Flood resilience of coastal communities in Jakarta – Indonesia

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Puck Merceij

Student number: 4620550

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Graduation committee

Chairperson	: Prof. Dr. T. Filatova Multi-Actor Systems
First Supervisor	: Prof. Dr. T. Filatova Multi-Actor Systems
Second Supervisor	: Dr. H.G. van der Voort, Multi-Actor Systems

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An exploratory agent-based study on emergence of flood adaptation and migration behavior under various socio-environmental policy conditions.

Engineering Policy Analysis - Master Thesis

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Student Name	Student Number
Puck Merceij	4620550

Head Supervisor:	Tatiana Filatova
Second Supervisor:	Haiko van der Voort
Teaching Assistants:	Brayton Noll & Alessandro Taberna
Institution:	Delft University of Technology
Place:	Faculty of Technical Policy Management, Delft
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Cover Image: Thousands caught in floods in Jakarta, Indonesia's sinking capital, USA Today (feb, 2020)

Preface

Before you lies the master thesis “Flood resilience of coastal communities in Jakarta - Indonesia”. It has been written to fulfill the graduation requirements of the Engineering Policy Analysis program at the University of Technology in Delft, the Netherlands. I was engaged in researching and writing this thesis from March to October 2022.

This thesis would not be possible without the opportunity to work with the survey data collected thanks to the European Research Council project SCALAR (grant agreement no. 758014) funded under the European Union’s Horizon 2020 Research and Innovation Program. For the provision of the flood map, which were integral to my research, I would like to sincerely thank Dr. Budhy Soeksmantono from the Institute of Technology in Bandung, Indonesia.

I could not have undertaken this journey without the amazing help I received from supervisors, friends and family throughout the thesis process.

First of all, I would like to thank my graduation committee with whom I had the privilege of working on this project. I am immensely grateful to my first supervisor, Prof. Tatiana Filatova, who was always there for academic expert advice, good literary tips and positive encouragement. She inspires me tremendously as a woman at the academic top, committed to work for making the world a better and sustainable place, trying to bring out the best in people and giving them the chance to flourish. Secondly, I would like to express my deepest gratitude to Dr. Haiko van der Voort, my second supervisor, for his keen eye, cheerful talks and provision of comfort at the right moments. I greatly appreciate Haiko’s enthusiasm in bringing people together the warm and welcoming feeling you always gave me, the opportunity to walk by the office at any time and steer in the right direction for the green light. Furthermore, I would like to thank Brayton Noll for his exceptional help with the survey data and analysis methods and the willingness to help me with question throughout my whole thesis project. Another big thanks to Alessandro Taberna, for tips during the modeling process and the support and fun times in Milan.

Finally, I would like to thank my family and friends. First of all, a tremendous shout-out to my parents, Karin Dubbeldam and Henny Merceij, who, although they never had the opportunity to go to university, gave me all the freedom and resources I needed to get an academic degree. My parents were always there for me and made me the person I am today. Your love, wise advice and support always carried me through. I am extremely proud and grateful to be your daughter. On top of that, I am extremely grateful to my sister, Isis Merceij, whom I love dearly. I want to thank you for your sweet call and the little reminders not to lose sight of myself. A special thank you to Thorid for the graduation process and cosy dinners we undertook together. In addition, I would like to thank Olivier, Tom, Roosmarijn, Robin, Amon and Tim for the pleasant time during the EPA master, without you studying was a lot less fun. Moreover, I would like to thank Roel, Malan, Maki, Sabine, Thijs, Dafne and Sjaakie from the kiteboardschool for sporting relaxation alongside my studies. Last but not least, I would like to thank Olivier and Jay for evenings full of life lessons, personal growth, support, advice but also enjoyment and rock n roll.

Puck Merceij
Delft, October 2022

Summary

People's health, livelihoods, and assets are increasingly affected by the hazards of heat waves, storms, droughts and floods, as well as by slow-moving changes, including rising sea levels (IPCC, 2022). Floods are one of the costliest natural hazards occurring worldwide (S. Du et al., 2020). In order to prevent increasing flood hazard damage, ambitious and accelerated measures are needed to adapt to climate change (Garschagen et al., 2018; Hanson et al., 2011; Muis et al., 2015). Progress in flood adaptation is observed in many places and turns out to be beneficial, but the level of adaptation and actions taken are insufficient to keep up with rising flood risks (IPCC, 2022). A combination of both government-led public planned adaptation and community or households-led private adaptation initiatives is most effective and robust (Bott et al., 2021; Marfai et al., 2015). However, offering public protection can unintentionally increase vulnerability to flooding through the so-called levee effect, referring to the creation of false safety, which counteracts household adaptation and leads to more settlement in flood-prone areas (Garschagen et al., 2018; Haer et al., 2020). Moreover, often only low-effort private adaptation actions are taken while transformation adaptation stays-out (IPCC, 2022). This is a matter of concern because in case of failure of top-down mitigating measures, a flood can have catastrophic consequences for households.

To ultimately know how best to reduce flood damage and limit adverse consequences of irreversible public adaptation choices for current and future generations, politicians need to understand the aggregate impact of both public and private adaptation. Moreover, there is a need to engage citizens' awareness to adapt their homes to flooding and to look for policy interventions that encourage household adaptation (Marfai et al., 2015). For a long time studies focused on risk perceptions to explain local adaptation or migration behaviour. However, recent studies found that flood risk perceptions are not sufficient enough to fully understand and explain the local flood adaptation or migration behaviour. Rather social, psychological and cultural values seem to play a more salient role in individual household and community adaptation (Marfai et al., 2015; Noll et al., 2021; Putra et al., 2019; Putro & Zain, 2021). Since human behaviour and their interaction are complex, this implies a need for more socio-behaviourally rich risk assessment methods as well. As Agent-Based Modeling (ABM) is capable of modeling behaviour and interactions between autonomous and heterogeneous agents (households) and its environment, it starts to become a more frequently used simulation tool in flood risk management (Zhuo & Han, 2020).

This study uses Agent-based Modeling to explore the aggregated impact of increasing flood risk, public adaptation measures and policy interventions on household flood adaptation and migration behaviour, flood damage and resilience for a case study in Jakarta, Indonesia. Within the ABM's households are exposed to floods, in response to which they can take adaptive actions; dry proofing, wet proofing, elevation or migration. The protection motivation theory is used as a social theoretical foundation and framework for household adaptation decision-making, as it allows non-rational behaviour due to consideration of more social, emotional and personal behaviour drivers (Grothmann & Reusswig, 2006). The case-study selection for Jakarta is made based on available survey data confirm PMT, which is used to assign the agents attributes in an accurate way. Additionally, ways are explored to stimulate household adaptation and migration behaviour and create a better understanding on the potential impact of policy interventions. Lastly, lots of ABM's measure the system performance on flood risk or damage only, while the increasing uncertainty, frequency, and severity of natural hazards has triggered a paradigm shift from focusing on hazard risk, exposure and vulnerability towards tracing the evolution of resilience (Filatova et al., 2013; Mcclymont et al., 2019). Therefore, this study included five system performance indicators based on the Five Capitals of Zurich Flood Alliance, that aim to provide better measurement of flood resilience of coastal cities and explore ways in which resilience outcomes could emerge.

The main findings of the ABM for the Jakarta case study were:

- The total flood damage of Jakarta increases over time as flooding become more severe.

- It seems around 30 % of the population ends up in a situation of continuous recovery and flooding in 2050. Only 3 % of the population will not be affected by flooding through adaptation and about 67% of the population decides to migrate Jakarta, when no additional public protection measures are taken. As a result the human, financial, physical and social capital slightly decrease while the nature capital increases. Meaning, in general the flood resilience of Jakarta households decreases over time, due to migration of the more flood resilience households.
- When floods or water level rise become more severe, the percentage of households continuously flooding and recovering increases, while the percentage of households who do nothing or migrate decreases.
- Especially households in flood prone areas seem to be extra vulnerable, as more households in these areas end up in a lock-in situation of continuous flooding and recovering without being able to migrate, when flooding becomes more severe.
- In a more extreme flood scenario, the performance of the human, social, physical and financial capitals still shows a slight decrease. However, the psychical capital is a bit higher compared to a less extreme flood scenario and the nature capital a bit lower, meaning households in Jakarta become better adapted over time when flooding is more severe due to which the number of times households get flooded over 30 years reduces.

Looking the policy interventions, the gigantic sea wall could reduce the total experience flood damage of Jakarta the most (by 100 %), due to which less highly educated and high income people migrate, which has a positive influence on the Five capital scores. A side effect of the gigantic sea wall is that adaptation or migration behaviour is not stimulated and turns out to be lower than when no extra public protection is offered (Levee effect). Providing additional job security, could increase the amount of token adaptation measures, but doesn't stimulate households to migrate. Therefore, more research needs be done on the long term effects of the implementation of the wall in relation to water level rise and its effect on adaptation and migration actions; as the wall is likely to cause more urbanisation and perhaps more subsidence, the long-term damage may be worse than can be imagined today. Providing an equal increase in public protection mitigates the total flood damage (by 69%) and strongly stimulates households to adapt of migrate, especially in combination with non-structural policy measures. In the long run, however the Five capital score and thus the flood resilience of Jakarta reduces, due to migration of more high educated and high income households, leaving relatively more less adapted poor, low educated households to stay. These people might become trapped, as they might have the intention to move but lack the money and abilities to do so.

By using Agent-Based Modeling to explore the aggregated impact of increasing flood risk, public adaptation measures and policy interventions on flood adaptation and migration behaviour of households and their flood resilience, a scientific contribution to current research on the usage of ABM's in the development of flood risk management strategies is made. Additionally, ways are explored to stimulate household adaptation and migration behaviour by policy interventions. This knowledge is useful in the design of flood management adaptation strategies. Therefore, this study makes a societal contribution as well.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
ABM	Agent-based model
CCA	Climate change adaptation
EPA	Engineering Policy Analysis
EU	Expected Utility Theory
FRM	Flood risk management
IPCC	Intergovernmental Panel on Climate Change
OSM	OpenStreetMap
PMT	Protection Motivation Theory
PT	Prospect Theory
SQ	Subquestion

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1
Introduction

1.1. Research Problem

Climate change is happening and has a great impact on nature, ecosystems, biodiversity and human society. People's health and livelihoods, as well as their assets and critical infrastructure, including energy and transport systems, are increasingly affected by the hazards of heat waves, storms, droughts and floods, as well as by slow-moving changes, including rising sea levels (IPCC, 2022). Especially cities are seen as hotspots for climate change impacts and risks due to the high concentration of population, making the people that live in such crowded areas extra vulnerable (IPCC, 2022).

Human behavior plays an important role, as it is one of the biggest drivers of climate change risks. As environmental changes and human behavior are closely intertwined, human activity could cause cascading effects that have an irreversible impact on society for current and future generations (IPCC, 2022). The construction of dykes, pumping systems and polders, for example, results in increasing urbanisation of land below sea level, which has irreversible consequences for the biodiversity, nature and society of an area.

Floods are one of the costliest natural hazards occurring worldwide (S. Du et al., 2020). They are life-threatening, cause considerable damage and can force migration (Akmalah & Grigg, 2011; Hanson et al., 2011). Therefore, in this thesis the focus is set on adaptation to flooding as a form of climate change adaptation. In order to prevent increasing flood hazard damage, ambitious and accelerated measures are needed to adapt to climate change (Garschagen et al., 2018; Hanson et al., 2011; Muis et al., 2015). Progress in flood adaptation is observed in many places and turns out to be beneficial, but the level of adaptation and actions taken are insufficient to keep up with rising flood risks (IPCC, 2022). A combination of both government-led public planned adaptation and community or households-led private adaptation initiatives is most effective and robust (Bott et al., 2021; Marfai et al., 2015). However, often only low-effort private adaptation actions are taken while transformation adaptation stays-out (IPCC, 2022). This is a matter of concern because in case of failure of top-down mitigating measures, a flood can have catastrophic consequences for households. Furthermore, despite the need to take joint action, coordination and alignment of actions does not always take place, which could increase flood hazards expose on others (Bott et al., 2021; Marfai et al., 2015; Neil Adger et al., 2005). Another worrying phenomena is maladaptation, which are efforts aimed to reduce vulnerability to climate change hazards like flooding, but unintendedly lead to an adverse outcome and thereby increase the vulnerability to floods instead (IPCC, 2022). Improved flood defenses, for example, could trigger more settlement and urbanisation of flood-prone areas, meaning not only an increase of people and assets at risk, but also extra human activity which could cause subsidence, deforestation, groundwater extraction or river pollution and thereby increases flood risk (Haer et al., 2020). Moreover, upgrading public protection could slow down or counteract household adaptations, due to this increased feeling safety (Noll et al., 2021). This cycle of increased protection, development, increased risk, could create a lock-in situation of vulnerability and exposure from which it is difficult and expensive to escape (Haer et al., 2020; Haer et al., 2017; IPCC, 2022). The false sense of safety that prompts extra development in the area behind a dike is called the ”levee effect” (Garschagen et al., 2018; Haer et al., 2020).

Passivity in private adaptation, counterproductive public and private adaptation actions or a lock-in situation is worrying, as the increasing threat of flooding call for rapid and ambitious flood adaption actions on all levels to save cities from destruction (Bucx et al., 2015; Garschagen et al., 2018; Hanson et al., 2011; Mcleod et al., 2010; Muis et al., 2015). There is a need for policy interventions that stimulate the bottom-up adaptation actions taken at household level (Bott et al., 2021; Sunarharum et al., 2014). Knowing how coastal communities perceive, react, and adapt to flooding events is useful in developing strategies to support flood adaptation (Boissiere et al., 2013). Thus, a better understanding of the decision-making process and adaptation behaviour of households in flood-prone areas is needed, to find ways to stimulate household adaptation (Bott et al., 2020; Sunarharum et al., 2014). Especially, the most affected and vulnerable groups need support and to be taken into account (Bott et al., 2020; Esteban et al., 2017; Garschagen et al., 2018; Mcleod et al., 2010; Rudiarto & Pamungkas, 2020; Taylor, 2015).

1.2. Research Gap

Recognising the crucial role humans play in climate change development, there is a need to include human behaviour and its interactions with society and nature, the ability to learn, reorganise and adapt within flood risk analysis (J. Aerts et al., 2014). As agent-based modeling (ABM) is capable of modeling behaviour and interactions between autonomous and heterogeneous agents (households) and its environment, it starts to become a more frequently used simulation tool in flood risk and adaptation studies (Zhou et al., 2010). However, to use ABM's in the development of resilient flood disaster risk reduction strategies is still in its infancy (Zhuo & Han, 2020).

This study uses Agent-based Modeling to explore the aggregated impact of increasing flood risk, public adaptation measures and policy interventions on household flood adaptation and migration behaviour, flood damage and resilience for a case study in **Jakarta, Indonesia**. Thereby, **a scientific contribution** to current research on behaviourally rich agent-based models for testing (long-term) policy strategies on flood adaptation behaviour is made, by selecting a case-study for which flooding is a serious threat, but not much research was done until now due to data insufficiency. Furthermore, this study shall provide policy-makers with more insight on how flood adaptation and migration decisions among households are made, test ways to stimulate private adaptation and inform the local government of Jakarta on the potential impact of policy interventions on household adaptation behaviour. This knowledge is useful in the design of flood management adaptation strategies and can help policy makers take informed decisions on public adaptation in flood risk management. Thereby this study shall make its **societal contribution**.

1.3. Research Questions

In order to know how to best reduce flood damage and limit adverse consequences of irreversible public adaptation choices for current and future generations, one needs to know the aggregated impact of public and private adaptation under flood risks. This leads to the following **main research question** of this thesis for a selected case-study on Jakarta:

What is the aggregated impact of public and private adaptation actions on Jakarta's flood resilience?

By answering this research question, we aim to provide the policy makers of Jakarta with new insides on the long-term impact of top-down policy measures on household adaptation to be able to make an more informed decisions on public adaptation in flood risk management.

Sub-questions

To address the main research question of this study, the following sub questions (SQ) shall be answered. An overview of how all subquestion relate to each other can be found in figure 1.1

SQ1*: How to measure flood resilience of coastal communities in Jakarta?*

The first subquestion aims to establish the key performance indicator based on which flood resilience in social simulations can be measured.

SQ2*: What household adaptation actions are performed in Jakarta and how do they reduce* *flood damage?*

The second subquestion aims to identify the adaptation action households could take and understand how these actions interact with flooding.

***SQ3**: What factors influence Jakarta's household adaptation decision-making and what is their impact?*

The third subquestion aims to understand how household adaptation or migration behaviour comes about and how it can be influenced.

***SQ4**: What policy interventions could influence household adaptation or migration decisions?*

Now that we know the factors that play a role in adaptation or migration decisions, we could start looking for policy measures that influence these factors and try to estimates its impact.

***SQ5**: What is the aggregated impact of policy interventions on Jakarta's household adaptation and migration behaviour, flood resilience and expected flood damage?*

The previous sub questions provide us the knowledge needed to measure Jakarta's flood resilience, flood damage and adaptation and migration behaviour of households under various policy interventions. By analysing the aggregated impact of public and private adaptation on flood resilience, we can ultimately see under what socio-environmental policy conditions a lock-in situation of vulnerability and risk, stimulation of adaptation and migration behaviour and positive or negative flood resilient development in Jakarta could emerge.

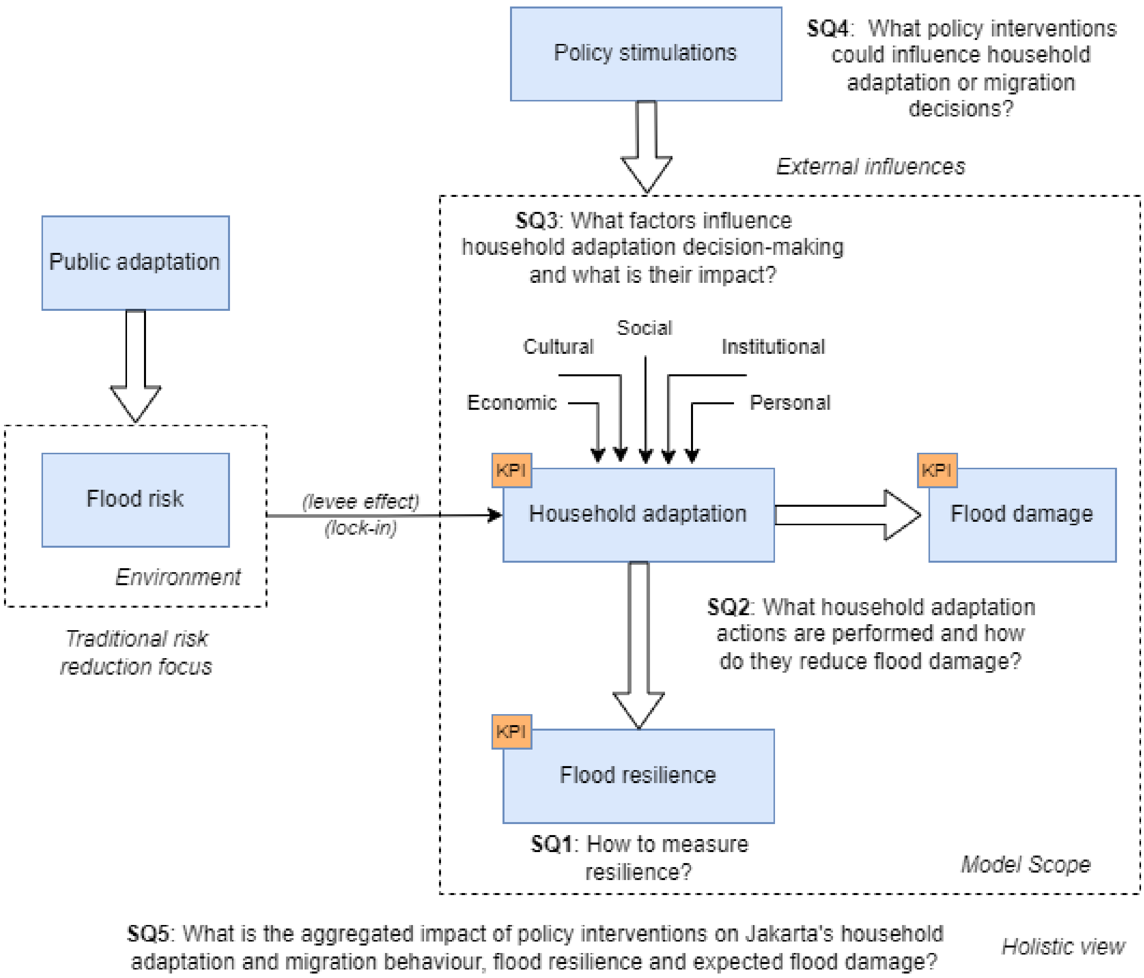

Figure 1.1: Research scope and subquestions overview

1.4. Link to the EPA masters program

To measure the aggregate impact of public and private adaptation on flood resilience, one needs to be able to bring the behavioral, policy, engineering, and physical hazard components of flood risk to the table and combine insights. On the one hand there is the human adaptation behaviour, which requires social and psychological insights. On the other hand, this behaviour results in physical structural adaptation of houses, which impact flood damage. To map this effect, a very different, more technical engineering insight in the field of water management is necessary. Moreover, policies exerts its influence on both human behaviour and technical flood reduction aspects. By mapping and analysing all of the interaction effects between policies, human behaviour, flooding and adaptation actions, to eventually form a policy advise, this Master Thesis study aligns well with the Engineering Policy Analysis masters program.

1.5. Research Approach

The main objective of this study is to explore the aggregated impact of autonomous bottom-up household adaptation decisions under flood risk for various policy strategies. Analyzing how household adaptation behavior could develop under various political strategies gives the government more insight in their actions. This is necessary to ultimately know how best to reduce flood damage and limit adverse consequences of irreversible public adaptation choices for current and future generations. However, because government-led adaptation measures often involve large investments and take a very long time (e.g., 30 years or more) to implement and verify, there is a desire for a simulation model that could measure the effect of various policy strategies in advance for improved decision-making.

A modeling approach enables one to measure and visualize the impact of policy interventions on the adaptation behavior of agents, in this case households of Jakarta. A great advantage of a simulation model is that it allows you to perform multiple analyses for the same system and compare them against each other (Bonabeau, 2002; E. Du et al., 2017). In reality, this is never possible because each policy intervention changes the original system in such a way that you cannot return to the original state (Zeigler et al., 2000).

The recognition of the crucial role of human behaviour in relation to flood risks and resilience of hazard-prone cities, calls for using behaviorally-rich simulation models that couple social and environmental dynamics in flood resilience assessments (J. Aerts et al., 2014; Taberna et al., 2020). Since the system under study involves interactions between households, floods and policy interventions, a simulation technique is needed that is capable of handling these interactions. Currently **Agent-Based modelling (ABM)** is the most suited modelling language used to model human behaviour with interactions (Luo et al., 2008; Park et al., 2012; Zhou et al., 2010). Furthermore, ABM have the ability to measure aggregated impacts of heterogeneous agents, making it a well suited modeling technique for this study.

Given the global differences in flood risk, public adaptation, policy measures and social, cultural, economic and institutional factors influencing adaptation decisions, the data needed to map aggregate impacts varies between countries. Hence, **a case study approach** is applied. Because collecting and analysing all the data is a time-consuming task, a single case study will be conducted.

1.6. Thesis layout

First, the theoretical frameworks is discussed in chapter 2. Next, a case-study was selected: Jakarta, which is examined in chapter 3. In chapter 4, the research methods used to answer the sub questions are discussed and presented in a research framework that will be guide us trough the rest of this thesis. Next, we dive into the case-study of Jakarta to first see how flood resilience in relation to household adaptation behavior could be measured (chapter 5). Secondly, the household adaptation actions an their reducing impact on flood damage is discussed in chapter 6. Thirdly, the decision-making drivers of adaptation behaviour among Jakarta's citizens are discussed in chapter 7. Fourthly, policy interventions influencing adaptation or migration decisions are discussed in chapter 8. Chapter 9 reports the inner workings of the agent-based model according the ODD protocol. After which the experimental design, policy and flood scenario's are discussed in chapter 10. The results of the model experiments are presented in chapter 11, based on which the aggregated impact of policy interventions on Jakarta's household adaptation and migration behaviour, flood resilience and expected flood damage is discussed in chapter 12. Lastly, a model discussion and main conclusion is given in chapter 13 and 14.

2 Theoretical framework

Before we can detail the research methods, we need to define the theoretical frameworks and core concepts our methods build upon. First important key concepts and definitions regarding climate change hazards will be given. Next, the paradigm shift from traditional climate change risk assessments to behaviorally-rich models that couple social and environmental dynamics will be discussed. Followed by an explanation of what definition and framework of flood resilience will be conducted throughout this research. Thirdly with an overview of studies that integrate human behaviour in flood risk assessments by using behavioral-rich simulation models will be given. From these studies a selection of studies focusing on household adaptation behaviour shall be made. For this selection, shall be analysed what type adaptation actions households perform, what decision-making theory is applied, what policy interventions are tested, what key-performance indicators are used to measure the system performance, since these are the main subjects of this thesis. All this information shall lead to the research gap, that will be address in this study to make a scientific and societal contribution.

2.1. Key concepts regarding Climate Change hazards

In this research lots of important concepts regarding climate change hazards are used. To have a clear understanding of their meaning, the definitions according to the International Panel on Climate Change (IPCC) will be adopted for this study. To apply the IPCC definitions on this research on flooding, climate change hazard shall be replaced with *flooding*, see table 2.1.

Table 2.1: IPCC definitions

Concept	Definition
Flood Risk	"have potentially severe adverse consequences for humans and social-ecological systems resulting from the interaction of *flood* hazards with vulnerabilities of societies and systems exposed. Often risk is represented as probability of occurrence of flooding multiplied by the impacts if one events or trends occur." **- vulnerability**: "the propensity or predisposition to be adversely affected and encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt." **- exposure**: "the presence of people; livelihoods; species or ecosystems; environmental functions, services and resources; infrastructure; or economic, social or cultural assets in places and settings that could be adversely affected." **- hazard**: "the potential occurrence of a natural or human-induced physical event or trend that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems and environmental resources."
resilience	"the capacity of social, economic and ecosystems to cope with a hazardous event or trend or disturbance, responding or reorganising in ways that maintain their essential function, identity and structure as well as biodiversity in case of ecosystems while also maintaining the capacity for adaptation, learning and transformation. Resilience is a positive attribute when it maintains such a capacity for adaptation, learning, and/or transformation."
adaptation	"defined, in human systems, as the process of adjustment to actual or expected climate and its effects in order to moderate harm or take advantage of beneficial opportunities. In natural systems, adaptation is the process of adjustment to actual climate and its effects; human intervention may facilitate this."
maladaptation	"refers to actions that may lead to increased risk of adverse climate-related outcomes, including via increased greenhouse gas emissions, increased or shifted vulnerability to climate change, more inequitable outcomes, or diminished welfare, now or in the future. Most often, maladaptation is an unintended consequence."
lock-in	"a situation in which the future development of a system, including infrastructure, technologies, investments, institutions, and behavioural norms, is determined or constrained ("locked in") by historic developments.
risk assesment	"the qualitative and/or quantitative scientific estimation of risks."
risk management	"plans, actions, strategies or policies to reduce the likelihood and/or consequences of risks or to respond to consequences"

Definition come from IPCC, 2022.

The reason for selecting IPCC's definitions in particular is because these definitions are used in international climate change negotiations worldwide. Furthermore IPCC provides governments with scientific information on climate change hazards, which can be used to develop policies (IPCC, 2022). As this study also aspires to produce knowledge useful in policy making for flood risk management, it is important that the definitions used in this study are consistent with those known to policy makers. This will not only increase understanding among policy makers, but also increase the likelihood that the knowledge can be applied.

2.2. Paradigm shift from traditional risk assessments to behaviourally-rich simulation models

The majority of the world population is living in cities (Arup, 2022). People are drawn to cities because of economic opportunities, social activities and innovation. However, cities also know their risk like epidemics, terrorist attacks or hazards. That's why risk assessments and development strategies started to play a more important role (Arup, 2022; Oktari et al., 2020). Since 1950, top-down governmental and public planned flood adaptation measures has been the dominant societal response to flooding (Taberna et al., 2020). Back then, the focus of traditional flood risk management was very much on the prevention and mitigation of floods alone (Colven, 2020; Garschagen et al., 2018; Muis et al., 2015). Traditional risk assessments analysed flooding by looking at expected damages, flood risk probabilities, exposure and vulnerability adjustments (Taberna et al., 2020). Additionally, many research on climate change adaptation focused on public protection measures for which cost-benefit analysis can be performed. Within a cost-benefit analysis a rational consideration and optimisation of factors can be made during making the decision-making process (J. Aerts et al., 2014). However, as the population living in cities kept increasing, the complexity and interconnections of societal systems grew, meaning disruptions like floods started to have more severe consequences. Furthermore, due to climate change, the impact and occurrence of flooding increased rapidly, putting the traditional risk reduction assessments under pressure. That's when the realisation came that flood risk derives from many interactions between element which are part of multiple other systems as well, what can cause disruptions (Conant, 1981). Meaning a flood cannot be seen as isolated phenomenon, but are part of a larger social economical and environmental systems. This insight triggered a shift from traditional risk reduction management, which focused on prevention or mitigation of a specif shock on his own (reductionist perspective), towards a more holistic approach that looks at the overall performance of the system that faces the hazard (systems thinking) (Arup, 2022; Conant, 1981). The way system changes are the result of cumulative societal choices and actions within multiple arenas (Conant, 1981). Thereby, it became acknowledged that interactions between institutions, infrastructures, nature, social networks, economic activities and government interventions could have unforeseeable reinforcing effects, which need to be taken into account in risk reduction management (Arup, 2022; IPCC, 2022; Oktari et al., 2020). Furthermore, it became apparent that human behaviour played a much bigger role in climate change and thus in the development of flood risk than was initially thought (IPCC, 2022). Consequently, human behaviour needs to be integrated into flood risk analyses (Oktari et al., 2020). For a long time studies focused on risk perceptions to explain local adaptation or migration behaviour. However, recent studies found that flood risk perceptions are not sufficient enough to fully understand and explain the local flood adaptation or migration behaviour. Rather social, psychological and cultural values seem to play a more salient role in individual household and community adaptation (Marfai et al., 2015; Noll et al., 2021; Putra et al., 2019; Putro & Zain, 2021). Noll et al., 2021 found that social influences, worry, climate change beliefs, self-efficacy and perceived costs have a significant and similar effects on household adaptations decisions in general, despite countries' differences (Noll et al., 2021). However, local differences in the influence of flood response efficacy, flood experience, beliefs in governmental actions, demographics and social media occur. Since human behaviour and their interaction are complex, this implies a need for more socio-behaviourally rich risk assessment methods as well. As Agent-Based Modeling (ABM) is capable of modeling behaviour and interactions between agents (households), it starts to become a more frequently used simulation tool in flood risk management. However, to use ABM's in the development of resilient flood disaster risk reduction strategies is still in its infancy (Zhuo & Han, 2020). Therefore, there is an important need to keep exploring ABM applications and research in the flood risk management field.

Resilience

Another consequence of this paradigm shift was a change in focus from hazard risk, exposure and vulnerability towards tracing the evolution of resilience (Filatova et al., 2013; Mcclymont et al., 2019). During the Third World Conference on Disaster Risk Reduction in 2015, an international commitment was formed to build societies more "resilient" to disasters (Arosio et al., 2021). As there is a urgent need for resilient flood disaster risk reduction strategies globally (Zhuo & Han, 2020). Through increased scientific and political attention for resilience, a still ongoing debate on the definition and indicators of resilience began (Arosio et al., 2021; IPCC, 2022; Oktari et al., 2020). Originally resilience refers to the Latin word resilio, which means " to jump back"(Arosio et al., 2021). The early definitions used during the traditional risk reduction time, described resilience as the capacity of a system to prepare (before a hazard), response (during a hazard) and recover (post-hazard) from disruptions (see Godschalk, 2003, Cutter et al., 2013 and Tierney and Bruneau, 2007 in table 2.2). These definitions are strongly focused on the hazard, risk and damage, but don't necessary capture the complex interconnected way cities functions or handle disruptions. More recent definitions, define resilience much more from a holistic point of view and apply the systems thinking. The definition of Meerow et al., 2016 for example, not only refers to an urban system in itself, but also to multiple socio-ecological subsystems which are connected via networks and are able to adapt themselves, see table 2.2. Meerow's definition is however strongly focussed on urbanisation, talking about socio-technical rather than the social, economic and ecological systems Zurich Flood Resilience Alliance, 2022 and IPCC, 2022 mention. Since in this research the focus is on the socio, economic and ecological impact of flooding on households and not on the technical aspect of adaptation actions, this definition will not be used. Wheareas Zurrich Flood Alliance uses the words, grow and development, IPCC uses adapt, learn and transform, which can more easiliy be related to household adaptation action. Therefore, eventually the IPCC definition is chosen for this study, as it mentions both the social, economic and ecological systems and their ability to adapt, learn and transform. Another reason for choosing the IPCC definition is that policy makers are familiar with it, since IPCC provides them scientific knowledge on climate change hazards.

Table 2.2: Definitions of resilience

Definition of resilience
A resilient city is "a city that is able to deal with various types of pressure without causing chaos or permanent damage at the time of pressure". Resilient City are designed with the aim to anticipate, survive, and recover from the impact of disasters (Godschalk, 2003)
The resilience and policy committees of the National Academy of Sciences (NAS) defined resilience as "the ability of the system to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" (Cutter et al., 2013).
"the ability of social units (e.g., organizations, communities) to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways that minimize social disruption and mitigate the effects of future disasters" (Tierney & Bruneau, 2007).
"Urban resilience refers to the ability of an urban system-and all its constituent socio-ecological and socio-technical networks across temporal and spatial scales-to maintain or rapidly return to desired functions in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity." (Meerow et al., 2016)
"the ability of a system, community, or society to pursue its social, ecological, and economic development and growth objectives, while managing its disaster risk over time in a mutually reinforcing way." (Zurich Flood Resilience Alliance, 2022)
"the capacity of social, economic and ecosystems to cope with a hazardous event or trend or disturbance, responding or reorganising in ways that maintain their essential function, identity and structure as well as biodiversity in case of ecosystems while also maintaining the capacity for adaptation, learning and transformation. Resilience is a positive attribute when it maintains such a capacity for adaptation, learning, and/or transformation." (IPCC, 2022)

As this study not solemnly aims to define, but in particular wants to measure flood resilience, a literature search on disaster resilience frameworks was performed. It seems, several assessment tool that enables the evaluation of cities' resilience towards climate change impacts of hazards exist, see table 2.3. Each frameworks use different resilience aspects, which are treated as equally important in the resilience assessment. Most of these frameworks could be applied to multiple hazards (Oktari et al., 2020). Indicators of resilience can be used by national and local governments, local authorities, practitioners working in coastal communities, NGO's, academicians, private industries or individuals to measure the current state of city resilience, monitor cities' resilience over time. This is helpful in designing and improving resilience strategies, prioritising action plans and evaluation of policies. In addition, indicators of resilience enable one to compare the social, economic and environmental performance of any city, of any size around the world. Moreover, frameworks of resilience could help to form a common understanding on its indicators and engage civil society, businesses or governments in ideas to make cities more resilient.

Table 2.3: Resilience Frameworks

Name framework	Year	Indicators of resilience
NOAA Coastal Community Resilience Guide	2007	governance, society & economy, coastal resource management, land use & structural design, risk knowledge, warning & evacuation, emergency response, disaster recovery
UNISDR City Resilience Scorecard	2015	”Ten essentials” which cover governance and financial issues (essentials 1-3); many dimensions of planning and disaster preparations, (essentials 4-8); the disaster response itself and post-event recovery (essentials 9-10)
City Resilience Framework (CRF)	2014	Infrastructure and environment, leadership and strategy, health and well-being, economy and society (12 goals, 52 indicators and 156 variable)
Climate and Disaster Resilience Index (CDRI)	2010	social, physical, economic, institutional, natural (25 parameters, 125 variables)
Zurich Flood Alliance	2018	Five Capitals: social, physical, financial, human, natural

*Source.*Arup, 2022; Oktari et al., 2020; UNDRR, 2022; Wan Mohd Rani et al., 2018; Zurich Flood Resilience Alliance, 2022

Looking at the frameworks presented above, we see that resilience can be measures by a lot of different indicators. Whereas the UNISDR City Resilience Scorecard and NOAA Coastal Community Resilience Guide focus more on the phases of a a flood (before, during and after) confirm the traditional risk reduction and old resilience definitions from Godschalk, 2003, Cutter et al., 2013 and Tierney and Bruneau, 2007. The other definitions reflect the broader view of resilience by highlighting aspects confirm the social, economical and ecologial systems in the definitions of resilience from Zurich Flood Resilience Alliance, 2022 and IPCC, 2022. Since in this research the focus is on the socio, economic and ecological impact of flooding on households and not on traditional flood risk planning, one of the broader frameworks will be chosen. The five capitals of Zurich flood alliance show quite some many resemblances to the CRF and CDRI frameworks: human/health and well-being, social/society, physical/infrastructure, natural/environment and financial/economic/economy and strategy/institutional, see table 2.3. However, the City Resilience Framework (CRF) and Climate and Disaster Resilience Index (CDRI) are quit extensive, so implying all these indicators within an flood risk assessment or simulation model would not be feasible. Leaving the Five Capital of the Zurich Flood Alliance framework, which shall be used as a tool to measure flood resilience in this case-study.

2.3. Agent-based models (ABM) on flood adaptation behavior of civil societies

The recognition of the crucial role of human behaviour in relation to climate change risks and resilience of hazard-prone cities, calls for using behaviorally-rich simulation models that couple social and environmental dynamics in flood resilience assessments (J. Aerts et al., 2014). Currently Agent-Based modelling (ABM) is the most suited modelling language used to model human behaviour with interactions (Luo et al., 2008; Park et al., 2012; Zhou et al., 2010). ABM models have been developed to research social phenomena (Macal, 2016). The application of ABM simulations within the field of social sciences has grown significantly since the 1990s (Macal, 2016). This recent vast growing development is due to the significant increase in computing power, which was needed to run such complex behaviourally-rich simulation model (Luo et al., 2008). However, to use ABM's in the development of resilient flood disaster risk reduction strategies is still in its infancy (Zhuo & Han, 2020). A comprehensive literature search on agent-based modeling (ABM) in flood risk management from Zhuo and Han, 2020, only found 61 papers but performed across all continents, although most studies were performed in Europe (UK and the Netherlands), Australia, China or the USA. This implies much more research in this field, also for other countries could be done.

A typical ABM consist of three components; its agents (representations of real-world decision-makers), rules an interactions (which define the behaviour) and the environment in which it interacts(Zhuo & Han, 2020). ABMs are able to simulate this emergent behaviour by checking its own state, the state of others and the environmental influences every time tick (Bonabeau, 2002; Macal, 2016; Pan et al., 2012). Therefore, ABM enables one to deal with more complex individual behavior, including learning and adaptation of agents (Bonabeau, 2002). Due to all the interaction, learning and adaptation abilities of individual agents, ABM is the perfect tool to model households adaptation behaviour, because in reality people learn, interact and adapt as well. Whereas other modeling languages like Discrete Event Simulation (DES), formally rooted in math or System Dynamics (SD), which is based on mathematical differential equations, are less suited to model human adaptation behaviour. DES is mostly used to optimize pre-defined processes, whereas human behaviour is not predefined but emerges based on interactions with its environment or social network (Dubiel & Tsimhoni, 2005). SD works with mathematical equations of stock and flows, so doesn't even consider agents with a certain behaviour or decision-making (Zeigler et al., 2000). Therefore, ABM is a good match, while DES or SD is not. ABM's in particular are useful to simulate situations where individual behaviour can lead to collective outcomes, which cannot be done in aggregated models (Zhu et al., 2019). Meaning migration or adaptation trend could be captured by ABM's as well. Another advantage of Agent-Based Modelling is that it allows each agent to have different personality traits, perceptions, social interactions or possessions (Luo et al., 2008). Using ABM as a tool thus allows use to create such differences between households within the simulation model. This is use-full for this research, as it was found people response different to floods, depend on their experience, background and personal viewpoints (Grothmann & Reusswig, 2006). With the use of an ABM, research question 5: *What is the aggregated impact of policy interventions on Jakarta's household adaptation and migration behaviour, flood resilience and expected flood damage?* can be answered.

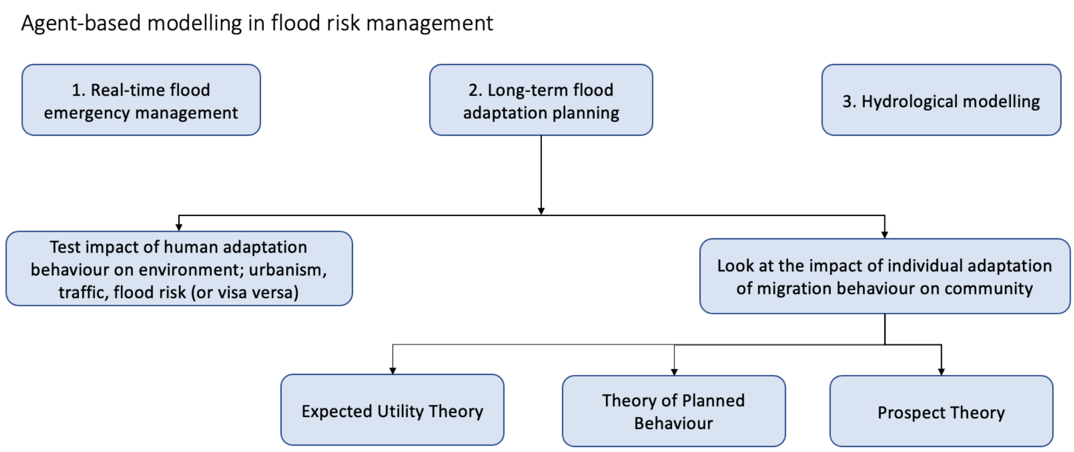

Figure 2.1: Overview of literature on agent-based modeling in flood risk management.

Zhuo and Han, 2020, distinguishes three categories with in the Agent-Based Modeling field of flood risk management: real-time flood emergence management, long-term adaptation planning and flood hydrology modeling, see figure 2.1. The first category, real-time flood emergence management is about human response to immediate flooding, so models flight responses, movements of households, evacuation strategies and warning systems. The second category, long-term adaptation planning, is about public and private adaptation, migration behaviour, policy interventions and developing adaptation strategies. Most ABM's in this field aim to test the effectiveness of rules, regulations or policies that aim to reduce flood risk, while considering its impact on the environment or individuals (Tonn & Guikema, 2018). The third and last category, hydrology modelling focuses more on the water flow, rainfall and storms. As we are interested in emergent patterns of public and private adaptation behavior of civil societies on flood resilience, we investigate the second category.

Within the second category, long-term adaptation planning, we filter on studies that test policies to reduce flood risk and methodically consider socio-economic psychological factors (risk perceptions, social preferences ect.) on household adaptation. The consideration of more complex behaviourally factors is import for these research, as the focus is on the interaction between policies or public protection and private household adaptation, while considering socio psychological influences, for example the levee effect. Basing behavioral rules of agents' decisions, learning and interactions on social theoretical and empirical grounds is preferred as it provides a framework and transparency in the underlying model assumption (Filatova et al., 2013). Furthermore using established behavioural theories reduces the amount of ad hoc implementations and assumptions, which makes a model less prone to subjectivity and biases (Zhuo & Han, 2020). Additionally, the use of social behavioural theories encourages interdisciplinary collaborations, which speeds up the model process and makes it more robust (Zhuo & Han, 2020).

Study	Model aim	Psychological social decision-making theory	Place
Han et al., n.d.	evaluated community adaptation outcomes by simulating agents' risk mitigation decisions under alternative policy scenarios and dynamic storm surges.	Bayesian learning model into the protection motivation theory (PMT) to evaluate households' risk perceptions and adaptive behaviors.	Florida
Tonn and Guikema, 2018	analyse the influence of flood protection measures, individual behavior, and the occurrence of floods and near-miss flood events on community flood risk.	Protection motivation theory (PMT); flood experience, near-miss flood events, socio-demographic factors, neighbours and friends.	North Dakota
Tonn et al. (2020)	enhance understanding of how individual and community-level behavior may influence flood risk in a future climate.	An agent will consider taking adaptation actions if the risk perception and coping perception values exceed specified thresholds (PMT).	North Dakota
Haer et al., 2016	examining the effect of communication on each individual, and how flood risk communication can propagate through an individual's social network.	Protection motivation theory (PMT); social network, self-efficacy, perceived probability and damage, protected area, flood experience, age and income.	Netherlands
Haer et al., 2017	household investments in loss-reducing measures are examined under three economic decision models.	(1) expected utility theory, which is the traditional economic model of rational agents; (2) prospect theory, which takes account of bounded rationality; and (3) a prospect theory model, which accounts for changing risk perceptions and social interactions through a process of Bayesian updating.	Netherlands
Haer et al., 2020	Demonstrate how flood risk and adaptation might develop and can be steered by policies, based on flood risk.	Expected Utility, with rational and bounded rational risk perceptions.	EU

Table 2.4: Studies ABM's with social theoretical foundation on household adaptation behavior under policy conditions.

Looking at studies that consider the effect of socio-economic and psychological interactions on human decision-making, we find several ABM studies, which consider the interaction between flooding, policies and household adaptation decisions and aim to test policy making on household decision-making, see table 2.4. For this of studies selection, is analysed what agents play a role, what type adaptation actions are performed, how they impact flooding, what decision-making theory is applied, what policy interventions are tested and what key-performance indicators are used to measure the system performance, since these are the main subjects of this thesis, see table 2.5

Study	Han et al. 2021	Tonn et al. (2018) & (2020)	Haer et al. (2016)	Haer et al. (2017)	Haer et al. (2019)
Agent	Household	Household, Community	Household	Households, Insurance	Government, Household
Adaptation actions	Elevation, buying insurance	Move, elevation, elevating assets, complain	elevation, wetproofing, adaptive building use, insurance, flood barrier	Take or cancel insurance, loss-reducing measures (water barriers 1m).	Elevation, flood dry-proofing, Insurance. Increase public protection
Impact	Reduced insurance costs, transfer of cost	Information campaign, mitigation project	none	Reduce damage 70% or cost	Reduce flood risk
Decision-making theory	PMT, Beta–Bernoulli Bayesian learning	PMT (rerun every year). If coping and threat > thresholds, action	PMT	EU, PT	Cost-benefit; Proactive, Reactive government. EU; Rational, bounded-rational or no household adaptation.
Decision-making factors	Flood experience, community undertaken actions, risk belief (probability and severity), willingness-to-pay	Treat, coping appraisal, flood experience, near miss floods, socio-economic, neighbors.	Treat, coping appraisal, flood experience, public protection trust, socio-economic, social network.	Utility (house value, cost, discount versus flood probability x loss. Bayesian learning, of social media on flood probability.	Utility (house value, cost, discount) vs. flood probability x loss.
Policy intervention	Flood insurance	Community mitigation	One-size fits all and people centered champagnes focusing on risk or coping appraisal.	Discount	Voluntary or mandatory insurance, with or without discount influencing the cost of measures.
Environment	Stochastic flood, based on flood zones.	Stochastic flood, with GIS data. Depth-damage curve; damage value percentage, which is multiplied by the agent's property value to estimate damage.	No flooding. With or without social network.	Flood risk by Climate change scenario, Inundation map, land-use map, Depth-damage curve.	Stochastic flood.
Key performance indicators	Annual flood damage, total adaptation cost, total insurance cost, discount cost.	Average total damage, number of agents migrated, % token mitigation actions.	Implementation rate (%) on all actions.	Annual flood damage, % took loss-reducing measures.	Annual flood damage, % took elevation or dry proofing.

Table 2.5: ABM's characteristics.

Agents, adaptation actions, impact

Looking at the actions households can perform, both structural and non-structural measures are taken. Structural mitigation focuses on physical constructions to reduce or avoid possible hazard impacts; dykes, dams, buildings, whereas non-structural measures focus on knowledge, public awareness raising, training, and education, evacuation, insurance along with practice or agreements (Buchori et al., 2018). Elevation is the most common structural measure and reduces the flood risk or flood damage of households in almost all agent-based models of table 2.5. Additionally, in same studies elevation lowers the price of buying an insurance, which in itself can transfer or reduce damage costs, see Haer et al., 2017; Han et al., n.d. Other structural measures are elevation of assets and flood barriers also described as dry proofing measures. Non-structural measures are buying insurance or adaptive building use or complaining, which leads to community mitigation projects in the model of Tonn and Guikema, 2018. So in the end, all structural or non-structural lead to risk or damage reduction for households. For this study, only structural adaptation actions shall be considered, since the effect of structural adaptation can be estimated reasonably well from hydrology studies and quantified with the use of a flood damage curve, while the effect of non-structural actions such as complaining about floods, is too difficult to quantify. Insurance will also be excluded from this study, as it only shifts costs from households to insurance companies, while costs are not the focus of this study. Public adaptation will play a role in the model, but shall be tested through scenarios with a focus on the effect of the policy measures on the decision-making process. The effect of campaigns focusing on risk or coping perceptions like in the model of Haer et al., 2016 shall be tested in this study as well, as it directly influences the household adaptation decision-making process. Discounts like in the study of Haer et al., 2020; Haer et al., 2017 on insurance, shall be included in the form of a subsidy on migration or adaptation instead, to explore the importance of the money barrier between the intention to take actions and the actual performance. Thus, this study aims to exploratively examine how households might adapt under various public adaptation options, in order to provide additional insight into the response of household adaptation to government measures. A conscious decision was made not to include the government as an agent in the model in order to keep the scope of study manageable and limited. Therefore, the factors that play a role in the considerations of government public adaptation will be left out as they go beyond the focus of this study, think of the housing market, cost-benefit trade-offs between various government projects, political interests, market values, economic developments of the country and various political interests. Tonn and Guikema, 2018 also includes movement of households in the model, but by assuming that after seven year a households will move after which it is removed from the model and a random household fulfills its place. This study, shall also includes migration, but will base the decision-making on various socio-economical and institutional factors as they play an important role in flood adaptation decision-making (Noll et al., 2021).

Decision-making

Three different decision-making theories are applied within the agent-based models; protection motivation theory, expected utility theory and prospect theory. Both expected utility (EU) and prospect theory (PT) come form a (traditional) economic background. The protection motivation theory (PMT) in contrast comes from social studies and is used to analyze human behavior under risk situations. Starting with expected utility theory, which assumes all agents are rational and posses of full-information about their options, risks and utility, so therefore could choose the most optimal utility (Haer et al., 2017). However, households in flood-prone areas do not posses over full information of future flood risk and loss. Furthermore, the evolution of flood risk depends on public and private adaptation actions and its interactions, which cannot be estimate by a household on forehand. Prospect theory accounts for bounded rationality (limited information availability) in the decision-making process, but still assumes a rational agent who makes a trade-off between the potential damage saved by an adaptation action versus its cost, without consideration of social influences or emotions such as worry (Haer et al., 2017). Contrary, the protection motivation theory considers more emotional responses and allows non-rational responses of agents due to a normalised threat perception, denial of risk, wish full thinking or fatalism (Grothmann & Reusswig, 2006; Noll et al., 2021). Moreover, past experiences, social norms, trust in public protection and various socio-economic differences between households can be included in the protection motivation theory (Grothmann & Reusswig, 2006). This is of importance, as socio-economic and institutional factors play an important role in households adaptation decision-making (Noll et al., 2021). So whereas the expected utility and prospect theory mainly focus on the implementation and effect of adaptation measures itself, confirm the traditional flood risk reduction assessments. The protection motivation theory, on the other hand, considers a broader range of socio-economical decision-making factors and allows non-rational behaviour due to emotional responses, which is needed to capture the adaptive nature of households in flood-prone areas in flood risk assessments. Therefore, the protection motivation theory shall be applied in this study as well. The values of the decision-making attributes can be obtained by performing a survey, which is preferred as also the intervariable relationships between socio-demographic attributes and perceptions for example can be analysed in survey data (Noll et al., 2021). This increases the accuracy of the agent population in a model. The other option is to base agents attribute values on data sets or numbers from institutions, however the relations between variables needs to be estimated then, meaning the model becomes more assumption based (Taberna et al., 2020). Therefore, for this study a case study shall be selected for which survey data confirm the protection motivation theory is available.

Key performance indicators
All studies include flood damage as a key performance indicator (KPI) within the agent-based model. Most studies take the annual flood damage, whereas the total damage is measured as migration is included. Furthermore the percentage of number of agents performing adaptation or migration actions is reported. Within this study these KPI's will be used as well. In addition, key performance indicators measuring the social, economic and human impact of flooding on coastal communities shall be measured as well.

Flooding
Lastly, looking at the way flooding is simulated in the agent-based model, stochastic floods are mostly used. Floods can vary per location, zone or based on GIS coordinated. GIS data in combination with land-use and inundation maps are most precise, however are not always available. In case not much data is available simplifications in flood risk scenario's are made.

2.4. Protection motivation theory

The Protection Motivation Theory (PMT) is developed by Rogers with the original purpose to be applied in the context of health threats (Rogers, 1975). Although later on PMT is more widely applied, for example to explain human response on technological or natural hazards, like flooding (Zhuo & Han, 2020). Depending on the local context of the case-study, extra variables like socio-demographic factors, attitudes, perceptions, norms, flood experience and social networks can be included (see table 2.4). Figure 2.2 shows an overview of individual perceptions playing a role in taking preventive flood protection actions applied to a German case using the Protection Motivation Theory (Grothmann & Reusswig, 2006). The factors of the original PMT-model in figure 2.2 are shown in normal type, whereas italic letters indicate the factors that the authors have inserted, specific to this study.

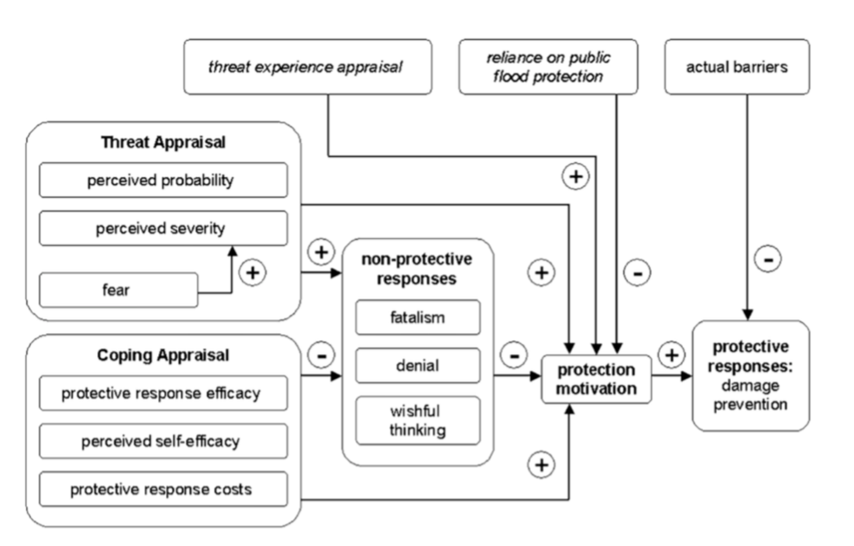

Figure 2.2: Overview of individual perceptions playing a role in taking preventive flood protection actions applied to the Protection Motivation Theory, according to Grothmann and Reusswig, 2006

The Protection Motivation Theory uses two perceptual processes; threat and coping appraisal (Rogers, 1975). Threat appraisal describes one's risk perception of a hazard, which includes a person's perceived threat probability and vulnerability. The coping appraisal describes a person's evaluation on his or hers ability to mitigate and cope with the damage of a hazard, along with the costs of taking measures. Coping appraisal takes place after the threat appraisal process and is only executed if a minimal level of threat concern is reached, because only then people start to ask themselves, whether they are capable of dealing with the threat and what measures they could take to reduce its impact.

Threat appraisal has three subcomponents. Perceived probability is the expectation of being exposed by a threat, such as a flood reaching the house (Grothmann & Reusswig, 2006). Perceived severity is the person's estimate of how harmful the damage of personal properties would be if the threat would actually occur. Fear, the third component, is the emotion that affects the perceived severity of a flood.

Coping appraisal has three subcomponents as well. First, the perceived protective response efficacy, is a person's belief on the effectiveness of protective actions from being harmed by the threat (Grothmann & Reusswig, 2006). Second, perceived self-efficacy, is a person's estimation on his ability to actually take protective measures (e.g., a non-technical skilled person might find it rather difficult to install a water pump system). Thirdly, perceived protective response costs, is the assumed cost in term of money, time and effort of taking action.

Based on the outcomes of the threat- and coping-appraisal processes, a person could have a protective or non-protective response (Grothmann & Reusswig, 2006). Protective responses are those that prevent hazard damage and are taken if the threat appraisal and the coping appraisal are high. Non-protective responses occurs if the threat appraisal is high but the coping appraisal is low, and include three processes: denial of threat, wishful thinking and fatalism. However, whether a person actually performs a protective response, depends on whether a person can turn its intention (protection motivation) into action. Some barriers that could play a role are for example, a lack of resources, time, money, knowledge or social support. The study of Grothmann and Reusswig, 2006 included previous flood experience and reliability of public flood protection as extra variables, influencing the protection motivation.

Lastly, several important feedbackloops play a role in the PMT model of flood preparedness (Grothmann & Reusswig, 2006). The threat appraisal is reduced after people experienced a protective or non-protective response. After a protective response, people experience less flood risk, while after a non-protective response people loss themselves in wishful thinking or denial. In addition, taking protective measures has a positive impact on the coping appraisal.

2.5. Knowledge Gap

To Summarise, due to recognition of the crucial role human behaviour plays in climate change risk development and resilience of hazard-prone cities, there is a need to include human interaction with society and nature, the ability to learn, reorganize and adapt within climate change risk analysis (J. Aerts et al., 2014). As agent-based modeling (ABM) is capable of modeling behaviour and interactions between autonomous and heterogeneous agents (households) and its environment, it starts to become a more frequently used simulation tool in flood risk and adaptation studies (Zhou et al., 2010). However, to use ABM's in the development of resilient flood disaster risk reduction strategies is still in its infancy (Zhuo & Han, 2020).

Therefore, there is an important **need to keep exploring ABM applications and research in designing flood risk management strategies**, as ABM can be used to explore what behaviour outcomes could emerge under various socio-political and environment conditions (Bonabeau, 2002; E. Du et al., 2017). Furthermore, only few flood ABMs **base behavioural rules of agents' decisions, learning and interactions on social theoretical and empirical grounds**. Using established behavioural theories is important as it provides a framework and transparency in the model foundation and reduces the amount of ad hoc implementations and assumptions, which makes a model less prone to subjectivity and biases (Filatova et al., 2013; Zhuo & Han, 2020). It also enable comparison between case-studies worldwide, which increases the general understanding of differences in social, environmental and institutional dynamics of flood risk between countries (Noll et al., 2021). Additionally, the use of social behavioural theories encourages interdisciplinary collaborations, which speeds up the model process and makes it more robust (Zhuo & Han, 2020). The usage of survey data as an empirical foundation is important because it increases the accuracy of distributions and interrelationships between agent's socio-demographics, perceptions and undertaken actions in the model (Noll et al., 2021). **Especially, in Latin-America, Middle East, parts of Asia research on flood adaptation behaviour with a social theoretical and empirical foundation based is scares**, due to (survey) data deficits (Berrang-Ford et al., 2021; Noll et al., 2021).

This study makes a scientific contribution to the above defined literature gaps by **using Agent-based Modeling** to explore the aggregated impact of increasing flood risk, public adaptation measures and policy interventions on household flood adaptation and migration behaviour, flood damage and resilience for a case study in **Jakarta, Indonesia**. **The protection motivation theory** shall be used as **a social theoretical foundation and framework for household adaptation decision-making**, as it allows non-rational behaviour due to consideration of more social, emotional and personal behaviour drivers (Grothmann & Reusswig, 2006). The case-study selection for Jakarta is made based on **available survey data confirm PMT** which is used to assign the agents attributes in an accurate way, see chapter 3. Additionally, ways are explored to stimulate household adaptation and migration behaviour by policy interventions, to inform the local government of Jakarta on the potential impact of policies. This knowledge is **useful in the design of flood management adaptation strategies.** Lastly, **lots of ABM's measure the system performance on flood risk or damage only**, while the increasing uncertainty, frequency, and severity of natural hazards has triggered a paradigm shift from focusing on hazard risk, exposure and vulnerability towards tracing the evolution of resilience (Filatova et al., 2013; Mcclymont et al., 2019). Therefore, this study shall **include five system performance indicators based on the Five Capitals of Zurich Flood Alliance**, that aim to provide better measurement of flood resilience of coastal cities and explore ways in which resilience outcomes could emerge. By establishing key performance indicators for flood resilience that can be used in social simulations to measure the aggregated impact of adaptation actions on flood resilience of coastal cities, this study will make a **scientific contribution** as well. Quantifying the social, financial, physical, ecological and health impacts of household flood resilience is of high relevance because it provides additional information on the self-sufficiency of citizens and the coping and adaptive capacity of society. This information can help policy makers take informed decisions on public adaptation in flood risk management.

3

Case-study Jakarta

3.1. Case study selection

Since the protection motivation theory shall be used as a social theoretical foundation and framework for household flood adaptation decision-making, there is a need for survey data on adaptation and migration behaviour drivers confirm PMT. Noll et al., 2021 developed an extensive survey (N = 4,688) as part of the European Research Council project 'SCALAR', to research contextually differences between flood adaptation decision-making factors among households worldwide, see 4.2.2 for more information. The results of this survey has been made available for my master thesis as well. As Noll et al., 2021 found that the emergence of adaptation behavior is complex, differs locally and is influenced by lots of cultural, socio, environment and institutional factors, there is a need to select a case-study. One case-study shall be performed, due a limitation in time of this master thesis project. Looking at previous agent-based studies in flood risk management focusing on long-term flood adaptation behaviour and policy strategies (see table 2.5), most research was performed in the Netherlands or US (Florida and North Dakota). Therefore, choosing either China or Indonesia for a case-study would be of more scientific relevance. Both Shanghai and Jakarta are within the top twenty of port cities with the highest flood risk in the world so very interesting cases to look at (Hanson et al., 2011). Due to personal interest in the old Dutch colony, I will choice Jakarta, Indonesia, as a case study.

3.2. Case description Jakarta

Jakarta, Indonesia, is also known as the sinking city (Colven, 2020; Garschagen et al., 2018; van Dijk, 2016). Due to its historically well-located trade position and fertile agricultural conditions, Jakarta is located in this very flood-prone area (Garschagen et al., 2018). The flood hazards in Jakarta are driven by rapid land subsidence (currently 5 to 10 centimeters per year), heavy rain showers and the rising global sea level (Garschagen et al., 2018; Hanson et al., 2011). Despite the accelerating flood hazards, urbanization and exploitation of Jakarta continues due to its ever-growing population, which intensifies the pressure on the environment and exacerbates risk even more (Akmalah & Grigg, 2011; Hanson et al., 2011). If no adaptation is considered, Indonesia will become the most affected country by coastal floods in 2100, with approximately 5.9 million people being exposed to floods annually (Mcleod et al., 2010). To reduce the number of people adversely affected, flood risk management strategies stimulating both public and private adaptation must be considered as it has the potential to reduce the projected damage by 68 to 99% (Mcleod et al., 2010). As the impact of flood adaptation could make such a significant impact, Jakarta is a very interesting case-study to look at. Flood adaptation is already happening at various levels, from bottom-up citizen and community adaptation to top-down government-led adaptation (Neil Adger et al., 2005; Yoga Putra et al., 2019). Yet, currently household adaptation is lagging behind and is not sufficient to keep up with the increased risk of flooding (Marfai et al., 2015). Passivity of households is worrying, as the increasing threat of flooding call for rapid and ambitious flood adaption actions at all levels to prevent Jakarta from destruction (Akmalah & Grigg, 2011; Bott et al., 2021; Bucx et al., 2015; Esteban et al., 2017; Garschagen et al., 2018; Hanson et al., 2011; Mcleod et al., 2010; Muis et al., 2015; Taylor, 2015). Therefore, there is a need for policy interventions that support the bottom-up adaptation actions taken at household level (Bott et al., 2021; Sunarharum et al., 2014). This study aims to explore ways to stimulate household adaptation by polici stimuli, by first creating a better understanding of the decision-making process and adaptation and migration drivers itself, to gain more insides in policy influences as well. This knowledge could be used in the development of flood management strategies for Jakarta.

Concerns over the sustainability of the congested rapidly sinking political center of Jakarta already prompted the need for a new capital named Nusantara, located in a jungle-covered area on the east of Borneo island (CNN, 2022). The relocation of the capital is based on regional advantages and opportunities for birth of a new economic centre and welfare (CNN, 2022). However, due to the importance of a careful consideration of the environmental impact of the development of the new capital on 256,143 hectares (around 2,561 square kilometers) of forest area, the project is still under debate (CNN, 2022). At the same time, plans for building a gigantic sea wall also known as the National Capital Integrated Coastal Development plan (NCICD) are currently on the table, making this study even more relevant and interesting to look at. The NCICD includes the construction of a giant sea wall, located north of the bay in Jakarta, which must protect Jakarta against floods from sea (Garschagen et al., 2018). The gigantic sea wall (47 kilometer-wide) will be built in the form of a Garuda, a mythical large bird which is the national symbol of Indonesia (Adi Renaldi, 2022). Inside the wall large lagoons will be constructed, serving as a water buffer in case of heavy rainfall or river flooding and water reservoir for clean water for the entire city (Adi Renaldi, 2022). Additionally, the existing dikes will be strengthened, a pumping system and a water treating system will be installed (Adi Renaldi, 2022). The surrounding areas will be used as a harbor, industry and business area, including an airport. The costs of the project are estimated on 20-58 billion dollar financed by an international collaboration of the Dutch and Indonesia government (Adi Renaldi, 2022). The completion of the project is estimated in 2030. However, the gigantic sea wall is heavily debated because of the enormous environmental and social impact with irreversible consequences (Garschagen et al., 2018). Therefore, this study will explore the impact of the gigantic sea wall on household adaptation behaviour, to provide some more insight in the often overseen indirect consequences.

4
Methodology

This chapter shows how the theories, concepts and tools discusses in chapter 2 will be used in this case-study to address the defined research gap. Throughout the entire report of this master thesis, the modeling and simulations steps from the book ”Agent-Based modeling of socio-technical system” by K. H. Dam et al., 2013 are used as a guidance to structure the model development. In section 4.1, the research framework of this mixed-method study is described according to the model and simulation phases. Figure 4.1 shows an overview of the research framework for this study. In this framework the main research question and its sub question are presented, together with the applied method to address these questions. In section 4.2 a description of the survey data and floodmap data is given. Additionally, the data processing is described.

4.1. Research flow

Problem formulation and actor identification. To identify the main research question, research scope and theoretical framework, multiple literature researches on Scopus were performed. The academic license for students provided by the TU Delft is used to access academic papers. Starting with a literature search on flood adaptation to get a feeling for the topic, with the following search term: (flood OR flooding OR floods) AND (household adaptation OR human adaptation OR private adaptation) AND (public adaptation OR policy). The abstract of ten most highly cited sources were analysed. The main take-away from the first search was that a combination of public and private flood adaptation reduces flood risk the most, but trans formal household adaptation often stays out. That’s why a second a literature search on adaptation drivers for Jakarta specific was conducted, with the following search term (Jakarta OR Indonesia) AND (household adaptation OR community adaptation) AND (decision-making OR drivers OR factors). The ten most relevant and recent papers were analysed in more detail by scanning the abstract, introduction, discussion and conclusion. Thirdly, the report of IPCC, 2022 was analysed to identify and investigate key concepts of climate change adaptation of hazards (see section 2.1). After this, a literature search was performed on resilience in particular, with the following search term (Climate change OR hazard OR disaster) AND (resilience) AND (framework). The five most relevant sources were analysed. Additionally some resilience frameworks were tipped by my supervisor, which were investigated in detail. Fourthly, a more specific literature search on flood ABMs was performed, with search term (flood OR flooding OR floods) AND (agent-based OR agent based modeling OR ABM). By performing this search, the extensive literature review on ABM’s in flood risk management from Zhuo and Han, 2020 came up. This study served as a theoretical basis from which multiple ABM studies were analysed according to the snowball effect. Additionally many good sources (35+) were recommended by my supervisor professor Tatiana Filatova, who is an expert in the field of flood ABMs. The recommend papers were read in detail. Lastly, some online meetings and email contact with professor Budhy from the Institute of Technology in Bandung were done, to get a local insight on flood adaptation and policies in Jakarta.

Research scope This study aims to improve the understanding of flood resilience development, through a combined analysis of the behavioral, policy engineering and physical hazard components of flooding. As discussed in the research gap 2.5, the focus of this study lies on the household adaptation behaviour component. The simulations of flooding is not an inherent component of the system, but is treated as an external influence from the environment, as not enough data on local water levels was available to capture the interaction between households and water levels. The simplification of floods is acceptable, as the focus of this study is not on the hydrological aspects, but on the effect of a flood threat and exposure on the adaptation behaviour of households. Policy interventions, are treated as external influences as well, as the focus of this study is on the effect of policy measures on household adaptation and not on the trade-offs made by governments themselves. The government is thus not an actor in the system and the factors that governments consider in policy-making are outside the scope of this study. After the scope was set, the system identification and decomposition began.

System Identification and Decomposition. Starting with the measurement of flood resilience itself (SQ1). The Five Capitals of Zurich Flood Alliance is used as a theoretical framework to operationalise five key performance indicators from the available survey data from research by Noll et al., 2021. The reason for selection of the Five Capitals as a theoretical framework can be found in section 2.2. First, desk research on the Five Capital framework of Zurich Flood Alliance was done. After which the Five Capitals were matched on survey data variables from Noll et al., 2021. To validate the selected survey variables per capital, a meeting was organised with Tatiana Filatova and PhD'ers Brayton Noll and Alessandro Taberna in which the capitals were discussed. The five established resilience capitals serve together with the total flood damage and percentage of token adaptation measures within the agent population, as the performance indicators of the ABM. Secondly, the impact of household adaptation actions on flooding was established (SQ2). First, the local flood adaptation actions performed by households in Jakarta are identified within the available survey data. Only adaptation actions for which survey data is available were considered, in order to make an empirically based flood ABM. Next, the floodmap data was analysed and cleaned to see what data would be available to simulate flooding, see section 4.2.1 for more information. Since only the flood height in meters from 2020 was of use and it is important to search for a country-specific flood damage curve because the impact of floods varies globally (Huizinga et al., 2017), desk research on a depth-damage curves for Jakarta households in particular was performed, using literature recommended by my supervisor professor Tatiana Filatova. After this, desk research in the impact of household adaptation actions on flood damage curves was done. Subsequently, a selection and combination of the survey data adaptation actions was made for which the reducing impact on flood damage could be determined. Lastly, a case-specific flood damage curve for Jakarta with the selected flood adaptation actions was created and discussed in one of the regular team meetings at TU Delft for validation. This flood damage curve is used to shape the interaction between floods and households with in the agent-based model. Thirdly, there is the behavioural component, capturing the influence of social, policy and environmental factors on adaptation decision-making of households (SQ3). First, a literature search on flood adaptation drivers and barrier for Jakarta households was performed, to identify the decision-making factors that play a role in adaptation and migration behaviour in Jakarta specifically. This is important as we learned that adaptation drivers and barrier differ locally (Noll et al., 2021). Next, the survey data was analysed and cleaned to see what data would be available to simulate household adaptation behaviour, see section 4.2.2 for more information. Subsequently, a search in the available survey data was done to match the survey questions with the decision-making factors confirm the Protection Motivation Theory. Only decision-making factors out of literature for which survey data was available were selected to be able to make create an empirically based flood ABM. Next, a conceptual model on the decision-making process of household adaptation in Jakarta, with integration of the selected survey data variables confirm the protection motivation theory was made. Therefore, the framework of PMT is extended with the identified adaptation drivers for Jakarta households specifically. To formalise the conceptual model, the data distributions and survey questions of the selected survey data were analysed and described in Appendix A. To find out what role the decision-making factor play in adaptation behaviour, a Logit regression analyse is performed. The output of the Logit regression analyse are regression coefficients for all identified decision-making variables, which are used to calculate the agents intention per adaptation action, see appendix B. Fourthly, policy interventions that could influence the household adaptation or migration decision-making are identified (SQ4). First a literature search on policy interventions affecting household's adaptation and migration response in facing flood hazards and their influence was done. Based on these founding, several policy interventions were operationalised to use during the experimentation of the ABM model. The impact of the policy policy measures were estimated, as no qualitative data on this was found.

Conceptualisation and Model formalisation. Now that the system components are identified, conceptualised and formalised, a first conceptual agent-based model can be created, using flow chart diagrams as a tool. To validate and improve the conceptual model, regular meetings with the research team of Tatiana Filatova working on flood ABMs on TU Delft were held to discuss the model progression. After a consensus on the conceptualisation was reached, the conceptual model was transferred into a formal model, described in pseudo code. Lastly, the conceptual and formal model were described confirm the ODD protocol, to standardize the agent-based model description and to increase the understandably (Grimm et al., 2020).

Software implementation and model verification. Next, the formal model is transformed into a computational model. The software Agentpy, a Python-based modeling and simulation tool, is used to create the ABM model and run experiments. Agentpy can be run through Jupiter Notebooks and is designed to ingrate packages like numpy, scipy, networkx, pandas, ema workbench, seaborn, and SALib (Foramitti, 2021). The code is build up step by step through continuously adding separate model component to keep the code manageable. After adding a model component, each model component is verified by performing test runs, in which the model attributes of interest are reported. In this way a continuously verification of the model workings is done.

Experimentation. To be able to test the influences of policy interventions on household adaptation behaviour under flood risk, the designed agent-based model was used to conduct simulation experiments. In the experimental design, an XLRM diagram was used; designed to structure experiments that test different policy levers under exogenous uncertainties. First, various flood risk and policy strategies were designed under which the model performance are tested. Both the direct influence of policy interventions on household adaptation decision making and the indirect effect of public adaptation on household flood risk were investigated in an exploratory manner. As no survey data on the influence of the policy interventions on the decision-making variables confirm PMT is available, its impact was estimated. However, since lots of uncertainty is involved in making these estimations, a sensitivity analysis was performed to see if a variations in the size of the policy effects cause a significant difference on household adaptation and migration behaviour. Furthermore a sensitivity analysis on the water level rise per year was done, as this is an uncertain external environmental factor as well. All experimental runs were performed a hundred times with a fixed random seed, to allow variation but maintain reproducability of the model runs. The experiments were ran sequentially on the TU Delft Supercomputer DelftBlue for improved computational power and speed. To be able to run the experiments on the TU Delft Supercomputer, a batch code was designed to upload the computational model and experiment file, using a TU Delft Net-ID to get excess in the first place. After the runs were completed, the experimental results were transferred to a personal TU Delft account. The software Agentpy, provided tools for parameter sampling, Monte Carlo or Latin Hypercube experiments, stochastic processes and sensitivity analysis, which we were used throughout the experimentation.

Data analysis - results. In this phase, the experimental outcomes were analysed using Jupiter Notebooks in Python. First, the mean of the hundred performed samples per experimental run were calculated and reported in Appendix C.1. Secondly, the results on the experienced flood damage, the undertaken adaptation and migration actions and five capitals of resilience were described for all flood scenario's but no policy interventions. Lastly, the experimental results of all policy interventions under all flood scenario's were described.

Model use - policy advise. The experimental results are used to write a policy advise for the Jakarta Government. In this policy advise, the aggregated impact of public and private adaptation is analysed (SQ5), to see under what socio-environmental policy conditions a lock-in situation of vulnerability and risk, stimulation of adaptation and migration behaviour and positive or negative flood resilient development in Jakarta could emerge.

Conclusion In the last section, the insights from the result, policy advise and discussion section are combined, to answer the main research question. Furthermore, the scientific and societal impacts of this study is discussed.

Model validation - discussion. In the discussion section, the model and experimental results are validated. The designed agent-based model and its components are compared to the existing knowledge on flood ABM's, see section 2.3. Lastly, suggestions for future research are given.

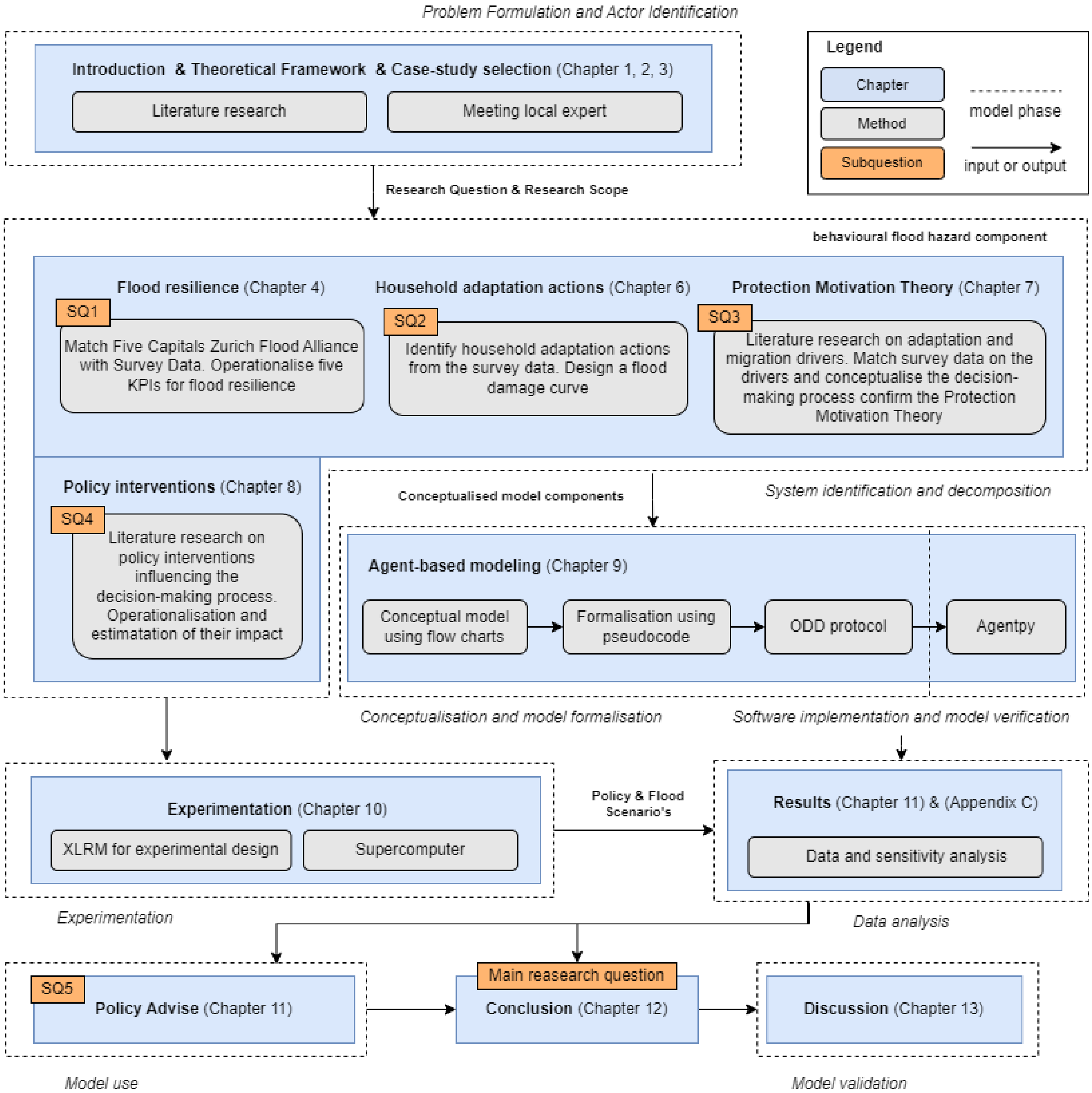

Figure 4.1: Research diagram

4.2. Data sources

Two important datasets were used in this study: 1) Flood height data on Jakarta DKI, section 4.2.1 and 2) Survey data on household flood adaptation actions and drivers, section 4.2.2. For each dataset, first a general description of the dataset itself is given. Secondly, the data cleaning is explained. In appendix A the selected survey data questions, mean and standard deviations can be found.

4.2.1. Jakarta Flood height data

The available data on flooding was obtain via Budhy, Professor on the Institute of Technology Bandung and adviser of the Jakarta government. The data can be sorted per district; Jakarta Barat, Jakarta Seletan, Jakarta Utara, Jakarta Timur and Jakarta Pusat, but also on sub-district or village. The smallest spatial unit is Rukan-Warga (RW), which is comparable to a large neighborhood. In total, information on 3365 (RW) in the province DKI Jakarta is available. The data-set contained information on whether neighborhoods in Jakarta were flooded (YES or No) in the year 2013, 2014, 2015, 2016, 2017. Furthermore, a vulnerability score is assigned to each neighborhood, but it is unclear how the vulnerability is measured and on what scale. Therefore, this data is not used. Most importantly, there was data on the maximum measured flood height in meters for the year 2020 and 2021, which is used to simulate flooding. However, the information on 2021 was incomplete (only half a year was measured) so therefore is was decide only to use the 2020 data. The flood height measured during flooding in 2020 is used to develop three flood risk scenario's in chapter 10, which shall be used to explore the impact of actual flooding on household adaptation and migration behaviour.

Data preparation

First, the raw data was loaded in Jupyter Notebook, after which the columns, response numbers and data types per column were analysed. Since only the flood height data from 2020 was complete and useful for simulation of flooding, the flooded (YES or NO) columns for the year 2013, 2014, 2015, 2016, 2017, the vulnerability scores and the incomplete flood height data of 2021 were deleted. Leaving a dataset containing the columns Province, District, Sub-district, Village name, Rukan-Warga (RW) and flood height 2020. To be able to link the flood height data with GIS coordinates for a valid spacial distribution of the water heights, first a shape-file with detail level RW for Jakarta DKI was found on Perkumpulan OpenStreetMap Indonesia, 2022. The shapefile contained information per RW on the municipality, province, district and village it was located in. Though a quick check between the shapefile and flood height data on corresponding county, district and village names, some syntactic differences in the village names were spotted. By first merging the shapefile and flood height data on RW and village names and analysing the missing links, the syntactic errors were traced. The syntactic errors were fixed manually, like changing "Rawabadak Utara" into "Rawa Badak Utara". After all syntactic errors were resolved, the shapefile could succesfully be matched on the flood height data. Through merging the shapefile from Open Street Map onto the flood dataset, all RW were given a geometry (GIS); a latitude longitude coordinates, which made it possible to plot flood heights on a map. So finally, a visualisation of the water heights measured during flooding in 2020 was made to provide spatial insight.

4.2.2. Survey data on household adaptation and migration behaviour for Jakarta

Noll et al., 2021 developed an extensive survey (N = 4,688) as part of the European Research Council project 'SCALAR', to research contextually differences between flood adaptation decision-making factors among households worldwide. The survey data contained 365 columns on socio-demographics or economic attributes, perceptions, norms, undertaken adaptation actions, flood experiences and adaptation intentions, used to explore adaptation drivers and barriers confirm the protection motivation theory. The survey was launched in March-April 2020 and spread among households in flood-prone coastal cities in the United States (Miami, Houston, New Orleans), China (Shanghai and surrounding area), Indonesia (Jakarta and surrounding area), and the Netherlands (Rotterdam, Dordrecht, and towns in the Zeeland province). Only one member per household was allowed to participate in the survey. There was a small under representation of elderly and an over representation of highly-educated people, for which is controlled in the analysis to avoid a bias in effect due to a squid distribution.

Data preparation

First, the raw survey data provided by Noll et al., 2021 for Indonesia was loaded. The number of responses was (N = 2061) in total, for Jakarta and surrounding areas. However, as Jakarta is the only city of interest, the data base needed to be filtered. Since all survey respondents where asked to fill in their postcode, a spatial selection based on postcodes could be made. Therefore, first a search on the internet on the postcode range for Jakarta DKI was done. Through this search the site Normor, 2022 was found, were the 'kodepos' (postcode) for all village names in Jakarta were found. It was found that the postcode range for Jakarta DKI lies between 10110 - 14540 (Normor, 2022). Analysing the postcode range of the survey data, it was found that half the data came from Jakarta and the surrounding urban area (postcodes between 10100 - 18000). Whereas, the other half of the survey data come from another city, with postcodes between 60100 - 72000. A search on the internet for postcode Indonesia 60000, revealed that the other city was called "Surabaya", which is located on the other site of the island Java, 780 km away from Jakarta (Cybo, 2015). By merging the survey data with the merged flood height data and shapefile of Jakarta (containing the GIS coordinates for Jakarta DKI), the survey responses could be filtered. In total 633 survey responses from Jakarta DKI were left for which both survey data and the flood height data per postcode was available. The last rows of the data set contained some empty rows, data type NaN. As empty data is not of use, the NaN values were dropped. After dropping the NaN values, 647 responses remained. With this dataset (N = 647), a Logit regression analysis is performed to obtain the Logit coordinates of all decision-making factors of interest for Jakarta households according to PMT, see chapter 7. An overview of the used survey questions per variable, its response option and mean is given in appendix A.

5

Flood resilience Jakarta

In this chapter ***SQ1****: How to measure flood resilience of coastal communities in Jakarta?* will be answered.

The structure of the chapter is the following. First, the Five Capital framework of Zurich Flood Alliance is briefly discussed in section 5.1. After which, in section 5.2 the Five Capitals are operationalised into Key Performance Indicator based on survey data from Noll et al., 2021. The reason for selection of the Five Capitals as a theoretical framework can be found in section 2.2. In the end, the operationalised five capitals serve to score and compare the experimental model outcomes on flood resilience.

5.1. Five Capitals of Zurich Flood Alliance

Zurich Flood Alliance distinguish five capitals of flood resilience, see the description of these capitals in figure 5.1. These five capitals characterize the assets of a community and resources that sustain of improve a communities' well-being, collective wealth, provide a sense of security and environmental stewardship (Zurich Flood Resilience Alliance, 2022). The indicators associated with the Five Capitals are presented in table 5.1.

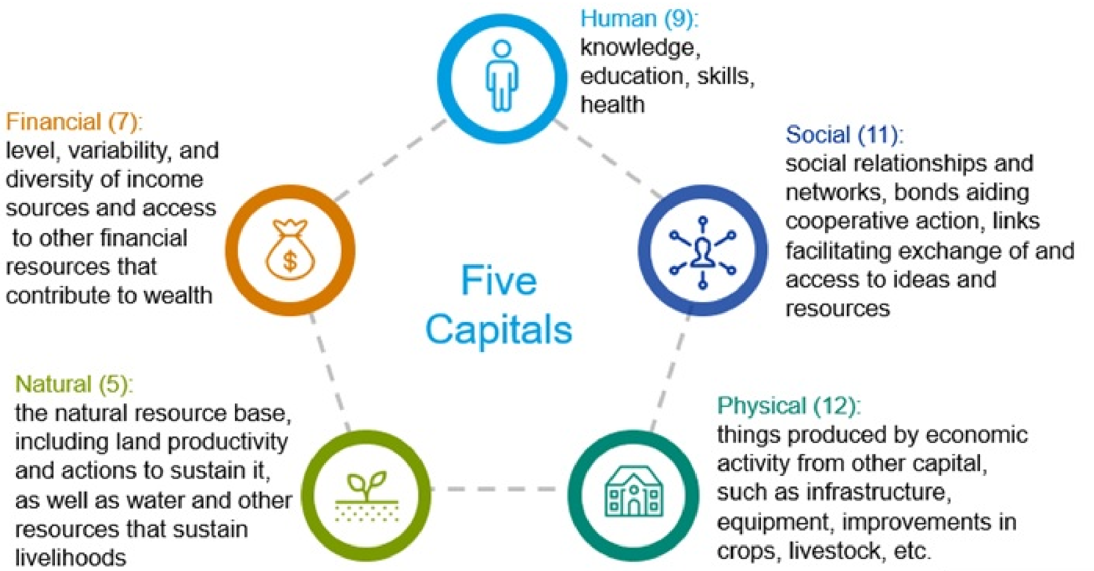

Figure 5.1: Five Capitals - Zurich Flood Resilience Alliance, 2022

Table 5.1: Five Capitals indicators

Capital of resilience	Indicators
I. Human	the educational level, political awareness, environmental awareness, flood exposure perception, personal safety, flood protection knowledge, vulnerability perception and health status
II. Social	social participation in flood management, community initiatives, social norms, social support in supplies, information sharing and coordination
III. Physical	communal living facilities, such as excess to healthcare, education, transport, food security and energy sources, but also by individual household flood vulnerability management
IV. Nature	habitat connectivity, sustainable use of natural resources, basin health, natural habitats maintained for flood resilience and nature legislation
V. Financial	household savings, income, affordability, insurance, job opportunities and a social safety net

Source.Zurich Flood Resilience Alliance, 2016

5.2. Flood resilience indicators for Jakarta

For each capital, several survey data variables within the scope of this study were selected to act as indicators for the selected capital, in order to measure the aggregated flood resilience in Jakarta. Only the defined factors from section 5.1 for which survey data was available were included to maintain an empirically based background. In table 5.2 an overview of the operationalisated five capitals are shown. Also, the term based on which the survey data was matched are presented.

Table 5.2: Operationalised flood resilience indicator for Jakarta, based on the Five Capitals

Capital of resilience	Indicators	matched on
I. Human	education climate change belief worry	*education level* *political awareness, environmental awareness* *flood exposure perception, personal safety, vulnerability perception*
II. Social	social support social network	*social support*) (*social norm, social participation, information sharing*
III. Physical	token adaptation measures	*individual household flood vulnerability management*
IV. Nature	flood occurrence	-
V. Financial	economic comfort financial support governmental support savings flexibility income level	*affordability* *insurance* *social safety net* *household savings* *income*

The Human Capital consists of the education level, CC belief and worry of households. The health aspect of the human capital was neglected as no significant influence of health on adaptation behaviour in literature was found, see section 7.1. The Social Capital is defined by its social support and its social network. The coordination and community initiatives falls out of the scope of this study, see 4.1. The Physical Capital contains all token flood adaptation action of households in Jakarta. The communal living facilities were not included in this study as this falls out of this study. The Nature Capital is described by the average number of times households get flooded. Lastly, the Financial Capital is measured by a households level of economic comfort, financial support, governmental support, savings flexibility and income level. See appendix: Survey Data A, to find out how these indicators are measured. Per capital, the mean value over all households living in Jakarta will be reported as an KPI in the ABM.

6

Household flood adaptation actions

In this chapter ***SQ2****: What household adaptation actions are performed in Jakarta and how do they reduce flood damage?* will be answered.

The structure of the chapter is as follows. First, the identified local flood adaptation actions of households in Jakarta from the survey data by Noll et al., 2021 are presented in section 6.1. Next, the main findings of the desk research on flood damage curves for Jakarta households and the impact of adaptation actions on depth-damage curves are discussed in section 6.2. Subsequently, the operationalisation of adaptation actions for this study is explained. Lastly, the designed flood damage curve for Jakarta households with the identified adaptation actions is presented.

6.1. Household adaptation actions confirm survey data

There are several adaptation actions a household can take, varying from high-effort structural measures like raising the ground level, reconstruct walls to low-effort non-structural information like asking information or buying emergency water barriers. Noll et al., 2021 identified 18 household adaptation actions which can be found in table 6.1. To provide an empirically based flood ABM, the household adaptation action are based on survey data.

Table 6.1: Adaptation actions confirm survey data

Structural adaptation measures
- Raising the level of the ground floor above the most likely flood level. - Strengthen the housing foundations to withstand water pressures. - Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials. - Raising the electricity meter above the most likely flood level or on an upper floor. - Installing anti-backflow valves on pipes. - Installing a pump and/or one or more system(s) to drain flood water. - Fixing water barriers" (e.g., water-proof basement windows).
Non-structural measures
- Keeping a working flashlight and/or a battery-operated radio and/or emergency kit. - Purchasing sandbags, or other water barriers. - Buying a spare power generator to power your home. - Being an active member in a community group aimed at making the community safe. - Coordination with the neighbors. - Installing a refuge zone, or an opening in the roof of your home or apartment. - Storing or placing important possessions in such a manner to avoid flood damage. - Asking information about flooding and emergencies at local government, Civil Defense, etc. - Asking/ petitioning government representative to increase the public protection measures. - Storing emergency food and water supplies. - Moving/ storing valuable assets on higher floors or elevated areas.

Note. Actions come from Noll et al., 2021.

The distinction between structural and non-structural actions was made, since adaptation measures vary in effort and costs, which could trigger different decision-making pathways (Noll et al., 2021). Structural adaptation actions (7) usually involve high-effort measures with irreversible modification to one's home, whereas non-structural measures (11) generally entail low-effort measures with temporary protection or communication actions (Noll et al., 2021). Since this study focuses long-term physical adaptation actions, only the structural measures are considered. Moreover, the effect of structural adaptation can be estimated based on hydrology studies by means of a flood damage curve, while the effect of non-structural actions such as complaining about floods, is too difficult to quantify.

6.2. Literature on flood damage curves for Jakarta households

Since flooding differ locally, a case-specific depth-damage curve is needed (Huizinga et al., 2017). Therefore, a depth-damage curves for Jakarta households in particular was searched. The study of Budiyono, 2018, recommended by my supervisor Tatiana Filatova, contained a depth-damage curve for Jakarta for an inundation depth up until 5 meters. As the available flood height data from 2020 had a range between zero and five meter, Budiyono, 2018's flood damage curve matches perfectly. Budiyono, 2018 found that the flood damage percentage for Jakarta households increase up until 0.6 within the first 2.0 meters of water (linear regression), after which the damage remains sixty percent. Generally, depth-damage curves are used to calculate the economic damage of flooding Budiyono, 2018. However, as we saw in section 2.3 from studies of Haer et al., 2017; Tonn and Guikema, 2018, flood depth-damage curves can also be adjusted to quantify the effect of household adaptation actions. Therefore, desk research on the reducing impact of household adaptation actions on flood damage curves was done. The thesis of (F. Dam, 2021), recommended by Tatiana Filatova as well, researched the effect of both public and private adaptation actions on flood damage curves. F. Dam, 2021 categorised the adaptation actions by measure type (structural, non-structural or nature-based solutions) and reduction type (consequentially or probabilistic), see table 6.2. Even though the same distinction between structural and non-structural actions is made, F. Dam, 2021's definition differs from Noll et al., 2021's. F. Dam, 2021 identifies structural adaptation with infrastructure projects (both private and public) and non-structural with activities and policy, while Noll et al., 2021 distinguished the actions based on effort and costs.

Table 6.2: Flood adaptation action by F. Dam, 2021

Measure type	Measure	Reduction
Non-structural adaptation	Spatial relocation	Consequence
	Early warning system	Consequence
Structural adaptation	Levee system	Probability
	Landfill	Probability
	Water retention	Probability
	Temporary barrier	Probability
	Dry proofing	Consequence
	Wet proofing	Consequence
	Elevating buildings	Consequence
Nature-based solutions	Delay rainwater runoff	Probability
	Living shoreline	Probability

Source. Actions come from F. Dam, 2021

Since we aim to identify the effect of structural household adaptation actions, the nature-based solutions, the early warning system, landfill and water retention fall out of scope because these are public adaptation actions. Based on the same reasoning, the temporary barrier will not be included in this study as the focus is on structural measures. Leaving elevation, wet proofing and dry proofing. According F. Dam, 2021, elevating buildings prevents flooding up to 1 meter, after which the original flood damage curve portraits the same pattern, but only 1 metre higher. Dry proofing prevents flooding up to 1.5 meters by means of flood walls, sealed windows or doors that serve as water barriers, after which it reverts to its original function (F. Dam, 2021). Wet proofing on the other hand reduces the original damage by forty percent up to 3 metres, by creating spaces in which the water is allowed to get in or effectively deal with its consequences (F. Dam, 2021).

6.3. Operationalisation of household adaptation actions

Now that the households adaptation actions with the survey data are identified, a flood depth-damage curve for Jakarta households is found and the reducing effect of structural adaptation actions is known, the operationalisation of adaptation for the ABM can begin. In table 6.3 the structural adaptation actions from the survey are placed within the adaptation categories from F. Dam, 2021, so that the reducing impact on flood damage can be determined. Additionally, a search for the cost of elevation, dry proofing and wet proofing measures was done, but with no success. However, a study by (J. C. J. H. Aerts, 2018) was found, estimating costs for several other countries, including Vietnam. As Vietnam is a close country and with a similar economy to Indonesia, those costs were adopted as an estimation for Indonesia as well. J. C. J. H. Aerts, 2018 reported the costs in Dollar, but since the currency of Jakarta is Rupiah, the costs are reported as such as well. Elevation is most expensive, followed by dry proofing and lastly wet proofing.

Table 6.3: Operationalised structural household flood adaptation actions

Measure type	Measures	Reduction	Cost
Elevation	- Raising the level of the ground floor above the most likely flood level	prevents flooding up to 1 meter	31.1 * $10^6 Rupiah$
Dry proofing	- Strengthen the housing foundations to withstand water pressures - Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials - Fixing water barriers" (e.g., water-proof basement windows)	prevents flooding up to 1.5 meters	13.5 * $10^6 Rupiah$
Wet proofing	- Raising the electricity meter above the most likely flood level or on an upper floor - Installing anti-backflow valves on pipes - Installing a pump system to drain flood water	40% up to 3 meters	3.7 * $10^6 Rupiah$

Source. Measure type confirm F. Dam, 2021, Measure confirm survey data Noll et al., 2021, Reducing impact from F. Dam, 2021. Costs from J. C. J. H. Aerts, 2018.

6.4. Flood damage curve for Jakarta household adaptation

Lastly, a case-specific flood damage curve for Jakarta with the selected flood adaptation actions was created based on section 6.2, see figure 6.1. This flood damage curve is used to shape the interaction between floods and households with in the agent-based model. Undertaking adaptation actions reduces the experienced flood damage confirm table 6.3. Only the single adaptation effects are shown. However, the combinations of adaptation actions are possible and more effective.

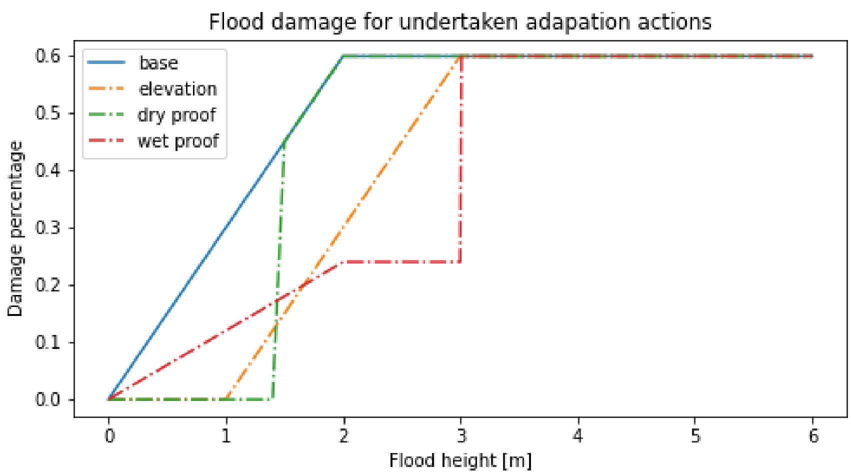

Figure 6.1: Flood damage percentages per adaptation action

7

Adaptation decision-making of Jakarta Households

In this chapter ***SQ3****: What factors influence Jakarta's household adaptation decision-making and what is their impact?* will be answered.

The structure of the chapter is as follows. First the results of a literature search on flood adaptation drivers and barrier for Jakarta households are presented in section 7.1. Secondly, the operationalisation of the adaptation drivers from literature is discussed in section 7.2. Thirdly, the conceptual model of the decision-making process is shown in section 7.3. Here, also the decision-making factors are discussed. Lastly, the Logit regression analysis can be found in section B.

7.1. Literature on adaptation drivers and barriers of Jakarta households

To identify the decision-making factors that play a role in adaptation and migration behaviour of households in Jakarta specifically, a literature search is performed. This is important as we learned that adaptation drivers and barrier differ locally (Noll et al., 2021). It was found that the willingness to stay, adapt or migrate varies among households in Jakarta, depending per location on the severity of flooding, vulnerability level and household capacity to respond and adapt (Buchori et al., 2018; Raleigh & Jordan, 2008). The capacity of households from local communities in Indonesia to adapt to flooding, seems to be based on experience, participatory capacity, shared knowledge and self-organization abilities (Bott & Braun, 2019; Buchori et al., 2018; Kapiarsa & Sariffuddin, 2018). Furthermore, the kind of adaptation measures taken by households dependent on economic considerations, which varies per household (Marfai et al., 2015). Generally, the costs of building additional floors are considered very expensive, whereas raising the levels of houses is medium expensive and the costs for building small water barriers are considered relatively low in Indonesia (Marfai et al., 2015). Nevertheless, all types of adaptation measures can taken by households regardless of their income, as low-income households make use cheaper or re-used materials (Marfai et al., 2015). Additionally, Bott et al., 2020 found that households with a higher number of social ties are more likely to take proactive measures against flooding. Multiple studies indicate the importance of a social network because they support local adaptation, share knowledge and serves as a social safety net, which helps to reduce community vulnerability (Bott et al., 2020; Marfai et al., 2015; Rudiarto & Pamungkas, 2020; Taylor, 2015). The decision to migrate is a response to experienced community stress and the extent of community support for relocation, which can lead to a willingness to find alternative housing locations (Buchori et al., 2018; Hunter, 2005). However, despite the vulnerable position of some communities, many residents of coastal areas in Indonesia prefer to stay and adapt rather than having to leave, as they value their community relationships, work and living space (Bott & Braun, 2019; Bott et al., 2020; Bott et al., 2021; Buchori et al., 2018; Esteban et al., 2020).

7.2. Operationalisation of decision-making factors

As explained in section 2.3 and 2.4, Protection Motication Theory is used as a framework for the household adaptation decision-making process of this study. The above identified adaptation drivers are confirm PMT, because the threat appraisal corresponds with the perceived flood severity, vulnerability and experienced stress, while the adaptive capacity, self-organizing abilities and shared knowledge and perceived costs match the coping appraisal. The additional recognised adaptation drivers, like social network ties, social expectations, flood experience ect. can be included in the PMT as well as was done in the study of Grothmann and Reusswig, 2006 for example. However, to create an empirically based flood ABM, the decision-making factors found in literature, need to be matched on the available survey data from Noll et al., 2021. Therefore, a search in the survey data was done. An overview of the matched survey data variables on the identified adaptation drivers and barriers from literature confirm PMT can be found in table 7.1.

Table 7.1: Adaptation drivers from literature matched on survey data

Literature	**Survey variable**	**PMT -** driver(+) barrier(-)
Severity of flooding	Perceived flood damage	Threat appraisal (+)
Vulnerability	Perceived flood probability Flood likelihood	Threat appraisal (-) Extended variable (-)
Stress	Worry	Threat appraisal (+)
Capacity to adapt Self-organization abilities	Self-efficacy	Coping appraisal (+)
Costs	Perceived costs	Coping appraisal (-)
Shared knowledge	Response-efficacy	Coping appraisal (+)
Participatory capacity	Trust in public protection	Extended variable (-)
Experience	Flood experience Taken adaptation actions Moved houses Moved city	Extended variable (+) (-) (+) (-)
Knowledge	Climate change belief Education level	Extended variable (+)
Economic consideration	Income level Economic comfort level Find Job Impact of job lost	Extended variable (+)
Social ties	Social network	Extended variable (+)
Shared knowledge	Social media	Extended variable (+)
Local adaptation	Social norm Social expectation	Extended variable (+)
Social safety net	Social support	Extended variable (+)
Value of living space	Difficulty to leave	Extended variable (-)

Source. Survey variables from F. Dam, 2021, see appendix A.

The survey questions and data distributions of the selected decision-making variables were analysed and described in Appendix A. Next, a conceptual model on the decision-making process of household adaptation in Jakarta, with integration of the selected survey data variables confirm the Protection Motivation Theory is made, see figure 7.1. To find out what role the decision-making factor play in adaptation behaviour, a Logit regression analyse is performed, see appendix B. Logit can be used to estimate the probability of an event taking place, in our case adaptation or migration, by having the log-odds for an event (a linear combination of independent variables multiplied by their regression coefficients). The logit regression coefficient for all variables on all adaptation and migration actions are reported in table B.1 and B.2 and are discussed below the conceptual model. The probability distributions of all adaptation and migration actions for Jakarta's household population can be found in appendix B as well.

7.3. Conceptualisation of adaptation decision-making

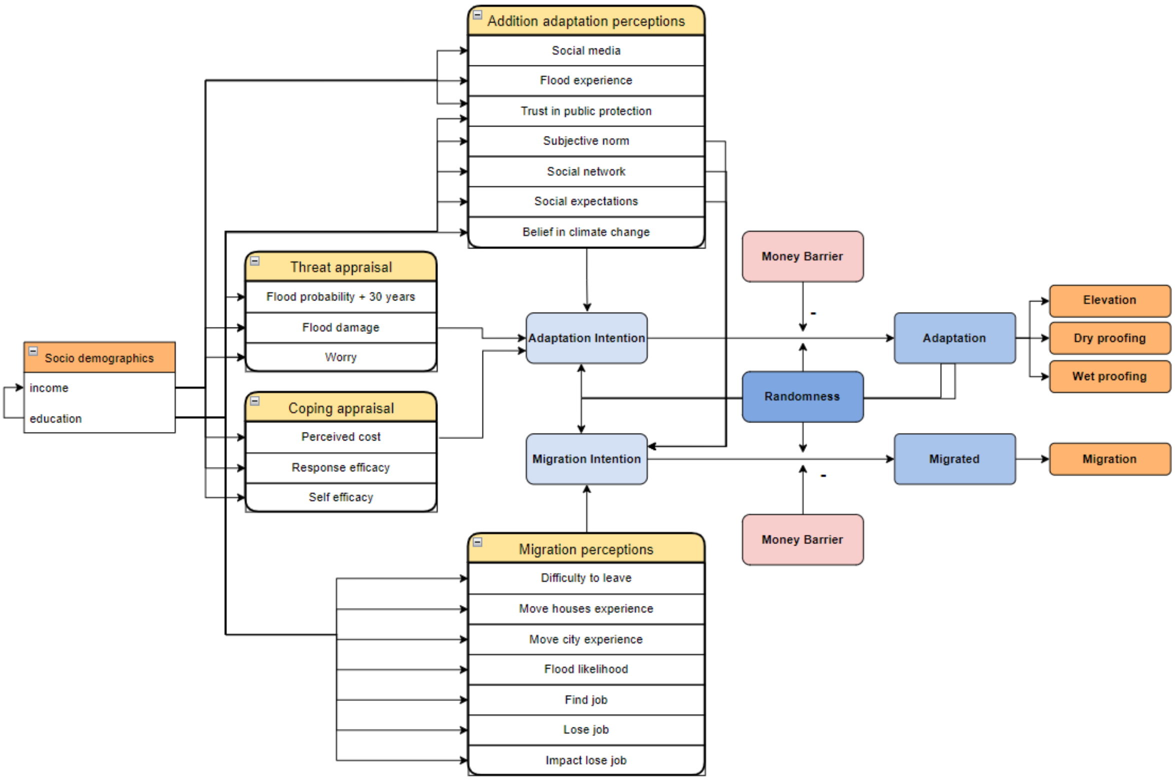

Figure 7.1: Conceptualisation Protection Motivation Theory

The threat appraisal consists out of three variables: perceived flood probability, perceived flood damage and worry about flooding. In general, household that experience a higher threat of flooding (worry and perceived flood damage) are more likely to take action. The probability over thirty years, has a negative effect on adaptation though, see figure B.1. Perhaps this due to the feeling that there is no point in adapting, if flooding keep increasing and occur more often. The coping appraisal consists out of three variables: response efficacy, perceived cost, perceived self-efficacy. In general, self-efficacy and response efficacy have a positive effect on the adaptation intention, whereas the perceived cost has a negative effect. Meaning, the more effective, cheaper and easy to undertake a measure is perceived, the more capable and confident someone is in performing the measure. Therefore the measure is more likely to be implemented. Next, flood experience is positively related to all adaptation actions. Meaning that people who experienced floods are more likely to take (or have taken) structural flood adaptation measures. The social expectation has a positive coefficient towards adaptation, but a negative coefficient for migration. This mean the higher the expectation to adapt, the more likely households are to undertake adaptation action and less likely they are to migrate. Furthermore, it seems, that the more people you know that have undertaken an adaptation or migration action, the more likely a household is to take it themselves as well. Previously undertaken measures by a household themselves, seem to have a negative effect on intention to adapt though. Probability this is due to the increase feeling of safety after adapting. Although, the intention to migrate seems to increase, when several adaptation action are undertaken already. Next, the lower the trust in public protection, the more likely households are to take actions by themselves. Furthermore, a strong climate change belief has a positive effect on the intention to adapt and the more you hear about it via social media, the more likely one is to take action. When a household has already moved houses before, it is more likely to do it again. However, when a household has moved cities before, it is more likely to stay. The higher the perception on easiness to leave this place, the higher the intention to move. Lastly, when it is difficult for a household to find a job, it is more likely to leave in a situation of no flood damage, while it will stay if flood damage occurs. Whereas households that could easily get another job are more likely to stay when no flood damage occur, but move as soon as flooding happen more severely. Losing a job, causes people to migrate, especially when the impact is big.

8
Policy interventions

In this chapter ***SQ4**: What policy interventions could influence household adaptation or migration decisions?* will be answered.

The structure of the chapter is the following. First the results of a literature search on policy interventions on adaptation or migration behaviour are discussed in section 8.1. Secondly, the operationalisation of the policy interventions from literature is discussed in section 8.2. The influence of the designed policy measures on the adaptation and migration decision-making factors is discussed here as well. Thirdly, the conceptual model of the decision-making process is shown in section 7.3. Here, also the decision-making factors are discussed. Lastly, the Logit regression analysis can be found in section B.

8.1. Literature on policy interventions

Because of the interest the aggregated impact of public and private adaptation within this study, additionally, a literature search on policy interventions affecting the communal adaptation and migration response in facing flood hazards was done. Starting with structural policy interventions, it was found that increased public protection could have a negative influence on flood adaptation and migration behaviour of households in Indonesia, due to a false sense of safety that prompts extra development in the area behind a dike, which is called the levee effect (Garschagen et al., 2018; Haer et al., 2020). Public protection could thus indirectly reduce the worry among households, affecting the threat appraisal within the PMT. Looking at non-structural policy interventions in literature, it was found that most of the identified policy interventions aiming to stimulate private flood adaptation behaviour are of an economic nature: obtaining flood damage compensation, donated aid, government support, resettlement programs and the possibility of recovery and improvement of income (Buchori et al., 2018; Raleigh & Jordan, 2008). Although policy interventions focusing on increasing knowledge are also recognised: raising public awareness, education, training or campaigns (Buchori et al., 2018; UNDRR, 2022).

8.2. Operationalisation of policy interventions

Starting with the structural policy interventions, the construction of a levee to protect from flooding has a direct impact on the experienced water levels of households (F. Dam, 2021). As a consequence of reduced flooding, the worry of households could be reduced, which then in its turn could lead to less private adaptation (Garschagen et al., 2018; Haer et al., 2020). Therefore, the percentage of the population undertaking adaptation or migration actions are chosen as a key performance indicators, which are measured and reported at the end of all experimental model runs. To be able to compared different public protection strategies to see whether and when the levee effect occurs, three different public adaptation strategies are tested: protecting the most flood prone areas, building a gigantic seawall and providing equal protection. The effect of reducing all flood heights higher than 3 meters to 2.5 meter is tested in the strategy of improved protection in the most flood prone areas. For the gigantic sea wall is assumed that its successfully prevents all possible flooding, because of the installation of a pumping system, water buffer, increase a dyke and the sea wall itself. See the case-study chapter 3, for more information on the gigantic sea wall. The public adaptation strategy to provide equal protection, tests an reducing effect of two meters on the measured flood height in 2020. How public protection should be designed or implemented to achieve these effect, is not the focus of this study. The designed experiments purely serve to explore the effect of reduced water height in certain areas on household adaption behaviour. Whether the policies are feasible, have public support and their impact on biodiversity ect. falls outside the scope of this study as well. Looking at the impact of non-structural measures with an economic impact, three policy interventions are designed. Starting with providing security of income through a job in case of migration. This has an effect on the households perception on how fast one can find another job, which is set to less than a month. The other two monetary focused policy interventions are a form of donated aid, through providing a subsidy on migration and adaptation. These policy interventions impact the actual cost and perceived cost by households. It is assumed the subsidy cover half of the cost and the perceived cost lowers one on a scale form one to five. Since the impact on the perceived cost is a rough estimation thus an uncertainty, a sensitivity analysis is performed. Lastly, two non-structural policy intervention focusing on knowledge are designed. One in the form of education and training on adaptation measures, increasing the self-efficacy and response-efficacy of adaptation among Jakarta households by one on a five point scale. The other in the form of a campaign raising risk awareness, influencing the worry perceptions of households. As the effects of the knowledge based policies on the household perceptions are uncertain as well, a sensitivity analysis over these factors is performed. An overview of the designed policy interventions and its effect is shown in the table below.

Table 8.1: Policy interventions from literature matched on adaptation drivers

Policy type	Policy measure	Influenced factor	Effect
Structural Public adaptation	Most flood prone areas	Flood height >= 3m	2.5 m
	Gigantic seawall	Flood height	0.0 m
	Equal protection	Flood height	-2.0 m
Non-structural with economic impact	Job offer migration	Find job	1 = less than a month
	Subsidy on adaptation	Perceived cost	-1
		Actual cost	* 0.5
	Subsidy on migration	To leave	+ 1
		Actual cost	* 0.5
Non-structural with knowledge impact	Education and training on adaptation	Response-efficacy	+ 1
		Self-efficacy	+ 1
	Raising flood risk awareness	Worry	+ 1

Based on literature section 8.1.

9

Agent-based model to explore household flood adaptation in Jakarta

In this chapter the designed agent-based model on household flood adaptation and migration is discussed. The model description follows the ODD (Overview, Design concepts, Details) protocol for describing individual- and agent-based models (Grimm et al., 2020).

9.1. Purpose

The main purpose of the agent-based model is to explore the aggregated impact of increasing flood risk, public adaptation measures and policy interventions on household flood adaptation and migration behaviour, flood damage and resilience for a case study in Jakarta, Indonesia. This is important as there is a need to include human behaviour and its interactions with society and nature, the ability to learn, reorganise and adapt within flood risk analysis (J. Aerts et al., 2014). Since human behaviour and their interaction are complex, this implies a need for more socio-behaviourally rich risk assessment methods like ABM. The model is used to provide policy-makers with more insight on how flood adaptation and migration decisions among households are made, test ways to stimulate private adaptation and inform the local government of Jakarta on the potential impact of policy interventions on household adaptation behaviour. This knowledge is useful in the design of flood management adaptation strategies and can help policy makers take informed decisions on public adaptation in flood risk management. The model can also be of use for scientists, who like to explore ABM applications and research in designing flood risk management strategies. The purpose of the model is thus not to predict flooding, flood damage or household adaptation behaviour, but to increase the understanding of household adaptation decision-making and explore the effect of policy interventions and flood exposure on household adaptation behaviour.

9.2. Entities, state variables, and scales

9.2.1. Entities

There are three kind of entities in the model, agents, spatial units and the environment, representing households under flood risk in Jakarta.

Agents - The agents in the model represent households living in Jakarta, who can get exposed by flooding from the environment. No other type of agents like institutions or companies are included. The households are static representations of the houses in which citizens from Jakarta live.

Spatial units - Jakarta is divided in 3365 Rukan-Warga's (RW) spatial units representing large neighborhoods of communities within Jakarta. The RW's are the smallest spatial scale and are part of villages (one spatial unit higher), which can be placed in sub-district, who are part of five main districts: Jakarta Barat, Jakarta Seletan, Jakarta Utara, Jakarta Timur and Jakarta Pusat representing Jakarta DKI (the environment).

Environment - Jakarta DKI is the model environment and represents the place in which all households live.

9.2.2. State variables

Agents - First of all, households have a two socio-demographic attributes: a total yearly household income measured in Rupiah and an education level. Based on their yearly income, the amount of savings is determined. Age and gender are not included, because variation among households members occurs, so these variables cannot be generalised. Furthermore each household has four attributes representing the physical status of the house; the house price value and the amount of undertaken adaptation actions consisting of elevation, dry proofing and wet proofing (1 = yes or 0 = no). Additionally, every household has an address in the form of an GIS location, which can be placed on the map of Jakarta within a certain RW, see figure 9.1. Every agent has a number of social ties, presented in a list of household living in the same RW with whom the agent has a close connection. Furthermore, households have a lot of perceptions, norms and attitudes that play a role in the decision-making of adaptation or migration behaviour confirm the Protection Motivation Theory, measured on a five point likert-scale. Starting with the perceived flood damage, flood probability over thirty years and worry perception, which form the threat appraisal. The perceived self-efficacy of households to adapt or migration, the perceived response-efficacy of adaptation or migration actions and the perceived cost, form the coping appraisal. Furthermore households have perceptions on climate change beliefs, trust in public protection, social expectations flood likeliness, the easiness to leave their place, easiness on finding a new job and the impact of losing their job. Furthermore, the attitude towards social media, raising risk awareness on flooding is included. Additionally, past experiences play a role in the form of flood experience and moving experience of houses and cities. Lastly, five perceptions of the agent's households resilience are included.

There are five status a household could have:

- **Flooded:** if the experience water level from the environment is higher than the house protection level.
- **Recovering:** if the a household has flood damage.
- **Do nothing:** if there is no flood damage and a household doesn't take any adaptation or migration action.
- **Adapting:** if a household is undertaking one of the adaptation measures; elevation, dry proofing or wet proofing.
- **Migrated:** if a household decides or has decided to leave Jakarta.

Spatial units - all spatial units can be located on a map within Jakarta, so therefore have a geometry containing GIS coordinates presenting its reach. RW's can be flooded or not, with a certain **flood height** between **0-5 meter** measured in 2020.

Environment - Jakarta can be hit by flooding (external event), the climate change hazard of focus in this model, which affects the households living in it. The status of the environment can thus either be **flooded** (1) or **not flooded** (0), depending on the measured flood height within all RW's (spatial units). If one or more of the spatial units has a flood height higher than zero meters, the environment is flooded.

9.2.3. Scales

The model scale can be described based on time and space.

Spatial scale - the spatial environment represents Jakarta DKI, the capital city of Indonesia, with a province area of 664.01 square kilometer, which can be divided in five districts: Jakarta Barat, Jakarta Seletan, Jakarta Utara, Jakarta Timur and Jakarta Pusat (Normor, 2022). Its postcode range is between 10 xxx - 14540 (Normor, 2022). In this model, Jakarta is divided in 3365 Rukan-Warga's (RW) spatial units representing large neighborhoods of communities within Jakarta.

Temporal scale - is defined by three factors: the time step, starting point and time horizon.

- **Time step:** one model step, represents a month as in Indonesia flooding happens multiple time a year, especially during the rain season (Adi Renaldi, 2022).
- **Starting point:** the year 2020 is chosen for time initialisation, as both the available survey data and flood height data come form that year.

- **Time horizon:** the main goal of the model is to explore the aggregated impact of policy interventions and public protection on household adaptation and migration behaviour, their experienced flood damage and flood resilience. As it takes some time before the effect of policies interventions on household behaviour can be seen, a time horizon of 30 years is chosen. A longer time period is also not desirable because the uncertainty about the representation of the data and the course of behaviour and flooding then becomes increasingly uncertain (Taberna et al., 2020).

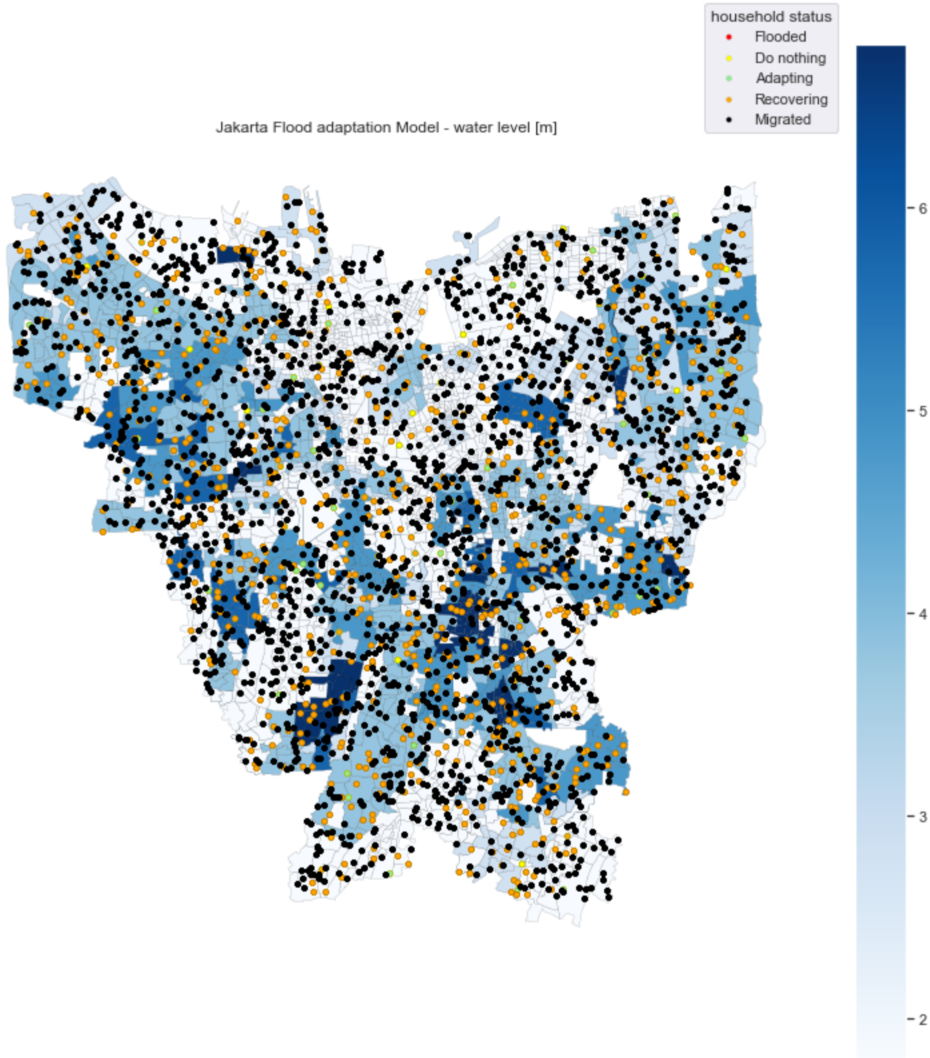

Figure 9.1: Map of household status after 30 years - no policy strategy & flood risk scenario 1

9.3. Process overview and scheduling

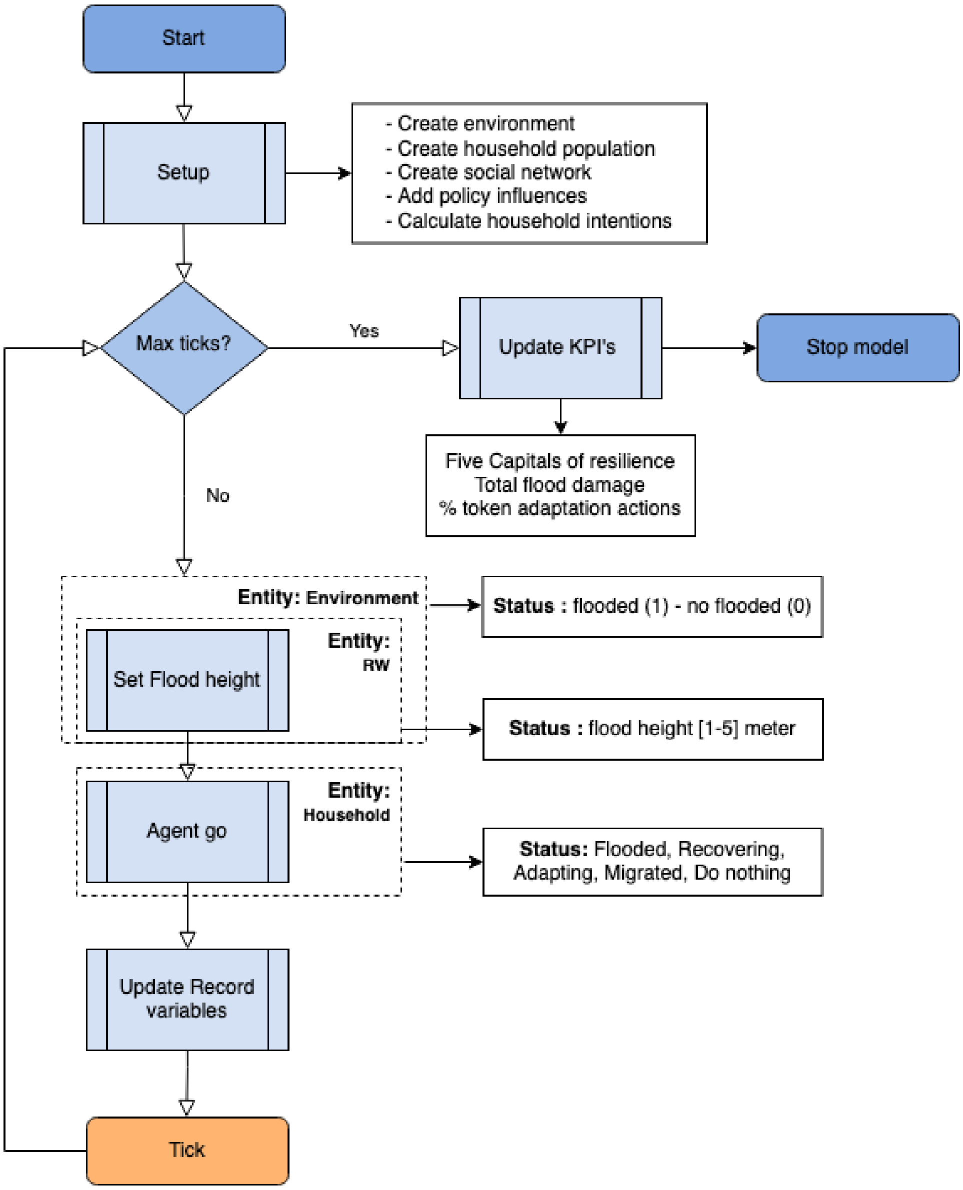

Figure 9.2: Flow chart ABM Jakarta model overview

The model start with a setup function, in which the environment, household population and its social network is created. Next, the policy influences are updated, after which the initial households adaptation intentions are calculated, see section 9.7.2 for more detail. After the setup is done, the model starts running its ticks. Every tick, represents a month in time. The total amount of tick is 360, representing 30 years in time. Within in a tick, a flood can occur, depending on the pre-assigned flood and policy scenario of the environment. The flood height per tick per RW is set in the flood height function 9.7.3. Only if a flood in the environment occurs, the flood height in the RW can be higher than zero. After the flood height of all RW's is set, the Households run their Agent go function, determining the status of every household per tick, see 9.7.4. There are five statuses in total; a Household could 1) get flooded, 2) is recovering, 3) could do nothing 4) adapts 5) or is migrated. When all households have run their Agent go function, the agent and model variables get updated synchronously. Additionally, the recording of variables of interest per tick could be done for all agent attributes, which is used for continuous model validation. After this the tick is done and the model checks whether it has reached the maximum assigned number of ticks yet; if not another tick starts. Once the maximum number is reached, the Model KPI's are calculated and the model stops. A visualisation of the model overview can be found in figure 9.2.

9.4. Design concepts

Nine design concept are discussed below; basic principles, emergence, adaptation, learning, sensing, interaction, stochasticity, collectives and observations. These concepts describe the ABM characteristics and important design decisions that have been made.

Basic principles - The Protection Motivation Theory by Rogers, 1975 forms the basis of this ABM and is used as a framework for the Household decision-making process on adaptation and migration behaviour. PMT is used in the social science studies to explain human behaviour under risk and is applied in multiple ABM studies to explain household flood adaptation behaviour (Rogers, 1975; Zhuo & Han, 2020). The traditional PMT model consist of the threat and coping appraisal, which both must be high enough to form a high intention, but the model can be extended with other variables of interest as well (Grothmann & Reusswig, 2006). The variables included in the PMT of this study on flood adaptation behaviour in Jakarta are based on literature and matched on survey data, used as an input to create an emperially based ABM. See chapter 7.3 for a description and overview of all included decision-making factors.

Emergence - Taking adaptation actions could prevent flood exposure or reduce the experience flood damage for households. Adaptation or migration behaviour depends on many social, environmental, personal and institutional factors (Noll et al., 2021). The values of the decision-making factors vary per household and are continuously influenced by flooding from the environment, policy interventions, their own actions or adaptation actions of neighbors. Hence, the cumulative adaptation and migration behavior is a result from the interactions of multiple heterogeneous households within a by policy influenced flood prone environment, which could lead to emergent system-level behaviour.

Adaptation - Taking adaptation actions could prevent flood exposure or reduce the experience flood damage for households. Households make adaptation or migration decisions confirm the PMT. All decision-making factors together form an intention to take action in the form of a probability. Every time a household gets flooded, a random number is drawn, which is compared to the probability to take action. If the random number is bigger, nothing happens, if it is smaller or equal, the action is taken when enough money is available. Thus households with a high intention have a higher chance of taking adaptive action, whereas households with a low intention have a lower probability to take action.

Learning - The migration intention of agents depends on the amount of flood damage they experience at the moment. In general, the higher the experienced flood damage and flood severity, the higher the intention to migrate. Meaning that the more flooding agents experience, the more likely it is they migrate.

Sensing - Households are assumed to know if their houses is flooded in a month, which increases their worry perception. Secondly, households know what adaptation or migration actions households within their social network have taken. Furthermore, they know whether and how much flood damage their houses experience and if they have the money to repair, migrate or adapt. Lastly, the policy interventions have an effect on all households, see chapter 8 for the exact effects. So all households are influenced by the risk awareness campaigns for example.

Interaction - After an adaptation or migration action is performed by a household, the social norm and the response efficacy of the performed adaptation action of the households within their social network increases. Meaning household could stimulate each other to undertake action and increase each other's perceptions on the performance of an action. Undertaking adaptation actions does not affect the waterlevels within the environment.

Stochasticity - Based on the survey data an initial household population is created and used as an input for the ABM. Since we keep the created population including their address (location on the map) constant, no randomness is involved here which could effect the model runs. Although it is an option to vary the initial agent population, then a totally different heterogenous distribution of agent variables can be used due to the randomness involved. Next, the neighbors of a household are randomly selected from the same RW. Lastly, a personal random number is drawn after a household is flooded. This random number used in the PMT to determine whether agents put their intentions (probability to take action) into reality.

Collectives - Every agent has a small social network of maximum eight households living within the same RW. These households influence each other's social norm and response efficacy of all actions by undertaking adaptation actions.

Observations - During the model implementation, each model or agent variable could be reported after each tick to be able to track changes in variables, used for continuous validation.

Once the model is build and verified, in between reporting is stopped to save computational power. During the experimentation, at the end of every run the total amount of flood damage and the percentage of undertaken adaptation and migration actions of the whole populations are reported. Additionally, the average Five capital scores for the households still living in Jakarta (non-migrated) are recorded. These key performance indicators are used to compare the system performances under various flood scenario's and policy interventions.

9.5. Initialization

In the initial state of the model, the Jakarta environment consists of 3365 RW's with a flood height of zero meter, as no flooding yet occurs. A total of 10000 households are compiled from the survey data from Noll et al., 2021 (year 2020) for a valid model population representation. The households are placed on the Jakarta map and used to simulate the flood adaptation behaviour of the Javanese population. The extraction of the 10000 households from the survey data goes as follows. First an empty dataset with 10000 rows is created, with column names equal to all agents' attributes. Each row represents one household, sampled one by one from the survey data. The sampling starts with picking a random sample from the education level. Next, the survey data is filtered on respondents with that education level only, from which the next sample is drawn: income and income level. Then, from the survey data selection on the chosen education and income level, an initial number of months of savings and a house value is drawn. The economic comfort level is then based on the income level and number of savings. Subsequently, the social media influence on flood awareness and flood experience is based on a survey data selection on income level. Climate change belief is based a survey data selection on education level. Next, a households perception on trust in public protection, worry and their own resilience is based on both the education and income level. A survey data selection on the worry perception and income level of households is used to determine the flood damage, flood probability and flood likeliness perception. The response efficacy, self efficacy and perceived cost for elevation are based on ones economic comfort and income level. The corresponding attributes for dry proofing are based on the elevation values, which are used together to form the response efficacy, self efficacy and perceived cost perception on wet proofing per household. Self-efficacy is then the guiding attribute in determining whether that adaptation action in particular is already undergone. Next, the economic comfort level and income is used to base the resilience perception on available financial support or saving flexibility in case its needed. Additionally, the households perception on their own resilience in combination with their education level is used to construct the experienced social support and government support. Lastly, a households experience in moving houses or cities, the number of social connection within their network, their perception of easiness to leave a place, find a job or impact of losing a job is all based on the education level. The interrelationships between the variables are based on correlations. Highly correlated variable were used as selection variables during sampling. To see if the created population matches the original survey data, the correlation matrices were compared with each other, see figure 9.3 & 9.4. It can be seen that the correlations between them match, so the sampling was done successfully. Finally, all households were assigned a random address (GIS location) within an RW, after which initialisation of the population is completed. The dataset containing all agent attributes from 10000 household is used as a constant model input throughout the experimental simulation runs. The data distributions of the original survey data variables can be found in appendix A.

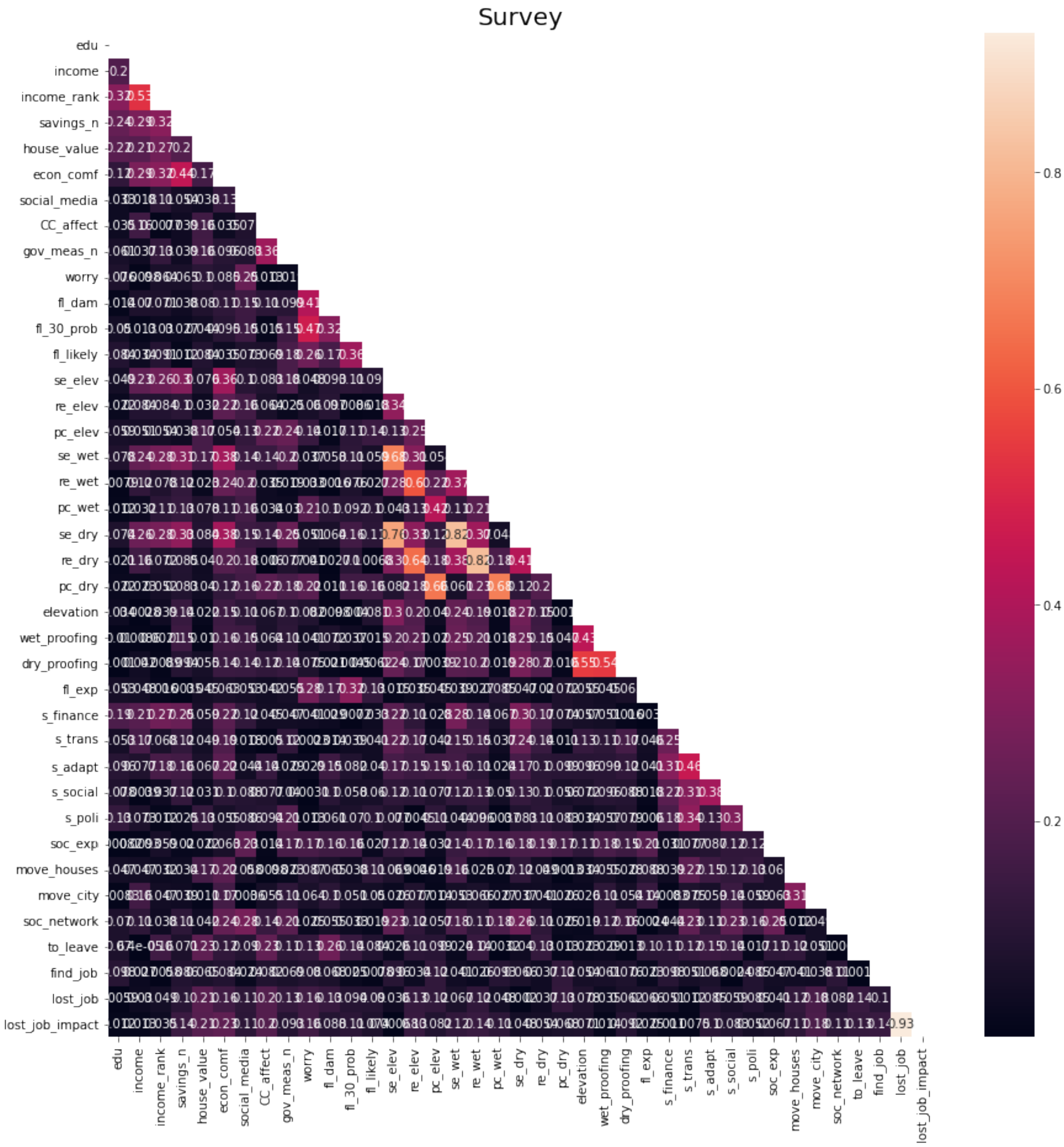

Figure 9.3: Survey data of Jakarta households used for sampling

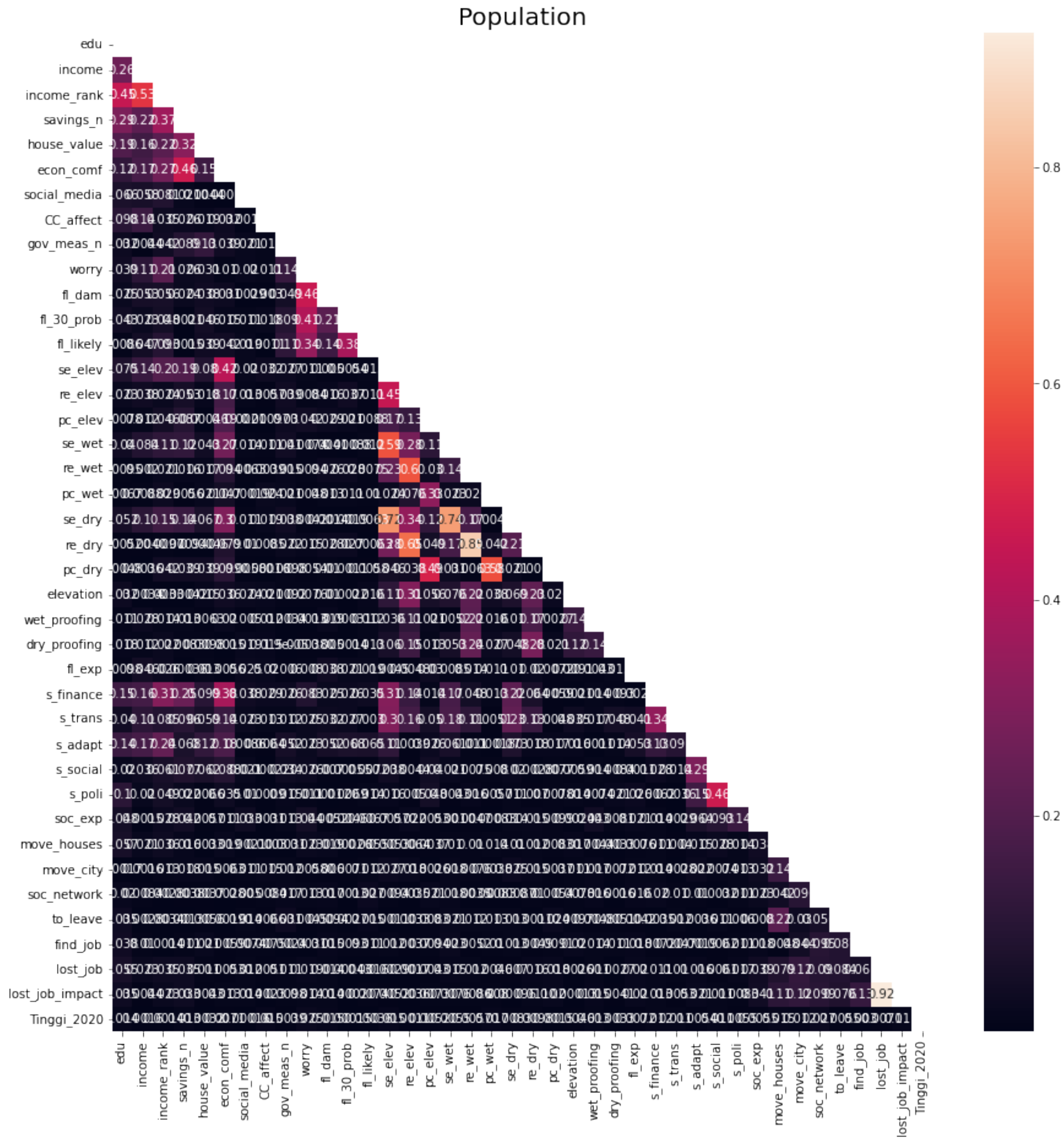

Figure 9.4: Created population representing Jakarta's household in the simulation

9.6. Input data

Four files were used as input data within the ABM model.

- The synthetic population dataframe of 10000 household described in section 9.5, based on survey data from Noll et al., 2021 described in chapter 4.2.2.
- The Jakarta floodmap data set (described in 4.2.1).
- The PMT coefients (see figure B.1 & B.2).

The synthetic population data set is used to create the household agents and assign the agent's attributes according the original survey data distributions. The Jakarta floodmap data is used to create the Jakarta environments and its RW's in which the households are located. The RW's are being flooded throughout the simulation with a certain flood height varying between the 1 - 5 meter, causing flood damage by households. The PMT coeffients are used to calculate the Logit odd probability to take adaptation or migration action, based on the assigned agents attribute values, which drives the household adaptation behaviour within the ABM.

9.7. Submodels

In this section, the submodel processes and model parameterisation is explained. For each submodel, a conceptualisation in the form of a flow-chart and formalisation in pseudo-code of the function is shown.

9.7.1. Model parameters

Lets start with the model parameters of the ABM model.

```
parameters = {
'agents' : 10000,
'flood scenario' : [1,2,3],
'steps' : (12 * 30),
'seed' : 21,

'waterlevelrise' : 0.04,

'policy_increase_public_protection_most_flood_prone' : [True, False],
'policy_increase_public_protection_giantic_seawall' : [True, False],
'policy_increase_public_protection_equal_reduction' : [True, False],

'policy_subsidie_adaptation' : [True, False],
'effect_PC_subsidie_adaptation' : -1,
'effect_cost_subsidie_adaptation' : 0,5,

'policy_subsidie_migration' : [True, False],
'effect_leave_subsidie_migration' : +1,
'effect_cost_subsidie_migration' : 0,5,

'policy_job_offer_migration' : [True, False],
'effect_job_offer_migration' : 1,

'policy_education_CCFloods' : [True, False],
'effect_worry_education_CCFloods' : +1,

'policy_education_adaptation' : [True, False],
'effect_RE_education_adaptation' : +1,

'effect_SE_education_adaptation' : +1 }


model = JakartaModel(parameters)
results = model.run( )
```

The number of agents, model steps and seed, are constants during the experimental runs, whereas the flood scenario's and policy interventions are varied. Over the effects of the policy interventions and the waterlevelrise a sensitivity analysis is performed latter on, see chapter 10. These parameters values are used as input variables within the setup function of the ABM.

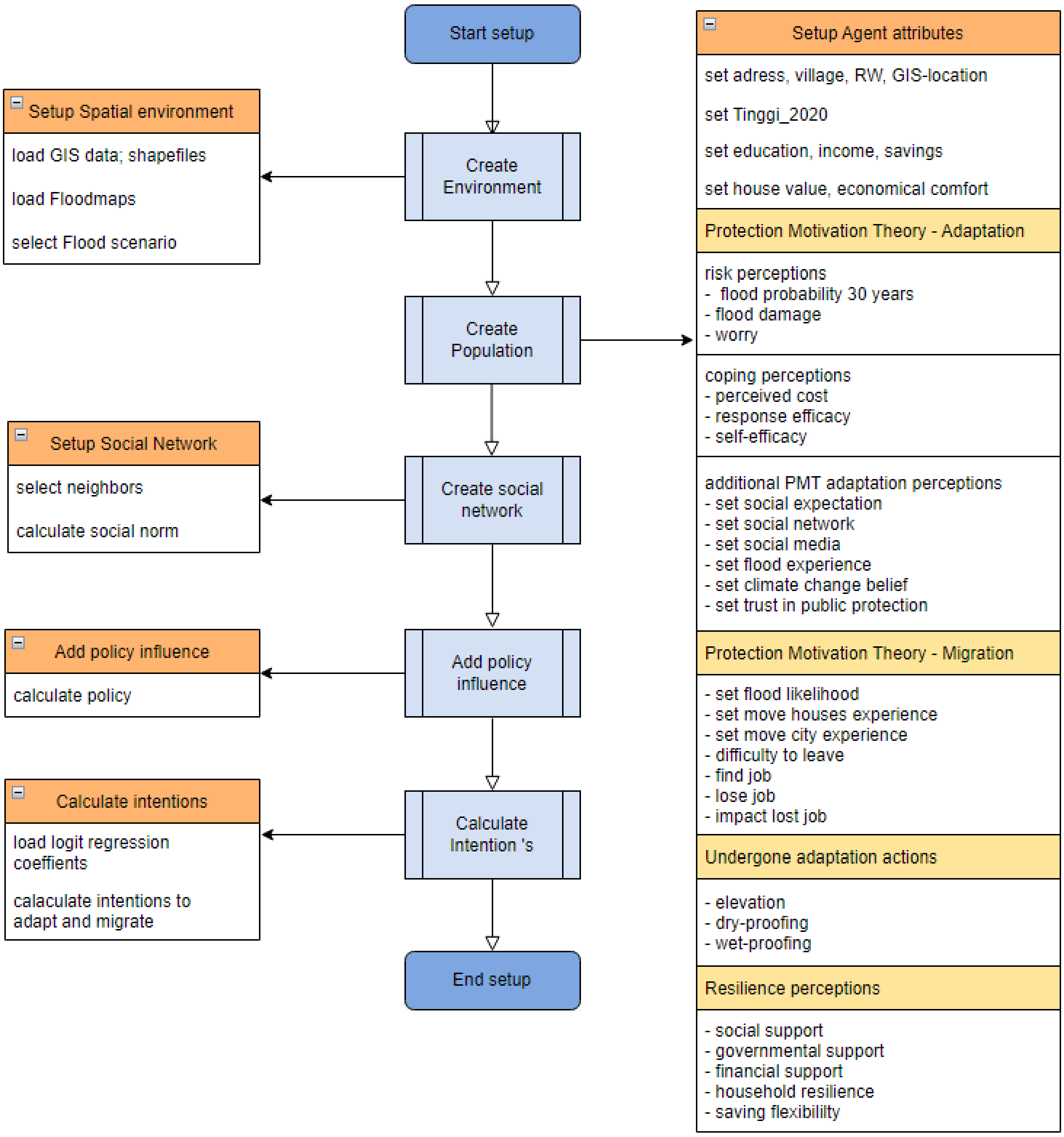

Figure 9.5: Flow chart Setup

9.7.2. Setup function

In figure 9.5 an overview of the setup function is shown. First step in the setup, is creating the environment; uploading the Jakarta floodmap data containing the maximum measured flood height per RW location for the year 2020, the shapefile of Jakarta and the GIS locations per polygon. This data enables us to plot the measured flood height per polygon for various scenario's on a map. Secondly, the created synthetic population is loaded, representing the households of Jakarta. Thirdly, the agents' social network is created, consisting of no more than eight neighbours, living in the same village and RW. Agents who are part of a social network influence the perspectives of others through their adaptation or migration actions. Fourthly, the influence of the policy measures are executed. Additional public protection influence the flood height, whereas the other policies like education or subsidies influence the agents' perceptions. Lastly, the PMT Logit regression coefficients are uploaded, which are used to calculate the agents intention to adapt and migrate. After the setup is done, the functions that run every tick (set flood height & Agent go function) will be performed in a loop until the maximum number of ticks is reached, see 9.2.

formalisation setup

```
def setup(self):
""" Initialize agents and floodmap"""

self.scenario = self.array_scenario()

# floodmap
self.floodmap = gpd.read_file(r'Jakarta_floodmap.gpkg')

# population
self.population = gpd.read_file("Population.gpkg")

# pmt parameters, logit coeffients per adaptation action (function above)
self.pmt_params = self.PMT_Parameters()
self.move_params = self.Move_Parameters()

# Households
self.agents = ap.AgentList(self, self.p.agents, Household)
self.agents.calculate_cost_adaptation_actions()
self.agents.neighbors()
self.agents.calculate_social_norm()
self.agents.policies()
self.agents.recalculate_probability_to_take_action()
```

First, the parameter value from the flood scenario (1,2 or 3) is transformed in a flood array with values representing the flood exposure scale compared to the measured 2020 within the floodmap.

```
def array_scenario(self):
    if self.p.scenario == 1:
        return tuple([1/4,0,0,0,0,0,0,0,0,0,0,0,
        1/3,0,0,0,0,0,0,0,0,0,0,0,
        1/4,0,0,0,0,0,0,0,0,0,0,0])
    if self.p.scenario == 2:
        return tuple([1/4,0,0,0,0,0,0,0,0,0,0,0,
        1/2,0,0,0,0,0,0,0,0,0,0,0,
        1/4,0,0,0,0,0,0,0,0,0,0,0])
    if self.p.scenario == 3:
        return tuple([1/4,0,0,0,0,0,0,0,0,0,0,0,
        1,0,0,0,0,0,0,0,0,0,0,0,
        1/4,0,0,0,0,0,0,0,0,0,0,0])
```

Next, all input data sets are loaded; the floodmap data, synthetic population and Logit regression coefficients. Then, the initialisation of the Household agent-class begins. First, the households are created confirm the synthetic population data set.

```
def setup_agents(self):
seed = self.model.random.getrandbits(128)
self.random = random.Random(seed)
self.r = self.random.random() np.nan

#agent attributes
row = pop_gdf.iloc[self.id-1]
self.adress = row['geometry']
self.village = row['Village']
self.RW = row['RW']
self.tinggi_2020 = row['Tinggi_2020']
self.tinggi = row['Tinggi_2020']
self.edu = row['edu']
self.income = row['income']
self.income_rank = row['income_rank']
self.savings = row['savings_n'] * (self.income/12)
self.house_value = row['house_value']
self.econ_comf = row['econ_comf']

#PMT
self.perceived_flood_probability = row['fl_30_prob']
self.perceived_flood_damage = row['fl_dam']
self.worry = row['worry']
self.PC_elevation = row['pc_elev']
self.PC_dry_proofing = row['pc_dry']
self.PC_wet_proofing = row['pc_wet']
self.RE_elevation = row['re_elev']
self.RE_dry_proofing = row['re_dry']
self.RE_wet_proofing = row['re_wet']
self.SE_elevation = row['se_elev']
self.SE_dry_proofing = row['se_dry']
self.SE_wet_proofing = row['se_wet']
self.social_expectations = row['soc_exp']
self.social_network = row['soc_network']
self.flood_experience = row['fl_exp']
self.gov_meas_suf = row['gov_meas_n']
self.social_media = row['social_media']
self.cc_affect = row['CC_affect']

# Move
self.flood_likely = row['fl_likely']
self.move_houses = row['move_houses']
self.move_city = row['move_city']
self.to_leave = row['to_leave']
self.find_job = row['find_job']
self.lost_job = row['lost_job']
self.lost_job_impact = row['lost_job_impact']

#Actions
self.elevation = row['elevation']
self.dry_proofing = row['dry_proofing']
self.wet_proofing = row['wet_proofing']
self.token_adaptation_measures = self.elevation + self.dry_proofing + self.wet_proofing
self.moved = False


#Resilience
self.social_support = row['s_social']
self.governmental_support = row['s_poli']
self.financial_support = row['s_finance']
self.household_resilience = row['s_adapt']
self.saving_flexibility = row['s_trans']
```

```
if self.elevation == 1:
    self.house_height = 1
    self.probability_to_elevate = ”Already taken”
else:
    self.house_height = 0

if self.dry_proofing == 1:
    self.probability_to_dry_proof = ”Already taken”

if self.wet_proofing == 1:
    self.probability_to_wet_proof = ”Already taken”

self.flood_height = 0
self.status = ”Do nothing”
self.prevention_flood = 0
self.flooded = 0
self.flood_damage = 0
self.total_damage = 0

if self.model.p.policy_increase_public_protection_equal_reduction == True:
    self.tinggi = max(0, self.tinggi - 2)

if self.model.p.policy_increase_public_protection_most_flood_prone == True:
    if self.tinggi >= 3:
        self.tinggi = 2.5

if self.model.p.policy_increase_public_protection_giantic_seawall == True:
    self.flood_height = 0
```

Next the cost for the adaptation actions are set. The cost for the adaptation measures are slightly balanced depending on the house value of the agents. The reason behind this choice is it that for bigger or more expensive houses, the construction costs are also a bit higher. The costs were based on the study from J. C. J. H. Aerts, 2018, who estimated the costs for flood adaptation actions for several countries, missing Indonesia but including Vietnam. As Vietnam is a close country and with a similar economy to Indonesia, those costs were adopted as an estimation for Indonesia as well. J. C. J. H. Aerts, 2018 reported the costs in Dollars, but since the currency of Jakarta is Rupiah, the costs are reported as such. Next, the social network of the households is created.

```
def calculate_cost_adaptation_actions(self):
    normalize = self.house_value/ np.mean([self.model.agents.house_value])
    self.cost_elevation = 31.1 * normalize
    self.cost_dry_proofing = 13.5 * normalize
    self.cost_wet_proofing = 3.7 * normalize
    self.cost_moving = 2 * (self.income12)
```

Every household gets a list of eight random neighbor households living within the same Village name and RW. The households within this social network are influenced by the agent's performed adaptation actions, since they increase each others social norms, see the neighbors() and caluclute_social_norm() function below.

```
def neighbors(self):
    l = []
    for i in self.model.agents:
    if i.village == self.village and i.RW == self.RW and i.id != self.id:
        l.append(i)
    if len(l) > 8:
        self.neighbors = random.sample(l, 8)
    else:
        self.neighbors = random.sample(l, len(l))
```

```
def calculate_social_norm(self):
    self.social_norm_elevation = 0
    self.social_norm_dry_proof = 0
    self.social_norm_wet_proof = 0
    self.social_norm_move = 0

    if len(self.neighbors) != 0:
        for i in self.neighbors:
            if i.elevation == 1:
                self.social_norm_elevation = min(6, self.social_norm_elevation + 1)
            if i.dry_proofing == 1:
                self.social_norm_dry_proof = min(6, self.social_norm_dry_proof + 1)
            if i.wet_proofing == 1:
                self.social_norm_wet_proof = min(6, self.social_norm_wet_proof + 1)
            if i.moved == True:
                self.social_norm_move = min(6, self.social_norm_move + 1)
```

Next, the non-structural policy influences are added, confirm chapter 8. The subsidy policies reduces the perceived cost and actual cost. The job offer in case of migration provides households job security, changing the period to find a job. Next, the policy on raising flood risk awareness increase the worry perception. Lastly, the education on adaptation increases the response efficacy and self efficacy perceptions of households. The influence of policy measures is applied in the setup of the ABM model and does not change throughout the model run itself. Furthermore, the influence of the policy measures is the same for all agents.

```
def policies(self):

if self.model.p.policy_subsidie_adaptation == True:
    self.PC_elevation = max(1, self.PC_elevation + self.model.p.effect_PC_subsidie_adaptation)
    self.PC_dry_proofing = max(1, self.PC_dry_proofing + self.model.p.effect_PC_subsidie_adaptation)
    self.PC_wet_proofing = max(1, self.PC_wet_proofing + self.model.p.effect_PC_subsidie_adaptation)
    self.cost_elevation = self.cost_elevation * self.model.p.effect_cost_subsidie_adaptation
    self.cost_dry_proofing = self.cost_dry_proofing * self.model.p.effect_cost_subsidie_adaptation
    self.cost_wet_proofing = self.cost_wet_proofing * self.model.p.effect_cost_subsidie_adaptation

if self.model.p.policy_subsidie_migration == True:
    self.to_leave = min(5, self.to_leave + self.model.p.effect_leave_subsidie_migration)
    self.cost_moving = self.cost_moving * self.model.p.effect_cost_subsidie_migration

if self.model.p.policy_job_offer_migration == True:
    self.find_job = self.model.p.effect_job_offer_migration

if self.model.p.policy_education_CCFloods == True:
    self.worry = min(5,self.worry + self.model.p.effect_worry_education_CCFloods)

if self.model.p.policy_education_adaptation == True:
    self.RE_elevation = min(5,self.RE_elevation + self.model.p.effect_RE_education_adaptation)
    self.RE_dry_proofing = min(5,self.RE_dry_proofing + self.model.p.effect_RE_education_adaptation)
    self.RE_wet_proofing = min(5,self.RE_wet_proofing + self.model.p.effect_RE_education_adaptation)

    self.SE_elevation = min(5,self.SE_elevation + self.model.p.effect_SE_education_adaptation)
    self.SE_dry_proofing = min(5,self.SE_dry_proofing + self.model.p.effect_SE_education_adaptation)
    self.SE_wet_proofing = min(5,self.SE_wet_proofing + self.model.p.effect_SE_education_adaptation)
```

Lastly, in the setup the recalculate_probability_to_take_action() function is run for each agent. Since this function is also part of of the agent go function, the function is described in section 9.7.4. Within this function the Logit regression coefficients are multiplied by the agents initial attribute values to calculate their initial intention to elevate, dry proof, wet proof and migrate. The probability is saved as an agent attribute as well, to save computational power.
This was the end of the setup function.

```
def step(self):
    """ Modeling events per simulation step """
    self.agents.set_flood_height()
    self.agents.Agent_go()
```

9.7.3. Flood height function

The flood height function is the first function to perform every tick, see 9.2. It assigns the experienced flood height per tick per agent, depending on their location on the floodmap. Flooding happen on an annual basis, with varying intensity, which will be tested in three flood scenario's, see section 10.1. The initial water level can reach a value between zero and five meters, confirm the maximum measured water levels of the floods in 2020. Over time the water level increases a few cm's per year due to sea water rise, subsidence, river pollution. The water level rise itself is not simulated in the model, but used as an input parameter on which a sensitivity analysis is performed, see 10.6. Public protection measures could reduce the flood height accordingly, see 10.2.

```
def set_flood_height(self):
    self.tinggi += self.model.p.waterlevelrise /12
    self.flood_height = self.model.scenario[(self.model.t % 36)-1] * self.tinggi

    if self.model.p.policy_increase_public_protection_giantic_seawall == True:
        self.flood_height = 0
```

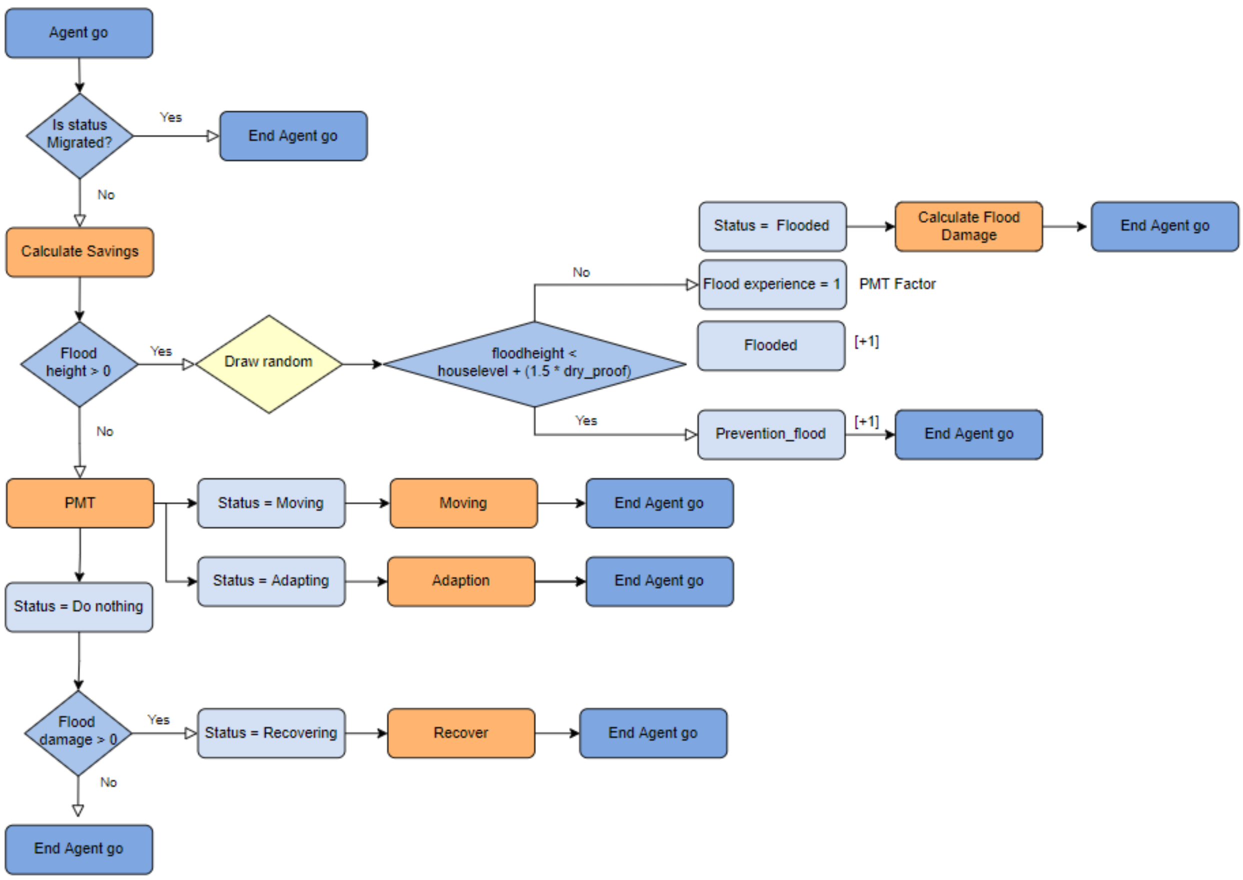

Figure 9.6: Flow chart Agent-go

9.7.4. Agent go function

The second and last function that is performed every tick is the Agent go function, see 9.2. First the function checks whether the agents is migrated. If that's the case, the Agent go function ends. Otherwise the savings are calculated. Next, it is checked whether a flood has occurred on the location of the agent. If a flooding has occurred, a new random number is drawn and saved as an agent variable, which will be used in the PMT function. After that, it looks at whether the household has been flooded, depending on the adaptation actions taken. In case the house is flooded, the flood damage is calculated. If the flood is prevented, the Agent go functions ends. If there has been no flooding in the first place, the Protection Motivation Theory (PMT) function is run. In the PMT function, the intention to adapt and migrate is calculated. Whether an agent puts his intention into action is based on the random number that is (re-)drawn after a flooding and the agent' available savings. An agent can either adapt, migrate or do nothing. In case no action is taken, but a household still has some remaining flood damage, it will continue to recover. After this the Agent go function ends.

```
def Agent_go(self):
    if self.status == "Migrated":
        return

    self.calculate_savings()

    if self.flood_height > 0:
        self.r = self.random.random()

        if self.flood_height <= (self.house_height + 1.5 * self.dry_proofing):
            self.prevention_flood += 1
        else:
            self.status = "Flooded"
            self.flooded += 1
            self.flood_experience = 1
            self.calculate_flood_damage()

    elif self.flood_damage > 0:
        self.PMT()
        if self.status != "Adapting" and self.status != "Migrated":
            self.recover()
    else:
        self.PMT()
```

Savings function
Savings can be used by an agent to pay for recovery, adaptation or to migrate. Every tick, a percentage of their monthly income is added to the agents' available savings based on their income rank, see table 9.1.

Table 9.1: Savings

Income rank	1	2	3	4	5
Percentage of savings	0.05	0.0675	0.085	0.010	0.0125

Indonesia Investments, 2016

```
def calculate_savings(self):
    if self.income_rank == 1:
        saving_percentage = 0.05
    elif self.income_rank == 2:
        saving_percentage = 0.0675
    elif self.income_rank == 3:
        saving_percentage = 0.085
    elif self.income_rank == 4:
        saving_percentage = 0.10
    elif self.income_rank == 5:
        saving_percentage = 0.125

self.savings += saving_percentage * (self.income/12)
```

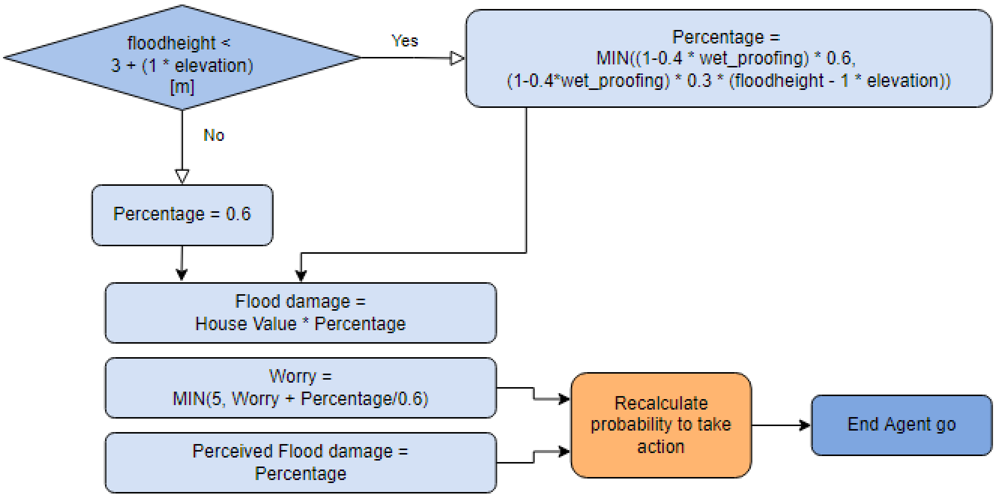

Figure 9.7: Flowchart Flood damage

Flood damage function

To determine the flood damage after flooding, the depth-damage function from chapter 6.4 based on the study of Budiyono, 2018 is used. In Budiyono, 2018's thesis, the flood damage percentage for Jakarta increase up until 0.6 within the first 2.0 meter of water, after which the damage remains sixty percent. Undertaking adaptation actions reduces the experienced flood damage to a certain height, see figure 6.1. Elevation prevents flooding up to 1 meter, after which the flood damage curve follows the same pattern, but from a different starting point (F. Dam, 2021). Dryproofing prevents flooding up to 1.5 meters after which it reverts to its original function. Wetproofing on the other hand reduces the original damage by forty percent up to 3 metres.

After the percentage is set, the flood damage is calculated by multiplying the house value with the flood damage percentage, see fig 9.7. Next, the perceived flood damage perception is set equal to the flood damage perception. Lastly, the worry perception increases depending on the flood damage percentage. In case of maximum flood damage (percentage 0.6), worry increases with one, but can reach a maximum value of five. Since the agent's perceptions are changed, the probability to take action also changes. That's why the agents migration and adaptation intentions are being recalculated with the Logit function after which the Agent go function ends.

```
def calculate_flood_damage(self):
    if self.flood_height <= 3 + (1 * self.elevation):
        flood_damage_percentage = min((1 - 0.4 * self.wet_proofing) * 0.6,
        (1 - 0.4 * self.wet_proofing) * 0.3 * (self.flood_height - 1 * self.elevation))
    else:
        flood_damage_percentage = 0.6

    self.flood_damage = flood_damage_percentage * self.house_value
    self.total_damage += self.flood_damage

    self.worry = min(5, (self.worry + flood_damage_percentage/0.6))
    self.perceived_flood_damage = flood_damage_percentage

    self.recalculate_probability_to_take_action()
```

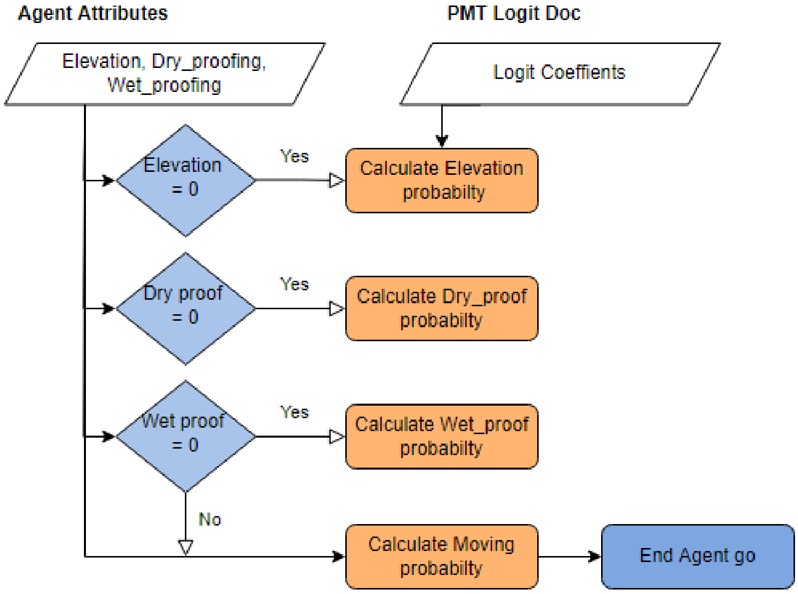

Figure 9.8: Flowchart Probability to take action

Recalculate probability to take action

The action probabilities are calculated by the Logit function, which multiplies the agents' personal values and perceptions by the Logit regression coefficients. Every time an agents changes its perception, the probability to take action is recalculated. For example after a flood, see figure 9.7. The Logit coeffients for the adapation action can be found in table B.1 and for moving in table B.2.

```
def recalculate_probability_to_take_action(self):
    if self.elevation == 0:
        self.calculate_elevation_probability()
    if self.dry_proofing == 0:
        self.calculate_dry_proof_probability()
    if self.wet_proofing == 0:
        self.calculate_wet_proof_probability()
    if self.moved == False:
        self.calculate_move_base_probability()
        self.calculate_move_medium_flood_probability()
        self.calculate_move_severe_flood_probability()
```

```
def calculate_elevation_probability(self):
x = self.model.pmt_params.Elevation
y_hat = (x["Intercept"] + x["fl_dam"] * self.perceived_flood_damage + x["fl_30_prob"] * self.perceived_flood_probability + x["worry"] * self.worry + x["fl_dam:worry"] * self.perceived_flood_damage * self.worry + x["RE"] * self.RE_elevation + x["SE"] * self.SE_elevation + x["PC"] * self.PC_elevation + x["fl_exp"] * self.flood_experience + x["soc_exp"] * self.social_expectations + x["soc_norm"] * self.social_norm_elevation + x["UG_wet_proof_bi"] * self.wet_proofing + x["UG_dry_proof_bi"] * self.dry_proofing + x["gov_meas_n"] * self.gov_meas_suf + x["social_media"] * self.social_media + x["CC_affect"] * self.cc_affect)

self.probability_to_elevate = np.exp(y_hat)/(1 + np.exp(y_hat))
```

```
def calculate_dry_proof_probability(self):
x = self.model.pmt_params.Dry_proof
y_hat = (x["Intercept"] + x["fl_dam"] * self.perceived_flood_damage + x["fl_30_prob"] *
self.perceived_flood_probability + x["worry"] * self.worry + x["fl_dam:worry"] * self.perceived_flood_damage
* self.worry + x["RE"] * self.RE_dry_proofing + x["SE"] * self.SE_dry_proofing + x["PC"] *
self.PC_dry_proofing + x["fl_exp"] * self.flood_experience + x["soc_exp"] * self.social_expectations
+ x["soc_norm"] * self.social_norm_dry_proofing + x["UG_wet_proof_bi"] * self.wet_proofing + x["S_UG1"]
* self.elevation + x["gov_meas_n"] * self.gov_meas_suf + x["social_media"] * self.social_media +
x["CC_affect"] * self.cc_affect)

self.probability_to_dry_proof = np.exp(y_hat)/(1 + np.exp(y_hat))
```

```
def calculate_wet_proof_probability(self):
x = self.model.pmt_params.Wet_proof
y_hat = (x["Intercept"] + x["fl_dam"] * self.perceived_flood_damage + x["fl_30_prob"] *
self.perceived_flood_probability + x["worry"] * self.worry + x["fl_dam:worry"] * self.perceived_flood_damage
* self.worry + x["RE"] * self.RE_wet_proofing + x["SE"] * self.SE_wet_proofing + x["PC"] *
self.PC_wet_proofing + x["fl_exp"] * self.flood_experience + x["soc_exp"] * self.social_expectations
+ x["soc_norm"] * self.social_norm_wet_proofing + x["UG_dry_proof_bi"] * self.dry_proofing + x["S_UG1"]
* self.elevation + x["gov_meas_n"] * self.gov_meas_suf + x["social_media"] * self.social_media +
x["CC_affect"] * self.cc_affect)

self.probability_to_wet_proof = np.exp(y_hat)/(1 + np.exp(y_hat))
```

```
def calculate_move_base_probability(self):
x = self.model.pmt_params.Move_base
y_hat = (x["Intercept"] + x["fl_dam"] * self.perceived_flood_damage + x["fl_30_prob"] *
self.perceived_flood_probability + x["fl_likely"] * self.flood_likely + x["soc_exp"] * self.social_expectations
+ x["soc_norm"] * self.social_norm_move + x["soc_network_scale"] * self.social_network + x["S_UG1"]
* self.elevation + x["UG_dry_proof_bi"] * self.dry_proofing + x["UG_wet_proof_bi"] * self.wet_proofing +
x["move_houses"] * self.move_houses + x["move_city"] * self.move_city + x["find_job"] * self.find_job +
x["lost_job"] * self.lost_job + x["lost_job_impact"] * self.lost_job_impact + x["to_leave"] * self.to_leave

self.probability_to_move_base = np.exp(y_hat)/(1 + np.exp(y_hat))
```

```
def calculate_move_medium_flood_probability(self):
x = self.model.pmt_params.Move_medium_flood
y_hat = (x["Intercept"] + x["fl_dam"] * self.perceived_flood_damage + x["fl_30_prob"] *
self.perceived_flood_probability + x["fl_likely"] * self.flood_likely + x["soc_exp"] * self.social_expectations
+ x["soc_norm"] * self.social_norm_move + x["soc_network_scale"] * self.social_network + x["S_UG1"]
* self.elevation + x["UG_dry_proof_bi"] * self.dry_proofing + x["UG_wet_proof_bi"] * self.wet_proofing +
x["move_houses"] * self.move_houses + x["move_city"] * self.move_city + x["find_job"] * self.find_job +
x["lost_job"] * self.lost_job + x["lost_job_impact"] * self.lost_job_impact + x["to_leave"] * self.to_leave

self.probability_to_move_medium_flood = np.exp(y_hat)/(1 + np.exp(y_hat))
```

```
def calculate_move_severe_flood_probability(self):
x = self.model.pmt_params.Move_severe_flood
y_hat = (x["Intercept"] + x["fl_dam"] * self.perceived_flood_damage + x["fl_30_prob"] *
self.perceived_flood_probability + x["fl_likely"] * self.flood_likely + x["soc_exp"] * self.social_expectations
+ x["soc_norm"] * self.social_norm_move + x["soc_network_scale"] * self.social_network + x["S_UG1"]
* self.elevation + x["UG_dry_proof_bi"] * self.dry_proofing + x["UG_wet_proof_bi"] * self.wet_proofing +
x["move_houses"] * self.move_houses + x["move_city"] * self.move_city + x["find_job"] * self.find_job +
x["lost_job"] * self.lost_job + x["lost_job_impact"] * self.lost_job_impact + x["to_leave"] * self.to_leave

self.probability_to_move_severe_flood = np.exp(y_hat)/(1 + np.exp(y_hat))
```

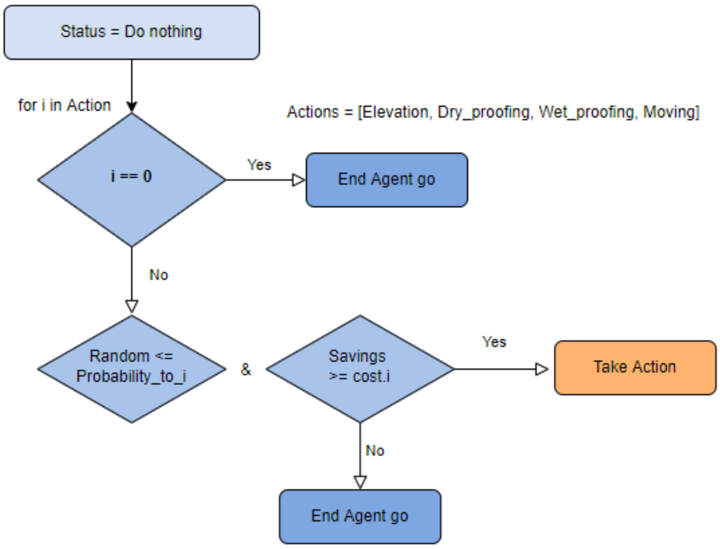

Figure 9.9: Flowchart Protection motivation

PMT function

The PMT function is performed, when no flooding occurs. First, the agents status is set on: do nothing. Secondly, only if an action is not taken already and there is enough savings to pay for the costs of the action, the random number (drawn and saved after a the occurrence of a flood) is compared to ones probability to undertake the action. If the intention to take action and the savings are high enough, the action is performed, otherwise the Agent-go function ends. The PMT function is performed separately for all adaptation or migration actions. Multiple adaptation actions can be performed in the same tick. However, the option to migrate is only executed if no adaptation action is performed. Furthermore, the probability to move depends on an agent's flood damage attribute. If the damage is greater than or equal to four months of income, the severe probability is invoked. For damage between two and four months, the medium probability is used and for damage less than two months, the basic probability.

```
def PMT(self):
    self.status = "Do nothing"

    if self.elevation == 0:
        if self.savings >= self.cost_elevation:
            if self.r <= self.probability_to_elevate:
                self.elevate()

    if self.dry_proofing == 0:
        if self.savings >= self.cost_dry_proofing:
            if self.r <= self.probability_to_dry_proof:
                self.dry_proof()

    if self.wet_proofing == 0:
        if self.savings >= self.cost_wet_proofing:
            if self.r <= self.probability_to_wet_proof:
                self.wet_proof()

    if self.status != "Adapting":
        if self.savings >= self.cost_moving:
            if self.flood_damage >= (self.income/12) * 4:
                if self.r <= self.probability_to_move_sev:
                    self.moving()
            elif self.flood_damage >= (self.income/12) * 2:
                if self.r <= self.probability_to_move_med:
                    self.moving()
            else:
                if self.r <= self.probability_to_move_base:
                    self.moving()
```

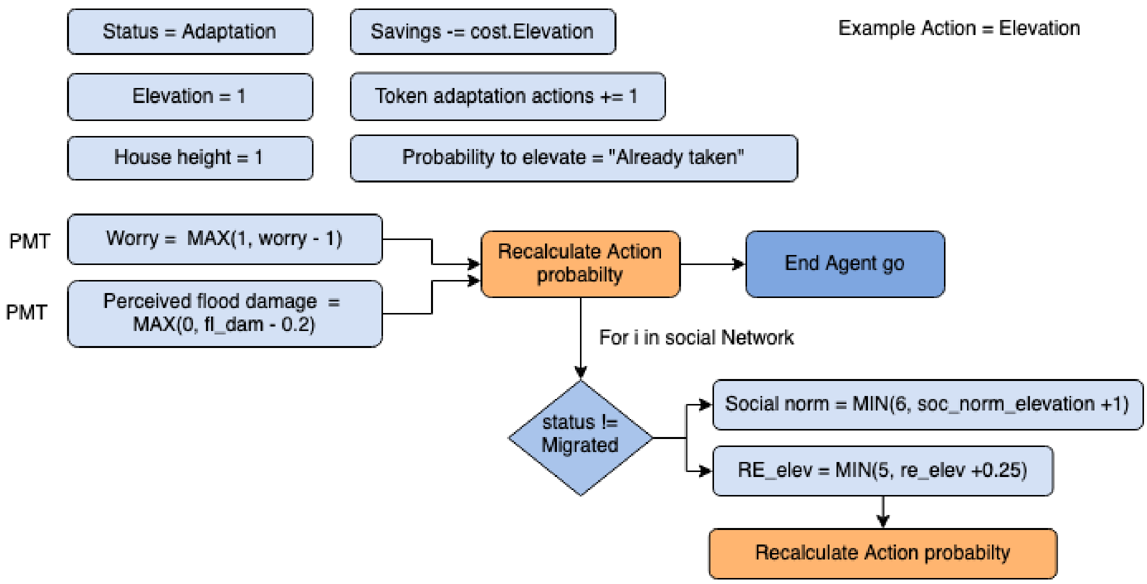

Figure 9.10: Flowchart Action

Adaptation and Migration actions

Once an agent's intention is put into action in the PMT function, the status, action, token adaptation actions and probability to action attributes get updated, see fig 9.10. Furthermore, the cost of the adaptation action are being subtracted by the savings. Next, the agents PMT attributes worry, perceived flood damage and the self-efficacy of the other adaptation actions are changed. Afterwards, the probabilities to take action are being recalculated, after which the Agent go function ends. Lastly, the agent's attributes of the households within the same social network who are not migrated yet are influenced by the undertaken action as well. The social norm and response efficacy go up by one, after which the probabilities to actions of the households in the social network are being recalculated.

```
def elevate(self):
    self.elevation = 1
    self.status = "Adapting"
    self.token_adaptation_measures += 1
    self.house_height = 1
    self.probability_to_elevate = "Already taken"

    self.worry = max(1, self.worry - 1)
    self.perceived_flood_damage = max(0.1, self.perceived_flood_damage - 0.2)

    self.savings -= self.cost_elevation
    self.recalculate_probability_to_take_action()

    for i in self.neighbors:
        if i.status != "Migrated":
            i.social_norm_elevation = min(6, i.social_norm_elevation + 1)
            i.RE_elevation = min(5, i.RE_elevation + 0.25)
            i.recalculate_probability_to_take_action()
```

```
def dry_proof(self):
    self.dry_proofing = 1
    self.status = "Adapting"
    self.token_adaptation_measures += 1
    self.house_height = 1
    self.probability_to_dry_proof = "Already taken"

    self.worry = max(1, self.worry - 1)
    self.perceived_flood_damage = max(0.1, self.perceived_flood_damage - 0.2)

    self.savings -= self.cost_dry_proofing
    self.recalculate_probability_to_take_action()

    for i in self.neighbors:
        if i.status != "Migrated":
            i.social_norm_dry_proof = min(6, i.social_norm_dry_proof + 1)
            i.RE_dry_proofing = min(5, i.RE_dry_proofing + 0.25)
            i.recalculate_probability_to_take_action()
```

```
def wet_proof(self):
    self.wet_proofing = 1
    self.status = "Adapting"
    self.token_adaptation_measures += 1
    self.house_height = 1
    self.probability_to_wet_proof = "Already taken"

    self.worry = max(1, self.worry - 1)
    self.perceived_flood_damage = max(0.1, self.perceived_flood_damage - 0.2)

    self.savings -= self.cost_wet_proofing
    self.recalculate_probability_to_take_action()

    for i in self.neighbors:
        if i.status != "Migrated":
            i.social_norm_wet_proof = min(6, i.social_norm_wet_proof + 1)
            i.RE_wet_proofing = min(5, i.RE_wet_proofing + 0.25)
            i.recalculate_probability_to_take_action()
```

```
def moving(self):
    self.moved = True
    self.status = "Migrated"
    self.probability_to_move_base = "Already taken"
    self.probability_to_move_med = "Already taken"
    self.probability_to_move_sev = "Already taken"

    self.savings -= self.cost_moving

    for i in self.neighbors:
        if i.status != "Migrated":
            i.social_norm_move = min(6, i.social_norm_move + 1)
            i.recalculate_probability_to_take_action()
```

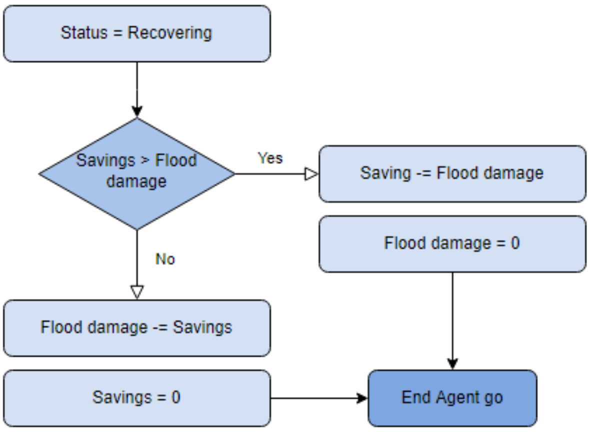

Figure 9.11: Flowchart Recovery

Recovery

The recover function is only executed when no flooding, adaptation or migration action is performed and the household's flood damage is higher than zero, see fig 9.6. First the status is set to Recovering. Secondly, it is checked whether the household has enough savings to pay for the remaining damage at once. If that's the case, the flood damage is set to zero and the money is being subtracted by the savings. Otherwise, when not enough money is available, the savings are being subtracted by the flood damage, after which the savings are set to zero. After this the Agent go function ends.

```
def recover(self):
    self.status = "Recovering"
    if self.savings >= self.flood_damage:
        self.savings -= self.flood_damage
        self.flood_damage = 0
    else:
        self.flood_damage -= self.savings
        self.savings = 0
```

This was the end of the agent-go function.

9.7.5. Collection of results - KPI's

Once the maximum number of ticks is reached, it's time to collect the model run results. First, the total flood damage of all households is being reported. Secondly, the percentage of households that performed elevation, dry proofing, wet proofing and migration is reported. Thirdly, the average of the five capitals that define the socio-economic resilience of Jakarta among the non-migrated households is reported. The composition of factors that make up the five capitals can be found in table 5.2.

```
def end(self):
    """ Recordings at end of simulation """
    self.report('Total flood damage', round(sum(self.agents.total_damage)))

    self.report('Total % elevation - KPI Physical', sum(self.agents.elevation)/self.p.agents)
    self.report('Total% dry proofing - KPI Physical', sum(self.agents.dry_proofing)/self.p.agents)
    self.report('Total % wet proofing - KPI Physical', sum(self.agents.wet_proofing)/self.p.agents)
    self.report('Total % migrated - KPI Physial', sum(self.agents.status == "Migrated")/self.p.agents)

    self.report('Average Human capital',
                np.mean([self.rescore(self.agents.select(self.agents.status != 'Migrated').worry),
                self.agents.select(self.agents.status != 'Migrated').cc_affect,
                self.agents.select(self.agents.status != 'Migrated').edu]))
    self.report('Average Financial capital',
                np.mean([self.agents.select(self.agents.status != 'Migrated').econ_comf,
                self.agents.select(self.agents.status != 'Migrated').financial_support,
                self.agents.select(self.agents.status != 'Migrated').governmental_support,
                self.agents.select(self.agents.status != 'Migrated').saving_flexibility,
                self.agents.select(self.agents.status != 'Migrated').income_rank]))
    self.report('Average Social capital',
                np.mean ([self.agents.select(self.agents.status != 'Migrated').social_support,
                self.agents.select(self.agents.status != 'Migrated').social_network]))
    self.report('Average times flooded - Nature capital',
                np.mean ([self.agents.select(self.agents.status != 'Migrated').flooded]))
    self.report('Average token measures - Physical capital',
            np.mean([self.agents.select(self.agents.status != 'Migrated').token_adaptation_measures]))
```

10

Experimental design

In this chapter the experimental design for the flood risk and policy scenario's are discussed. First an overview of the experimental setup with the ABM is presented in section 10.1. Here, the flood and policy scenario's are discussed as well. Next, the designed experiments are shown in section 10.2 . Lastly, a description of the sensitivity analysis is given in section 10.3.

10.1. Model experiments

To give an overview on experimenting with the model works, an XLRM framework is used. The XLRM framework components are defined as follows (Lempert et. al. 2003):

- **Xs - Exogenous uncertainties**; are factors outside the control of decision-makers that may nonetheless prove important in determining the success of their strategies.
- **Ls - Policy levers**; are near-term actions that, in various combinations, comprise the alternative strategies decision-makers want to explore.
- **Rs - Relationships**; are potential ways in which the future, and in particular those attributes addressed by the measures, evolve over time based on the decision-maker's choices of levers and the manifestation of the uncertainties. A particular choice of Rs and Xs represents the future state of the world.
- **Ms - Measures**; are the performance standards that decision-makers and other interested communities would use to rank the desirability of various scenarios.

For the Jakarta-case, the XLRM components consist of the following model attributes, see figure 10.1. To start, the exogenous uncertainties (X) and the policy levers (L) are the model parameters, which form the input variables of the Jakarta model. The input variables will be varied during the experiments and sensitivity analysis. The relationships (R) are defined by the model functions, which remain the same during the whole process. Lastly, the recorded model KPI's form the measures (M), on which the experiment outputs can be compared.

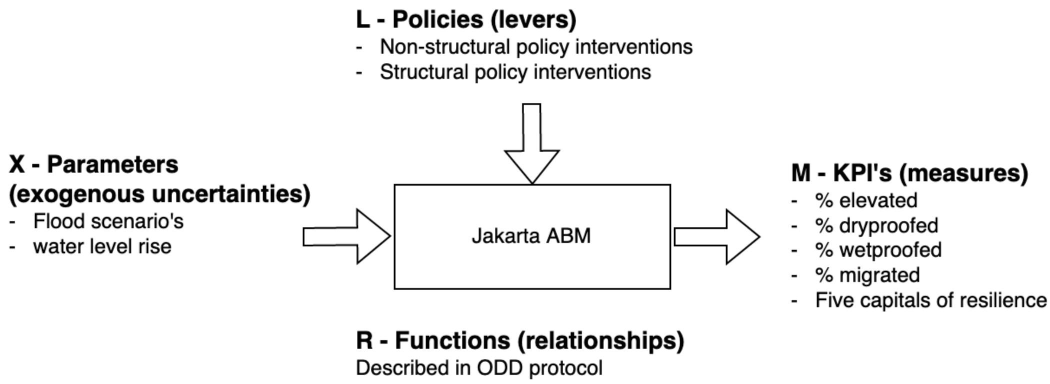

Figure 10.1: XLRM Jakarta model

10.1.1. Flood scenario's

Since flooding is an external uncertainty, three different flood scenario's are designed under which the emerge of adaptation and migration behaviour is tested. Because of limited available flood height data in Jakarta (see section 4.2.1 for more information), the maximum flood height of the extreme flooding early 2020 is taken as a reference point for each polygon to build the scenario's upon. The flood scenario's are designed as follows. Every year in the first month, a flood occurs. A medium flood the size of 1/4 of the maximum flood height of the flooding in 2020, is most commonly used; two out of three times. Although once every three years, a bigger floods occurs, varying in height per scenario, see table 10.1. In the first scenario: small flooding, a flood of 1/3 times the flood height from 2020 was used. The second scenario: medium flooding, involves a flood half of the recorded flood height from 2020. Finally, in the third scenario: severe flooding, a flood equal to the one of 2020 will occur every three years. The simplification of flooding is made, because the focus of this study is not on the hydrology aspects, but aims to explore the effect of a flood threat and exposure on the adaptation behaviour of households.

Table 10.1: Flood scenario's

Scenario	**Flood scenario array**
1	[1/4,0,0,0,0,0,0,0,0,0,0,0] , [1/3,0,0,0,0,0,0,0,0,0,0,0], [1/4,0,0,0,0,0,0,0,0,0,0,0]
2	[1/4,0,0,0,0,0,0,0,0,0,0,0] , [1/2,0,0,0,0,0,0,0,0,0,0,0], [1/4,0,0,0,0,0,0,0,0,0,0,0]
3	[1/4,0,0,0,0,0,0,0,0,0,0,0] , [1,0,0,0,0,0,0,0,0,0,0,0], [1/4,0,0,0,0,0,0,0,0,0,0,0]

Note: The numbers from the array represent the flood height per month (one tick in the model). The flood scenario's designed in cycles of three years.

10.1.2. Policy scenario's

To explore the emerge of adaptation and migration behaviour under socio-political conditions, three public protection policies and one job-related migration policy are designed. In addition, two monetary stimuli in a form of a subsidy will be tested. Lastly, two educational policies influencing the risk and coping perceptions have been devised. The effects of the policies can be found in table 10.2. More back-ground information on the policy interventions and the estimated effects can be found in chapter 8.

Table 10.2: Policy interventions

Policy measure	**Influenced variable**	**Effect**
Structural (Public protection)		
Most flood prone areas	Flood height >= 3m	2.5 m
Gigantic seawall	Flood height	0.0 m
Equal protection	Flood height	-2.0 m
Non-structural		
Job offer migration	Find job	1 = less than a month
Subsidy on adaptation	Perceived cost	-1
	Actual cost	* 0.5
Subsidy on migration	To leave	+ 1
	Actual cost	* 0.5
Education and training on adaptation	Response-efficacy	+ 1
	Self-efficacy	+ 1
Raising flood risk awareness	Worry	+ 1

Based on literature section 8.1.

10.2. Policy Strategies under flood risk scenario's

All policy scenario's are tested under the three flood scenarios to explore the singular effect of policy interventions while testing the robustness of policy strategies and potential vulnerabilities under flood risk, see table 10.3. The policy interventions are tested separately first, to be able to explore the isolated impacts. Later on, the public protection measures are combined with all non-structural policies into flood management strategies. Since testing all possible policy combinations is very time consuming and undesirable, smart combinations needed to be made in the experimental design. These combinations were chosen, as the most impact was expected.

Table 10.3: Policy experiments under flood risk scenario's

Experiment number	Policies	Flood scenario's
1	-	1,2,3
2	Public protection- most flood prone	1,2,3
3	Public protection- gigantic seawall	1,2,3
4	Public protection- equal protection	1,2,3
5	Subsidy - adaptation	1,2,3
6	Subsidy - migration	1,2,3
7	Job offer migration	1,2,3
8	Education - flood risk	1,2,3
9	Education - adaptation	1,2,3
10	All public protection + others	1,2,3
11	Public protection- most flood prone + others*	1,2,3
12	Public protection- gigantic seawall + others*	1,2,3
13	Public protection- equal protection + others*	1,2,3

*others = all policy measures apart from public protection

During the experimentation, the number of steps, agents, random seed and water level rise are kept constant to be able to compare the experimental results. See table 10.4 for an overview of the parameter values. The number of steps is 360 month to collect the model results over thirty years of time. A time horizon of 30 years is chosen, because it takes some time before the effect of policies interventions on the aggregated adaptation behaviour of Jakarta can be seen. A longer time period is not desirable, because the uncertainty about the representation of the data and the course of behaviour and flooding then becomes increasingly uncertain (Taberna et al., 2020). The seed is fixed, to allow randomness but in a reproducible order which is needed to compare the results. The number of agents is set to 10.000 households; a big enough sample to represent the Jakarta population. Lastly, the water level rise in Jakarta is set on 4 cm yearly, which is based on a study from IPB University, 2021 on subsidence in Jakarta between 2019-2020. IPB University, 2021 found that North Jakarta faces the highest level of land subsidence, 4.9 cm per year, whereas the lowest areas in East Jakarta sink 2.5 cm on average, making a rounded average of 4cm a year.

Table 10.4: Model basic experiment parameters

Model parameter	Value	Unit
steps	360	ticks
seed	21	-
number of agents	10.000	households
water level rise	0.04	meter

10.3. Sensitivity analysis

In total two sensitivity analysis are performed. The first, on the effect of the non-structural policy measures influencing the household perceptions, see table 10.5. A range of two out five on the likert-scale with steps of 0.5 is chosen, assuming households' perceptions could get influenced but some of the original opinion remains. A higher change in perceptions would cause a too extreme effect in the agents attribute making it not relatable to the survey data anymore. The second sensitivity analyse was done on the water level rise, with a range between 1 and 10 cm per year, see table 10.6. The range of water level rise values was based on the study of IPB University, 2021 who found a range in subsidence varying between 1.8 and 10.7 cm per year in Jakarta during 2019 and 2020.

10.3.1. Policy measures effects

Table 10.5: Sensitivity analysis policy measures effect

Experiment number	Policies	Influenced variable	Effect values
14	Subsidy - adaptation	PC	-2, -1.5, -1, -0.5
15	Subsidy - migration	to leave	+0.5, +1, +1.5, +2
16	Education - flood risk	worry	+0.5, +1, +1.5, +2
17	Education - adaptation	RE	+0.5, +1, +1.5, +2
18	Education - adaptation	SE	+0.5, +1, +1.5, +2

10.3.2. Water level rise

Table 10.6: Sensitivity analysis water level rise

Experiment number	Policies	Water level rise values
19	-	0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1

11

Results

In this chapter the experimental results are presented. The structure of chapter is the following. First, the experiment outcomes on the key performance indicators of the ABM are presented in section 11.1. The KPI scores are discussed one by one, for the designed policy strategies under all flood scenario's confirm table 10.3. Starting with the experiment results on the total flood damage, in section 11.1.1. Secondly, in section 11.1.2 the adaptation and migration behaviour is discussed. Thirdly, the Five capital scores to measure Jakarta's flood resilience are covered in section 11.1.3. The exact outcomes on all KPI's per experiment can be found in appendix C.1. Lastly, the results of the sensitivity analysis designed in 10.3 are presented in section 11.2.

11.1. Experimental results of the key performance indicators

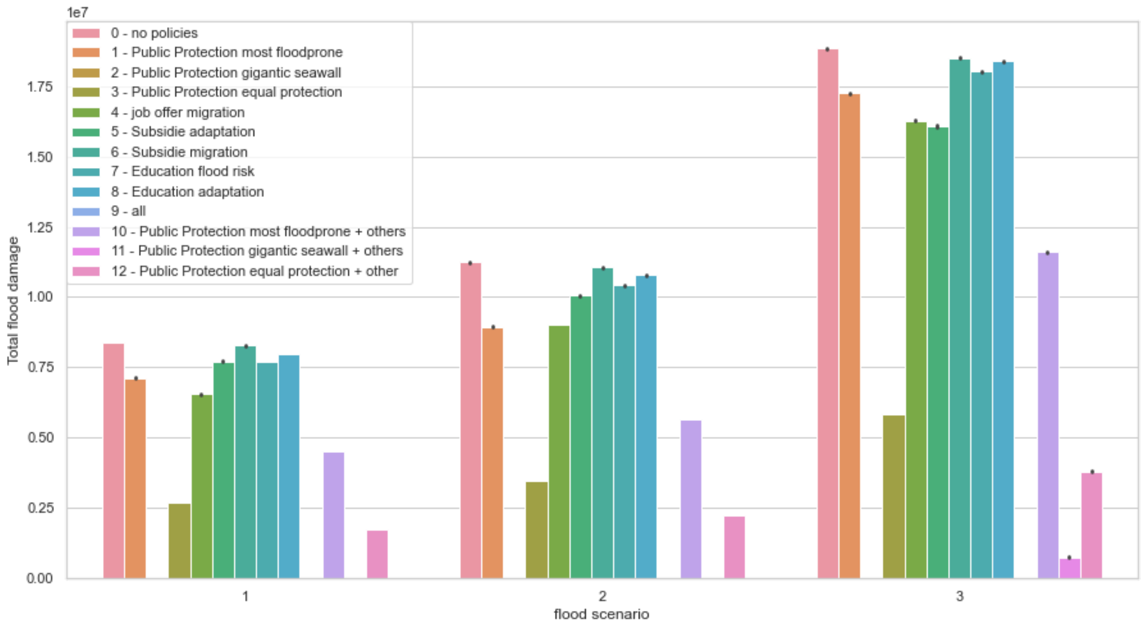

Figure 11.1: Flood damage per policy strategy and flood scenario

11.1.1. Flood damage

First thing to notice is that the total flood damage of Jakarta increases as flooding become more severe. The total amount of flood damage of Jakarta's households under no policy interventions is 8386327.72 Rupiah in scenario one, 11234503.42 Rupiah in scenario two and 18843555.25 Rupiah in scenario three. Meaning more than twice as much flood damage in scenario three compared to scenario one. Furthermore, all policies have a reducing effect on flood damage, however there is a wide variation in the size of the effect, see figure 11.1. The biggest flood damage reduction is achieved by the gigantic sea wall, which reduces the flood damage to zero under scenario one, two and three. Next in line, is providing equal protection, which reduces the flood damage to 2699065.75 Rupiah in scenario one, 3468199.27 Rupiah in scenario two and 5837400.33 Rupiah in scenario three. Focusing on protecting the most flood prone areas only, on the other hand, does not score as well as the other public protection policies; 7123493.41 Rupiah in scenario one, 8939687.99 Rupiah in scenario two and 17252432.41 Rupiah in scenario three. Job security in the case of migration scores about the same as only providing public protection in the most flood-prone areas, for the exact numbers per flood scenario see appendix C.1. The subsidy and education policies only have a small effect on the total flood damage, expect for the subsidy on migration in the worst-case flood scenario. Looking at the policy strategy combinations of public protection with all other policy measures, it can be seen that the additional job offer, subsidies and education measures on top of the public protection make a significant difference compared to just public protection only. The combination of all public protection measures and additional policies is most effective over all flood scenario.

11.1.2. Adaptation and migration behaviour

Flood scenario's

Looking at the evolution of household status' over time, it can be seen that around 23 % of the population in flood risk scenario one, 28% in scenario two and 42% in scenario three, is flooded and recovering all the time. The percentage of people doing nothing starts around 60 %, but exponentially decreases until 3% in scenario one and two and 1% in scenario three over a period over thirty years, see figure 11.2, 11.3, 11.4. In the household adaptation behaviour almost no difference between flood scenarios can be found (see appendix C.1). Looking at the number of people migrating on the other hand, a difference between flood scenario's can be found. The percentage of migration starts at zero but increases exponentially at first, after which it stabilises around 74% in scenario one, 69% in scenario two and 57% in scenario three. Thus, when floods become more severe, the percentage of households continuously flooding and recovering increases, while the percentage of households who do nothing or migrate decreases, see figure 11.4. Meaning households in flood prone areas seem to be extra vulnerable for increasing flood risk, as more households in these areas end up in a lock-in situation of continuous flooding and recovering without being able to migrate when flooding becomes more severe.

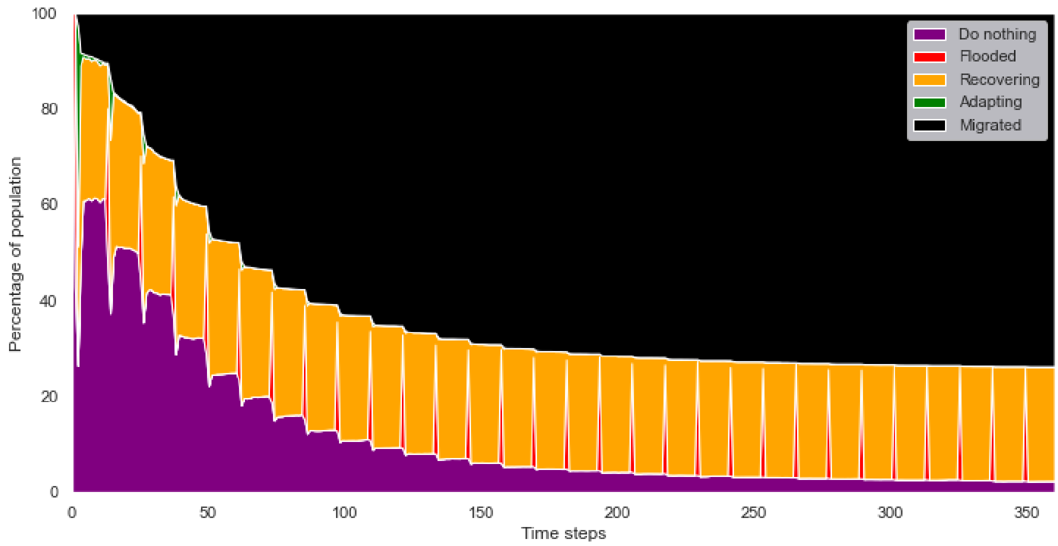

Figure 11.2: Emergence of household status over time - no policy strategy & flood risk scenario 1

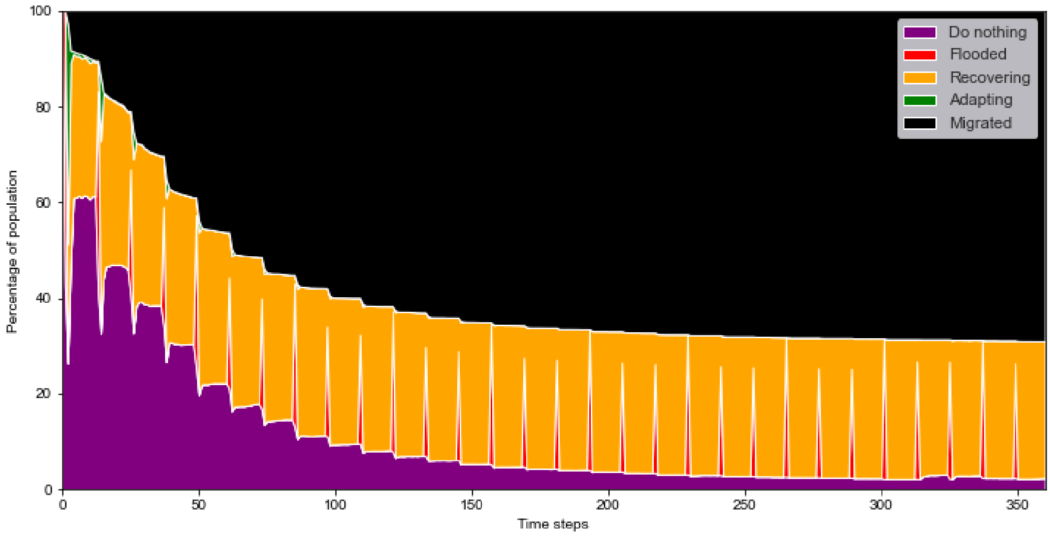

Figure 11.3: Emergence of household status over time - no policy strategy & flood risk scenario 2

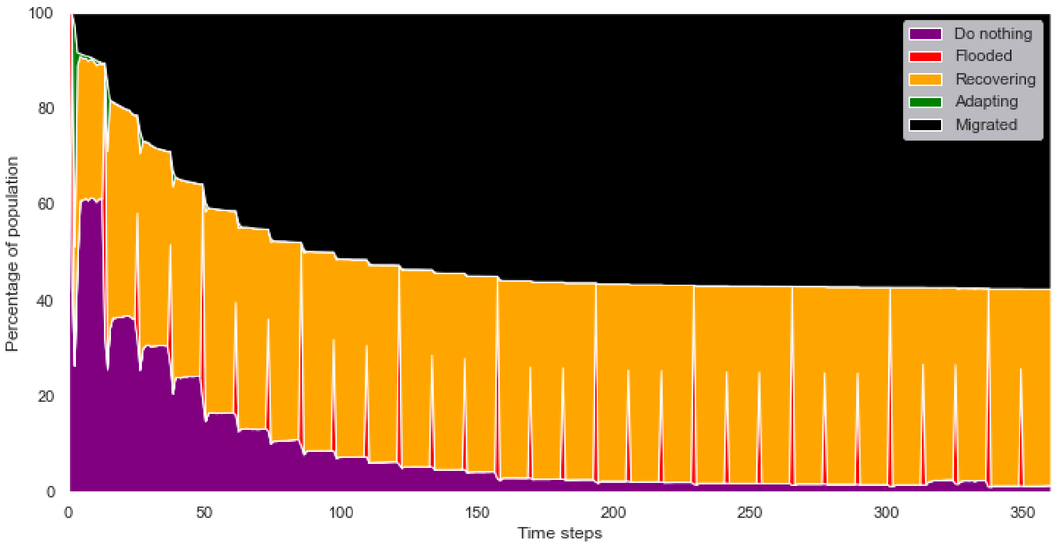

Figure 11.4: Emergence of household status over time - no policy strategy & flood risk scenario 3

Policy scenario's

In line with the conclusions drawn above, there is little difference in adaptation behaviour (for all adaptation actions) between flood scenarios under the various policy strategies, see figure 11.5, 11.6 and 11.7. However, the percentage of households migrating under different policy strategies decreases under a more severe flood scenario, see figure 11.8.

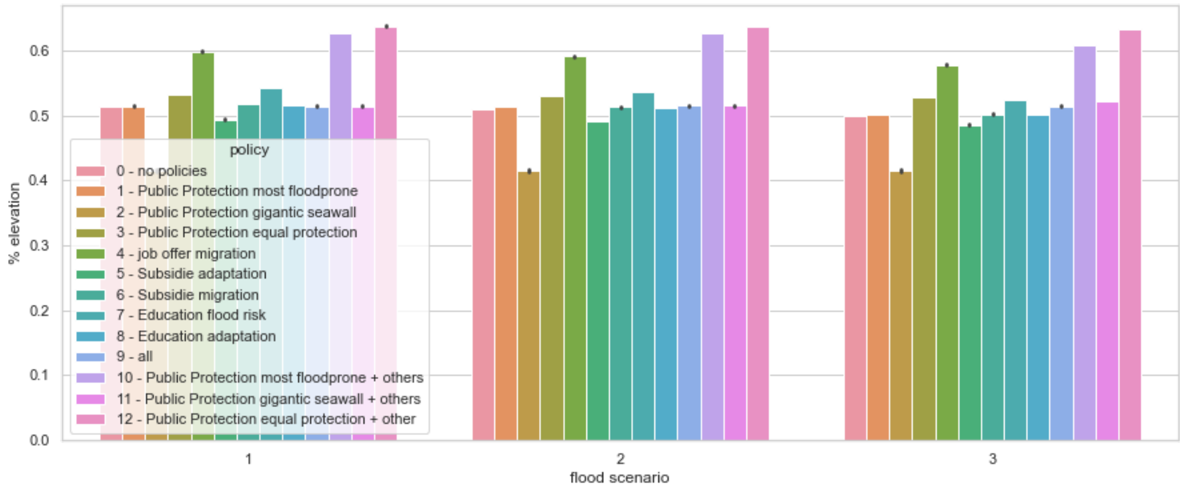

Figure 11.5: Percentage elevation per policy strategy and flood scenario

The percentage of households undertaking elevation lies around 50% in the no-policy scenario, but can range from 42% (in the Gigantic seawall strategy) til 64% (in the equal protection plus other policies strategies), see figure 11.5 and appendix C.1 for the exact numbers per flood scenario.

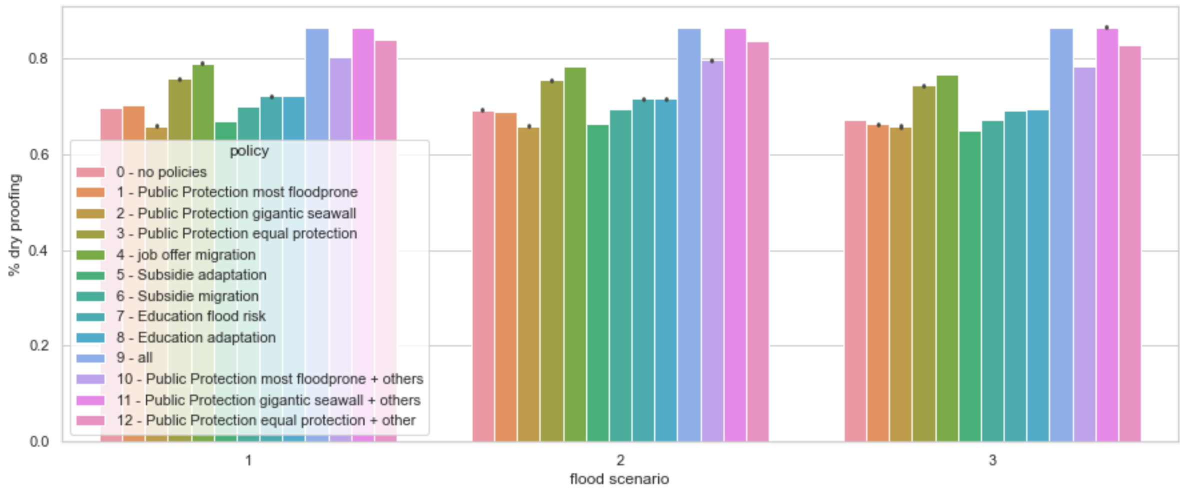

Figure 11.6: Percentage dry proofing per policy strategy and flood scenario

The percentage of households undertaking dry proof measures lies around 69% in the no-policy scenario, but can range from 66% (in the Gigantic seawall strategy) til 86% (in the Gigantic seawall plus other policy strategies), see figure 11.6 and appendix C.1 for the exact numbers per flood scenario.

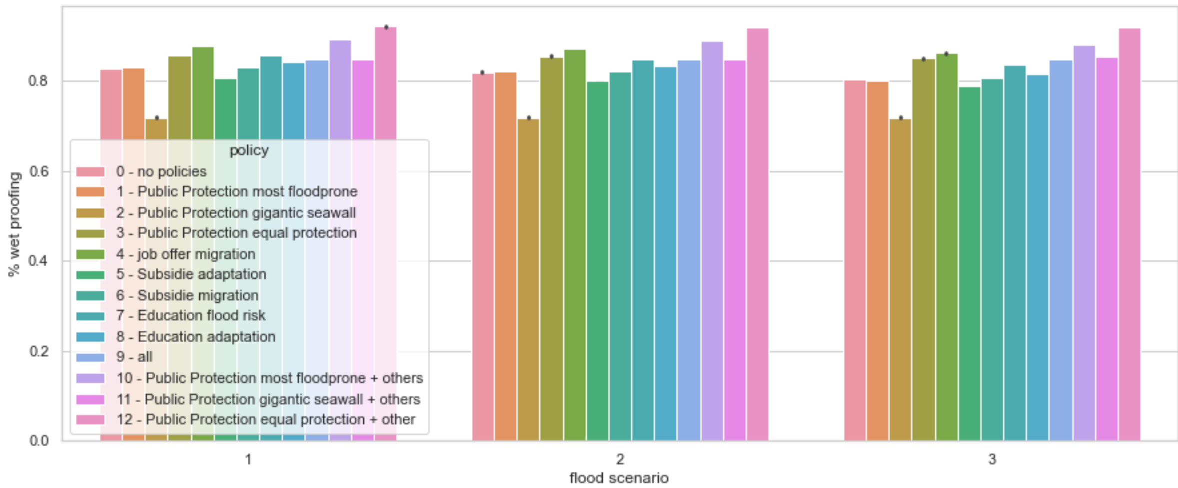

Figure 11.7: Percentage wet proofing per policy strategy and flood scenario

The percentage of households undertaking wet proof measures lies around 82% in the no-policy scenario, but can range from 72% (in the Gigantic seawall strategy) til 92% (in the equal protection plus other policies strategies), see figure 11.7 and appendix C.1 for the exact numbers per flood scenario.

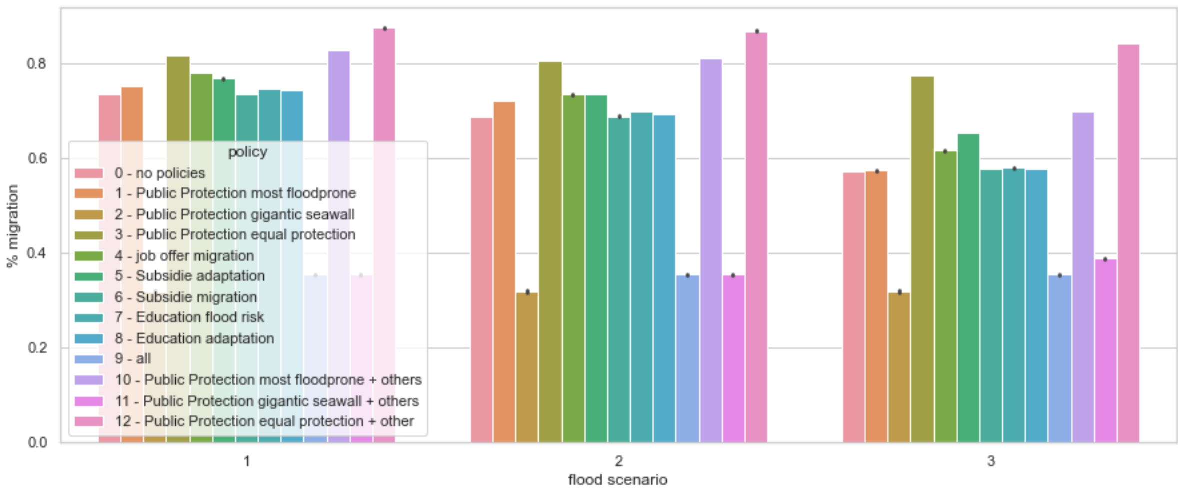

Figure 11.8: Percentage migration per policy strategy and flood scenario

The percentage of households migrating lies around 74% in the no-policy scenario, but can range from 32% (in the Gigantic seawall strategy) til 86% (in the equal protection plus other policies strategies), see figure 11.8 and appendix C.1 for the exact numbers per flood scenario.

11.1.3. Five Capitals

Flood scenario's

Looking at the evolution of the five capitals over time, it can be seen that the human, financial, physical and social capital slightly decrease while the nature capital on the other hand increases, when flooding become more severe. Meaning, in general the flood resilience of Jakarta households decreases over time, due to migration of the more flood resilience households. Furthermore, the slight decrease of the human, social and financial capitals under the different flood scenario's is quite the same, whereas the physical capital remains higher for a more extreme flood scenario, see figures 11.9, 11.10, 11.11. Meaning, households who remain in Jakarta become better adapted over time when flooding becomes more severe. The exact numbers of the five capitals for all flood risk scenario's can be found in appendix C.1.

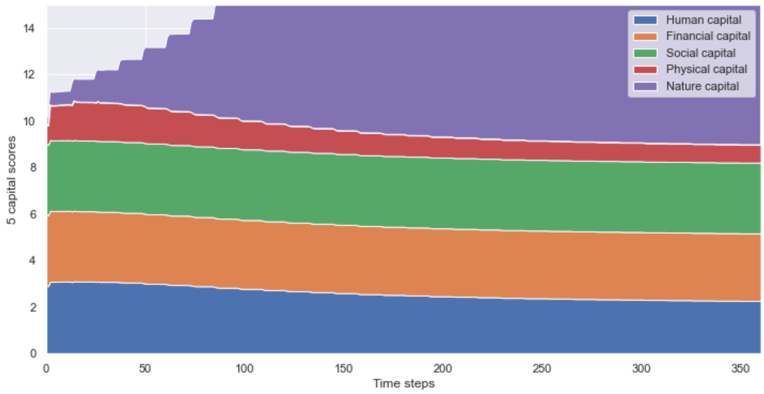

Figure 11.9: Emergence of the five capitals over time - no policy strategy & flood risk scenario 1

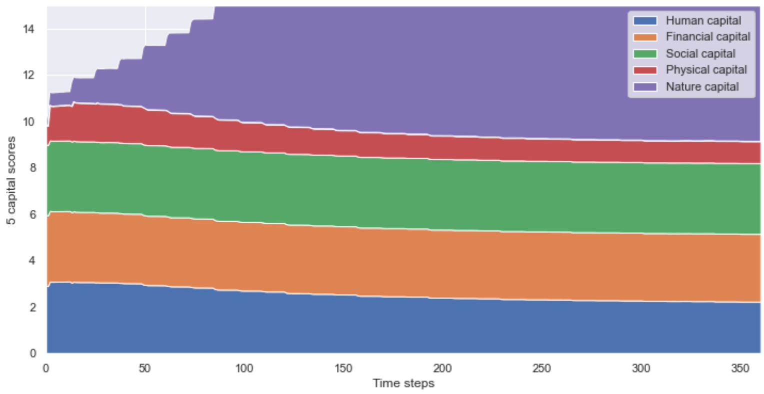

Figure 11.10: Emergence of the five capitals over time - no policy strategy & flood risk scenario 2

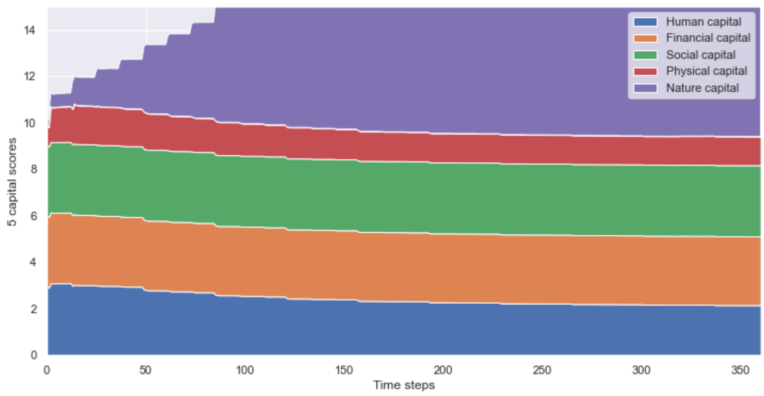

Figure 11.11: Emergence of the five capitals over time - no policy strategy & flood risk scenario 3

Policy scenario's

In line with the conclusions drawn above, little difference among the human, financial and social capitals can be found between the flood scenario's under various policy strategies, see figures 11.12, 11.13 and 11.14. However, the physical capital, measured as the average number of token adaptation measures per household, slightly increases when flooding becomes more severe, see figure 11.16. Furthermore the nature capital, measured as the number of times households living in Jakarta get flooded over 30 years, reduces under the more extreme flood scenario, see figure 11.15. Meaning in a more extreme flood scenario, on average more adaptation actions are performed, which subsequently reduces the number of times households get flooded.

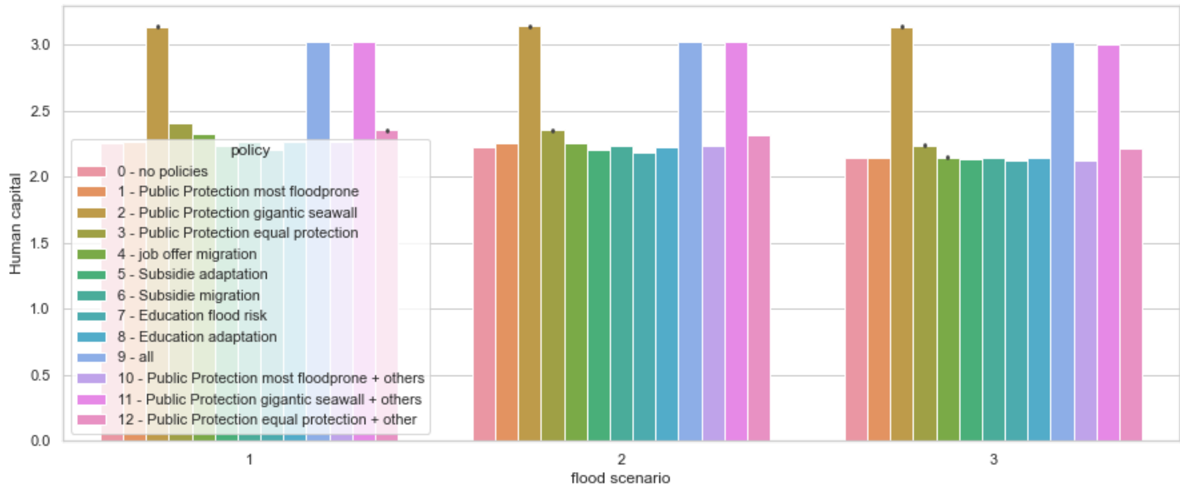

Figure 11.12: Human capital - Five Capital per policy strategy and flood scenario

The average Human capital in the no policy scenario is 2.2 and ranges between 2.2 (in the education flood risk strategy) and 3.1 (in the Gigantic seawall scenario) , see figure 11.12 and appendix C.1 for the exact numbers per flood scenario.

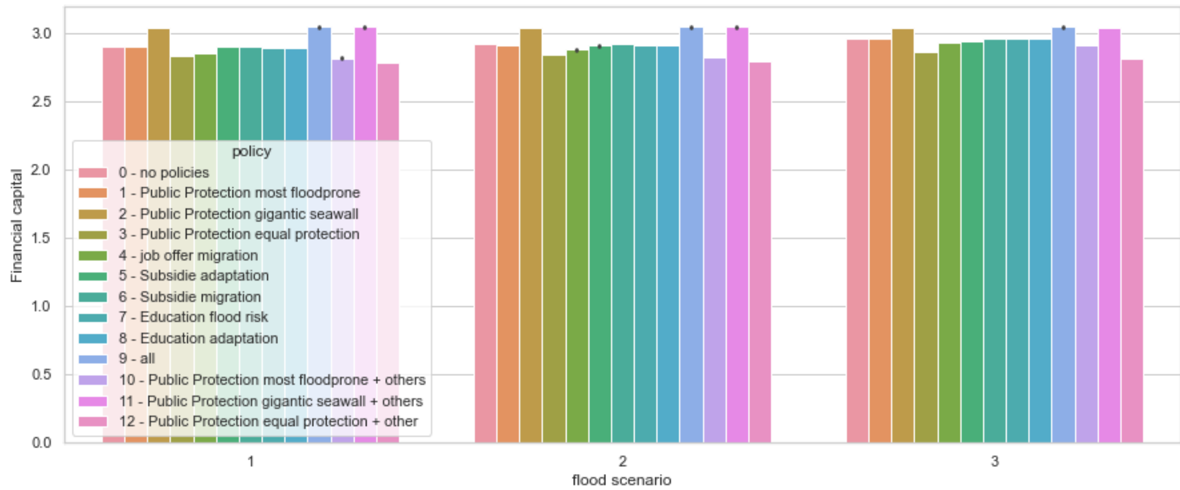

Figure 11.13: Financial capital - Five Capital per policy strategy and flood scenario

The average Financial capital in the no policy scenario is 2.9 and ranges between 2.8 (in the equal protection plus other policies strategy) and 3.0 (in the Gigantic seawall scenario's) , see figure 11.13 and appendix C.1 for the exact numbers per flood scenario.

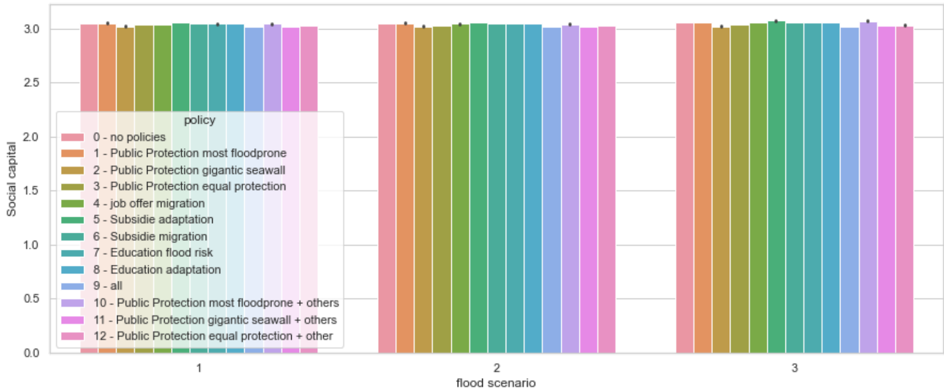

Figure 11.14: Social capital - Five Capital per policy strategy and flood scenario

The average Social capital ranges 3.05 and 3.1 for all policy scenario's, see figure 11.14 and appendix C.1 for the exact numbers per flood scenario.

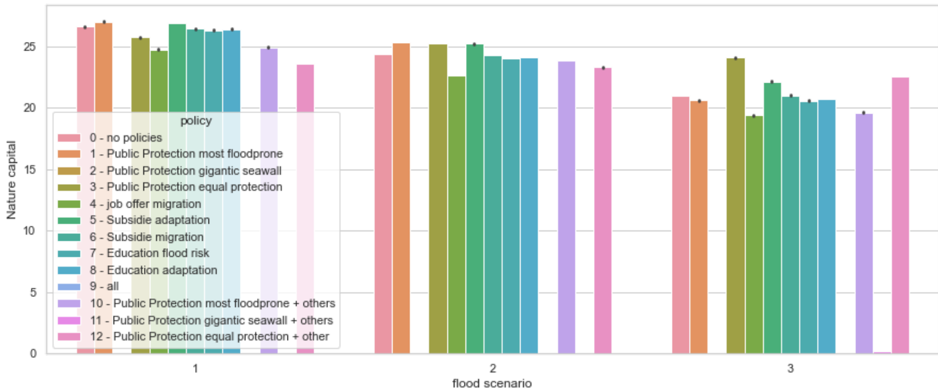

Figure 11.15: Nature capital - Five Capital per policy strategy and flood scenario

The average Nature capital in the no policy scenario is 24 floods on average per household over 30 years and ranges between 0 (in all gigantic sea wall scenario's) and 27 (in the only public protection most flood prone area strategy) , see figure 11.15 and appendix C.1 for the exact numbers per flood scenario.

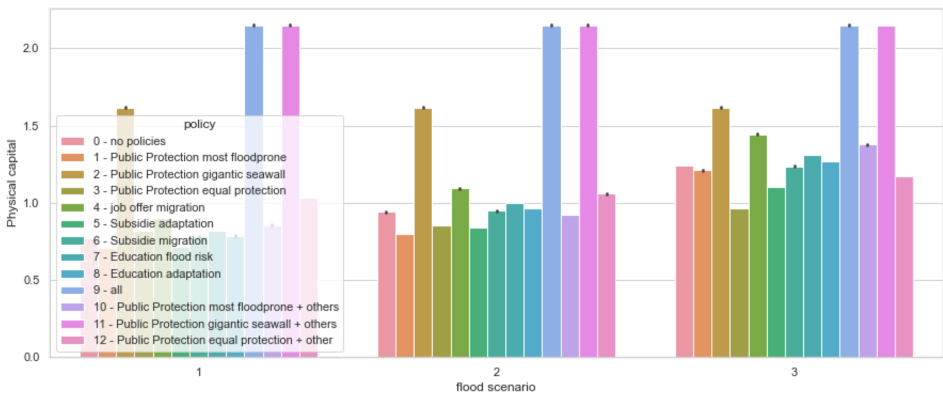

Figure 11.16: Physical capital - Five Capital per policy strategy and flood scenario

The average Physical capital in the no policy scenario is 0.98 and ranges between 0.91 (in the only public protection most flood prone area strategy) and 2.15 (in the the gigantic sea wall scenario plus other policies strategy), see figure 11.16 and appendix C.1 for the exact numbers per flood scenario.

11.2. Sensitivity Analysis

11.2.1. Non-structural policy interventions

Since the non-structural policy interventions directly influence the households perceptions, aiming to stimulate adaptation or migration behaviour, the sensitivity analyses is scored on the percentage of households taking adaptation or migration actions and the average number of token adaptation measures (the physical capital).

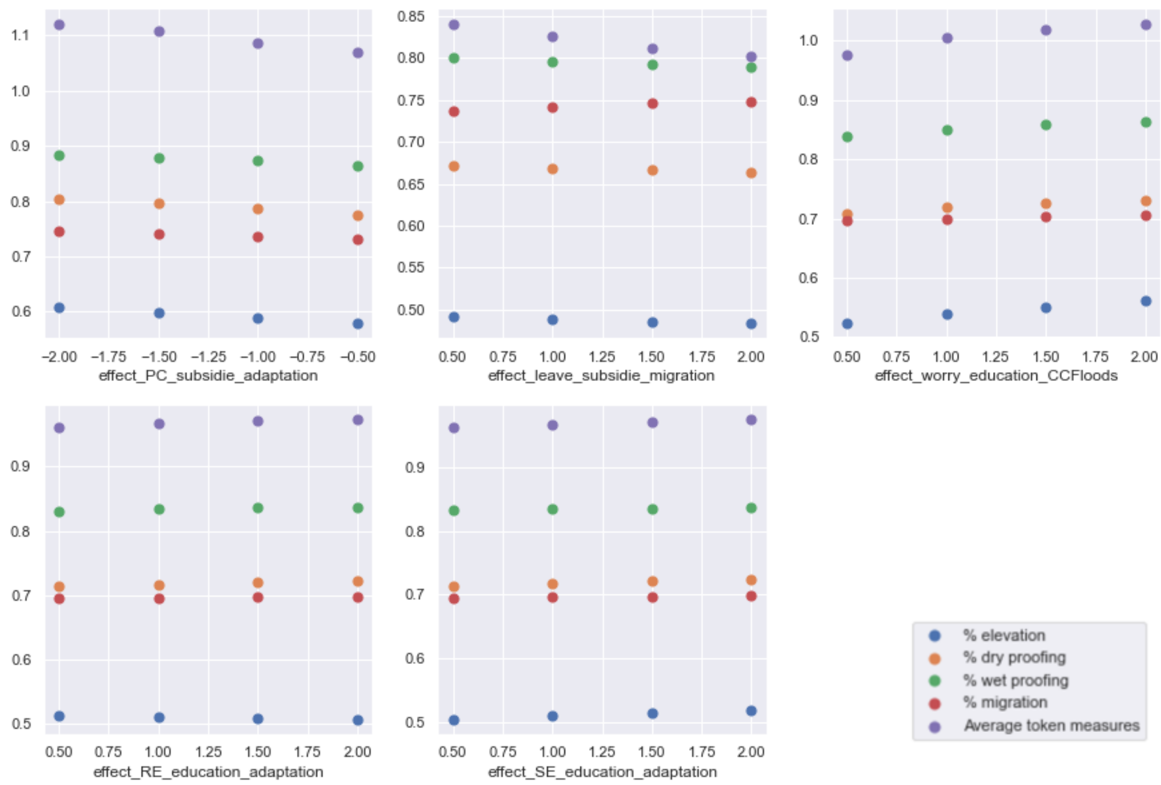

Figure 11.17: Sensitivity policy measures effects

Starting with the effect of a subsidy on adaptation measures. Under the assumption that a subsidy on adaptation has a strong effect (-2) on how households perceive the cost of adaptation actions, it can be seen that the percentage of all adaptation actions (elevation, dry proofing and wet proofing) is slightly higher than under the assumption that the subsidy only has a small effect (-0.5). This is the same for the average number of adaptation actions taken per household, which is slightly higher in the case the subsidy on adaptation has a large effect on the perceived costs. The percentage of households that migrate remains almost the same, regardless of the effect of the subsidy on adaptation, which makes sense.

Next, is the effect of a subsidy on migration. Under the assumption that a subsidy on migration has a strong effect (+2) on how easy households find it to leave their place, it can be seen that the percentage of households that migrate is slightly higher than under the assumption that the subsidy on migration has a small effect (+0.5). Subsequently, the average number of token adaptation or migration actions decrease in case the subsidy on migration has a bigger effect, due to migration of better adapted households.

Following with raising flood risk awareness. Under the assumption that a campaign on flood risk awareness has a strong effect (+2) on the worry perception of households, it can be seen that the percentage of households taking adaptation and migration actions is slightly higher than under the assumption that education on flood risk has a small effect (+0.5). The effect of raising flood risk awareness seems to trigger adaptation actions more than migration.

Lastly, the education on adaptation of which the effect is two-fold; on the response efficacy and self efficacy of adaptation measures. Under the assumption that education on adaptation has a strong effect (+2) on the RE and SE perception of households compared to the assumption that it has a small effect (+0.5), it can be seen that the variation in the percentage of households taking adaptation and migration actions is minimal.

11.2.2. Water level rise

Water level rise directly influences the measured flood height within the environment, influencing the amount of flood damage households could experience. Therefore the sensitivity analysis on water level rise is scored on flood damage. However, since flood damage could affect adaptation or migration behaviour of households as well, the percentage of adaptation and migration actions is checked as well.

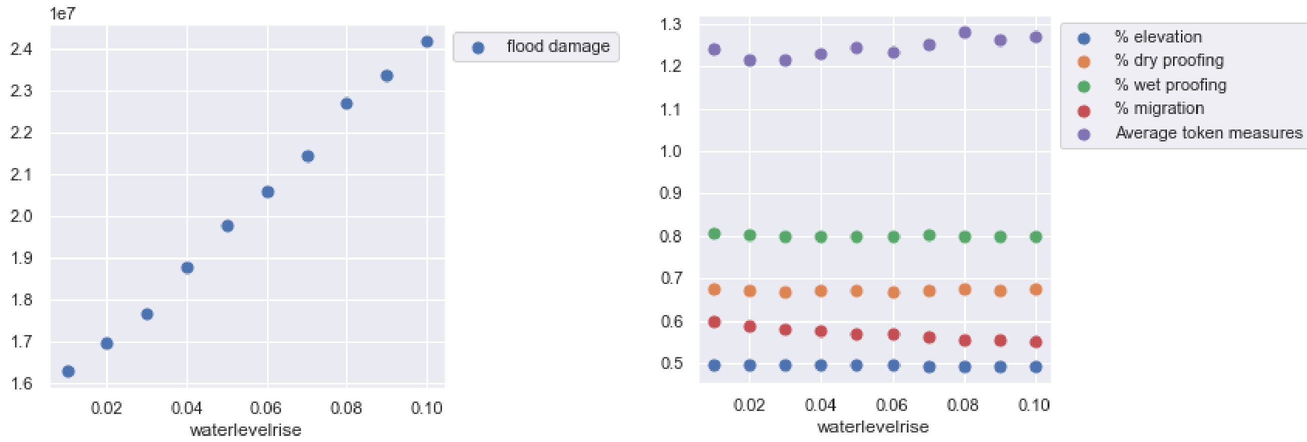

Figure 11.18: Sensitivity water level rise

Looking at the sensitivity of water level rise on the total flood damage, a major increase in the amount of flood damage can be seen when the water level rise per year increases. This implies that the flood damage scores for the performed experiments greatly increase, in case the water level rise per year turns out to be more than 0.04 m a year in the future. Looking at the effect of water level rise on adaptation and migration behaviour of households, it can be seen that the percentage of households migrating decrease when the water level rise increases. Meaning the lock-in effect of flooding becomes bigger, enabling less households to migrate, when the water level rise increases more rapidly. Furthermore, no change in adaptation behaviour under a stronger water level rise is observed. Although the average amount of token adaptation actions fluctuates a bit under more extreme water level rise.

12
Policy advise

In this chapter ***SQ5**: What is the aggregated impact of policy interventions on Jakarta's household adaptation and migration behaviour, flood resilience and expected flood damage?* will be answered.

The structure of this chapter is as follows. First the structural policy interventions in the form of public protection measures are discussed in section 12.1. Secondly, the non-structural policy interventions are addressed in section 12.2. Followed by the flood management strategies; combinations of public protection measures with all non-structural policy interventions in section 12.3. The performances of the designed policy interventions or flood management strategies on the key performance indicators are discussed per paragraph. Within a paragraph, first the performance on the total amount of flood damage is discussed. Secondly, the effect of the policy measures on the adaptation and migration behaviour of Jakarta households is debated. Thirdly, the performance on the Five Capital scores is discussed. Finally, a policy advise is given to the government of Jakarta on how to support bottom-up household adaptation and migration behaviour and increase the flood resilience of Jakarta's households in section 12.4.

12.1. Structural policy interventions - public protection

12.1.1. The gigantic seawall

To start, the gigantic seawall is the most effective policy intervention for reduction of flood damage, as it reduces the flood damage by a 100% percent under all flood scenario's. However, when building the giant sea wall, the number of households adapting their houses to flooding is lower than when no extra public protection is offered. The gigantic seawall only slightly decreases the amount of households that undertake dry proofing measures, but has a more negative effect on the percentage of households elevating or wet proofing their houses. Moreover, the percentage of households who decide to migrate drops massively (by fifty percent). This can probably be explained by the levee effect; the psychological phenomenon of a false sense of safety, due to which people no longer feel the threat of floods and therefore do not take adaptation or migration action (Garschagen et al., 2018; Haer et al., 2020). Looking at the performance of the gigantic sea wall on the Five Capital scores, the human capital first of all shows a major increase compared to the situation in which no increase of public protection occurs. This is due to less high educated people migrating and a better mental health due to less worry on flooding. The financial capital also slightly increases in the gigantic sea wall policy strategy, meaning more high income households will stay in Jakarta. The social capital, on the other hand, doesn't change compare to the no extra public protection case. Next, the nature capital becomes zero, as on average no flooding occurs. Lastly, the physical capital strongly increases, meaning that on average the amount of token adaptation action per household increases. This is probably due to less migration of well adapted households.

12.1.2. Equal increase of public protection

Providing an equal increase of public protection also does a good job on mitigating the total flood damage; 68% in scenario 1, 69% in scenario two and three. Furthermore as an equal increase of public protection is offered, more adaptation actions among households are taken and way more households migrate. So equally improving public protection enables more households who intent to adapt or migrate to take this action and therefore this policy reduces the amount of households ending up in a lock-in situation. Looking at the performance of providing an equal increase of public protection on the Five Capitals, first of all, the human capital slightly increases while the financial capital slightly decreases. This implies that a little more highly educated people decide to stay in Jakarta, while some more higher income households decide to leave compared to the situation in which no extra public protection is offered. The social capital doesn't change compare to the no increase of public protection case. The natural capital also doesn't change much, expect in the most severe flood scenario, were the average number of times households get flooded is higher than when no public protection was offered. This is due to migration of well adapted households, therefore the physical capital decreases as well in the most severe flood scenario.

12.1.3. Increased protection of the most flood prone areas

Increasing public protection in the most flood prone areas only mitigates the flood damage by 15% in scenario one, 20% in scenario two and 8% in scenario three, making it the worst performing public protection strategy. Furthermore, offering increased public protection in the most flood prone areas only, has almost no effect on the adaptation behaviour of Jakarta households. Although it causes an small increase in migration. This is probably due to the fact that households in flood prone areas generally already have taken adaptation actions and a little more households living in flood prone areas that have the intention to migrate, but normally do not have the money to do so, (lock-in situation) can now suddenly leave. Offering protection in the most flood prone areas only, has no impact on the human, financial and social capital, but causes a very slight increase on the nature capital (number of times households living in Jakarta get flooded on average) and a slight decrease in the physical capital (number of undertaken adaptation action by Jakarta households).

12.2. Non-structural policy interventions

12.2.1. Job security in case of migration

Job security in case of migration could reduce the total experienced flood damage by 22% in scenario one, 20% in scenario two and 14% in scenario three, making it the best performing non-structural policy intervention on flood damage reduction. Furthermore, providing job security seems to stimulate adaptation behaviour among Jakarta households the most as well compared to the other non-structural policy interventions. Surprisingly enough job security only has a small positive impact on migration though. This phenomenon might be explained by households keeping less money in reserve for emergencies (such as job loss or extreme flooding), which makes them more inclined to invest in adaptation actions. Looking at the performance of providing job security on the Five Capitals; job security has almost no effect on the human, financial and social, but causes a small decrease in the nature capital and big increase on the physical capital. This means the average number of token adaptation action among Jakarta households increases, due to which the average number of floods experience by Jakarta households over 30 years decreases.

12.2.2. Subsidy on migration and adaptation

The subsidy on adaptation reduces the total experienced flood damage of households by 8% in scenario one, 10 % in scenario two and 15% in scenario three. So thereby performs a lot better on flood damage reduction than the subsidy on migration, which reduces the flood damage only by 1% in scenario one and two and by 2% in scenario three. Furthermore, both subsidies very slightly decrease the percentage of people taking adaptation actions, but slightly increase the amount of households who migrate, although the effects are minimal. Same goes for the performance of subsidies on the Five Capital scores. A subsidy on migration has almost no impact at all on the five capitals of resilience. The subsidy on adaptation, on the other hand, has no impact on the human, financial and social capital but causes a slight increase of the nature capital and decrease in the physical capital. Meaning the average amount of token adaptation actions among households decrease, due to which the average number of times households get flooded over 30 years increases.

12.2.3. Education on adaptation and raising flood risk awareness

Education has a small effect on flood damage reduction in general. The performance of raising flood risk awareness performs a little better; 8% damage reduction in scenario one, 7% in scenario two and 4% in scenario three, than education on adaptation with 5% damage reduction in scenario one, 4% in scenario two and 2% in scenario three. Furthermore, the impact of education on household adaptation or migration behaviour is almost none. Raising risk awareness on the other hand increases adaptation behaviour among Jakarta households, especially elevation, but has no effect on migration behaviour. Lastly, the performance of education on the Five Capitals is of no significance.

12.3. Flood management strategies

Looking at the policy strategies in which increasing public protection is combined with the non-structural policy interventions. The additional non-structural policies could reduce the flood damage by an extra 31% in the increased protection in **the most flood prone areas strategy**, resulting in 46% total damage reduction in flood scenario one, 50% in scenario two and 38% in scenario three. Furthermore a stimulus of both adaptation and migration behaviour can be found, around 10% for all actions. However, the increased performance on the Five Capital scores is minimal. In **the gigantic sea wall strategy**, no extra flood damage reduction can be achieved. The additional non-structural policies have a positive effect on the adaptation behaviour of households compared to the scenario of the gigantic sea wall without additional policies, which increase the physical capital. No additional effect on migration is found, therefore the human, financial and social capital remain the same. In **the equal increase of public protection strategy** the additional non-structural policies reduce an extra 12%, resulting in 79% damage reduction in flood risk scenario one and 80% in scenario two and three. Furthermore, the non-structural policies have an additional positive effect on the adaptation and migration behaviour of households, As a result, the physical capital slightly increases and the nature capital reduces, meaning households get less times flooded on average. The human, social and financial capital remain the same as in the equal protection strategy only. Lastly, the combination of **all public protection measures** and additional policies is most effective in reduction of the total flood damage, as it reduces the damage by a 100% percent under all flood scenario's. Although it is not the most effective strategy to stimulate household adaptation behaviour. The percentage of people taking elevation and wet proofing actions is the same as the no policy interventions scenario, only the percentage of dry proof measures increases. Furthermore, the percentage of households migrating drops massively, which is probability due to the levee effect caused by the gigantic sea wall. Looking at the performance of implementing all policy measures, the human capital has a major increase compared to the no-policy scenario, but not as much as in the policy strategy of building the gigantic sea wall alone. Te rest of the capitals have the same performance as implementing the gigantic sea wall only.

12.4. Policy advise

To conclude, the gigantic sea wall could reduce the total experience flood damage of Jakarta the most, due to which less high educated and high income people migrate, which has a positive influence on the Five capital scores. A side effect of the gigantic sea wall is that adaptation and migration behaviour is not stimulated that much and ends up to be lower than when no public protection is offered. Additional policy measures (subsidy, education and job security) could increase the amount of token adaptation measures, but doesn't stimulate households to migrate. Therefore more research needs be done on the long term effects of the implementation of the wall in relation to water level rise and its effect on adaptation and migration actions; as the wall is likely to cause more urbanisation and perhaps more subsidence, the long-term damage may be worse than can be imagined today. An equal increase of public protection with additional non-structural policy measures on the other hand can strongly stimulate adaptation and especially migration actions. This can be in line with the plans to develop a new capital of Indonesia on Borneo for further development of welfare but in a different location from Jakarta (CNN, 2022). In the long run, however, the Five capital scores of Jakarta reduces, due to the fact that better adapted, high educated and high income households migrate, leaving more less adapted, poorer, low educated households to stay. Less flood resilient households might become trapped, as they might have the intention to move or adapt but lack the money and abilities to do so. Financial and social support will be necessary to get these people to migrate.

13

Conclusion

In this report, an exploratory ABM on the aggregated impact of increasing flood risk, public adaptation measures and policy interventions on household flood adaptation and migration behaviour, flood damage and resilience for Jakarta, Indonesia was made.

To be able to answer the main research question":

> "*What is the aggregated impact of public and private adaptation actions on Jakarta's flood resilience?*"

First, Five Capitals to measure flood resilience based on the framework of Zurich Flood Alliance were established in chapter 5; the Human, Social, Financial, Physical and Nature capital. The capital scores are measured on the individual level, but collectively analysed in the ABM, by taking the mean of the capital scores for all non-migrated Jakarta households. Secondly, the adaptation actions Jakarta households perform were identified in chapter 6 Additionally, the reducing effect of the adaptation actions on flood damage was established. Thirdly, the barriers and drivers of adaptation and migration behaviour in Jakarta were found, which were used to find the survey variables to apply within the Protection Motivation Theory in chapter 7. Next, the effect of the decision-making factors on the intention to migrate or adapt was found by performing a Logit analysis. The output of the Logit analysis, are regression coefficients for all decision-making factors, forming an important input in the the ABM for simulation of household adaptation and migration behaviour. Fourthly, policy interventions that could influence the decision-making factors of adaptation or migration behaviour, were identified from literature in chapter 8. These policy interventions were used in the experimentation with the ABM to explore the aggregated impact of policy interventions on Jakarta's household adaptation and migration behaviour, flood resilience and expected flood damage.

The main findings are:

- The total flood damage of Jakarta increases over time as flooding become more severe.
- It seems around 30 % of the population ends up in a situation of continuous recovery and flooding in 2050. Only 3 % of the population will not be affected by flooding through adaptation and about 67% of the population decides to migrate Jakarta, when no additional public protection measures are taken. As a result the human, financial, physical and social capital slightly decrease while the nature capital increases. Meaning, in general the flood resilience of Jakarta households decreases over time, due to migration of the more flood resilience households.
- When floods or water level rise become more severe, the percentage of households continuously flooding and recovering increases, while the percentage of households who do nothing or migrate decreases.
- Especially households in flood prone areas seem to be extra vulnerable, as more households in these areas end up in a lock-in situation of continuous flooding and recovering without being able to migrate, when flooding becomes more severe.
- In a more extreme flood scenario, the performance of the human, social, physical and financial capitals still shows a slight decrease. However, the psychical capital is a bit higher

compared to a less extreme flood scenario and the nature capital a bit lower, meaning households in Jakarta become better adapted over time when flooding is more severe due to which the number of times households get flooded over 30 years reduces.

Looking the policy interventions, the gigantic sea wall could reduce the total experience flood damage of Jakarta the most (by 100 %), due to which less highly educated and high income people migrate, which has a positive influence on the Five capital scores. A side effect of the gigantic sea wall is that adaptation or migration behaviour is not stimulated and turns out to be lower than when no extra public protection is offered (Levee effect). Providing additional job security, could increase the amount of token adaptation measures, but doesn't stimulate households to migrate. Therefore, more research needs be done on the long term effects of the implementation of the wall in relation to water level rise and its effect on adaptation and migration actions; as the wall is likely to cause more urbanisation and perhaps more subsidence, the long-term damage may be worse than can be imagined today. Providing an equal increase in public protection mitigates the total flood damage (by 69%) and strongly stimulates households to adapt of migrate, especially in combination with non-structural policy measures. In the long run, however the Five capital score and thus the flood resilience of Jakarta reduces, due to migration of more high educated and high income households, leaving relatively more less adapted poor, low educated households to stay. These people might become trapped, as they might have the intention to move but lack the money and abilities to do so.

13.1. Scientific and societal contribution

By using Agent-Based Modeling to explore the aggregated impact of increasing flood risk, public adaptation measures and policy interventions on flood adaptation and migration behaviour of households and their flood resilience, a scientific contribution to current research on the usage of ABM's in the development of flood risk management strategies is made. Secondly, by selecting an Indonesian case study on the emergence of adaptation and migration behavior of households, on which little research has been done so far due to limitations in available data, a contribution in knowledge on worldwide flood adaptation behaviour is made. Furthermore, the usage of the Protection Motivation Theory as a social theoretical foundation and framework for the household decision making within the ABM, enables comparison between case studies worldwide on the emergence of adaptation and migration behaviour under flood risk with policy interventions. Therefore, a contribution to the debate on social simulations of flood adaptation and migration behaviour is made. Describing the ABM in the ODD protocol furthermore increases the re-usability of the developed ABM model. The model description can be used to encourage more people to use survey data as an input for setting up the agent population, which increases the accuracy of model. By drawing up the Five Capitals, the overall performance of Jakarta's flood resilience under various flood risk and policy scenarios can more easily be analysed and discussed. In case more studies implement the Five Capitals as KPI's to measure flood resilience, comparisons between case studies could be made as well. Quantifying the social, financial, physical, ecological and health impacts of household flood resilience is of high relevance because it provides additional information on the self-sufficiency of citizens and the coping and adaptive capacity of society. This information can help policy makers take informed decisions on public adaptation in flood risk management. Lastly, as the implementation and evaluation of government adaptation strategies is difficult in terms of achieving social and political support, often takes lot of time, effort and money and could have an irreversible impact on society for current and future generations, using a model to explore the impact of policy intervention on adaptation and migration behavior could be an outcome. This study used an ABM to inform the local government of Jakarta on the potential impact of policies. Additionally, ways are explored to stimulate household adaptation and migration behaviour by policy interventions. This knowledge is useful in the design of flood management adaptation strategies. Therefore, this study makes a societal contributions as well.

14

Discussion

14.1. Thesis discussion

First of all, there is a need for studies that look at emergent adaptation and migration behaviour in relation to flood resilience, which consider social interactions, feedback with its environment and policy interventions. Research on this is relevant as climate change is happening and flooding worldwide start to become a bigger problem. This study focused on the interaction between public and private adaptation under flood risk in particular. Additionally, the impact of non-structural policy interventions were tested. With usage of an ABM, it was possible to test the aggregated effect of various policy interventions on household adaptation and migration behaviour with consideration of social, cultural and personal differences. Thereby, this study provided more inside in the effect of policy interventions on human behaviour under flood risk, which is of use for the Javanese government in designing flood management strategies. It is therefore encouraged to conduct more research on the application of ABM's in the design of flood management strategies. Especially in collaboration with multiple stakeholders, an ABM could help to provide more inside in each others perspectives and actions, while working on a mutual goal. Furthermore, the usage of real-life data to mitigate model biases is recommended. Moreover, the use of social or psychological science theories in ABMs to underpin agent decision-making processes is encouraged because it not only makes human behaviour more realistic, but also encourages interdisciplinary collaborations between scientists, which is needed to address increasing climate change hazards. Not only cooperation between social studies and modellers should be improved. Politicians should also be involved in the modelling process to avoid misunderstandings on how the model could be used and it reduces the risk of misinterpreting or misapplying the model results.

However, some simplifications in the interactions and feedback between flooding, social networks and households adaptation actions needed to be made, which are discussed below. The designed agent-based model and its components are compared to the existing knowledge on flood ABM's or reality. Additionally, suggestions for further research or recommendations to improve this study are given.

14.2. Model components

First, a review on the model KPI's to measure flood resilience is done in section 14.2.1. Secondly, a reflection on the simulation of floods is given in section 14.2.2. Following with a discussion on the agent decision-making within the Jakarta ABM model, in section 14.2.3. Here, a review on the Protection motivation theory, social network influences and the agents' action will be given. Next, a reflection on experimenting under high uncertainty and the policy measures is given in section 14.2.4. Followed by a discussion on the tested policy interventions in section 14.2.5. Lastly, the experimental results of the aggregated impact are discussed in section 14.2.6.

14.2.1. KPI's to measure flood resilience

Most agent based model studying the emergence of adaptation and migration behaviour under various policy scenarios, only report the percentages of agents undergoing adaptation or migration actions and the flood damage. In this study five additional capital scores were added to measure the performance of policies and the effect of adaptation and migration actions on overall flood resilience in Jakarta. The five capital scores are based on the Zurich Flood Alliance framework, see figure 5.1. Luckily, there was quite a lot of survey data available for Jakarta to find matching indicators for flood resilience. However, these combinations of data variables per capita are obviously not available for all case studies. Meaning, generalisation and comparing flood resilience performance on a global scale still remains difficult. Very few ABMs up to now have measured the aggregated impact of public and private adaptation on flood resilience performance indicators, making it is difficult to compare the performance of operationalised Five Capitals in general. Using the Five Capital as model KPI's in the ABM however, was quite useful, as it provided additional information on what type of households migrated the city. Moreover, it gave a picture of the flood resilience status of households that remained in the city. Therefore, using key performance indicators to measure the flood resilience performance of cities would be recommended for other ABM case studies on flood adaptation with policy interventions as well. More research could be done on standardisation of resilience indicator as this would improve the quality and enables comparison between case-studies.

14.2.2. Simulation of floods

The simulation of flooding in this study was done based on flood height data from the year 2020 only, since limited data was available from other years which could be used for the simulation of floods for the Jakarta case specifically. Furthermore, there was no information available on the frequency and height of floods per month (the model time ticks). Consequently, very simplified flood risk scenarios were developed based with a flood happening once a year varying in size by three flood scenario's. The simplification of floods is acceptable, as the focus of this study is not on the hydrological aspects, but on the effect of a flood threat and exposure on the adaptation behaviour of households. However, as a result of this data limitation, the same districts and households in the Jakarta flood model get heavily flooded all the time. Whereas in reality, there is more variation in the location of flood zones depending on the cause of flooding, which can be from a tsunami, heavy rainfall or river flooding. Furthermore, there was not enough data available on the water level rise per neighborhood. Therefore the water level rise per year in the model increase every year for all neighborhoods by the same amount regardless of agents actions or policy measures taken. In contrast to reality, where some areas experience heavy subsidence while other don't. Other flood risk related ABM studies often use advanced water level maps, which allow for a more realistic simulation of floods than was done in this case study. Therefore the development and implementation of an advanced water level map for Jakarta would be a first recommendation on future research work. Subsequently, it would be interesting to see if more variation in flood exposure would lead to different adaptation and migration behaviour.

14.2.3. Agent decision-making

For the Jakarta case study enough literature and survey data was available to use the Protection Motivation Theory as a theoretical framework of the decision-making process of households. All decision-making factors from literature could be matched on the survey data, making the initialisation of the ABM empirically based on survey data. The selected random sampling of variables based on high correlations, resulted in a good match between the synthetic population of 10.000 households compared to the real survey responses of 647 households. However since the survey data is only a pinpoint in time, it is still difficult to properly quantify the changes in values of variables due to interactions between household, flooding or policy interventions per household taking into account its experiences, perceptions and norms ect. Good estimations on the impact of policy interventions on the decision-making variables were tried to be made based on literature. However, to improve its accuracy more research on the impact of policy interventions on the decision-making factors needs to be done. Thereby, individual differences in the impact of policy interventions on the decisions making factors depending on the household status, experience, perceptions and norms need to be taken into account.

PMT

In the Protection theory of Rogers, 1975 actions are only taken when ones threat appraisal and coping appraisal are high enough. Additionally there is a barrier between ones intention to take action and the actual performance of it. To model this barrier however is quite difficult, as it is hard or even impossible to determine how and when someones intention is put into action and when not. To deal with this complexity, a random number per agent in the model simulation is drawn, which is compared to the probability to take action. When the random number is lower than the probability to take action, the action is performed. Consequently, also people with low intentions could undertake adaptation or migration actions, but with a low probability of course. This implies that the implementation of the Protection Motivation Theory in the agent-based model can only be done to a certain extent. The number of times the random number is re-drawn has a great impact on the model outcomes; the more often the random number is drawn, the more likely the change that the action is performed. In the Jakarta case, the random number is drawn as a flood occurs (once every year), but the results would have play out differently as the random number was drawn every month. Therefore, further research on the effect of the way PMT is implemented needs to be done, by making multiple ABM versions of the same phenomena using PMT and comparing its model results to test the robustness of the model implementations.

Social network
In the beginning of the model a social network is created of eight random neighbors, living in the same neighborhood. The number of social ties is the same for all agent. In reality, the number of friends or family differs. Furthermore, they don't live all in the same neighborhood and are not chosen randomly; mostly people become friends with people from the same income class or education level. Additionally, the social influence of agents actions on their network is the same for all agents, while in reality some people are more sensitive to social pressure than others. Moreover, the influence of the social network in this model is very simplified. Only the actual adaptation behaviour influences other households' perceptions. In reality, however, perceptions are often changed through conversations or social events. There are agent-based models that use more sophisticated social network interactions. This would be a good addition to the current ABM for Jakarta, as the literature suggests that communities can play a large role in adaptation or migration behaviour. Thus, future research can be done on the model of social network influences in Jakarta.

Actions
In this study only private household adaptation actions were considered, while in reality communal actions like cleaning rivers, strengthening dykes, building channels, or early warning systems also play an important role in flood damage reduction and have an effect on adaptation and migration behaviour. There are ABM studies that do incorporate community adaptation actions as well, like Haer et al., 2017 for example. Since community seem to play an important role as a social safety net in Jakarta, this would be a good step to include next in the model. Additionally research needs to be done on the effect of communal adaptation in the environment as this can probably stimulate but also paralyse private household adaptation behaviour. Furthermore, in this ABM model only migration outside Jakarta was considered, while in reality households can also move between district inside Jakarta. To be able to model inside migration, a lot of extra data and research is needed on house market effects, urbanisation development or job opportunities per neighborhood for example.

14.2.4. Experimenting under high uncertainty

As the influence of the policy measures on the households perceptions was uncertain, a sensitivity analysis was performed. The results didn't show a huge sensitivity on the assumed effectiveness of policies on the adaptation or migration behaviour scores. Therefore, this uncertainty doesn't play a big role in the model and experiment outcomes. The sensitivity on the water level rise on the other hand showed a big sensitivity on the flood damage KPI, thus does play an important role in the experiment outcomes of flood damage in particular. However as determining the amount of experienced flood damage was not the purpose of this study, this is not seen as a major limitation. The variation in adaptation behaviour under different water rise level was almost nothing, meaning water level rise is not such an important external driver or barrier for adaptation. Looking at the impact of water level rise on migration on the other hand, more sensitivity was measured. Due to more flood damage in case of extreme water level rise, the percentage of migration dropped caused by the money barrier between intention and action. Since the cause of the sensitivity can be explained the impact of the uncertainty is reduced by clear communication.

14.2.5. Policy interventions

The effects of the designed public protection strategies used in this model were extremely simplified and generalised, as no difference in effect for different flood areas were made. In the same line, the influences of the additionally policy measures had the same effect on all agents, without differentiation between income or education groups. Furthermore, the policy influences in the Jakarta model didn't changed throughout the mode run itself, while in reality a continuous increase or decrease in public protection due to construction and flood destruction occurs. Also, in reality an increase and decrease in worry goes in waves through the occasional deployment of risk raising awareness campaigns, instead of having a constant effect like in the model, as peoples worry perceptions get normalised in the long run. This would add another layer of complexity to the ABM model, making the government an agent in itself, which could take public protection measures or start and stop non-structural policy measures during the model run. Households would then constantly be exposed to different flood height levels due to implementation of public protection in certain areas, which influences their adaptation and migration behaviour.

14.2.6. Aggregated impact

Looking at the total experienced flood damage first of all, it makes sense that more damage occurs when flooding or the water level rise becomes more extreme, because a higher water level results in a higher damage percentage of the house value. Additionally, it was found that adaptation reduces the number of times households get flooded, which holds in reality. Next finding, was that around 30% of the population ends up in a situation of continuous recovery and flooding in 2050. Only 3 % of the population will not be affected by flooding through adaptation and about 67% of the population decides to migrate Jakarta, when no additional public protection measures are taken. This fierce prevision is in line with BBC predictions, which indicate that probably 95% of areas in Jakarta will face flooding by 2050 (BBC, 2018). Confirming the negative trend in flood resilience. Following with the next founding of this study, that when floods or water level rise become more severe, the percentage of households continuously flooding and recovering increases, while the percentage of households who do nothing or migrate decreases. That more flooding leads to more damage and recovery is true to reality, but that fewer people will migrate is not necessarily true. Indeed, some people will not have the means to move so they might as well stay because they cannot settle in another area either. Especially if their social network does too. However, there will also be households who decide to leave just when they have nothing left, to build a future somewhere else. Or hope for help from outside. However, this is not included in the model because the assumption was made that people will only take action if they have the means and money to actually do so. It is recommended to explore other ways to model the migration decision-making, to be able to compare the model results and improve the decision-making rules. Moreover, humanitarian aid is not included in the model. If this is added, more people under extreme flood scenarios might actually leave making the migration rate even higher. As a last remark, the effect of a financial, social or health disruptions were not taken into account. Future research could be done on the emergence of flood resilience and household adaptation and migration behaviour under various socio-economic conditions, like inflation.

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A

Survey data

A.1. PMT factors confirm survey data

Noll et al., 2021 distributed a survey among Indonesian households, see section 4.2.2 for more information on how the survey was performed. The factor, survey question, response options and mean of the filtered dataset for Jakarta specifically (N = 647), is shown in the table below. The data distributions of all variables can be found underneath the table.

Table A.1: Agent attributes confirm survey data

Factor	Survey Question	Response option mean
Flood experience	*Have you ever personally experienced a flood of any kind?*	Yes (1) or No (0) 0.63
Flood Probability 30 years	*Imagine you stay in your house for the next 30 years what is the likelihood you believe your household will experience a flood?*	...% 28.95%
Flood likeliness	*You expect a ... flood risk*	(1) decreased (2) constant (3) increased 1.71
Flood damage	*In the event of a future major flood in your area on a similar scale to 2020 floods in Jakarta how severe (or not) do you think the physical damage to your house would be?*	(1) not at all severe - (5) very severe 2.53
Worry	*How worried are you about the potential impact of flooding on your home?*	(1) not at all worried - (5) very worried 2.87
Response efficacy	*How effective do you belief implementing this measure would be in reducing the risk of flood damage to your home and possessions?*	(1) extremely ineffective - (5) extremely effective elevation: 3.58, dry proofing: 3.46, wet proofing: 3.51

Note. Variables come from survey data designed by Noll et al., 2021, see section 4.2.2.

Table A.2: Agent attributes confirm survey data

Factor	Survey Question	Response option mean
Perceived cost	*When do you think in terms of your income and other expenses, do you believe implementing (or paying someone to implement) this measure would be cheap of expensive?*	(1) very cheap - (5) very expensive elevation: 3.88, dry proofing: 3.83, wet proofing: 3.50
Self-efficacy	*Do you have the ability to undertake this measure either by yourself or paying a professional to do so?*	(1) I am unable - (5) I am vary able elevation: 2.86, dry proofing: 3.00, wet proofing: 3.03
Social media I	*How frequently do you read information about flooding and other hazards from social media?*	(1) Very infrequently - (5) Very frequently 3.65
Social media II	*To what extent, if at all, do you trust information about flooding and other hazards?*	(1) Do not trust at all - (5) Trust Completely 3.29
Trust in public protection	*Do you think the current measures that the municipal government have implemented are sufficient to stop the risk of floods and heavy rain?*	- Yes, they are sufficient and will last for the foreseeable future (30+ years) - Yes, but they will need to be updated within the next decade - No, they are not currently sufficient - Other opinion 2.25
Social norm	*Thinking about your friends, families, and neighbours, how many households have taken some adaptive action towards flooding?*	(1) None, (2) One...(7) more than five 3.23
Social expectation	*Do your family, friends and/or social network expect you to prepare your household for flooding?*	(1) = My family, friends and/or social network do NOT expect me to prepare for flooding ... (5) = My family and friends strongly expect me to prepare for flooding 3.41
Climate Change belief	*There is a lot of discussion about global climate change and its connection to extreme weather events. Which of the following statements do you agree most with?*	- CC is already happening - CC isn't happening yet, but we will experience the consequences in the coming decades - CC won't be felt in the coming decades, but the next generation will experience its consequences - Other opinion 2.68

Note. Variables come from survey data designed by Noll et al., 2021, see section 4.2.2.

Table A.3: Agent attributes confirm survey data

Factor	Survey Question	Response option mean
Previous undertaken measures	*I have already implemented this measure*	Yes (1) or No (0) for each measure elevation: 0.23, dry proofing: 0.22, wet proofing: 0.25
To leave	*How easy or difficult would it be to leave the place you currently live?*	5 point scale (1) t would be very difficult to leave this area - (5) I could leave this area very easily 1.71
Move city	*In the last 10 years, how many different places (different cities/towns/villages have you lived in?*	... times 3.77
Move houses	*In the last 10 years, how many times have you moved houses?*	... times 1.54
Find job	*If you were to become unemployed, what is your best guess on how much time it would take you to find employment?*	- Less than a month - Between 1-3 months - Between 4-6 months - More than 6 months 2.32
Lost job	*In the last 6 months, have you or another financially contributing member of your household lost their job?*	(1) Yes, (0) No 0.48
Impact lost job	*How much has this job loss impacted you financially*	(1) Very little - (5) A considerable amount 1.94
Education	*What is your education level?*	(1) < high school, (2) high school (3) > college 2.64
Income	*Please fill in your TOTAL annual income*	... Rupiah 152.920 * $10^6 Rupiah$
Savings	*With regards to your household's savings, what statement most closely reflects your current household situation?*	My household has - little to no savings - roughly a half month wage in savings - roughly a one month wage in savings - roughly one and a half month wage in savings - roughly 2 months wage in savings - roughly 3 months wage in savings - roughly 4 or more months wage in savings 1.44

Note. Variables come from survey data designed by Noll et al., 2021, see section 4.2.2.

Table A.4: Agent attributes confirm survey data

Factor	Survey Question	Response option mean
House value	*If you were to put your accommodation on the market today, how much do you believe it would sell for?*	788.01* $10^6 Rupiah$
Social network	*How would you describe your social network where you currently live?*	(1) I have very few friends and/or family living near me – (5) I have many friends and/or family living near me 3.51
Economic comfort	*When considering your salary along with your expenses, how would you describe your level of "economic comfort"?*	- Very difficult to live - Difficult to live - Coping - Living comfortable - Living very comfortable 3.46
Social support	*My household can rely on the support of family and friends when I need help*	(1) Strongly agree - (5) Strongly disagree 2.60
Governmental support	*My household can rely on the support from my government when I need help (e.g. receiving funding or support in the event of a natural disaster*	(1) Strongly agree - (5) Strongly disagree 3.05
Financial support	*During times of hardship, my household can access the financial support I need (e.g. such as access to credit at a bank)*	(1) Strongly agree - (5) Strongly disagree 2.88
Household resilience	*If hardships or natural disasters became more frequent and intense, my household would still find a way to get by*	(1) Strongly agree - (5) Strongly disagree 2.27
Savings flexibility	*During times of hardship, my household can change its primary income or source of livelihood if needed*	(1) Strongly agree - (5) Strongly disagree 2.67

Note. Variables come from survey data designed by Noll et al., 2021, see section 4.2.2.

A.2. Data distributions PMT factors

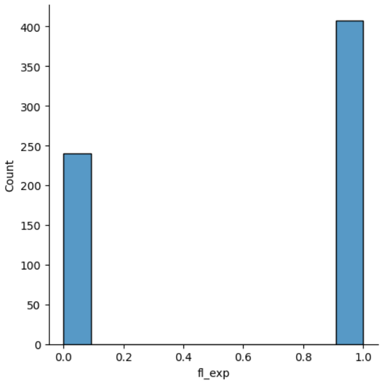

Figure A.1: flood experience

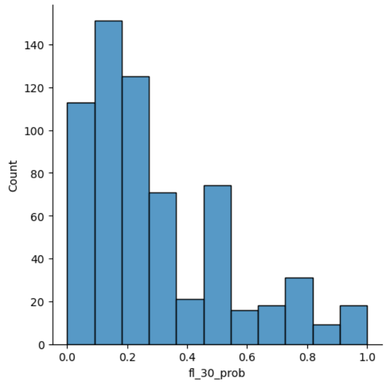

Figure A.2: flood probability 30 year

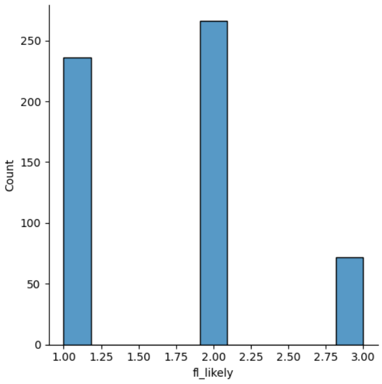

Figure A.3: flood likely

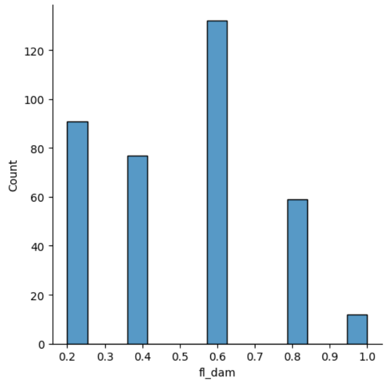

Figure A.4: flood damage

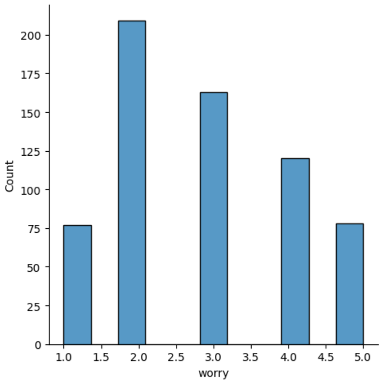

Figure A.5: worry

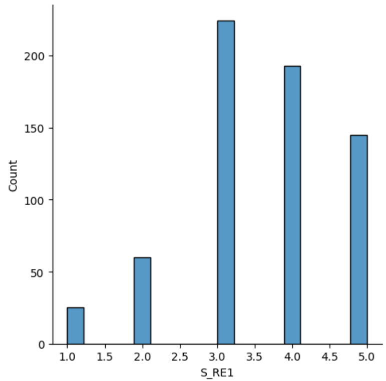

Figure A.6: response efficacy elevation

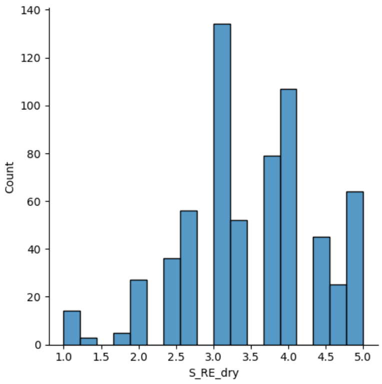

Figure A.7: response efficacy dry proofing

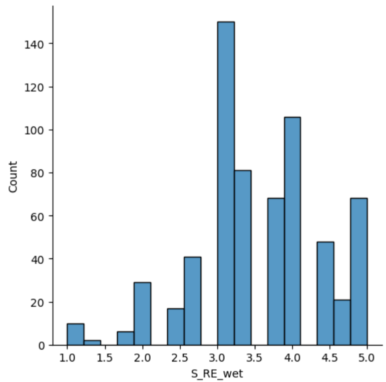

Figure A.8: response efficacy wet proofing

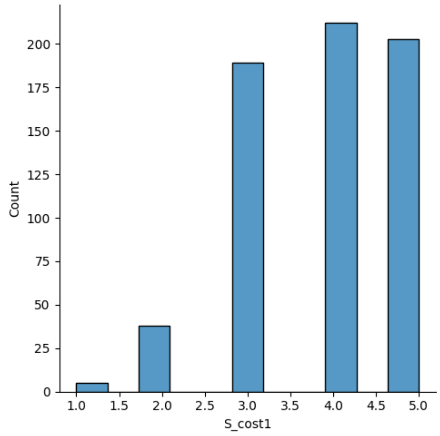

Figure A.9: perceived cost elevation

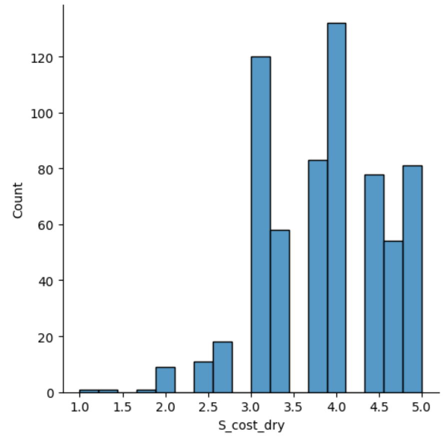

Figure A.10: perceived cost dry proofing

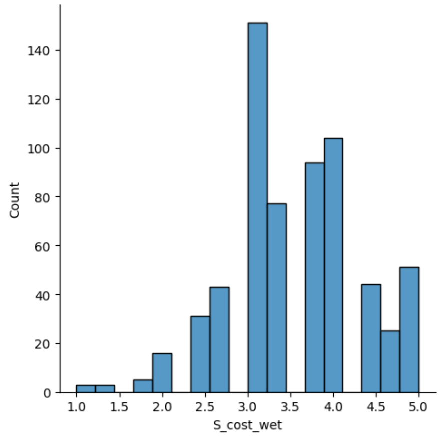

Figure A.11: perceived cost wet proofing

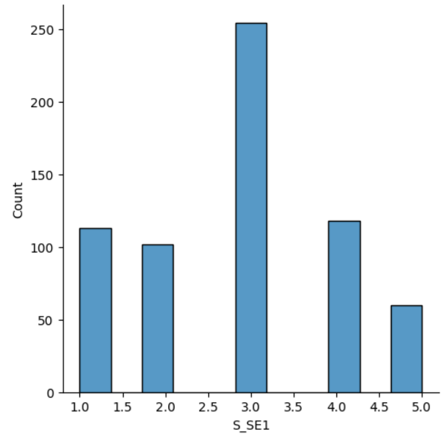

Figure A.12: self efficacy elevation

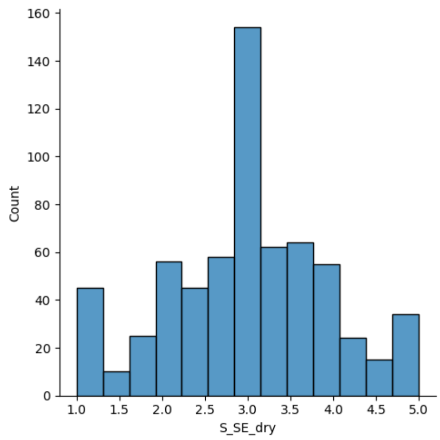

Figure A.13: self efficacy dry proofing

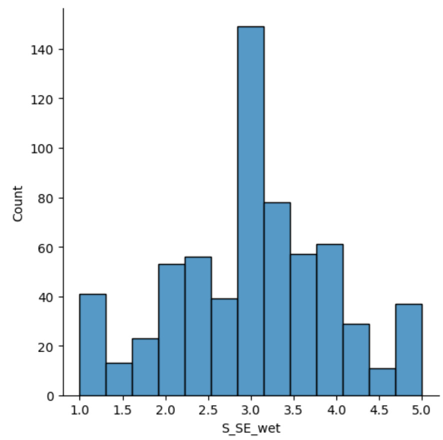

Figure A.14: self efficacy wet proofing

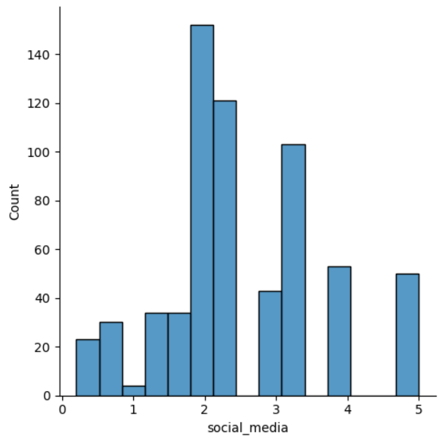

Figure A.15: social media

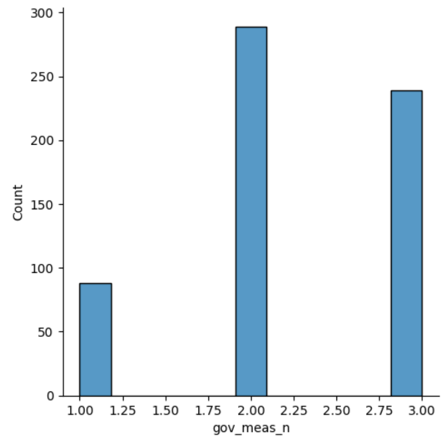

Figure A.16: trust public protection

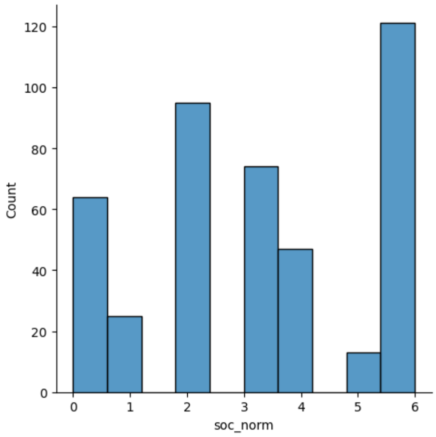

Figure A.17: social norm

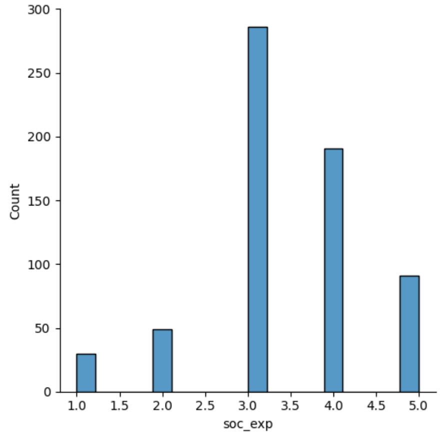

Figure A.18: social expectation

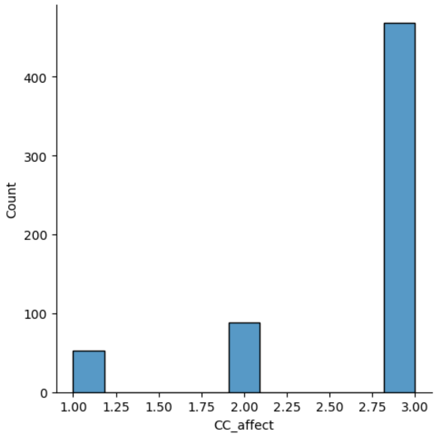

Figure A.19: Climate change belief

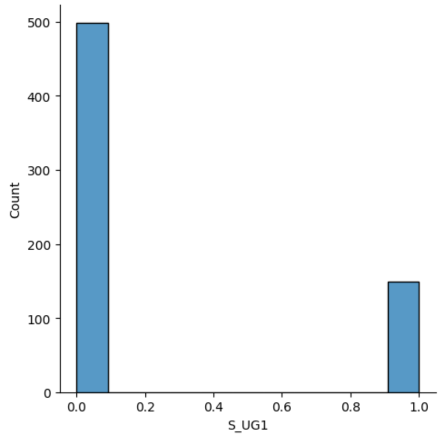

Figure A.20: undergone elevation

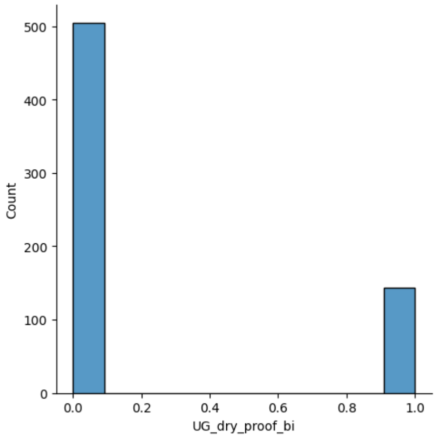

Figure A.21: Undergone dry proofing

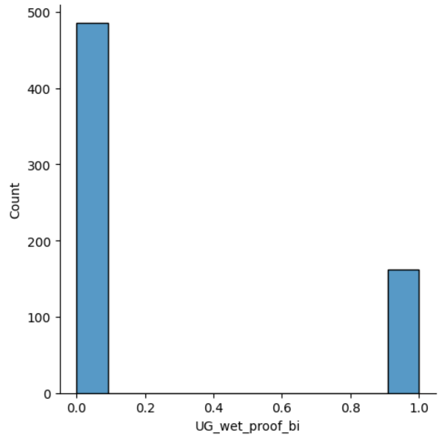

Figure A.22: Undergone wet proofing

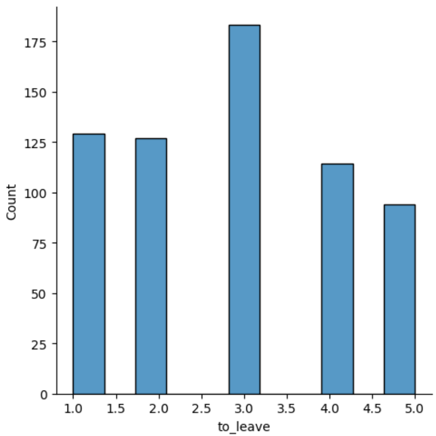

Figure A.23: to leave

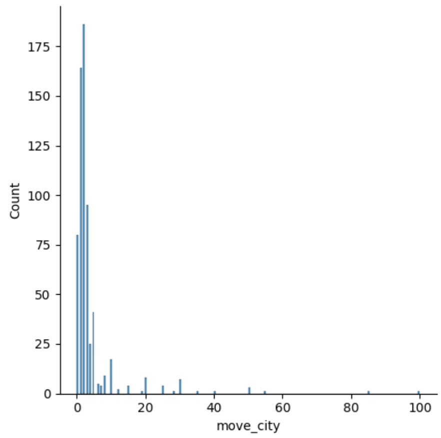

Figure A.24: move city

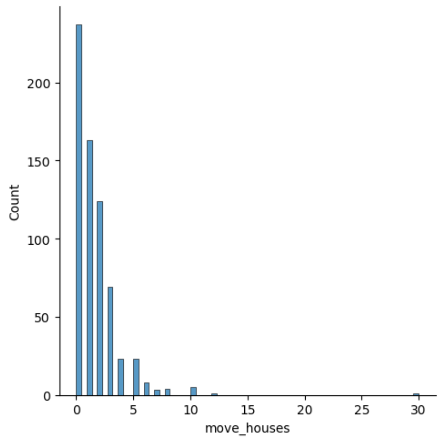

Figure A.25: move houses

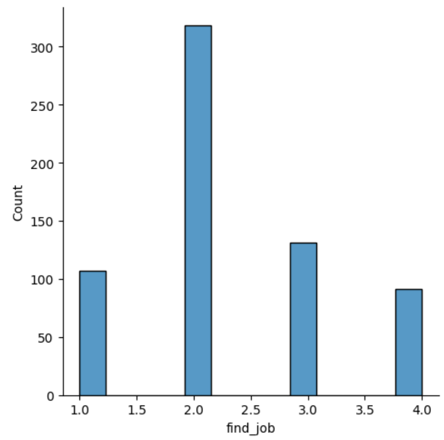

Figure A.26: find job

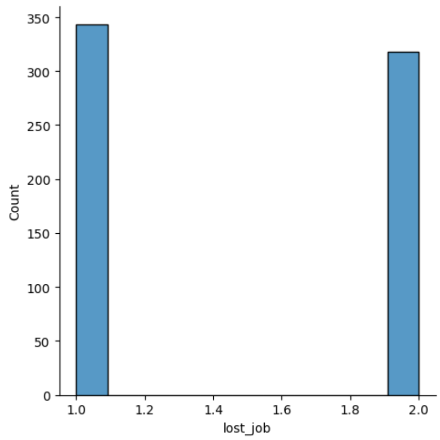

Figure A.27: lost job

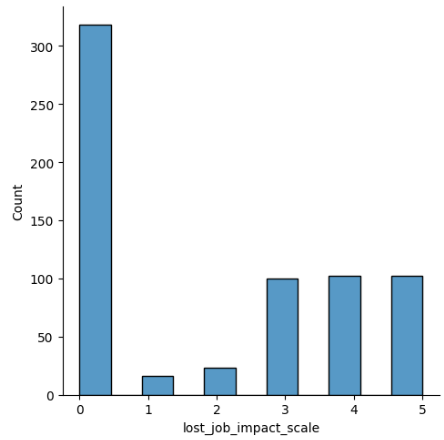

Figure A.28: lost job impact

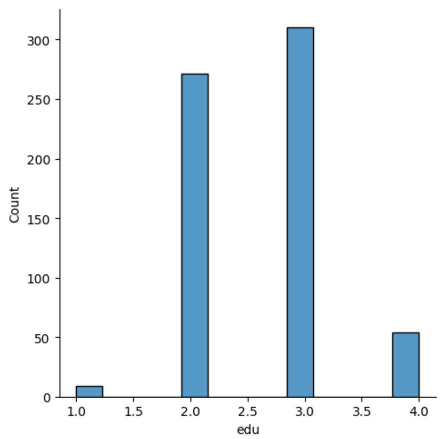

Figure A.29: education

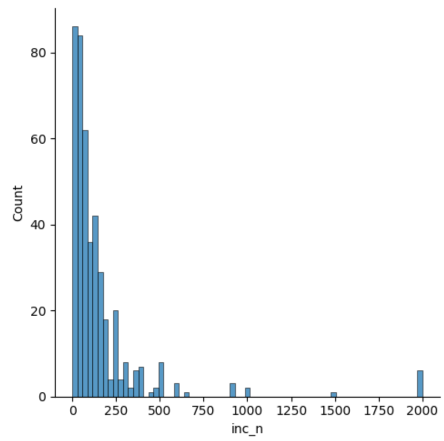

Figure A.30: income

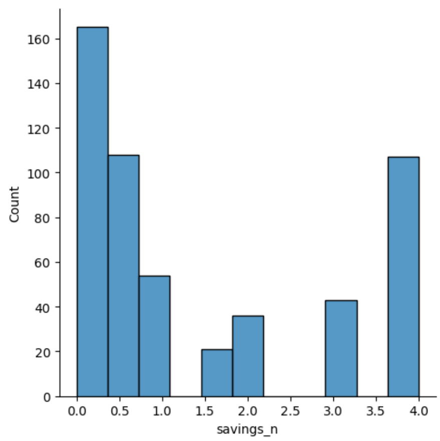

Figure A.31: savings

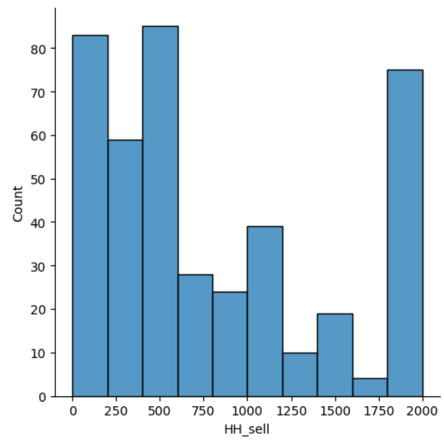

Figure A.32: house value

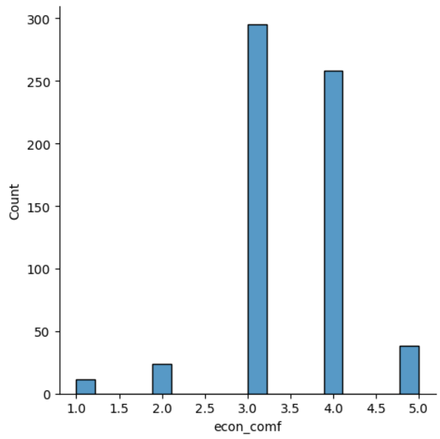

Figure A.33: economic comfort

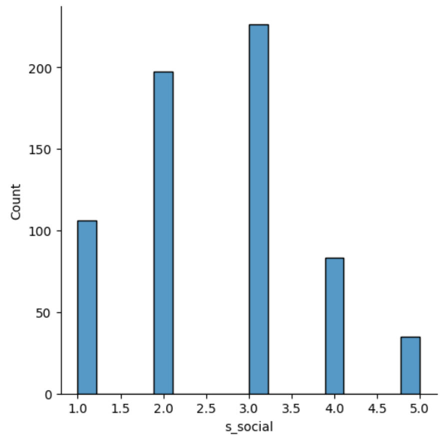

Figure A.34: social support

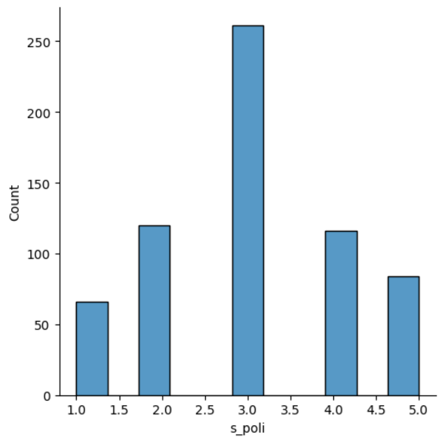

Figure A.35: government support

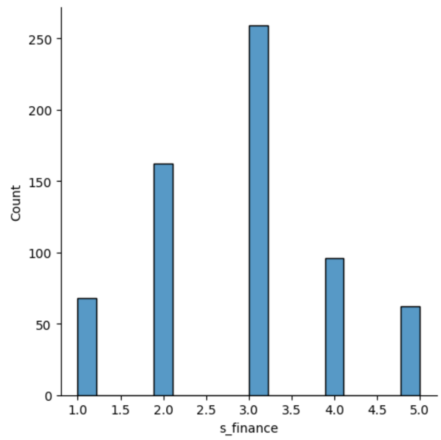

Figure A.36: financial support

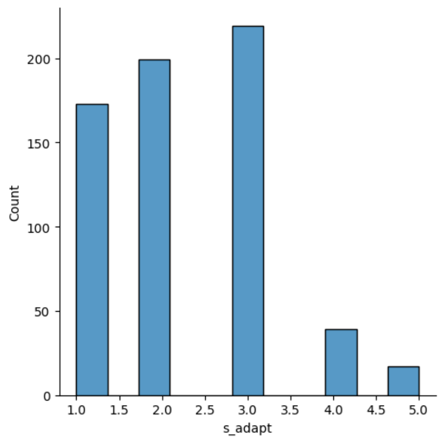

Figure A.37: household resilience

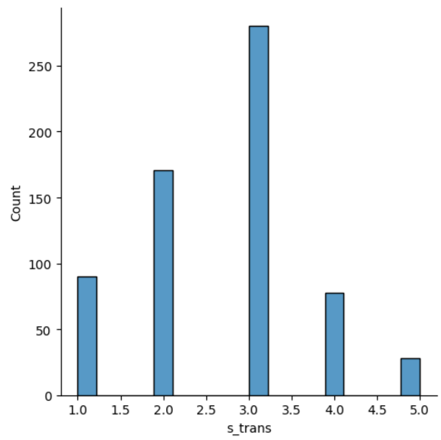

Figure A.38: saving flexibility

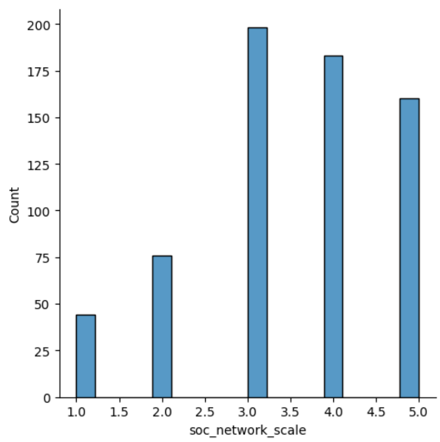

Figure A.39: social network

B

Logit analysis

First, the cleaned and filtered survey data for Jakarta (N=647), see 4.2.2 was loaded in Jupyter Notebook. Next two new variables were created, ”UG_dry_proof” and ”UG_wet_proof”. Undergone dry proofing consist of strengthen the housing foundation, reconstructing the walls or ground with water resistant materials and fixing water barriers. Undergone wet proofing consists of raising the electricity meter, installing anti-backflow valves on pipes and installing a pump system to drain water, see table 6.3.

```
df [ 'UG_dry_proof'] = df ['S_UG2'] + df ['S_UG3'] + df ['S_UG7']

df [ 'UG_wet_proof'] = df ['S_UG4'] + df ['S_UG5'] + df ['S_UG6']

df [ 'Int_dry_proof'] = df ['S_int2'] + df ['S_int3'] + df ['S_int7']

df [ 'Int_wet_proof'] = df ['S_int4'] + df ['S_int5'] + df ['S_int6']
```

As one of the identified adaptation measures for either dry proofing or wet proofing is taken, the value of undergone dry proofing or undergone wet proofing is set 1 (True). The same is done for the intention to dry proof (”Int_dry_proof”) and intention to wet proof (”Int_wet_proof”). This did not need to be done for elevation because it consisted of only 1 of Noll et al., 2021’s already defined adaptation actions.

```
df.loc[ df [ 'UG_dry_proof' ] == 0, 'UG_dry_proof_bi' ] = 0
df.loc[ df [ 'UG_wet_proof' ] == 0, 'UG_wet_proof_bi' ] = 0

df.loc[ df [ 'UG_dry_proof' ] != 0, 'UG_dry_proof_bi' ] = 1
df.loc[ df [ 'UG_wet_proof' ] != 0, 'UG_wet_proof_bi' ] = 1

df.loc[ df [ 'Int_dry_proof' ] == 0, 'Int_dry_proof_bi' ] = 0
df.loc[ df [ 'Int_wet_proof' ] == 0, 'Int_wet_proof_bi' ] = 0

df.loc[ df [ 'Int_dry_proof' ] != 0, 'Int_dry_proof_bi' ] = 1
df.loc[ df [ 'Int_wet_proof' ] != 0, 'Int_wet_proof_bi' ] = 1
```

For migration, the intention to migrate was measured through a choice-experiment of three flood damage scenario’s, in which respondents were asked to either adapt, do nothing or migrated. Therefore, each respondent has three different intentions to migrate, depending on the experienced flood damage.

Secondly, the correlations between the intention to adapt or migrate, the other undergone adaptation actions and the identified survey decision-making variables for that particular measure, were analysed to see what factors highly correlate with the intention. Factors with a high correlation are probably also going to have a high impact on intention.

Thirdly the Logit coeffients for all adaptation and migration intentions were calculated using statsmodels.formula.api.

Example elevation:

```
mod = smf.logit ( formula = str('S_int1 ~ fl_dam + fl_30_prob + worry + fl_dam * worry +
S_RE1 + S_SE1 + S_cost1 + fl_exp + soc_exp + soc_norm + UG_wet_proof_bi +
UG_dry_proof_bi + gov_meas_n + social_media + CC_affect'), data = model_vars_elev,).fit()

elev_params = mod.params
mod.summary()
```

Results:

	Elevation	Wet_proof	Dry_proof
Intercept	-0.510936	-1.846540	-0.963712
fl_dam	4.418653	5.752486	3.272715
fl_30_prob	-1.593110	-1.490752	-2.603203
worry	1.052746	1.630566	1.178203
fl_dam:worry	-1.500594	-2.077722	-1.055044
RE	-0.072515	0.256253	0.328397
SE	0.189438	0.138112	0.404549
PC	-0.266594	-0.478546	-0.668741
fl_exp	0.159769	0.653639	0.362707
soc_exp	0.066037	0.098983	0.167008
soc_norm	-0.085086	0.034060	0.070644
UG_wet_proof_bi	-1.216284	NaN	-0.899297
UG_dry_proof_bi	-0.814890	-0.241303	NaN
gov_meas_n	0.166529	0.145396	0.188099
social_media	0.182487	-0.137074	-0.132077
CC_affect	-0.629077	-0.462896	-0.360561
S_UG1	NaN	-0.348144	-0.687490

Figure B.1: Logit coeffients Adaptation

	Move_base	Move_medium_flood	Move_severe_flood
Intercept	-0.665873	-2.812244	0.701980
fl_likely	-0.045192	0.088265	0.404632
fl_30_prob	-1.274059	-0.583566	0.434107
S_UG1	-0.557153	-0.430340	-1.190090
UG_dry_proof_bi	0.546740	0.831272	0.790659
UG_wet_proof_bi	0.232280	0.372439	1.017381
move_houses	0.114402	0.147022	-0.071873
move_city	-0.121464	-0.059241	0.045847
soc_exp	-0.003209	0.093104	-0.273683
soc_norm	0.121767	-0.011669	0.225038
soc_network_scale	-0.010939	0.077301	-0.322306
find_job	0.084391	-0.077480	-0.245502
lost_job	-0.694280	0.109907	-0.376820
lost_job_impact_scale	0.049089	0.126922	-0.099150
to_leave	0.227974	0.239360	0.262516

Figure B.2: Logit coeffients Move

A negative coefficient means a negative relation towards the adaptation or migration action, whereas a positive coefficient stands for a positive relation between the agent attribute and the selected action. As the probability to move was measured by various choice experiments, three different probabilities to move are calculated. Depending on the amount of flood damage an agent experienced, the right probability is chosen: Move_base (0 up to 2 months of wages), Move_medium_flood (2 up to 4 months of income), Move_severe_flood (more than 4 months of income).

Lastly, the probability to take the action of all adaptation and migration actions are calculated using the Logit function. For each household, per action, the agent attribute value of all decision-making factors are multiplied by the Logit regression coeffients and summed up, see alpha. Next, alpha is filled in the logit-odd function. The output is the probability to undertaken an action for one household.

for i $\in$ [household_1, household_2, ... household_647]

for a$_i$ $\in$ [elevation, dry proofing, wet proofing, migration]

$$\alpha_a = (\beta_0 + \beta_1 \text{fl\_dam} + \beta_2 \text{worry} + ...\beta_{12} \text{CC\_affect}) \qquad \text{logit-odd}(\alpha_a) = \frac{\exp(\alpha_a)}{1+\exp(\alpha_a)} \tag{B.1}$$

To analyse the probability to action for all adaptation and migration action for the Jakarta population, the probabilities per action for all households were added to a list. The distribution of these lists is plotted below, representing the odds probability of the Jakarta population to take action.

adaptation **migration**

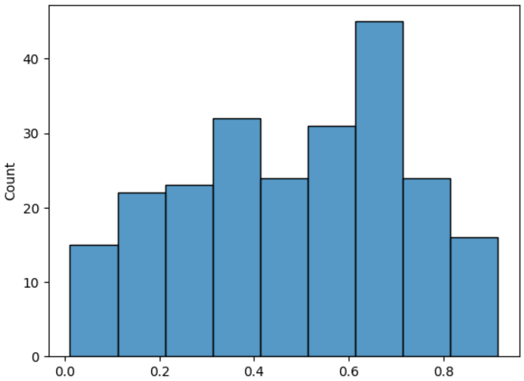

Figure B.3: p-list elevation

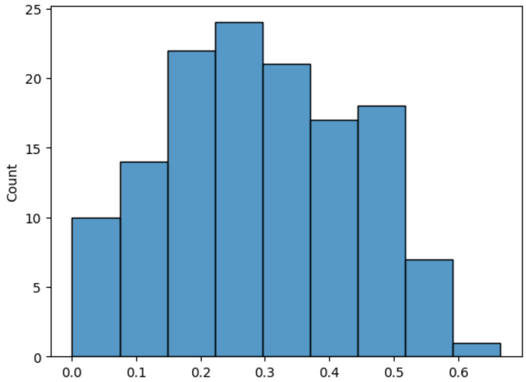

Figure B.4: p-list move base

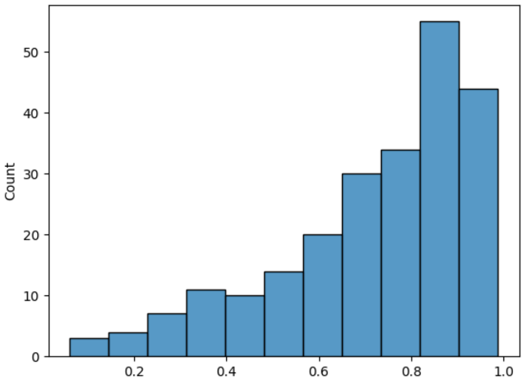

Figure B.5: p-list dry proofing

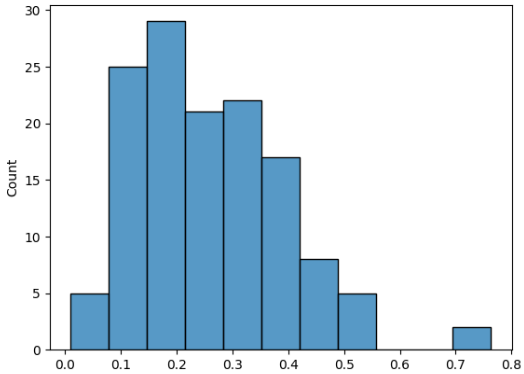

Figure B.6: p-list move medium

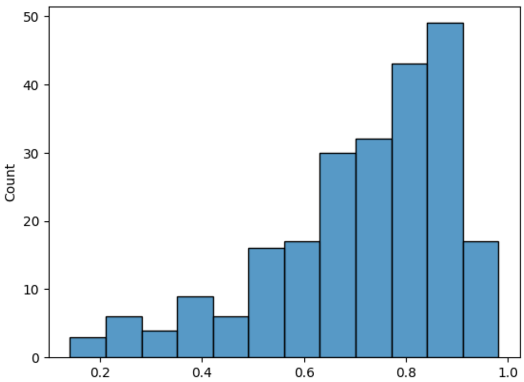

Figure B.7: p-list wet proofing

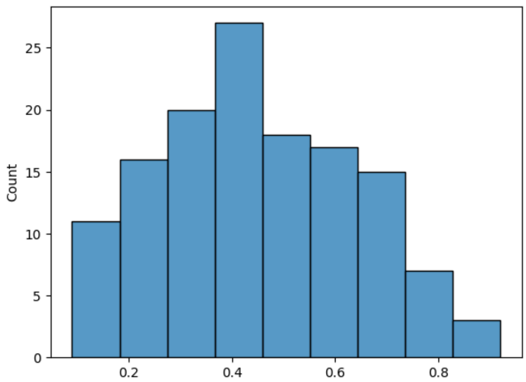

Figure B.8: p-list move severe

Looking at the adaptation actions, we see that distributions are left-skewed. Furthermore, the mean of the probability to elevate (0.49) lies lower than the probability to dry proof (0.72) or wet proof (0.71). Probability this is due to the higher perceived cost for elevation than for dry or wet proofing. The migration distribution are right-skewed. The mean of the probability to migration is the highest in the severe case (0.45), than base case (0.29) and medium severe case (0.26). Meaning with a lot of experienced flood damage, households have a higher intention to migrate compared to the base case with little or no damage, but lowest in case of medium flood damage.

C
Experimental results

C.1. Experiments

In this section, all KPI's per experiment are reported. Each sample is run a hundred times, of which the **mean** is presented. In total 22 experiments were performed; 13 policy strategy scenario's and 9 sensitivity analysis runs.

C.1.1. Experiment 1 - No policy measures

Table C.1: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	8386327.72	0.513714	0.697685	0.827559	0.735360
2	11234503.42	0.509603	0.692392	0.819609	0.687130
3	18843555.25	0.499799	0.670802	0.803657	0.571892

Table C.2: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.258776	2.907614	3.045861	26.609081	0.769066
2	2.228336	2.923313	3.050933	24.374193	0.940498
3	2.145014	2.963859	3.058263	21.009439	1.239441

C.1.2. Experiment 2 - Public protection: most flood prone

Table C.3: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	7123493.41	0.514770	0.703527	0.830020	0.752063
2	8939687.99	0.513819	0.689257	0.822401	0.721667
3	17252432.41	0.501713	0.662236	0.801310	0.573950

Table C.4: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.261531	2.902685	3.052219	27.029108	0.707111
2	2.256254	2.913593	3.052441	25.339060	0.797489
3	2.143647	2.962705	3.058745	20.605278	1.210638

C.1.3. Experiment 3 - Public protection: gigantic seawall

Table C.5: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	0.00	0.41488	0.65878	0.71895	0.31855
2	0.00	0.41494	0.65875	0.71890	0.31831
3	0.00	0.41493	0.65850	0.71866	0.31856

Table C.6: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	3.139757	3.042694	3.022584	0.000000	1.616765
2	3.139987	3.042714	3.022701	0.000000	1.617356
3	3.139590	3.042750	3.022637	0.000000	1.616840

C.1.4. Experiment 4 - Public protection: equal protection

Table C.7: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	2699065.75	0.532113	0.757150	0.857814	0.817823
2	3468199.27	0.530819	0.754335	0.855352	0.806397
3	5837400.33	0.528266	0.743091	0.849501	0.775048

Table C.8: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.403664	2.834243	3.034608	25.743498	0.818599
2	2.351480	2.843141	3.030784	25.258249	0.852953
3	2.239343	2.869170	3.035338	24.091498	0.963486

C.1.5. Experiment 5 - Job offer migration

Table C.9: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	6538735.11	0.598868	0.790200	0.877278	0.781519
2	9015610.82	0.591203	0.784193	0.871881	0.734832
3	16283908.55	0.578397	0.766748	0.861397	0.616420

Table C.10: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.329705	2.858258	3.040818	24.758292	0.901849
2	2.257854	2.880779	3.043826	22.645516	1.093079
3	2.148839	2.937809	3.057847	19.384120	1.444255

C.1.6. Experiment 6 - Subsidy: adaptation

Table C.11: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	7705547.25	0.494234	0.668861	0.806466	0.768498
2	10064154.39	0.491782	0.664154	0.800410	0.735977
3	16087005.34	0.485827	0.649010	0.787659	0.653830

Table C.12: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.230808	2.903483	3.055080	26.903678	0.713382
2	2.203990	2.910321	3.059165	25.210111	0.840124
3	2.133400	2.944635	3.072922	22.154197	1.100613

C.1.7. Experiment 7 - Subsidy: migration

Table C.13: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	8274629.46	0.517564	0.700521	0.830287	0.736105
2	11066115.79	0.512980	0.694604	0.821982	0.689166
3	18514970.35	0.502414	0.672318	0.805729	0.577500

Table C.14: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.265810	2.908573	3.046347	26.445319	0.780652
2	2.233590	2.923609	3.050905	24.286327	0.946359
3	2.146287	2.962858	3.059267	21.018437	1.235914

C.1.8. Experiment 8 - Education: flood risk

Table C.15: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	7697094.02	0.542612	0.720848	0.855619	0.747129
2	10422418.21	0.537244	0.715283	0.848816	0.698485
3	18025230.28	0.524881	0.691726	0.835065	0.579447

Table C.16: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.204722	2.893802	3.043233	26.338950	0.817378
2	2.182686	2.913856	3.048859	24.019255	0.997917
3	2.128182	2.961562	3.058606	20.588906	1.311842

C.1.9. Experiment 9 - Education: adaptation

Table C.17: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	7974967.13	0.516005	0.721141	0.841261	0.743905
2	10790526.11	0.511729	0.715218	0.832855	0.694535
3	18400230.57	0.501586	0.693735	0.816428	0.577913

Table C.18: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.261154	2.897398	3.044532	26.421069	0.785529
2	2.228656	2.916992	3.049573	24.092790	0.964164
3	2.144468	2.961419	3.058440	20.707819	1.270064

C.1.10. Experiment 10 - All public protection + others

Table C.19: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	0.0	0.514970	0.864803	0.847141	0.354367
2	0.0	0.515053	0.864754	0.847149	0.354156
3	0.0	0.514973	0.864836	0.847168	0.354308

Table C.20: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	3.021871	3.047587	3.021397	0.0	2.150976
2	3.021861	3.047597	3.021227	0.0	2.151124
3	3.021881	3.047643	3.021023	0.0	2.151159

C.1.11. Experiment 11 - Public protection: most flood prone + others

Table C.21: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	4516057.38	0.627494	0.803643	0.893595	0.828212
2	5652590.18	0.626558	0.795909	0.890539	0.811888
3	11606729.36	0.608788	0.782787	0.880985	0.700245

Table C.22: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.265738	2.821386	3.043818	24.923601	0.855618
2	2.231398	2.827021	3.042254	23.864065	0.920142
3	2.124841	2.912771	3.072458	19.631632	1.375681

C.1.12. Experiment 12 - Public protection: gigantic seawall + others

Table C.23: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	0.00	0.514984	0.864851	0.847154	0.354258
2	0.00	0.515064	0.864781	0.847128	0.354259
3	746256.24	0.522586	0.865447	0.853731	0.388536

Table C.24: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	3.021861	3.047641	3.021157	0.000000	2.151196
2	3.021850	3.047746	3.021304	0.000000	2.151283
3	3.001038	3.045059	3.026085	0.211406	2.149107

C.1.13. Experiment 13 - Public protection: equal protection + others

Table C.25: Flood damage and adaptation actions

scenario	flood damage	% elevation	% dry proofing	% wet proofing	% migration
1	1746959.65	0.638204	0.838831	0.920785	0.875616
2	2224853.65	0.636898	0.836868	0.920046	0.869795
3	3799416.36	0.633803	0.829035	0.918125	0.842802

Table C.26: 5 capitals of resilience

scenario	Human capital	Financial capital	Social capital	Nature capital	Physical capital
1	2.352010	2.788493	3.029946	23.584065	1.032348
2	2.313271	2.794913	3.030622	23.308269	1.058710
3	2.218058	2.816638	3.032888	22.569896	1.172063