelter searching algorithm. This algorithm uses a certain **safety margin**, which is the distance between the possible shelter locations and the vulnerable area to look for possible locations that can shelter the evacuees. The second building block is the optimization part. This sub model optimizes over the complete set of possible shelter locations and selects a given **number of shelters** that minimizes the weighted distance between the evacuees and the shelters. This weighted distance minimization is also known as the Minisum optimization model (Boonmee et al., 2017). The third and final building block simulates an evacuation using the previous generated data and captures the results in key performance indicators, so that the effect of the different policy levers can be compared and the balance between timeliness and uncertainty reduction can be found. The models are connected to each other using a Python interface. The model is applied to two different case studies, on which the results and conclusions are based.

Three levers that define the shelter location decisions are found relevant in balancing the trade-off between timeliness and uncertainty reduction.
The first is the evacuation moment. It shows that a later evacuation moment reduces the number of total evacuees, but it also reduces the evacuees that are saved from the impact of the cyclone. More precisely, the model shows a clear break point, which means that there is a point in time after which it is no longer possible to evacuate all evacuees in danger. The two case studies have shown that this break point is around two days in advance of landfall. This means that the balance in this trade-off lies before this break point. Too early evacuations however, result in a high number of total evacuees, which is not desired as well. This reduction in evacuees over time is not always linear and depends on how the cyclone is forecasted and the characteristics of the geographical area that is under threat. Therefore, it can be concluded that evacuation should happen before the break point, but the exact moment also depends on the forecast reports and the

geographical terrain, and is also dependent on the other two levers. However, it is shown that vertical shelter locations significantly reduce the evacuation time and enable later evacuations or evacuations with less shelters.
The second lever is the safety margin. This research concludes that a relatively high safety margin is advised in early evacuation moments, but in later evacuation moments it is advised to make use of vertical shelter locations, which means that a low safety margin should be used. The low safety margin is the only way, in later evacuation moments, to save as many evacuees as possible, but it also reduces the accessibility and security of the shelter locations.
The third and final lever is the number of shelters. In early evacuation moments, there are many evacuees, which increases the need for sufficient shelters. Therefore, in early evacuations, it is shown that additional shelters have a relatively high reduction in travel distance and high increase of rescued evacuees when compared to later evacuation moments. However, the marginal benefit of an extra shelter is reduced with each additional shelter, which means that the cost of each additional shelter should be balanced against the reduction in travel time and the increase in safely evacuated evacuees. Furthermore, when a distance minimization model is used, the largest shelters will be located closest to the areas with the highest population density. Regarding the sizes of the shelters, later evacuation decisions often means there is need for more shelters. This means that those shelters tend to be smaller, but there will always be larger shelters because of the larger cities.

In summary, three policy levers have been identified that define the shelter location decision and that have an impact on the balance between timeliness and uncertainty reduction. None of these levers can single-handedly define how the right balance, and they should therefore be used all-together to define the best balance the trade-off. However, it has also been found that in both case studies the cyclone evolved differently and the geographical area is far from identical as well, which also influences the right balance. This means that every answer about how to balance the trade-off, will also be different in every case.

Additionally, it is concluded that the trade-off between timeliness and uncertainty reduction is especially relevant for evacuees who are evacuating by foot. When their travel speed increases, the relevance of the trade-off decreases. This confirms the hypothesis that most evacuation models with motorized vehicles do not account for this trade-off because evacuees have a higher travel speed.

Furthermore, this research concludes that when a cyclone is advancing and there is no time to deploy an evacuation model, a heatmap of the population density, together with an elevation map, can give rough estimates of where the largest shelters should be located. The elevation map gives insights into the possible shelter spots because it will point out the elevated locations, either within or outside of the estimated vulnerable area. Those spots that are located closest to the most dense populated areas will probably prove to be suitable shelter locations. Furthermore, in both case studies it is shown that the latest evacuation moment is around two days in advance of landfall of the cyclone and that after that moment it is highly advised to make use of vertical shelter locations.

To conclude, this research recommends that the evaluation of the model results will be changed from retrospective to prospective, which means that the model can be deployed in real-time disaster management. Only then, the real value of the model can be shown.

Preface

This journey, that led to this report, has been most interesting, inspiring, challenging as it was educational. It provided me with many opportunities to learn and broaden my perspective. Not only I learned many new and innovative technical applications, but it was also most insightful to learn more about disaster response and how much is being done already, but also how much still can be done. I am thankful for having received the opportunity to work on this project, and I hope to continue in this field in some way. After all, reading many personal eye reports and seeing all those pictures of affected people, it is something that stays with you.

I could not have gone through this journey alone and I am most thankful to my graduation committee for their guidance and enthusiasm, which means a lot. A special thanks to Tina Comes, which whom I have had bi-weekly meetings in which she always provided me with the critical and constructive feedback I needed. She helped me finding and sticking to the bigger story line, especially in the beginning and helped me with a lot of knowledge that is specific to humanitarian aid. Also a special thanks to Edwin Wanner, who was always enthusiastic, with whom I could always brainstorm and who offered me a critical sounding board. Due to Covid-19, I have not seen my other two committee members, Bartel van de Walle and Martijn Warnier, as much as I had planned, but it was good to know they were always available when needed. I would like to thank them for their feedback and their subject-specific knowledge during all the general meetings. Especially the lectures from Martijn, both in my bachelor and masters, proved to have fully prepared me in working with Netlogo. Seeing how much work this thesis already was, I'm also thankful to Martijn for talking me out of the idea to couple the evacuation model with a hydrological model, because this thesis would have become way too extensive. Instead, it is now a big recommendation for future research.

Next to my graduation committee, I received the most useful feedback from different experts with local knowledge that deepened this research and took it to the next level. A special thanks to Freek Huthoff, who is connected to the water institute HKV and the university of Twente and assisted in the disaster response to cyclone Idai, which is one of the case studies in this research. The meetings with him were very insightful and his feedback is used throughout the report. Furthermore I would like to thank Francesco Torresani, who works for UNhabitat, and explained to me how an evacuation process would be coordinated. This helped me to understand the evacuation context and what was done for cyclone Kenneth.
I would also like to thank Wouter Rhebergen, who works for the Red Cross, for validating parts of my results. This deepened the reflection and the validation and offers a broader perspective to decision makers.

Lastly, I would like to thank everyone who helped me throughout this project, and especially a big thanks to Emma and my parents. Enjoy the read and know that I'm always open to discussing this subject further.

R. Dregmans
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Contents

List of Figures ix

List of Tables xii

1 Introduction 1
- 1.1 Problem introduction . . . 1
- 1.2 Research focus . . . 1
- 1.3 Report structure. . . . 2

2 Literature review 3
- 2.1 Location & allocation optimization . . . 3
- 2.2 Routing optimization . . . 4
- 2.3 Behavioral aspects . . . 4
  - 2.3.1 Physiological and Empirical research into evacuation factors . . . 4
  - 2.3.2 Including behavioral factors in evacuation models. . . . 4
- 2.4 Trade-off between timeliness and uncertainty reduction . . . 5
- 2.5 Classification of current models. . . . 6
- 2.6 Knowledge gaps. . . . 7
  - 2.6.1 Concept of time in pre-disaster evacuation . . . 7
  - 2.6.2 Predefined set of shelters . . . 7
- 2.7 Research question . . . 7

3 Research questions and methodology 9
- 3.1 Sub questions . . . 9
  - 3.1.1 Calculating cyclone induced flood risk . . . 9
  - 3.1.2 Optimize shelter location decisions . . . 9
  - 3.1.3 Behavior exploration . . . 9
  - 3.1.4 Researching the trade-off . . . 10
- 3.2 Methodology . . . 10

4 Cyclone induced flood risk 12
- 4.1 Software implementation . . . 12
  - 4.1.1 Elevation data . . . 12
  - 4.1.2 Forecast data. . . . 13
  - 4.1.3 Model scope . . . 13
- 4.2 Vulnerability calculation . . . 13
  - 4.2.1 Uncertainty in the forecast . . . 13
  - 4.2.2 Impact of the elevation data . . . 14
  - 4.2.3 Determining the vulnerable area . . . 14

5 Location optimization 15
- 5.1 Demand and shelter points . . . 15
- 5.2 Finding possible shelter locations . . . 15
- 5.3 The mathematical model and how it is solved. . . . 17
  - 5.3.1 Determining the distance between demand point i and shelter location j . . . 18
  - 5.3.2 Determining the shelter capacities . . . 19
  - 5.3.3 Determining the maximum number of shelters . . . 19
  - 5.3.4 Determining the population that needs to be evacuated . . . 19
  - 5.3.5 Determining the distance limit. . . . 19

6 Behavior exploration 20
6.1 Agent implementation 20
6.2 Behavioral rules 20

7 Model application 23
7.1 Input parameters 23
7.1.1 Moment of evacuation 23
7.1.2 Safety margin 23
7.1.3 Amount and capacity of the shelters 23
7.2 Key performance indicators 24

8 Case study Idai 25
8.1 Cyclone Idai 25
8.1.1 Situation report 25
8.1.2 Relevant characteristics 25
8.1.3 Involved organizations 26
8.2 Experiments 27
8.2.1 Describing the external parameter values 27
8.2.2 Experiments setup 27
8.3 Results 28
8.4 Result analysis 29
8.4.1 Identifying the latest evacuation possibility 29
8.4.2 Finding the balance before the break point 30
8.4.3 Break point analysis 33
8.4.4 Location and size of the shelters 34
8.5 Conclusion case study Idai 38

9 Case study Kenneth 40
9.1 Cyclone Kenneth 40
9.1.1 Situation report 40
9.1.2 Relevant characteristics 40
9.1.3 Involved organizations 40
9.2 Experiments 41
9.2.1 Describing the external parameter values 41
9.2.2 Experiments setup 41
9.3 Results 42
9.4 Results analysis 43
9.4.1 Identifying the latest evacuation possibility 43
9.4.2 Finding the balance before the break point 44
9.4.3 Break point analysis 47
9.4.4 Location and size of the shelters 48
9.5 Conclusion case study Kenneth 52
9.6 Comparing the Idai and Kenneth case study 53
9.6.1 Comparing the break point 53
9.6.2 Comparing the trade-off 53
9.6.3 Comparing the situation after the break point 54
9.6.4 Comparing the shelter locations and sizes 54

10 Discussion and limitations 55
10.1 Model limitations 55
10.2 Critical assumptions 56
10.3 Reflection on the research approach 57
10.4 Implication for the policy makers 58

11 Model verification and validation 59
11.1 Verification . . . 59
11.2 Validation . . . 59
11.2.1 Empirical validation . . . 60
11.2.2 Theoretical validation . . . 61
11.2.3 Evaluation by other comparisons . . . 61
11.2.4 Sensitivity analysis . . . 63

12 Conclusions and recommendations 65
12.1 Answering the sub questions . . . 65
12.2 Answering the main research question . . . 67
12.3 Societal contribution . . . 68
12.4 Scientific contribution . . . 68
12.5 Suggestions for future research . . . 69
12.5.1 Improving the vulnerability assessment model . . . 69
12.5.2 Distinction between rural and urban areas. . . . 70
12.5.3 Including the vertical shelter location sites and capacities . . . 70
12.5.4 Surveying behavioral characteristics . . . 70
12.5.5 Making the model prospective instead of retrospective . . . 70

Bibliography 72

A Experiment results Case Study Idai 75
A.1 Key performance indicators . . . 75
A.2 Table results. . . . 76
A.3 Fraction saved KPI . . . 81
A.4 Fraction saved of all evacuees KPI. . . . 82
A.5 Average travel distance KPI . . . 83

B Experiment results Case Study Kenneth 84
B.1 Key performance indicators . . . 84
B.2 Table results. . . . 84
B.3 Fraction saved KPI . . . 88
B.4 Fraction saved of all evacuees KPI. . . . 89
B.5 Average travel distance KPI . . . 90

C Validation 91
C.1 Theoretical validation . . . 91
C.2 Sensitivity analysis . . . 94
C.2.1 Variables independent of the evacuation moment . . . 94
C.2.2 Variables dependent of the evacuation moment . . . 95

D The models explained 104
D.1 Vulnerability assessment model explained . . . 104
D.1.1 Preparing the data . . . 104
D.1.2 Assessing vulnerability . . . 104
D.1.3 Determining possible shelter locations . . . 105
D.2 Optimization model explained . . . 106
D.3 Evacuation simulation model explained . . . 109

E Impact of a population threshold 111

F Assumptions 113
F.1 Assumptions regarding the vulnerability assessment model . . . 113
F.2 Assumptions regarding the optimization model . . . 113
F.3 Assumptions regarding the evacuation simulation model. . . . 113

G Forecast report 114

H Calculating distances using OSM data 115

I Software and packages 118

I.1 Software programs 118

I.2 Python dependencies 118

List of Figures

2.1 Timeliness and uncertainty reduction trade-off in evacuation decisions 5
2.2 Timeliness and uncertainty reduction trade-off in evacuation decisions based on periodically updated forecast reports 6

3.1 Methodology: the interaction between the different building blocks of the model 11

5.1 Illustration of the shelter searching algorithm: an fictive area that needs to be evacuated in yellow 16
5.2 Illustration of the shelter searching algorithm: an fictive area that needs to be evacuated in yellow with shelters at a safety distance of 3 units 16
5.3 Illustration of the shelter searching algorithm: an fictive area that needs to be evacuated in yellow with shelters at a safety distance of 5 patches 17

6.1 Agent logic visualized. The rectangular boxes represent actions, either by the decision maker or the agent. The diamond shaped boxes represent the actions of the agent 22

7.1 Relation between external parameters, policy levers, the computer model and the KPIs 24

8.1 Path of cyclone Idai in Mozambique, March 2019 The size of the circles represent the relative strength 26
8.2 GSM coverage, used for communication purposes 26
8.3 Evacuation area per forecast moment - March 9th, 0600 shown in yellow, March 13th, 0000 shown in blue, March 13th, 1800 shown in orange. The area that is impacted is shown in red . . 29
8.4 The effect of the forecast moment and the safety margin on the fraction saved, represented by a 95% confidence interval over 20 simulation runs. A break point is visible between March 13th, 0000 and March 13th, 1800 30
8.5 The effect of the forecast moment on the average travel distance. Left figure shows all combinations of the safety margin and the number of shelters. Right figure shows the average over the different safety margins, which highlights the relation between the number of shelters and the average travel distance. 31
8.6 The effect of the number of shelters and the forecast moment on the fraction saved for the first seven forecast moments. Results show relative low fraction saved and more uncertainty for the option of 10 shelters. 31
8.7 The effect of the forecast moment and the safety margin on the total number of evacuees. From March 11th onwards there is a visible decline in the total number of evacuees 32
8.8 The effect of the safety margin and the number of shelters for the three forecast moments of interest 33
8.9 Spatial heatmap of the travel distance for an evacuation on March 13th, 1800 PM, a margin of 10 kilometer and 20 shelters 34
8.10 Spatial heatmap of the travel distance for an evacuation on March 13th, 1800 PM, a margin of 5 kilometer and 20 shelters 34
8.11 Spatial heatmap of the population density. The color shows the residents per patch, for all patches up to 2500 residents. This equals to around 400 residents per square kilometer. The more densely populated areas are centered around rivers or big cities 35
8.12 Cities with a population above 400 residents per square kilometer. The size of the circle represents the size of the city. The largest city 35
8.13 Shelters and their size for an evacuation on March 10th, 0000 AM with a safety margin of 10 km and 10 shelters. The color represents the size of the shelters 37
8.14 Shelters and their size for an evacuation on March 12th, 0600 AM with a safety margin of 20 km and 20 shelters. The color represents the size of the shelters 37

8.15 Shelters and their size for an evacuation on March 13th, 0000 AM with a safety margin of 5 km and 20 shelters. The color represents the size of the shelters 37
8.16 Shelters and their size for an evacuation on March 13th, 0000 AM with a safety margin of 10 km and 80 shelters. The color represents the size of the shelters 37

9.1 Path of cyclone Kenneth (and Idai) in Mozambique, April 2019 41
9.2 Evacuation area per forecast moment - April 22th, 1400 shown in yellow, April 23th, 1400 shown in blue and April 25th, 0800 shown in orange. The area that is impacted is shown in red 43
9.3 The effect of the forecast moment and the safety margin on the fraction that is saved, represented by a 95% confidence interval over 20 simulation runs. The break point is visible between March 24th, 0200 AM and March 25th, 0200 AM 44
9.4 The evacuees in danger not saved by the forecast moment and the safety margin. The evacuees not saved increases rapidly after March 24th, 0200 and also determine on the safety margin . . . 44
9.5 The effect of the forecast moment on the average travel distance. Left figure shows all combinations of the safety margin and the number of shelters. Right figure shows the average over the different safety margins, which highlights the relation between the number of shelters and the average travel distance. 45
9.6 Fraction saved by number of shelters and forecast moment for a safety margin of 5 kilometer. The option with 10 shelters shows a lower fraction saved and more uncertainty, compared to the other number of shelters 45
9.7 The total number of evacuees for each forecast moment and safety margin 46
9.8 The effect of the safety margin and the number of shelters for the four forecast moments of interest 47
9.9 April 25th, 0200 AM, margin: 10, shelters: 20 48
9.10 April 25th, 0200 AM, margin: 5, shelters: 20 48
9.11 Heatmap of the population density (in residents per patch) of the area that is possibly at risk to the effects of cyclone Kenneth, based on the earliest forecast available 49
9.12 The five biggest city in the area that is possibly at risk to the effects of cyclone Kenneth, based on the earliest forecast available 49
9.13 Shelters and their size for an evacuation on April 22nd, 1400 PM with a safety margin of 10 km and 40 shelters. The color represents the size of the shelters 51
9.14 Shelters and their size for an evacuation on April 23rd, 0800 AM with a safety margin of 5 km and 20 shelters. The color represents the size of the shelters 51
9.15 Shelters and their size for an evacuation on April 23rd, 1400 PM with a safety margin of 5 km and 80 shelters. The color represents the size of the shelters 51

11.1 Satellite image on March, 19th of the inundated area next to Beira 60
11.2 Vulnerable area with a vulnerability threshold of 0.15. Impacted area is shown in red 60
11.3 Precipitation levels of cyclone Idai on March 16th 61
11.4 Precipitation levels of cyclone Idai on March 14th 61
11.5 Precipitation levels of cyclone Idai on March 13th 61
11.6 Sensitivity of the safety margin, measured by the fraction saved 63

A.1 Shortest routes for evacuee 1 76
A.2 The fraction saved of the residents in danger with a 95% confidence interval for all the combinations of the policy levers. The squared data points represent combinations of the policy levers where the entire confidence interval lies above 99.5% 81
A.3 The fraction saved of the entire population with a 95% confidence interval for all the combinations of the policy levers. The squared data points represent combinations of the policy levers where the entire confidence interval lies above 99.5% 82
A.4 The average travel distance of the population in danger for all the combinations of the policy levers 83

B.1 The fraction saved of the residents in danger with a 95% confidence interval for all the combinations of the policy levers. The squared data points represent combinations of the policy levers where the entire confidence interval lies above 99.5% 88

B.2 The fraction saved of the entire population with a 95% confidence interval for all the combinations of the policy levers. The squared data points represent combinations of the policy levers where the entire confidence interval lies above 99.5% . . . 89
B.3 The average travel distance of the population in danger for all the combinations of the policy levers . . . 90

C.1 Setup with a safety margin of 5 kilometer . . . 92
C.2 Setup with a safety margin of 50 kilometer . . . 92
C.3 An evacuation on March 13th, 1800 PM with a safety margin of 5 kilometer and 20 shelters. The figure shows that evacuees start arriving earlier with a lower safety margin . . . 93
C.4 An evacuation on March 13th, 1800 PM with a safety margin of 20 kilometer and 20 shelters. The figure shows that evacuees start arriving later with a higher safety margin . . . 93
C.5 Extreme value test for two different lengths of day light . . . 94
C.6 Sensitivity of the alerting range, measured by the fraction saved KPI . . . 96
C.7 Sensitivity of the safety margin, measured by the fraction saved . . . 97
C.8 Sensitivity of the safety margin, measured by the average travel distance . . . 97
C.9 Sensitivity of the number of shelters measure by the evacuees in danger . . . 98
C.10 Sensitivity of the number of shelters measured by all the evacuees . . . 99
C.11 Sensitivity of the cyclone uncertainty . . . 99
C.12 Sensitivity of the cyclone uncertainty . . . 100
C.13 Sensitivity of the decision delay for March 09th . . . 100
C.14 Sensitivity of the decision delay for March 13th . . . 100
C.15 Sensitivity of the decision time for March 11th . . . 101
C.16 Sensitivity of the travel speed for March 9th . . . 101
C.17 Sensitivity of the travel speed for March 13th . . . 101
C.18 Sensitivity of the travel speed for March 11th . . . 102
C.19 Sensitivity of the interaction effect . . . 102

D.1 The relation between input and output explained for the vulnerability assessment model . . . 106
D.2 The relation between input and output explained for the optimization model . . . 109
D.3 The relation between input and output explained for the evacuation simulation model . . . 110
D.4 Agent logic visualized . . . 110

E.1 Fraction saved over time without a population threshold . . . 111
E.2 Fraction saved over time with a population threshold . . . 112

G.1 Cyclone current information . . . 114
G.2 Cyclone forecast . . . 114

H.1 Dummy data with evacuees in red and shelter locations in yellow . . . 115
H.2 Shortest routes for evacuee 1 . . . 116
H.3 Shortest routes for evacuee 2 . . . 116
H.4 Optimizes solution with two selected shelters. . . . 117
H.5 Shortest routes for evacuee 3 . . . 117

List of Tables

2.1 Different works classified according to the identified aspects in evacuation models 7

4.1 Uncertainty depending on the forecast period (NHC, 2020) 13

8.1 Parameter values in the Idai case study 27
8.2 Forecast moments 28
8.3 Safety margins 28
8.4 Amount of shelters 28
8.5 Experiment number 87 explained 28
8.6 Four promising configurations of the policy levers in the Idai case study 38

9.1 Parameter values in the Kenneth case study 41
9.2 Forecast moments 42
9.3 Safety margins 42
9.4 Amount of shelters 42
9.5 Experiment number 14 explained 42
9.6 Three promising configurations of the policy levers in the Kenneth case study 52
9.7 Hours that are needed in the latest evacuation possibility where all the evacuees in the impacted area can reach their shelter 53

C.1 Parameter values for the extreme value test 91
C.2 Experiment 90, case study Idai 94
C.3 Parameter values for the sensitivity analysis 95
C.4 Parameter values for the sensitivity analysis 96

1 Introduction

1.1. Problem introduction

As Needham et al. (2015) concluded based on researching 700 storm surge events: “tropical cyclone induced floods are among the world’s deadliest and destructive natural hazards”. Woodruff et al. (2013) finds that cyclone induced floods should even be considered as of primary importance when assessing flood risk. Peduzzi et al. (2012) found that over the years, coastal populations are becoming more prone to extreme flooding from cyclones. Knutson et al. (2010) adds to this, that current models point out that tropical cyclones will not only increase in number of occurrences, but also in strength. Therefore, there is a growing need to prevent, prepare and mitigate for the negative effects of cyclone induced floods. But across the world, the situations are extremely different. The more developed countries are often well prepared and have sufficient shelter locations to evacuate residents, using advanced early-warning systems (for example cyclone prone state New-Orleans, USA). Poor and less developed countries, on the contrary, are often less prepared and are often not resilient enough to withstand the force of natural disasters (for example Mozambique). Those countries often rely on the aid of humanitarian organizations. This implicates that the focus is often more on recovery and mitigation instead of prevention, and therefore, most casualties of natural disasters fall in less developed countries (Cross, 2020). Ritchie, H. & Roser, M. (2020) report that those who live in extreme poverty, are more vulnerable to the consequences of natural disasters. Those low-to-middle income countries often lack necessary infrastructure and resources to adequately prevent, respond to and mitigate the effects of climate disasters.

1.2. Research focus

It is highly important to improve the resilience of less developed countries, through for example the construction of adequate water protection measures and shelter locations. Unfortunately, this is not yet reality (Cross, 2020). Therefore, this research will focus on short-time pre-disaster evacuation of people in less developed countries that are prone to cyclone induced floods, focusing specifically on people living in rural areas. Predisaster is defined as a time period starting around six days in advance of a cyclone, because this is the time period in which the path of a cyclone can be predicted (Samost, 2006). Evacuation is defined as evacuating people from areas that are possibly vulnerable to cyclone induced floods towards safety. This means, that since there are often no shelter locations in rural areas in less developed countries, evacuating residents to safety means they are evacuated to areas that are not projected to be in danger. Chapter 5 will elaborate on this. And lastly, in rural areas, people are living more dispersed and the area is often less populated, compared to urban areas, like cities. This makes it more difficult for humanitarian organizations to reach and assist all the affected residents. Where most research is focused on urban areas only (as shown in Chapter 2), this research will place emphasis on rural areas. Furthermore, much evacuation research has been dedicated to developed nations, whilst characteristics differ significantly between developing and developed countries. Chapter 6 will explain how the conditions in a developing country influence the best evacuation strategy.

1.3. Report structure

Chapter 2 will continue with outlining the current literature around evacuation models. It will explain what distinct focuses are used in different evacuation models. Chapter 2 will end with an identified knowledge gap that leads to the research question of this paper. Chapter 3 will explain the research approach that will be applied to solve the research question. It will do so for all the specified sub questions in this research and will link the different building blocks together. Chapters 4 to 6 will give a detailed explanation of how the different building blocks of the model have been constructed. Chapter 7 will define the final inputs and outputs of the model of this research and will define key performance indicators, in order to assess the outcomes of the experiments that are ran with the model. Chapter 8 and 9 will show the application of the model, applying it to the two case studies. This will illustrate the usefulness and the applicability of the model. Chapter 9 will conclude with a comparison between the two case studies. Chapter 10 will offer the reader a discussion on the limitations of the model and will give insight into all the assumptions underlying the model. Verification and validation of the model are described in chapter 11. Finally, chapter 12 will combine the conclusions of the two individual case studies, in order to offer a more general and wider applicable policy recommendation. The chapter will discuss technological and societal relevance and will conclude with suggestions for future research.

2

Literature review

Many different evacuation models exist. Therefore, this literature overview will structure them, in order to indicate what knowledge gap this research proposal aims to fill. Besides the different evacuation models, this chapter will also elaborate upon the aspect of time in the preparation phase of natural disasters.

Evacuation models are either aimed at evacuating residents pre-disaster or post-disaster (Caunhye et al., 2012). Because the research in this paper will focus on pre-disaster evacuation, only papers modeling pre-disaster evacuation are considered. The literature review below, describes three main facets in those evacuation models: location & allocation optimization, routing optimization and behavioral aspects. Each of them will be explained in the paragraphs below. Furthermore, since the focus in this research will be on cyclone induced floods, it will not consider other natural disaster models, since different dynamics are at play there. Next to the three model facets, the concept of time in pre-disaster evacuation management will be explained, which is the main focus in this research.

2.1. Location & allocation optimization

Location and allocation models generally focus on optimizing a (set of) shelter location(s) and the demand that needs to be covered. In evacuation models this demand refers to the number of people that need to be evacuated. User-specified constraints for these optimization models can include

a) a maximum capacity per shelter location,
b) a maximum distance people can travel to reach the shelter location,
c) a maximum amount of shelters and
d) a minimum percentage of people that are covered by at least one shelter location (Pan, 2010).

Often, it is not possible to meet all of the constraints, meaning there is a trade-off to be made. For example, this is the case when the latter three constraints come up. The amount of shelters is often insufficient due to limited funding or limited staff that can equip the shelter location (Li et al., 2012). This means that some people are possibly located too far for the most nearby shelter. There are different optimization models that focus on these location and allocation problems. Some of the most common are explained below.
One of these models is the P-Median Problem (PMP) with the objective to minimize the total or average distance between the evacuees and the shelter locations. This is also known as the Minisum facility location problem (Boonmee et al., 2017). Another model is the P-Center Problem (PCP), which minimizes the longest distances (Hamacher and Nickel, 1998). In the Location Set Covering Problem (LSCP), the amount of facilities is optimized, with the constraint that all evacuees are covered by at least one shelter (Eiselt and Sandblom, 2012). For the Maximal Covering Location Problem (MCLP), the maximum amount of shelter locations is a restraint and it aims to maximize the demand covered, given a maximum service distance (Church and Revelle, 1972). Many (variations) of these models assume a pre-specified set of shelter locations and aim to allocate the evacuees over a selection of the shelters, meeting some, or all, of the constraints. See Boonmee et al. (2017) for a broader overview of all location-allocation formulations.

2.2. Routing optimization

Whereas the decision for shelter locations is often a strategic long-term decision, routing traffic towards them is more of an operational challenge. The focus in many of these models is placed on reducing congestion, that follows a large scale evacuation of urban areas (Pel et al., 2012, for overview). In the traditional location & allocation models, the focus is on matching demand to supply, but the path between those is not taken into consideration. Many formulations in section 2.1 take the shortest distance and do not consider possible traffic induced congestion. Routing optimization aims to allocate people in a way that reduces congestion. This means that overall evacuation time is reduced, leading to less loss of lives. In these evacuation planning procedures, routing entails the planning and controlling or encouraging of certain traffic flows in order to minimize total evacuation time. For example, Cova and Johnson (2003) suggest a lane-based routing as a strategy for reducing congestion during evacuation. To summarize, where location-allocation optimization aims to allocate evacuees over a set of shelters, routing optimization focuses on how evacuees should reach those shelters in a way that evacuation time is reduced.

2.3. Behavioral aspects

Another level in evacuation is the behavior of the individual. Even though models can optimize the set of locations and the allocation of all the evacuees and use routing optimization for the most efficient evacuation, it is not a given that all people will abide by those instructions. Therefore, various authors research how behavioral factors influence evacuation decisions and the effect on efficiency of evacuations. This literature review identified two main ways of researching those behavioral aspects. The first is psychological and empirical research into the behavioral aspects that influence evacuation decisions. For example, taking surveys to assess what factors influenced people's behavior during evacuation. This gives insights that can be translated into policy advice for future evacuation orders. The second is to include those behavioral aspects in an evacuation model and to research specifically the consequences of different behavioral factors on the efficiency of the evacuation. By way of simulation, it is possible to determine relations between those behavioral factors and how they determine the evacuation policy efficiency. The two sections below will explain the two concepts in more depth.

2.3.1. Physiological and Empirical research into evacuation factors

Since evacuation factors can greatly determine individual responses to the threat of a natural disaster, many authors researched what factors influence an evacuation decision. Since the research centered around this topic is voluminous, the most important factors will shortly be addressed. Riad et al. (1999) defined three basic social psychological processes that determine whether someone decides to evacuate or not. For every individual this decision is based on risk perception, social influence and access to resources. Laska (1990) defined four phases at the individual level regarding evacuation, that is

a) prior experience with an hazard,
b) material wealth of the individuals concerned,
c) personality treats such as sense of control and
d) the perceived role of the individual vis-à-vis the group.

Tai et al. (2010) & Adeola (2009) also concluded that the extent to which people have prior experience of a natural disaster in the form of severe hydro-meteorological weather is a clear influencer of evacuation behavior. Also the duration of residency in an area that is prone to disaster affects the willingness to flee for an impending disaster. Charnkol and Tanaboriboon (2006) investigated the influence on evacuation of the time it takes people to decide whether or not to evacuate. These factors can be applied in models to better understand evacuation processes.

2.3.2. Including behavioral factors in evacuation models

Various authors account for those behavioral aspects in evacuation models and include this in the optimization. Li et al. (2012) underline that when a evacuees' travel choice is considered in the optimization, "most studies assume that static traffic patterns prevail on the transportation network, but this lacks realism for analyses spanning the peak hours and for evacuation applications". Therefore, including behavior of individual evacuees, will give a better resemblance of reality. Some authors specifically focus on how different configurations and weights of those behavioral factors influence the evacuation process and efficiency. As a final note, in general, formalizing behavior is always subject to subjectivity and often involves making at least some assumptions. The main reason for including behavioral factors in evacuation models is simply to ensure they are not only theoretical of nature, but also try to resemble realistic evacuation behavior. Excluding behavioral factors from an evacuation model would in most cases simply reduce the practical applicability of the models, since the mismatch between the model and reality might be too big to translate model results to real world policy.

2.4. Trade-off between timeliness and uncertainty reduction

So far, this paper identified three main facets in evacuation models, based on the papers that are included in this review. Many of those models do not take into account the concept of time during the evacuation decision making process. Instead, they focus on reducing the total evacuation time, but do not relate this to the time that is left before the natural disaster will strike. In the time a cyclone progresses, the prediction error reduces and the predicted path gets more accurate. This means that areas that are prone to cyclone induced floods can be better determined (Samost, 2006). The advantage is that, with higher accuracy, it can be determined which people need to be evacuated and also where they can be safely evacuated to. However, the longer decision makers wait for accurate cyclone forecasts, the less time there is until impact, and therefore the time for the evacuees to flee from the impact zone to safety is reduced. In evacuation models, this aspect is often not, or only partly, accounted for, since most models focus on urban developed areas, where people can relatively travel large distances in a short time period using motorized vehicles.

In other fields, this concept of time has often been applied. For example, the pre-disaster phase is not only used to evacuate residents at risk, but to pre-position relief goods as well. The aim here is to locate the relief goods close to the affected residents to distribute them directly before or after the disaster. To efficiently position those relief-goods, several authors researched the best timing to decide on the locations for those relief goods. For example, Blanco (2017) researched when and where to pre-position relief goods across the affected area, using periodically updated forecast information. Even though this research will focus on evacuation and not on pre-positioning of relief goods, valuable lessons can still be learned regarding this time aspect in research about pre-positioning. Especially because, as illustrated in table 2.1, this aspect of time in evacuation models is currently underexposed. In this research, the time aspect is defined as the trade-off between waiting until forecast reports further reduce the uncertainty about the path of the cyclone on the one hand, and timeliness in evacuation decisions on the other hand. This is illustrated in figure 2.1. Including this aspect in evacuation models could add value to them. This would hold especially true for areas where time is more of the essence. This is the case in most developing rural areas, where access to motorized vehicles is often limited or non-existent.

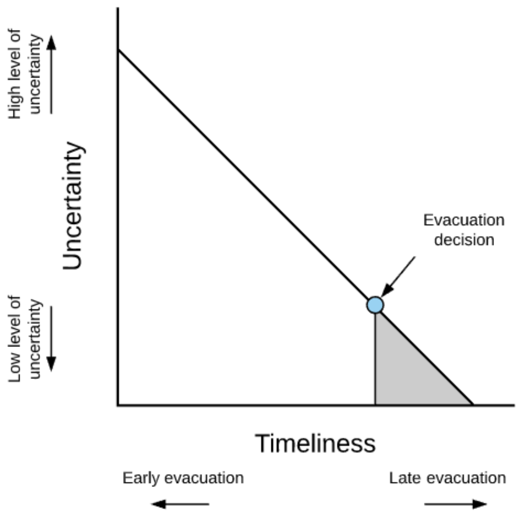

Figure 2.1: Timeliness and uncertainty reduction trade-off in evacuation decisions

Important remark here is regarding the irreversibility in evacuation decisions. The concept of irreversibility is first introduced by Henry (1974). He states that a decision is irreversible if, once it is taken, it cannot be (easily) reversed. This research defines the decision to evacuate as irreversible, since once the evacuation order is issued, it will no longer be possible to revert this decision in the next time-step. Since this decision is

a one-off decision, there is a need to determine the best moment in time to take it, which means timeliness and uncertainty reduction need to be balanced. Figure 2.1 illustrates how uncertainty is reduced when time passes by. However, in case of a late evacuation there is less time for the evacuation itself.
Even though a cyclone is a continuous real life event, the forecasts about it are often updated periodically. This means, in actual practice, uncertainty is not constantly reduced in a linear way. In reality, uncertainty is reduced when a new forecast becomes available. Therefore, the trade-off between timeliness and uncertainty reduction is better represented by figure 2.2.

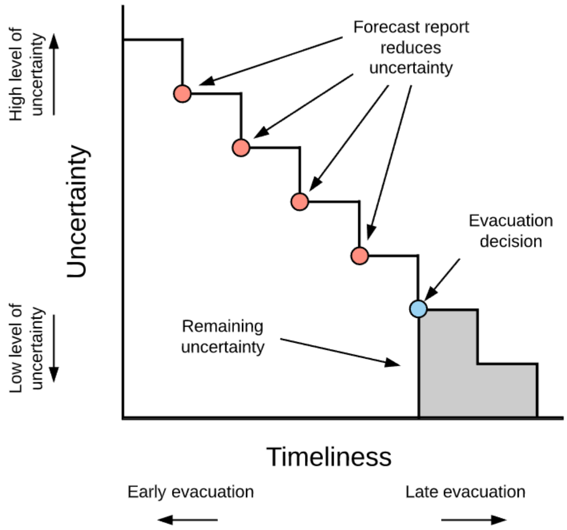

Figure 2.2: Timeliness and uncertainty reduction trade-off in evacuation decisions based on periodically updated forecast reports

This means that the (sub-)optimal balance between timeliness and uncertainty reduction will always be found directly after a forecast report has been published.

2.5. Classification of current models

Three different model (optimization) concepts and the aspect of time have been outlined. In table 2.1, the addressed papers on pre-disaster flood evacuation are linked to the four concepts that the particular pre-disaster model accounts for. The rural and urban column and the motorized vehicles column have been added for the reason that the dynamics that are captured, differentiate significantly between urban and rural areas and whether evacuees have access to motorized vehicles during their evacuation. The papers are ordered by the year in which they are published. Important note is that some models do account for example location problems, but do not optimize this. This is then categorized as “partly”. Furthermore, "yes" is specified for behavioral aspects if the paper takes into account at least one behavioral aspect. n/a is specified for the motorized vehicle column if a paper does not actually simulate the actual evacuation and there is nothing specified about the travel speed of the evacuees.

Table 2.1: Different works classified according to the identified aspects in evacuation models

Author	Location optimization	Routing optimization	Behavioral aspect	Time aspect	Urban / rural	Use of motorized vehicles
Sherali et al. (1991)	yes	yes	yes	no	urban	yes
Kongsomsaksakul et al. (2005)	yes	yes	yes	no	urban	yes
Simonovic and Ahmad (2005)	no	partly	yes	no	both	no
Uno and Kashiyama (2008)	no	no	yes	no	urban	no
LIU et al. (2009)	partly	no	yes	no	urban	no
Pan (2010)	yes	no	no	no	rural	no
Dawson et al. (2011)	no	yes	yes	no	urban	yes
Krzhizhanovskaya and Sloot (2014)	no	partly	yes	no	urban	no
Lim et al. (2016)	no	no	yes	no	urban	n/a
Watts et al. (2019)	no	no	yes	yes	both	n/a
This research (2020)	**yes**	**no**	**yes**	**yes**	**rural**	**no**

Analyzing the research included in table 2.1, some conclusions can be drawn. First of all, due to increased computational power, models are getting more and more complex. Over the years, they either study the dynamics more in depth, or they model evacuation over bigger areas. Second, only the work of Pan (2010) researches evacuation specifically in rural areas, but he merely optimizes shelter locations and does not model actual evacuation. Third, where in pre-positioning of relief goods the concept of time is often accounted for, in most evacuation models it gets little to no attention.

2.6. Knowledge gaps

Based on the literature review above, as summarized in table 2.1, two knowledge gaps have been identified: the concept of time in pre-disaster evacuation and the lack of a predefined set of shelter locations. They will be explained in the subsections below. Section 2.7 will explain how these knowledge gaps are included in the Research Question.

2.6.1. Concept of time in pre-disaster evacuation

The most important knowledge gap is about the trade-off between timeliness and uncertainty reduction in pre-disaster evacuation. As shown in table 2.1, only Watts et al. (2019) do account for the concept of time, but the authors models the relation between evacuation decisions of residents and the forecast information they receive. Therefore, they do not model the actual evacuation, only the decision to evacuate, based on perceived risk. That most authors do not account for this trade-off is not unexpected, since many of these researches focus on urban and developed areas, where this trade-off is assumed to be of less relevance. Based on the researched papers, none of them developed a model that would be suitable to inform decision makers on the best timing to evacuate for rural and developing areas, with little or no access to motorized vehicles.

2.6.2. Predefined set of shelters

Building on the previous knowledge gap, in developed countries, shelter locations are constructed in case of a natural disaster. This means that evacuation models need to take into account the already existing infrastructure. In most of the research presented in table 2.1 , a pre-defined set of shelters is used for optimization. However, in less developed countries there is often not a sufficient amount of shelters. This knowledge gap states that there is a need to cope with evacuation decisions where shelters are not pre-defined.

2.7. Research question

Building on the current evacuation models and addressing the identified knowledge gaps, the focus of this research will be on balancing the trade-off between timeliness and uncertainty reduction (time concept) for pre-disaster evacuation in rural and developing areas. A shelter searching algorithm has been developed, to account for situations where there is no pre-defined set of shelters. The main focus on rural and developing countries, means that modelling congestion (routing optimization) is deemed unnecessary and is not considered in this research. Location-allocation optimization and behavioral aspects will be included in the evacuation model in this research, in order to answer the research question. The research question is as follows:

How to balance the trade-off between timeliness and uncertainty reduction in making shelter location decisions in rural and developing areas, under impending cyclone induced floods, while accounting for behavioral aspects of the vulnerable residents?

Chapter 3 will explain the research approach that is chosen to answer this question. Chapter 6 will discuss what relevant behavioral aspects are included in the evacuation model in this research.

3

Research questions and methodology

This chapter will divide the main research question in multiple sub questions and will shortly address the approach to answer them (section 3.1). The first three sub questions each represent a building block of the bigger model that is developed in this research. Section 3.2 will discuss the interaction of the three building blocks and will give a graphic overview of the complete model that is used to study pre-disaster evacuation.

3.1. Sub questions

The main research question (repeated):

How to balance the trade-off between timeliness and uncertainty reduction in making shelter location decisions in rural and developing areas, under impending cyclone induced floods, while accounting for behavioral aspects of the vulnerable residents?

Because a research question can often not be answered at once, it is common practice to divide the main research question in multiple sub questions. The sub questions are all based on the identified concepts in chapter 2. The first question is about the vulnerability to floods, based on the forecasted data of the cyclone, whereas the second and third sub question are about the location optimization and the behavioral aspects, respectively. The fourth question is about how to use the model to research the trade-off between timeliness and uncertainty reduction in evacuation decisions.

3.1.1. Calculating cyclone induced flood risk

Building block 1 - How to calculate vulnerability regarding cyclone induced floods, based on the predicted trajectory of the cyclone?
This question will explore how to define and implement vulnerability regarding cyclone induced floods. It will do so, based on different elevation data sets and the related risk to floods in combination with the probability of being in the predicted path of the cyclone. This question will be answered in chapter 4.

3.1.2. Optimize shelter location decisions

Building block 2 - How to apply optimization in shelter selection, based on the expected vulnerability and the demand that needs to be covered?
Early evacuations will result in more uncertainty, which will mean that a larger area needs to be evacuated. This will influence the decision on where to place the shelters, given the uncertainty in the forecasts. This question will research how optimization of shelters can be used to reduce the travel distance for the evacuees. This question will be answered in chapter 5.

3.1.3. Behavior exploration

Building block 3 - How can the identified relevant behavioral aspects in literature be conceptualized and used for simulation?
This question will answer how the identified behavioral aspects in the literature from chapter 2 can be conceptualized for rural and developing areas. In order to do so, it will elaborate on what the concepts rural and

developing mean in an evacuation context. The answer to this question will also explain how the conceptualization can be implemented in a model. This question will be answered in chapter 6.

3.1.4. Researching the trade-off

How do timeliness and uncertainty reduction in evacuation decisions relate to the efficiency and effectiveness of the evacuation?
Finally, the trade-off between timeliness and uncertainty reduction can be researched. For this question the model will be implemented for the case study of cyclone Idai and cyclone Kenneth. It will explain how the model can be used to evaluate the impact of the different policy levers that can be used by the decision makers. This question will be answered in chapter 7.

3.2. Methodology

This section will explain the methodology of this research and how the different building blocks, as summarized by the sub questions in section 3.1, will interact. This means that this chapter explains at an abstract level what the model does, but not how it is done. For the specifics of all the building blocks of the model, the reader is referred to the chapters 4 through 7. For an even more detailed explanation of the different building blocks, the reader is referred to appendix D.

The purpose of the model is to answer the research question about the trade-off between timeliness and uncertainty reduction in pre-disaster evacuation decisions. To research this trade-off, different forecast moments are chosen to analyze a potential evacuation decision. The forecast moments are dependent on the moments the responsible forecast agency publishes a forecast about the cyclone. This means that there are several discrete decision moments over time. The time in between different forecast moments is not considered as an evacuation decision point, since evacuation time will be shorter, without the uncertainty being reduced (see figure 2.2).
Next, for every discrete decision moment, the vulnerability is assessed, based on the uncertainty that is related to the forecast moment and based on the elevation levels. The area that needs to be evacuated is defined as all the places that have a vulnerability value that exceeds a certain threshold. This vulnerability calculation is described in chapter 4.
To evacuate the residents, possible shelter locations are determined. They are found based on a certain distance to the area that needs to be evacuated. Next, a subset of those possible shelter locations is selected, that minimizes the average travel distance for the evacuees. This process is described in chapter 5.
The data from the previous two building blocks are saved in a Netlogo file format, from which the simulations are executed. That means that for every forecast moment the vulnerable area has been determined, a subset of shelter locations has been selected, and every group of evacuees is assigned to one of those shelters. The third building block simulates an evacuation and captures the results in order to compare the different decision moments to evacuate. Figure 3.1 illustrates this process graphically. The model is initialized for two different case studies (which are described in chapter 8 and 9). They show the usefulness and applicability of the model in these type of pre-disaster evacuation decisions.

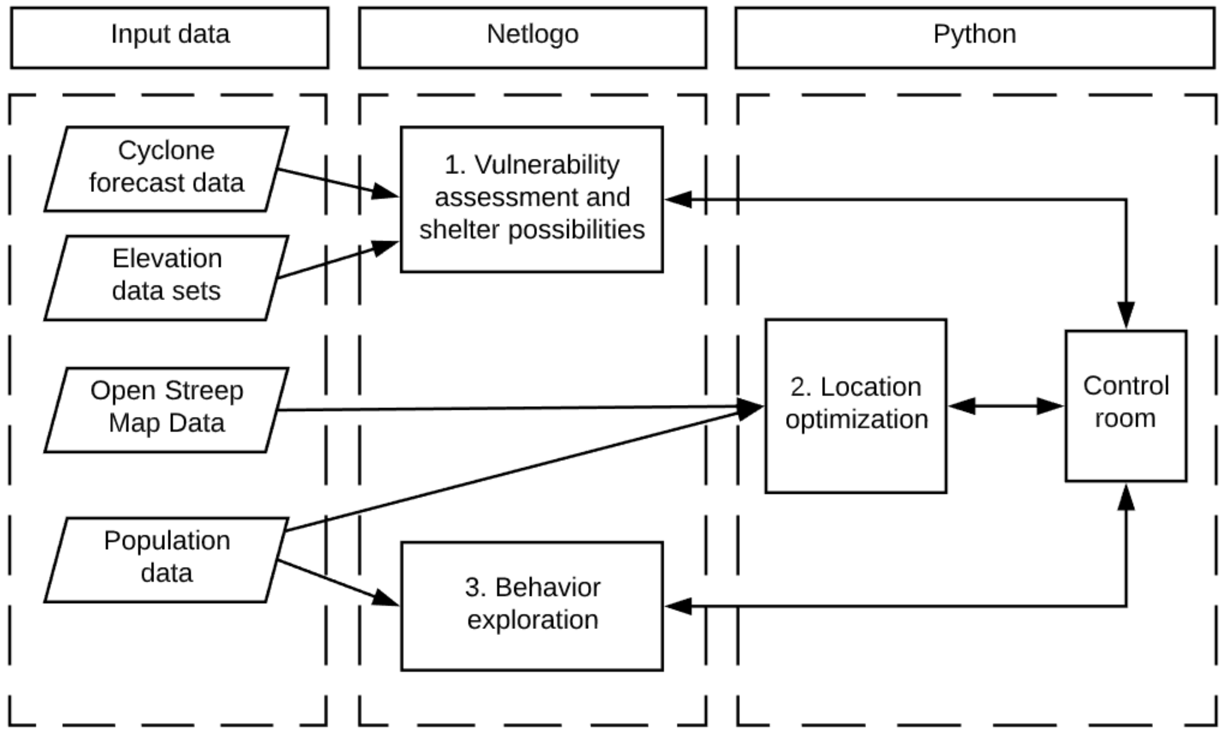

Figure 3.1: Methodology: the interaction between the different building blocks of the model

The left side of figure 3.1 shows the data input. The middle part shows the processes that are executed using Netlogo. Based on the sub questions, finding possible shelters is actually part of the optimization part. However, since the shelter finding algorithm is implemented in the first Netlogo model, it is shown under building block 1. The different models are executed from within Python, which is also used to connect all the different building blocks. This is why all the building blocks are connected to the control room.

Step by step walk through

The input parameters are specified in the control room. Then, the control room executes the first building block. As a result, the control room receives possible shelter locations and a vulnerable area that needs to be evacuated. It then executes the second building block to optimize over the complete shelter set, based on the population data and the Open Street Map data. This data set of evacuees and their assigned shelter is sent to the third building block where the simulation is executed. The results are captured in key performance indicators, which are sent back to the control room where they are visualized. This processes describes one experiment, but multiple experiments are executed. One experiment consist of one configuration of all the three policy levers.

4
Cyclone induced flood risk

The first part of the model in this research assesses the vulnerability of the residents, based on the forecast reports about the cyclone. However, that is easier said than done, because a cyclone is a complex natural hazard that is hard to predict, especially after landfall. Appendix G shows an example of a forecast report of cyclone Idai. Such a report typically entails the following aspects: the date, time and location (tenths of a degree) of the center of the cyclone and the direction and speed of the cyclone. The current location information also includes: an estimate of the lowest atmospheric air pressure, diameter of the storms eye, maximum sustained winds, radii of the maximum winds, which are specified for each of the four quadrants of the cyclone and are given in three categories; ≥64 kt, ≥50 kt and ≥34 kt. Next to the current information, a forecast report also reports the expected position and wind radii for a 12-, 24-, 36-, 48-, 72-, 96- and 120-hour period (NHC, 2020). All this information can be used in flood modeling software to calculate precipitation, which together with current rivers, can predict floods. Flood modeling software also enables to account for run-off of the precipitation, which means that rainfall water may cause floods in other places than it actually falls down. However, because this is a heavy computational demanding process, this research will make use of a static predictor of cyclone induced floods, which is described in section 4.1. Next, section 4.2 will explain how the relative vulnerability as a consequence of an impending cyclone is calculated.

4.1. Software implementation

Section 4.2 describes how the vulnerability is calculated, but to do so, different data inputs are necessary. These data need to be imported in a software program. The agent-based software modeling package Netlogo (Wilensky, 1999) is chosen, because it is possible to connect it with a Geographical Information System (GIS) using the already provided GIS-connector. Other reasons for choosing Netlogo are explained in chapter 6. Many authors make use of a GIS for evacuation purposes and demonstrate the usefulness and the simplicity of it (see for example the works of Chen et al. (2011), Crooks and Wise (2013), Chen (2014), Hébert et al. (2018) and Watts et al. (2019)). For example, the implementation of a GIS in Netlogo, enables the user to account for the current road infrastructure during the evacuation process. Netlogo is a discrete software program and divides the "Netlogo world" up in patches. Because Netlogo is coupled with a GIS in this research, those patches represent a two-dimensional real-world space with a certain width and height. Different inputs in this Netlogo world are used to determine the vulnerability. They are discussed in the subsections 4.1.1 and 4.1.2. Subsection 4.1.3 explains the different scopes of this research.

4.1.1. Elevation data

The elevation data consists out of two parts: the absolute elevation above sea level, and the relative elevation compared to the height of the nearest drainage network. This second type of elevation data is known as HAND (Height Above the Nearest Drainage). The HAND model is a terrain model, developed by Nobre et al. (2011), and shows comparable hydrological significance and proves to be a suitable predictor for floods. For more details regarding the HAND model, refer to Nobre et al. (2011).

However, it can vary across different geographical areas and different cyclones, what areas up to what height might be affected. Therefore, the HAND model is compared to the absolute elevation level. This means that the HAND data is used for calculating vulnerability, but only for elevation levels up to an absolute elevation threshold. This consideration has been made, because residents in more hilly areas mostly know best themselves how to interpret the possible floods and where they would be safest. However, in other cyclones the most danger did not come from floods, but from landslides. These can also occur at higher altitudes. Therefore, the model can be set with an absolute elevation threshold, based on what type of danger is being researched. If only floods are taken into account, the threshold can be set to for example ten meters, because it is unlikely floods will occur at a higher altitude. For land and mud slides however, the value can be set much higher, also taking into consideration residents that live on higher grounds.

4.1.2. Forecast data

The forecast data is retrieved from the Meteo France institute. The forecast data consists of the forecasted path of the cyclone at different moments in time. The forecast is specified as combinations of latitude and longitude. The further in time the path is forecasted, the more uncertainty exists. An example of a forecast report is included in appendix G. Section 4.2.1 will explain how this uncertainty is accounted for in the model. Another important factor is the width of the cyclone that can cause heavy floods. This can differ between cyclones and therefore this parameter is included in the model.

4.1.3. Model scope

The geographical scope of this research is based on the largest uncertainty at the earliest forecast. For cyclone Idai, this results in a geographical scope of -15.5°North, -22.5°South, 33°West and 40°East, which equals an area of around 735 by 778 kilometer. For cyclone Kenneth, this results in a geographical scope of -8.5°North, -17.5°South, 35.5°West and 44.5°East, which equals an area of around 975 by 1000 kilometer. Regarding the period of interest, the model runs from the earliest forecast (six days in advance for cyclone Idai and three days in advance for cyclone Kenneth) up to the landfall of the cyclone. Since this research focuses on pre-disaster evacuation, it will not take into account the post-disaster effects of the cyclone.

4.2. Vulnerability calculation

Using the data inputs, the vulnerable area can be calculated for different moments in time, given the different forecasts. This section will first describe the effect of the uncertainty that is inherent to the cyclone and will continue with the effect of the HAND data on the vulnerability. The vulnerability is then calculated as directly proportional to the relative elevation and the chance of being in the location of the path of the cyclone.

4.2.1. Uncertainty in the forecast

The further the path of the cyclone is forecasted in time, the more uncertainty there is. A common way is to calculate the uncertainty cone, which is defined as a 2/3 probability that the eye of the cyclone will move within the uncertainty cone. Table 4.1 displays the uncertainty of this cone, relative to the forecast moment. The model in this research will use these uncertainties as the maximum deviation the cyclone can take.

Table 4.1: Uncertainty depending on the forecast period (NHC, 2020)

Forecast periods (hours)	2/3 Probability Circle (nautical miles)
12	39
24	69
36	99
48	124
72	179
96	252
120	326

Because these uncertainties are measured from the path, the width of the cyclone is not taken into account. Therefore, the width that has been determined for each specific cyclone has been added to the uncertainty. Together, this forms the uncertainty range.
The probability of being hit by the cyclone is then formulated as:

$$1 - \frac{\text{distance to the forecasted path of the cyclone}}{\text{uncertainty range}}$$

This means that a linear relation is assumed between the distance to the forecasted path and the probability of being hit by the cyclone.

4.2.2. Impact of the elevation data

The height above the nearest drainage is measured in meters. The lower this value, the more likely it is the area will be flooded.

4.2.3. Determining the vulnerable area

The final vulnerability is calculated as

$$\frac{\text{probability of being hit by a cyclone}}{\text{height above the nearest drainage}} \quad \forall \quad \text{absolute elevation level} \leq \text{elevation threshold}$$

The final step in determining what areas are too vulnerable that they need to be evacuated, is to put a threshold on the vulnerability value for every patch. This means that patches with a vulnerability value above the threshold are deemed at risk and should be evacuated. This threshold is determined using calibration. A value of this threshold is chosen in such a way, that the vulnerable area in the model matches the area that is inundated in the real world. For calibration purpose, the actual path of the cyclone is loaded in the model, and the uncertainty range is reduced to the width of the cyclone only. Appendix C shows this process for the Idai case study.

5

Location optimization

Location-allocation problems are a well-known studied subject and is known in many different forms. Whereas in many situations location-allocation optimization is used to determine what factories need to cover what demand, here it is applied in a reversed way. In the original formulation, a source point is where the demand is produced and is then distributed to a demand point, for example the customers. However, in the case of assigning the evacuees to shelters, supplies will not flow from source to demand, but evacuees will travel from demand to source. Even though this reverts the practical applicability of location-allocation problems, the mathematical model to solve both problems is the same. Despite the direction of the flow of goods, or in this case evacuees, demand and capacity still need to be matched. This chapter will first elaborate upon how the source and the demand points are defined. It will then continue with an illustration of how possible shelter locations are determined using a shelter-search algorithm (section 5.2). Section 5.3 will continue with the mathematical formulation of the location-allocation problem and will describe in detail how the input for the model is defined and how it is implemented in the optimizing software Gurobi. The objective of this chapter can be summarized as selecting a subset of the possible shelters, that minimizes the distance that evacuees need to travel to their assigned shelter. Based on this information, an answer to sub question 2 can be formulated.

5.1. Demand and shelter points

A demand point is defined as an area that is classified by the model as vulnerable and therefore needs to be evacuated. Because vulnerability is calculated in a discrete manner, a vulnerable area has a width and height of 2.625 kilometer. This area has a certain population, which is defined as the weight that is associated with that demand point. A shelter point is a possible shelter location where the population at a demand point can possibly evacuate to in order to satisfy the demand at the demand points.

5.2. Finding possible shelter locations

To find the best shelter locations that minimize the total travel time of the evacuees, a set of suitable locations need to be found first. These locations are either outside of the projected inundated area, or on higher located grounds within the projected inundated area. This second type of locations is also known as vertical evacuation, whereas the first type can be seen as horizontal evacuation. Vertical evacuation is a well-studied concept in evacuation in danger of a tsunami. Vertical evacuation is then sometimes the only possible option due to the lack of time before the tsunami will hit (see for example Yeh et al. (2005); Park et al. (2012); Wood et al. (2014)). Also within evacuation because of flood risk, vertical evacuation instead of horizontal evacuation is getting more attention. Kolen and Helsloot (2012) researched vertical evacuation in the Netherlands, because 48 hours before the predicted flood was not enough time for horizontal evacuation only. Since both vertical and horizontal evacuation might be effective, both will be taken into account.

To illustrate the algorithm that searches for possible shelters, a fictive zone that needs to be evacuated is shown in Figure 5.1 in yellow. The locations of the shelters that are found by the algorithm should be close to the area that is in danger, since that will make them easier to reach, but not to close, since that would make the shelter locations unsafe. Therefore, a margin between the area in danger and the possible shelter locations is necessary. The smaller the margin, the closer the shelters will be to the people who will need them, but also the more unsafe the shelters will be.

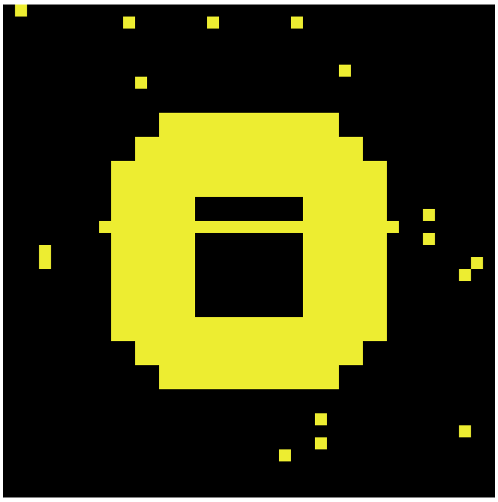

Figure 5.1: Illustration of the shelter searching algorithm: an fictive area that needs to be evacuated in yellow

In Figure 5.2, shelter are shown in green that have a distance to the area in danger of around 3 patches. The distance is measured between the center of each patch. The shelters in the middle of the yellow area can be considered as vertical shelter locations, since the area itself is deemed as safe, but it is surrounded by area that is deemed to be in danger. These vertical shelter locations have two disadvantages. First, they are more difficult to reach for humanitarian aid organizations, since they may be surrounded by area that is impassible after the natural disaster has struck. And second, since the area is surrounded by an area that is projected to be in danger, the area therein may also be considered to be more dangerous, even though it is not classified by the model as such. This means that, if vertical shelter locations are deemed necessary, the margin should be chosen wisely, taking into consideration the two disadvantages discussed above.

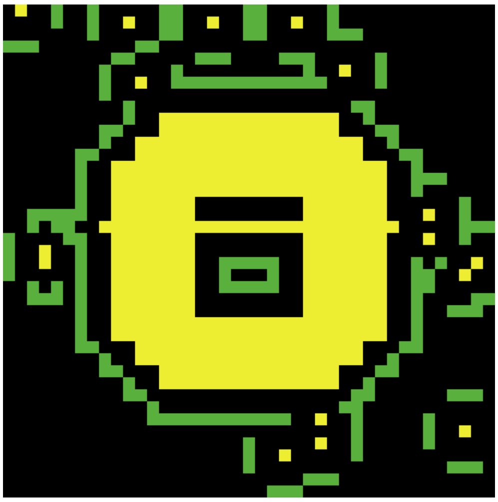

Figure 5.2: Illustration of the shelter searching algorithm: an fictive area that needs to be evacuated in yellow with shelters at a safety distance of 3 units

Figure 5.3 shows shelters in green that have a margin of five patches. This results in no vertical shelter locations, since the area within the danger zone is not big enough to satisfy this margin of 5 patches. Even though these shelter locations are safer in general, the distance for the people that need to be evacuated is also larger.

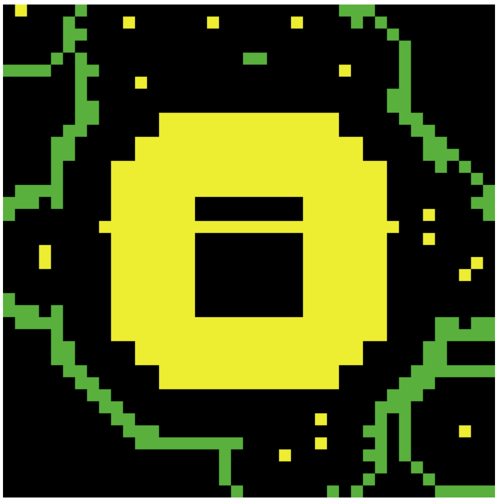

Figure 5.3: Illustration of the shelter searching algorithm: an fictive area that needs to be evacuated in yellow with shelters at a safety distance of 5 patches

5.3. The mathematical model and how it is solved

Location-allocation optimization can either be done using exact algorithms or by using heuristic algorithms. Exact algorithms explore all possible locations and will always find the exact optimum. However, the use of exact optimization is highly time consuming, because computational time increases exponentially with the number of dimensions. Heuristic algorithms may not always find the best solution, but are more suited because they find sub-optimal solutions within significant less time. Using optimizing software Gurobi, the Pareto-optimal front is estimated and the solution converges towards the Pareto-optimal front.
Inherent to the trade-off between timeliness and uncertainty reduction in this research, is that for some evacuees it is not possible to reach any shelter within the time that is left before the disaster will struck. An example may be the population in one of the middle yellow patches in Figure 5.3. Their shortest distance to any one of the shelters may be too far, and therefore the population at this patch will not be considered in the optimization. Although this may be perceived as unethical, it is rather a direct consequence of a late or timely evacuation.
The next step in the optimization is to choose a optimization model. Various options have been discussed in section 2.1 and the Minisum facility location problem has been selected. The main reason for this choice is that time is of the essence and it is important to save as many people as possible, but in order to do so, a high compliance of the residents is also needed. Since traveling large distances are a heavy burden and residents are more likely to heed the advice to evacuate when the distance is smaller, the average distance of the evacuees is minimized. The coverage models are not considered, since those are more relevant when there is no time pressure and it is more important that all the demand is covered. Furthermore, because some resident will always be out of reach of any of the shelters, 100% coverage will not always be possible. The location-allocation is solved using the Minisum facility location problem formulation. This formulation selects a maximum number of facilities that can be placed and seeks to minimize the total travel distance between the source and demand points (Boonmee et al., 2017). This means that the coverage constraint is relaxed in this formulation. The formulation for this mathematical model is as follows:

Indices and Index sets:
I set of demand nodes: $i \epsilon I$
J set of shelters: $j \epsilon J$

Decision variables:
$X_j = 1$ if a shelter is located at eligible site *j*, and 0 otherwise
$Y_{i_j} = 1$ if shelter *j* is shelter location for demand point *i*, and 0 otherwise

Input parameters:
d_{i_j} the distance between demand point i and candidate shelter *j*.
cap the capacity for the shelter.

P the maximum number of shelters that can be placed.
w_i the weight associated to each demand point.
L The distance limit that can be travelled before the disaster will strike.
N_i the set of eligible shelters located within the distance limit L that can be reached by demand point i ($N_i = \{j | d_{i_j} \leq L\}$)

With the objective to

$$\text{Minimize} \sum_i w_i d_{i_j} Y_{i_j} \tag{5.1}$$

Subject to

$$\sum_j X_j = P \tag{5.2}$$

$$\sum_j Y_{i_j} = 1 \qquad \forall i \tag{5.3}$$

$$\sum_i w_i Y_{i_j} \leq capX_j \qquad \forall j \tag{5.4}$$

$$Y_{i_j}, X_j \in \{0,1\} \qquad \forall i, \forall j \tag{5.5}$$

Equation 5.1 is the objective function and aims to minimize the weighted travel distance between the evacuees and their assigned shelter. The maximum number of shelters is enforced by Equation 5.2. Equation 5.3 makes sure that all evacuees get one shelter assigned to them. Equation 5.4 makes sure that the capacity per shelter is not exceeded. Lastly, Equation 5.5 forces the decision variables to take binary values.

Before the mathematical model can be implemented in optimizing software Gurobi, the input needs to be obtained. The following subsections will explain how the input parameters are obtained and defined.

5.3.1. Determining the distance between demand point *i* and shelter location *j*

Two main ways of calculating the distance between two points have been considered; that is either the euclidean distance or the distance using existing infrastructure. As this research examined, the first is very fast to implement and run, but is also less realistic, since it does not account for the actual roads, whereas the second option is more realistic, but also more computational expensive to calculate. Both options have been examined and the different results for the optimization will be discussed. First, it will be explained how the distance is calculated using infrastructure data.
Road data is obtained from OpenStreetMap and is loaded into Python using the OSMNX package. This package translates the road data into a graph with nodes and edges. The nodes represents the crossings and the edges represent the roads. This representation enables to use shortest path algorithms to calculate the shortest distance between a point A and B. To connect a geographical point defined in longitude and latitude to the graph representation, the node is chosen that has the shortest euclidean distance to that point. Using the Idai case study as an example, the graph representation of the Mozambican road network resulted in a graph of 127.000 nodes and 331.000 edges. Calculating the shortest distances in a scenario with 1721 source nodes and 291 target nodes (which is the case based on the forecast on March 13, 1800h with a patch resolution of around 2.6 by 2.6 kilometer), the run time was 47 hours. Since this is too computational heavy to have practical applicability, the run time is reduced by only searching for shortest paths between points that lie within a certain euclidean distance of each other. Since the optimization will minimize the total distance, this will most likely not result in a different outcome, but significantly reduces the run time to only 1.5 hours. Reducing the number of shortest paths within a certain distance is done by first calculating the euclidean distance between all source and target points, and consequently only calculate the shortest path between points that have an euclidean distance that is less than is specified. The high reduction in run time is because calculating the shortest path between two points on opposite sides of the graph takes the longest time, and they are now filtered out. Still, the run time between using real road data and the euclidean distance is significant, because the calculation of the euclidean distance on the same number of source nodes and target

nodes is only a matter of seconds, compared to 1.5 hours for using real road data. Another improvement has been made to reduce the computational time. Every time a path is calculated, it is saved in a database. For all consequent experiments, they first check whether the path has already been calculated. This means that if more experiments are ran, the computational time reduces, ultimately to half an hour per experiment. A small scale dummy example is included in Appendix D and H. It shows, step by step, how Netlogo coordinates are matched to nodes in the network, and how the shortest routes are determined.

5.3.2. Determining the shelter capacities

There are various reasons to place a capacity constraint on each shelter. For example, for logistical reasons it is unwanted if everyone would be traveling to the same shelter locations. Also, the physical constraint of the shelter locations is a reason to specify a maximum capacity. However, in this research the shelter locations are not actual buildings and they are only chosen because they are at a certain distance of the area that is projected to be in danger. Still it can be preferred to specify a maximum number of evacuees per location to efficiently organize humanitarian aid. For example, shelter locations that are too populated can easily result in fast spread of diseases like cholera. Therefore, there is the option to specify a capacity constraint that is the same for all possible shelter locations. The model can easily be adjusted to specifying a specific capacity per shelter, but for this research that option is not needed.

5.3.3. Determining the maximum number of shelters

The maximum number of shelters can, for example, be based on the available personnel that can assist the evacuees in those shelter locations. The maximum number of shelter locations is also dependent on the time that is left before the cyclone will strike. Earlier evacuation also gives more time to build shelters. What is important is that the model has a constraint, that everyone within a certain distance should be assigned a shelter location. That means that the combination of shelter amounts and their capacity should be adequate to meet the demand of the evacuees. In fact, the combination of number of shelters and the capacity per shelter can be used to spread out the evacuees over the different selected shelters.

5.3.4. Determining the population that needs to be evacuated

Since the objective is to minimize the weighted total travel time, the size of the population for each patch will influence the decision where to locate the shelters. The LandScan data set is used to obtain this population data, since census data is often not detailed enough in many developing countries. The LandScan data set specifies the estimated population per square kilometer. These data are aggregated to the right resolution using QGIS and programming language R, in order for it to match the resolution of the demand points.

5.3.5. Determining the distance limit

The distance limit is a consequence of when the decision to evacuate is made. The hours between this decision point in time and the forecasted arrival time of the cyclone will determine how much time is left before the cyclone will make landfall. This time will be translated to a distance using an estimate of the travel speed and the hours per day that people are able to travel. If, given this distance limit, a demand point i does not have any shelter within reach, it is not considered in the optimization. However, it is possible that a demand point i has a certain number of shelters within reach, but none of those shelters is chosen. This will mean that this evacuee will possibly not reach the shelter location in time.

6

Behavior exploration

Chapter 4 explained how the environment will be implemented in Netlogo (Wilensky, 1999). This chapter will explain how the residents (called agents in agent-based modeling) will be implemented in this environment and what kind of behavioral rules they will follow.

6.1. Agent implementation

Netlogo is chosen as the suitable software because it enables, amongst others, agent-agent communication, agent heterogeneity and is spatially explicit (Dawson et al., 2011). Even though not all options that are offered by Netlogo are thoroughly used, it provides future research with the flexibility to expand the model. In Netlogo, agents are representing individuals or collective entities, such as organizations or groups. In this research the population of one demand point is represented by one agent. This essentially means that all the residents in an area of 2.6 by 2.6 kilometer will have the same characteristics because they are represented by one agent with a weight that equals the population size in that area. This decision has been made since it can be assumed that residents that live close to each other, will also travel together to their assigned shelter. This means they have the same travel speed et cetera. Another reason for this representation is because it reduced the number of agents in the model and therefore shortens the run time. The distance that the agent needs to travel is taken from the optimization part, where it is calculated using the OSM road data. This means it would be otiose to include the road network in the simulation, since this research does not include congestion and the real distance is already known. This means that agents will travel in a direct line to their shelter, but with the time that corresponds to their travel time and the real world distance.

6.2. Behavioral rules

The literature about behavior during evacuation, as described in chapter 2, summarizes the factors that determine if and how people choose to evacuate. Including too many factors in the model will only increase the 'noise', making it more difficult to interpret the model results. Therefore, it is opted to include only the most important characteristics with respect to how the evacuation order is received and the time residents take to start evacuating. This means the following behavior is included in the model:

1. If agent is covered by a cell tower, he receives the evacuation order instantly.
2. If agent is not covered by a cell tower, he will receive the evacuation order from people who are traveling in his vicinity.
3. Agent takes a certain decision time before he starts evacuating, which is a taken from a uniform distribution.
4. Agent does not decide during the night, but waits until the morning.
5. When agent is traveling to his shelter, he will automatically alert others within a certain radius around him.
6. If agent is alerted by another agent (because he has no cell tower coverage), he will not travel to his designated shelter, but will go to the shelter of the agent that alerted them.
7. Agent has a certain travel speed, which is a taken from a uniform distribution.

8. Agent will only travel during day hours, because day light is needed to travel.
9. Agent will take the shortest path towards the designated shelter.

That means that, amongst others, the following assumptions are made:

1. Agent always heeds the advice of the evacuation order
2. Agent always evacuates to the designated shelter, unless he is informed by another agent.
3. Agent is aware of how to reach the designated shelter, using the fastest route.

Residents in rural areas are difficult to reach, especially when they are outside the reach of cell towers. Rule number 1 and 2 simulates that agents with no cell tower coverage are delayed in receiving the evacuation order and are dependent on other agents communicating the evacuation to them, with for example the use of local radios. Behavioral rule number 3 is implemented because residents in rural Mozambique often consult the village elders on how to respond to an evacuation order. Therefore, they will need some time to consult each other, gather their personal belongings and to secure what they need to leave behind. The uniform distribution is chosen because there is no real data available on how long it would take for residents to decide and a uniform distribution is not presumptuous about the spread of the data. However, if the model is applied to a case study where the distribution is known, it could easily be changed. According to Freek Huthoff, a Mozambican expert, in the areas where there is no electricity, life stops when it becomes dark, and therefore behavioral rule number 4 specifies that they cannot consult each other during the night, and will wait until it is light again. Rule number 5 defines that agents alert other unaware residents after they have made their decision and are evacuating to their shelter. This vicinity, in which an agent alerts others, depends on the specifics of the case study, but could for example be several kilometers when local radios are used. According to rule 6, agents change their destination to the shelter of the agent that informed them. This is more likely since people with no cell tower coverage also do not have any internet connection and are therefore dependent on the information they receive from others. That makes them more likely to follow the agent that alerted them, than to go to an arbitrary shelter location. Behavioral rule number 7 is meant to simulate different travel speeds, since some people will be older and will travel slower than young people. Another reason is that some people might take their cattle or other household items with them, slowing them down. Behavioral number 8 makes sure evacuees only travel during day light, because it is not possible to travel in darkness with no lighting. Lastly, rule number 9 is an assumption which means that it is assumed that residents have enough local knowledge to know the fastest route to their destination. It is believed that this simplified implementation of an agent, resembles actual behavior during evacuation in a realistic manner. Figure 6.1 displays the logic of the agents visually in a simplified manner. The rectangles represent actions that the agent executes, and the diamond shaped figures represent the actions for the agent. Note that a loop in the diagram is only executed after the model advances one hour.

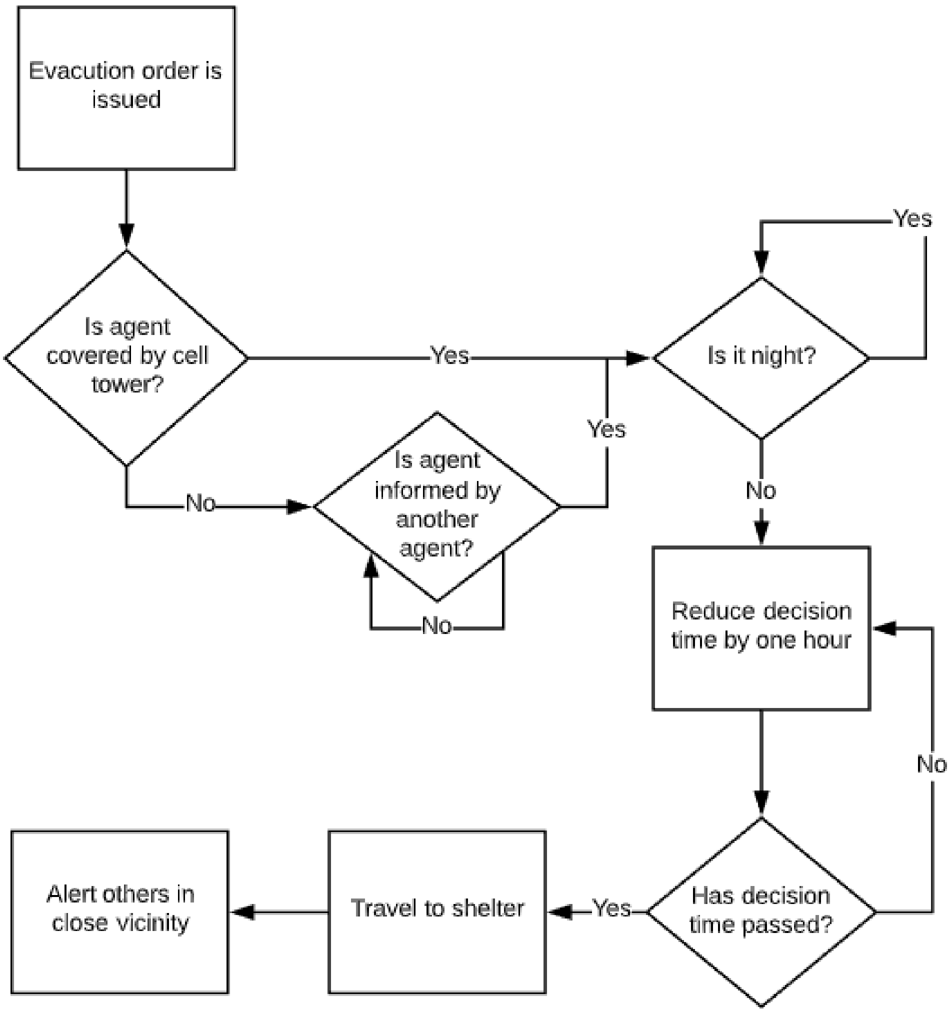

Figure 6.1: Agent logic visualized. The rectangular boxes represent actions, either by the decision maker or the agent. The diamond shaped boxes represent the actions of the agent

7

Model application

The three model building blocks, that together form the complete evacuation model, are described in the previous three chapters. This chapter is dedicated to explaining how the complete model interacts. This includes defining all the input parameters to initialize and run the model, but also defining the key performance indicators (KPIs), in order to assess and quantify the outcomes of the different experiments. The next two chapters will show the application for two different case studies: cyclone Idai & cyclone Kenneth.

7.1. Input parameters

There are two different types of input parameters; user controlled parameters and external parameters. The last type typically consist of parameters that take a value that cannot (easily) be changed, for example the decision time residents take before evacuating, or the uncertainty that is inherent to the forecast moment of the cyclone. Those parameters are either a given or their value is determined or estimated, with for example the use of literature or expert opinions. In the next two chapters those values will be given, but will not be part of the experiments, since they can not be controlled. The user defined parameters are the typical policy levers: the decision variables that the user can influence in order to test the effect of those decisions. These variables are used as input for the experiments in order to gain insights into the consequences of different value combinations of those parameters. These policy levers will shortly be described below.

7.1.1. Moment of evacuation

The moment of evacuation is the ultimate policy lever; what is the best time to evacuate? Evacuation can be best done directly after a forecast has become available, since waiting after a forecast will reduce the evacuation time available, but will not reduce uncertainty about the cyclone (see figure 2.2). Since forecasts are updated periodically, the decision moments to evacuate are discrete moments in time, and not continuous, and are aligned with the publication of the forecast reports.

7.1.2. Safety margin

The safety margin is the margin between the possible shelters and the area that is deemed vulnerable for cyclone induced floods. For an elaborate explanation of how the safety margin works, the reader is referred to section 5.2. In short, a higher safety margin improves the safety of the shelter locations, but it increases the distance for the evacuees as well, and vice versa for a lower safety margin. A low safety margin can also lead to vertical shelter locations.

7.1.3. Amount and capacity of the shelters

The amount and capacity of the shelters is an another important policy lever; it has a big influence on the travel distance for the evacuees, and therefore, on the number of residents that reach their shelter in time. Too few shelter locations could even result in the journey of evacuees from a safe area to the impacted area. With more shelters, this undesired effect is less likely. Important remark is that the user is not completely free to choose any combination of shelters and their capacity, because of two assumptions. First of all, it is assumed that one group of evacuees will always travel to the same shelter, and is therefore not dividable over multiple shelters. Therefore, the minimum capacity of each shelter should at least equal the size of the largest evacuation group. The second reason why the user is not free to choose any combination of capacity and number of shelters is because it is more important to save as many evacuees as possible than to prevent overcrowding of shelter locations. Therefore, the demand of all the shelters combined should always be sufficient to shelter the total demand of all the evacuees.

7.2. Key performance indicators

The key performance indicators (KPIs) below aim to capture all the relevant results that would possibly influence or have an effect on the best possible policy. These KPIs together inform decision makers on the effect of their decisions regarding different evacuation strategies.

1. The total number of evacuees that were evacuated.
2. The total number of evacuees that were evacuated from the impacted area.
3. The fraction of evacuees from the impacted area that reached their shelter in time (this includes the number of people that were never evacuated because of the distance constraint, see KPI 5).
4. The travel distance (average distance and the 20th and 80th quantile).
5. The residents that live in the impacted zone, but are not evacuated due to the distance constraint.

The difference between the first and the second tells us how many people were evacuated unnecessarily, because only the residents in the impacted area were in need of evacuation. The third tells us how many people that were in danger are actually safely evacuated. If some evacuees in danger have not been evacuated because of the distance constraint, the fraction can never reach 1. The travel distance is a measure for the burden of the evacuees. Asking residents to leave behind their belongings and go to a for them unknown location has an enormous impact on their well-being. Therefore it is important to reduce the travel distance as much as possible. Appendix A includes a graphic explanation of the KPIs.

In the end, these KPIs define the trade-off that needs to be made in the policy decision regarding what time to evacuate. Early evacuation will result in a high number of unnecessary evacuees (and high average travel distance, but that also depends on the number of shelters), but also a high fraction of people effectively evacuated from the inundated area, vice versa for a late evacuation. With the use of two case studies, the application of the model will be shown to illustrate how the computer model can assist decision makers in deciding on the optimal timing for evacuation.

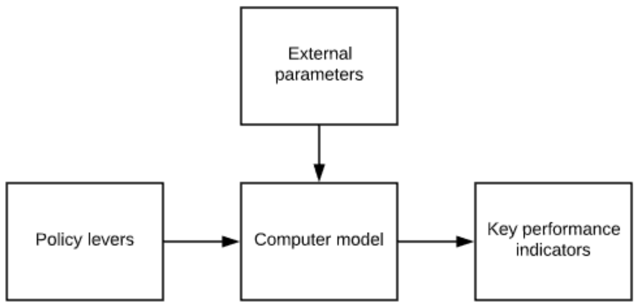

Figure 7.1: Relation between external parameters, policy levers, the computer model and the KPIs

8
Case study Idai

This chapter will show the implementation of the pre-disaster evacuation model for the case study of cyclone Idai. This chapter will first explain some background information about the case study in section 8.1. It will continue with detailing the experiment setup and will give an overview of the values for the external parameters that are specific to this case (section 8.2). Section 8.3 shows the results of the experiments and section 8.4 offers an analysis of the results of this specific case study. Section 8.5 will summarize the results from the Idai case study.

8.1. Cyclone Idai

This section will first give a short situation report of cyclone Idai and will continue with relevant characteristics of Mozambique to obtain an understanding of the evacuation situation and will finish with an overview of the relevant organizations that were involved in decision making and humanitarian aid before, during and after the disaster.

8.1.1. Situation report

The devastating natural disaster, later known as cyclone Idai, made landfall in Mozambique two times, as depicted in figure 8.1. The first landfall was on March 6th, primarily affecting the north-central provinces. Flooding from the tropical depression killed 66 people and injured 111 others. It was reported that 5.756 homes were destroyed, leaving 17.100 people displaced. It then set its way back into the Mozambique channel, where it grew in force and was officially classified as a tropical cyclone and it received the name Idai on March 11th. The second time Idai made landfall was on the night of March 14th and 15th and was much more devastating. It made landfall over the city of Beira, destroying 90% of the city. The cyclone continued inland and left a trail of devastation. Throughout Mozambique, Idai killed at least 602 people, injured 1,641 others and displaced 129.000 people. The powerful storm, which caused widespread flooding and destruction, is the most severe natural disaster to affect southern Africa in over three decades (Lutheran World Relief, 2019). Media reports that over 18.000 people were trapped on the roof of their houses or in trees, because they were surrounded by flood water. After 4 days, 15.000 people were still not rescued and had sometimes only been provided with basic food and medical supplies (BBC, 2019). What was particularly troublesome in case of cyclone Idai, was that even though residents were familiar with cyclones, they were caught off guard by the flooding due to overland runoff and rising groundwater levels and damage from multiple days of continuous strong winds, with devastating impacts. Mozambican interviewees at the community-level "relayed that their communities received warnings. However, most of them also relayed that they did not know how to translate those warnings into concrete actions they could take to protect themselves and their homes" (Cross, 2020). This research aims to coordinate such an evacuation, not only giving residents a clear location where they should go to, but also to decide on the best timing of such a pre-disaster evacuation decision. The focus in this case study will be on the second time cyclone Idai made landfall.

8.1.2. Relevant characteristics

In Mozambique, there are only 14 registered motorized vehicles per 1000 residents. Those vehicles are mostly located in the urban parts (over 40% is registered in the capital city), meaning that car ownership in rural

Figure 8.1: Path of cyclone Idai in Mozambique, March 2019
The size of the circles represent the relative strength

parts is nearly insignificant (Club of Mozambique, 2018). The reason is also clear, since only 20% of the roads are paved (mainly in the urban areas again), meaning that, according to Freek Huthoff, even if one has a car in rural areas, the maximum speed is somewhere between 5 and 30 kilometer, due to the poor road conditions. Another important aspect that is included in the model is the cell tower coverage. Figure 8.2 shows in red the area that is covered by the provider Vodacom (the provider with the best coverage in Mozambique) (GSMA, 2020). Cell tower coverage is important, since the evacuation message is transmitted using these towers.

Figure 8.2: GSM coverage, used for communication purposes

8.1.3. Involved organizations

The decision making authority during cyclone Idai lay with the responsible government department. In the Mozambican case, this is the Instituto Nacional de Gestão de Calamidades (National Disasters Management Institute, INGC). They are responsible for collecting data, undertaking preparedness measures and is the official body that would coordinate disaster response in Mozambique. They therefore have the legal power to issue an evacuation order and to coordinate the evacuation process (INGC, 2019)). In the case of cyclone Idai, they received assistance of many non-governmental organizations, private organizations and international organizations. For example, UN-Habitat, a programme of the United Nations, assisted in constructing shelter locations in order to provide first aid and other necessities to the internally displaced persons. They would also be the organization that would aid in constructing shelter locations in case of a pre-disaster evacuation plan. However, according to Cross (2020), even though various disaster risk reduction measures and disaster risk management policies have been put into place, most action is still responsive, instead of proactive. The post-disaster review (Cross, 2020) calls for more proactive collaboration: "The cyclones Idai and Kenneth also revealed the need to shift disaster response management efforts to focus more on proactive action and on disaster risk reduction to ensure that future losses do not outpace the capacity to respond". This pre-disaster evacuation would require such a proactive response, instead of reactive, since shelter locations will need to be set up before the cyclone will make landfall. However, based on the interview with Francesco Torresani, who works for UNhabitat, it came forward that the Mozambican government is increasing its focus to build cyclone proof school buildings, which can be used as shelter locations as well. This would ease the pre-disaster response phase, since shelter locations will not need to be build from scratch. However, data about these locations is not widely available and their capacity is by far not enough to shelter all the evacuees.

8.2. Experiments

This section discusses the specific external parameter values for this case study and continues with the experiment setup, that will be used to explore the main research question.

8.2.1. Describing the external parameter values

Throughout chapters 4, 5 and 6, various model parameters have been discussed, with some of them being specific to the case for which the model is used. Therefore those external parameters and their values are summarized in table 8.1. The different values for the policies levers are included in the experiment and described in section 8.2.2.

Table 8.1: Parameter values in the Idai case study

Parameter	Value
Cyclone width	100 (km radius)
Risk threshold	0.15
Elevation threshold	10 (meters)
Decision delay	$X \sim U(3,9)(hours)$
Travel speed	$X \sim U(2.5,5)(km/h)$
Day light	6 AM till 6 PM

The width of the cyclone has been determined, based on satellite images that show the rainfall that cyclone Idai has caused. A 100 kilometer radius of the cyclone corresponds to around 200 milliliter daily precipitation, that caused the cyclone induced floods. This value is validated in section 11.2.1. The risk threshold has been set to 0.15 as explained in section 4.2.3 and is validated in section 11.2.1. The last four parameters in table 8.1 have been determined based on interviews with Freek Huthoff and other people that were involved in aiding in the humanitarian response to cyclone Idai.

8.2.2. Experiments setup

Three different policy levers have been discussed in section 7.1. To start, there are nine different forecast moments included in the model, which are listed in table 8.2. The maximum width (at the earliest forecast with the highest uncertainty) of the vulnerable area is around 85 kilometers. Relative to this width, three different safety margins have been selected for the experiments. They are listed in table 8.3. The different amounts of selected shelter locations are given in table 8.4. The capacities of those shelters has been set equal to the size of the biggest group of evacuees. The options for the number of shelters have been based on the number of shelter locations that emerged after cyclone Idai. Government of Republic of Mozambique (2019) reported that 68 shelter locations have been created in the weeks after Idai made landfall. After a few weeks, many evacuees have been reallocated to other shelter locations. Since there is possible not enough time to construct 68 shelters, three options have been selected that are lower than 68 and one option that is more than 68.
There are as many experiments as there are combinations of those three policy levers. That means that there are 108 different experiments. Due to stochasticity in the parameters of the evacuation model, every evacuation simulation experiment will be ran 20 times to account for this stochasticity.

Table 8.2: Forecast moments

Evacuation moments
March 9th, 0600 AM
March 10th, 0000 AM
March 10th, 1800 PM
March 11th, 1200 PM
March 12th, 0600 AM
March 12th, 1800 PM
March 13th, 0000 AM
March 13th, 1800 PM
March 14th, 0000 AM

Table 8.3: Safety margins

Safety margins
5 kilometer
10 kilometer
20 kilometer

Table 8.4: Amount of shelters

Amount of shelters
10
20
40
80

8.3. Results

Since there are too many experiments to simply be displayed in one short table, the reader is referred to appendix A for a full overview of the results. This paragraph will instead describe one of the 108 experiments as an example. This section will conclude with an overview of the different areas that is evacuated in different evacuation moments.

Table 8.5 shows the results of experiment 87, with a evacuation decision based on the forecast moment at March 13th, 1800 PM, a safety margin of 5 and 40 selected shelters.

Table 8.5: Experiment number 87 explained

Policy lever / KPI	Value
Experiment number	87
Forecast moment	March 13th, 1800 PM
Safety margin	5 kilometer
Number of shelters	40
Total evacuees	242.046
Total evacuees in danger	84.663
Fraction saved	0.90
Evacuees in danger not saved	0
Average travel distance	30.11 kilometer
20th quantile of travel distance	9.34 kilometer
80th quantile of travel distance	30.81 kilometer

It shows that a total of 242.046 evacuees have been ordered to evacuate, of which 84.663 were actually in danger. The 84.663 residents were in actual danger because they lived in the area that was impacted by cyclone Idai, contrarily to the other evacuees, that in the end were not in need of evacuation (for reference, see section 4.2.3 and appendix A for an illustration of the area that is in danger). Of those 84.663 evacuees in danger, 90% safely reached their shelter before the cyclone made landfall. That means that (84.663 * (1 - 0.9) =) 8.466 evacuees were still traveling to their shelter at the time Idai made landfall. Especially those evacuees were extra vulnerable, because they neither had the protection of their own home, nor did they have the protection of the shelter location. In this particular experiment there were no residents in danger that have not been evacuated due to the distance constraint. The average travel distance for the evacuees was 30.11 kilometers, with the 20th and 80th quantile being 9.34 and 30.81 kilometer respectively. These results are based on a 20 run average. That means that the results are the average of 20 runs of the evacuation simulation model.

Regarding the evacuated area, figure 8.3 shows the size of the evacuation area, based on the forecast moment and the associated uncertainty. Note that the area always gets smaller, which means that for the forecast of March 9th, 0600 the whole area, including the other colors, is marked as vulnerable. Another interesting observation is that in later forecast also possible vertical evacuation locations start to appear. This can be seen because there are yellow spots in the blue area and blue spots in the orange area. The area that is inundated by cyclone Idai is shown in red.

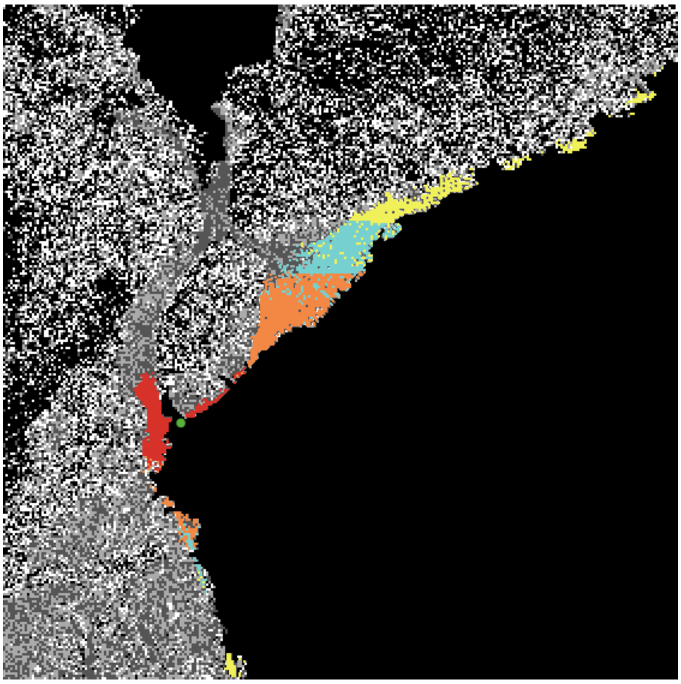

Figure 8.3: Evacuation area per forecast moment - March 9th, 0600 shown in yellow, March 13th, 0000 shown in blue, March 13th, 1800 shown in orange. The area that is impacted is shown in red

8.4. Result analysis

To effectively inform the decision maker about the consequences of each policy lever, their effects are discussed in the subsections below. Note that these effects are based on one case study and may not be directly generalized. Chapter 9 will discuss the combined implications of the two different case studies (cyclone Idai and cyclone Kenneth), which will offer a more generalized answer to the main research question.

8.4.1. Identifying the latest evacuation possibility

There are 9 different forecast moments and for each one of them, there are three values for the safety margin (5, 10 & 20 kilometer) and four for the number of shelters (10, 20, 40 & 80). This means that there are 12 possible combinations for each forecast moment. The first step in finding the right balance between timeliness and the reduction of uncertainty is to find the latest evacuation moment where all evacuees in danger can still be safely evacuated. This latest evacuation moment is defined as the break point. Figure 8.4 therefore shows the fraction that is saved for each forecast moment. Each forecast moment shows three different data points with a 95% confidence interval, which represent the different safety margins. This means that for example, with an evacuation on March 13th, 1800 PM and a safety margin of 20 kilometer, dependent on the number of shelters, somewhere between 15% and 33% of the population in danger was timely evacuated. Figure 8.4 also shows that for the first forecast moment, all the data points are stacked on top of each other. This means that, independent of the safety margin and the number of shelters, 100% of the population in danger is evacuated when an evacuation is started on March 9th, 0600 AM. Regarding the latest evacuation moment where all residents are saved, the figure shows that there is a clear break point between the forecast moment of March 13th, 0000 AM and March 13th, 1800 PM. That means that after this break point it is no longer possible to evacuate all residents safely. For the two forecast moments after the break point, it is shown that, if for some reason evacuation is not possible before the break point, a low safety margin should be chosen, because the figure shows a strong correlation between the safety margin and fraction that is saved. Because the aim should always be to save all residents if possible, this analysis continues with analyzing the first seven forecast moments. This means that the balance in the trade-off between timeliness and uncertainty reduction lies somewhere between March 9th, 0600 AM and March 13th, 0000 AM. An analysis of the specific break point is offered in section 8.4.3.

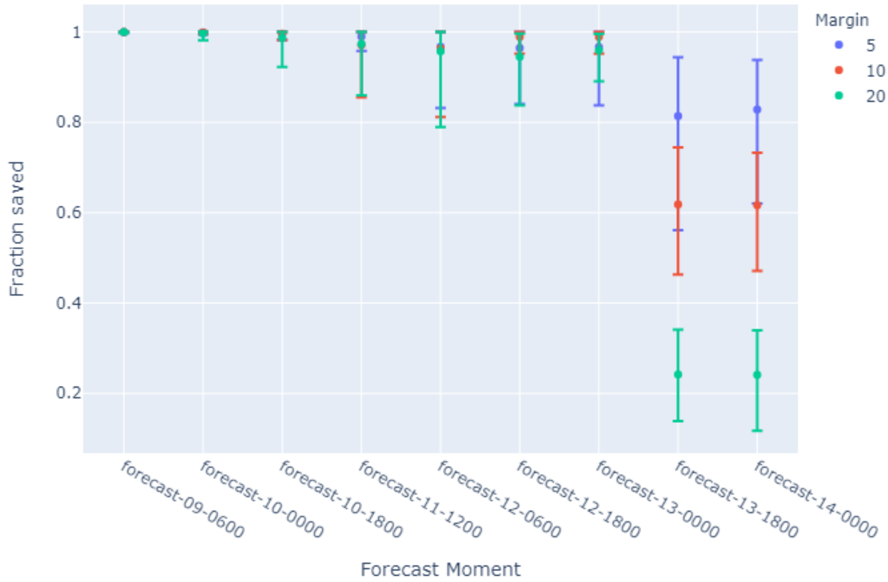

Figure 8.4: The effect of the forecast moment and the safety margin on the fraction saved, represented by a 95% confidence interval over 20 simulation runs. A break point is visible between March 13th, 0000 and March 13th, 1800

8.4.2. Finding the balance before the break point

Another key performance indicator is the average travel distance for the evacuees. A lower travel distance means that the burden of evacuating for the evacuees is reduced. Even though it is not included in the model, it also lowers the risks of the travel itself and it increases the chance that residents will heed the advice of the evacuation. Figure 8.5 shows the twelve combinations of the safety margin and the number of shelters, for each of the first seven forecast moments. In the left part of the figure, the data points are colored by the number of shelters and a data point is displayed for each value of the safety margin. The right figure, on the other hand, shows the average of the travel distance and the different safety margins for each number of shelters. This means that the most-left blue data point in the right sub figure is the average travel distance with 10 shelters for the safety margins of 5, 10 & 20 kilometer and an evacuation on March 9th, 0600 AM. This time there is no confidence interval because these results are directly obtained from the optimization model. This average over the safety margins highlights the correlation between the number of shelters and the travel distance. The figure shows that the reduction in average travel time between 10 and 20 shelters is relatively high when compared to the reduction between for example 20 and 40 shelters. Therefore, the option of 10 shelters is disregarded and the other options are further investigated.

Figure 8.6 shows the same policy lever configurations as in figure 8.5, but now the y-axis shows the fraction saved. The figure shows that the options of 10 shelters does not only result in a high travel distance, but also a lower fraction saved. This confirms that the option of 10 shelters is not a suitable option, based on the average travel distance and the fraction that is saved. Figure 8.6 also shows more uncertainty, measured in the fraction saved, for the last two forecast moments before the break point (March 12th, 0600 AM & March 13th, 0000 AM). This means that closer to the break point, not all the combinations of the safety margins and the number of shelters lead to the result that all of the residents in danger safely reach their shelter before the cyclone makes landfall. Another interesting observation is that, regarding the options with 10 shelters, the outcomes for the fraction saved first declines and then slowly increases again over time. An explanation of this trend is that in the twelve hours between March 12th, 0600 AM and March 12th, 1800 PM the number of evacuees quickly reduces. This happens when for example more densely populated areas are excluded, or when the area that is no longer in the uncertainty range is relatively wide (as can be seen in the orange and blue areas in figure 8.3). This results in a relative high reduction of the evacuation area and the number of evacuees in a relative short time period. This means that in the next evacuation moment, the evacuees can be divided over the shelters more efficiently and the shelters can be better located. Therefore, an earlier evacuation does not always results in more evacuees that are timely evacuated.

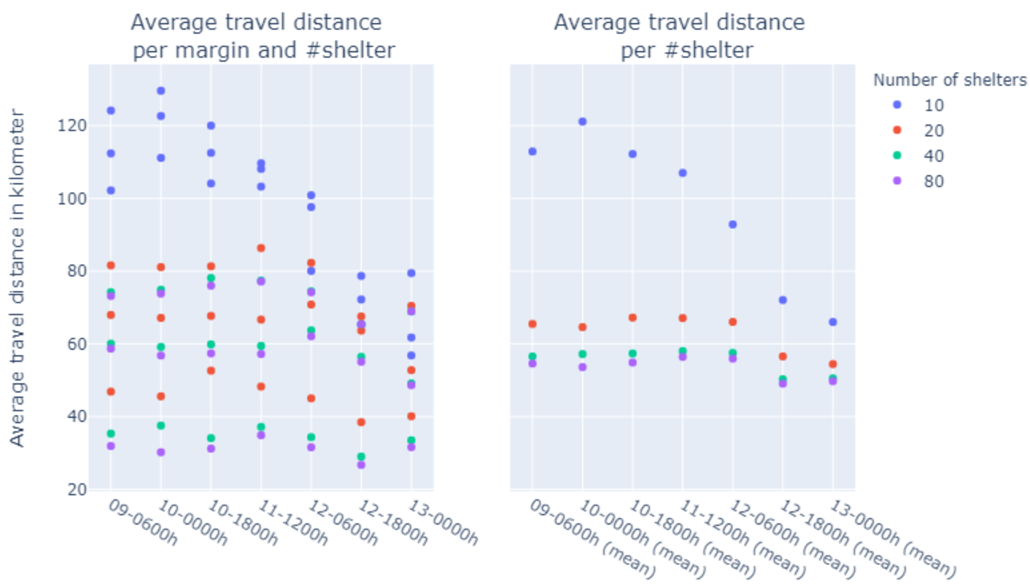

Figure 8.5: The effect of the forecast moment on the average travel distance. Left figure shows all combinations of the safety margin and the number of shelters. Right figure shows the average over the different safety margins, which highlights the relation between the number of shelters and the average travel distance.

Figure 8.6: The effect of the number of shelters and the forecast moment on the fraction saved for the first seven forecast moments. Results show relative low fraction saved and more uncertainty for the option of 10 shelters.

The exception to the conclusion that 10 shelters is not a viable option to save all evacuees in danger is for the first forecast moment: March 9th, 0600 AM. However, the evacuation area is larger in early evacuation moments, which means that there are also more residents that are evacuated. In order to minimize the residents that are evacuated unnecessarily, it is important to not evacuate as early as possible. Figure 8.7 shows the total number of evacuees for each forecast moment. In the beginning there is slow decline in the number of evacuees because in early forecast reports the cyclone was forecasted more to the north, directly over a area with high vulnerability due to the low elevation levels. This means that in the first three days this large area was included in the evacuation area.
The reason that there are multiple data points for the last two forecast moments is because some evacuees are no longer evacuated because of the distance constraint. This means that for some evacuees none of the shelters were in reach, even under the most ideal conditions. They are therefore not counted as evacuees. The data points are colored by the safety margin, because a higher safety margin means a higher average travel distance which means that more residents are excluded from the evacuation. However, none of those residents that were excluded from the evacuation because of the distance constraint were living in the impacted

area. In order to reduce the number of evacuees that are evacuated unnecessarily, but to also have all the evacuees in danger saved, the analysis zooms in further on the forecast moments from March 12th, 0600 AM to March 13th, 0000 AM, because in that moment there is a visible decline in the number of evacuees.

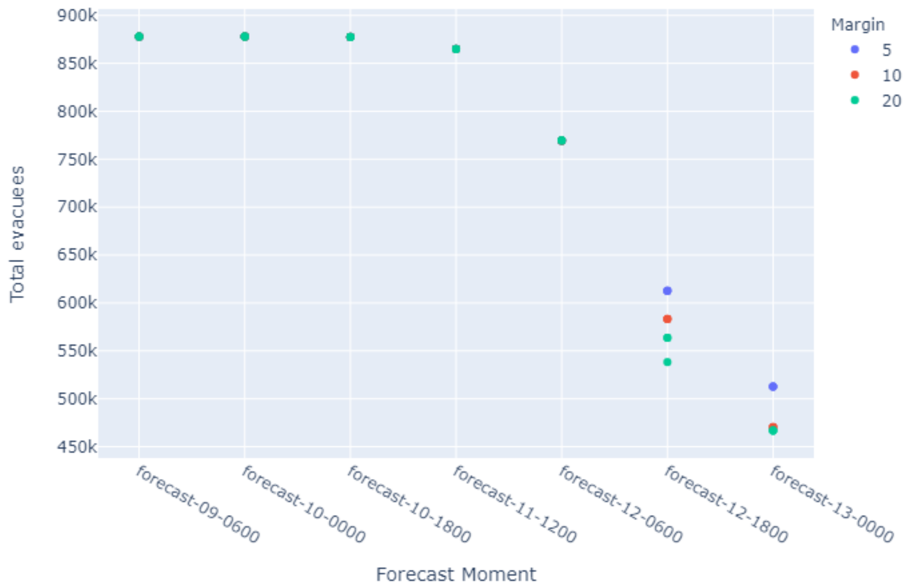

Figure 8.7: The effect of the forecast moment and the safety margin on the total number of evacuees. From March 11th onwards there is a visible decline in the total number of evacuees

When zoomed in on the last three forecast moments of figure 8.7, the results in figure 8.8 are obtained. The nine subplots each display a combination of the safety margin and the number of shelters and show for the three forecast moments what fraction of the population in danger is saved with a 95% confidence interval. The squared data points represent the combinations of the policy levers where the lower end of the confidence interval is higher than 99.5%. This 0.5% error is accepted because of some outliers in the Open Street Map data, which result in unrealistic high travel distances. The points of interest are the squared data points, because they show policy configurations where all of the population in danger is saved. The results show that for forecast moment of March 12th, 0600 AM in all cases 100% of the evacuees in danger are saved. For the evacuation moment of March 12th, 1800 PM and March 13th, 0000 AM, however, only with some combinations of the safety margin and the number of shelters all evacuees can be saved. For both evacuation moments the safety margin should be a maximum of 10 kilometers, and with one exception, there should be at least 40 shelters operational. Whether these options are actually possible depends on the capacity of the aid organizations to coordinate the disaster response with that many shelters.

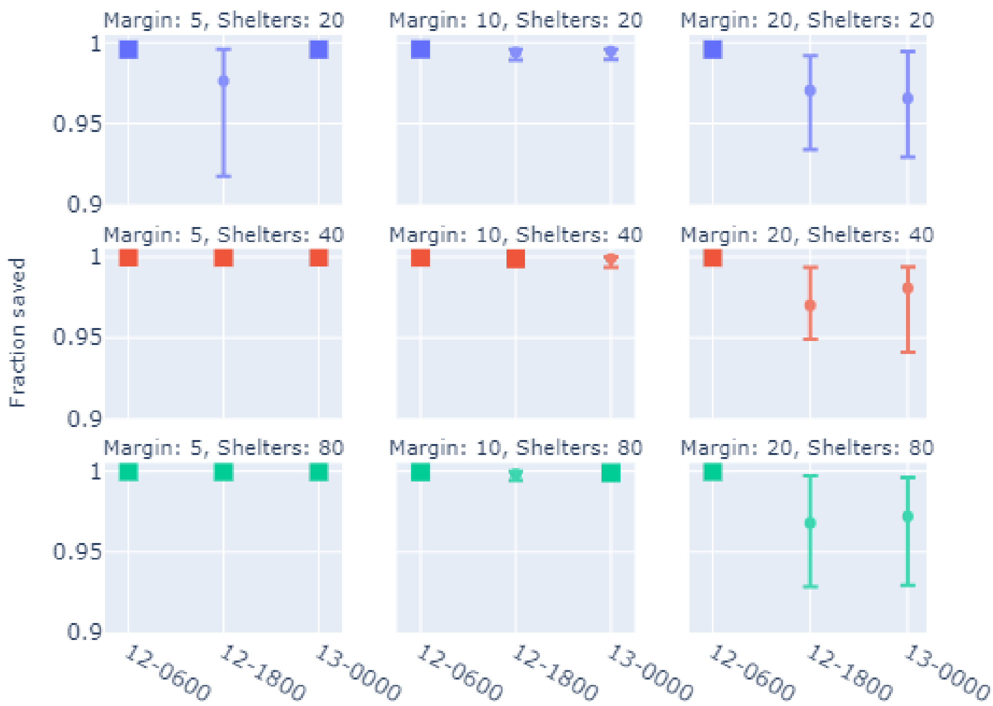

Figure 8.8: The effect of the safety margin and the number of shelters for the three forecast moments of interest

Based on the results in figure 8.8, there are at least three viable combinations of the policy levers where all of the residents in danger are saved. Those three options are described below and are chosen because they each score best on a different key performance indicator. The first interesting option is an evacuation on March 12th, 0600 AM, because it is the latest possibility with a safety margin of 20 kilometer. Because of the small reduction in travel distance between the different number of shelters, this option is chosen with 20 shelters. The second option is an evacuation on March 13th, 0000 AM with a safety margin of 5 kilometer and 20 shelters. This option is included because it is possible to evacuate at the latest moment before the break point, but with only 20 shelters. Another interesting option is at the same evacuation moment, but with a safety margin of 10 kilometer and 80 shelters. This last evacuation moment is interesting because with a safety margin of 5 kilometer there are vertical shelter locations selected, whereas with a safety margin of 10 kilometer they are all outside of the evacuation area. This last option improves the reachability for the aid organizations, but it also increases the spread of evacuees over the area due to its many shelters. In the case that it is not possible to have all the evacuees spread out over the 20 shelters or more, there is also the option to have 10 shelters. Even though this option was excluded in the analysis, it makes sure that a complete picture is offered on the possible evacuation strategies. The latest moment to have 10 shelters and evacuate all the evacuees is on March 10th, 0000 AM, with a safety margin of 10 kilometer. The different options are summarized and compared based on all the key performance indicators in the conclusion of this chapter in section 8.5.

8.4.3. Break point analysis

Before continuing with the most promising options, a analysis of the break point is offered. This analysis offers insights into why an evacuation where all evacuees in danger are saved is no longer possible after the break point. Figure 8.4 showed that the break point lies between March 13th, 0000 AM and March 13th, 1800 PM. This gap of 18 hours exists because of the availability of the forecast reports. To gain a better insight

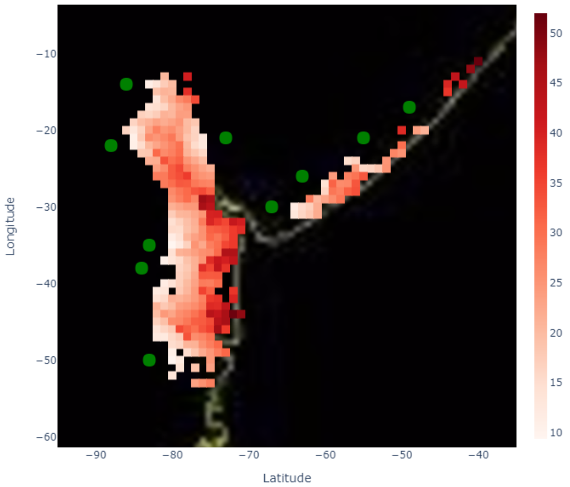

Figure 8.9: Spatial heatmap of the travel distance for an evacuation on March 13th, 1800 PM, a margin of 10 kilometer and 20 shelters

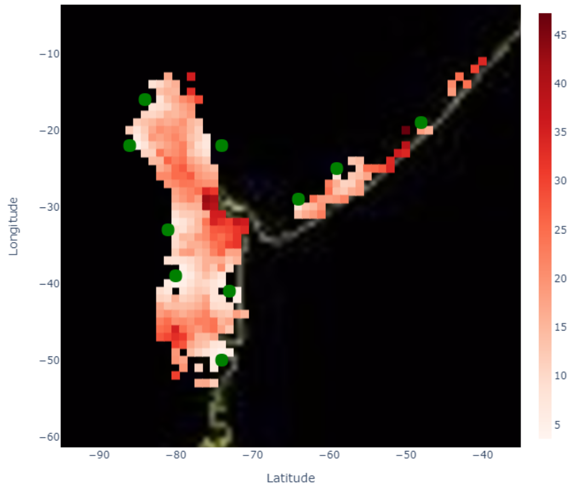

Figure 8.10: Spatial heatmap of the travel distance for an evacuation on March 13th, 1800 PM, a margin of 5 kilometer and 20 shelters

into what exactly happens in these 18 hours that make that not everyone can still be saved, the evacuation at March 13th, 1800 PM is investigated in more depth. Figures 8.9 and 8.10 show the travel distance for the evacuees based on a margin of 10 and 5 kilometer respectively. Both figures zoom in on the area that is impacted, instead of the total evacuated area. This is more relevant, since the fraction saved KPI only represents the evacuees that are living in the impacted area. The travel distance is displayed using a heatmap.

Figure 8.9 shows that a safety margin of 10 kilometer results in no vertical shelter location, which means that the travel distance is the highest for the population alongside the coast line because no shelters are possible there. Figure 8.10 shows a safety margin of 5 kilometer, which means there are vertical shelter locations selected. This means that the travel distance is reduced in the area directly surrounding that shelter.

When an evacuation is started at March 13th, 1800 PM, there are 30 hours left until impact, but only 12 hours of daylight. This means that with a travel distance between 2.5 and 5 km/h the maximum travel distance is 30 to 60 kilometer. However, the evacuees also need time to decide and prepare for the evacuation, which means they have 3 to 9 hours less for traveling. Since time is so limited, the reduction in travel distance because of the vertical shelters has a high impact. In comparison, with a safety margin of 10 only 58% to 70% reaches their shelter in time, while with a safety margin of 5 kilometer, 77% to 91% manages to reach their shelter in time. This example illustrates the need to have a low safety margin after the break point, even if that means that vertical shelter locations are selected. It also shows that the travel distance, together with the decision time, takes too long for most evacuees to reach their shelter in time. In comparison, an evacuation on March 13th, 0000 AM will not change the travel distances, but gives the evacuees an another 12 hours of day light to travel to their shelter. This means that with certain configurations of the safety margin and the number of shelters all evacuees can reach their shelter in time when an evacuation is issued on March 13th, 0000 AM, but not when the evacuation order is issued 18 hours later.

8.4.4. Location and size of the shelters

Furthermore, it is relevant for decision makers to have insight into the spread of the evacuees over the shelters and where those shelters are located. The first step in understanding how the shelters are located, is by analyzing the population density. Since the average travel distance between the evacuees and the shelter locations is minimized in the optimization, the largest shelters will be located closest to the largest demand points, e.g. the largest cities. Figures 8.11 and 8.12 show the population density per patch of 2.6 by 2.6 kilometer for all areas below or equal to 10 meters above sea level. Figure 8.11 shows all the patches that have a population density that is less than 400 residents per square kilometer. It shows that the more densely populated areas are centered around the rivers, which is problematic because those areas are more likely to be flooded. There is also a large area with relative high population close to a big city, which is shown in figure 8.12.

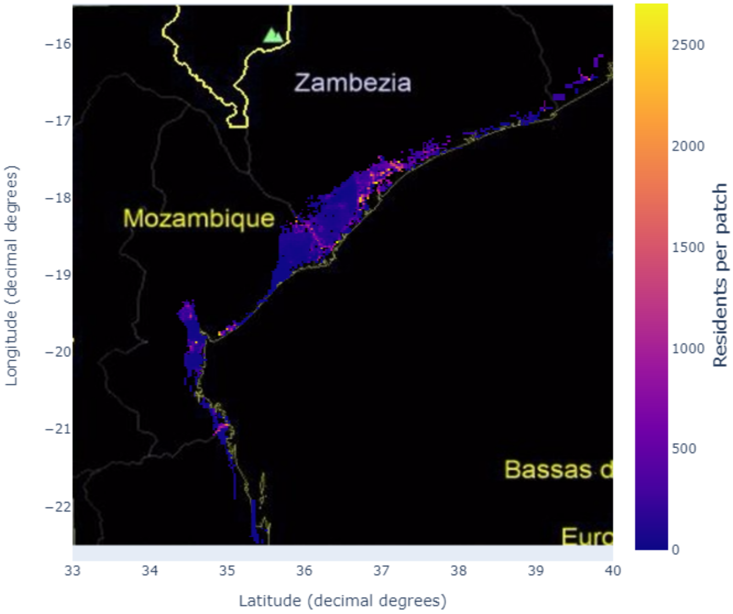

Figure 8.11: Spatial heatmap of the population density. The color shows the residents per patch, for all patches up to 2500 residents. This equals to around 400 residents per square kilometer. The more densely populated areas are centered around rivers or big cities

Figure 8.12 shows the areas above 400 residents per square kilometer. The figure displays that there is one city that stands out in terms of size and that is the city Quelimane. According to the LandScan data set it has a population of 280.000 residents (spread out over four patches). The shelter location analysis below will show that the largest shelter locations are close to that city.

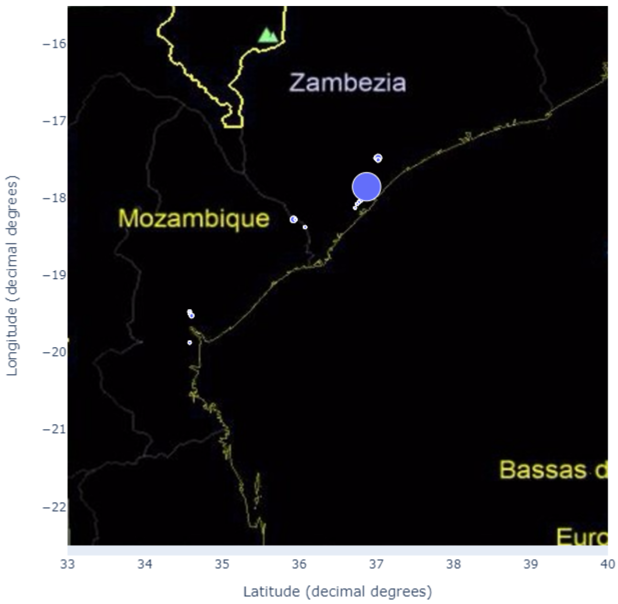

Figure 8.12: Cities with a population above 400 residents per square kilometer. The size of the circle represents the size of the city. The largest city

Section 8.3 has shown the possible policy configurations where all the evacuees in danger are saved. Four of them each score best on one of the key performance indicators and are therefore further analysed. Section 8.5

will discuss those four options in more detail, while in this section they are analyzed on their shelter locations and the size of those shelters. Figures 8.13 to 8.16 show the location and size of the different shelter locations for the four different options that are selected in section 8.3. The size of the locations is indicated by the color of each data point. The box plot below each figure shows the different sizes of the selected shelters. The size of each shelter that is shown in the figures does not show the results from the optimization, but the results from the evacuation simulation results. The difference between those two, is that because residents that are informed by others do not go to their own shelter, but will follow the residents they have been informed by. This leads to the results that some shelters end up with zero evacuees and some shelters end up with more evacuees than the initial capacity.

Figure 8.13 shows the location of the shelters for an evacuation on March 10th, 0000 AM with a safety margin of 10 kilometer and 10 shelters. Because there are only 10 shelters for a total population of 877.925 residents, there are mostly large shelter locations with a average of 81.337 residents per shelter location.

Figure 8.14 shows the location of the shelters for an evacuation on March 12th, 0600 AM with a safety margin of 20 kilometer and 20 shelters. Because the evacuated residents are reduced to 769.514 and there are twice as much shelters, they are smaller and have an average of 33.443 residents per shelter location.

Figure 8.15 shows the location of the shelters for an evacuation on March 13th, 0000 AM with a safety margin of 5 kilometer and 20 shelters. Because the evacuated residents are reduced to 512.733, the shelters are smaller than in the previous two options and now have an average of 25.306 residents per shelter location. This option also shows that vertical shelter locations are used. This is especially visible when figure 8.15 is compared to figure 8.16, where no vertical shelter locations are used.

Figure 8.16 shows the location of the shelters for an evacuation on March 13th, 0000 AM with a safety margin of 10 kilometer and 80 shelters. Because the evacuated residents are reduced to 470.427 and there are four times as much shelters, they are smaller and have an average of 7.652 residents per shelter location.

When the four promising options are compared based on the shelter location and sizes of those locations, it becomes clear that the largest shelters are located closest to the biggest cities and that more shelters mean that the shelters tend to be smaller, but in all cases there exists at least one shelter of over 100.000 residents. It should also be mentioned that the total evacuees and the average evacuees multiplied by the number of shelters is not equal to each other. The difference between those two, is because of the evacuees that did not reach their shelter in time, but were also not living in the impacted area. An interesting observation is that with the third option of an evacuation on March 13th, 0000 AM and a safety margin of 5 kilometer and 20 shelters, there are almost no evacuees that did not reach their shelter. This means that even if the cyclone would have taken a different trajectory, this would have been a robust option.

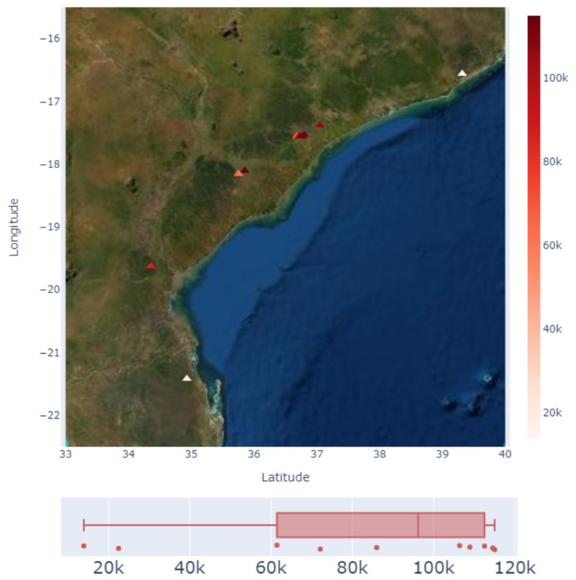

Figure 8.13: Shelters and their size for an evacuation on March 10th, 0000 AM with a safety margin of 10 km and 10 shelters. The color represents the size of the shelters

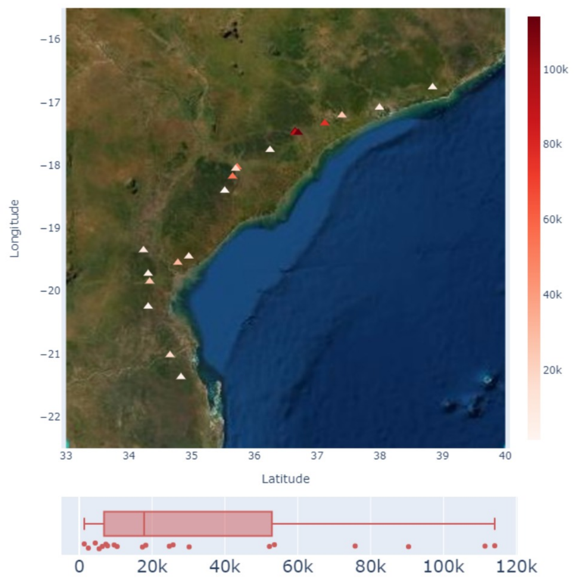

Figure 8.14: Shelters and their size for an evacuation on March 12th, 0600 AM with a safety margin of 20 km and 20 shelters. The color represents the size of the shelters

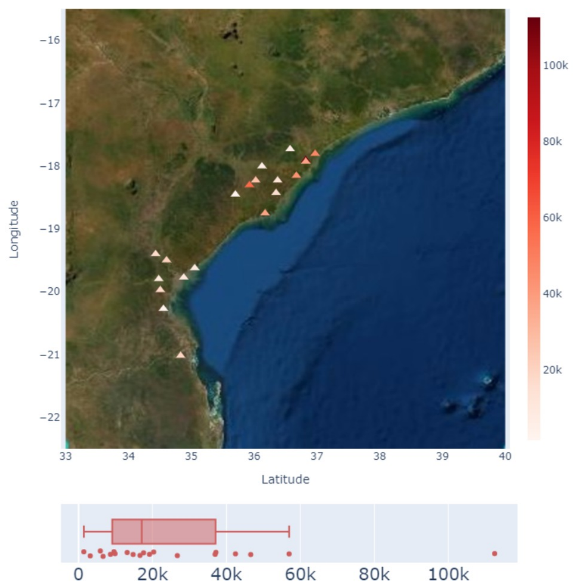

Figure 8.15: Shelters and their size for an evacuation on March 13th, 0000 AM with a safety margin of 5 km and 20 shelters. The color represents the size of the shelters

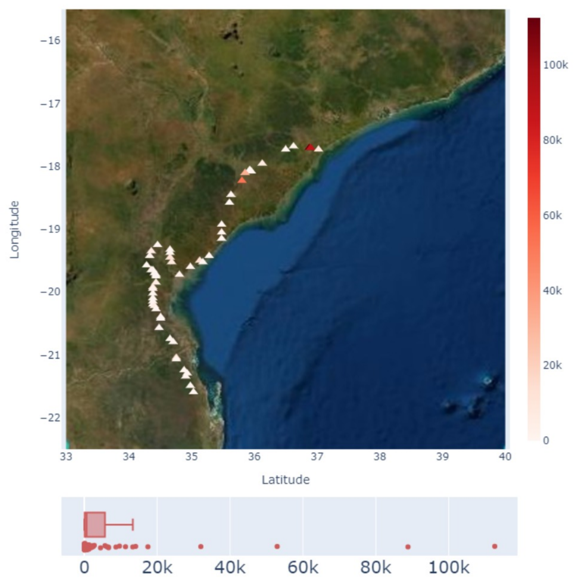

Figure 8.16: Shelters and their size for an evacuation on March 13th, 0000 AM with a safety margin of 10 km and 80 shelters. The color represents the size of the shelters

8.5. Conclusion case study Idai

To conclude, the results show that there is a clear break point on March 13th between 0000 AM and 1800 PM, after which it is no longer possible to evacuate all residents that are in danger. This means that evacuation should happen before the break point. Furthermore, it is shown that 10 shelters not only result in a relatively great travel distance, it also results in many of the residents in danger not being evacuated in time. The only exception is in the two earliest forecast moments, up to March 10th, five days in advance. However, because of the large evacuation area there are also many residents evacuated while they turned out not to be in danger. Because of the specific forecast reports, the number of evacuees decline rapidly from March 11th, 1200 PM onwards. Therefore, the period of interest lies between March 12th, 0600 AM and March 13th, 0000 AM. Four promising configuration of the policy levers have been identified. They are shown in table 8.6 and discussed below.

Table 8.6: Four promising configurations of the policy levers in the Idai case study

Experiment number	17	58	74	80
Forecast moment	March 10th, 0000 AM	March 12th, 0600 AM	March 13th, 0000 AM	March 13th, 0000 AM
Safety margin (km)	10	20	5	10
Number of shelters	10	20	20	80
Total evacuees	877.925	769.541	512.733	470.427
Total evacuees in danger	84.663	84.663	84.663	84.663
Fraction saved	1.00	1.00	1.00	1.00
Evacuees in danger not saved	0	0	0	0
Avg. travel distance (km)	111	82	40	49
20th quantile of travel distance (km)	46	44	11	22
80th quantile of travel distance (km)	92	84	33	47

The four experiments are selected because they have a fraction saved of 100% and they all show different combinations of the policy levers. Experiment 17 is for example the latest evacuation moment where all evacuees in danger are saved and where there are only 10 shelters needed. However, this results in many evacuees in total and a bigger travel distance compared to the other three options. Experiment 58 is the latest experiment where a safety margin of 20 kilometer is still possible, while saving all the evacuees. It shows a reduction of 29 kilometer in average travel distance compared to experiment 17, but this is still high when compared to experiment 74 and 80. The total number of evacuees is also relatively high when compared to the last two experiments. Experiment 74 is a suitable policy configuration when vertical elevation is accepted. Due to the safety margin of 5 kilometer, there are also shelter locations in safe areas within the vulnerable area. This explains the high reduction on the travel distance KPIs, but it makes the shelter locations also more difficult to reach for aid organizations and they are possibly less safe. If an evacuation is desired the last moment for the break point, but vertical evacuation is not preferred, the best option is experiment 80. However, there are 80 shelters needed and it is questionable whether it is feasible to set up such a distributed relief in that short time period of two days. Furthermore, experiment 80 also shows a further reduction in total evacuees, but that is not due to the reduction of uncertainty, but because many evacuees did not meet the distance constraint and were therefore not counted as evacuee. Since those residents that were excluded from the optimization were not living in the inundated area, they do not appear in any of the other KPIs. If the cyclone would have taken a different direction, things might not have turned out that well for these configurations of the policy levers. An evacuation on March 13th, 0000 AM with a safety margin of 5 kilometer and 20 shelters stands out, because not only all the residents in danger are saved, but also almost all of the other residents too.

Another conclusion is that an earlier evacuation does not always mean that more residents in danger get saved. This occurs when the evacuation area reduces faster than the time that is needed for the remaining evacuees to evacuate. The different experiments illustrate the trade-off between the total evacuees, the safety of the shelter locations, the travel distance for the evacuees and the number of shelters. In the end it is left to the decision maker to decide on the right balance between those. To assist in that decision, it is also shown in the break point analysis how the travel distances of the different groups of evacuees have determined the latest possible evacuation moment and how vertical shelter locations reduce the average travel distance. Lastly, the location and size of the shelters show that the largest shelters are located closest to the largest groups of evacuees. It can also be concluded that in all of the four promising options, there is at least one shelter with a size of over 100.000 evacuees and when there are more shelters or lesser evacuees, the shelter locations get smaller.

9

Case study Kenneth

Identical to chapter 8, where the implementation of the model for cyclone Idai is discussed, this chapter has the same layout. First, some background information to cyclone Kenneth will be offered (section 9.1), after which the experiment setup will be laid out in section 9.2. To conclude, section 9.3 and 9.4 will show the results and the interpretation thereof. Section 9.5 will conclude with a summary of the analysis that is offered in section 9.4. Lastly, section 9.6 will compare the two case studies.

9.1. Cyclone Kenneth

This section will first give a short situation report of cyclone Kenneth and will continue with relevant cultural and demographic characteristics of the impacted area to obtain an understanding of the evacuation situation and will conclude with an overview of the relevant parties that were involved in decision making and humanitarian aid before, during and after the disaster.

9.1.1. Situation report

Just six weeks after cyclone Idai, cyclone Kenneth made landfall in the northern part of Mozambique, close to the border with Tanzania. Météo-France la Réunion started monitoring the system on April 17th and then classified it as a tropical disturbance on April 21. This was just four days before the cyclone made landfall close to the city of Pemba, on April 25th, 4 PM local time (see figure 9.1). By that time, it was classified as a category 4 tropical cyclone. This was the first time in recorded history that two tropical cyclones of category 2 of higher affected Mozambique in the same season (cyclone Idai was the first that season) (Cross, 2020). With peak wind gust of 220 km/h at landfall, making it the strongest cyclone ever to hit Africa (Disaster and Assessment, 2019), it impacted 374.000 people, damaged or destroyed 35.000 homes (OCHA, 2019), triggered power outages, and damaged key transportation routes and bridges. The impact of the cyclone was intensified by the fact that it arrived just at the end of the rainy season, when water levels were already at its highest, causing many rivers and dams to overflow. In light of the fresh memory of what cyclone Idai had caused, a small scale evacuation has evacuated 30.000 residents, who were thought to be directly in the cyclone's path. According to Francesco Torresani they were evacuated by army trucks and brought to a shelter location outside of the reach of cyclone Kenneth. However, the numbers show that a lot more than 30.000 residents should have been evacuated, making this still an interesting case study.

9.1.2. Relevant characteristics

Both cyclone Kenneth and Idai made landfall in Mozambique, making the characteristics of cyclone Idai also applicable to the case of cyclone Kenneth. The demographic difference however, is that in the earliest forecast, with the highest uncertainty, southern parts of Tanzania were at risk as well, making this an international evacuation situation. For simplicity however, it is assumed that characteristics of Mozambique are true in Tanzania as well.

9.1.3. Involved organizations

Regarding the involved organizations, even though a hypothetical evacuation operation, that is researched in this paper, should involve national government bodies in both Mozambique and Tanzania to cooperate,

Figure 9.1: Path of cyclone Kenneth (and Idai) in Mozambique, April 2019

this additional complexity is not accounted for in the model. If countries would decide on a pre-disaster evacuation decision, it is assumed they would work together and co-coordinate on the matter.

9.2. Experiments

This section details the external parameter values that are specific to cyclone Kenneth (section 9.2.1), and continues with describing the possible values for the policy levers, which will define the experiments.

9.2.1. Describing the external parameter values

Similar to section 8.2.1, the values for the external parameters are displayed in table 9.1. Note that the bottom three parameters are the same for Kenneth as for Idai, as discussed in section 9.1.2. Even though Kenneth was classified as a category 4 (Idai was a category 2), the width of the destructive path is estimated at 50 kilometers (Update, 2019), which is smaller than that of Idai. However, the width of 50 kilometer describes the area that experienced have winds, but the area that endured high precipitation levels that caused floodings, was believed to be as twice as wide. The risk threshold value is calibrated based on satellite images, as described in section 4.2.3. The elevation threshold of 100 meters is chosen because of the steeper elevation along the coastline in the case of cyclone Kenneth, compared to cyclone Idai. Even though these higher grounds are not likely to be inundated, cyclone Kenneth caused many mud and land slides which posed a real threat to the residents (Cross, 2020). These mud and land slides also occur at higher grounds, which is why residents living up to an altitude of 100 meters are included in the evacuation.

Table 9.1: Parameter values in the Kenneth case study

Parameter	Value
Cyclone width	50 (km radius)
Risk threshold	0.03
Elevation threshold	100 (meters)
Decision delay	$X \sim U(3,9)(hours)$
Travel speed	$X \sim U(2.5,5)(km/h)$
Day light	6 AM till 6 PM

9.2.2. Experiments setup

Contrary to cyclone Idai, forecast reports were not published 6 days in advance, but just 3 days in advance. This led to 6 forecast reports (and thus evacuation decision points), instead of 9. The values for the safety margin and the amount of shelters is kept the same. This makes it better possible to compare the two case

Table 9.2: Forecast moments

Evacuation moments
April 22th, 1200 PM
April 23th, 0600 AM
April 23th, 1200 PM
April 24th, 0000 AM
April 25th, 0000 AM
April 25th, 0600 AM

Table 9.3: Safety margins

Safety margins
5 kilometer
10 kilometer
20 kilometer

Table 9.4: Amount of shelters

Amount of shelters
10
20
40
80

studies.
There are as many experiments as there are combinations of those three policy levers. That means that there are 72 different experiments. Due to stochasticity in the parameters of the evacuation model, every evacuation simulation experiment will be ran 20 times to account for this stochasticity.

9.3. Results

Since there are too many experiments to simply be displayed in one short table, the reader is referred to appendix B for a full overview of the results. This paragraph will instead describe one of the 72 experiments as an example. This section will conclude with an overview of the different areas that is evacuated in different evacuation moments.

Table 9.5 shows experiment 14 with the policy levers set at an evacuation on April 23rd, 0800 AM, a safety margin of 5 kilometer and 20 shelters.

Table 9.5: Experiment number 14 explained

Policy lever / KPI	Value
Experiment number	14
Forecast moment	April 23rd, 0800 AM
Safety margin	5 kilometer
Number of shelters	20
Total evacuees	879.405
Total evacuees in danger	78.909
Fraction saved	1.00
Evacuees in danger not saved	0
Average travel distance	36.33 kilometer
20th quantile of travel distance	19.01 kilometer
80th quantile of travel distance	42.01 kilometer

It shows that a total of 879.405 evacuees have been ordered to evacuate. of which 78.909 were actually in danger (see section 4.2.3 for a definition of the area that is in danger). Of those 78.909 evacuees in danger 100% safely reached their shelter before the cyclone made landfall. In this particular experiment there were no residents in danger that have not been evacuated due to the distance constraint. The average travel distance for the evacuees was 36.33 kilometers, with the 20th and 80th quantile being 19.01 and 42.01 kilometer respectively. These results are based on a 20 run average.

Regarding the evacuated area, figure 9.2 shows the size of the evacuation area based on the forecast moment and the associated uncertainty. Note that the area always gets smaller when uncertainty is reduced. This means that for the forecast of April 22th, 1400 the whole area in yellow, including the other colors, is marked as vulnerable. It can be observed that in later forecast also possible vertical evacuation locations start to appear. This can be seen because there are yellow spots in the blue area and blue spots in the orange area. The impacted part of the coastline is shown in the red color.

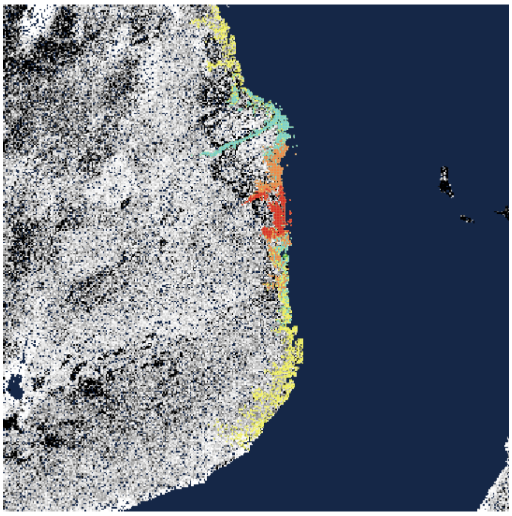

Figure 9.2: Evacuation area per forecast moment - April 22th, 1400 shown in yellow, April 23th, 1400 shown in blue and April 25th, 0800 shown in orange. The area that is impacted is shown in red

9.4. Results analysis

To effectively inform the decision maker about the consequences of each policy lever, their effects are discussed in the subsections below. Note that these effects are based on one case study and may not be directly generalized. This chapter will conclude with a discussion regarding the combined implications of the two different case studies (cyclone Idai and cyclone Kenneth), which will offer a more generalized answer to the main research question.

9.4.1. Identifying the latest evacuation possibility

Forecast reports about cyclone Kenneth were first issued around 3 days in advance. In total, there are six forecast reports before the cyclone made landfall. Identical to the Idai case study, there are four different number of shelters and three different safety margins analyzed for each forecast moment. That means that there exists 12 different combinations of the number of shelters and the safety margin for each forecast moment. Figure 9.3 shows the fraction that is saved by the forecast moment and by the safety margin. The error bars represents the confidence interval of 95% over 20 simulation runs. It shows that for the last two forecast moments, the fraction saved is never higher than 60%, which is why the latest evacuation moment is April 24th, 0200 AM. This means that the break point lies between April 24th, 0200 AM and April 25th, 0200 AM. Therefore, the balance in the trade-off between timeliness and uncertainty reduction lies between April 22th, 1400 PM and April 24th, 0200 AM. Figure 9.3 also shows that regarding an evacuation on April 24th, 0200 AM, only with a safety margin of 5 kilometer it is possible to save all evacuees in danger. For a safety margin of 10 or 20 kilometer, at that forecast moment, the fraction saved will never be higher than 93%.

The fact that the break point lies between April 22th, 1400 PM and April 24th, 0200 AM is also shown in figure 9.4. Here, the evacuees in danger that are not saved because of the distance constraint are displayed for the different forecast moments and the different safety margins. The figure shows that after the break point, the number of residents that are not evacuated increases rapidly, especially for a higher safety margin. This means that in the case of an evacuation after the break point, not only many of the evacuees do not reach their shelter in time, also many residents in danger are not evacuated because of the distance constraint. From the figure it also becomes clear that a low safety margin should be chosen after the break point, because that results in fewer residents in danger not evacuated and a higher fraction saved of those who are evacuated. Figure 9.4 also explains why there is no clear relation between the fraction saved and the safety margin for the forecasts after the break point in figure 9.3. This has to do with the fact that many evacuees are excluded from the evacuation when a safety margin of 20 kilometer is chosen, while figure 9.3 only shows the results for the residents that did evacuate. When the absolute number of evacuees, instead of the fraction saved, would be compared, it shows that a lower safety margin after the break point leads to more residents in danger that are safely evacuated. For the first four evacuation moments, there are no residents that are in danger and are not evacuated because of the distance constraint. Therefore, the analysis will continue with a focus on the first

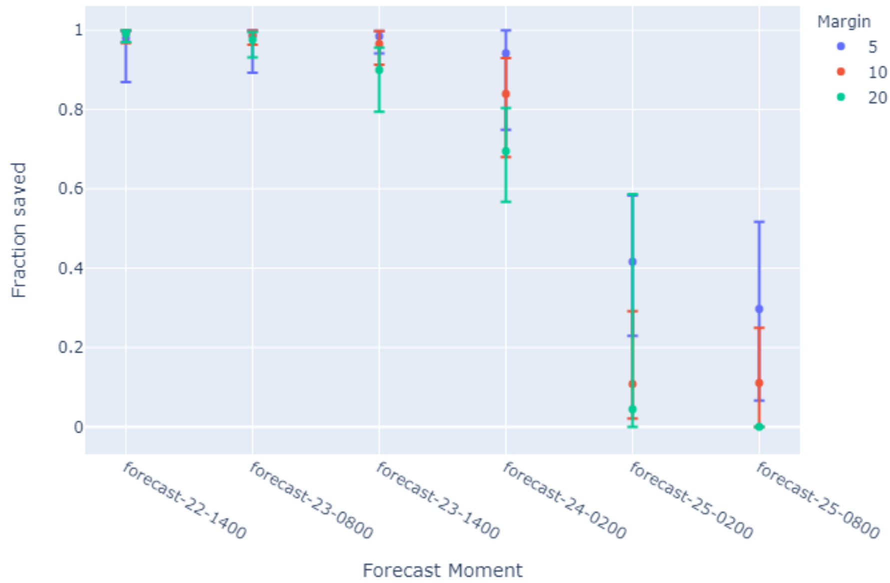

Figure 9.3: The effect of the forecast moment and the safety margin on the fraction that is saved, represented by a 95% confidence interval over 20 simulation runs. The break point is visible between March 24th, 0200 AM and March 25th, 0200 AM

four evacuation moments.

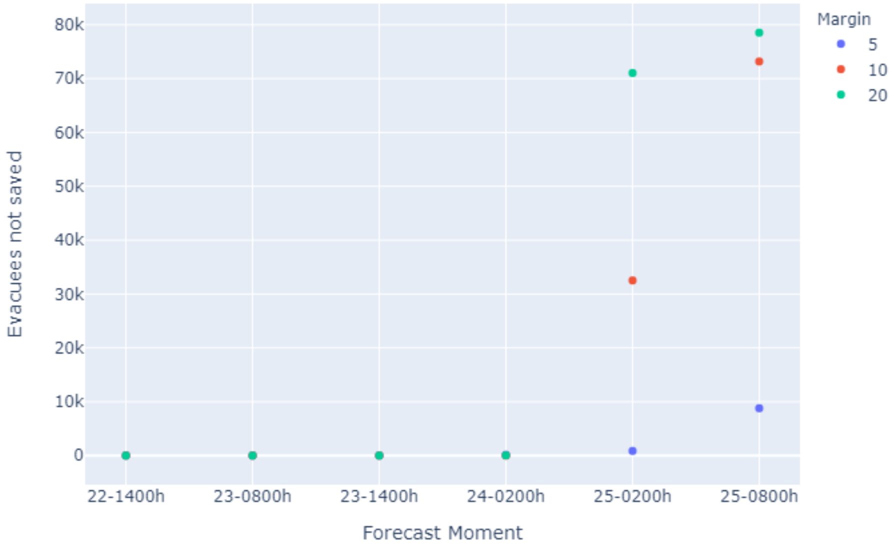

Figure 9.4: The evacuees in danger not saved by the forecast moment and the safety margin. The evacuees not saved increases rapidly after March 24th, 0200 and also determine on the safety margin

9.4.2. Finding the balance before the break point

Another key performance indicator is the average travel distance for the evacuees. A lower travel distance means that the burden of evacuating for the evacuees is reduced. Even though it is not included in the model, it also lowers the risks of the travel itself and it increases the chance that residents will heed the advice of the evacuation. Figure 9.5 shows the twelve combinations of the safety margin and the number of shelters, for each of the first four forecast moments. The data points are colored by the number of shelters. This time there is no confidence interval because these results are directly obtained from the optimization model. The figure shows that the reduction in average travel time between 10 and 20 shelters is relatively high when compared to the reduction between for example 20 and 40 shelters. Therefore, the option of 10 shelters is disregarded and the other options are further investigated. To clarify, the left sub figure in figure 9.5 shows the average travel distance of all evacuees for all the different safety margins. In the right sub figure, the average over the different safety margins is displayed. That means that the most-left blue data point in the right sub figure is the average travel distance with 10 shelters for the safety margins of 5, 10 & 20 kilometer for an evacuation on April 22nd, 1400 PM. This average over the safety margins highlights the correlation between the number of shelters and the average travel distance. The figure also shows that the average travel distance decreases over time. This is explained by the fact that over time the evacuation area reduces, and with that the number of evacuees is reduced. This means that less evacuees need to be divided over the same number of shelters, which results in a decrease in travel distance. The figure also shows that the reduction in travel distance is higher between 10 and 20 shelters than between the other combinations. Therefore, it is concluded that having at least 20 shelters instead of 10 is advised.

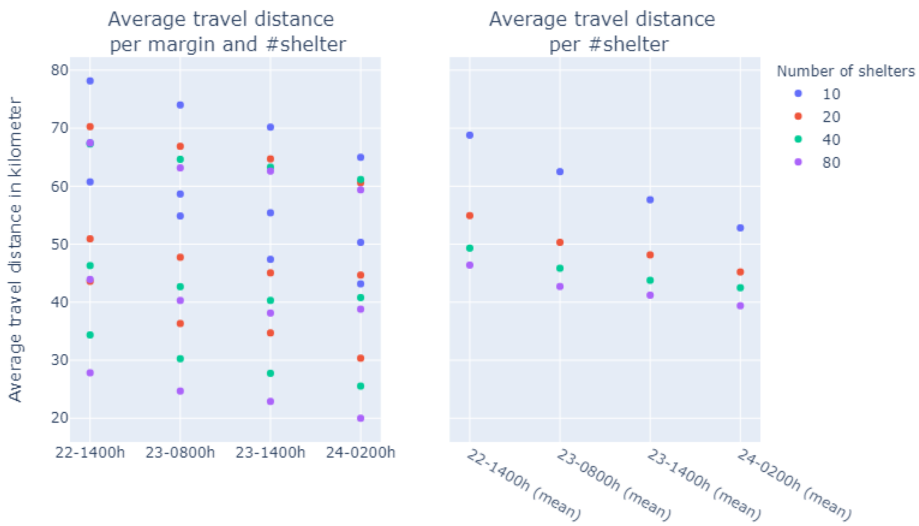

Figure 9.5: The effect of the forecast moment on the average travel distance. Left figure shows all combinations of the safety margin and the number of shelters. Right figure shows the average over the different safety margins, which highlights the relation between the number of shelters and the average travel distance.

Figure 9.6 shows for the first four forecast moments the fraction saved for the different number of shelters and a safety margin of 5 kilometer. The figure confirms that 10 shelters not only means a relative high travel distance, but also a low fraction saved. Based on these two key performance indicators, the option of 10 shelters is no longer considered in finding the right balance between timeliness and uncertainty reduction.

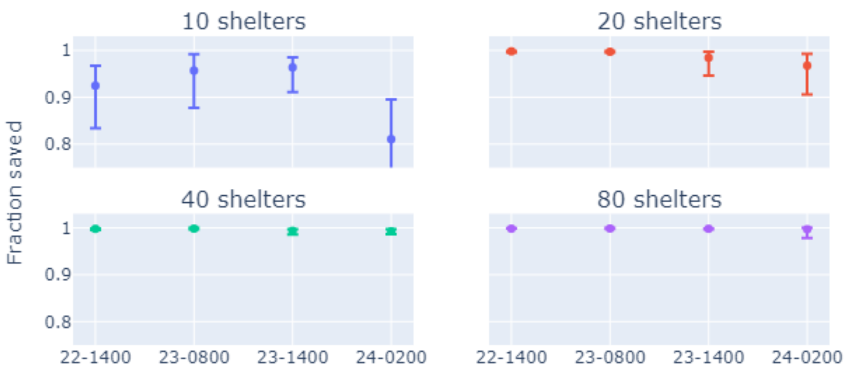

Figure 9.6: Fraction saved by number of shelters and forecast moment for a safety margin of 5 kilometer. The option with 10 shelters shows a lower fraction saved and more uncertainty, compared to the other number of shelters

The next step in finding the right balance before the break point is by analyzing the total number of evacuees. Figure 9.7 shows the total number of evacuees by forecast moment and by safety margin. The safety margin is displayed because with a higher safety margin, the travel distance increases, which can mean that residents are being excluded from the evacuation because of the distance constraint. This is the case for the forecast moment of April 24th, 0200 AM, where a safety margin of 20 kilometer results in a slightly lower number of evacuees. However, none of those people actually lived in the impacted area, as shown in figure 9.4. Figure 9.7 shows a relative high decline in total number of evacuees between the first two forecast moments, which makes it interesting to zoom in further on the last three forecast moments of figure 9.7.

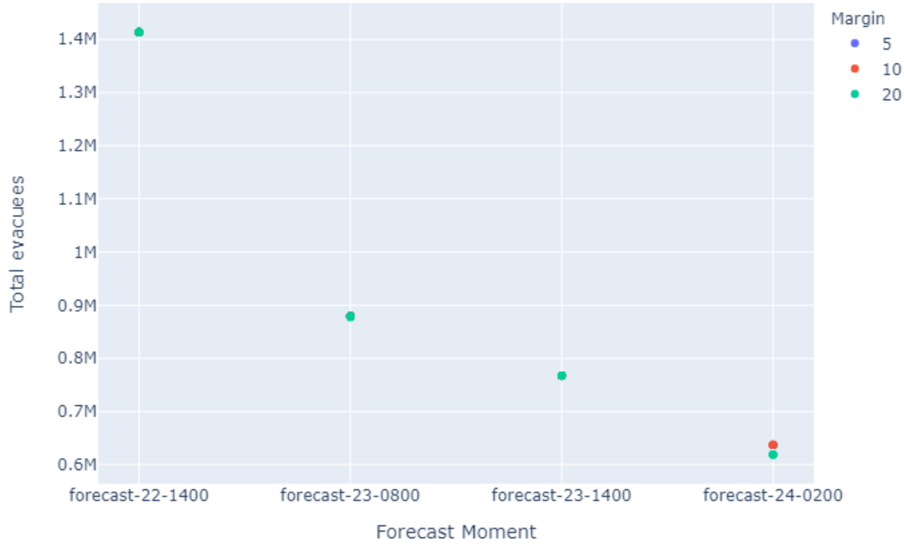

Figure 9.7: The total number of evacuees for each forecast moment and safety margin

However, before the first forecast moment is excluded because of its many evacuees, it needs to be made sure that there are other viable options in the other three evacuation moments where all of the residents in danger are saved. Figure 9.8 shows the fraction that is saved for each forecast moment, safety margin and number of shelters with a 95% confidence interval.

For example, the right data point in the top-left sub figure represents the fraction that is saved in case of an evacuation on April 24th, 0200 AM, with a safety margin of 5 kilometer and 20 shelters. It shows that with a 95% confidence interval, between 90% and 100% of the residents in danger will be safely evacuated. With the assumption that all evacuees in danger should be saved, only configurations where the entire confidence interval equals 1 are accepted. Therefore, the policy configurations where the lower end of the confidence interval lies above 99.5% are marked with a square. This 0.5% margin of error is used because of some data outliers in the Open Street Map data, which cause unrealistic long travel distances for some evacuees.

When analyzing the squared data points, the best policy configurations can be found. Regarding the option of 20 shelters, there is only the option for a safety margin of 5 kilometer with an evacuation no later than April 23rd, 0800 AM. When the option of 40 shelters is selected, there is the option to evacuate with a safety margin of 10 at April 22nd, 1400 PM. However, as shown in figure 9.7 this also results in a relative high number of total evacuees when compared to one forecast moment later. With 40 shelters, it is also possible to evacuate April 23rd, 0800 AM with a safety margin of 5 kilometer. The same applies to the situation where 80 shelters are selected, with the exception that with 80 shelters it is also possible to evacuate April 23rd, 1400 PM with a safety margin of 5 kilometer. Interestingly enough, there are no squared data points for the evacuation moment of March 24th, 0200 AM, even though this moment lies before the break point. Still, it is possible to safe all evacuees for this evacuation moment, for example with a safety margin of 5 kilometer and 40 shelters, but due to the uncertainty, a fraction saved of 1 can not be guaranteed. Section 9.5 will offer a summary of the most promising policy lever configurations.

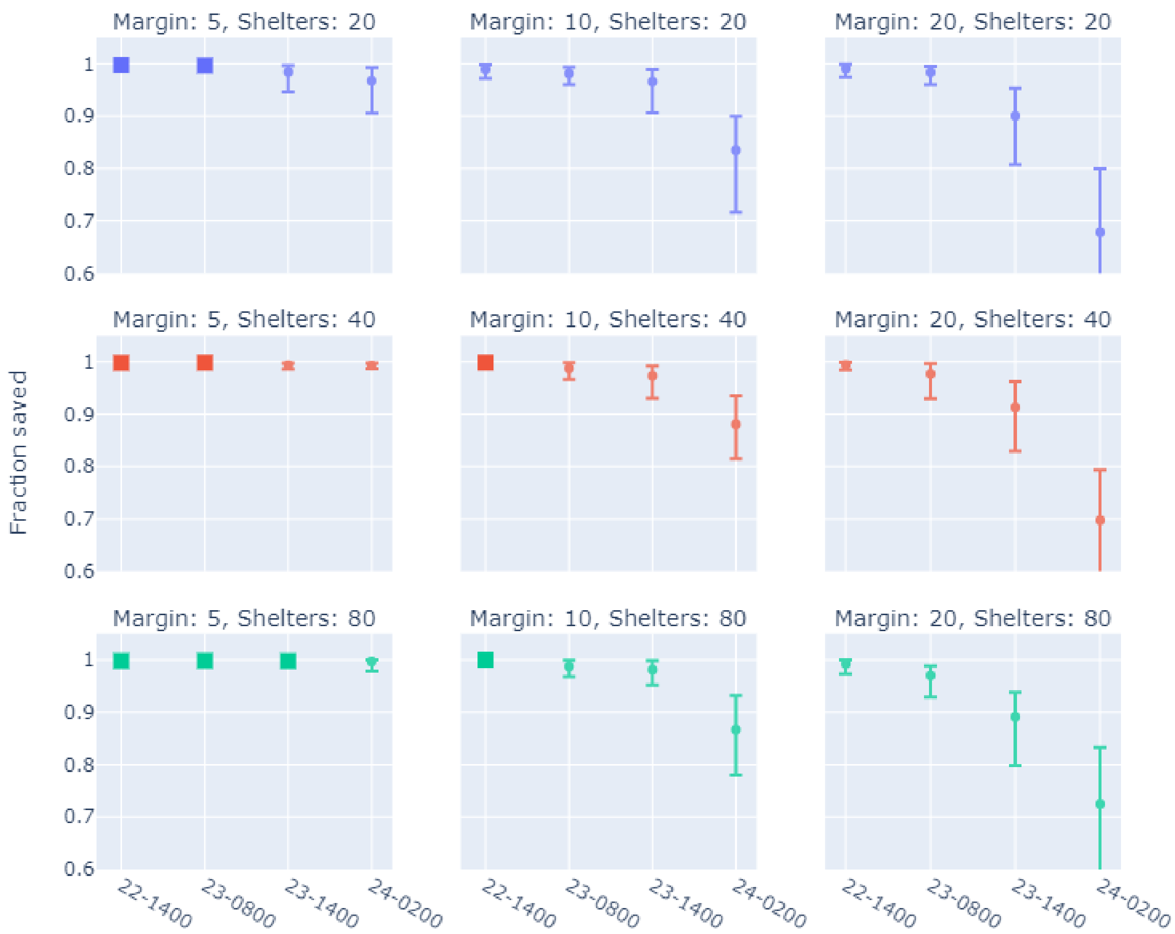

Figure 9.8: The effect of the safety margin and the number of shelters for the four forecast moments of interest

9.4.3. Break point analysis

Before continuing with the most promising options, an analysis of the break point is offered. This analysis offers insights into why an evacuation where all evacuees in danger are saved is no longer possible after the break point. Figure 9.3 showed that the break point lies between April 24th, 0200 AM and April 25th, 0200 AM. This gap of 24 hours exists because no forecast reports have been published in between. To gain better insight into what exactly happened in these 24 hours that make that not everyone can still be saved, the evacuation at April 25th, 0200 AM is investigated in more depth.

Figures 9.9 and 9.10 show the travel distance for the evacuees based on a margin of 10 and 5 kilometer respectively for the evacuees that live in the impacted coastal area. The residents that are excluded from the evacuation because of the distance constraint are shown in purple. The two figures show that with a higher safety margin (10 kilometer versus 5 kilometer), the number of residents that is excluded from the evacuation is larger. This illustrates the need to choose a low safety margin after the break point, because it increases the chance for more residents at risk to safely evacuate the area in time. Another observation is that the left-most data point (in dark-red) has a relative high travel distance of 142 kilometer, but it is not excluded from the optimization. When this area is investigated further, it shows that there are shelters within reach, but they are not selected in the optimizations, which explains the high travel distance for that area. In the event of an evacuation on April 25th, 0200 AM, there are 10 hours of daylight left before the cyclone will make landfall.

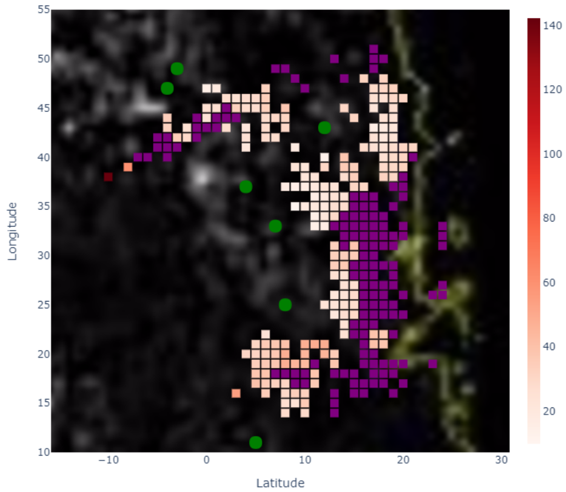

Figure 9.9: April 25th, 0200 AM, margin: 10, shelters: 20

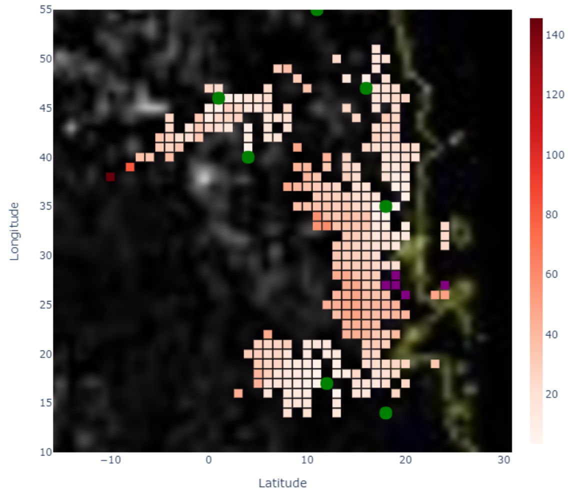

Figure 9.10: April 25th, 0200 AM, margin: 5, shelters: 20

With a travel speed of 2.5 to 5 km/h, this means a distance of 25 to 50 kilometer can be travelled. However, because of the decision time of 3 to 9 hours, the maximum travel distance is reduced to 35 kilometer (7 hours multiplied by 5 km/h). In figure 8.9 it shows that many evacuees have a travel distance around 35 kilometer and many residents are excluded from the evacuation. This results in 32.524 residents left behind, which means they will need to be rescued after the cyclone has made landfall. Of the 46.385 residents that are evacuated only 7% to 19% reaches their shelter in time. When a safety margin of 5 kilometer is selected (figure 8.10), 867 residents are not evacuated because of the distance constraint and between 27% and 44% of the 78.042 evacuated residents reaches their shelter in time. In absolute numbers that means that with a safety margin of 5 kilometer on average 27.705 residents are evacuated in time, while with a safety margin of 10 kilometer, this means that on average 6.030 residents are safely evacuated. However, with a safety margin of 5 kilometer, 50.377 evacuees are still traveling at the moment the cyclone makes landfall, while with a safety margin of 10 kilometer there are 40.355 evacuees still traveling. This is relevant, since evacuees who are still traveling at the moment the cyclone makes landfall may possibly be more vulnerable than the residents that still have the protection of their own home.

9.4.4. Location and size of the shelters

Furthermore, it is relevant for decision makers to have insight into the spread of the evacuees over the shelters and were those shelters are located. The first step in understanding how the shelters are located, is by analyzing the population density. Since the average travel distance between the evacuees and the shelter locations is minimized in the optimization, the largest shelters will be located closest to the largest demand points, e.g. the largest cities. Figure 9.11 shows the population density of the area that is possibly in danger to the effects of cyclone Kenneth, based on the earliest forecast report that became available. It shows that most of the population density lies below 5000 residents per patch, which equals to around 725 residents per square kilometer.

To identify the patches with large population groups, the larger cities are displayed in figure 9.12. The figure shows that there are five bigger cities that are located alongside the coast line. The population size is displayed below each circle.

Section 9.3 has shown the possible policy configurations where all the evacuees in danger are saved. Three of them each score best on one of the key performance indicators and are therefore further analysed. Section 9.5 will discuss those three options in more detail, while in this section they are analyzed on their shelter locations and the size of those shelters. Figures 9.13 to 9.15 show the location and size of the different shelter locations for the three different options that are selected in section 9.3. The size of the locations is indicated by the color of each data point. The box plot next to each figure shows the different sizes of the selected shelters. The size of each shelter that is shown in the figures does not show the results from the optimization, but

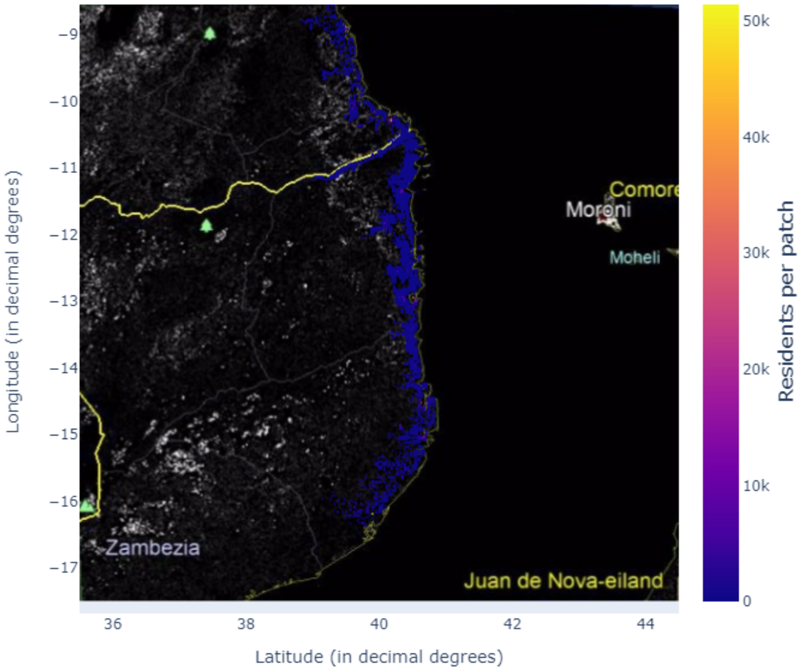

Figure 9.11: Heatmap of the population density (in residents per patch) of the area that is possibly at risk to the effects of cyclone Kenneth, based on the earliest forecast available

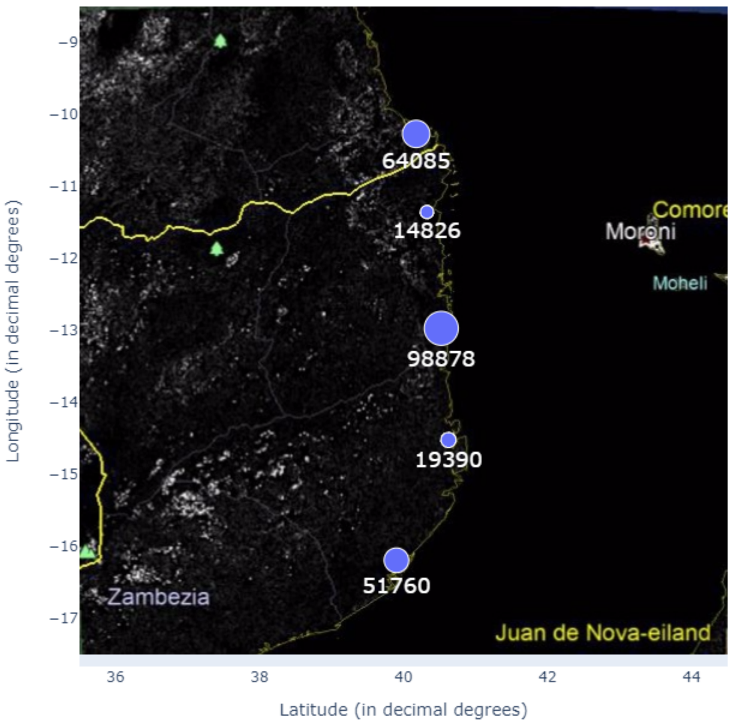

Figure 9.12: The five biggest city in the area that is possibly at risk to the effects of cyclone Kenneth, based on the earliest forecast available

the results from the evacuation simulation results. The difference is that in the results from the evacuation simulation evacuees possibly have changed their destination because they have been informed by other residents because they have no cell tower coverage. This leads to the results that some shelters end up with zero evacuees and some shelters with more evacuees than the initial maximum capacity.

Figure 9.13 shows the location of the shelters for an evacuation on April 22nd, 1400 PM with a safety margin of 10 kilometer and 40 shelters. The results show that the largest shelters are located closest to the largest cities

in figure 9.12. Because there are around 1.4 million evacuees in an evacuation on April 22nd, the shelters have an average size of 35.122 residents.
Figure 9.14 shows the location of the shelters for an evacuation on April 23rd, 0800 AM with a safety margin of 5 kilometer and 20 shelters. The evacuation area is smaller compared to the previous forecast report, which means that there are now 874.869 evacuees. They are spread out over 20 shelters, and therefore have an average shelter size of 43.743 evacuees. However, the spread of the shelters is smaller compared to the previous evacuation moment, with only one outlier of a shelter with a size of 120.000 residents.
Figure 9.15 shows the location of the shelters for an evacuation on April 23rd, 1400 PM with a safety margin of 5 kilometer and 80 shelters. Compared to the previous forecast with a difference of 6 hours, the total number of evacuees is now reduced to 766.477 evacuees. With four times as much shelters, they now have an average size of 9.581 evacuees.
Overall, when the different options are compared for their shelter locations and sizes, the first options stands out because of its many evacuees and the low number of shelters. This results in many large shelter locations. The other two options have less evacuees and also more shelters, which reduces the shelter size, but it also increases the spread of the evacuees, which may make it harder for aid organizations to distribute their relief operations.

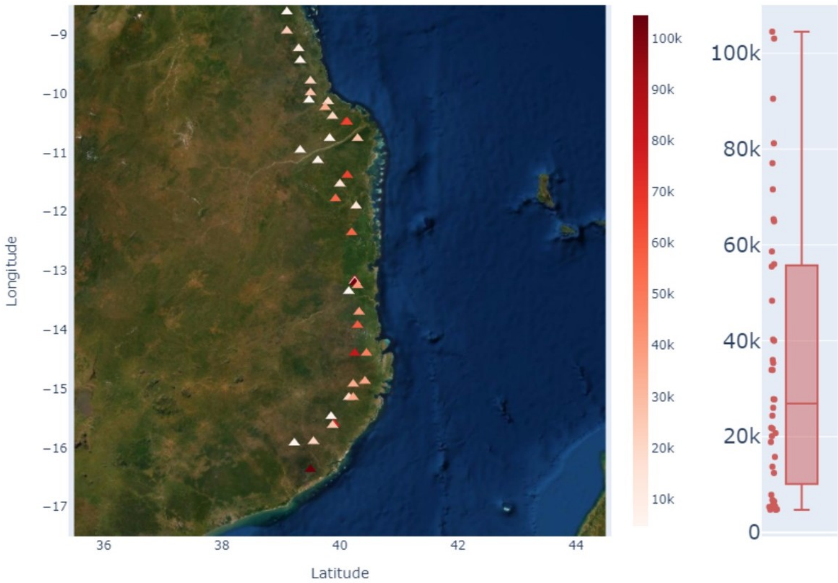

Figure 9.13: Shelters and their size for an evacuation on April 22nd, 1400 PM with a safety margin of 10 km and 40 shelters. The color represents the size of the shelters

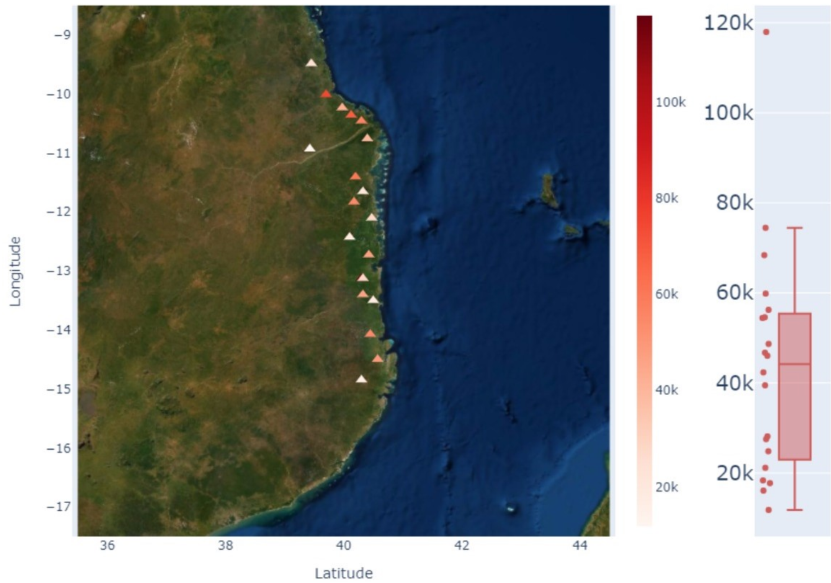

Figure 9.14: Shelters and their size for an evacuation on April 23rd, 0800 AM with a safety margin of 5 km and 20 shelters. The color represents the size of the shelters

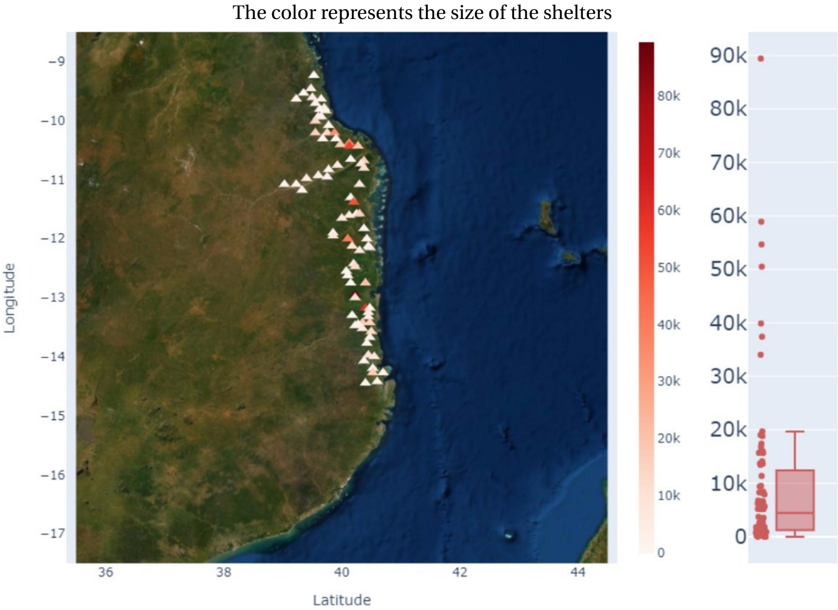

Figure 9.15: Shelters and their size for an evacuation on April 23rd, 1400 PM with a safety margin of 5 km and 80 shelters. The color represents the size of the shelters

9.5. Conclusion case study Kenneth

Three policy levers have been analyzed for the case study of cyclone Kenneth. This section will briefly summarize the main effects of those three policy levers. Forecast reports became available three days in advance of landfall. With the right configurations of the policy levers, it is possible to evacuate all the residents at risk safely, but only for the first four forecast moments, although for the fourth forecast moment, a fraction saved of 100% can not be guaranteed. When an evacuation order would be issued directly after the break point, on April 24th, 0200 AM, a maximum of 58% (figure 9.3 of the residents at risk will safely reach their shelter in time. As identified in the result analysis, three configurations of the policy levers seem to be especially promising when the different trade-offs are balanced. They are summarized in table 9.6.

Table 9.6: Three promising configurations of the policy levers in the Kenneth case study

Experiment number	7	14	28
Forecast moment	April 22nd, 1400 PM	April 23rd, 0800 AM	April 23rd, 1400 PM
Safety margin (km)	10	5	5
Number of shelters	40	20	80
Total evacuees	1.413.709	879.405	767.502
Total evacuees in danger	78.909	78.909	78.909
Fraction saved	1.00	1.00	1.00
Evacuees in danger not saved	0	0	0
Average travel distance (km)	46	36	23
20th quantile of travel distance (km)	28	19	14
80th quantile of travel distance (km)	61	42	30

Experiment 7 is the earliest of the three and therefore has the highest number of total evacuees. However, because there is enough time, it was possible to select 40 shelter locations with a safety margin of 10 kilometer, which makes them safer than the shelter locations with a margin of 5 kilometer in the experiments 14 & 28. In this experiment 7, the evacuees have a high average travel distance, compared to the other two options. Because many residents were unnecessarily evacuated and they had a relative high average travel distance, this configuration can be seen as a high burden for the evacuees. It is also the option with the highest number of evacuees. The second and the third option both have a safety margin of 5 kilometer, which means that vertical shelter locations are used. The largest differences between the last two options is that the second option has only 20 shelters, compared to 80 shelters in option 3. This results in large shelters in option 2 and many small shelters in option 3. The many shelters in option 3 also result in a lower average travel distance for the evacuees. In the end, it is up to the decision maker to decide on the balance between the spread of evacuees over the area and their travel distance.

9.6. Comparing the Idai and Kenneth case study

Two case studies have been performed and analyzed. This section is dedicated to comparing the two cases to see where and how they differ and what consequences this brings. It will also look into the aspects that they have in common, in order to see whether individual conclusions can be generalized. The same structure as the individual case studies will be used to compare them. This means that subsection 9.6.1 will first analyze both case studies for their specific break points. Subsection 9.6.2 will continue with outlining how the trade-off between timeliness and uncertainty reduction is related between the two case studies. Section 9.6.3 will analyze the comparison between the case studies for the situation after the break point, and section 9.6.4 for the size and location of the shelters of the most promising options.

9.6.1. Comparing the break point

The break point is defined as the latest possibility to safely evacuate all residents in danger to their shelter locations. Regarding the Kenneth case study, in the latest possibility before the break point, a fraction saved of 100% can not be guaranteed, because of the 95% confidence interval that falls below 99.5%. However, because rescuing all the residents in danger is still possible at that time, it is still regarded as the latest evacuation moment before the break point.
Table 9.7 shows the hours between the latest evacuation moment before the break point and the moment the cyclone makes landfall. They are categorized for each of the three different safety margins. Important note here is regarding the availability of the forecast reports. Because they are different between the two case studies, the comparison is not as precise as when the decision moments would have been continuous.

Table 9.7: Hours that are needed in the latest evacuation possibility where all the evacuees in the impacted area can reach their shelter

Safety margin	Idai	Kenneth
5 kilometer	48	50
10 kilometer	48	74
20 kilometer	66	NA

The table shows that the evacuation time needed for the area that is impacted is almost the same in both case studies (48 and 50 hours) when a safety margin of 5 kilometer is selected. This means, that because of the vertical shelter locations, the shape of the evacuation area becomes less important in terms of the time that is needed to evacuate. This is illustrated by the fact that there is a larger difference (48 and 74 hours) when a safety margin of 10 kilometer is used. This confirms that in situations with only horizontal evacuation, the shape of the area becomes more important. When the shapes of the impacted areas is compared between the two case studies (figures 8.9 and 9.9), it is shown that, in the Idai case study, the impacted area is not completely adjacent to the coast line with one side, whereas the eastern side of the impacted area in the Kenneth case study is fully along the coast line. This means that in the Idai case study, locating the shelters around the impacted area is a viable option, whereas in the Kenneth case study this option is more limited. Another explanation is that, because the shelter locations are determined before the impacted area is known, the shelters are not always centered around the impacted area, but focus on evacuating all the residents from the evacuation area. Because the entire population of evacuees is larger in the Kenneth case study, it has a lower chance of having the shelter locations centered around the impacted area. Since the hours in table 9.7 show the hours that are needed for the evacuation of the impacted area only, it can explain the difference in the results. Lastly, because the Kenneth case study only has forecast reports from up to three days in advance, it is not possible to evacuate with a safety margin of 20 kilometer. Regarding the Idai case study, it is shown that a safety margin of 20 kilometer, instead of 10 kilometer, means that the latest evacuation moment is 66 hours in advance of landfall. Therefore, it is also found important to have timely access to forecast reports, in order to have the possibility to evacuate with higher safety margins. To conclude, even though the case studies have a different geographical shape of the evacuation area, they both showed that the break point is around two days of landfall.

9.6.2. Comparing the trade-off

When comparing both studies, a similarity can be found in the trade-off before the break point. It is shown that, in both cases, vertical shelter locations enable postponing the evacuation decision or the possibility to choose less shelter locations. Both have the effect that the average travel distance decreases. Both case

studies also show that there is a diminishing marginal benefit of each additional shelter. Figures 8.5 and 9.5 showed that the reduction in average travel distance reduces when more shelters are added. Both case studies have also shown that 10 shelters are too few to cover the entire population at risk and that in most cases at least 20 shelters are needed.
Another interesting result in both case studies, is that later evacuation moments sometimes show better results in the fraction saved than earlier evacuation moments (see for example figures 8.6 and 9.6). This means that evacuating earlier does not always result in a higher amount of successful evacuations. This is explained with the fact that when time goes by, the uncertainty reduces, and with that, the evacuation area becomes smaller. Depending on the shape of the vulnerable area and the population density, it is possible that the size of the evacuation area reduces rapidly, or large cities are now suddenly excluded from the evacuation area. This results in the possibility to better position the shelter locations, because less evacuees need to be divided over the same number of shelters and the shelters can be located in new areas that are now outside of the evacuation area.

9.6.3. Comparing the situation after the break point

For both case studies, the first evacuation possibility after the break point is analyzed. This analysis gives insight into the reason why an evacuation is no longer possible after the break point. A heatmap of the travel distances is shown, for both an evacuation with a safety margin of 5 kilometer and a safety margin of 10 kilometer. The first difference between the two case studies was that in the Idai case study there were no residents excluded from the optimization due to the distance constraint, while in the Kenneth case study there were, especially with a higher safety margin. Therefore, in both case studies it is illustrated that if there is no other option to evacuate before the break point, a low safety margin with vertical shelter locations should always be chosen. This reduces the average travel distance, and with that, it increases the fraction of the population in danger that is saved. In the Kenneth case study, it is also shown that some evacuees can not reach their shelter in time, because they have to travel too far. This occurs when there are shelters in reach for a population group, but none of those shelters are selected in the optimization. This causes that they are not excluded from the evacuation, but end up with an allocated shelter that is unattainable.

9.6.4. Comparing the shelter locations and sizes

The location and the size of the chosen shelters is analyzed for the most promising policy configurations for both case studies. The analysis shows that the largest shelters are located close to the largest cities, which is a consequence of the distance minimization. Therefore, a population density heatmap is a suitable predictor for predicting in what area the largest shelters will be located. However, whether or not the decision makers choose for vertical shelter locations, will change the locations of the largest shelters in a way that is hard to predict, since it depends on the possibilities for vertical shelter locations. Therefore an elevation map can give insight into the possible vertical shelter locations that are located close to the most densely populated areas. Furthermore, in both case studies it is shown that more shelters reduce the average size of the shelter locations, but that in both cases there will always be larger shelters.

10

Discussion and limitations

This chapter, together with chapter 11, is centered around transparency and gaining the reader's trust. This chapter specifically, discusses the various limitations of the model (section 10.1), critical assumptions (section 10.2) and a reflection on the research approach (section 10.3). This chapter will conclude with section 10.4, which describes the implications for policy makers.

10.1. Model limitations

This section discusses the limitations of the model. This partly forms the input for the recommendations for future research (section 12.5), because when the limitations of the model can be resolved, the application possibilities of the model would be improved.

The current way in which vulnerability is determined is based on the forecasted path of the cyclone and on the Height Above the Nearest Drainage (HAND). Even though the HAND data proves to be a suitable predictor for floods (Nobre et al., 2011), it does not account for all the other effects a cyclone may cause. Those effects include heavy rainfall, tornadoes, strong gusts and storm surges (Stetson, 2019). This last effect is responsible for the most deaths and mostly occurs in coastal areas. But even the intense rainfall can cause mud and land slides, which are hard to predict. A cyclone can cause precipitation for many days in a row and the volume can equal the volume that is normally the total of a whole year. To correctly determine vulnerability in hilly areas, a flood modeling software should be applied that accounts for the run-off, which may cause floods in different places than the rainfall actually took place. This would also account for the effect that many floods only occurred several days later, because the rainfall took several days before it reached downstream areas. Furthermore, the intensity of the cyclone has not been taken into account, while this may influence the vulnerability as well, especially because a cyclone normally weakens after landfall. Because it is harder to predict the direction and strength of a cyclone over land, this research also limits itself to coastal areas only. However, in both case studies, the cyclone also impacted areas that were further inland. Lastly, the vulnerability assessment model could benefit from a flood modeling software component because with a better assessment, it would also be possible to prioritize certain areas over other areas because the vulnerability calculation is more reliable.

The second limitation is about the the rural and urban distinction. Regarding the two case studies in this research, most of the area is rural with only a small population size. However, this means that the big cities within the rural area make up a significant part of the total population. Therefore, those cities should receive a bespoke evacuation plan, instead of being treated the same as the rural parts of the country. However, this requires more local knowledge and it would make the model less easy to apply. Still the model would benefit from such a distinction between rural and urban because of the following reasons:

- The evacuation process between rural and urban parts is different. Access to motorized vehicles would be higher and the decision process would go differently as well.
- The population size of urban areas is significantly higher, which means that shelter locations need to be significantly bigger as well. When there would be a distinction between urban and rural it would be possible to select different shelter locations for the different groups.

- Because the urban population is concentrated in one place, it would be easier to organize transport, as was the case for cyclone Kenneth, where 30.000 people have been evacuated using trucks.

To assess the effects of such a distinction between rural and urban population, appendix E shows a specific experiment where a threshold is placed on the population size that is included in the optimization. Interesting enough, even though the location of the shelters and the number of evacuees were different, the arrival of the evacuees over time was nearly the same. They both had a similar fraction of the evacuees in danger that was saved (0.99 & and 1.00). With a threshold of 150 residents per square kilometer, the number of total evacuees was reduced from 877.925 to 351.950. For the residents that are not included in the evacuation because of the threshold, a different evacuation plan should be constructed.

The third limitation is that the data has been aggregated up to a resolution of 2.6 by 2.6 kilometer. This aggregation was necessary in order to reduce computational power, but it reduces the precision of the results. If there would be more computational power, the resolution can be improved and thus the results would be more precise. However, a higher resolution would also reduce the ease with which the model can be deployed. Since time is of the essence in pre-disaster evacuation, that would be an important downside. However, a first interesting approach would be to increase the resolution of the elevation map, in order to find better vertical shelter locations.

The fourth limitation that is discussed is regarding the data sparsity. To determine the distance between the evacuees and the possible shelter locations, Open Street Map data is used, together with a path finding algorithm. The way in which this works is by connecting an evacuee to the closest crossroad in the data and to calculate the shortest path from thereon (see appendix H). However, due to the sparsity of the data in some rural areas, this distance between an evacuee and the nearest crossroad can be rather large (up to several kilometers), which makes the calculated path less realistic. For that reason, the 0.5% error margin is accepted. One way of dealing with this limitation would be to improve the density of the data, but that is a time-demanding task.

The fifth limitation is about the shelter site selection and their capacities. Currently, the shelter searching algorithm searches for areas that are assessed as not vulnerable and that have the right safety margin to the vulnerable area. However, it does not assess whether or not the locations actually have the possibilities to shelter the number of evacuees that are send there. Since the capacity of each shelter locations needs to be at least the size of the biggest group (because one group of evacuees is always sent to the same location), the number of evacuees in one shelter can be very high. Although evacuees can be reallocated after arriving at their designated shelter location, the algorithm needs to be improved in a way that it also verifies the feasibility of the shelter locations.

Finally, The last limitation that is discussed here is that the pre-disaster evacuation presumes that humanitarian aid organizations will assist governmental aid organizations when necessary, even before the natural disaster actually took place. Currently, humanitarian aid organizations mostly assist and fly in after the disaster has taken place. In case of cyclone Idai, the disaster response only started several days after the cyclone had made landfall, while if evacuees would be sheltered pre-disaster, aid would need to be organized several days in advance of the natural disaster. To actually benefit from a pre-disaster evacuation it is needed that assistance is also offered pre-disaster.

10.2. Critical assumptions

Assumptions are needed when data is missing that would substantiate such a consideration. Assumptions are therefore extremely useful, because they enable to proceed with the research when data is missing. However, assumptions may be false and are often subject to the subjectivity of the researcher, because no one can be completely right and unbiased. One way to reduce the consequences of wrongly and unjustified assumptions is transparency. Therefore, this section will briefly describe the assumptions that are most important to this research and will quickly discuss the underlying reason for these assumptions. For a full comprehensive list of all the assumptions, see appendix F.

Continuing on the limitations to this research (section 10.1), one of the important assumptions is that vulnerability can be determined based on the Height Above the Nearest Drainage and the proximity to the predicted trajectory of the cyclone. This assumption should be tested with the use of better flood modeling software in order to validate this assumption.

Another critical assumption is regarding the logic of the evacuees. It is assumed, based on an interview with the Mozambican expert Freek Huthoff, that residents decide on evacuating within their community, but only during day light. They are therefore inactive during the night, which significantly delays their departure time. This consequently impacts the fraction that safely reaches their shelter location, especially in later evacuation moments. Next to the decision process, there are other assumptions made about the travel speed and the decision delay.

The last critical assumption is that the capacity of the shelter locations is practically unlimited. In the current case studies, the maximum capacity of the shelter locations can go up to 250.000 evacuees in extreme cases. The assumption that these high capacities are possible is taken because the other consequence would be that certain evacuees can not be evacuated. Therefore, the actual assumption is that it is better to have overcrowded shelter locations, than many evacuees who are in danger and who are not saved.

10.3. Reflection on the research approach

The methods that have been applied are a case study, expert validation and agent based modelling. This paragraph will briefly discuss the practical and theoretical drawbacks of these methods.

Agent based modelling is an excellent method to model individual agent behavior and their interactions with other agents and to study emergent behavior. However, the inherent limitation is that there is the possibility that an agent's choice is in fact undecidable. Therefore, this cannot be put in the model as the mathematical representation of the agent. The second limitation is that of computational power. Because even if these choices can be modelled, it can be of such complexity that the time it would take would exceed the available time (Epstein, 1999). Because of this, an agent-based model (in fact every model) is always a mere representation of the actual system, and therefore never gives an exact answer. For example, the way in which an evacuee makes his or her decision whether or not to leave may be much more complex and may depend on several factors that can not all be captured. However, the actual computational restraints were not in the agent-based models, but in the optimization model.
In this research, expert validation or elicitation is about "the synthesis of opinions of experts on a subject where there is uncertainty due to insufficient data, when such data is unobtainable because of physical constraints, lack of resources, or because of ethical restrictions". The limitations to this are that the methods for expert validation are often time demanding and in the end always rather subjective than objective (Flandoli et al., 2011). Still, expert validation has been a great help in gaining insights into the local dynamics that are at play and have greatly determined the way in which, especially the evacuation simulation model, have been developed.
Furthermore, the case study method knows various limitations, of which just a few will be discussed because of their relevance to this thesis. Hodkinson and Hodkinson (2001) describes first of all, case studies have the greatest effect when expertise and intuition about the case are maximized, but this raises doubts about the performers objectivity. Secondly, because case studies are highly specific, conclusions are hard to "generalize in the conventional sense", it mostly serves as validation and as an example of the model's application. Lastly, their message is easy to dismiss, as it is only one example. For this reason, a second case study has been explored. The differences underlined that every case study is very different and that conclusions can never be fully generalized. But on the other hand, a model that is too general, will not even be right about a single case. In the end, it always comes down to customization.

To conclude, this research approach coupled two agent-based models with an optimization model. Since the optimization model is a pure mathematical model, it does not contain any uncertainties. The two agent-based models however, are a representation of reality and are therefore subject to uncertainties. Because these models are coupled to each other, uncertainties flow from the first model to the second. Because of this flow of uncertainties, the uncertainties are amplified in the second Netlogo model. The sensitivity analysis researches these uncertainties in the individual models and partly how sensitivity can change throughout the entire model. However, because the different sub models are all needed to gain insights into the trade-off, the uncertainties should also be analyzed for the complete model. An example can be found in Lee et al.

(2013), where the sensitivity is analyzed for a stochastic model. The analysis in this paper also accounts for the interaction effects between the different variables, whereas in normal sensitivity analysis, ceteris paribus, one variable is researched at a time.

10.4. Implication for the policy makers

Policy makers should keep the limitations, the assumptions and the reflection to the research approach in mind when using such a pre-disaster evacuation model. A model will never be able to give the exact answer to questions with this level of complexity. However, what the model can do, is offer insights and reduce some of the complexities that are at play. Policy makers are therefore advised to use the model in full, but keep the limitations and the drawbacks in mind, and where necessary deviate from the model results.

11 Model verification and validation

Verification is the process of assuring that the implementation of a (computer) model is represented by the conceptual model with enough accuracy (Davis, 1998). Validation, on the other hand, is about ensuring that the model is adequate enough to fulfill the purpose for which the model is built (Andradóttir et al., 1997). In other words, the model should sufficiently resemble reality and be sufficiently accurate, in order to actually translate model results to real world policy. In this context, the aim is not to to prove that the model is 100% accurate, since a model never will be completely accurate, but to prove that the model is not inadequate to answer the main research question. In fact, verification and validation serves the purpose of gaining the user's trust in the model, in order for it to be used to assists in complex decision making processes. Therefore, this chapter is dedicated to verify (section 11.1) and validate (section 11.2) the computer model in this research. This research produced three different models, the vulnerability assessment model, the optimization model and the evacuation simulation model. The first and the latter will be subject to verification and validation, in contrary to the optimization model. Since the optimization model is a pure implementation of a mathematical model and does not include estimated parameter values, it only needs to be verified, but not validated.

11.1. Verification

To increase the trust of the user in the model, a pseudo code is included in Appendix D. This pseudo code is a detailed explanation of the high level overview as is sketched in chapter 3. There, the (syntax) logic of the model can be verified. The design of the pseudo code is also a verification in itself, since it is used to check whether the programming code is properly aligned with the conceptual model. Some common mistakes have been identified and solved, some of which are explained below to ensure that knowledge about common mistakes is shared.

When working with different data layers, it is necessary for them to match. For example, this research worked with a discrete classification of the vulnerable area and then later assigned population to that area. Since the resolution of both data files were not the same, they needed to be aggregated to the exact same solution in order for the population layer to be superimposed by the vulnerability layer.

Another issue was the information flow through the different models. Since the different models were all linked, it was key to understand what data was exchanged between the models, and where was this data saved? The developer should construct a clear blueprint of what information flows to the next model and how this can be stored in the most efficient and effective way.

11.2. Validation

A model can almost never be completely validated, especially when it involves social aspects. Still, an effort should be made to verify that the model is a good enough resemblance of reality in order for it to be rightfully used in real world policies. That said, even though the model will always contain flaws, it should be validated as well as possible. Davis (1998) recognizes three main ways of validating a computer model: 1) empirical validation, 2) theoretical validation and 3) evaluation by other comparisons. Each of those three will be explained and applied in the subsections below. Next, to conclude, a sensitivity analysis will be performed with the aim of mapping what output variance is explained by what input variance and to test the robustness of the model.

11.2.1. Empirical validation

Empirical validation is used to visually compare the model results to what really happened. The Idai case study is validated based on three empirical aspects: the number of people in need of rescue, the size of the area that is inundated and the size of the hurricane.

Validation based on the number of people displaced

Different sources report the number of residents that were affected by cyclone Idai. For example, a situation report, that was published on March 23rd by the Mozambican government, estimates that 1.85 million people have been affected, of which 77.800 were internally displaced (Lutheran World Relief, 2019). Since this research focuses on the evacuation of residents that are prone to cyclone induced floods, it is not the aim to evacuate all the 1.85 million people that are effected. Instead, it aims to evacuate the residents that need to leave their house because it becomes unlivable due to the cyclone induced floods. The situation report does not state specifically for what reason the 77.800 people are internally displaced, but since the cyclone induced floods are the biggest cause, it can be assumed that the model should match this number. Looking at the model for case study Idai, 84.663 residents are assessed as in need of evacuation. These numbers are in the same order size, which means that the model is well calibrated in terms of people that needed to be evacuated.

Validation based on the inundated area

Figure 11.1 displays the area that is inundated after cyclone Idai had passed (Sentinel Hub, 2020). Figure 11.2 shows the area that is classified by the model as vulnerable, setting the vulnerability threshold to a value of 0.15. Note that the scope of the area that is displayed in both figures is not the same. Using this vulnerability threshold of 0.15 it can be seen that the real inundated area (figure 11.1) and the area that is classified as a model are comparable. However, the shape of the areas can never be an exact match, because of the simplifications that are used to assess the inundated area. Therefore, this vulnerability value is also subject to the sensitivity analysis.

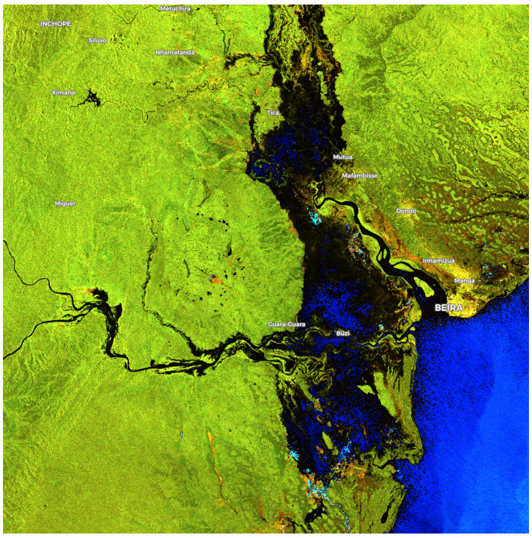

Figure 11.1: Satellite image on March, 19th of the inundated area next to Beira

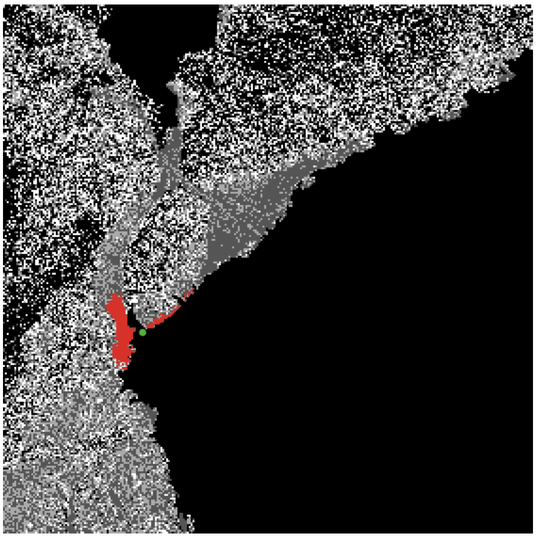

Figure 11.2: Vulnerable area with a vulnerability threshold of 0.15. Impacted area is shown in red

Validation based on the size of the hurricane

The width of the cyclone, which is one of the variables in the vulnerability assessment model, is validated based on satellite images that show daily accumulated precipitation estimates. After the cyclone makes landfall, it disperses and makes more relative unpredictable moves, compared to above the sea, where the surface is much more homogeneous. Therefore, the width of the cyclone is measured just before landfall (figure 11.4).

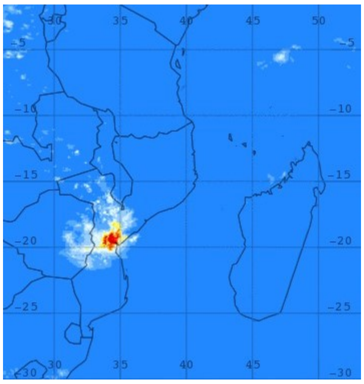

Figure 11.3: Precipitation levels of cyclone Idai on March 16th

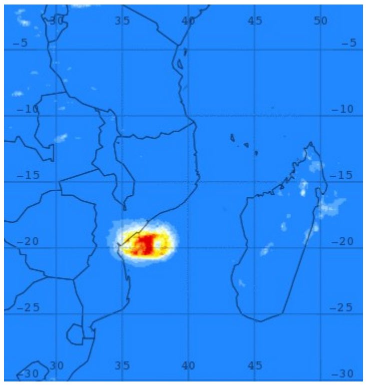

Figure 11.4: Precipitation levels of cyclone Idai on March 14th

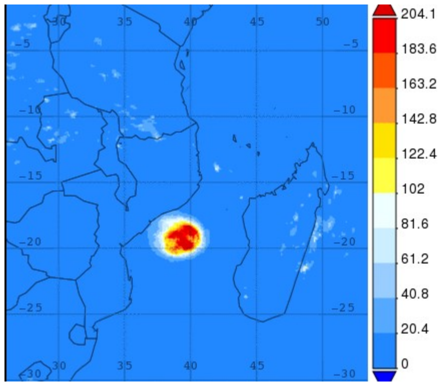

Figure 11.5: Precipitation levels of cyclone Idai on March 13th

The width is measured where the images show a dark red area, which means a daily accumulated precipitation of around 200 millimeter or higher. For the case study of Idai, it is measured at 200 kilometer width, which means the cyclone has a radius of 100 kilometer.

11.2.2. Theoretical validation

Theoretical validation is about verifying substantive logic, checking relevant verisimilitude and testing the reasonableness of the assumptions made (Davis, 1998). This is checked by submitting the model to various hypotheses. The first enumeration of hypotheses are about the vulnerability assessment model and the second enumeration of hypotheses is to validate the evacuation simulation model. The validation tests have been performed with the use of an extreme value test. This test assigns extreme values to the relevant variables in order to verify that even in the outer bandwidths, the model still produces logic results. Appendix C shows the elaborate validation results, whereas in this chapter it is simply verified whether or not the hypotheses are true. The hypotheses that are falsified in the validation are explained below.

The hypotheses for the vulnerability assessment model are:

1. The earlier the forecast moment, the bigger the area that is classified as vulnerable. ✓
2. The bigger the vulnerable area, the more people will be ordered to evacuate. ✓
3. The bigger the size of the cyclone, the bigger the area that is classified as vulnerable ✓/✗
4. The bigger the safety margin, the higher the average travel distance will be. ✓

The hypotheses for the evacuation simulation model are:

5. The more shelters, the lower the average travel distance will be. ✓
6. The lower the average travel distance, the earlier the evacuees will reach their assigned shelter. ✓
7. The higher the decision time, the later the evacuees will reach their designated shelter (or not reach them at all). ✓
8. The higher the travel speed, the earlier the evacuees will reach their designated shelter. ✓
9. The longer the day light, the earlier the evacuees will reach their designated shelter. ✓

Only hypotheses number 3 is not always true. In the earliest forecast moment, almost the whole area within the geographical scope is assessed as vulnerable. This is intended, since the geographical scope is matched to the largest uncertainty. However, that means that when the size of the cyclone is increased, there is no effect on the vulnerable area. For later forecasts the hypotheses is verified to be true.

11.2.3. Evaluation by other comparisons

The third and final way of validation by Davis (1998) is evaluation by other comparisons. The most important one is validation by expert opinions. Experts are people who, from experience and local knowledge, can validate whether or not the model results are accurate enough to be used. Expert opinions can also be used to discuss the usefulness of the model outcomes. In other words, whether the results from this study can also have practical applicability.

The first validation interview was with Wouter Rhebergen. He works for the Red Cross and was one of the first aid workers to arrive in Beira after the cyclone had passed. Because he experienced the situation on the ground, the interview with Wouter focused on the usefulness of a pre-disaster evacuation decision and the reality of such a policy. In the interview, it was discussed if it would be possible to organize such a large scale pre-disaster evacuation. The second validation interview was with Freek Huthoff. He works for the university of Twente and for HKV, a company that has expertise in flood risk and water resources management. Freek was involved in coordinating the disaster response and supplied various aid organizations with insights into the danger of floods. This information helped aid organizations to prioritize their response. Because of his hydrological expertise, the validation interview also focused on the validity of the vulnerability assessment model.

Current disaster preparedness

Before discussing the model results, Wouter was asked about the current preparedness of the organizations that were tasked with assisting the local population. He described that the disaster response in Mozambique is partly organized at the community level. Each small community or village has one elderly appointed that is in contact with the INGC and will receive an evacuation order when necessary and will communicate it to the residents in his or her community. These community leaders have access to a toolkit with various useful items to assist them in communicating the evacuation order and in the evacuation itself. They have received basic training on how to act when they receive an evacuation message. If the community has cell tower coverage, this message is received by a SMS-message. Otherwise the message is transmitted to more rural communities, using a flag system, which means there is a delay between the issue of the evacuation order and the reception. Using this system, warnings were send to the different communities that were thought to be at risk. However, many communities relayed that they did not know how to translate these warnings in concrete actions. Another difficulty was that almost know one had correctly predicted the flood that arrived two days after the cyclone had passed because of the intense precipitation on the border with Tanzania. These floods caught many residents by surprise, which meant there was no coordinated and effective pre-disaster evacuation. Another issue that Wouter brought to the attention is that many Mozambicans are reluctant to evacuate because of fear of looting, sometimes even by their own neighbours. Another issue is that not all community leaders can be completely trusted, because some of them saw the situation as a way to gain power and control over the community they were tasked to protect. To improve the pre-disaster evacuation possibilities, the government is investing in flood prove school buildings. They are built elevated and are equipped with the necessary supplies of food, water and blankets to provide cover for the residents that are living in that area. The benefits of these types of shelter locations is that they are often situated close to where the residents live, which means that they need less time to reach the locations and that they are more likely to heed the advice of the evacuation order. However, these locations also have their downsides. First of all, because these school buildings are vertical shelter locations, they are cut off from the aid organizations which means it can take up to several days or even weeks before help will arrive. Second, these buildings lack the capacity to shelter every evacuee in the surrounding. This means that some residents will still need to evacuate the area completely.

Validation of the results

Both Wouter and Freek were asked about the validity of the results. More specifically, they were asked whether they deemed it possible to evacuate that many residents out of such a big area in the limited time that was available. Because of the complexity of such a hypothetical evacuation, they were first asked about the validity of the underlying assumptions. They confirmed that the values for the specific variables like the travel speed and the decision time are aligned with their expectations, but that it is impossible to say with absolute certainty. More research would be necessary to improve the estimation. For example, Freek mentioned that the evacuation itself is also not without dangers. People could get trapped because of the poor road conditions or they could sustain an injury. This could mean an even lower travel speed or it would make the evacuation completely impossible. However, they mentioned that the residents have good local knowledge about the area they live in, which validates the assumption that they will know where they should go once they receive the evacuation order. Overall they concluded that the results could very well be accurate, but that it could never be 100% validated. They also both raised the issue that residents would be reluctant to evacuate, let alone to evacuate such large distances. They both confirmed that it would be more likely that residents would heed the advice of the evacuation order if their travel distance would be smaller. This is the case in the situation of the low safety margin of 5 kilometer, which meant that vertical shelter locations would be used. Even though this has the two downsides as discussed above, they both confirmed that it would be more important to evacuate the residents as close as possible to home then to have direct access to them.

Implication of the validation

According to Wouter, the maximum distance the evacuees would be willing to travel is around 15 kilometers. Even in the latest forecast before the break point (March 13th, 0000 AM), with a safety margin of 5 kilometers, the average travel distance is still at least double that of 15 kilometers. That means that with purely the current vertical shelter locations that are found by the model, it will not be possible to have 100% compliance of the residents. The latest evacuation moment where all of the evacuees are saved in the Kenneth case study, the evacuees need to travel on average a distance of 23 kilometer. This is quite close to the maximum of 15 kilometer, but still many evacuees will be reluctant to travel that distance. That means that specifically for central (Idai) and northern (Kenneth) Mozambique, more shelters are needed that can shelter all the evacuees in the vicinity, because otherwise the travel distance would be higher than the maximum of 15 kilometers. Furthermore, the behavior that communities inform each other with radios quite perfectly resembles the behavior of the flag system. Therefore, even though the process of informing the residents without cell tower coverage is a bit different, it does not have significant implications for the results.

11.2.4. Sensitivity analysis

The sensitivity analysis of all the variables in the model can be found in appendix C. This section will instead summarize the highlights of the sensitivity analysis. First of all, for some variables, the sensitivity depends on the evacuation moment that is chosen. For example, take the size of the cyclone, which is part of the total uncertainty in the vulnerability calculation. In early forecast there is more uncertainty, which means that the share of the cyclone size is smaller, which makes a change in that size less sensitive. However, in later forecasts, the uncertainty about the path is reduced and the size of the cyclone makes up a bigger part of the uncertainty, which also makes it more sensitive to small changes. Therefore, the sensitivity of the variables that are dependent on the forecast moment is tested for multiple of those forecast moments.

Figure 11.6 shows the sensitivity of a small change in the safety margin, measured by the fraction saved. It shows that the uncertainty increases with later forecast moments, and with that the sensitivity increases as well. There is no significant effect in a small change in the safety margin for forecast moment March 9th, 0600 AM (t=-0.76, p=0.542). The same applies to the forecast moment of March 11th, 1200 PM, were no significant difference was found either (t=0.21, p=0.837). A small change in the safety margin for the forecast moment of March 13th resulted in a significant difference in the fraction saved results (t=4.78, p=0.000).

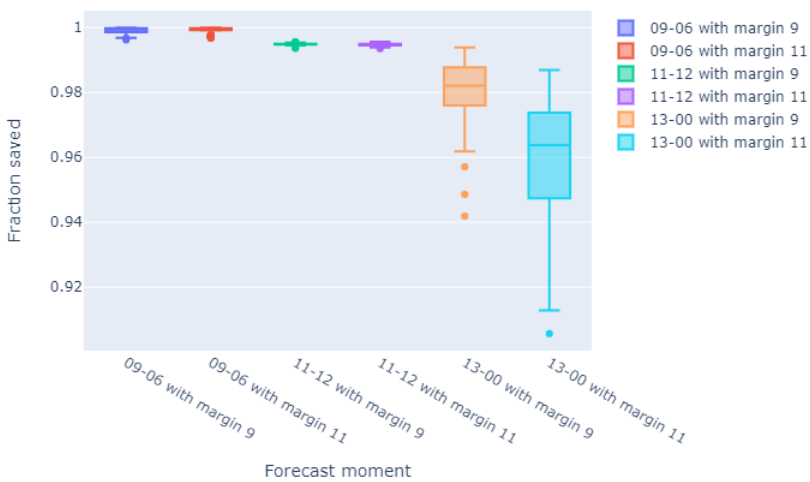

Figure 11.6: Sensitivity of the safety margin, measured by the fraction saved

The uncertainty analysis hereby confirmed that the sensitivity of the safety margin is high for late forecast moments, and is low for early forecast moments. The opposite is true for the number of shelters. Here the sensitivity is high for early forecast moments, and decreases in later forecast moments. This was expected, since in early forecast moments the safety margin only makes up a small part of the travel distance (since the vulnerable area is higher) and is therefore lower in terms of sensitivity. On the other hand, in early forecast moments, there are more evacuees which means that the number of shelters has a high impact and is therefore more sensitive.

Regarding the variables in the evacuation model, like the travel speed and decision delay, in general they are not very sensitive to small changes. However, except for moments where, for example, a lower travel speed caused many evacuees not to reach their shelter before nightfall. This meant that they needed to camp out another night, which significantly delayed their arrival time by one night of 12 hours.

12

Conclusions and recommendations

First, section 12.1 will formulate an answer to the sub questions that are first posed in chapter 3. Second, section 12.2 will answer the main research question. Third, section 12.3 and 12.4 will explain the contribution of this research to society and will discuss the scientific contribution it offers. Section 12.5 will conclude with three research proposals.

12.1. Answering the sub questions

Four sub questions have been formulated in order to provide this research with the proper structure. This section will, where relevant, reflect on the different sub questions and will summarize how they have been answered.

How to calculate vulnerability regarding cyclone induced floods, based on the predicted trajectory of the cyclone?

At first, the formulation by Samost (2006) was used to assess vulnerability. He states that the vulnerability is directly proportional to the elevation, the proximity to a major water body and the chance of being in the path of the cyclone. In a later stage of this research, the use of the height above the nearest drainage model by Nobre et al. (2011) was used instead of the formulation by Samost (2006). This static hydrological flood predictor replaced the need for the river data, because it already accounts for the elevation above the nearest drainage. The two methods showed to be quite comparable for areas with low elevation, while being contradictory for areas with high elevation. In the first formula by Samost (2006), areas with high elevation were unlikely to receive a high vulnerability value, whereas the HAND data also showed vulnerable values for areas at higher altitude, because it compared it to the nearest drainage instead of the absolute height. This makes the HAND data more useful when applying the model to areas with higher altitude. Furthermore, the HAND model is calibrated for flood prediction, which makes it the better candidate to assess cyclone induced flood prediction. However, to ensure which methods produces more reliable results, they should be compared to a hydrological model to validate them. Regarding the software implementation of this first sub question, the building block is implemented in the agent-based software Netlogo. Netlogo was, amongst others, chosen because it is spatially explicit, which made it relatively easy to assign a vulnerability value to different areas. The other benefit was that it was easier to couple with the second Netlogo model, since it means they have the same structure, and data was more easily exchanged. However, Netlogo is not primarily developed for this purpose, since the geographical information system extension of Netlogo is quite limited and the Netlogo attributes were not always adequate for calculating the vulnerable area.

How to apply optimization in shelter selection, based on the expected vulnerability and the demand that needs to be covered?

The first step in selecting the best shelters based on the vulnerable area is to have a set of shelters to optimize over. Section 5.2 described how a shelter algorithm is developed that uses a safety margin between the shelter locations and the vulnerable zone. This algorithm is implemented in Netlogo and can be used as a substitute in evacuation models when there is not a pre-defined set of shelters. This algorithm does not account for actual buildings but it does generate locations that are on higher grounds and assessed as not vulnerable to the impact of the cyclone. After selecting a subset of these possible shelter locations, suitable buildings can be found within that area that can serve the purpose of sheltering the evacuees. This means that possible locations are selected within the area that is selected in the optimization. Depending of the resolution that is used, this area can cover several square kilometers. This algorithm is an answer to the second knowledge gap about the lack of a set of pre-defined shelters. The algorithm is a good solution when no data is available about possible shelter locations, but it does require more manual work in selecting the exact spot that can be used as a shelter.

Before the optimization can be executed it is necessary to define the required optimization inputs. The most complex one of these was the distance matrix. This matrix defines all the shortest paths between all the demand points and the shelter locations. Open Street Map data was used to calculate these paths, using the OSMNX Python dependency. Although it takes some time to download and parse the network data, once this was saved locally, it is possible to determine the shortest paths relatively fast. Other improvements have been made to speed up the computation time. They have been discussed in section 5.3.1.

Once the demand and the source points and the other inputs are defined, the optimization changes to a purely mathematical model. At first, the coverage model was applied, instead of the distance minimization model. However, because 100% coverage was not always possible in every scenario, it made more sense to make sure that everyone that was in range of a shelter should be covered. Therefore, the optimization model was switched to a distance minimization variant called the Minisum model (Boonmee et al., 2017), which makes sure that everyone who meets the distance constraint is covered. This optimization accounts for the weight of the different population sizes at the different demand points. The implementation of the optimization was done through the Python interface of the Gurobi optimization software. This Python interface was a convenient solution for implementing the mathematical model in Gurobi, since there was no need to have knowledge of the syntax of Gurobi. Due to the PyNetlogo connector between Python and Netlogo, information was easily exchanged between the optimization and the vulnerability and simulation models.

How can the identified relevant behavioral aspects in literature be conceptualized and used for simulation?

As discussed in section 2.3, there are many behavioral aspects that can be included in an evacuation model. However, too many factors will only add noise to the results, which makes them harder to interpret. Therefore, the first step in conceptualizing relevant behavior is to determine which behavioral factors will influence what is being researched. Because the research is centered around the trade-off between timeliness and uncertainty, behavioral characteristics are included that relate to the time that residents need to leave and to the time they need to travel to their designated shelter. Those characteristics have been translated to a conceptual logic model. This model is then written in programming code and implemented in Netlogo. In terms of modeling behavioral aspects, Netlogo has been found a very suitable modelling program. Especially since it enables to define behavior at the lowest level (the agent level), it is possible to study emergent behavior.

How do timeliness and uncertainty reduction in evacuation decisions relate to the efficiency and effectiveness of the evacuation?

Three Policy levers have been identified, that can be used by decision makers to decide upon the moment and the way in which the evacuation will take place. The identified policy levers are: **moment of the evacuation**, the **safety margin** (the distance between the area that is assessed by the model as vulnerable and the shelter locations) and the **number of shelters** that will be used to shelter the evacuees. The moment of evacuation is always directly after a new forecast report is published, since in those moments there is a local optimum between reduced uncertainty and timeliness.

To assess the effects of those policy levers, key performance indicators have been drafted. They are used to measure the impact of the different policy levers. Evacuees are issued to evacuate to a shelter that is assigned to them, based on the three policy levers. However, because there is still uncertainty about the path of the cyclone when the evacuation decision was taken, not all evacuees were actually in danger. Therefore, the first key performance indicator (KPI) compares the total number of evacuees to the number of evacuees that turned out to be in actual danger of the cyclone. Another KPI is about the number of evacuees in danger that could not be saved because there was not enough time anymore, due to an evacuation moment that came to late. The third KPI is about the travel distance from the evacuees to their shelter. Since this travel sometimes even spans multiple days, which is a heavy burden for the evacuees, this travel distance should be minimized as well, if possible. In line with that, the last KPI is about the total evacuees. This KPI includes the residents that are evacuated because they were residing in the vulnerable zone, but turned out not to be in need of evacuation. The aim is to minimize the evacuees that are unnecessarily evacuated. The KPIs about the total evacuees versus the evacuees that were actually in danger and the average travel distance, represent the efficiency of the evacuation decision. The KPIs about the evacuees in danger that safely evacuated, represent the effectiveness of the evacuation decision.

Now that the policy levers and the key performance indicators have been defined, the main research question about the trade-off between timeliness and uncertainty reduction can be answered.

12.2. Answering the main research question

The main research question that stands central in this report is:

How to balance the trade-off between timeliness and uncertainty reduction in making shelter location decisions in rural and developing areas, under impending cyclone induced floods, while accounting for behavioral aspects of the vulnerable residents?

Three levers that define the shelter location decisions are found relevant in balancing the trade-off between timeliness and uncertainty reduction.
The first is the evacuation moment. It shows that a later evacuation moment reduces the number of total evacuees, but it also reduces the evacuees that are saved from the impact of the cyclone. More precisely, the model shows a clear break point, which means that there is a point in time after which it is no longer possible to evacuate all evacuees in danger. The two case studies have shown that this break point is around two days in advance of landfall. This means that the balance in this trade-off lies before this break point. Too early evacuations however, result in a high number of total evacuees, which is not desired as well. This reduction in evacuees over time is not always linear and depends on how the cyclone is forecasted and the characteristics of the geographical area that is under threat. Therefore, it can be concluded that evacuation should happen before the break point, but the exact moment also depends on the forecast reports and the geographical terrain, and is also dependent on the other two levers. However, it is shown that vertical shelter locations significantly reduce the evacuation time and enable later evacuations or evacuations with less shelters.
The second lever is the safety margin. This research concludes that a relatively high safety margin is advised in early evacuation moments, but in later evacuation moments it is advised to make use of vertical shelter locations, which means that a low safety margin should be used. The low safety margin is the only way, in later evacuation moments, to save as many evacuees as possible, but it also reduces the accessibility and security of the shelter locations.
The third and final lever is the number of shelters. In early evacuation moments, there are many evacuees, which increases the need for sufficient shelters. Therefore, in early evacuations, it is shown that additional shelters have a relatively high reduction in travel distance and high increase of rescued evacuees when compared to later evacuation moments. However, the marginal benefit of an extra shelter is reduced with each additional shelter, which means that the cost of each additional shelter should be balanced against the reduction in travel time and the increase in safely evacuated evacuees. Furthermore, when a distance minimization model is used, the largest shelters will be located closest to the areas with the highest population density. Regarding the sizes of the shelters, later evacuation decisions often means there is need for more shelters. This means that those shelters tend to be smaller, but there will always be larger shelters because of the larger cities.

In summary, three policy levers have been identified that define the shelter location decision and that have an impact on the balance between timeliness and uncertainty reduction. None of these levers can single-handedly define how the right balance, and they should therefore be used all-together to define the best balance the trade-off. However, it has also been found that in both case studies the cyclone evolved differently and the geographical area is far from identical as well, which also influences the right balance. This means that every answer about how to balance the trade-off, will also be different in every case.

Additionally, it is concluded that the trade-off between timeliness and uncertainty reduction is especially relevant for evacuees who are evacuating by foot. When their travel speed increases, the relevance of the trade-off decreases. This confirms the hypothesis that most evacuation models with motorized vehicles do not account for this trade-off because evacuees have a higher travel speed.

Furthermore, this research concludes that when a cyclone is advancing and there is no time to deploy an evacuation model, a heatmap of the population density, together with an elevation map, can give rough estimates of where the largest shelters should be located. The elevation map gives insights into the possible shelter spots because it will point out the elevated locations, either within or outside of the estimated vulnerable area. Those spots that are located closest to the most dense populated areas will probably prove to be suitable shelter locations. Furthermore, in both case studies it is shown that the latest evacuation moment is around two days in advance of landfall of the cyclone and that after that moment it is highly advised to make use of vertical shelter locations.

12.3. Societal contribution

As mentioned in chapter 1, the strength and occurrences of cyclones are expected to increase and it is especially the population in low to middle developed countries that will suffer the consequences. This research directly relates to their well-being and aims to minimize the impact a cyclone will have on the population, by evacuating them in time. The pre-disaster evacuation model is developed to assist decision makers because the implications of their choices are often not straightforward and this computer model can help them to make an informed decision.

Due to cyclone Idai and because pre-disaster evacuation was not coordinated, many residents were trapped by the floods and stuck on the roof of their houses or in trees for multiple days (BBC, 2019). Most of these people were rescued post-disaster by helicopters and boats, but this was an time-consuming task, since the residents first needed to be located and then extracted. Because many of them were living in rural areas and thus dispersed it would have been easier to offer them aid when they were evacuated pre-disaster and in a centralized place outside the impacted area. This study focuses especially on evacuating those people that are most in need of evacuation.

One of the conclusions in this research is that the model is able to show a clear break point, after which evacuation for all evacuees in danger is no longer possible. Because of this it can be ensured that the evacuation order will not be issued to late, but also that not to many residents will be unnecessary evacuated. This is relevant to them since for residents leaving their houses, they take the risk of them being looted, which is why residents will be hesitant to evacuate. Finding the right balance between timeliness and uncertainty reduction also balances their safety and the negative impact of an evacuation.

12.4. Scientific contribution

This section is included to reflect on the scientific and technological challenges that were solved, in order to advise or to not advise on the use of different scientific possibilities or technologies.

To start, the first knowledge gap described how there is currently not a pre-disaster evacuation model that accounts for the trade-off between timeliness and uncertainty reduction. The approach that was taken to include this trade-off was to combine location optimization with behavioral exploration. This research has shown another example of how these two concept can be seamlessly integrated. It offers a way to analyze how pure optimization choices influence the outcomes when behavioral characteristics are accounted for. Only when these two concepts are combined in one model, the real-world effects of a pure location optimization can be assessed.

Second, the last knowledge gap described how little research account for situations when there is no available list with shelter location possibilities. This research defined a new approach and developed a shelter searching algorithm that searches for locations that have a minimum safety margin to the vulnerable area and are located on higher grounds. The results of this algorithm needs to be interpreted because suitable locations need to be found in the direct vicinity of the location, or a temporary shelter location should be built. Even though the results require some human interpretation, the algorithm offers a quick solution do determine possible shelter locations based on the forecast report about the cyclone, without the need for additional data about the building infrastructures.

Third, this research made extensive use of the coupling between Netlogo and Python. Two different Netlogo models are coupled to an optimization model that is purely defined in Python. This coupling made it possible to generate results in a Netlogo model, sent them to Python, execute the optimization model and then sent this data through to another Netlogo model. This research demonstrated that these models can work together seamlessly and that they can all be controlled trough Python. This approach is especially convenient when certain parts of the model are better handled by Netlogo, like agent interaction, and some parts are better handled by Python, like optimization and data modification.

Fourth, another key part that is used in the optimization is the graph representation of the road network, which was generated with the Python package called OSMNX, which translates Open Street Map data to a graph with vertices and nodes. This network is used to calculate a distance matrix between all source and demand points. This distance matrix was then one of the inputs for the optimization model. However, generating all the shortest path between all the source and demand points is computationally very heavy. For one average experiment it took almost two days to generate the distance matrix, which is far too much in order for it to have practical relevance. But since the distance matrix was input for the distance minimization, it was not necessary to calculate the longest paths, because they were not used either way. Therefore, an euclidean range was implemented, which means that every point only calculates the distances to the other relevant points that are within this euclidean range. This method was evaluated, and found to deliver the same results, but was faster by a factor 30. Other ways that are implemented to reduce the computation time was to save every calculated shortest path and for the next calculation to first check whether this specific shortest path was already calculated. If so, it could be loaded instead of generated. Over time, when more experiments were executed, this reduced the run time by another factor of 3.

Lastly, in order to assess vulnerability, the GIS Netlogo extension was used to load GIS data sets into Netlogo. Although this makes it rather easy to execute calculations based on spatially explicit data, the extension was also quite limited. For example, it only supports some very specific file types, and Netlogo is not able to modify the GIS data. However, with the use of QGIS and programming language R, the data could be prepared in a format that was supported by Netlogo. To conclude, despite the rather strict conditions about the data formats, Netlogo still proofed valuable for executing calculations on spatially explicit data sets.

12.5. Suggestions for future research

To make sure that the work continues, this section describes five different proposals for future research. These proposals aim to increase the precision and the usefulness of the model.

12.5.1. Improving the vulnerability assessment model

The vulnerability assessment model is the first building block and translates forecast reports into a vulnerable area. As discussed in the limitations, the current way in which this is performed using the HAND model, it does not properly account for the complex nature of a cyclone. Therefore, the model would benefit from the coupling with a hydrological model. Such a model could account for 3D water movements over time. This means that delays in floods can be accounted for and that with more precision it can be determined which areas are at what time struck by the cyclone. This means that evacuation could be prioritized, instead of a one-time irreversible decision. This would also enable to abort the evacuation order for certain groups of residents that are no longer thought to be at risk. That means that they can return home sooner, reducing the burden of the evacuation. The first step in coupling the evacuation model with a hydrological model would be to make use of for example the rainfall-runoff model by the US Army Corps of Engineers. They developed (and continue improving) a rainfall-runoff model, called HEC-HMS, that would suit the aim of the vulnerability assessment. There are many papers that show the usefulness of the HEC-HMS model (eg. (Gebre, 2015), (Sanyal et al., 2014) & (Halwatura and Najim, 2013)). The HEC-HMS divides the geographical area up in 'boxes' and calculates for each of those boxes the water level based on the estimated precipitation. Based on the vertical elevation difference between the different boxes, water can flow from one box to another. This means that, opposed to the current vulnerability assessment model, precipitation can cause floods in different places than it actually fell down.

12.5.2. Distinction between rural and urban areas

As described in the limitations section, the model does currently not make a distinction between urban and rural areas. As discussed in the literature section, the focus in this evacuation model is on rural areas, but it would not make sense to leave out the urban areas completely, since they are vulnerable as well. That is why in the current model both the urban and rural areas are included in the evacuation decision. However, the dynamics that are at play differ significantly. For example, most rural places do not have electricity which means that life stops after it becomes dark. Therefore, they only decide about the evacuation decision after when it becomes light again. For urban areas this is an unrealistic decision process, since they will have electricity and are less bound to discuss the evacuation decision with the 'elderly' of the city, but will rather decide with their own family. Appendix E has shown an example of what happens when a population threshold is implemented. It shows that the behavior is quite the same, but the number of evacuees was nearly half of the situation without the population threshold. Since the population size and the decision dynamics are different, the model would benefit from a distinction between urban and rural places. That would mean that urban places are excluded from the current evacuation decision and will receive a bespoke evacuation plan. This is more convenient, since urban places also need bigger shelter locations. When drafting a tailored evacuation plan for the cities that are vulnerable, a better location can be found compared to when they are included in the current shelter searching algorithm and optimization. The evacuation for urban areas could also be automated, by for example automatically searching for other cities where the urban population can be sheltered.

12.5.3. Including the vertical shelter location sites and capacities

As discussed in the validation with experts, the Mozambican government is currently focusing on building elevated school buildings that can serve the purpose of a shelter location in case of floods. However, there is currently no comprehensive data set available with all the (proposed) shelters and their capacities. When a list with these shelters would be defined, it would be possible to include those shelters in the current evacuation model. This addition to the model will make it possible to determine the effects on the travel distance and the break point. With this information it would also be possible to advice the INGC about the best locations to build new elevated shelters. It will also be interesting to research with the specific capacities how many residents will be able to find shelter in the elevated school buildings and who will need to evacuate the area completely. To conclude, this research proposal suggests to draft a list with all the (proposed) elevated shelter locations and their capacities to see how this influences the evacuation decision. This addition can then also be used to advice the INGC on where to built the next elevated shelters.

12.5.4. Surveying behavioral characteristics

From the results in the two case studies it can be concluded that the behavior of the evacuees impact the best evacuation decision. When the evacuees would be faster in deciding and traveling for example, the evacuation time would be reduced which means that a later evacuation moment can be chosen. This would mean that less residents will need to be evacuated. A better understanding of the residents would therefore benefit the decision makers. This research proposal therefore suggests to gather data on the process the evacuees go through in reaching their shelter locations and to get a better understanding of realistic decision time and travel speed. It would also be interesting to research the relation between willingness to evacuate and the travel distance and the relation between willingness to evacuate and the fear of looting. The first relation can inform decision makers in how many shelters should be build to ensure the safe evacuation of the entire population. The second relation would indicate the necessity to prevent theft during an evacuation. If a strong relation is found between the fear of looting and the willingness to evacuate, reducing this fear would mean that more residents will be willing to evacuate.

12.5.5. Making the model prospective instead of retrospective

Currently, the model is build in a retrospective way, which means that it evaluates the evacuation decisions in hindsight. Since the impacted area is already known, it is possible to determine, not only the effectiveness of the evacuation, but also the efficiency of the evacuation process. This is one of the reasons which makes the model not suitable to deploy during a cyclone evolves. To use the model in such a way that it can offer real-time advice on evacuation decisions, the model should be able to cope with more uncertainty and should be made predictive. For example, since the impacted area is not known, new key performance indicators need to be defined, ones that do not presume full knowledge about the final damage the cyclone will inflict upon the population. A first concept of this is offered in appendix A.4 and B.4, where it is showed how the latest evacuation possibility changes if everyone in the evacuation area should be evacuated, instead of only the residents that were actually impacted. This example also shows that the essence of the three building blocks stays the same, which means it is mostly the key performance indicators that need to be changed. Another necessary improvement to use the model real-time would be a dashboard. This dashboard would simplify the use in which decision makers can interact with the model, which is necessary when decisions need to be taken quickly. Only then the model would be able to be deployed during impending cyclones and its use can be fully exploited.

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A

Experiment results Case Study Idai

A.1. Key performance indicators

This appendix shows the full results of the Idai case study in a table. Each of the rows represent one experiment, as described in section 8.2.2. Columns 2 to 4 show the values of the policy levers for that specific experiment. Columns 5 to 11 show the value for the different KPIs. Each of the KPIs will be shortly elucidated below.

The *total evacuees (1)* are all the residents who are within the vulnerable zone and are within the range of at least one shelter location. Residents living in in the vulnerable zone but do not meet the distance constraint are not counted as evacuee (3 + 4).

The *total evacuees in danger (2)* are the residents living in the impacted zone, who also meet the distance constraint. This means that they are within the range of at least one shelter location.

The *fraction saved* are the *total evacuees in danger* that safely reached their shelter before the cyclone made landfall, relative to the *total evacuees in danger (2)* plus the *evacuees in danger not saved (3)*.

The *evacuees in danger not saved (3)* represent the residents living in the impacted zone, but that are not evacuated due to the distance constraint.

The *average travel distance* is the average travel distance of the *total evacuees*.

the *Quan 20* and *Quan 80* are two other measures for the travel distance and are the 20th and 80th quantile respectively. That means that the middle 60% of the travel distances fall within these two values.

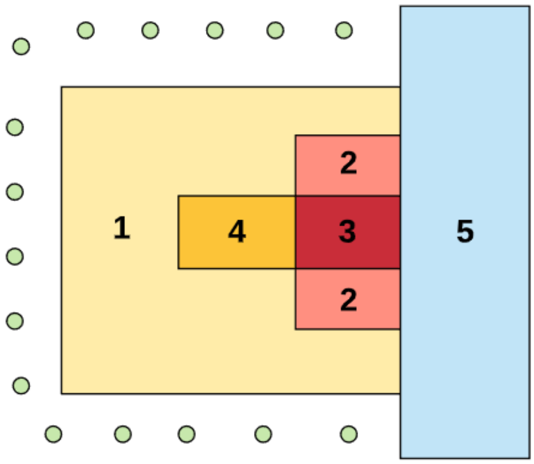

Figure A.1: Shortest routes for evacuee 1

Figure A.1 illustrates the first KPIs. Imagine the case where block 5 represents the sea and the green dots the possible shelter locations. The total evacuees consists of block 1 and block 2. Block 3 and 4 are not counted as evacuee because they do not meet the distance constraint (they are too far away from any the shelters). The fraction saved is calculated by the total evacuees from block 2 who safely reached their shelter, divided by the entire population in block 2 and 3. That means that if there are residents in danger that are not saved due to the distance constraint, the fraction saved can never reach 1. The residents in block 4 are not included in the KPIs, because even though they were too late to be evacuated, they also turned out not to be in danger.

A.2. Table results

The full results in table format offer a quick impression of the outcomes of the different experiments. It is especially convenient to compare the different outcomes for the key performance indicators for one specific experiment. However, the table results do not show the full picture regarding the fraction saved. The fraction saved KPI shows the average fraction saved over 20 simulation results in one single number. This means that it does not show the uncertainty, which can be misleading. For example, experiment 79 shows a fraction saved of 1, but the results in A.3 shows it is not a viable evacuation strategy. This has to do with the fact that the lower bound of the 95% confidence interval falls below the threshold of 99.5% fraction saved. This means that on average 100% of the residents in danger did timely evacuate, but there is still too much uncertainty.

n	Forecast Moment	Safety Margin	Number Of Shelters	Total Evacuees	Total Evacuees In Danger	Fraction Saved	Evacuees In Danger Not Saved	Avg Travel Distance	Quan 20	Quan 80
1	09-0600h	5	10	877925	84663	1.00	0	102.19	29.66	93.69
2	09-0600h	5	20	877925	84663	1.00	0	46.85	21.09	47.70
3	09-0600h	5	40	877925	84663	1.00	0	35.32	16.43	47.70
4	09-0600h	5	80	877925	84663	1.00	0	31.91	14.97	47.06
5	09-0600h	10	10	877925	84663	1.00	0	13427.61	45.21	88.54
6	09-0600h	10	20	877925	84663	1.00	0	67.95	31.89	67.08
7	09-0600h	10	40	877925	84663	1.00	0	60.03	28.98	65.09
8	09-0600h	10	80	877925	84663	1.00	0	58.68	28.91	66.39
9	09-0600h	20	10	877925	84663	1.00	0	124.16	56.26	100.09
10	09-0600h	20	20	877925	84663	1.00	0	81.59	45.11	77.76
11	09-0600h	20	40	877925	84663	1.00	0	74.21	44.92	75.41
12	09-0600h	20	80	877925	84663	1.00	0	73.17	44.63	74.52
13	10-0000h	5	10	877925	84663	0.99	0	122.66	22.48	119.90
14	10-0000h	5	20	877925	84663	1.00	0	45.57	17.97	39.42
15	10-0000h	5	40	877925	84663	1.00	0	37.52	15.43	29.39
16	10-0000h	5	80	877925	84663	1.00	0	30.19	14.26	27.91
17	10-0000h	10	10	877925	84663	1.00	0	111.15	46.48	91.75
18	10-0000h	10	20	877925	84663	1.00	0	67.14	33.24	65.34
19	10-0000h	10	40	877925	84663	1.00	0	59.15	28.85	62.72
20	10-0000h	10	80	877925	84663	1.00	0	56.79	28.17	61.72
21	10-0000h	20	10	877925	84663	0.98	0	129.61	61.44	106.52
22	10-0000h	20	20	877925	84663	1.00	0	81.10	48.98	81.67
23	10-0000h	20	40	877925	84663	1.00	0	74.88	45.50	83.10
24	10-0000h	20	80	877925	84663	1.00	0	73.83	45.48	79.69
25	10-1800h	5	10	877462	84663	0.99	0	104.10	26.87	91.07
26	10-1800h	5	20	877462	84663	1.00	0	52.63	22.48	39.66
27	10-1800h	5	40	877462	84663	1.00	0	34.07	16.25	31.27
28	10-1800h	5	80	877462	84663	1.00	0	31.19	14.46	30.81
29	10-1800h	10	10	877462	84663	0.99	0	112.52	42.64	96.16
30	10-1800h	10	20	877462	84663	1.00	0	67.68	32.82	67.36

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n	Forecast Moment	Safety Margin	Number Of Shelters	Total Evacuees	Total Evacuees In Danger	Fraction Saved	Evacuees In Danger Not Saved	Avg Travel Distance	Quan 20	Quan 80
31	10-1800h	10	40	877462	84663	1.00	0	59.85	28.79	66.04
32	10-1800h	10	80	877462	84663	1.00	0	57.38	27.96	61.23
33	10-1800h	20	10	877462	84663	0.95	0	120.02	61.34	101.95
34	10-1800h	20	20	877462	84663	1.00	0	81.33	48.01	83.35
35	10-1800h	20	40	877462	84663	1.00	0	78.12	45.00	80.69
36	10-1800h	20	80	877462	84663	1.00	0	76.01	45.00	81.95
37	11-1200h	5	10	864920	84663	0.97	0	103.25	16.17	92.27
38	11-1200h	5	20	864920	84663	1.00	0	48.25	16.17	39.73
39	11-1200h	5	40	864920	84663	1.00	0	37.16	14.85	32.29
40	11-1200h	5	80	864920	84663	1.00	0	34.88	14.21	31.44
41	11-1200h	10	10	864920	84663	0.87	0	109.65	43.15	96.87
42	11-1200h	10	20	864920	84663	1.00	0	66.66	31.48	63.71
43	11-1200h	10	40	864920	84663	1.00	0	59.44	30.53	62.03
44	11-1200h	10	80	864920	84663	1.00	0	57.21	28.57	61.54
45	11-1200h	20	10	864920	84663	0.91	0	108.11	61.53	103.16
46	11-1200h	20	20	864920	84663	1.00	0	86.35	49.68	83.91
47	11-1200h	20	40	864920	84663	1.00	0	77.38	48.07	78.63
48	11-1200h	20	80	864920	84663	1.00	0	77.15	46.14	79.72
49	12-0600h	5	10	769374	84663	0.87	0	80.05	24.77	68.07
50	12-0600h	5	20	769374	84663	1.00	0	45.02	18.97	37.60
51	12-0600h	5	40	769374	84663	1.00	0	34.34	15.52	34.69
52	12-0600h	5	80	769374	84663	1.00	0	31.55	14.85	33.55
53	12-0600h	10	10	769374	84663	0.84	0	97.61	40.14	100.34
54	12-0600h	10	20	769374	84663	1.00	0	70.81	32.88	66.42
55	12-0600h	10	40	769374	84663	1.00	0	63.72	30.03	63.15
56	12-0600h	10	80	769374	84663	1.00	0	62.08	29.31	66.20
57	12-0600h	20	10	769514	84663	0.83	0	100.86	56.56	101.95
58	12-0600h	20	20	769514	84663	1.00	0	82.28	44.45	83.87
59	12-0600h	20	40	769514	84663	1.00	0	74.43	44.05	85.69
60	12-0600h	20	80	769514	84663	1.00	0	74.18	44.95	84.88
61	12-1800h	5	10	612701	84663	0.87	0	65.28	20.35	45.13

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n	Forecast Moment	Safety Margin	Number Of Shelters	Total Evacuees	Total Evacuees In Danger	Fraction Saved	Evacuees In Danger Not Saved	Avg Travel Distance	Quan 20	Quan 80
62	12-1800h	5	20	612701	84663	0.98	0	38.45	16.43	32.67
63	12-1800h	5	40	612701	84663	1.00	0	28.98	13.37	30.13
64	12-1800h	5	80	612701	84663	1.00	0	26.70	12.47	29.70
65	12-1800h	10	10	583297	84663	0.97	0	72.19	31.32	71.64
66	12-1800h	10	20	583297	84663	0.99	0	63.65	27.94	63.83
67	12-1800h	10	40	583297	84663	1.00	0	56.42	27.21	63.11
68	12-1800h	10	80	583297	84663	1.00	0	55.09	26.00	59.79
69	12-1800h	20	10	563646	84663	0.88	0	78.68	46.28	75.83
70	12-1800h	20	20	538281	84663	0.97	0	67.53	43.66	72.42
71	12-1800h	20	40	563646	84663	0.97	0	65.40	43.47	74.30
72	12-1800h	20	80	563646	84663	0.96	0	65.40	43.47	74.30
73	13-0000h	5	10	512733	84663	0.87	0	56.81	10.94	50.13
74	13-0000h	5	20	512733	84663	1.00	0	40.08	10.94	32.60
75	13-0000h	5	40	512733	84663	1.00	0	33.48	10.94	27.91
76	13-0000h	5	80	512733	84663	1.00	0	31.59	10.94	27.81
77	13-0000h	10	10	470427	84663	0.96	0	61.74	26.08	51.99
78	13-0000h	10	20	470427	84663	0.99	0	52.77	23.00	50.29
79	13-0000h	10	40	470427	84663	1.00	0	49.13	22.69	46.78
80	13-0000h	10	80	470427	84663	1.00	0	48.64	22.18	46.78
81	13-0000h	20	10	466811	84663	0.91	0	79.46	42.56	70.00
82	13-0000h	20	20	466811	84663	0.98	0	70.44	42.56	68.61
83	13-0000h	20	40	466811	84663	0.97	0	68.92	39.23	67.91
84	13-0000h	20	80	466811	84663	0.97	0	68.92	39.23	67.91
85	13-1800h	5	10	242046	84663	0.63	0	44.82	11.38	37.51
86	13-1800h	5	20	242046	84663	0.85	0	33.29	10.12	32.81
87	13-1800h	5	40	242046	84663	0.90	0	30.11	9.34	30.81
88	13-1800h	5	80	242046	84663	0.90	0	28.79	8.61	30.53
89	13-1800h	10	10	241997	84663	0.52	0	61.76	21.40	78.51
90	13-1800h	10	20	241997	84663	0.62	0	49.89	18.55	71.19
91	13-1800h	10	40	241997	84663	0.67	0	47.58	18.29	71.19
92	13-1800h	10	80	241997	84663	0.67	0	47.31	18.29	71.19

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n	Forecast Moment	Safety Margin	Number Of Shelters	Total Evacuees	Total Evacuees In Danger	Fraction Saved	Evacuees In Danger Not Saved	Avg Travel Distance	Quan 20	Quan 80
93	13-1800h	20	10	190383	84663	0.21	0	69.22	34.45	70.02
94	13-1800h	20	20	190383	84663	0.25	0	57.97	33.06	70.02
95	13-1800h	20	40	190383	84663	0.23	0	56.35	32.49	70.02
96	13-1800h	20	80	190383	84663	0.24	0	56.35	32.49	70.02
97	14-0000h	5	10	215317	84663	0.67	0	45.71	10.08	35.51
98	14-0000h	5	20	215317	84663	0.87	0	33.66	8.85	30.87
99	14-0000h	5	40	215317	84663	0.88	0	29.55	7.50	30.46
100	14-0000h	5	80	215317	84663	0.90	0	29.17	7.26	30.34
101	14-0000h	10	10	215090	84663	0.50	0	53.46	20.81	54.76
102	14-0000h	10	20	215090	84663	0.65	0	43.36	18.06	54.76
103	14-0000h	10	40	215090	84663	0.65	0	39.86	18.06	54.20
104	14-0000h	10	80	215090	84663	0.66	0	39.73	18.06	54.15
105	14-0000h	20	10	178690	84659	0.22	4	64.60	32.86	55.78
106	14-0000h	20	20	178690	84659	0.23	4	52.16	32.10	54.38
107	14-0000h	20	40	178690	84659	0.24	4	50.29	32.10	54.38
108	14-0000h	20	80	178690	84659	0.24	4	50.29	32.10	54.38

A.3. Fraction saved KPI

Figure A.2 shows the results of the fraction saved key performance indicator from table A.2 more explicit. Each subplot shows an combination of the margin and the number of shelters and shows for each forecast moment the 95% confidence interval of the fraction of the evacuees in danger that is saved. A data point is shown as a square if the entire confidence interval lies above 99.5%. This margin or .5% is accepted due to some data outliers in the OpenStreetMap data, which means that some evacuees need to walk unrealistic long distances. The squared data points are especially interesting, because they show the combination of the three policy levers where all evacuees in danger are saved.

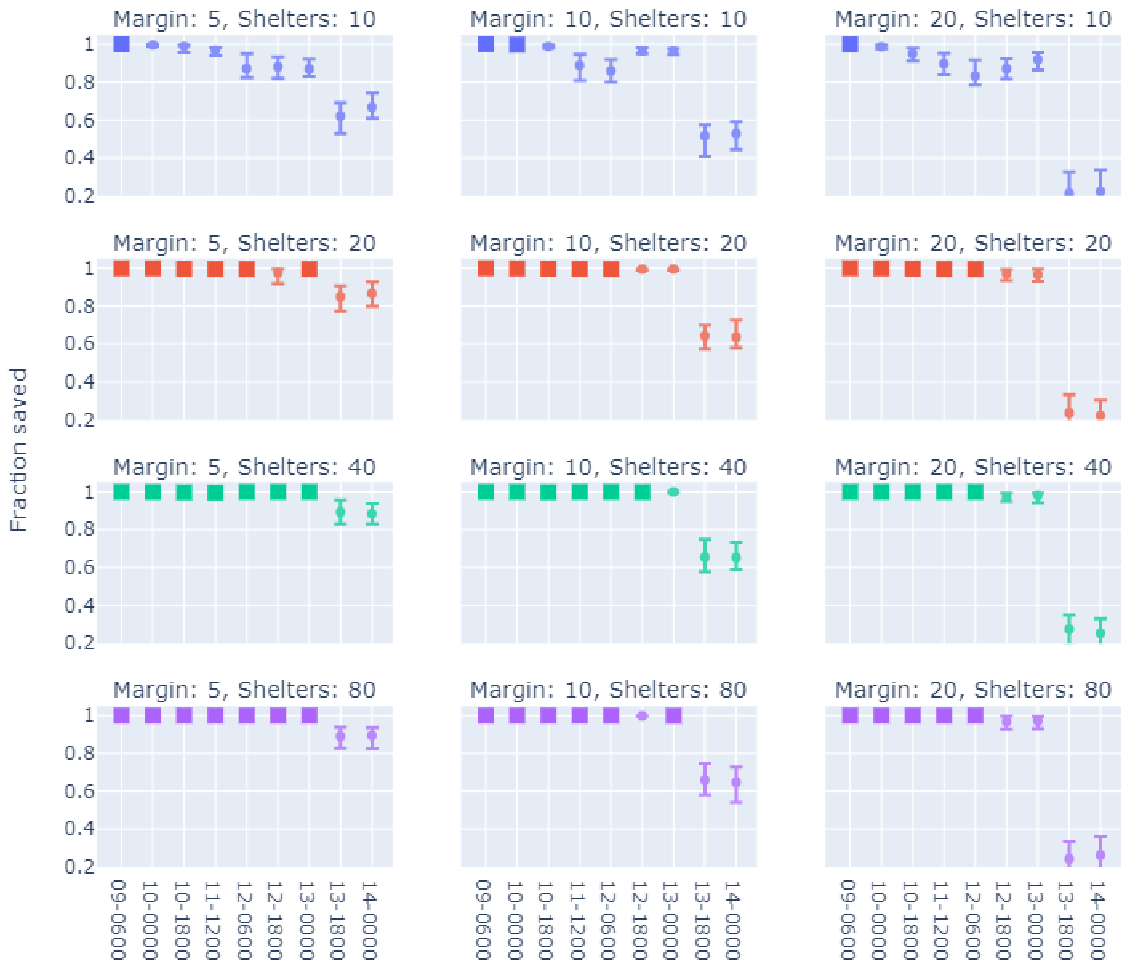

Figure A.2: The fraction saved of the residents in danger with a 95% confidence interval for all the combinations of the policy levers. The squared data points represent combinations of the policy levers where the entire confidence interval lies above 99.5%

A.4. Fraction saved of all evacuees KPI

Since this study analyzes the model retrospective, it is known what area is impacted in the end. Therefore, the most important key performance indicator is how many of those people that are impacted are evacuated in time. However, if this data was not known, the focus should shift to evacuate the entire population at risk. Figure A.3 shows the same graph as figure A.2, but now the values represent the fraction of the entire population that is evacuated. It shows that when the entire population needs to be evacuated, there are far less options to do so and evacuating should start sooner. It also shows that 10 shelters is in none of the cases a possibility to evacuate all residents at risk.

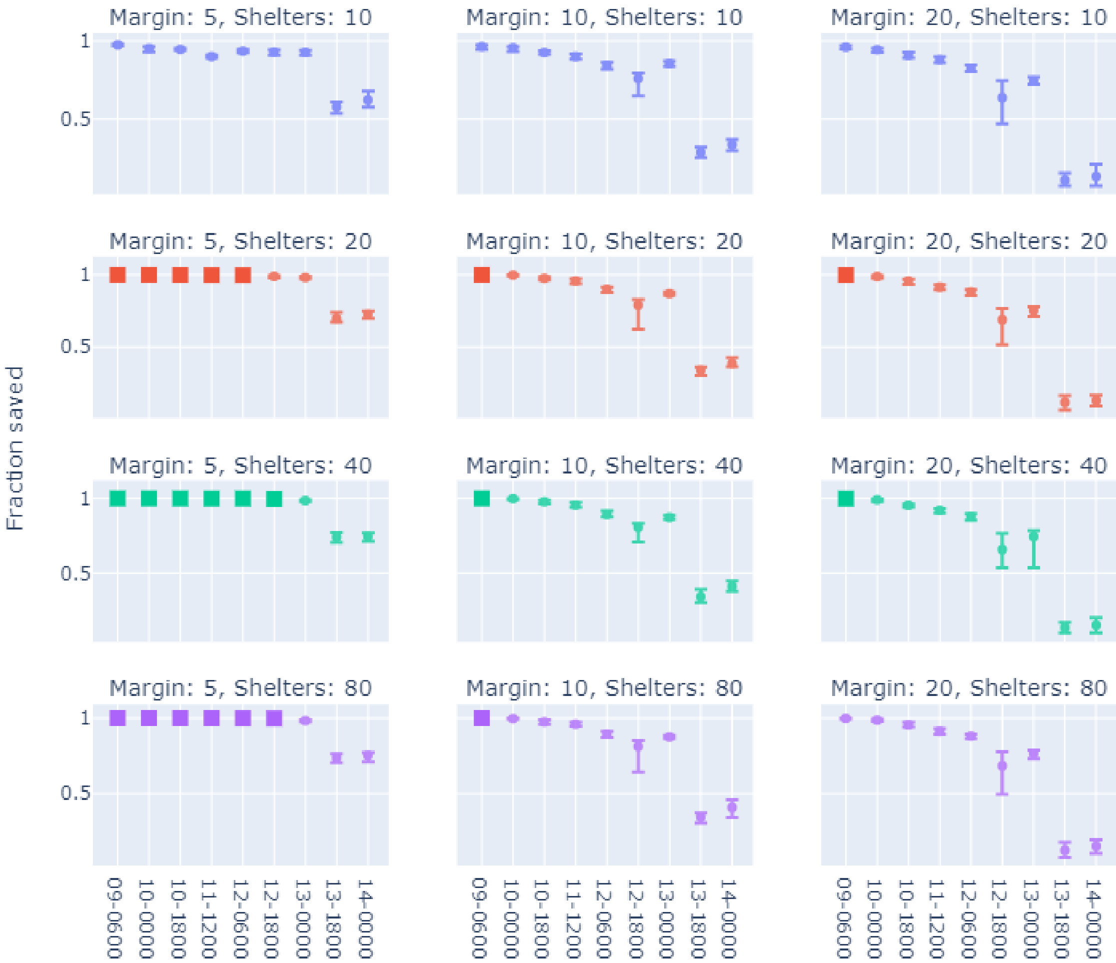

Figure A.3: The fraction saved of the entire population with a 95% confidence interval for all the combinations of the policy levers. The squared data points represent combinations of the policy levers where the entire confidence interval lies above 99.5%

A.5. Average travel distance KPI

Another important key performance indicator is the travel distance of the evacuees. This distance should be kept as low as possible to ease the burden of the evacuees and to increase the compliance with the evacuation order. Figure A.4 shows the average travel distance as shown in table A.2. From the figure it becomes clear that both a lower safety margin and a higher number of shelters result in a decrease in the average travel distance. This effect is most clear in the situations with 10 shelters operational.

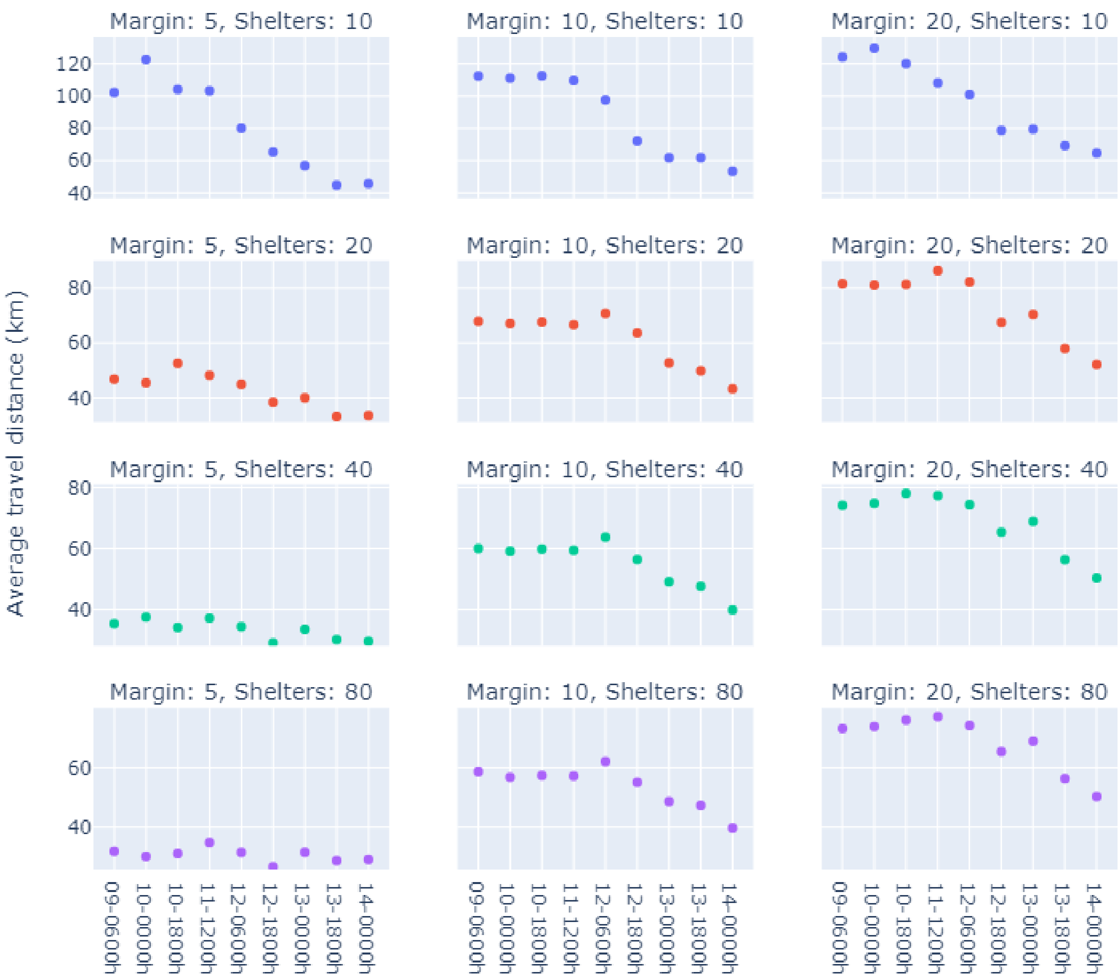

Figure A.4: The average travel distance of the population in danger for all the combinations of the policy levers

B

Experiment results Case Study Kenneth

B.1. Key performance indicators

This appendix shows the full results of the Idai case study in a table. Each of the rows represent one experiment, as described in section 9.2.2. Columns 2 to 4 show the values of the policy levers for that specific experiment. Columns 5 to 11 show the value for the different KPIs. Each of the KPIs will be shortly elucidated below.

The *total evacuees* are all the residents who are within the vulnerable zone and are within the range of at least one shelter location. Residents living in in the vulnerable zone but do not meet the distance constraint are not counted as evacuee.

The *total evacuees in danger* are the residents living in the impacted zone, who also meet the distance constraint. This means that they are within the range of at least one shelter location.

The *fraction saved* are the *total evacuees in danger* that safely reached their shelter before the cyclone made landfall, relative to the *total evacuees in danger* plus the *evacuees in danger not saved.*

The *evacuees in danger not saved* represent the residents living in the impacted zone, but that are not evacuated due to the distance constraint.

The *average travel distance* is the average travel distance of the *total evacuees.*

the *Quan 20* and *Quan 80* are two other measures for the travel distance and are the 20th and 80th quantile respectively. That means that the middle 60% of the travel distances fall within these two values.

For a graphical illustration of the first KPIs, the reader is referred to appendix A, figure A.1.

B.2. Table results

The full results in table format offer a quick impression of the outcomes of the different experiments. It is especially convenient to compare the different outcomes for the key performance indicators for one specific experiment. However, the table results do not show the full picture regarding the fraction saved. The fraction saved KPI shows the average fraction saved over 20 simulation results in one single number. This means that it does not show the uncertainty, which can be misleading.

n	Forecast Moment	Safety Margin	Number Of Shelters	Total Evacuees	Total Evacuees In Danger	Fraction Saved	Evacuees In Danger Not Saved	Avg Travel Distance	Quan 20	Quan 80
1	22-1400h	5	10	1413709	78909	0.92	0	60.74	27.16	69.37
2	22-1400h	5	20	1413709	78909	1.00	0	43.60	23.39	47.09
3	22-1400h	5	40	1413709	78909	1.00	0	34.36	19.75	40.14
4	22-1400h	5	80	1413709	78909	1.00	0	27.83	17.27	37.77
5	22-1400h	10	10	1413709	78909	0.96	0	67.49	31.42	75.44
6	22-1400h	10	20	1413709	78909	0.99	0	50.93	29.81	63.74
7	22-1400h	10	40	1413709	78909	1.00	0	46.31	27.81	61.39
8	22-1400h	10	80	1413709	78909	1.00	0	43.93	27.06	60.84
9	22-1400h	20	10	1413709	78909	0.99	0	78.15	56.26	82.90
10	22-1400h	20	20	1413709	78909	0.99	0	70.26	52.80	80.18
11	22-1400h	20	40	1413709	78909	0.99	0	67.28	52.22	81.12
12	22-1400h	20	80	1413709	78909	0.99	0	67.43	52.04	81.12
13	23-0800h	5	10	879405	78909	0.96	0	54.87	19.50	53.20
14	23-0800h	5	20	879405	78909	1.00	0	36.33	19.01	42.01
15	23-0800h	5	40	879405	78909	1.00	0	30.26	18.04	37.79
16	23-0800h	5	80	879405	78909	1.00	0	24.68	14.57	33.89
17	23-0800h	10	10	879405	78909	0.98	0	58.65	32.88	59.21
18	23-0800h	10	20	879405	78909	0.98	0	47.75	28.86	55.15
19	23-0800h	10	40	879405	78909	0.98	0	42.68	26.66	53.01
20	23-0800h	10	80	879405	78909	0.98	0	40.30	25.64	52.11
21	23-0800h	20	10	877179	78909	0.95	0	74.00	51.64	77.08
22	23-0800h	20	20	879405	78909	0.97	0	66.87	47.09	77.20
23	23-0800h	20	40	879405	78909	0.97	0	64.63	46.06	77.74
24	23-0800h	20	80	879405	78909	0.97	0	63.16	45.96	77.91
25	23-1400h	5	10	767502	78909	0.96	0	47.39	18.76	48.13
26	23-1400h	5	20	767502	78909	0.98	0	34.71	16.05	35.65
27	23-1400h	5	40	767502	78909	0.99	0	27.74	15.34	33.38
28	23-1400h	5	80	767502	78909	1.00	0	22.90	13.63	29.75
29	23-1400h	10	10	767502	78909	0.92	0	55.41	26.80	60.93
30	23-1400h	10	20	767502	78909	0.95	0	45.06	26.10	53.55

Continued on next page

n	Forecast Moment	Safety Margin	Number Of Shelters	Total Evacuees	Total Evacuees In Danger	Fraction Saved	Evacuees In Danger Not Saved	Avg Travel Distance	Quan 20	Quan 80
31	23-1400h	10	40	767502	78909	0.95	0	40.31	26.30	49.73
32	23-1400h	10	80	767502	78909	0.96	0	38.13	26.18	50.26
33	23-1400h	20	10	767502	78909	0.84	0	70.18	52.48	81.30
34	23-1400h	20	20	767502	78909	0.85	0	64.70	47.09	81.01
35	23-1400h	20	40	767500	78909	0.86	0	63.28	45.98	79.88
36	23-1400h	20	80	767502	78909	0.86	0	62.60	45.36	79.86
37	24-0200h	5	10	637275	78686	0.79	143	43.16	16.17	46.19
38	24-0200h	5	20	637275	78686	0.96	143	30.35	12.43	32.05
39	24-0200h	5	40	637275	78686	0.99	143	25.54	11.79	28.70
40	24-0200h	5	80	637275	78686	1.00	143	20.00	10.71	24.06
41	24-0200h	10	10	637418	78829	0.73	0	50.31	26.66	51.31
42	24-0200h	10	20	637418	78829	0.77	0	44.68	25.88	50.74
43	24-0200h	10	40	637418	78829	0.82	0	40.80	23.55	50.82
44	24-0200h	10	80	637418	78829	0.84	0	38.80	23.38	49.91
45	24-0200h	20	10	618862	78789	0.64	40	64.98	48.94	76.56
46	24-0200h	20	20	618862	78789	0.61	40	60.60	45.70	76.58
47	24-0200h	20	40	618862	78789	0.60	40	61.15	45.70	77.08
48	24-0200h	20	80	618862	78789	0.67	40	59.38	43.36	81.08
49	25-0200h	5	10	476990	78042	0.21	867	33.93	15.22	31.06
50	25-0200h	5	20	476990	78042	0.27	867	24.36	11.10	36.26
51	25-0200h	5	40	476990	78042	0.35	867	19.22	10.12	30.53
52	25-0200h	5	80	476990	78042	0.36	867	17.09	9.64	30.44
53	25-0200h	10	10	237198	46385	0.04	32524	36.50	23.55	35.95
54	25-0200h	10	20	251786	46385	0.08	32524	29.51	21.40	33.64
55	25-0200h	10	40	251786	46385	0.09	32524	26.96	21.38	33.61
56	25-0200h	10	80	251786	46385	0.10	32524	26.70	23.00	33.61
57	25-0200h	20	10	41993	7861	0.00	71048	34.96	31.06	37.15
58	25-0200h	20	20	41993	7861	0.01	71048	33.17	31.06	36.97
59	25-0200h	20	40	41993	7861	0.00	71048	33.17	31.06	36.97
60	25-0200h	20	80	41993	7861	0.01	71048	33.17	31.06	36.97
61	25-0800h	5	10	258215	69751	0.11	8791	26.17	7.49	24.46

Continued on next page

n	Forecast Moment	Safety Margin	Number Of Shelters	Total Evacuees	Total Evacuees In Danger	Fraction Saved	Evacuees In Danger Not Saved	Avg Travel Distance	Quan 20	Quan 80
62	25-0800h	5	20	258215	69751	0.20	8791	21.04	7.23	18.99
63	25-0800h	5	40	258215	69751	0.26	8791	16.53	7.59	18.36
64	25-0800h	5	80	258215	69751	0.26	8791	13.33	7.23	17.78
65	25-0800h	10	10	30757	5356	0.01	73186	33.69	16.70	31.33
66	25-0800h	10	20	30676	5275	0.05	73186	23.39	16.62	23.68
67	25-0800h	10	40	30757	5356	0.07	73186	18.43	15.83	22.09
68	25-0800h	10	80	30757	5356	0.07	73186	18.43	15.83	22.09
69	25-0800h	20	10	307	0	0.00	78542	27.26	23.59	30.12
70	25-0800h	20	20	307	0	0.00	78542	27.26	23.59	30.12
71	25-0800h	20	40	307	0	0.00	78542	27.26	23.59	30.12
72	25-0800h	20	80	307	0	0.00	78542	27.26	23.59	30.12

B.3. Fraction saved KPI

Figure B.1 shows the results of the fraction saved key performance indicator from table B.2 more explicit. Each subplot shows an combination of the margin and the number of shelters and shows for each forecast moment the 95% confidence interval of the fraction of the evacuees in danger that is saved. A data point is shown as a square if the entire confidence interval lies above 99.5%. This margin or .5% is accepted due to some data outliers in the OpenStreetMap data, which means that some evacuees need to walk unrealistic long distances. The squared data points are especially interesting, because they show the combination of the three policy levers where all evacuees in danger are saved.

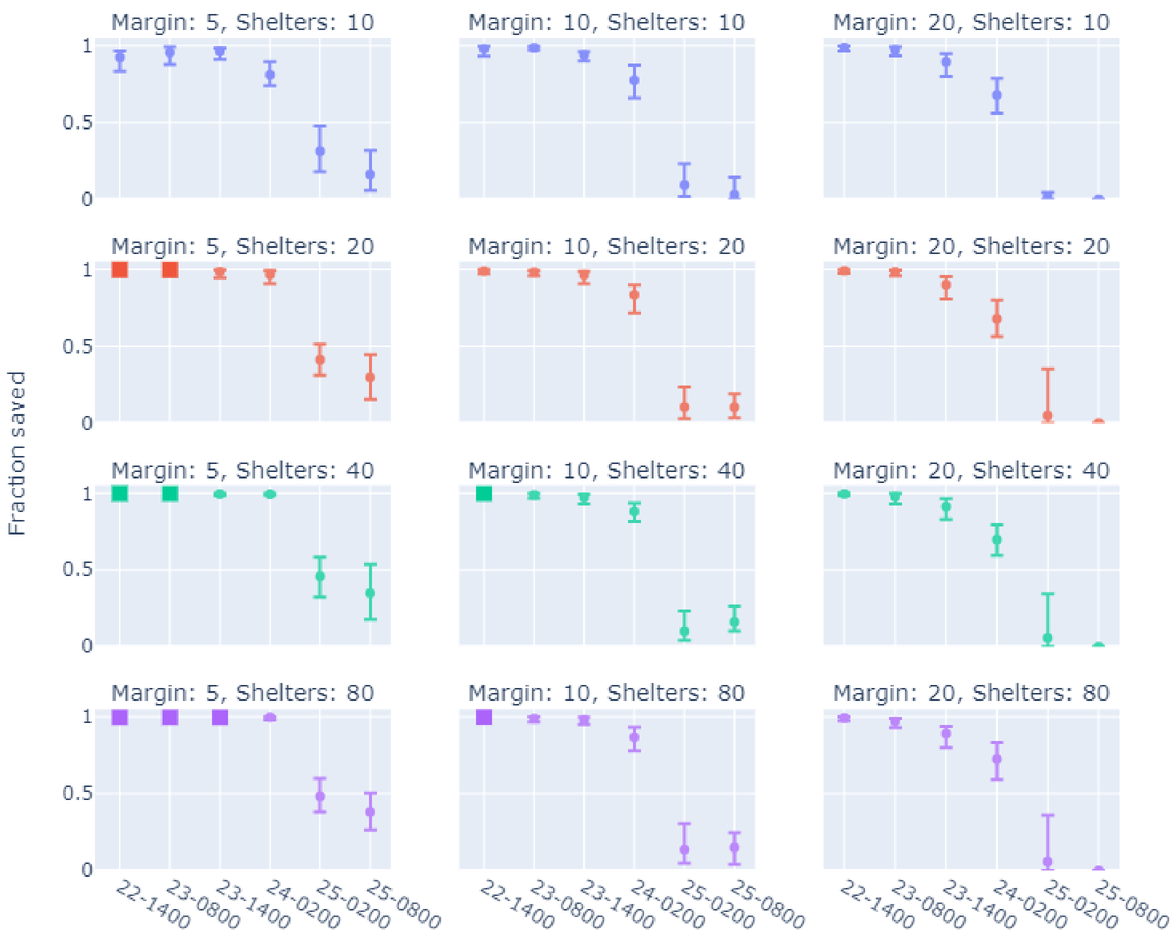

Figure B.1: The fraction saved of the residents in danger with a 95% confidence interval for all the combinations of the policy levers. The squared data points represent combinations of the policy levers where the entire confidence interval lies above 99.5%

B.4. Fraction saved of all evacuees KPI

Since this study analyzes the model retrospective, it is known what area is impacted in the end. Therefore, the most important key performance indicator is how many of those people that are impacted are evacuated in time. However, if this data was not known, the focus should shift to evacuate the entire population at risk. Figure B.2 shows the same graph as figure B.1, but now the values represent the fraction of the entire population that is evacuated. It shows that when the entire population needs to be evacuated, there are far less options to do so and evacuating should start sooner. It also shows that 10 and 20 shelters and a safety margin of 10 and 20 kilometer is in none of the cases a possibility to evacuate all residents at risk.

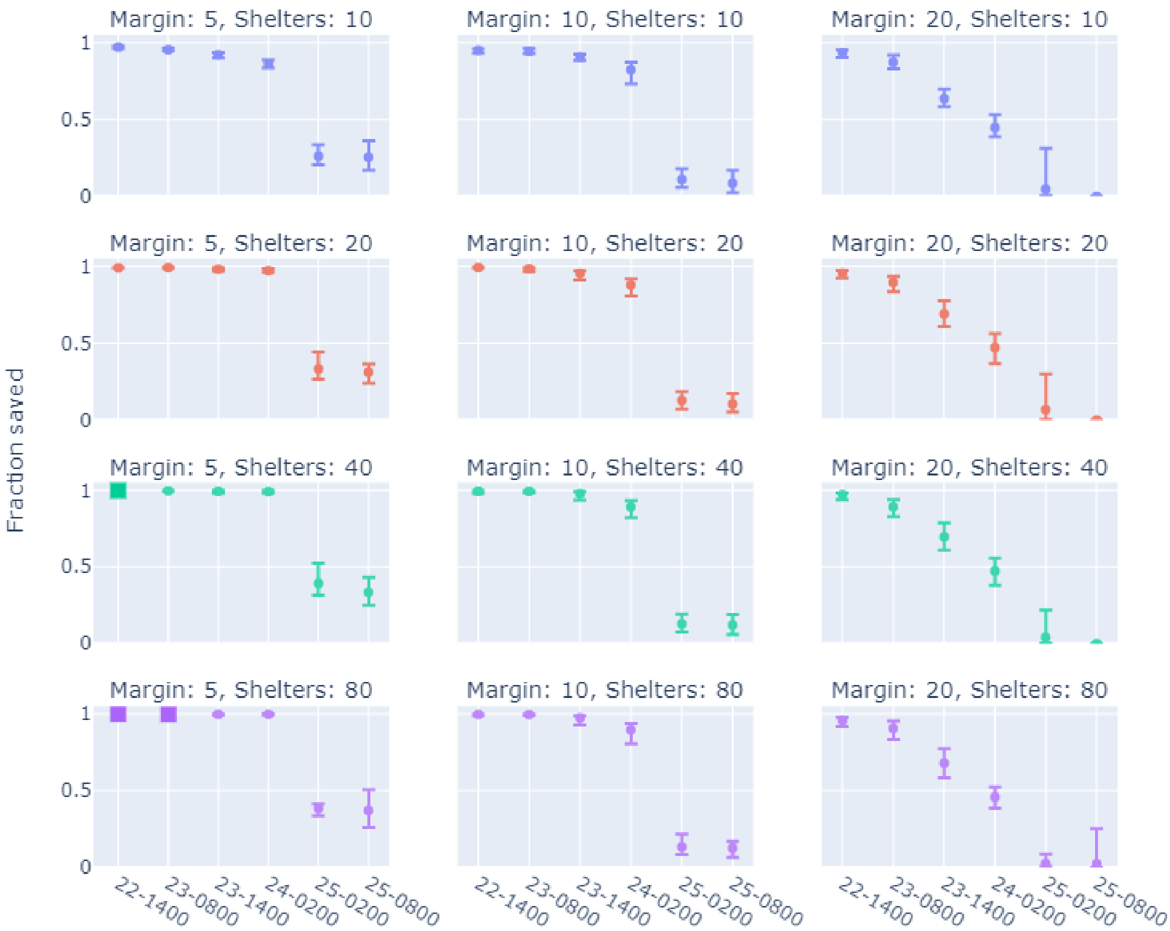

Figure B.2: The fraction saved of the entire population with a 95% confidence interval for all the combinations of the policy levers. The squared data points represent combinations of the policy levers where the entire confidence interval lies above 99.5%

B.5. Average travel distance KPI

Another important key performance indicator is the travel distance of the evacuees. This distance should be kept as low as possible to ease the burden of the evacuees and to increase the compliance with the evacuation order. Figure B.3 shows the average travel distance as shown in table B.2. From the figure it becomes clear that both a lower safety margin and a higher number of shelters result in a decrease in the average travel distance. This effect is most clear in the situations with 10 shelters operational.

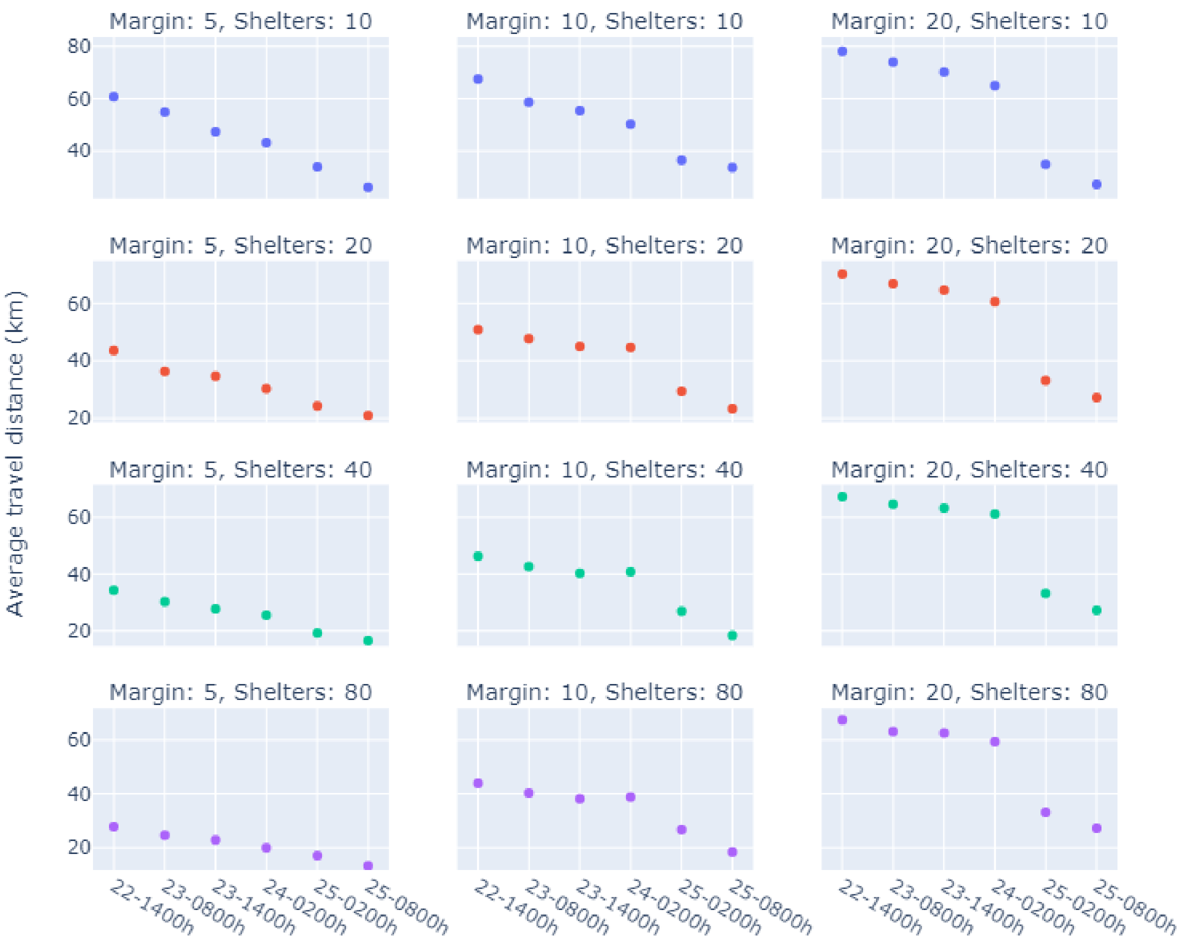

Figure B.3: The average travel distance of the population in danger for all the combinations of the policy levers

C
Validation

This appendix gives an elaborate report on the validation of the results. The most remarkable and important conclusions are summarized in chapter 11.

C.1. Theoretical validation

Theoretical validation is about verifying substantive logic, checking relevant verisimilitude and testing the reasonableness of the assumptions made (Davis, 1998). This is checked by submitting the model to various hypotheses. The first enumeration of hypotheses are about the vulnerability assessment model and the second enumeration of hypotheses is to validate the evacuation simulation model.

The hypotheses for the vulnerability assessment model are:

1. The earlier the forecast moment, the bigger the area that is classified as vulnerable.
2. The bigger the vulnerable area, the more people will be ordered to evacuate.
3. The bigger the size of the cyclone, the bigger the area that is classified as impacted.
4. The bigger the safety margin, the higher the average travel distance will be.

The hypotheses for the evacuation simulation model are:

5. The more shelters, the lower the average travel distance will be.
6. The lower the average travel distance, the earlier the evacuees will reach their assigned shelter.
7. The higher the decision time, the later the evacuees will reach their designated shelter (or not reach them at all).
8. The higher the travel speed, the earlier the evacuees will reach their designated shelter.
9. The longer the day light, the earlier the evacuees will reach their designated shelter.

In order to test these hypotheses (and their opposites), a low and a high value is chosen for every parameter. This is known as the extreme value test, where the parameter values are set to extreme values, in order to verify that the model still produces logic results, even in the outer bandwidths of the model. Table C.1 shows the model parameters that are described above and their low and high value. Ceteris paribus, the high and low value of every parameter are compared.

Table C.1: Parameter values for the extreme value test

Parameter	Low value	High value
Forecast moment	March 9th, 0600	March 14th, 0000
Cyclone size	10 (km)	200 (km)
Safety margin	5 (km)	50 (km)
Shelters	10	80
Decision delay	1 (hour)	15 (hours)
Travel speed	1 (km/h)	20 (km/h)
Day light	9 AM till 3 PM	3 AM till 9 PM

1. The earlier the forecast moment, the bigger the area that is classified as vulnerable
The two forecast are loaded in the vulnerability assessment model and the vulnerability calculation is executed. The size of the vulnerable area is 15.263 square kilometer for the forecast of March 9th and 9647 square kilometers for the forecast moment of March 14th. This shows a decline in the vulnerable area which means that the hypothesis is verified.

Hypothesis 1: ✓

2. The bigger the vulnerable area, the more people will be ordered to evacuate
For the same forecast moments as above, the total evacuees can be found in experiment 1 and experiment 97 of appendix A. They amount to 877.925 and 215.317 evacuees respectively. This means that the number of evacuees decreases with later forecasts.

Hypothesis 2: ✓

3. The bigger the size of the cyclone, the bigger the area that is classified as impacted
When the cyclone size is changed from 10 kilometers width to 200 kilometer width, the area that is impacted changes from 262 square kilometers to 4658 square kilometers. This means that the impacted area increases when the size of the cyclone increases and the hypothesis can be verified. However, from other experiments the model showed that in early forecast moments the model already assessed the whole geographical area as vulnerable, which means that a bigger cyclone size will not affect the size of the vulnerable area anymore. In order to see the effect of a bigger cyclone, the geographical scope of the case study should be increased, but this would also increase computational time. To conclude, this hypotheses is partly verified and partly falsified.

Hypothesis 3: ✓/ ✗

4. The bigger the safety margin, the higher the average travel distance will be
To test the safety margin, this variable is varied from 5 to 50 kilometers with an evacuation moment on March 9th and 20 shelters. In case of safety margin of 5 kilometer the average travel distance is 47 kilometer, while with a safety margin of 50 kilometer, the average travel distance is 127 kilometer. These numbers do not have a difference of exactly 45 kilometers, since the safety margin is an euclidean distance, while the travel distance is the real distance when using the road network. Another reason why the difference is more than 45 kilometer is because in the case of the 5 kilometer safety margin there are also shelter locations that are within the vulnerable zone, but on higher grounds (see figure C.1). This is known as vertical evacuation. This results in a more than normal reduction in average travel time since evacuees will now not longer need to travel all the way out of the vulnerable area. The figures C.1 and C.2 show the evacuees in blue and the shelters in green.

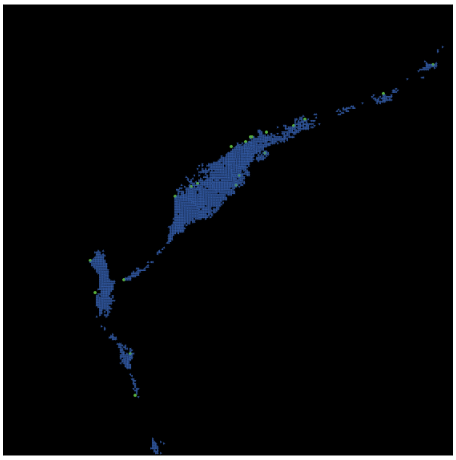

Figure C.1: Setup with a safety margin of 5 kilometer

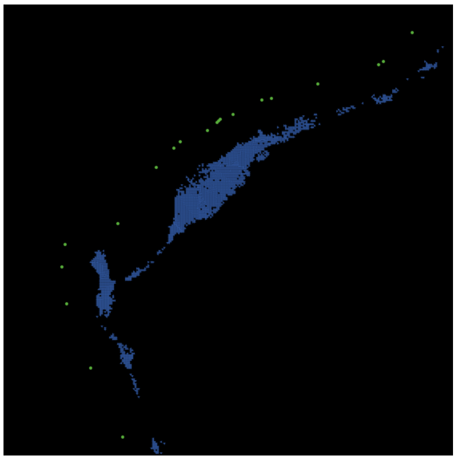

Figure C.2: Setup with a safety margin of 50 kilometer

Hypothesis 4: ✓

5. The more shelters, the lower the average travel distance will be
This hypotheses is verified by multiple experiments, both for the case study of Idai and of Kenneth. For example, when looking at experiment 1 and 4 (appendix A), the average travel distance is 102 kilometer with 10 shelters, and 32 kilometer with 80 shelters. This means that the average travel time is reduced with more selected shelters.

Hypothesis 5: ✓

6. The lower the average travel distance, the earlier the evacuees will reach their assigned shelter
This hypotheses is verified in figures C.3 and C.4 where the arrival of the evacuees is shown over time. Figure C.3 shows a forecast moment on March 13th, a safety margin of 5 kilometer and 20 shelters, which resulted in an average travel distance of 33 kilometer. Figure C.4 has the same values for the policy levers, except for the safety margin, which has been set to 20 kilometer. This resulted in an average travel distance of 58 kilometer. The figure show that with a safety margin of 5 kilometer, compared to a safety margin of 20 kilometer, the evacuees not only arrive earlier, there are also more evacuees that arrive in time (85% compared to 25%).

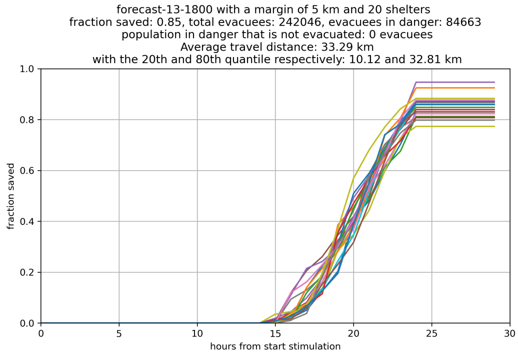

Figure C.3: An evacuation on March 13th, 1800 PM with a safety margin of 5 kilometer and 20 shelters. The figure shows that evacuees start arriving earlier with a lower safety margin

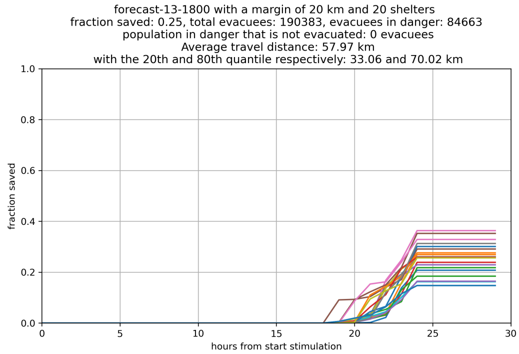

Figure C.4: An evacuation on March 13th, 1800 PM with a safety margin of 20 kilometer and 20 shelters. The figure shows that evacuees start arriving later with a higher safety margin

Hypothesis 6: ✓

7. The higher the decision time, the later the evacuees will reach their designated shelter
This hypothesis is verified using a forecast moment at March 9th, a safety margin of 10 kilometer and 20 shelters. When the decision delay is set to 1 hour, it takes 31 hours before the first 75% of the evacuees reach their shelter. When the decision delay is changed to 15 hours, it now takes 58 hours before 75% of the evacuees reached their designated shelter. This difference between the decision delay (of 14 hours) and the time difference before 75% of the evacuees are sheltered (27) does not match because of the interaction effect. Evacuees only start alerting others without cell tower coverage when they made up their own minds and are traveling towards their shelter. Since evacuees take longer to decide in the experiment with a decision delay of 15 hours, it also takes longer before they start to alert other evacuees. Based on this experiment, the hypothesis is verified.

Hypothesis 7: ✓

8. The higher the travel speed, the earlier the evacuees will reach their designated shelter
To test the hypothesis about the travel speed, the same policy levers as hypothesis 7 are used. Now, instead of the decision delay, the travel speed is set at 1 kilometer per hour and at 20 kilometer per hour. The 20 kilometer is to simulate that residents would be able to make use of vehicles. In the first scenario it takes 128 hours before 75% of the evacuees have reached their shelter. With a travel speed of 20 km/h it only takes 10 hours to reach the same number of sheltered evacuees. This means that the hypothesis is verified. This is also important because it highlights that the trade-off between timeliness and uncertainty reduction only exists with low travel speeds (walking pace).

Hypothesis 8: ✓

9. The longer the day light, the earlier the evacuees will reach their designated shelter

Again, the same policy levers are used as above, but now the day light is changed to research its effect. Figure C.5 compares a long day of 18 hours (from 3 AM till 9 PM), to a short day from 9 AM till 3 PM. The figure shows that with a long day it takes the evacuees between 27 and 35 hours to have 75% saved. With a short day this increases to 79 to 105 hours. This increase shows that the hypothesis is verified there is a big difference between the two day lengths which verifies this hypothesis.

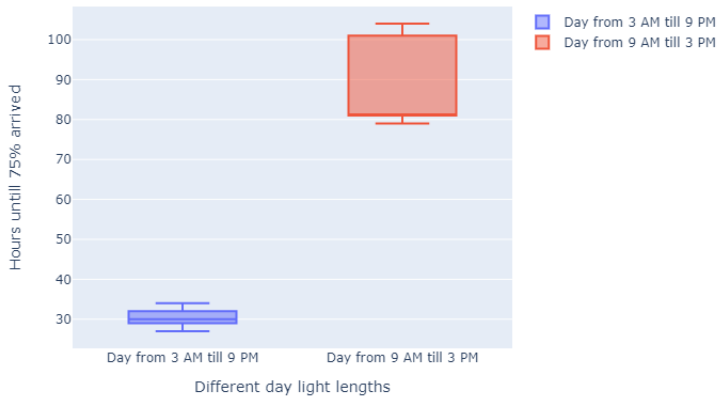

Figure C.5: Extreme value test for two different lengths of day light

Hypothesis 9: ✓

C.2. Sensitivity analysis

The parameters that are included in the sensitivity analysis are mostly the same as the parameters for the extreme value test (section 11.2.2). Some parameters are excluded and some are added, because the focus in this sensitivity analysis is to explain the impact of the parameter values that are estimated or assumed. If a small difference in their value has a big impact on the outcomes, than the model would be less robust and more time should be spend to accurately estimating those parameter values. It is normal practice to select one base case and vary each parameter one at a time. However, because the sensitivity of various factors significantly depend on the moment of evacuation, the sensitivity of those variables is calculated for multiple evacuation moments. When the variable in question is not dependent on the evacuation moment, it is tested using one base case. First, section C.2.1 will discuss the independent variables using the base case, after which section C.2.2 will discuss the variables where the sensitivity depends on the evacuation moment.

C.2.1. Variables independent of the evacuation moment

Experiment 90, appendix A is selected as the base case. Table C.2 summarizes the values for the policy levers and the KPIs of experiment 90.

Table C.2: Experiment 90, case study Idai

Policy lever / KPI	Value
Experiment number	90
Forecast moment	March 13th, 1800 PM
Safety margin	10 kilometer
Number of shelters	20
Total evacuees	241.997
Total evacuees in danger	84.663
Fraction saved	0.62
Evacuees in danger not saved	0
Average travel distance	50 kilometer
20th quantile of travel distance	19 kilometer
80th quantile of travel distance	71 kilometer

Using the base case, the parameter values in table C.3 are varied by -20% and +20%. To measure the variance in the output that is related to the variance in the input, the relevant KPI to indicate that difference in variance is listed in the last column. For the elevation threshold and the risk threshold the number of evacuation patches is chosen as KPI, instead of the number of evacuees (which is used in the experiments). The reason for this, is because the number of evacuees can rise rapidly with only one additional evacuation patch (if it concerns a city for example), which will not correctly represent the variance of the parameters being explored.

Table C.3: Parameter values for the sensitivity analysis

Parameter	Base case value	-20%	+20%	Relevant KPI
Elevation threshold	10	12	8	Evacuation patches
Risk threshold	0.15	0.12	0.18	Evacuation patches
Alerting range (km)	10 - 20	8 - 16	12 - 24	Fraction Saved

There are 1295 evacuation patches in the base case. Since a patch has a width and height of 2.625 kilometer, that means that an area of 2.626 * 2.625 * 1295 = 8923 square kilometers is assessed as vulnerable and should be evacuated. When the elevation threshold is set to 12, the number of evacuation patches increases with 111 to 1406. That is a percentage change of +8.6%. When the elevation threshold is set to 8, there are 1131 evacuation patches, a percentage decrease of 12.7%. That means that the output variance is less than the input variance, but not insignificant. Therefore, the value of this parameter should be researched more precisely.

When the risk threshold is changed to 0.12 instead of 0.15 the number of evacuation patches changes from 1295 to 1488. This means that a 20% change in input, results in a 15% change in output for this specific KPI. When the risk threshold is set to 0.18 there are 1106 evacuation patches, a -15% change. This means that the risk threshold is not highly sensitive, but it does have a significant influence on the area that will be evacuated. Both the elevation threshold and the risk threshold are shown to have a significant impact on the vulnerable area.

Lastly, the alerting range is tested for sensitivity. The alerting range is the distance in which evacuees inform other uninformed residents about the evacuation order. The range depends on the size of the group: the bigger the group, the bigger the range in which they inform others. Figure C.6 shows the values for the KPI fraction saved when the alerting range variable is varied by -20% and +20%. The base case is shown in the middle. Figure C.6 shows that there is no significant relation between the alerting range and the fraction saved. This was to be expected since the fraction saved only takes into account the evacuees that are actually in danger and all of those evacuees were covered by a cell tower. They were therefore not influenced by the alerting variable range, which is why the model is insensitive for this case study.

C.2.2. Variables dependent of the evacuation moment

The sensitivity of the variables in table C.4 are dependent on the forecast moment. For example, take the cyclone width and vary it by +20% and -20% and use the evacuation patches to test the effect of that variation. In earlier forecast moments this effect will be less strong than in later forecasts because in earlier forecast the width makes up a smaller part of the total cyclone uncertainty. To account for this effect, the sensitivity for these variables are analysed for all the forecast moments.

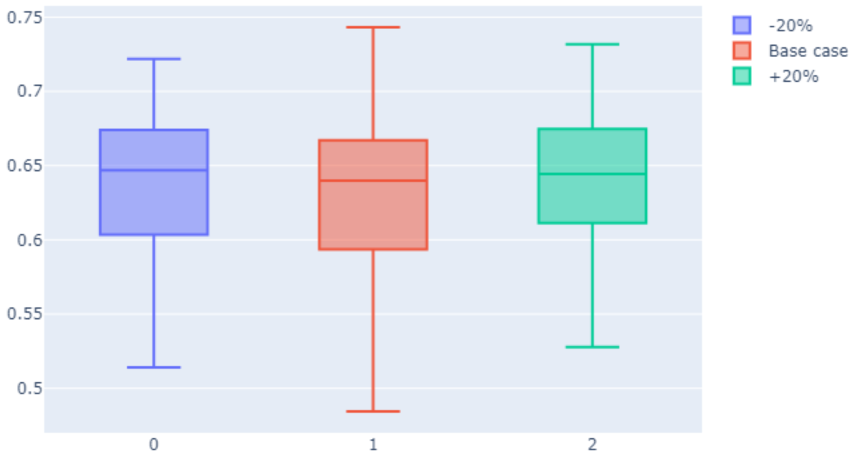

Figure C.6: Sensitivity of the alerting range, measured by the fraction saved KPI

Table C.4: Parameter values for the sensitivity analysis

Parameter	Base case value	-20%	+20%	Relevant KPI
Safety margin (km)	10	8	12	Avg. travel distance, fraction saved
Number of shelters	20	16	24	Avg. travel distance, fraction saved
Cyclone uncertainty	n/a	n/a	n/a	Evacuation patches
Cyclone width (km)	100	80	120	Evacuation patches
Decision delay (hours)	$X \sim U(3,9)$	$X \sim U(2,8)$	$X \sim U(4,10)$	Fraction saved
Travel speed (km/h)	$X \sim U(2.5,5)$	$X \sim U(2.25,4.5)$	$X \sim U(2.75,5.5)$	Fraction saved
Interaction effect	On	Off	On	Evacuees changed

Sensitivity of the safety margin

The sensitivity of the safety margin is assessed for three different evacuation moments and measured by the average travel distance and the fraction saved KPI. figure C.7 shows a 10% increase and decrease of the safety margin and compares this to the fraction of evacuees that are in danger and saved.
For the first forecast moment of March 9th there is no sensitivity between a safety margin of 9 and 11 kilometer. This was to be expected since in both experiments almost all evacuees reach their shelter in time. Also for the forecast moment on March 11th, there is no significant difference between a safety margin of 9 and 11 kilometer. However, it is shown that March 13th shows the largest sensitivity for the safety margin, even though there is also some variance between the different runs. Based on figure C.7 it can be concluded that sensitivity of the safety margin increases with later forecast moments.

The next key performance indicator that is used to assess the sensitivity of the safety margin is the average travel distance. Figure C.8 shows the average travel distance of all the evacuees for three different forecast moments and the two different safety margins of 9 and 11 kilometer. The figure shows that there is no clear trend between the different forecast moments. In the forecast moment of March 9th a difference of 2 kilometer in the safety margin results in a difference of 5 kilometer in travel distance, while in only makes a difference of 2 kilometers for the forecast moment of March 11th. The reason for this is straightforward, since the safety margin is an euclidean distance, it will depend on the actual road network what that will mean for the additional average travel distance. In most experiments, a 5 kilometer increase in safety margins results in a 5 to

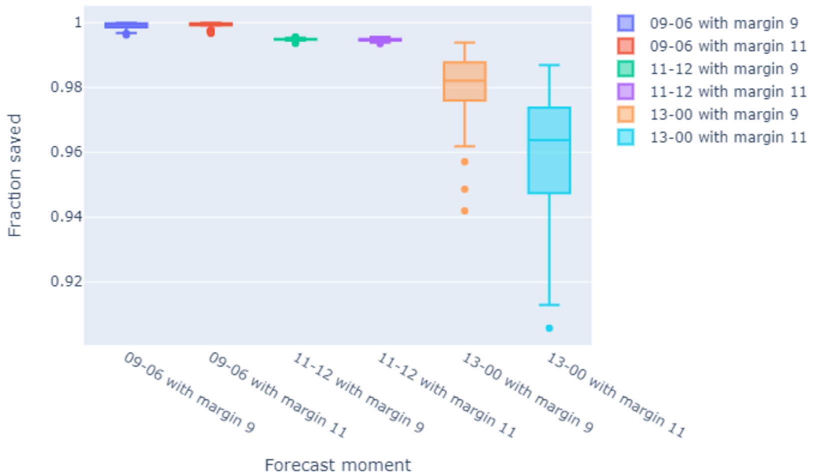

Figure C.7: Sensitivity of the safety margin, measured by the fraction saved

10 kilometer increase in average travel distance.

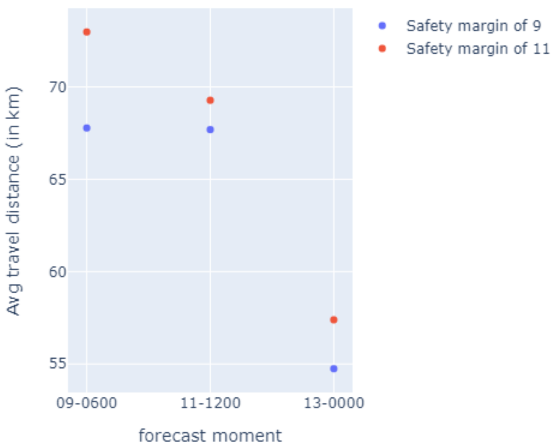

Figure C.8: Sensitivity of the safety margin, measured by the average travel distance

Sensitivity of the numbers of shelters

The number of shelters is one of the policy levers and is subject to the sensitivity analysis to give decision makers insight into the effect of a small change in this policy lever. Only in that way, the cost of an additional shelter location can be balanced against the positive marginal effect in for example the additional evacuees that reach their shelter, or the reduction in average travel distance. Figure C.9 shows the result of a 20% in the number of shelters for three different forecast moments. The y-axis represent the time it took to reach a 90& fraction saved for the evacuees that were residents in the impacted area. What jumps out is the high sensitivity for the experiment with 16 shelters at March 11th, 1200 PM. This reduction of 4 shelters suddenly resulted in a increase of 15 hours on average. This is particular, since in the other forecast moments the sensitivity for the shelters is far less. To understand this trend, it is important to know that figure C.9 only shows the arrival of the evacuees that were actually in danger, while the shelters are spread over the entire vulnerable area. Taking a closer look at the position of the shelters, it becomes clear that for the forecast moment of March 11th, the additional 4 and 8 shelters were placed mostly centered around the impacted area. This meant that especially the travel time and distance of the evacuees from the impacted area was reduced. On the other hand, in the case of 16 shelters, there were far less around the impacted area, which meant a rapid increase in travel time for those evacuees.

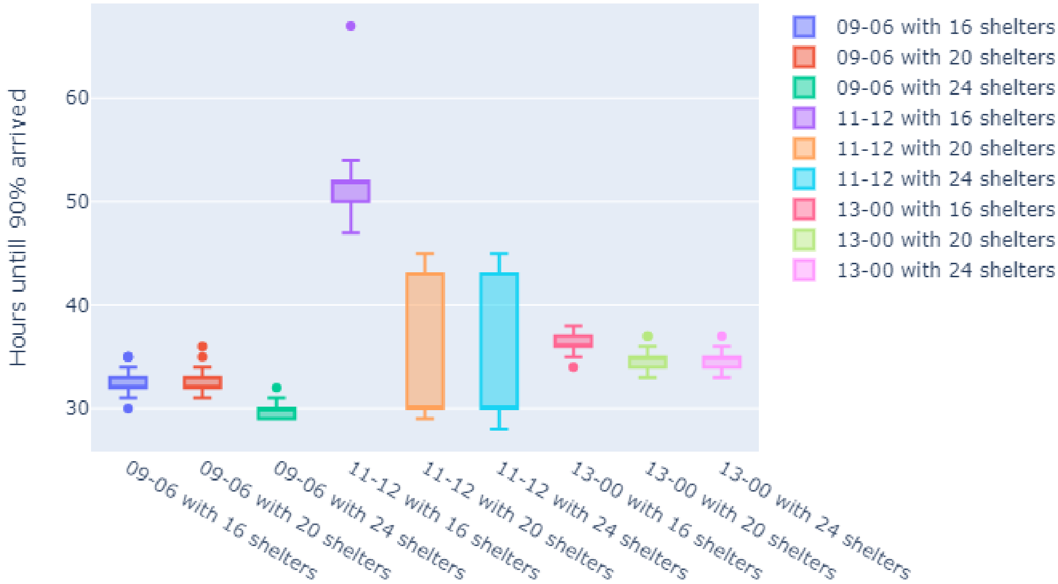

Figure C.9: Sensitivity of the number of shelters measure by the evacuees in danger

To verify this hypotheses, the same analysis is run, but now with the arrival of all the evacuees, instead of the evacuees that were actually in danger. Figure C.10 displays the result of this experiment. Now the y-axis shows the hours it took until 75% of all of the evacuees safely reached their shelter. This value is changed from 90% to 75% because in the latest forecast not in all cases were 90% of the evacuees sheltered in time. The value of the y-axis can not directly be compared between experiments, since the time it takes for 75% of the evacuees to reach their shelter also depends on the total number of evacuees and the size of the vulnerable area (which both differ between forecast moments). Figure C.10 shows that the variance within the different experiments is much higher for earlier forecast moments than later forecast moments (this is indicated by the spread of the results and thus the size of the box plot). This is caused by the fact that in earlier forecast moments the travel distance is often higher (when the same number of shelters are chosen in later forecast moments), which means that the effect of for example the differences in travel speed is much more influential. To conclude, in none of the forecast moments, the number of shelters is very sensitive. Except for the forecast moment of March 11th, where with a small increase in the number of shelters there is also a small decrease in the hours it takes before 75% of the evacuees have reached their shelter.

Sensitivity of the cyclone uncertainty

The cyclone uncertainty range involves the width of the cyclone plus the cyclone uncertainty that is inherent to the forecast moment. The uncertainty that is associated with the forecast period is taken based on a average of different historical cyclones and the forecast preciseness of those cyclones. The sensitivity of the cyclone uncertainty is tested for 4 different forecast moments and is displayed in figure C.11. It shows that the sensitivity increases rapidly with the forecast moment.

This is in contrast with what was expected, since the hypotheses was that in the beginning the cyclone uncertainty made up a bigger part of the total uncertainty, which would make it more sensitive in earlier forecasts. However, in the earlier forecast almost the whole geographical scope was assessed as in need of evacuation, which means that there is not much change possible. Whereas in later forecast, the forecasted path of the cyclone moved away from a big area that is highly vulnerable because of its low elevation. This caused the number of evacuation patches to decline rapidly, which increased sensitivity.

Sensitivity of the cyclone width

The width of the cyclone that brings precipitation above a level that can cause heavy floods and storm surges, which can be measured by satellite images. However, this still involves some estimation, which is why this variable is also subject to the sensitivity analysis. According to the hypotheses that sensitivity would increase with later forecasts, this is confirmed in figure C.12. In later forecasts, the width of the cyclone makes up

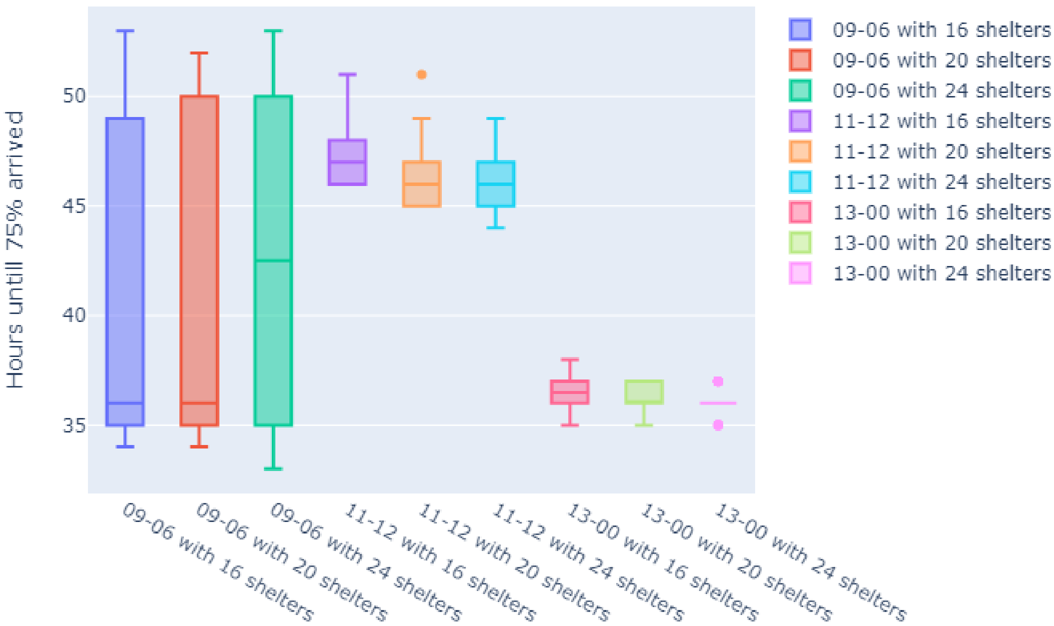

Figure C.10: Sensitivity of the number of shelters measured by all the evacuees

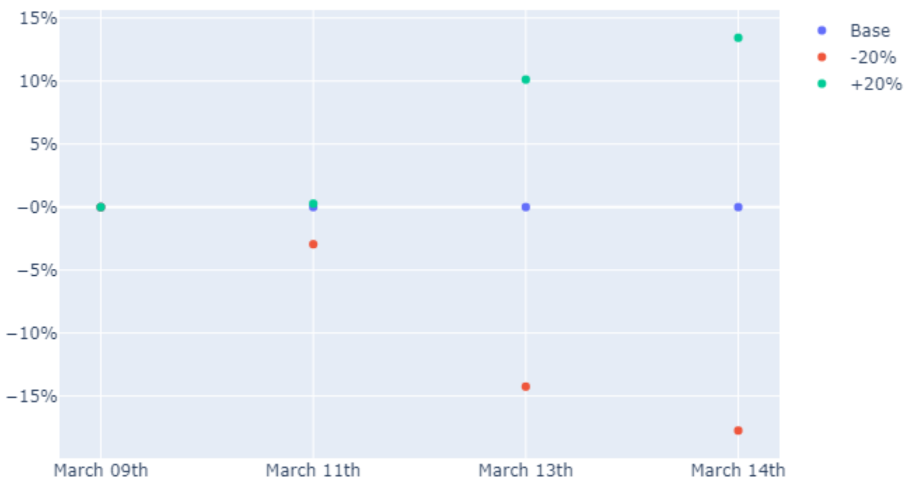

Figure C.11: Sensitivity of the cyclone uncertainty

a bigger part of the total uncertainty, which makes it more important to have reliable estimations in later forecasts. The figure shows the percentage change in output for a 20% change in input. For example, when the width of the cyclone is increased by 20%, the number of evacuation patches increases with 13% at forecast moment of March 14th.

Sensitivity of the decision delay

To investigate the change in sensitivity, three forecast moments are chosen. The decision delay variable assigns a value from a uniform distribution to every group of evacuee to account for the time that evacuees take to make their decision and to prepare for the evacuation. Due to the stochasticity in the evacuation simulation model, every experiment is ran 50 times, after which the values are displayed in a box plot. Because in the first forecast moments the fraction saved KPI is always 1, which means that all evacuees in danger are

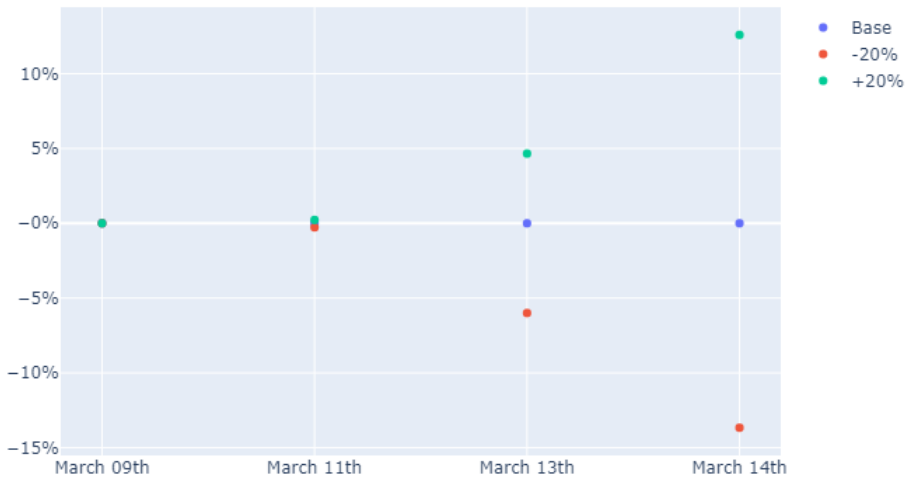

Figure C.12: Sensitivity of the cyclone uncertainty

saved, a different measurement is chosen to assess the sensitivity. The y-axes display the hours until 90% of the evacuees that were in danger reached their shelter. Essentially, the box plot shows the time it takes to reach a value of 0.9 for the fraction saved KPI.

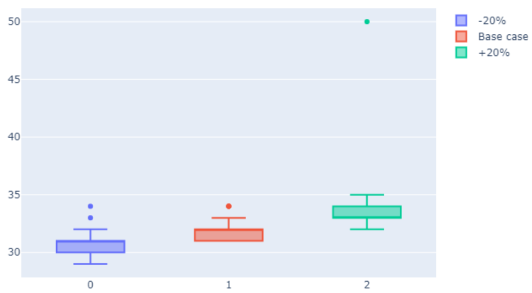

Figure C.13: Sensitivity of the decision delay for March 09th

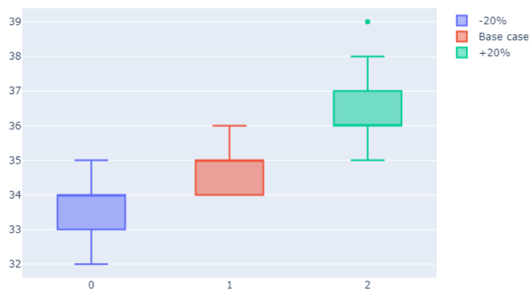

Figure C.14: Sensitivity of the decision delay for March 13th

Figures C.13 and C.14 show that the sensitivity does not significantly changes between forecast moments, since except for the outliers, both box plots show the same change on the y-axis. This is contrarily to what was expected. The decision delay variable, however, shows to be sensitive for each forecast moment separately. That means that the decision delay variable has a significant effect on the amount of people that are saved. For example, looking at figure C.14, a +20% change in the decision delay variable means an increase of 2.9% in the hours that are needed to reach a 90% fraction saved. More interestingly, when looking at figure C.15 there is a far bigger spread in the travel time for the base case. Most probably because exactly at that value, many residents needed to spend another night before they reach their shelter location. This explains the gap of around 12 hours, because this is the same length as one night.

Sensitivity of the travel speed

The last variable for which the sensitivity is analyzed is the travel speed. A value from a uniform distribution is assigned to every group of evacuees as their travel speed. This variation in travel speed represent the difference in age or the difference in the household belongings that evacuees take with them, which influences their travel speed. The uniform distribution is chosen because it is least presumptuous about the distribution of the travel speed. The sensitivity is tested through increasing and decreasing the parameters of the uniform distribution function by 20%. This is evaluated for three different forecast moments, in order to test if the

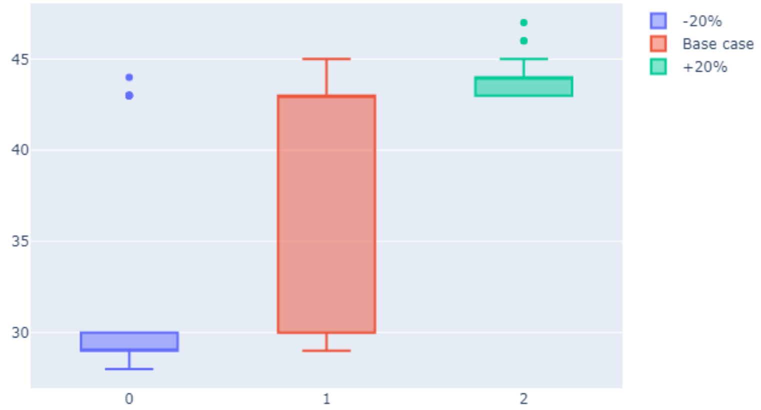

Figure C.15: Sensitivity of the decision time for March 11th

sensitivity of the travel speed depends on the forecast moment. The y-axis shows the number of hours it took before 90% of the evacuees that were in danger safely reached their shelter location. The travel speed is varied as is specified in table C.4.

First of all, looking at figure C.16 and C.17, they show that the sensitivity of the travel speed is higher in the forecast of March 9th, compared to the forecast at March 13th. This was to be expected, since in later forecast the vulnerable area was smaller, which meant that there were less evacuees for the same amount of shelters. This reduced their average travel distance which makes the speed at which they travel less relevant. Still, even in the early forecast of March 9th the sensitivity is not high. A 20% increase in the travel speed only resulted in the the first 90% of the evacuees arriving around 2 hours earlier.

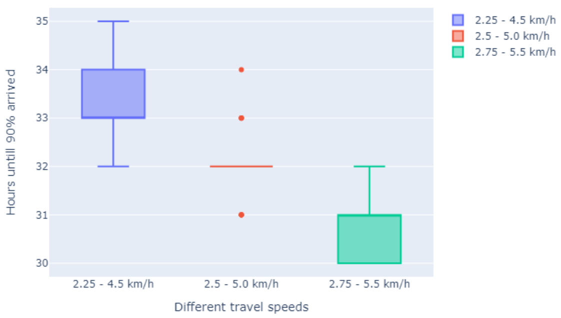

Figure C.16: Sensitivity of the travel speed for March 9th

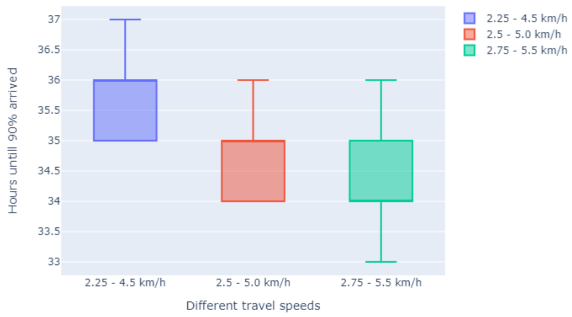

Figure C.17: Sensitivity of the travel speed for March 13th

The same conclusion does not apply to the variations in travel speed for the forecast moment of March 11th. Figure C.18 shows a high output variance between the base case of a travel speed between 2.5 - 5 km/h and the 2.25 - 4.5 km/h. This is directly explainable because of behavior rule number 8 in chapter 6, which describes that evacuees only travel during day hours. This means that with a travel speed of 2.25 - 4.5 in none of the cases 90% of the evacuees reaches their shelter before the night falls. For the base case, in some cases 90% of the evacuees in danger reaches their shelter in time, although the median is still close to the travel speed of 2.25 - 4.5 km/h. In the most right scenario however, the median has shifted to the bottom, which means that with that travel speed, in most of the cases 90% of the evacuees in danger reaches their shelter before dark.

Sensitivity of the interaction effect

The interaction effect between evacuees simulates the process where evacuees do not directly receive the evacuation order because they are not covered by a cell tower. Instead, they receive the evacuation order from evacuees who are travelling to their shelter and are passing them on their way. When the interaction effect is turned on, the evacuees that are informed by other evacuees change their shelter destination to

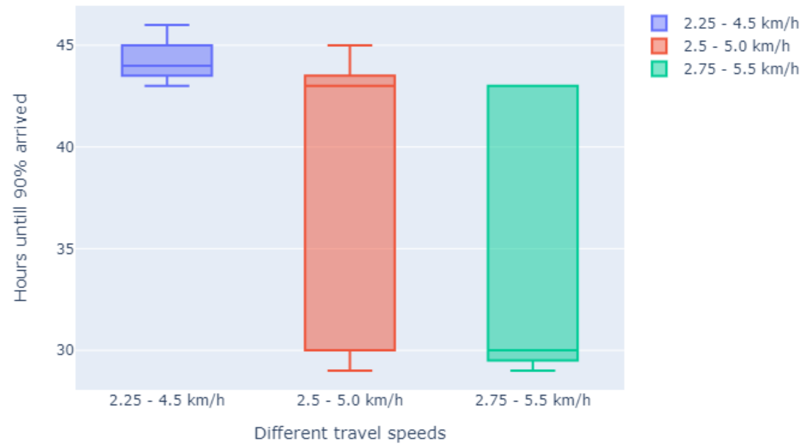

Figure C.18: Sensitivity of the travel speed for March 11th

the destination of the evacuees who informed them. That means that the spread over the shelters, which is calculated in the optimization, changes. If this interaction effect is turned off, evacuees will be informed, but will still travel to their original designated shelter. To investigate the effect of this interaction effect and thus how many evacuees change their destination, the effect is turned off and on to compare the effects. First of all, it can be concluded that the number of evacuees that change their destination only differs per forecast moment, and is not dependent on the number of shelters and the safety margin. This has to do with the fact that evacuees are informed by residents living in their close vicinity, and that is not changed by what shelter they are assigned to.

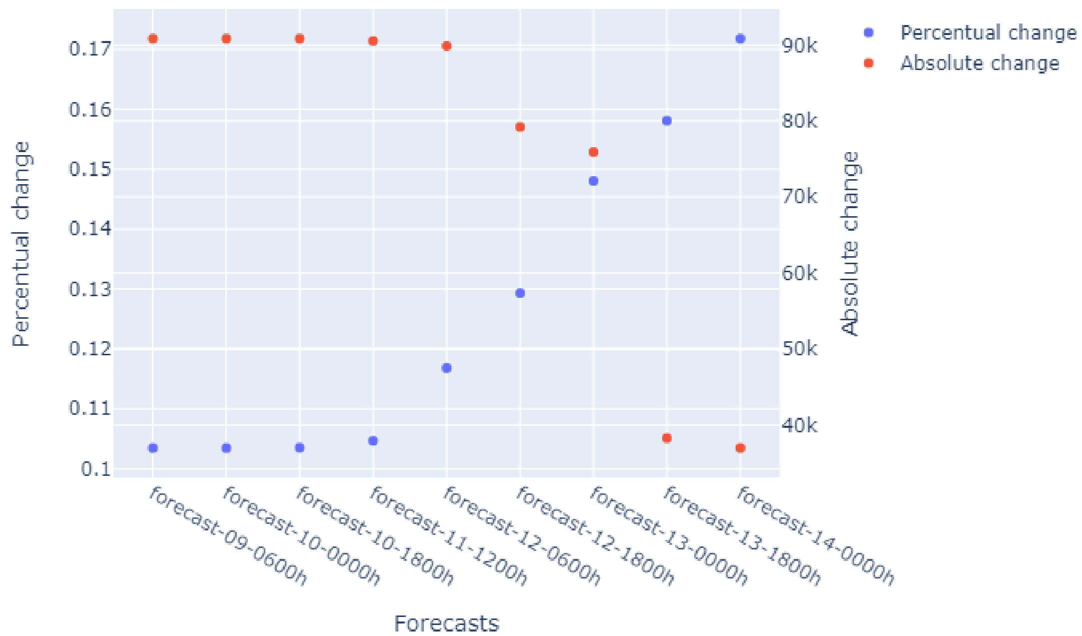

Figure C.19: Sensitivity of the interaction effect

Figure C.19 shows the absolute number of evacuees that changed their destination and the percentage change compared to the total number of evacuees. The figure shows that the absolute number shows a decline over the forecast moments, but there is an increase in the percentage change over time. In the earlier forecast moments, the interaction effect can lead to 90.840 evacuees changing their location to another shelter. This means that aid organizations should be aware that the actual number of evacuees per location might not be the same as the one that is determined in the evacuation. The effect of the interaction effect diminishes when the cell tower coverage increases, because then less evacuees will be indirectly informed by other evacuees.

D
The models explained

This research combined three different building blocks, also called sub models, and combined them into one. Those three different building blocks are described in the chapters 4, 5 & 6. This appendix will offer a more detailed walk through of every model in order to give the reader a better understanding of how they work individually and how they work together. This walk through serves the purpose of understanding the model at a level where it can be re-used for other similar purposes. The three sections each review one building block, in the order in which they interact.

D.1. Vulnerability assessment model explained

The vulnerability assessment model knows three parts: preparing the data, determining vulnerability and to find possible shelter locations. This model can be found in the folder *SQ1 - Vulnerability*. Each part of the model is discussed below.

D.1.1. Preparing the data

The first step is to prepare the data for it to be used in the model. For the elevation data and the relative elevation data (Height Above the Nearest Drainage), the data is cropped to fit the geographical scope and it is aggregated to the desired resolution level. For both case studies the data is aggregated to a resolution of 2.625 by 2.625 kilometer. This resolution is chosen because the higher the resolution the more computational power is needed for the other processes, but a resolution that is too low will no longer be realistic. The value of 2.625 has been selected because it optimizes computational power and precision. The data is cropped and aggregated using QGIS. This happens in the following steps:

1. Download the relevant elevation tiles from `https://dwtkns.com/srtm/`
2. Load and merge them in QGIS by selecting Raster > Diversen > Merge and save them as a .tif file
3. Save the .tif file as an .asc extension file, using Raster > Conversion > Translate. This is necessary because Netlogo cannot handle .tif files.
4. Run the fileprepping.r file to crop and aggregate the data to the right resolution (geographical boundaries and resolution can be specified).
5. Repeat this process for the HAND data, which can be downloaded from `http://hydro.iss.u-tokyo.ac.jp/~yamadai/MERIT_Hydro/`

D.1.2. Assessing vulnerability

The next step is to load both data files into Netlogo. This is done using the GIS extension, that is offered by Netlogo. The data is loaded using the *gis:load-dataset* command, after which every patch get the right value assigned for the absolute elevation and the relative elevation using the *gis:apply-raster* command. Then the world is colored based on the relative elevation using the *gis:paint* command. The *gis:load-coordinate-system* command is used to define the outer geographical boundaries of the Netlogo world. This command uses the

.prj file, which is automatically created when an .asc file is created. After the outer coordinates is known, the center coordinates are calculated based on the number of patches. These coordinates are stored as *pxcord* and *pycord* for every individual patch. The other part of the data that is used consists out of the different forecasts. A forecast contains latitude and longitude coordinates for different moments in times. An example of a forecast can be found in appendix G. This data is inserted manually because different forecast agencies use different document styling, automatically parsing the data is more complicated. Especially since there are only a dozen or less forecast reports per cyclone, inserting the data manually is a good alternative. Since the forecasts are not necessarily an exact fit with the geographical scope of the Netlogo model, they are either interpolated or extrapolated.

- They are interpolated when there are data points that fall outside the map. In those cases, an additional interpolated data point is created that falls exactly within the map. This ensures that the forecast nicely falls within the map
- They are extrapolated when the data points are not sufficient to cover the whole map. In an early forecast there exist the possibility that the cyclone is only forecast over parts of the land. In those cases, the latest data point is extrapolated in order to cover the end of the map.

Next, every forecast report forecasts the cyclone several hours ahead of expected landfall. This amount of time is translated into uncertainty using the values in table 4.1. These values are transformed in a formula using a regression technique, which makes it possible to obtain an uncertainty value for forecast hours that differentiate from the ones provided in table 4.1.
The next step is to calculate the vulnerability of individual patches. Every patch represents a real world geographical square area of 2.625 by 2.625 kilometer. Vulnerability is only calculated for areas up to a certain elevation. This elevation level depends on the aim of the case. For example, for the cyclone of Idai, the model is used to assess the vulnerability to floodings, which is why this elevation parameter is set to 10 meters, since areas higher than 10 meters are highly unlikely to be flooded. For the case of cyclone Kenneth, where land slides were a much bigger problem, this elevation value is set to 100 meters, because land slides can occur at higher altitudes as well. For those patches below the elevation threshold, vulnerability is calculated based on the following two formulas:
The probability of being hit by the cyclone is formulated as:

$$1 - \frac{\text{distance to the forecasted path of the cyclone}}{\text{uncertainty range}}$$

where the uncertainty range is composed of the uncertainty that is inherent to the forecast moment combined with the width of the cyclone that caused the devastating impacts.

The final vulnerability is then calculated as

$$\frac{\text{probability of being hit by a cyclone}}{\text{height above the nearest drainage}} \quad \forall \quad \text{absolute elevation level} \leq \text{elevation threshold}$$

However, the process for determining the impacted area is slightly different. Because there is no longer any uncertainty involved, the same formulas are applied with the difference that the uncertainty range is now changed for the width of the cyclone only.
After all the required patches obtained a value for their vulnerability, a vulnerability threshold is used to determine what patches are vulnerable enough to be needed to evacuate. Patches that have a vulnerability value that is above the vulnerability threshold, it is marked as an patch that needs to be evacuated.

D.1.3. Determining possible shelter locations

The final step that is executed in this Netlogo model, is defining the possible shelter locations. The algorithm operates as follows:

1. Ask all patches with a vulnerability value lower than the vulnerability threshold to ask all patches that have a
   (a) distance to me that equals the specified safety margin
   (b) has a vulnerability value that is lower than the vulnerability threshold

(c) and has an absolute elevation that is higher than 0

2. Those patches are asked to check the vulnerability level of the patches around them in a radius that equals the safety margin. If all of the patches in their surrounding have a vulnerability value lower than the threshold, they set their surrounded risk to 0.

3. If their surrounded risk is equal to 0 they are selected as possible shelter location.

Because there may be many shelter locations that are directly adjacent to each other, and there is only the need for a rough estimation of the shelter location, there are 200 shelters randomly selected from all the shelters that are selected by the algorithm. This makes sure there is a nice even spread of possible shelter locations around the vulnerable area and computational time is reduced. Figure D.1 explains the process of the vulnerability assessment model graphically. Note that an evacuation moment always matches with a forecast (see section 2.4 for explanation).

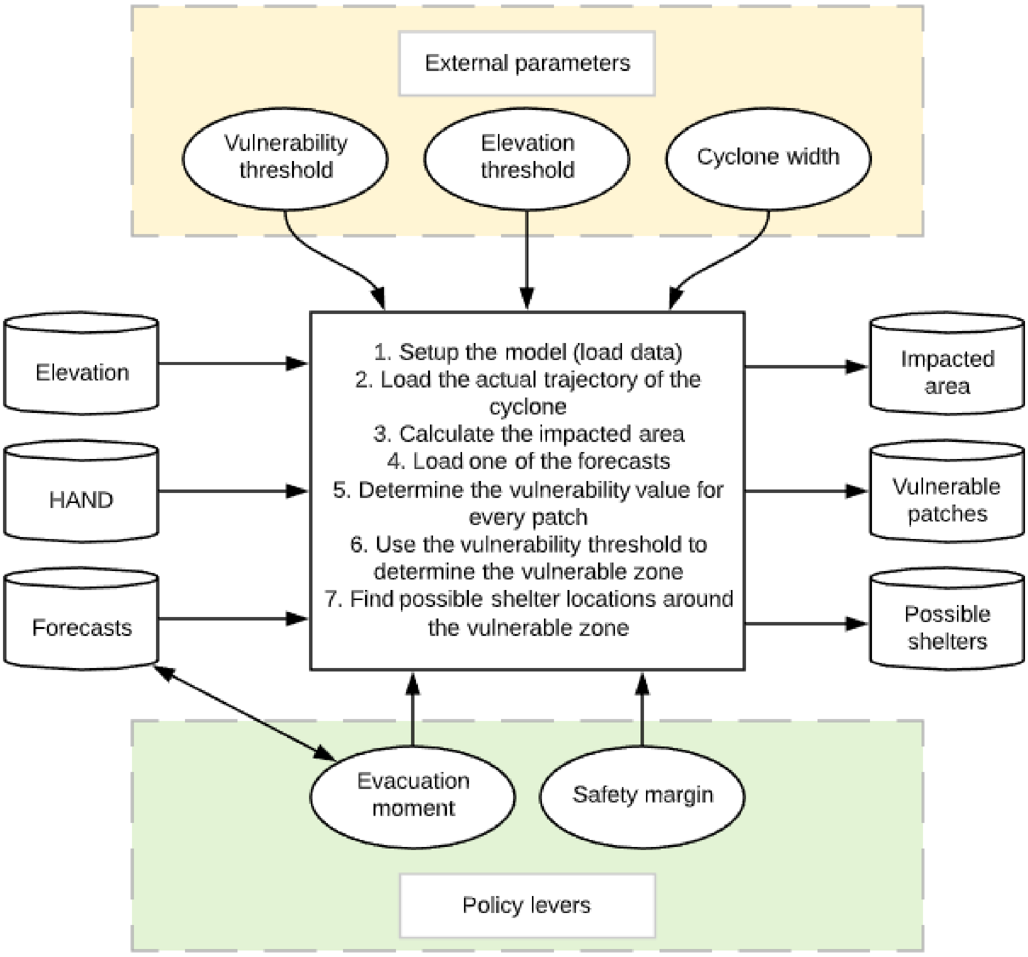

Figure D.1: The relation between input and output explained for the vulnerability assessment model

D.2. Optimization model explained

The optimization model consists of everything that is executed in Python in between the two Netlogo models. The code has been written in a Jupyter notebook and is also available on GitHub. This section takes the reader through all the code, so it can be simply understood.

The different pieces of code have been put into functions, so they can easily be called at the bottom of the Jupyter notebook. The first step is to define the Python - Netlogo connector, which is provided by the PyNetlogo package. The Graphical User Interface has been set to False because it speeds up the execution time.

If the user wants to get a visual understanding of the processes within Netlogo, it can be set to True. Using the PyNetlogo connector, the vulnerability assessment model is ran, with the different parameters that can be specified. This means that the forecast moment, the safety margin and the vulnerability threshold can be specified. The model is than ran as explained in section D.1. The generated Netlogo data is then saved as a .csv file using the *export-world* command. This saves all the variables, patch information and other relevant data. Next, this exported Netlogo data is imported in Python using pandas. A lookup is used to determine which lines of the .csv files are necessary in order to prevent loading in unnecessary data. Some data types are corrected (from strings to integers or floats) and the irrelevant data is omitted from the data frame. What remains is a pandas data frame with all the patches on the rows and with the following columns:

- ID
- X coordinate & Y coordinate (in decimal degrees)
- pxcor & pycor (the original Netlogo coordinate system)
- vulnerability value
- shelter location (True/False)

After the Netlogo data is correctly stored in the pandas data frame, the data is used to obtain all the necessary data to run the optimization. The first step is to use the OSMNX package to calculate the distances between all the evacuation patches and the possible shelter locations. An explanation of this process can be found in appendix H. In order to reduce computational time, only the distances between evacuation patch and shelter location are calculated that lie within a certain euclidean distance from each other. This saved computational power since the final distance between evacuation patch and shelter point will be minimized, meaning a high distance will most likely not be selected and therefore there is no need to calculate it. Another feature is that the distances between evacuation patches and shelter locations is not calculated directly, but only for the unique nodes. This process is explained below:

1. Load a graph representation of the geographical area. This means that roads are represented by edges and crossings are represented by nodes. This graph representation enables to make use of shortest path algorithms.
2. Find the nearest nodes for all the patches by matching their real geographical coordinates and the coordinates of the nodes in the network. (this has been pre-calculated for the most common nodes and is saved in the file nearest_ odes_df.csv. If the specific node is not present it is yet calculated using the OSMX function *get_nearest_node()*.)
3. Create an unique list of all the evacuation patches nodes and of the shelter locations nodes (some have duplicates because there aren't many nodes in that area).
4. Check if a pair of evacuation patch node and shelter location node is already calculated in the *UltimateDistanceDict.npy*.
    (a) If the path has been calculated before retrieve the distance between the nodes from that file and store it in the *DistanceDict*.
    (b) If the path is not present, calculate the distances between the evacuation patch node and the shelter location node and store it in both the *DistanceDict* and the *UltimateDistanceDict.npy*.
5. For every patch in the data frame, that has a vulnerability value that is higher than the vulnerability threshold, determine their distances to all the shelter locations based on the distance from the *DistanceDict* and the euclidean distance from the shelter location to node of that shelter location and save this in *DistanceDictID*. (Now the distance for every individual patch is determined without executing commands twice without necessity.)

The next step is to find the population that lives at every patch. The LandScan data set is used, and is cropped and aggregated to the right resolution. The process is the same as for the elevation data (see section D.1.1). The LandScan data is loaded using the georaster package and is stored in a pandas data frame Since the coordinates of both systems are not an exact match, they are matched by minimizing the euclidean distance.

The last data input is whether or not a patch is covered by a cell tower. The cell tower coverage is obtained from `https://www.gsma.com/coverage/`. A screenshot of the data is saved as a .png file and loaded in Python. The pixels of the image are analyzed and the locations of the red pixels (they indicate there is cell tower coverage) are matched to their coordinates, based on the outer coordinates of the screenshot. Then, those coordinates are matched with the original data frame to indicate whether or not a patch is covered by a cell tower.

The data frame with all the patches is now expanded with the following columns:

- Population size (variable name: *value*)
- Cell tower coverage (True/False)

Now that the right input data is generated, the input parameters for the optimization can be defined. The distance range constraint is calculated based on the day time there is left until the cyclone makes landfall, multiplied by the most optimal travel speed of 5 kilometer per hour. Based on the distance range constraint, for every patch it is calculated whether there is at least one shelter that is within reach. if so, they are included in the optimization. If not, they are excluded and saved with their ID in the variable *not covered*.
Then the optimization is executed using the Gurobi Python interface, called GurobiPy. The mathematical model is already explained in section 5.3 and won't be repeated here.
After the optimization is finished, the results are processed. The results consist of a list of shelters that have been selected and which shelter every group of evacuees have been assigned to (this is based on the ID of the evacuation patches and the shelter locations). This data is stored in the *solutiondict*. This dictionary variable type contains for every patch that is covered and thus included in the optimization what shelter he is assigned to. This information is used to expand the information available for every evacuation patch. This means the data frame has now been expanded with the following columns:

- Whether or not a patch is covered (variable name: *covered*)
- The distance to the target (variable name: *distance_to_target*)
- Which shelters are chosen (variable name: *shelter_chosen* - True/False)

The last step is to write the results of the optimization to Netlogo, in order for it to be used in the evacuation simulation model. The data that is written to Netlogo consists of the evacuation patches and of the shelter locations.

For the evacuation patches the following variables are included:

- pxcor & pycor
- cell tower coverage
- population size
- pxcor & pycor of shelter location
- travel speed (based on the distance calculated earlier)
- ID (for verification purposes)

Optionally, it is possible to write to Netlogo the data about the population that is not covered and the patches that have no population as well. However, this is only for visual purposes since it will not influence the simulation results.
Once the data has been written to Netlogo, it is stored in a .csv file using the *export-world* command. This file is then loaded to run the simulations. How the evacuation simulation model works is explained in the next section. A simplified version of the input/output relation of the second model is graphically illustrated in figure D.2.

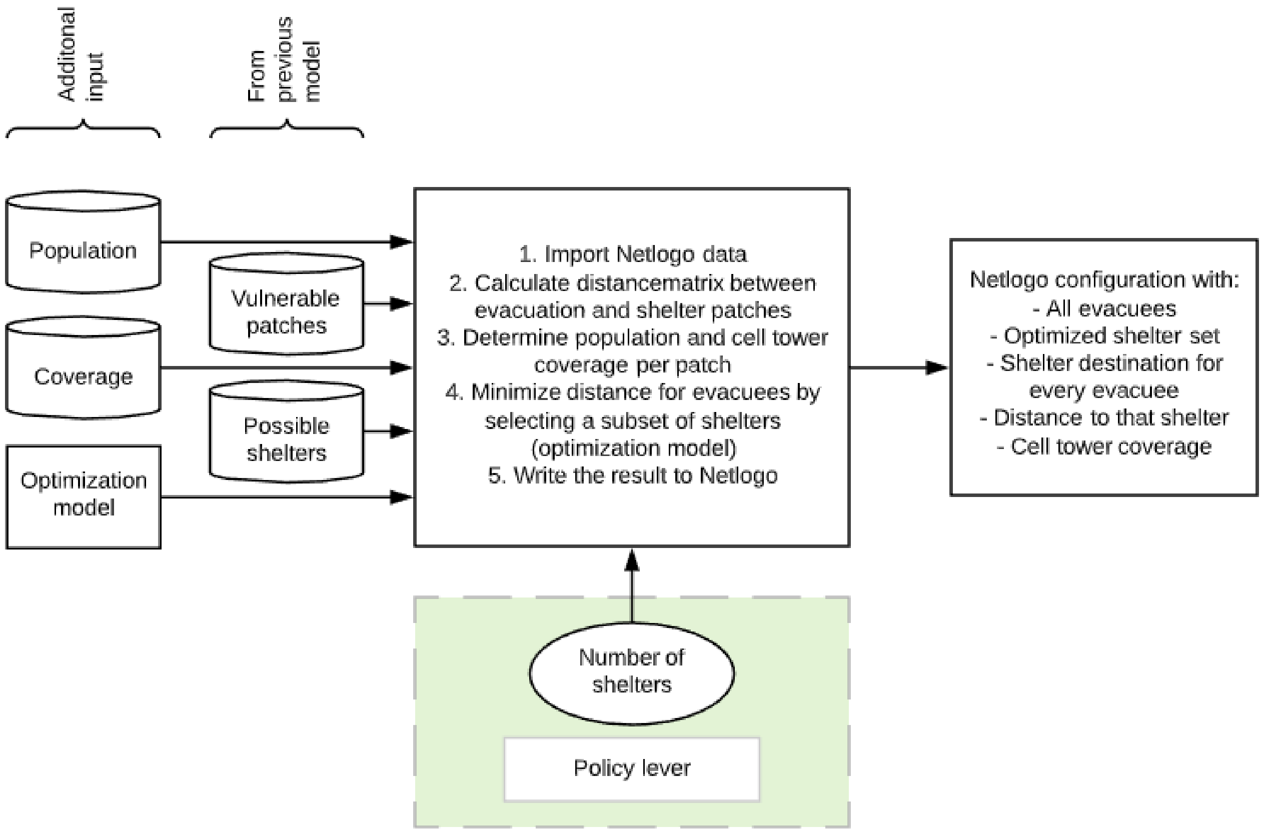

Figure D.2: The relation between input and output explained for the optimization model

D.3. Evacuation simulation model explained

The last and final building block is the evacuation simulation model. The previous model optimized over all the possible shelter locations and selected a subset that minimizes the average travel distance for the evacuees. It is now possible to simulate such an evacuation, which enables to test under more realistic simulated circumstances what the real effects would be of an evacuation decision at a certain time, with a certain safety margin and a certain amount of shelters. Figure D.3 shows the input and output of the evacuation simulation model.

The setup of the model has already been generated by the previous model. That means that this model effectively executes the logic of every agent and captures the results in different key performance indicators (KPIs). The agent logic that is executed is described by figure D.4.

The loops in figure D.4 are only executed when the model advances one hour. This means that for example when it is 2 AM and the agent has received the evacuation order it checks whether it is day of night. If it 2 AM, the agent stays inactive and checks again the next time step, which will be 3 AM. 3 Hours later the night has passed and he reduces his decision time by one hour. If decision time is not 0 yet, he waits again until the next round before he checks his decision time again. When an agent is on the move, he will alert others in his close vicinity. The distance in which he alerts other depends on the size of the group and can vary between 1 and 7.5 kilometers (using local radios).

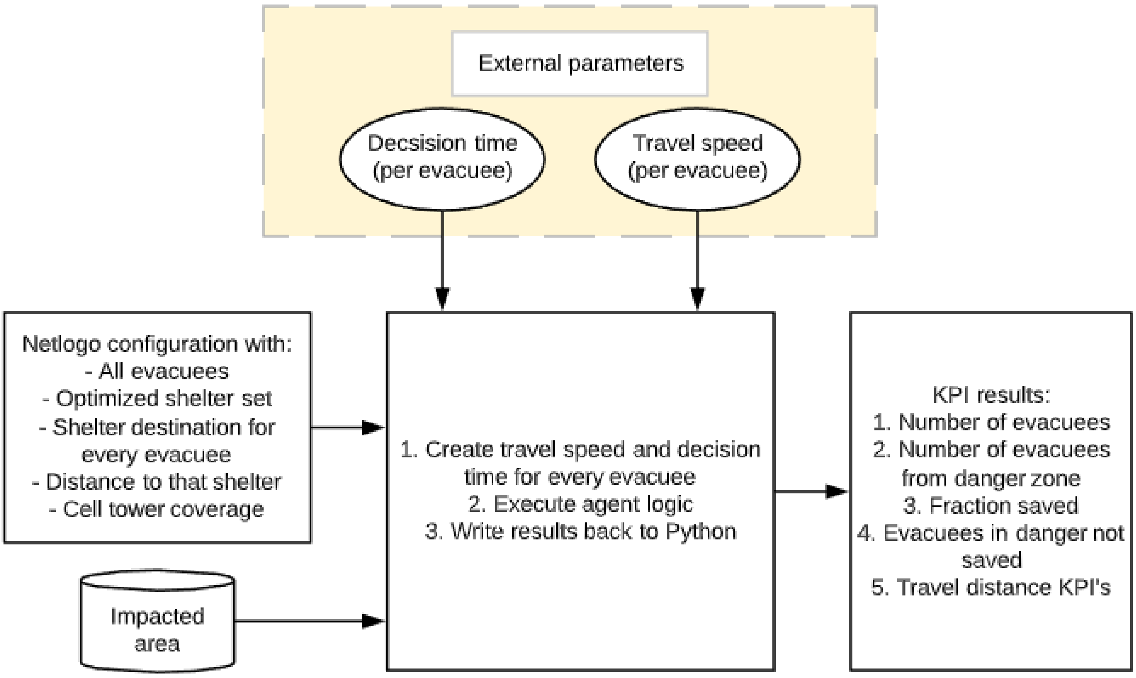

Figure D.3: The relation between input and output explained for the evacuation simulation model

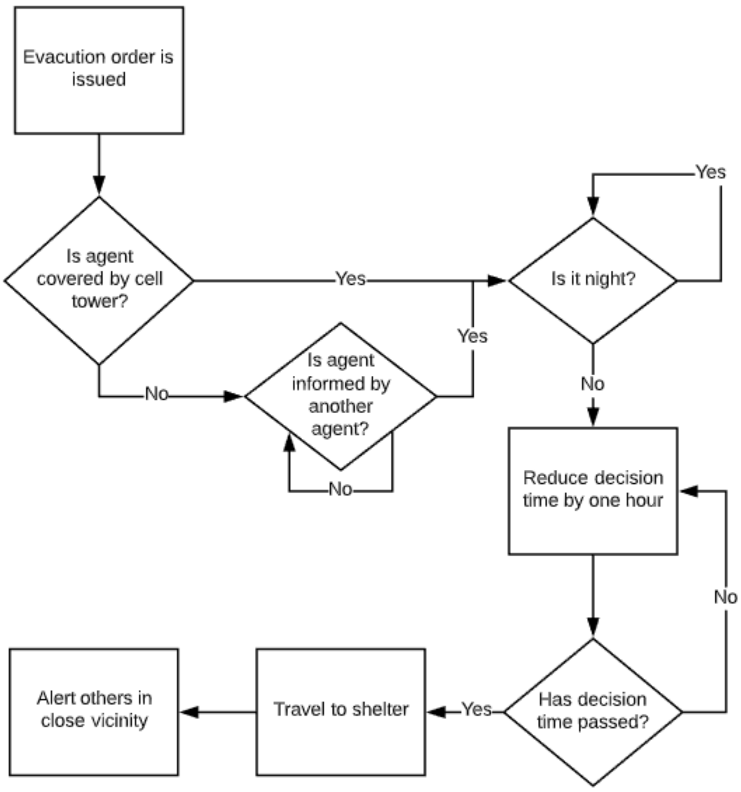

Figure D.4: Agent logic visualized

E
Impact of a population threshold

This appendix discusses the effects of a *population threshold* on the residents that are included in the evacuation plan. The pre-disaster evacuation model in this research is especially effective for residents in rural areas because it is hard to arrange transport for them, because of the low population density. On the other hand, for cities, it might be more effective to arrange transport and to draft a bespoke evacuation plan, instead of treating them the same as the rural population. Therefore this appendix describes the effects when only the population is included when they have a population density below a certain *population threshold*.

To describe the effects, an example case is chosen with a evacuation moment on March 10th, 0000 AM and a safety margin of 5 kilometer and 10 selected shelters. The population threshold is set equal to 150 residents per square kilometer. The results of the two experiments are displayed in figure E.1 and E.2. The first figure shows the arrival of the evacuees in danger over time without a threshold on the population that is evacuated. That means that a higher number is evacuated, compared to figure E.2, where the population threshold is implemented.

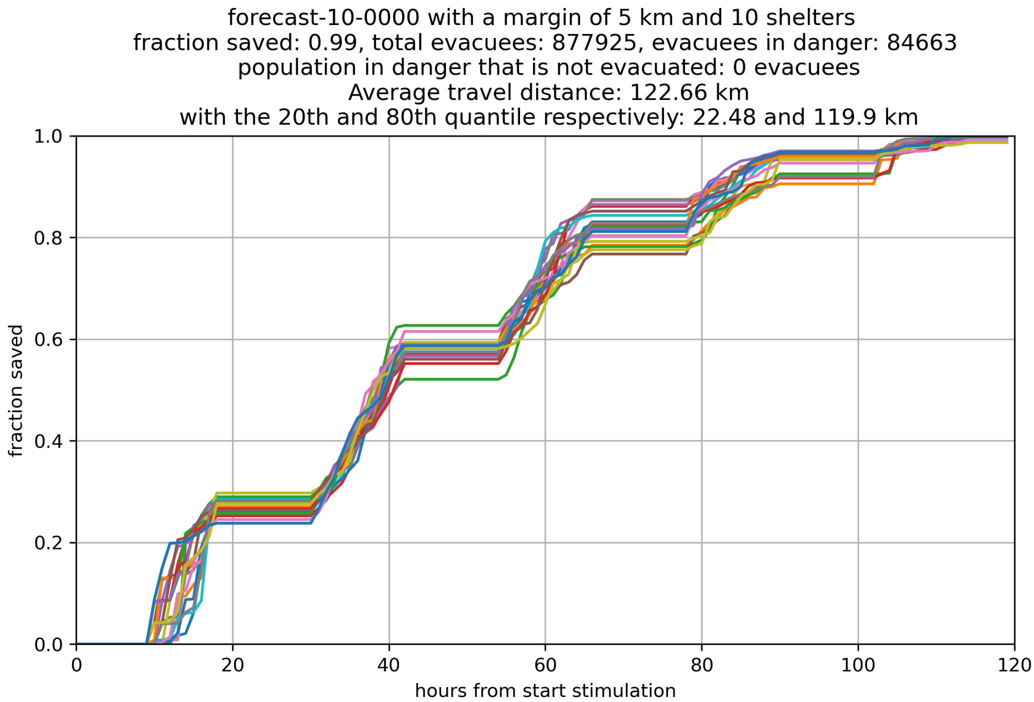

Figure E.1: Fraction saved over time without a population threshold

The experiments shows that in the case of a population threshold the total evacuees and the evacuees that are in danger is about half, but that the general behavior is the same; both experiments nearly have the same

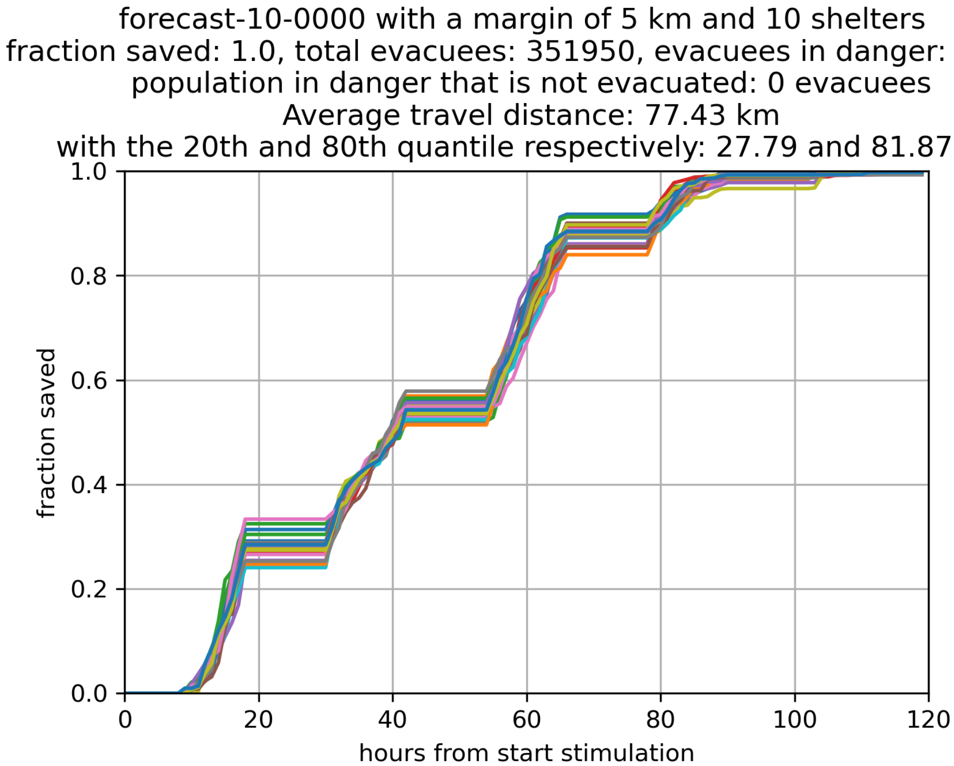

Figure E.2: Fraction saved over time with a population threshold

fraction saved (0.99 & 1.00). However, the average travel distance is much lower in the case of a population threshold. This is because without a population threshold, the shelter locations are as close as possible to the big cities, meaning there is a relative high travel distance for the rural residents. Now that the big cities are not included, the optimization can focus on minimizing the distance for the rural residents. That also means that the 20th quantile of the travel distance is a bit higher because there is no longer a shelter location close to a big city, which can make up 20% of the population. The 80th quantile of the travel distance is significantly lower however, because the optimization can now better minimize the distance of the residents that live further away. That means that in terms of reducing the travel distance, the distinction between rural and urban residents has a siginifcant influence.

F
Assumptions

The assumptions that are made are described per model. The assumptions that are most critical to the validity of the research are discussed in section 10.2.

F.1. Assumptions regarding the vulnerability assessment model

1. Vulnerability can be calculated based on the Height above the Nearest Drainage and the proximity to the forecasted path of the cyclone
2. Areas with an altitude above the elevation threshold are not at risk
3. The relation between the proximity to the center of path of the cyclone and the uncertainty that is associated with the forecast time is linear. In other words, someone who is twice as close to the forecasted path of the cyclone, also has a risk level that is twice as high

F.2. Assumptions regarding the optimization model

Since the optimization part is mostly the execution of a mathematical model, it are rather decisions than assumptions that are made in this model. However, one assumption needed to be made in order to reduce computational time.

> Residents living on the same patch can simply be represented by one agent. This assumption is made because it is computationally speaking to heavy to account for every individual agent in the data preparation for the optimization. Especially in the distance matrix, where computational time increases exponentially with every additional row or column.

F.3. Assumptions regarding the evacuation simulation model

1. Agents always heed the advice of the evacuation order
2. Agents always travel together when they live in the same area (defined as a patch of 2.6 by 2.6 kilometer)
3. Residents who live in cities and residents living in rural areas show the same behavior

G

Forecast report

This appendix shows how to interpret the forecast files.

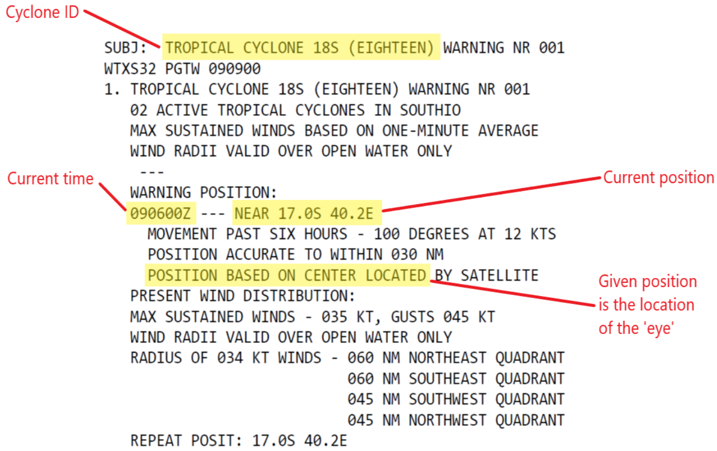
```
SUBJ: TROPICAL CYCLONE 18S (EIGHTEEN) WARNING NR 001
WTXS32 PGTW 090900
1. TROPICAL CYCLONE 18S (EIGHTEEN) WARNING NR 001
   02 ACTIVE TROPICAL CYCLONES IN SOUTHIO
   MAX SUSTAINED WINDS BASED ON ONE-MINUTE AVERAGE
   WIND RADII VALID OVER OPEN WATER ONLY
    ---
   WARNING POSITION:
   090600Z --- NEAR 17.0S 40.2E
     MOVEMENT PAST SIX HOURS - 100 DEGREES AT 12 KTS
     POSITION ACCURATE TO WITHIN 030 NM
     POSITION BASED ON CENTER LOCATED BY SATELLITE
   PRESENT WIND DISTRIBUTION:
   MAX SUSTAINED WINDS - 035 KT, GUSTS 045 KT
   WIND RADII VALID OVER OPEN WATER ONLY
   RADIUS OF 034 KT WINDS - 060 NM NORTHEAST QUADRANT
                            060 NM SOUTHEAST QUADRANT
                            045 NM SOUTHWEST QUADRANT
                            045 NM NORTHWEST QUADRANT
   REPEAT POSIT: 17.0S 40.2E
```

Figure G.1: Cyclone current information

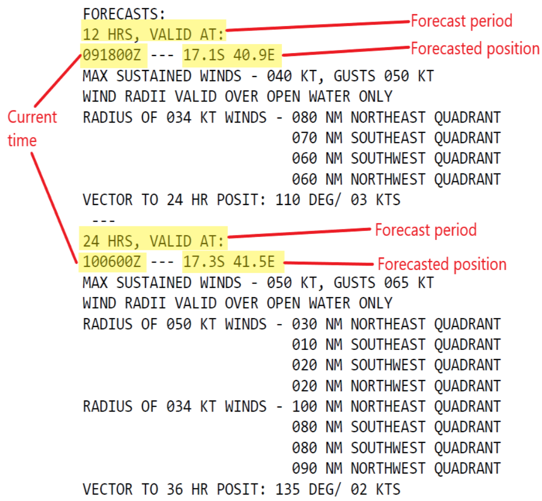
```
FORECASTS:
12 HRS, VALID AT:
091800Z --- 17.1S 40.9E
MAX SUSTAINED WINDS - 040 KT, GUSTS 050 KT
WIND RADII VALID OVER OPEN WATER ONLY
RADIUS OF 034 KT WINDS - 080 NM NORTHEAST QUADRANT
                         070 NM SOUTHEAST QUADRANT
                         060 NM SOUTHWEST QUADRANT
                         060 NM NORTHWEST QUADRANT
VECTOR TO 24 HR POSIT: 110 DEG/ 03 KTS
 ---
24 HRS, VALID AT:
100600Z --- 17.3S 41.5E
MAX SUSTAINED WINDS - 050 KT, GUSTS 065 KT
WIND RADII VALID OVER OPEN WATER ONLY
RADIUS OF 050 KT WINDS - 030 NM NORTHEAST QUADRANT
                         010 NM SOUTHEAST QUADRANT
                         020 NM SOUTHWEST QUADRANT
                         020 NM NORTHWEST QUADRANT
RADIUS OF 034 KT WINDS - 100 NM NORTHEAST QUADRANT
                         080 NM SOUTHEAST QUADRANT
                         080 NM SOUTHWEST QUADRANT
                         090 NM NORTHWEST QUADRANT
VECTOR TO 36 HR POSIT: 135 DEG/ 02 KTS
```

Figure G.2: Cyclone forecast

H

Calculating distances using OSM data

This appendix briefly explains with a very small scale dummy data example how the distances are calculated between the demand points and the shelter locations.

Figure H.1 displays the dummy data that is used to explain the path finding process.

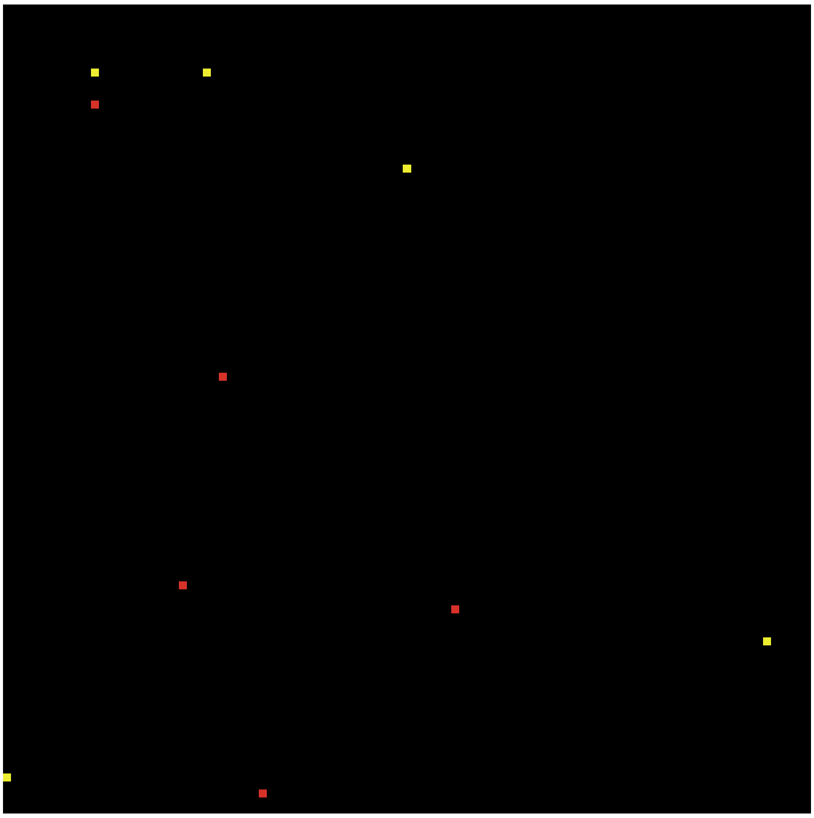

Figure H.1: Dummy data with evacuees in red and shelter locations in yellow

The yellow points represent the possible shelter locations (5 possible shelter locations) and the red points represent 5 different evacuees that need to be evacuated to one of the shelters. First, for every evacuee we need to know the shortest distances to all the different shelters. OSM data is used to couple the coordinates to a node in the graph representation of the Mozambican road network and a weighted shortest path algorithm is used to find all shortest routes.
Figure H.2 shows the shortest routes to the five different shelters for evacuee 1 (evacuee 1 is displayed in red). Since evacuee 2 (top left corner) is very close to one of the shelters, he has been assigned the same node as

Figure H.2: Shortest routes for evacuee 1

that shelter. This means their node distance is 0, and their real distance only consists of their euclidean distances to that node. Figure H.3 shows the shortest routes for evacuee 2 (evacuee 2 is displayed in red).

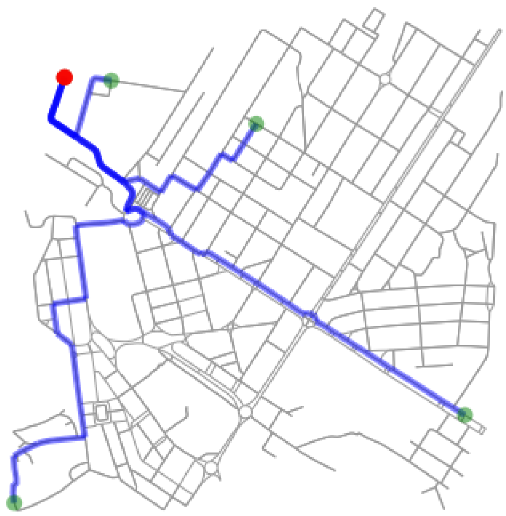

Figure H.3: Shortest routes for evacuee 2

When the optimization is executed with the constraint that only two shelters can be selected, it finds the solution, as displayed in figure H.4.

The chosen shelters are shown in green and the evacuees have an arrow to the shelter that they have been assigned to. Only evacuee 3 (shown in red) has not been assigned to a shelter, due to the distance constraint. Figure H.5 shows the calculated shortest path for evacuee 3. Looking at the euclidean distances, it seems he is not that far away from the most right shelter, but looking at figure H.5 we see that the real distance (following the roads) is quite longer.

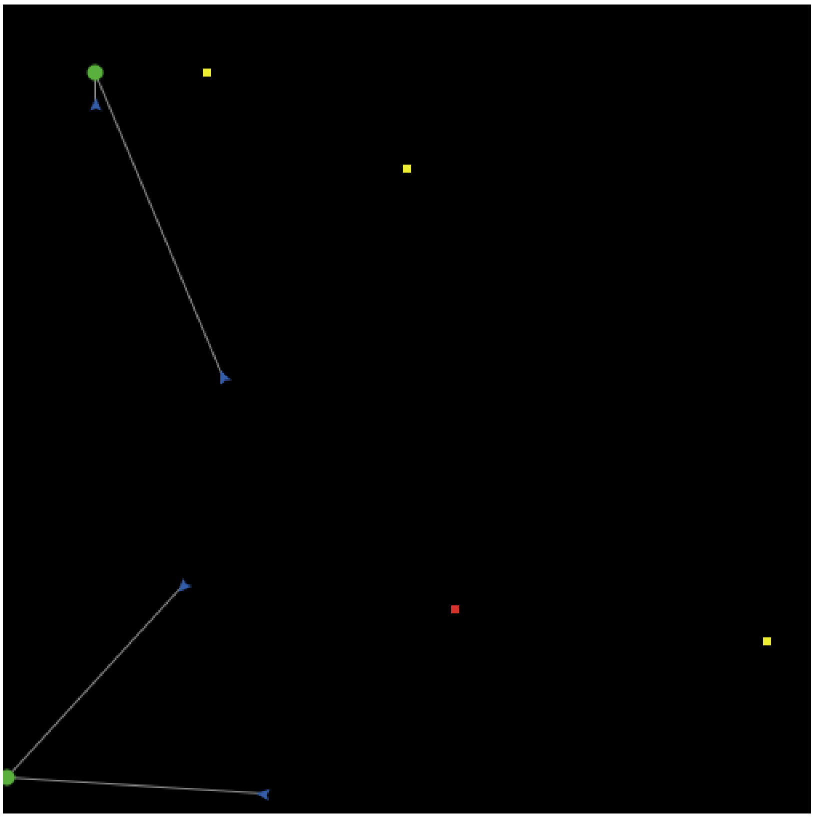

Figure H.4: Optimizes solution with two selected shelters.

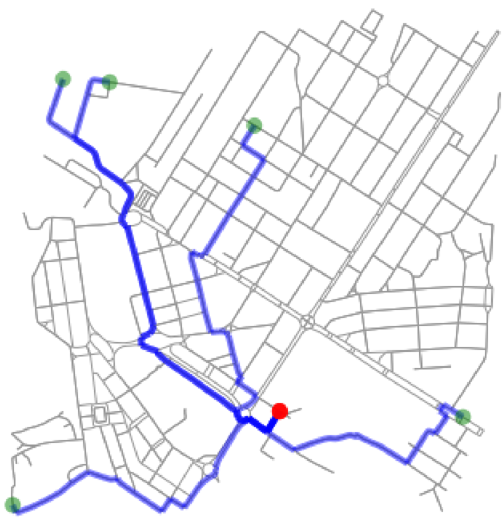

Figure H.5: Shortest routes for evacuee 3

I

Software and packages

For the reason of re-using the model, this appendix will describe all the software programs and their versions that are used. Running the model without any errors can only be guaranteed when the version numbers of all programs and dependencies are equal.

I.1. Software programs

The following software programs are utilised to either prepare the data or to run the models.

Jupyter notebook	1.0.0
Netlogo	6.1.1
Python	3.7.4
QGIS	3.10.2
RStudio	1.2.5033

I.2. Python dependencies

Listed below are the most important packages that are used in Python to prepare or generate data or too run the optimization model with.

geopandas	0.6.3
georasters	0.5.15
gurobi	9.0.1
matplotlib	3.1.1
numpy	1.16.5
osmnx	0.11
pandas	0.25.1
plotly	4.8.1
pynetlogo	0.4.1
scipy	1.3.1
shapely	1.6.4